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Modelling relationships between road access and recreational fishing site choice while accounting for spatial complexities

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by

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Abstract

This study examined the relationships between road access and the fishing site choices of northern Ontario recreational anglers. A revealed preference choice model (random utility model) was estimated with fishing trip data from an angling diary with resident anglers from the Thunder Bay and Wawa areas. The results showed that poor quality gravel roads and trails heavily and negatively impacted fishing site choices by Thunder Bay anglers who fished only during the open water season. Poorer quality roads and trails had much less impact on the fishing site choices of other Thunder Bay anglers. Wawa area anglers were, on average, less impacted by poor quality roads and trails than were Thunder Bay area anglers.

Several methods of incorporating spatial complexities into the fishing site choice models were also investigated. First, an accessibility attribute was included in the models to account for potential spatial cognitive limitations of anglers when choosing fishing sites. While this attribute had a significant effect in the models, the effect was different for Thunder Bay and Wawa area anglers. A second spatial measure focused on whether anglers took fishing trips near their previously chosen fishing sites. Anglers often took fishing trips back to the fishing sites they previously chose. Thunder Bay area anglers also tended to take fishing trips that were close to their previously chosen fishing site. Finally, various generalized extreme value models were used to determine if nearby sites have correlated unobserved utilities. Results from a cross-nested logit model, which permit researchers to allocate fishing alternatives into more than one nest, showed that spatially near fishing alternatives shared some unobserved utility. Therefore, nearby fishing sites were better substitutes than were far away fishing sites. Generalized nested logit models were estimated to assess whether one global parameter could capture the correlation pattern among the unobserved utilities for the fishing sites. A global parameter was rejected in favour of nest specific parameters. While not truly a local level analysis, the generalized nested logit model

was sufficient to capture some spatial heterogeneity present in the correlations among the unobserved utilities.

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I thank the Living Legacy Trust, Ontario Ministry of Natural Resources, Ontario Federation of Anglers and Hunters, Northwestern Ontario Sportsmen's Alliance, and Northern Ontario Tourist Outfitters Association for supporting this research. I hope that this research and subsequent products from the research will provide your staff and members with important information for managing our natural resources. Finally, I thank Sarah Browne, Jeff Moore, and Mandie Ross for their assistance with the collection and assimilation of data.

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Chapter 1: Relevance of recreational fishing site choice information to resource managers

Resource management often involves wicked problems that are characterized by complexity, change, uncertainty and conflict (Mitchell, 2000). Science may assist in dealing with these problems by providing information that enables decision-makers to devise possible solutions and to test the effectiveness of such solutions in empirical settings. Unlike natural science information, social science information often is absent or is rarely present in a form that directly supports the needs of resource managers.

One area where resource management decision-makers require additional social science information is outdoor recreation. Many individuals enjoy conducting various recreational activities in a diversity of settings. Within Canada's managed forests, there is little guidance provided to decision-makers about the effects that different management actions may have on the spatial pattern of recreational participation and the value of recreational activities. Decision-makers, therefore, make decisions without the benefit of information that could help to mitigate conflicts among competing forest users.

Recreational fishing is among the most popular outdoor recreation activities. In 1996, about 4.2 million Canadians over the age of 15 participated in recreational fishing (DuWors *et al.*, 1999). Given this popularity, it is not surprising that many research studies have examined recreational fishing. While these studies provide information on many topics, the research to date has given little if any meaningful attention to the importance of road accessibility and road quality on recreational fishing. This void is surprising since some important Canadian fishing sites are only accessible through logging road networks that vary greatly in their quality.

This dissertation examines the seemingly simple topic of understanding the relationships between road access and the fishing site choices made by northern Ontario resident anglers. As well, the study hopes to provide information to resource management decision-makers on how changes to the quality and presence of road access are likely to affect the spatial distribution of angling effort and the economic value of angling.

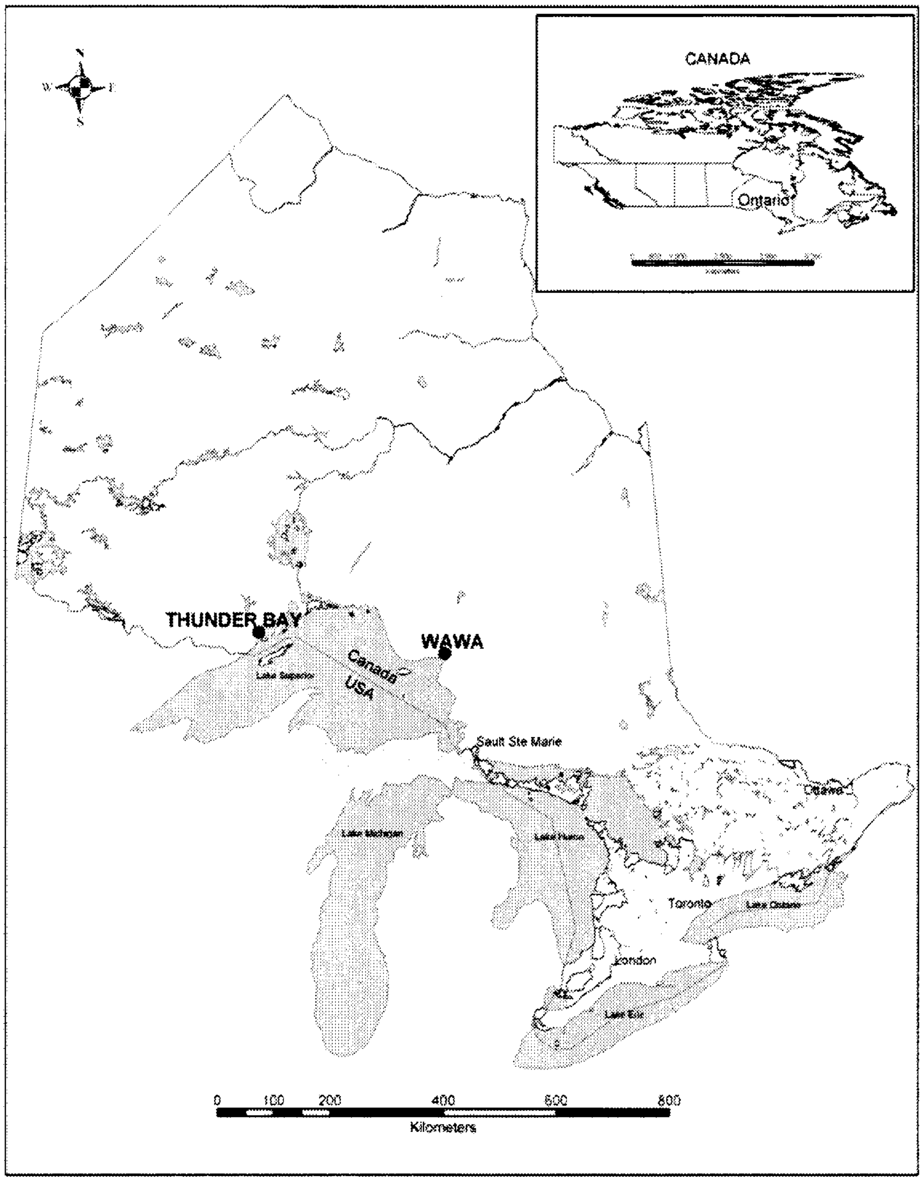
The study focuses on the open water fishing site choices made by residents of the Wawa and Thunder Bay areas (see Figure 1.1.1). The narrowed focus on open water resident fishing is necessitated by project funding and is supported by the greater popularity for open water than ice fishing among most northern Ontario anglers. The use of two study areas permits one to assess the consistency of results in these two very different communities. If the results are consistent, this may offer an opportunity to transfer the research findings to other northern Ontario jurisdictions. Before explaining the organization of the dissertation, two sections focus on the managerial significance of the research and the potential distortions of space on recreational fishing site choice models, respectively.

1.1: Management context for research

Road access is an especially important resource management issue in northern Ontario. The development of road networks for forest harvesting provides vehicular access that individuals use to arrive at many Crown land (i.e., public) fishing sites in northern Ontario.

Many natural science researchers are concerned about the negative effects that road networks may have on ecosystem health. One concern is forest fragmentation that occurs when road networks divide forests and increase the amount of forest edges. Another concern arises indirectly from the presence of roads. Road networks provide a vector that outdoor recreationists can use to exploit fish and wildlife populations. In Ontario, studies have suggested that the construction of forest harvesting roads may lead to collapses of small lake trout (*Salvelinus namaycush*) fisheries (Gunn, & Sein, 2000) and to reductions in moose (*Alces alces*) populations (Rempel, Elkie, Rodgers, & Gluck, 1997). Additional work by fisheries biologists in Canada suggests that access, travel distance and population are very important determinants of the health of fisheries (Cox, & Walters, 2002; Post *et al.*, 2002; Walters, & Cox, 1999). These concerns lead some to suggest that forest managers and planners should actively decommission road networks after completing forest harvesting operations.

Figure 1.1.1: Northern Ontario study areas



Maintenance of road access is also being questioned on economic grounds. Road maintenance costs may be quite prohibitive in areas without active forest harvesting operations. The sustainable forest licence holder (i.e., the forestry company) often pays for road maintenance.

The government and the forest industry are also concerned about the liability associated with the maintenance of road networks, particularly at water crossings. Finally, the resource-based tourist industry has concerns that road access into areas with tourism may lead to exploitation of fauna and to conflicts between road-based recreationists and resource-based tourists (Haider, & Hunt, 1997; Hunt, Haider, & Johnson, 2000; McKercher, 1992).

These economic and ecological concerns have convinced some resource management decision-makers to employ road management strategies that accelerate the natural deterioration of roads. Discussions related to road management strategies rarely involve any formal accounting for the recreational values that flow from the provision of roaded environments. Instead, recreational values enter the decision-making framework through stakeholder input and public protests of draft decisions. The management decisions often become highly politicized without information on recreational values.

While a study of angling cannot provide information on all values that recreationists obtain from roads, the study would provide resource management decision-makers with much needed information about the consequences of road abandonment on recreational fishing. The study would also assist the Ontario Ministry of Natural Resources (OMNR) and forest stakeholders in many other ways. An examination of the benefits that Crown land anglers derive from road access would help to meet legal obligations of the Ontario Ministry of Natural Resources. For example, one of the two principles of the Crown Forest Sustainability Act (Ontario Government, 1994, c. 25, s. 2(3)) is:

> The long term health and vigour of Crown forests should be provided for by using forest practices that, within the limits of silvicultural requirements, emulate natural disturbances and landscape patterns while minimizing adverse effects on plant life, animal life, water, soil, air and social and economic values, including **recreational values** and heritage values.

The act requires information on recreational values (emphasis added) such as angling that is not formally measured in current forest management planning efforts. The principle also requires planners to consider the impacts of road abandonment strategies (i.e., emulating natural disturbance and landscape patterns) on recreational values such as angling.

The Forest Class Environmental Assessment (Forest Class EA) (OMNR, 2002) also provides guidance for conducting the research. Several terms and conditions discuss the needs for better social and economic information. Specifically, term and condition 12 (OMNR, 2002, emphasis added) states:

> The Forest Management Planning Manual shall contain requirements for corridor planning for new primary roads (i.e., any road that provides principal access for the management unit) and branch roads (i.e., any road that branches off an existing or new primary or branch road, including those roads that provide access to separate areas of operations). The requirements shall include the following planning provisions for the preparation of the Forest Management Plan for the ten year period.
>
> (c) In identifying a reasonable range of practical alternative primary road corridors for analysis, there shall be consideration of the degree to which the physical conditions, **non-timber values**, and significant engineering or safety factors in the area act as constraints or provide opportunities.
>
> (d) The environmental analysis of the practical alternative primary road corridors shall consist of:
> (i) an assessment of the advantages and disadvantages of:
> • potential effects on **non-timber values**; and

As well, term and condition 46 (OMNR, 2002) states:

> MNR shall continue to maintain and further develop methodologies for use in forest management planning which:
>
> (a) address social and economic considerations when developing prescriptions and making forest management decisions;

Socio-economic tools are required in forest management and managers must make reasonable efforts to enumerate the potential benefits and costs on activities like recreational fishing associated with new road access. This research on resident angling and road access may provide information on how changes to road networks may affect where people fish and how they value recreational fishing.

Finally, the Forest Class EA (term and condition 31) requires research on the effectiveness of forest management guidelines including guidelines relating to tourism (Forest Management

Branch, 2001). The tourism guidelines discuss many strategies to mitigate road access concerns for the tourist industry. This study can assess the effectiveness of physical tools and techniques such as natural abandonment strategies for limiting the number of recreationists using these roads to access lakes with tourist sites.

Besides meeting legal obligations, this study may provide other needed information to OMNR. The development of a predictive model could illustrate the likely consequences that changes to road systems may have on the spatial pattern of angling effort. Such a model may identify ways to reshape angling effort into managerially desirable areas without adding new regulations on existing angling behaviours. This carrot or rewards based management approach would likely increase the trust and co-operation between OMNR and angling stakeholders, require no new funds for enforcement, and not affect the number of licenced anglers that help fund fish and wildlife management programs. The use of rewards in addition to restrictions would represent a fundamental shift in the management of road access. As such, managers and planners could carefully choose the enhancements to offset losses to resident anglers resulting from necessary road access restrictions.

A study on angling and road access would also benefit many other forest stakeholders. The results of this study could demonstrate how the maintenance of logging roads by the forest industry provides measurable benefits to anglers. The forest industry could use this information to demonstrate how their management actions provide tangible benefits to northern Ontario anglers. This study could also benefit stakeholders that represent recreational anglers and hunters and tourist operators. The information provided by the study may permit resource management decision-makers to develop creative management solutions that respect tourist industry interests without adversely affecting resident anglers' experiences or opportunities.

1.2: Potential effects of space on recreational fishing site choices

Any attempt to understand the relationships between road access and recreational fishing requires some effort to account for the effects of other factors that also lead anglers to choose fishing sites. Rather than simply accounting for these other factors, this dissertation attempts to understand the behavioural process that anglers use to select fishing sites. This focus on the behavioural process allows the dissertation to provide a much fuller description of recreational fishing site choice than would a simple study of road access and recreational fishing. In particular, the models developed in this dissertation permit users to forecast the effects of many changes to resources or management of resources (including changes to road access) on the spatial pattern of recreational fishing site choices.

The development of a forecasting model that attempts to understand the behavioural process that anglers use when selecting fishing sites should not ignore the role of space. As is discussed more fully in Chapter 2, space has the potential to complicate the behavioural choice processes. Without accounting for these spatial complexities, forecasts of fishing site choices will likely be misspecified. This misspecification may hide the true effect of space especially when anglers decide to substitute their choices among fishing sites. This substitution information is paramount to decision-makers who must make sense of how changes to some fishing sites are likely going to impact use at other fishing sites.

This dissertation is committed to identify an approach that can incorporate spatial complexities into a study of fishing site choice. This commitment will involve adopting a new modelling approach that while consistent with theories of behavioural choice, will provide great latitude to capture general and more local-like effects of space than have previous studies that employed various spatial choice models.

1.3: Organization of dissertation

The dissertation is structured to discuss the modelling approach, data collection, results and management implications of the results. The study employs a choice modelling framework that Chapter 2 explains in detail. The chapter also discusses many choice model developments that have greatly increased the generality of these models. These choice model generalizations free researchers from potentially restrictive and unrealistic assumptions about substitution patterns among fishing sites, preference homogeneity among anglers, and dynamic like effects among past and present fishing site choices.

Chapter 2 also provides much background information about spatial data properties that may complicate spatial choice models. Although some geographers abandoned early choice models because of their inability to account for space (see Pellegrini, & Fotheringham (2002) for a review), I believe that the choice model generalizations are now sufficient to account for the complexity of space.

The third chapter reviews some approaches that researchers have used to account for preference heterogeneity, participation decisions, and dynamic like effects in choice models. These issues are important to consider for a model of fishing site choices by northern Ontario anglers. The third chapter also identifies those attributes that are likely important to a northern Ontario angler when choosing a fishing site. These attributes and their expected relationships to choice are drawn from past studies of fishing site choice.

The data collection methods are found in Chapter 4. Field crews helped to collect data on the location of available fishing sites around the Thunder Bay and Wawa areas. The field inspections also afforded an opportunity to collect information on many potentially salient site attributes related to fishing site choice. The chapter also discusses the development and use of an angling diary that provided information about the choices of fishing sites by anglers from these two study areas.

Chapter 5 highlights many basic findings. These findings are drawn from qualitative interviews conducted with resident anglers, questions asked to anglers during recruitment into the diary program, and questions within the dairies distributed to anglers. Many results highlight the different general or trip specific contexts that anglers face when making choices about fishing.

The sixth chapter documents the methods and assumptions used to estimate the fishing site choice models. The chapter also presents some basic statistics related to potentially relevant attributes used to estimate the fishing site choice models.

The results are presented in the seventh chapter. Efforts are also made to validate the models by using some data that was withheld from the model estimation. Scenarios that demonstrate the benefits of more complex approaches to estimate site choice highlight the managerial usefulness of the results. The final chapter summarizes the managerial and academic contributions of the dissertation.

Chapter 2: Space and choice modelling[1]

Space has the potential to influence choices made by individuals for decisions such as recreational fishing site choice. These influences may arise from relationships among decision-makers, from differing levels of substitutability among fishing site alternatives and from an angler's cognition of fishing sites. As such, models that do not formally account for the role of space may paint an incomplete portrait of choice behaviours, and, forecasts from such models may be highly inaccurate. For these reasons, this dissertation attempts formally to account for spatial complexities in fishing site choice models.

Several sections that provide necessary background information related to space, choice and spatial choice divide this chapter. The next section provides a basic overview of space and discusses how spatial complexities affect data analyses. Section two introduces readers to choice models. Section three discusses increasing generalizations to the family of choice models. The issue of choice sets is described in the fourth section. The fifth section reviews choice model applications that account for space. Finally, in section six, the chapter summarizes likely fruitful paths for researchers to incorporate the complexity of space into choice models.

In many instances, this chapter adjusts the notation of equations from the cited literature. While this adjustment may cause some grief to readers who are intimately familiar with the specific literature, the adjustment enhances the comparability between the different approaches presented below.

2.1: Spatial data and complexities introduced in spatial data analysis

All data sets consist of observations and variables that provide measures linked to the observations. In the spatial context, observations are physical areas, or in rare instances true lines or points, that researchers or others typically aggregate. The size, number and location of spatial observations provide important information related to spatial structure (Fotheringham, 1981).

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[1] Much of this chapter is similar to the review article produced by Hunt, Boots and Kanaroglou (2004).

Of interest to geographers is the fact that spatial observations and/or variables linked to these observations may be non-randomly distributed over space. While individuals may be able to discover non-random patterns in spatial data, the source of the pattern is not obvious. A spatial pattern may arise from a substantive spatial process or from a nuisance effect that arises from measurement errors, aggregation, and/or model misspecification (Anselin, & Rey, 1991).

Substantive spatial processes include diffusion, exchange and transfer, interaction, and dispersal (Haining, 1990, p. 24-25). Diffusion occurs when part of a population adopts some aspect (e.g., product, technology, etc.). Exchange and transfer relate to the commodity exchanges between individuals or other economic agents. Interaction occurs when the events at one location influence the events at another location. Finally, dispersal occurs when populations with particular characteristics disperse. Although having different causes, the effect of these spatial processes on a data generating process may be indistinguishable (Haining, 1990, p. 25).

Regardless of its cause, a spatial pattern may exhibit constancy (i.e., stationarity) or variability over a study area. If a pattern is constant over space, researchers can model the pattern with one or more global spatial parameters. If the pattern exhibits variability (i.e., spatial heterogeneity), the use of global spatial parameters may be highly misleading. In these instances, researchers should employ approaches that allow parameters to vary over space (e.g., local level analyses).

Space also contains three properties that greatly complicate analyses aimed at identifying and modelling spatial effects. First, space is multidimensional whereby observations may be oriented in two or three dimensions. Second, spatial observations are arbitrary since they are aggregates that do not have common metrics like hours, days and years as do temporal observations. Finally, spatial observations lack predeterminedness whereby dependence among values of observations follows a progression (e.g., past observations are assumed to affect future observations, but not vice versa). These multidimensionality, arbitrariness, and indeterminacy properties all make the analysis of spatial data much more complex than the analysis of temporal data. These properties also produce three issues that may each greatly complicate analyses designed to examine the role of space.

2.1.1: Spatial connectivity

To assess or to model spatial effects among observations, one needs to specify whether and to what extent observations are spatially connected. This connectivity structure may be implicit (e.g., regional based analyses) or it may be explicitly part of a model. In some cases, researchers may model the connectivity structure of the observations based on a geostatistical approach that models the covariance between observations as some function of distance[2]. In other instances, researchers *a priori* specify a connectivity structure and use this structure to estimate spatial parameters (i.e., the lattice approach).

The *a priori* specification of the connectivity structure is typically termed a spatial weights matrix. This spatial weights matrix identifies the connectivity weight, if any, between pairs of observations. Researchers may choose from three general approaches to identify connected neighbours. First, one can simply specify the number (k) of spatial neighbours for each observation (e.g., k nearest neighbours). Second, one could identify neighbours as those observations that share contiguous borders with a given observation. Third, one could identify neighbours as those observations that fall within a prespecified distance surrounding a given observation. This distance band may be measured in different metrics (e.g., Euclidean, driving distance, etc.) and the distance band may vary by direction (e.g., administrative and/or physical barriers may truncate the distance band).

After identifying the neighbours, a researcher must determine the spatial weights for these neighbours. At one extreme, a researcher could specify identical weights for all neighbours. At another extreme, researchers may set the weight for each neighbour to account for the physical closeness of the neighbours to the observation in question. Past approaches for measuring

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[2] Getis and Aldstadt (2004) also describe an approach for spatial connectivity that abandons the assumption that spatial effects are global.

physical closeness include: inverse distance to a power; negative exponential distance to a power; and length of common border compared to perimeter (Haining, 1990, p.74). More recent applications borrow from geostatistics and use negative exponential, Gaussian and spherical distributions (Dubin, 1998).

Another decision that researchers must consider is whether to adjust the spatial weights matrix to account for differing numbers and weights assigned for each observation. Tiefelsdorf (2000, p.29-31) describes three different methods to adjust the spatial weights[3]. First, a globally standardized coding scheme or C-coding scheme simply ensures that the spatial weights matrix sums to the number of observations. A row-sum standardized or W-coding scheme normalizes the sum of weights associated with each observation to equal one. While there is no statistical necessity for this row standardization, the method does facilitate the interpretation of any parameter estimate associated with the spatial weights matrix (Cliff, & Ord, 1973, p.90). Finally, Tiefelsdorf, Griffith, and Boots (1998) introduce the variance stabilizing S-coding scheme. This S-coding scheme employs a row standardization that depends on the square root of the sum of squared weights for each row. A second transformation step is also required to scale the values of the new matrix by the normalization used for the C-coding scheme. The S-coding scheme provides a middle point between the C and W coding schemes. Although the S-coding scheme down weights the overall contribution of observations with many weights, it does not provide the same leverage to observations with few neighbours as does the W-coding scheme.

Clearly, all three properties of spatial data lead researchers to make many arbitrary decisions when specifying the spatial weights matrix. In fact, Griffith (1996, p.65) notes that the construction of spatial weights matrices "… mostly is done in an *ad hoc* manner, and seems to be

---

[3] Bolduc, Dagenais, and Gaudry (1989) describe another normalization that retains the symmetry of the spatial weights matrix. This approach divides each weight by the product of the square roots of the row and column sums.

governed primarily by convenience and/or convention". For this reason, a few researchers[4] (Florax, & Rey, 1995; Griffith 1996; Stetzer, 1982) have investigated the consequences of misspecification of the spatial weights matrix on mean response, variance and spatial parameters. This literature suggests that, within the limits of reason, the consequences of over specifying the matrix are graver than under specifying the spatial weights matrix.

2.1.2: Modifiable areal unit problem

The second property of spatial data suggests that researchers have no available heuristic for aggregating spatial observations. Therefore, a given realization of aggregated spatial data represents an arbitrary partitioning of space.

Individuals have known for a long time that statistical results obtained from aggregated spatial data may be partially dependent on the spatial partitioning chosen to aggregate the data (Gehlke, & Biehl, 1934; Robinson 1950; Yule, & Kendall 1950). However, Openshaw (1977, 1978, 1984) and Openshaw and Taylor (1979, 1981) exposed researchers to the seriousness of the issue. These studies helped to demonstrate that researchers could manipulate the number of aggregated areas (i.e., the scale) and the arrangement of a given number of aggregated areas (i.e., the zoning) of the areal units to produce correlation coefficients that almost range from plus to minus one. As well, the authors noted that in the presence of spatial dependence among the aggregates, aggregating the data into fewer zones yielded an upward biased mean correlation coefficient. Openshaw and Taylor (1979) termed the effects from scale and zoning the modifiable areal unit problem (MAUP).

The upward bias of the correlation coefficient that occurs when spatially dependent variables are aggregated into fewer and fewer regions arises from the differing effects that aggregation has on the covariance and variance estimates of the variables (Arbia, 1989). For aggregated data exhibiting positive spatial autocorrelation, the percentage reduction in variance exceeds the

[4] Kelejian and Robinson (1998) also examined spatial weight matrix misspecification. The results of the misspecification, which were not the primary focus of their paper, were not clear.

percentage reduction in covariance. This fact leads to an upward bias in the correlation coefficient and a bias in any other statistic that depends upon variance and covariance measures.

While the source of MAUP has been known for some time, researchers have developed few methods to account for MAUP effects in data analyses. As an exception, Holt, Steel, Tranmer, and Wrigley (1996) illustrated an approach that accounts for scale effects by using information from auxiliary variables. The authors contend that if one knows the variance-covariance matrix for a set of representative variables at an individual level, one can adjust aggregated statistics to account for much of the scale effects.

2.1.3: Spatial boundaries

The first spatial data property suggests that spatial data have many observations located on edges because spatial data has two or three dimensions. While in time series data, researchers can often discard one boundary observation without much consequence, this strategy may not work for spatial data since many observations are located on edges.

A study area is unlikely to capture the entire range of the spatial data generating process (i.e., the spatial data generating process is truncated). This truncation may result from data availability or a conscious decision of a researcher to limit the scope of her work. A truncated study area may cause problems with the creation of spatial weights matrices since not all relevant neighbours may be identified for each observation. This misspecification is especially acute for those observations located near the edges of the study. Therefore, statistical analyses of data with a spatially truncated area may cause problems (Upton, & Fingelton, 1985, p. 365-366). Haining (1990, p. 101-110) discusses some approaches to account for boundary effects including treating the geographic process as locationally stationary or specifying a separate model to account for boundary locations.

2.1.4: Identification and measurement of non-random spatial patterns

A spatial autocorrelation coefficient is probably the most popular method that researchers have devised to test whether non-random spatial patterns exist among data sets (i.e., spatial dependence does exist). Spatial autocorrelation assesses whether observations with high values for a variable are clustered, dispersed or randomly located over space.

The two most popular measures of spatial autocorrelation are Moran's *I* statistic (Moran, 1948) and Geary's *c* statistic (Geary, 1954). Moran employed a modified Pearson product correlation coefficient to assess whether the distribution of values for a variable are spatially autocorrelated. Positive values of *I* indicate positive spatial autocorrelation (i.e., observations with similar values of a variable are located near each other) while negative values indicate negative spatial autocorrelation[5]. Although it is tempting to interpret the *I* statistic as a correlation coefficient that has a range of +1 to -1, Cliff and Ord (1981, p. 21-22) show that this need not be the case.

Geary's *c* statistic provides another method to estimate spatial autocorrelation in a variable. The statistic was developed from the Durbin-Watson test statistic to measure autocorrelation (i.e., in time-series data). Therefore, this statistic contains a spatially weighted contribution of squared differences between all pairs. Values of the *c* statistic near zero (i.e., spatially close observations have the same values for the variable) indicate positive spatial autocorrelation. A value of one indicates no spatial autocorrelation while values greater than one indicate negative spatial autocorrelation.

Although one may use either autocorrelation statistic to test inferentially whether spatial dependence is present, any results are conditional upon the spatial weights matrix employed. In other words, varying the spatial weights matrix may vary the conclusions that one makes from the results of a spatial autocorrelation statistic.

Researchers have produced many other tests for spatial dependence that account for a variety of situations. Most researchers use these tests to determine the appropriateness of spatial autoregressive models. These Lagrange Multiplier (LM) like tests are normally based from the residuals of the restricted ordinary least squares regression (i.e., a regression that does not account

[5] Technically, the expectation under the null hypotheses (i.e., no spatial dependence) equals $-1/(N-1)$.

for spatial relationships). Anselin and Florax (1995) provide a review of several spatial dependence tests. A host of newer context specific tests for assessing spatial dependence have flooded the literature over the past decade (e.g., Anselin, Bera, Florax, & Yoon, 1996; Baltagi, & Li, 2001; Kelijian, & Robinson, 1998; Mur, 1999; Paez, Uchida, & Miyamoto, 2002a). Despite the development of these newer tests, Anselin and Florax (1995) and Kelejian and Robinson (1998) suggest that in certain conditions the Moran's *I* statistic remains a very powerful test statistic for assessing spatial dependence.

The above approaches that measure spatial dependence in variables or statistics are based on a global approach. This stationarity assumption is, however, likely to hide interesting pockets of spatial heterogeneity. As such, many researchers have developed and employed local based statistics to identify these pockets or in other cases, identify sources of high leverage on global statistics (e.g., Anselin, 1995).

If a researcher identifies a significant local spatial statistic, the cause of this significance is not easily determined. Significant local spatial statistics may identify sources of misspecification of the global statistic, a substantive failure of the global modelling approach or sampling error (Fotheringham, 1997; Fotheringham, & Brunsdon, 1999). In fact, assessing the statistical significance of local statistics is no trivial issue as it involves considerations of sampling variability, global spatial autocorrelation and multiple comparisons (Boots, 2001).

The first statistics developed to measure local spatial dependence were the Getis and Ord statistics (Getis, & Ord, 1992; Ord, & Getis, 1995). Unlike Moran's *I*, these statistics work without transforming observations into mean deviations. Anselin (1995) later developed a family of local indicators of spatial association (LISA). To be part of LISA, Anselin argued that the statistic should provide an indication of local spatial dependence and that the global indicator should be equivalent to a scalar of the summation of local level indicators. Good overviews of local indicators of spatial dependence are found in Boots (2001) and Sokal, Oden, and Thomson (1998).

2.1.5: Estimation of models that account for spatial effects

If significant spatial dependence is present in a statistic such as a regression residual, a researcher may wish to model the spatial data generating process that leads to the observed pattern. This section discusses two such approaches for modelling a spatial data generating process. The first subsection describes a global modelling approach. The second subsection examines some approaches that researchers have used to examine spatial heterogeneity in statistical models.

<u>2.1.5.1: Modelling global spatial dependence</u>

This subsection is restricted to the linear simultaneous spatial autoregressive models[6]. This focus is warranted since some researchers have employed this family of models in the choice modelling context (see Sections 2.5.1.1 and 2.5.2.3). Spatial autoregressive models are close analogues of their time-series cousins. In fact, the only difference between these modelling approaches is that spatial autoregressive models use a spatial weights matrix rather than time to lag the variables.

Spatial autoregressive models may reflect a variety of forms with equation 1 representing the most general spatial autoregressive model. In this equation, $\mathbf{y}$ represents the vector of the dependent variable, $\mathbf{X}$ the matrix independent variables, $\mathbf{W}_1$ and $\mathbf{W}_2$ spatial weights matrices, the ρ scalar and $\boldsymbol{\lambda}$ and $\boldsymbol{\beta}$ vectors are parameters to be estimated, and $\mathbf{I}$ represents an identity matrix. It is typical to assume that the vector of error terms ($\boldsymbol{\varepsilon}$) is identically and independently distributed (i.i.d.) from a normal distribution with a mean of zero and variance (σ^2). In this model, the parameter estimates (ρ *and* $\boldsymbol{\lambda}$) for the spatially lagged dependent and independent variables are uniquely determined. Furthermore, the spatial weights matrices for the spatially lagged variables may differ. This model implies that the value of a dependent variable is a function of spatially dynamic values of the dependent and independent variables.

[6] Anselin (1988) provides an extensive overview of regression models with conditional and simultaneous spatial autoregressive and spatial moving average errors.

$$\mathbf{y} = \mathbf{X\beta} + \rho \mathbf{W}_1 \mathbf{y} - \boldsymbol{\lambda} \mathbf{W}_2 \mathbf{X\beta} + \boldsymbol{\varepsilon}, \quad \boldsymbol{\varepsilon} \sim N\left(0, \sigma^2 \mathbf{I}\right) \tag{1}$$

While equation 1 is most general, researchers often place restrictions on the spatial parameters and spatial weights matrices to facilitate analyses. It is assumed below that one spatial weight matrix is sufficient to capture any spatial effect (i.e., $\mathbf{W}_1 = \mathbf{W}_2$).

Restricting the $\boldsymbol{\lambda}$ to zero (i.e., removing these terms) in equation 1 yields the spatially lagged dynamic model shown in equation 2. This spatially lagged linear regression model suggests that a dependent variable is a function of exogenous variables **X** and a spatial lag of the dependent variable[7]. If ρ is non-zero (i.e., a spatial lag exists), ordinary least squares (OLS) regression will produce biased parameter estimates since the error terms are dependent on the lagged dependent variable.

$$\mathbf{y} = \mathbf{X\beta} + \rho \mathbf{W}_1 \mathbf{y} + \boldsymbol{\varepsilon}, \quad \boldsymbol{\varepsilon} \sim N\left(0, \sigma^2 \mathbf{I}\right) \tag{2}$$

One can create another spatial autoregressive model by restricting ρ *and* $\boldsymbol{\lambda}$ to be equal (i.e., a common factor restriction). With some algebraic manipulation, equation 3 arises from equation 1 for the common factor restriction model. In this equation, several terms replace the error term $\boldsymbol{\varepsilon}$. The **v** term, which is another i.i.d. error term, is divided by an identity matrix (**I**) minus the parameterized spatial weights matrix ($p\mathbf{W}$).

$$\mathbf{Y} = \mathbf{X\beta} + \frac{\mathbf{v}}{(\mathbf{I} - p\mathbf{W}_1)}, \quad \mathbf{v} \sim N\left(0, \sigma^2 \mathbf{I}\right) \tag{3}$$

Estimation of equation 3 by OLS yields unbiased parameter estimates. However, the parameter estimates are inefficient because the error variance-covariance matrix assumes that the observations contain more information than actually exists (i.e., some variation among the error terms is common). Furthermore, although the **v** terms are not heteroscedastic, the division of these terms by the identity matrix (**I**) minus the $\rho\mathbf{W}_1$ term may induce heteroscedasticity.

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[7] Since the instantaneous spatial lag in equation 1 is often unrealistic (Upton, & Fingelton, 1985, p. 369), it may be desirable to employ a spatio-temporal lag to model spatial dynamics.

Equation 3 may arise from a misspecification of the regression model. In particular, if one omits a spatially correlated explanatory variable from the regression, this omission will produce a pattern of spatially autocorrelated residuals.

Researchers typically estimate both equations 2 and 3 with maximum likelihood estimation. Maximum likelihood parameter estimates are consistent and efficient if one correctly assumes the distribution for the error terms and if the resulting residuals are uncorrelated.

2.1.5.2: Modelling spatial heterogeneity

Geographers have an interest in developing statistical approaches that account for spatial heterogeneity. This subsection briefly discusses the geographic weighted regression, spatial expansion, and multi-level approaches since researchers have applied these approaches to limited dependent variable models. Anselin (1988, Chapter 9) and Fotheringham and Brunsdon (1999) discuss other approaches such as spatial adaptive filtering and random coefficients modelling.

Researchers (Brunsdon, Fotheringham, & Charlton, 1996, 1998) developed the geographic weighted regression (GWR) to estimate location specific parameter estimates for each explanatory variable. The approach works by conducting a separate regression model for each observation. These separate regression models employ spatially weighted observations to estimate the parameters (i.e., the GWR was originally designed for estimation with weighted least squares).

It is difficult to assess whether the different local regression models arise from sampling variability or actual heterogeneity differences (Brunsdon *et al.*, 1996; Paez *et al.*, 2002a). To alleviate this problem, Paez *et al.* (2002a, 2002b) have developed the GWR from an error variance heterogeneity perspective (i.e., variance is modelled for each observation). These authors argue that this approach allows for simpler testing of the global model and permits endogenous estimation of bandwidths for the local spatial weights matrices.

The expansion method (Casetti, 1972), which is the varying parameters model of Vaughan and Russell (1982), was developed to let the parameters of a regression model drift with the values of other variables. The expansion model simply interacts the exogenous variables (**X**) from a regression (including the constant) with a constant and other explanatory variables (**Z**). From this expanded model, a researcher can determine an observation specific weight (termed a parameter) for each exogenous variable **X**[8]. Anselin (1988, p.124-129) reviews several other methods that incorporate spatial coordinates and spatial structure to the **Z** variables. This spatial drift produces parameter estimates that vary over the landscape in a trend-like fashion. From a local statistic perspective, the approach is limited since spatial heterogeneity may not follow an obvious trend (Fotheringham, & Brunsdon, 1999).

Jones (1991) introduced the multi-level model to geographers. The multi-level model is a hierarchical model that consists of both micro and macro-level models. The micro-level model is typically specified at the individual level with a regression equation. In the spatial context, a macro-level model is typically specified for some regional aggregation of the observations (i.e., the spatial weights matrix is formed with discrete boundaries). In the macro-level model, additional random elements are identified that serve as the basis for the random effects form of the model.

The following equations from Jones (1991) provide a more formal explanation. Equation 4 shows the micro-level model that defines the value of a dependent variable (y) for an individual (n) to equal a parameterized estimate (β_2) of an independent variable (x_2) a parameterized constant (β_1) and an error term (ε). This example only includes a simple specification for the macro-level model (equation 5). This macro-level model argues that the constant (β_{1h}) for a given neighbourhood (h) equals a global constant (β_1) plus a neighbourhood difference (δ_h) from this global constant. Equation 6 combines the micro and macro level models. The differences between equations 4 and 6 are the regional notations (h) for the variables and the presence of a second component (δ_h) in the error term. The multi-level model proceeds by treating this additional

[8] In choice modelling, the approach is equivalent to interacting socio-demographic variables with the alternative specific constants or other explanatory variables.

component as a random variable and the value of this random variable induces spatial heterogeneity among observations from different regions. One may easily extend the simple example to include macro-level models with other parameter estimates (e.g., β_2) and additional covariates other than a global average.

$$y_n = \beta_1 + \beta_2 x_{2n} + \varepsilon_n, \quad \varepsilon_n \sim i.i.d.N(0, \sigma^2) \tag{4}$$

$$\beta_{1h} = \beta_1 + \delta_h \tag{5}$$

$$y_{nh} = \beta_1 + \beta_2 x_{2nh} + (\delta_h + \varepsilon_{nh}) \tag{6}$$

The multi-level approach is rather similar to an error components perspective with the difference that multilevel models rely on places or regions as components of the error terms. Fotheringham and Brunsdon (1999) criticized the assumption in multi-level analysis that place effects are identical within arbitrary zonings of space. However, as Duncan and Jones (2000) note, researchers are free to choose from a variety of place structures that include cross-level hierarchies that allow researchers to employ a variety of zoning systems that may contain the same alternative multiple times.

A few aspects of the multi-level approach may limit its usefulness as a truly local estimator. First, Duncan and Jones (2000) note that multi-level modelling does not fully account for local level heterogeneity. Instead, the approach assesses between region heterogeneity. Second, Duncan and Jones (2000)[9] demonstrate that the multi-level model is highly sensitive to model misspecification and that researchers must spend considerable effort to test a variety of regional fixed effects and both regional and individual level random effects. However, this mining approach invalidates the statistical hypothesis testing that the authors use to judge the suitability of the different model forms.

[9] Actually, the extent of misspecification was not possible to assess since the authors could not know the data generating process for the empirical data set.

2.2: Choice modelling

For many decisions, an individual is unable to choose a quantity of a good or service (e.g., amount of ground beef to purchase) and instead the individual is faced with a dichotomous decision to either choose or not choose a good or service. Furthermore, many choice decisions are polychotomous since an individual must choose between competing goods and services (e.g., sites for a fishing trip). Standard models such as ordinary least squares regression are incapable of accounting for these discrete choice decisions made by individuals. Instead, it is necessary to employ a statistical model that is capable of accounting for the discrete nature of choices.

The objective of a choice model is to explain and to predict patterns of choices made by individuals. Without further guidance, a researcher is free to select any statistical model that is suitable for analyzing discrete choices and that provides a good prediction of choice patterns. Although this purely statistical approach is tempting, it does not provide insights into the choice process that leads to observed choice patterns. This is an important omission since the purpose of a choice model is to explain and to predict choice patterns under a unifying theory for the behavioural process of choice.

By far the most popular unifying theory of choice is random utility theory (Thurstone, 1927). Thurstone assumed utility randomness to arise from respondent inconsistency that led an individual to take a random draw of utility for a given situation. The contemporary interpretation of random utility theory (Ben-Akiva, & Lerman, 1985; Manski, 1977) takes a different view about the source of randomness. Researchers now assume that the randomness arises from the uncertainty of the researcher. Measurement errors, individual tastes, and proxy and omitted variables all may lead to errors in modelling the behaviour of individuals (Manski, 1973).

Since researchers can never hope to uncover all aspects that lead to choices by individuals, they can only model choice behaviours probabilistically. For example, a researcher can only specify a probability that an angler would select a fishing site from a set of sites. Formally, equation 7 separates the latent (i.e., unobserved) utility (U_{in}*) of alternative i for individual n into systematic (V_{in}) and stochastic (ε_{in}) parts. The systematic utility is defined to include K independent variables that describe the alternative and possibly characteristics of the individual choice maker (X_{ink}). The X_{ink} variables are weighted by parameters (β_{ik}) that convert the variable measurements into a utility metric. This dissertation uses the linear-in-parameters specification shown in equation 8.

$$U_{in}^{*} = V_{in} + \varepsilon_{in} \tag{7}$$

$$V_{in} = \sum_{k=1}^{K} \beta_{ik} X_{ink} = \mathbf{\beta_i' X_{in}} \tag{8}$$

The stochastic utilities (ε_{in}) are random variables that take on values according to an assumed distribution. This fact leads researchers to specify a probability that an individual will select an alternative from a choice set. Equation 9 states that the probability of individual n selecting alternative i from a set of C_n alternatives equals the probability that the latent utility of alternative i is greater than or equal at best to the latent utility of all other alternatives.

$$P_n(i) = P(V_{in} + \varepsilon_{in} \geq V_{jn} + \varepsilon_{in}), \forall j \neq i, j \in C_n \tag{9}$$

In a fishing context, equation 10 simply acknowledges that a researcher can measure the systematic utility differences between the fishing sites, but she does not know the values of the stochastic utilities. Therefore, the probability of choosing a fishing site depends partially on the unobserved values for the random stochastic utilities for all alternatives.

$$P_n(i) = P(\varepsilon_{jn} < V_{in} - V_{jn} + \varepsilon_{in}), \forall j \neq i, j \in C_n \tag{10}$$

At this point, I introduce two very important properties of all choice models. These properties are that "the scale of utility is arbitrary" and that "only differences in utility matter" (Train, 2003: 23). Both properties arise since utility is a latent (i.e., unobserved) variable. Since the scale of utility is unobserved, one cannot separate the variance of the utility from the parameters used to identify the weights β_{ik} for each variable. Therefore, one must fix (i.e., normalize) the variance of the utility to some arbitrary value in order to identify the remaining parameter estimates.

The interval nature of utility also impacts the identification of constants in the systematic utility and any parameter estimates relating to the stochastic utility. For example, for five fishing alternatives, one can only identify four alternative specific constants. This is because with five alternatives one can specify a maximum of four unique utility differences. Thus, one must fix the value for one alternative specific constant to an arbitrary value, allowing the identification of the other four alternative specific constants. In this sense, our remaining four alternative specific constants actually measure the difference between the constant for the fishing site in question and the one fishing site fixed for identification. This same need to fix some parameter estimates for identification also affects any attempts to identify all elements of the stochastic utility covariance matrix.

The obvious problem in estimating equation 10 is that one does not know the values of the stochastic utilities (ε_{in}). Therefore, one must make assumptions about the joint probability distributions for these random variables. If one makes a restrictive assumption that the ε_{in} are independently and identically distributed (i.i.d.) according to a type I extreme value distribution, the multinomial logit (MNL) model arises (Domencich, & McFadden, 1975; McFadden, 1974).

Equation 11 shows the MNL model, which remains the workhorse for choice model applications (Louviere, Hensher, & Swait, 2000, p. 13). The probability that individual *n* will select choice alternative *i* is expressed as the ratio of the systematic utility ($\boldsymbol{\beta}_{\mathbf{i}}'\mathbf{X}_{\mathbf{in}}$) of the alternative relative to the summation of the systematic utilities for all alternatives belonging to choice set C_n. The scale parameter (μ) is inversely related to the variance of the stochastic utilities (i.e., variance = $\pi^2/6\mu^2$). To identify the $\boldsymbol{\beta}_{\mathbf{i}}$ parameter estimates, researchers innocuously assume that the scale parameter equals one. This normalization is not so benign if one wishes to compare model results or pool data from different sources (i.e., different groups may have different variances).

$$P_n(i) = \frac{e^{\mu(\boldsymbol{\beta}_i^{'}\mathbf{X}_{in})}}{\sum_{j=1}^{J} e^{\mu(\boldsymbol{\beta}_j^{'}\mathbf{X}_{jn})}}, i \in C_n, j \in C_n \quad (11)$$

The estimation of the $\boldsymbol{\beta}_i$ parameters is relatively simple through maximum likelihood. Maximum likelihood estimation finds the set of $\boldsymbol{\beta}_i$ parameters most likely to arise given the attribute measures ($\mathbf{X}_{in}$) and choices made by the observed decision-makers. If one obtains the parameter estimates from fishing site choices, the resulting set of parameter estimates will produce the highest estimated choice probabilities for fishing sites that the anglers actually selected.

While the advantage of the MNL is its simple closed form (i.e., no integration is necessary for the calculation of probabilities), the model has limitations. Train (2003, p. 46) describes limitations related to the ways that the MNL accounts: for substitution among the alternatives; for unobserved preference heterogeneity (i.e., differences in preferences among individuals); and for unobserved factors for repeated choices. Koppelman and Sethi (2000) and Bhat (2002, 2003) also note that the MNL assumes that the error variance-covariance structure of the alternatives is identical across individuals.

The limited pattern of substitution in the MNL arises from the independence from irrelevant alternatives (IIA) property (Luce, 1959), a direct outcome of the assumption that the error terms ε_{in} are independent and identically distributed. The IIA property ensures that the ratio of choice probabilities for two alternatives is unaffected by the presence or change to any other alternative. Therefore, a change to the probability of one alternative will lead to identical changes in relative choice probabilities for all other alternatives.

The following example should help to clarify the IIA property. Let us assume that anglers have five available fishing alternatives and that the predicted choice probabilities from equation 11 equal 0.30, 0.12, 0.15, 0.18, and 0.25, respectively. Next, let us assume that fishing site 5 is temporarily closed because of an over harvest of fish. Equation 11 would now predict that the remaining four alternatives would have choice probabilities equal to 0.40, 0.16, 0.20, and 0.24, respectively. Clearly, the choice probability for every remaining fishing site increased by one-third (i.e., a 33.33% relative change to choice probabilities). This rigid substitution pattern ignores that some sites may be better substitutes for the closed site (e.g., because of spatial proximity to that site). While it is an empirical question whether IIA holds for a given data set, the IIA property is unlikely to hold for spatial choice applications.

An MNL choice model is incapable of accounting for unobserved effects. Therefore, the model must assume that any preference heterogeneity among individuals is explainable by observed factors. The MNL also assumes that the stochastic utilities associated with repeated choices made by individuals are independent. In other words, the MNL assumes that no common unobserved factors exist among the choices. Finally, the MNL assumes that the scale factor is identical for all individuals (i.e., variance in utility scales among individuals does not exist).

2.3: Choice model generalizations

To combat the restrictive assumptions required by the multinomial logit, researchers have pursued generalized choice models that are consistent with random utility theory. These generalizations have occurred because of developments to generalized extreme value theory (McFadden, 1978, 1981) and techniques to estimate open form choice models.

2.3.1: Generalized extreme value models

Most generalized extreme value (GEV) models work by separating unobserved utility (i.e., stochastic utility) into shared components among nests (i.e., groups of alternatives) and a component unique to each alternative. This separation allows researchers using GEV models to permit patterns of substitution among the alternatives that differ from the MNL. Specifically, the alternatives within a nest will share some unobserved utility. If the systematic utility of an alternative declines, the shared unobserved utility will cause the choice probabilities of alternatives within the same nest to increase relatively more than will the choice probabilities for alternatives in different nests. For example, one may nest fishing sites into regions to account for unobserved utilities associated with landscape, accessibility, etc. If one closed a fishing site, a nested logit would distribute a relatively larger percentage of the affected anglers to sites within the same region than it would to other sites.

Williams (1977), Daly and Zachary (1978) and McFadden (1978) independently developed the nested logit (NL), which is the simplest GEV model other than the MNL. This NL model permits different substitution among alternatives within than outside of *a priori* defined nests. Many researchers incorrectly state that a NL assumes a hierarchical decision-making process. The reality is that the NL only assumes that some unobserved aspects of utility are common to groups of alternatives. As such, the NL makes no behavioural stance on the decision-making process. While the NL permits a richer pattern of substitution than does the MNL, the IIA property still holds for alternatives within a nest. Many individuals also note that the NL requires researchers to *a priori* specify a grouping structure for the alternatives. Consequently, the NL results are contingent upon the grouping scheme employed by the researcher. Researchers (e.g., Pellegrini, & Fotheringham, 2002) often use this fact to dismiss the NL as a suitable candidate for incorporating spatial substitution effects in a choice model.

The GEV family is not limited to the MNL and NL models. Other GEV models include: ordered GEV (Small, 1987), cross-nested logit (Vovsha, 1997), product differentiation logit (Bresnahan, Stern, & Trajtenberg, 1997), MNL-ordered GEV (Bhat, 1998), paired combinatorial logit (Koppleman, & Wen, 2000), generation logit (Swait, 2001a), and the generalized nested logit (Wen, & Koppleman, 2001).

Owing to its general form, I discuss the generalized nested logit (GNL) model. The GNL model consists of M nests with dissimilarity parameters (i.e., scale parameters) for each nest (μ_m) (see equation 12). As a dissimilarity parameter increases in size, the correlation of the unobserved utility between two alternatives weakens. The GNL also includes allocation parameters (α_{im}) that specify the proportion of an alternative associated with a nest given a typical constraint that the allocation parameters for each alternative sum to unity (Bierlaire, forthcoming). These allocation parameters permit an alternative to share unobserved variation with more than one nest (i.e., it permits cross-nesting). For example, one can specify an angling site to belong to multiple regions rather than forcing the site to fall into one researcher defined region.

$$P_{in} = \sum_{m=1}^{M} \left[\frac{\left(\alpha_{im} e^{\beta_i' X_{in}}\right)^{\frac{1}{\mu_m}} \left(\sum_{j=1}^{J_m} \left(\alpha_{jm} e^{\beta_j' X_{jn}}\right)^{\frac{1}{\mu_m}} \right)^{\mu_m - 1}}{\sum_{l=1}^{M} \left(\sum_{j=1}^{J_l} \left(\alpha_{jl} e^{\beta_j' X_{jn}}\right)^{\frac{1}{\mu_l}} \right)^{\mu_l}} \right] \quad (12)$$

Equation 12 is explained by starting from its most restrictive form and proceeding to an unrestricted model. If one restricts all dissimilarity parameters (μ_m) to one, the model collapses to the MNL (i.e., no shared unobserved utility exists among members in any nest). A less restrictive model form would allow the dissimilarity parameters to differ from one but would allocate alternatives discretely among the M nests (i.e., α_{im} will equal one for one nest and zero for all other M-1 nests). Under this assumption, equation 12 reduces to the familiar two-level nested logit model. Restricting the allocation parameters to be equal and specifying nests for all pairs of alternatives yields the paired combinatorial logit. If one assumes that all dissimilarity parameters are equal but different from one, the cross-nested logit model arises. Finally, the unrestricted GNL permits estimation of dissimilarity coefficients for each nest along with allocation parameters that assign a portion of each alternative to each nest.

Table 2.3.1 shows the cross-elasticities of several different GEV models. Cross-elasticities refer to "…the percentage changes in the probability of choosing a particular alternative in the choice set with respect to a given percentage change in an attribute of a competing alternative" (Louviere *et al.,* 2000,p. 58). The cross-elasticities of the MNL are constant because of the IIA property. The table shows that the more general GEV models permit increasingly complex cross-elasticities.

Table 2.3.1: Cross-elasticities from various Generalized Extreme Value models

Model	Cross-elasticity for alternative j	
Multinomial Logit	$-P_i\beta_{ik}X_{ik}$	
Nested Logit	$-P_i\beta_{ik}X_{ik}$	(non-nested alternatives)
	$-\left[P_i+\left(\dfrac{1-\mu_m}{\mu_m}\right)P_i \mid m\right]\beta_{ik}X_{ik}$	(nested alternatives)
Paired Combinatorial Logit	$-\left[P_i+\left(\dfrac{1-\mu_m}{\mu_m}\right)\dfrac{P_{ij}P_{i\mid ij}P_{j\mid ij}}{P_j}\right]\beta_{ik}X_{ik}$	
Cross-nested logit	$-\left[P_i+\left(\dfrac{1-\mu}{\mu}\right)\sum_{m=1}^{M}\dfrac{P_mP_{i\mid m}P_{j\mid m}}{P_j}\right]\beta_{ik}X_{ik}$	
Generalized nested logit	$-\left[P_i+\sum_{m=1}^{M}\left(\dfrac{1-\mu_m}{\mu_m}\right)\dfrac{P_mP_{i\mid m}P_{j\mid m}}{P_j}\right]\beta_{ik}X_{ik}$	

After: Koppelman and Sethi (2000)

P_i – the probability of selecting alternative i (from equation 9 with appropriate restrictions)
β_{ik} – the parameter estimate for the k_{th} attribute for alternative i
X_{ik} – the k_{th} attribute measure for alternative i
μ_m – the dissimilarity (inclusive value) parameter for the m_{th} nest

Table 2.3.1 clearly shows that very complex substitution patterns are possible from GEV models. All GEV models are consistent with random utility theory if the dissimilarity parameters lie between zero and one (Daly, & Zachary, 1978; McFadden, 1981). Furthermore, the GNL model sheds many criticisms that individuals levy against using the NL model to study spatial choices. For example, the ability to estimate the proportion of each alternative associated with each nest eliminates the concern that a researcher must *a priori* define a regional structure for spatial choice alternatives. Given this flexibility, GEV models offer a convenient approach to account for complex patterns of substitution among spatial alternatives. Although the GEV models are technically global models, their extreme flexibility may also allow researchers to estimate different patterns of substitution for almost every choice alternative. Furthermore, researchers would be able to test whether heterogeneity exists in the substitution patterns for different alternatives.

While the GEV models may permit complex patterns of substitution among the alternatives, the models are not without restrictions and problems. Choice model applications frequently violate the utility maximization requirement that the dissimilarity parameters lie between zero and one (Bhat, 2002, 2003). If the dissimilarity parameter lies outside this range, the model may not be consistent with random utility theory. The GEV models also neither account for unobserved preference heterogeneity or heteroscedasticity of the stochastic terms among alternatives. Bhat (1997), however, does offer a method that researchers could use to parameterize the scale factor in a nested logit.

2.3.2: Open form choice models

Until recently, researchers who wished to employ open form choice models were only able to estimate problems with less than a handful of integrals. Since the early attempt by Manski and Lerman (1981), researchers have made key advances to the simulation of choice probabilities (e.g., Bhat, 2001; McFadden, 1989; Train, 2001, 2003) and the estimation of choice models through Bayesian approaches (Albert, & Chib, 1993; Allenby, & Lenk, 1994; McCulloch, & Rossi, 1994). These approaches combined with ever increasing computational speed and memory free researchers to estimate very general and complex choice models. While researchers may choose between Bayesian and classical (i.e., maximum simulated likelihood or method of simulated moments) estimation approaches, Train (2001) showed that this decision will not have any noticeable effects on parameter estimates.

The open form choice models include the multinomial probit, mixed probit and mixed logit. I focus solely on the mixed logit model, as much of this discussion is transferable to the mixed probit model. The multinomial probit also shares some aspects with the mixed logit and mixed probit, albeit in a restricted form (i.e., only one error component that must follow a normal distribution).

The mixed logit notation is borrowed from Ben-Akiva, Bolduc, and Walker (2001) and Walker (2001) who employed a factor analytic approach. Unlike the MNL, the mixed logit separates the stochastic (unobserved) utility into two components. One component (ε_{in}) retains the independently and identically distributed (i.i.d.) type I extreme value terms, thus enabling the model to have a multinomial logit form[10]. The second component ($\mathbf{F}_{in}'\boldsymbol{\xi}_n$) consists of *R* random variables (ξ) with mean equal to zero and a vector of factor loadings ($\mathbf{F}_{in}$) that may include parameters and/or covariates. Equation 13 shows the latent utility of individual *n* for alternative *i* with the two unobserved utility components.

$$U_{in}^{*} = \boldsymbol{\beta}_i'\mathbf{X}_{in} + \mathbf{F}_{in}'\boldsymbol{\xi}_n + \varepsilon_{in}, \quad \varepsilon_{in} \sim i.i.d.\,EVI\left(0, \frac{\pi^2}{6\mu^2}\right) \tag{13}$$

The ξ_n terms are further reduced into a set of independent random variables (ζ_n) and **T**, which is the Cholesky factorization (i.e., matrix square root) of the covariance matrix of ξ_n (see equation 14). Estimation of the diagonal elements of **T** reveal the standard deviations for the ξ_n random variables. Off diagonal elements of **T** provide association measures among the random variables (**TT′** *produces* the covariance matrix of ξ_n). If one knew the ζ_n random values, the estimation would proceed as the MNL shown in equation 15.

$$U_{in} = \boldsymbol{\beta}_i'\mathbf{X}_{in} + \mathbf{F}_{in}'\mathbf{T}\boldsymbol{\zeta}_n + \varepsilon_{in} \tag{14}$$

$$P_n(i \mid \zeta_n) = \frac{e^{\mu(\boldsymbol{\beta}_i'\mathbf{X}_{in} + \mathbf{F}_{in}'\mathbf{T}\boldsymbol{\zeta}_n)}}{\sum_{j=1}^{J} e^{\mu(\boldsymbol{\beta}_j'\mathbf{X}_{jn} - \mathbf{F}_{jn}'\mathbf{T}\boldsymbol{\zeta}_n)}}, \forall j \in C_n \tag{15}$$

Since the ζ_n are random variables, one must integrate equation 15 over the joint distribution of the ζ_n values weighted by the probability density, see equation 16. As with any random variables, the researcher must specify *a priori* the distributions for ζ_n. Equation 16 is termed a mixed logit because the choice probability is a mixture of MNL models with the joint distribution of ζ_n acting as the mixing distribution (Hensher, & Greene, 2003).

[10] If one assumed that this component was i.i.d. normal, a mixed probit would arise.

$$P_n(i) = \int_{\zeta} \frac{e^{\mu(\boldsymbol{\beta}_i^{'}\mathbf{X}_{in} + \mathbf{F}_{in}^{'}\mathbf{T}\boldsymbol{\zeta}_n)}}{\sum_{j=1}^{J} e^{\mu(\boldsymbol{\beta}_j^{'}\mathbf{X}_{jn} + \mathbf{F}_{jn}^{'}\mathbf{T}\boldsymbol{\zeta}_n)}} f(\zeta)\partial\zeta, \forall j \in C_n \tag{16}$$

Simple forms of open choice models have been estimated for some time (e.g., Hausman and Wise (1978) and Daganzo (1979) for the multinomial probit and Boyd and Mellman (1980) and Cardell and Dunbar (1980) for the mixed logit). However, the advent of classical simulation and Bayesian estimation approaches has made complex model estimation feasible.

Maximum simulated likelihood is one method to estimate equation 16. This method exploits the fact that the likelihood function for equation 16 only requires information about estimated choice probabilities for the chosen alternatives. One can estimate unbiased choice probabilities for equation 16 by following the steps below. First, with the starting values for the parameters set (i.e., $\boldsymbol{\beta}_i$ and $\mathbf{T}$), take a draw from the assumed distribution of the $\boldsymbol{\zeta}_n$ random variables and calculate $P_n(i)$. Second, repeat the above step with new random numbers many times. Third, average the $P_n(i)$ and use the average $P_n(i)$ for the estimation of new parameters. This process is iterated until the maximum likelihood estimates reach a maximum.

Researchers are abandoning pure random draws in step two for artificial draws that contain desirable properties (e.g., a reduction in variance). A popular artificial draw is a Halton sequence that Bhat (2001) has shown to estimate reliable parameter estimates with few replications in step 2. However, Hess, Train, and Polak (forthcoming) have noted that randomly shifted (i.e., different starting points for a sequence) and shuffled (i.e., a different order for a sequence) uniformly distributed vectors may outperform the estimation conducted with Halton sequences.

The simplicity of equation 16 masks its extreme flexibility. The mixed logit does not contain the IIA property because of the integration of the random variables. When the mixed logit model contains a GEV kernel (e.g., MNL), the model is consistent with random utility theory (McFadden and Train, 2000). McFadden and Train (2000) also showed that individuals could use a mixed logit form to estimate any type of choice model.

Researchers typically interpret the mixed logit from one of two perspectives. First, a random parameters logit arises when $\mathbf{F}_{in}$ includes some attribute measurements ($\mathbf{X}_{in}$). The diagonal elements of $\mathbf{T}$ are the standard deviations for the associated parameter estimates ($\boldsymbol{\beta}_i$) from the included $\mathbf{X}_{in}$ covariates. The following example should help to clarify the random parameters logit model. Imagine a fishing choice study with only two attributes in $\mathbf{F}_{in}$ that measure travel distance and catch rates. The estimation of equation 16 will produce a mean parameter and standard deviation estimate for both travel distance and catch rates. The mean estimate tells us an average preference for the attributes while the standard deviation estimate tells us the degree of variability in preferences for these attributes[11] (i.e., the model does not assume that all anglers have identical preferences for travel distance and catch rates).

An error components model arises from equation 16 by specifying $\mathbf{F}_{in}$ to consist of measures that are not included among the K attributes. For example, a researcher may specify $\mathbf{F}_{in}$ to consist of indicator variables that represent whether or not a fishing site belongs to different nests. Under this interpretation, the $\mathbf{T}$ diagonal elements measure the extent of shared unobserved variation within a nest. It is relatively simple to use the mixed logit to account for all types of nests that may include cross-nesting of alternatives. As such, the mixed logit is a flexible model that accounts for complex substitution patterns among the alternatives. From this perspective, the mixed logit holds much promise for incorporating a wide range of spatial substitution patterns.

While the mixed logit is very flexible, it has some problems. Researchers must take great care to ensure that their model is identified (Ben-Akiva *et al.*, 2001; Ben-Akiva *et al.*, 2002; Walker, 2002; Walker, & Ben-Akiva, 2002). These identification problems partially arise from the "only differences in utilities matter" property of choice models. Bhat (2003) also recommends that researchers should use closed form models to the maximum extent before turning to open form models like mixed logit.

[11] Louviere *et al.* (2002) suggest that the random parameters logit may measure unobserved variation rather than preference heterogeneity.

2.4: Choice set issues

While a strong theoretical basis exists for choice models (Manski, 1977; McFadden, 1974; Thurstone, 1927), little guidance exists about the set of alternatives (i.e., the choice sets) from which individuals select a preferred alternative. An obvious approach to define a choice set is to include all possible alternatives (i.e., a universal choice set). However, the universal choice set is an illusive concept. For example, it is reasonable to assume that the universal choice set should include every leisure alternative available to a person who is contemplating a fishing trip. To reduce this almost infinite sized choice set, researchers studying angling behaviours implicitly narrow the universal choice set to only angling alternatives and possibly the alternative of non-participation (i.e., researchers assume that weak separability holds). Although this strategy greatly reduces the size of a choice set, literarily hundreds of thousands of alternatives are available to an individual! Even if one limits a study to day fishing trips, individuals may travel vast distances by road, rail, air, and water to fish. For model tractability, one typically further reduces the number of alternatives available to an angler. As such, the term universal choice set is difficult to employ.

Two primary motivations drive research on choice sets (see Table 2.4.1). First, researchers may estimate the impacts of employing reduced choice sets instead of universal choice sets. This approach acknowledges that a universal choice set is appropriate, but for reasons of data availability, data collection costs and software limitations, one cannot use the universal choice set for modelling purposes. Possible approaches include *ad hoc* narrowing, sampling, and aggregation of alternatives from choice sets that approximate universal choice sets.

Table 2.4.1 Motivations and approaches for choice set research

Motivation	General Approach	Specific Approach
Reducing the burden of universal choice set modelling	Researcher defined	Narrow Sample Aggregate
Abandon the universal choice set concept	Respondent defined	Awareness Consideration
	Explicit choice set model	Availability Threshold Accessibility Other
	Implicit choice set model	

Second, some researchers believe that the universal choice set is a flawed concept because individuals are either not aware or do not consider all available alternatives when making choices. Popular approaches to account for different choice sets include respondent defined choice sets and explicit and implicit choice set models.

2.4.1: Reducing the burden of universal choice set modelling

A primary motivation for research on choice sets is to assess whether one can reduce the choice set size without adversely affecting model estimates. The three approaches that follow take slightly different tacks to these issues. First, the narrowed choice set approach assesses whether researchers can reduce the extent of the universal choice set without biasing parameter estimates. The second approach assesses whether results obtained from a sample of alternatives yields unbiased parameter estimates. Finally, the aggregation approach assesses whether estimating models with grouped alternatives can provide unbiased parameter estimates.

2.4.1.1: Narrowing choice sets

Researchers may employ narrowed choice sets in situations when a universal choice set consists of many alternatives. Under this premise, it is assumed that some valid alternatives are chosen so infrequently that their exclusion will not dramatically impact parameter estimates from a choice model. Some recreational researchers have focused on removing choice alternatives that do not meet *a priori* defined thresholds of site popularity (Kling, 1987), minimum catch rates (Whitehead, & Haab, 1999), and minimum choice frequency (Jakus, Downing, Bevelhimer, & Fly, 1997; Pendelton, & Mendelsohn, 1998; Romano, Scarpa, Spalatro, & Vigano, 2000). However, a distance or travel time threshold is the most popular narrowing approach among researchers using spatial recreation site choice models (Chen, & Cosslett, 1998; Hicks, & Strand, 2000; Montgomery, & Needleman, 1997; Needleman, & Kealy, 1995; Parsons, & Hauber, 1998; Whitehead, & Haab, 1999).

The few articles that have studied the effects of different distance thresholds on parameter estimates suggest that the notion of a distance threshold is valid. Parsons and Hauber (1998) assessed the consistency of parameter estimates in situations where they narrowed fishing alternatives based on driving distance. This study used five replications of randomly drawn choice sets from a given angling choice set. Parsons and Hauber incrementally expanded the choice set to include all alternatives within various driving times of the respondents' origins. The one-way driving times varied from 0.8 to 4 hours by increments of 20 minutes. The authors found a ceiling on economic welfare estimates (and therefore, the distance parameter) at about a 1.6 hour one-way trip. Whitehead and Haab (1999) and Hicks and Strand (2000) also examined the effect of narrowing angling choice sets by driving time and found little effects of choice set narrowing beyond 4.5 and 2.5 hours, respectively.

2.4.1.2: Sampling alternatives

A second approach to reduce the number of alternatives in a choice set involves sampling from the universal choice set. These approaches rely on the results of McFadden (1978) who exploited the independence of irrelevant alternatives (IIA) property of the multinomial logit model. Essentially, McFadden demonstrated that when IIA is present, model estimates from a random sample of alternatives remain unbiased.

Parsons and Kealy (1992) conducted further empirical tests to determine a suitable number of alternatives that researchers should draw from the universal choice set. Parsons and Kealy examined the choices of Wisconsin lakes for recreationists pursuing angling, boating, swimming and viewing activities. The authors used only one random draw for choice sets that equalled three, six, twelve, and twenty-four sites from the 1133 available sites. One additional draw of 24 sites was made from the set of lakes that received at least one trip from the respondents (i.e., the visited choice set). The authors found that a sample of 11 alternatives plus the chosen site provided similar parameter estimates, as did the model with 24 alternatives. As well, little difference existed between the parameter estimates based on the 24 sites drawn from the universal choice set or the visited choice set. However, the lack of formal tests between parameter estimates and the use of only one realization at each sample size greatly reduce the reliability of the findings.

Feather (1994) extended the work of Parsons and Kealy by employing several realizations of random samples to assess the variability of parameter estimates. Feather (1994) examined random sampling, importance sampling[12], and aggregation of alternatives on data from Minnesota anglers. Feather found that parameter estimates from random sampling were very sensitive to the size of the random sample. Substantial variation in parameter estimates existed among the three draws taken at a given sample size. Feather concluded that researchers who use a random sampling approach should employ large sized samples and should use more than one random draw.

[12] Importance based sampling (Ben Akiva, & Lerman, 1985) refers to a stratified sampling approach that over samples from popular alternatives.

The study by Pellegrini, Fotheringham, and Lin (1997) also extended the work of Parsons and Kealy (1992). Pellegrini *et al.* assessed parameter sensitivity for shopping centre choices made by residents of Gainesville, Florida. While the objective of the paper was to assess the sensitivity of results to misspecified choice sets, the paper also assessed the effects of parameter sensitivity on random sampling. The authors found that substantial variation in parameter estimates existed for random samples from the fourteen alternatives, but the variation was not constant for all attributes. While the authors discussed the reasons for the different variation in parameter estimates, their results require replication before one can draw any general findings.

Many recreation-focused papers have applied the random sampling approach to spatial choice modelling (Montgomery, & Needleman, 1997; Needleman, & Kealy, 1995; Parsons, & Hauber, 1998; Parsons, & Kealy, 1994; Parsons, & Needleman, 1992; Parsons, Plantinga, & Boyle, 2000; Pendelton, & Mendelsohn, 1998; Peters, Adamowicz, & Boxall, 1995). Other authors have argued that an importance based sampling approach may be better than the random sampling approach (Ben Akiva, & Lerman, 1985). As already stated, Feather (1994) did assess the sensitivity of parameter estimates obtained from importance sampling of Minnesota anglers. Not surprisingly, Feather found that the variability of parameter estimates at a given size sample was lower for results based upon importance sampling than results based upon random sampling. Despite the interest in using importance-based sampling, only two additional applications (Tay, & McCarthy, 1994; Tay, McCarthy, & Fletcher, 1996) are found in the recreational spatial choice literature.

Finally, with the advent of open form choice models, new interest exists in assessing the performance of sampling approaches on these choice models. To date only McConnell and Tseng (1999) have conducted this type of analysis. McConnell and Tseng examined the sensitivity of parameter and welfare estimates from both multinomial (MNL) and random parameters logit (RPL) models for beach use in Maryland. The authors first examined the stability of parameter estimates by comparing the universal choice set models (N=10) to models derived from 15 replications at size four. The average parameter estimates from the fifteen randomly drawn choice sets (n=4) were compared to the parameter estimates from the universal choice set by both ratios and a relative mean squared error calculation[13]. These tests suggested that the use of random sampling for RPL had about the same effect as the use of random sampling for MNL. The authors next compared economic welfare estimates derived from 15 replications of choice sets of size six and eight and 100 replications of choice sets of size four. It appeared that the economic welfare estimates from the RPL were more consistent than those estimates from the MNL for any given size random sample. Although the study was an empirical investigation, the results do provide important information to researchers who consider using random sampling approaches when employing RPL models.

2.4.1.3: Aggregating alternatives

Aggregation is another approach to handle large numbers of alternatives. Researchers, however, have discovered that including only the average value of attributes as independent variables for a given group of alternatives produces a misleading choice model (Kitamura, Kostyniuk, & Ting, 1979). The work of Kitamura *et al.* (1979) showed that a heterogeneity term was needed in addition to a size effect and an average attribute measure to describe the variability of the elemental alternatives within an aggregate. While Ben-Akiva and Lerman (1985) brought the issue of an aggregated logit model to the attention of a large readership, few researchers have incorporated all three aspects of aggregation (i.e., average, size, and heterogeneity measures). As an exception, Ferguson and Kanaroglou (Ferguson, 1995; Ferguson, & Kanaroglou, 1997; Haener, Boxall, Adamowicz, & Kuhnke, 2004; Kanaroglou, & Ferguson, 1996, 1998) developed methods for estimating spatial choice models with the heterogeneity term. However, Ferguson and Kanaroglou did not compare their model results to disaggregated choices since their Canadian migration data only contained aggregated choice data.

[13] The relative mean squared error from McConnell and Tseng (1999) equalled the square root of the average squared deviation between a parameter estimate from a random draw and the universal choice set divided by the parameter estimate from the universal choice set.

Several other researchers have compared the results from aggregated models to the results obtained from disaggregated models (Kaoru, Smith, & Liu, 1995; Parsons, & Needleman, 1992; Parsons *et al.,* 2000)[14]. However, only Parsons and Needleman (1992) incorporated a heterogeneity term in the utility function. When many alternatives are present, Parsons and Needleman argued that researchers should use a random sample rather than aggregating alternatives. While Ferguson (1995) was critical of the work of Parsons and Needleman[15], it is probably sage advice to use disaggregated data whenever possible.

Applications of spatial choice models that employ spatially aggregated alternatives are too great in number to mention. In the recreational literature, increasing interest exists to model some sites at a disaggregated level and other sites at an aggregated level. Lupi and Feather (1998) tested whether disaggregating only the most popular fishing sites yielded reliable parameter estimates. Their approach argued that unpopular sites are likely to have similar characteristics and therefore, the omission of the heterogeneity term should not drastically affect the results. In their study, Lupi and Feather found that the partially aggregated model did perform reasonably well in comparison to a disaggregated model of Minnesotans' angling behaviour. The recreational choice model literature includes several other applications of partially disaggregated models (Hausman, Leonard, & McFadden, 1995; Morey, Breffle, Rowe, & Waldman, 2002; Morey, Rowe, & Watson, 1993; Parsons *et al.*, 2000).

Some individuals have also used aspatial methods to aggregate alternatives. These aspatial aggregation methods include fish species (Hauber, & Parsons, 2000; Jones, & Lupi, 1999) and similarity among alternatives defined by a factor-cluster approach (Lin, Peterson, & Rogerson, 1988).

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[14] Phaneuf and Herriges (1999) also compared the effects of different levels of aggregation on welfare estimates based from a Kuhn-Tucker model of participation and site choice.
[15] Ferguson (1995) was troubled by: the sequential estimation of the heterogeneity term; the assumption that the scale terms for aggregates were equal; the use of a proxy variable for size; and the ambiguity whether a nested or multinomial logit provides the base for comparisons.

2.4.2: Abandoning the universal choice set concept

In many instances, researchers may eschew the assumption that individuals actually choose from a universal choice set. It is argued, instead, that an individual may not have full awareness of all alternatives or that an individual does not actively consider all alternatives when making a choice.

Several researchers have attempted to determine the impacts of an incorrectly specified choice set on choice models (e.g., Pellegrini *et al.*, 1997; Peters *et al.*, 1995; Thill, & Horowitz, 1997a; Williams, & Ortuzar, 1982). However, an incorrectly specified choice set will only affect parameter estimates of IIA choice models when the incorrect choice set is related to some or all factors that lead to the actual choice. In other words, a choice set that is reduced from the universal choice set will <u>only</u> affect parameter estimates of an IIA choice model if the process that leads to the reduced choice set is correlated with the process that leads to the actual choice. It is an empirical issue whether this fact holds for non-IIA choice models.

Researchers may employ three popular strategies when they are unwilling to assume that all individuals choose from a universal choice set. First, a researcher may ask the choice makers to define their choice sets. Second, researchers may explicitly model the choice set generating process. Finally, a researcher may implicitly model the fuzziness that alternatives belong to a choice set.

<u>2.4.2.1: Respondent defined</u>

While having respondents define their choice sets is logical, it can be controversial (e.g., see discussions from Haab and Hicks (1999) and Thill (1992)). One very poignant question relates to the definition of a choice set. Peters *et al.* (1995) defined a choice set based on whether an individual considers fishing at a particular site[16]. These authors discovered that the parameter estimates for angling site choice in Alberta based on random draws of alternatives from the

[16] Roberts and Lattin (1991) conducted a similar approach in a marketing study based on cereal choice in Australia.

respondent's consideration set differed from those estimates obtained from random draws of alternatives from the universal choice set.

Several individuals have noted that this consideration set approach may purge important information about the choice process (Hicks, & Strand, 2000; Horowitz, & Louviere, 1995; Parsons, Massey, & Tomasi, 1999). This purging of information may occur if individuals initially discount alternatives based on various criteria that are linked to utility (e.g., sites must be a minimum distance from home).

Hicks and Strand (2000) and to a lesser extent (Adamowicz, Swait, Boxall, Louviere, & Williams, 1997; Milon, 1988a) based choice sets on familiarity (i.e., awareness) of respondents[17]. While producing choice sets from awareness may make more sense than from consideration, problems still exist with using and operationalizing awareness sets. For example, individuals may be more aware of better sites from educated search processes (i.e., individuals will learn about good sites from other informed individuals).

Parsons *et al.* (1999a) examined the effects of defining choice sets for beach users in Delaware based on favourite and familiar sites on model estimation. The use of favourite sites paralleled a consideration set approach while the familiar sites represented an awareness set. Unlike the previous applications of user defined choice sets, the authors did not remove any choice sets from estimation. For the familiar site model, the authors modelled familiar and unfamiliar sites in a nested logit model. The favourite site model was estimated by adjusting the log likelihood to account for whether a site was a favourite. This approach is consistent with the call from Horowitz and Louviere (1995) that choice sets and choice can be simultaneously modelled from the utility function. The work of Parsons *et al.* also demonstrated the difficulties in measuring familiar and favourite sites. Specifically, the authors only included sites that beach users had previously visited as familiar and sites that beach users considered for future trips as

[17] Parsons *et al.* (1999) stated that Caulkins, Bishop, and Bouwes (1986) used choice sets based on sites that recreationists visited in the past. However, Caulkins *et al.* (1986) only mentions defining choice sets by some distance for each respondent.

favourites. Finally, the authors estimated models analogous to those of Peters *et al.* (1995) and Hicks and Strand (2000) with reduced choice sets and found that these models did not substantially differ from models based with all alternatives.

2.4.2.2: Explicit choice set modelling

Another common approach to abandon the universal choice set concept involves an explicit attempt to model individuals' choice set generating processes. The model of Manski (1977) of choice as a two-stage process unifies almost all of these approaches. The first stage involves the determination of the actual choice set from the universal choice set (M) of an individual. The first part of equation 17 estimates the probability that a choice set (C) is an individual's real choice set. The probabilistic representation suggests that researchers do not know either the actual choice set or all salient factors that produce this choice set. The second stage involves the evaluation of an alternative (i) conditional on choice set (C). Therefore, the probability of selecting alternative i equals the sum of the products of the choice set and the conditional choice probabilities.

$$P_n(i) = \sum_{C=1}^{M} P_n(i \mid C) P_n(C), \forall C \text{ where } i \in C \tag{17}$$

Explicit choice set modelling arises from one of four different perspectives. First, the choice set screening may arise from the unavailability of certain alternatives. Researchers (Andrews, & Srinivisan, 1995; Ben-Akiva, & Boccara, 1995; Swait, & Ben-Akiva, 1987a, 1987b; Thill, & Horowitz, 1997a, 1997b) typically model unavailability through random constraints whereby a researcher does not know all constraints faced by all individuals. Second, the choice set screening may operate on a search basis that attempts to limit the number of alternatives that individuals consider. Researchers typically assume that these search processes relate to thresholds (Klein, & Bither, 1987; Meyer, 1980; Roberts, & Lattin, 1991; Shugan, 1980; Swait, 2001a), to cost-benefits (Hauser, & Wernerfelt, 1990; Ratchford, 1980; Richardson, 1982; Shugan, 1980; Stigler, 1961) or to preference based approaches (Swait, 2001b). Third, the membership of an alternative in a choice set may occur because of its accessibility and the memory recall of individuals

(Nedungadi, 1990). This model assumes that by priming alternatives in the mind of decision-makers (e.g., advertising of a product) it is possible to increase the likelihood that an individual will select that alternative. Finally, some purely statistical explicit choice set models exist, as they estimate choice set probabilities without a behavioural reason for the reduced choice set (e.g., Chiang, Chib, & Narasimhan, 1999; Haab, & Hicks, 1997).

The explicit choice set generating models hold very little promise for studying spatial choices. The model is limited since one must estimate the probability of all possible choice subsets that may arise from a universal choice set. While this approach is tractable when the number of alternatives is small, the approach quickly becomes intractable as the number of alternatives grows in size. In most spatial choice model applications, the number of possible alternatives is too large for an explicit choice set modelling approach.

2.4.2.3: Implicit choice set modelling

Implicit choice set models embrace a notion of a fuzzy rather than a discrete membership of alternatives within a choice set using weights. For a spatial choice model, this fuzziness is consistent with Meyer's (1980) notion that individuals may have limited knowledge of some spatial alternatives based on locational proximity. Since implicit choice set models assume that all alternatives belong to a choice set, albeit to varying degrees, the computational intractability that affects explicit choice set generating models does not affect implicit choice set generating models (i.e., the modelling complexity grows linearly and not exponentially with an increasing number of possible alternatives).

The most general implicit choice set model is the implicit availability/perception random utility (IAPRU) model (Cascetta, & Papola, 2001). This IAPRU model works by penalizing the systematic utility of choice alternatives by factors related to the awareness of alternatives or by factors related to the availability of the alternative (e.g., constraints). One introduces the penalty as the logarithm of a parameterized estimate that is constrained to lie between zero and one. When an individual fully perceives an alternative, the penalty to the systematic utility is zero.

Conversely, if an individual does not fully perceive an alternative, the penalty to the systematic utility is negative infinity, which results in a choice probability of zero.

Equation 18 operationalizes one possible open form model that is estimable with simulation approaches[18]. The $\bar{\tau}_{inC}$ represents the expected value of the choice set (C) availability or perception for alternative i by individual n. The random variable ξ_{in} represents the deviation of the expected $\bar{\tau}_{inC}$ from its actual value. Cascetta and Papola noted that one could parameterize the $\bar{\tau}_{inC}$ term by elements of the alternatives and/or the individuals (see equation 19). Although $\bar{\tau}_{inC}$ represents the expected value of the choice set availability, the use of a natural logarithm transformation of $\bar{\tau}_{inC}$ makes this new expectation more complex. The authors use a second-order Taylor series expansion of ln($\bar{\tau}_{inC}$) at the $\bar{\tau}_{inC}$ point. With an additional assumption about the variability of the τ_{inC} value, equation 18 arises.

$$P_n(i) = \int_{\xi} \frac{e^{\mu\left[\boldsymbol{\beta}_i^{'}\mathbf{X}_{in} - \ln \bar{\tau}_{inC} - \frac{1-\bar{\tau}_{inC}}{2\bar{\tau}_{inC}} - \xi_{in}\right]}}{\sum_{j=1}^{J} e^{\mu\left[\boldsymbol{\beta}_j^{'}\mathbf{X}_{jn} - \ln \bar{\tau}_{jnC} - \frac{1-\bar{\tau}_{jnC}}{2\bar{\tau}_{jnC}} + \xi_{jn}\right]}} \tag{18}$$

$$\bar{\tau}_{inC} = \frac{1}{1+e^{\gamma \mathbf{Y}_{in}}} \tag{19}$$

In equation 19, the $\mathbf{Y}_{in}$ vector includes L measures that are related to the availability or perception of alternative i and the $\boldsymbol{\gamma}$ term represents the vector of parameters to be estimated. A researcher can include any variables for $\mathbf{Y}_{in}$ including variables that relate to space.

2.5: Review of past attempts to incorporate space in choice models

The previous material provides a necessary background to understand past attempts to incorporate space into choice models and to identify possible new ways to account for space in choice models. A small but growing amount of literature has attempted to incorporate spatial

[18] If one assumes that the ξ_i are i.i.d. extreme value type I, the model has a simple closed form solution (Cascetta, & Papola, 2001).

effects into choice models or other statistical models designed for limited dependent variables. This section reviews these attempts starting first with attempts to incorporate spatial effects among decision-makers followed by a review of attempts to incorporate spatial effects among choice alternatives.

All equations below assume that the parameters associated with the systematic and unobserved utilities are only identifiable in differenced form (i.e., the parameters for one alternative must be fixed for identification purposes). This section purposively omits the transcendental logarithmic indirect utility (translog) function approach of Lo (1990, 1991) since it lacks an empirical foothold in the literature.

2.5.1: Incorporating spatial effects from decision-makers

The choice made by one individual may relate to the choices made by neighbouring individuals. While this spatial pattern of choices may arise because of model misspecification (i.e., a nuisance perspective), the pattern may also arise from substantive spatial processes. For example, individuals may interact with one another thereby leading to a spatial homogenization of choices and/or preferences. Another possibility is that individuals may be attracted to areas where people have similar values and preferences to their own. This dispersal spatial process may lead individuals to choose similar alternatives, as do their neighbours.

To assess whether space influences the choices made by individuals, researchers have used three general approaches. First, many researchers have worked to extend global spatial statistical models to dichotomous limited dependent variable models. Second, increasing interest exists to incorporate spatial dynamics into choice models. Finally, other researchers have extended statistical models designed to capture the effects of spatial heterogeneity to limited dependent variable models.

2.5.1.1: General spatial effects in dichotomous limited dependent variable models

Several researchers have used a simultaneous spatial autoregressive (SAR) model (see equations 2 and 3) to specify spatial effects in probit (or at least dichotomous) models[19]. In most cases, researchers view the dichotomous dependent variable as an indicator of a latent continuous variable that is estimable by regression techniques. Fleming (2004) thoroughly reviews the different estimation approaches used by researchers including EM (expectation maximization) (McMillen, 1992, 1995), generalized methods of moments (Pinske, & Slade, 1998), Bayesian approaches (LeSage, 2000) and GHK (i.e., similar to maximum simulated likelihood) (Beron and Vijverberg, 2004). McMillen (1992) also estimated a model with a spatial expansion approach and the model of LeSage (2000) is more general than a probit model. While these spatial autoregressive models are interesting, the static treatment of interaction leads to complications in analyses (Beron and Vivjerberg, 2004) and is behaviourally unappealing since there must be a dynamic component for any substantive spatial effect (Upton, & Fingelton, 1985, p. 369).

2.5.1.2: Spatial dynamic effects among neighbouring individuals

Interactions among spatially near individuals may influence the preferences and choices of other individuals. Along with the possibility of technology diffusion, several researchers have developed approaches to model these spatial dynamics among individuals.

Case (1992) used a spatial probit model to assess whether the attitudes[20] of neighbouring individuals influenced the farming practices of Indonesian farmers. A spatial lag spatial autoregressive (SAR) process was included into a regression model of the latent agricultural profits of farmers. The spatial probit arose from the censoring of the latent profits into only two outcomes (i.e., using new or traditional rice harvesting tools). By using a regional spatial weights

[19] This does not suggest that a spatial autoregressive structure is required for spatial probit models. Indeed, Haegerty and Lele (1998) used a geostatistical approach to specify the covariance function for a spatial probit model applied to gypsy moth defoliation in Massachusetts. The model was estimated by a composite likelihood approach.
[20] While attitudes may lead to similar preferences among neighbours, the choice model used by Case was incapable of drawing a link between the common preferences from the model and attitudes.

matrix (i.e., block diagonal), Case was able to show that one could reduce the expansion of a spatial lag SAR model to a parameterized weight of the independent variables along with a scaled parameterized weight of the regional averages for the independent variables. In matrix form (see equation 20), the $\mathbf{c}_1$ and $\mathbf{C}_2$ parameters partially depend upon the spatial parameter (ρ), a matrix of independent variables ($\mathbf{X}$), a vector of parameters ($\boldsymbol{\beta}$), the regional spatial weights matrix ($\mathbf{W}$), and an independently and identically distributed (i.i.d.) error term ($\mathbf{v}$).

$$\mathbf{y}^* = \mathbf{c}_1\left[\mathbf{X}\boldsymbol{\beta} + \mathbf{C}_2\overline{\mathbf{X}}\boldsymbol{\beta}\right] + \frac{\mathbf{v}}{(\mathbf{I} - \rho\mathbf{W})}, \quad \mathbf{v} \sim N\left(0, \sigma^2\mathbf{I}\right) \tag{20}$$

This model form provided a statistically significant improvement over a model without the neighbours' characteristics. Although the author found that the common factor restriction was rejected by a statistical test (i.e., the $\boldsymbol{\beta}$ vector for the independent variables was significantly different from the $\boldsymbol{\beta}$ vector for the regional average independent variables*)*, oddly, this finding was discarded. Finally, Case tested whether the spatial relationships were manifested solely in the error terms through common neighbourhood shocks (i.e., the final term on the right hand side of equation 20). However, including spatially correlated errors provided no significant improvement over the common factor restriction model.

Dubin (1995) developed a spatial logit model to account for spatial dynamic relationships among individuals who were considering adopting a new technology. Equation 21 shows the factor (d) that was included to the systematic utility of individual n for adopting a technology. The equation sums a distance (d_{nm}) weighted (i.e., negative exponential) contribution over all individuals (m) in the previous time (t-1) that have adopted the alternative (y).

$$d_n = \sum_{m=1}^{N} \beta_1 e^{\left(\frac{-d_{mn}}{\beta_2}\right)} y_{m,t-1} \tag{21}$$

Dubin advanced the work of Case in several ways. First, Dubin specified a spatial logit that defined the systematic utility function for an individual to consist of his/her characteristics along with a spatially weighted effect of neighbours' past choices. This temporal effect made the model of Dubin much more behaviourally pleasing than the model of Case (1992). Dubin also specified a more general spatial weights matrix (i.e., negative exponential) than Case's regional approach. It was also argued that the past choices and not attitudes of neighbours should influence the choice of an individual. The potential of this spatial logit model was illustrated with simulated data.

Mohammadian, Kanaroglou, and Haider (2003) extended the spatial dynamic choice models to the multinomial case. The authors extended the model to the multinomial case by changing equation 21 to be specific for a chosen alternative (see equation 22). The only two differences between equations 21 and 22 are that the statistic (d_n) and choice response (y_m) now have alternative specific subscripts (i) and that other individuals' choices of the same alternatives (y_m) are now from the any previous time periods ($t \leq -1$) in the sample.

$$d_{ni} = \sum_{m=1}^{N} \beta_1 e^{\left(\frac{-d_{nm}}{\beta_2}\right)} y_{mi,t\leq -1} \tag{22}$$

The authors examined 1384 development choices (i.e., detached, semi-detached, apartments, and other) made by developers from 1997 to 2001 in the Greater Toronto Area. The results showed that the two parameters specified for the negative exponential spatial weight were significant and positive in sign. These parameter estimates demonstrated, *ceteris paribus*, that a development alternative was more likely in areas with similar development than in areas further from similar development.

Hautsch and Klotz (2003) also generalized the model of Dubin to the polychotomous case. While the authors used the basic form of equation 22, Hautsch and Klotz suggested that the physical distance measure be generalized to a social distance measure that reflected the similarity of the choice context of two decision-makers. Finally, this new model also permitted researchers to include an effect of the decision-maker's past decisions to enter the deterministic utility function.

2.5.1.3: Spatial preference heterogeneity effects

Choice or other limited dependent variable models that account for preference heterogeneity are not new. However, only a few studies have attempted to explain preference heterogeneity by the spatial locations of the individuals. Two of these applications employed a multi-level modelling approach[21]. The other two studies focused on a Bayesian approach and a geographic weighted regression approach, respectively.

Bhat (2000) used a mixed logit specification to estimate a multi-level choice model of transportation mode choice. Data on San Francisco area work trips between traffic home and work zones was used to develop a cross-classification approach for the multi-level model. This cross-classification system included place effects for both the home and work zones of the individuals. Bhat simplified the analysis by aggregating the 558 work zones into five different work zone groups (e.g., central business district). Equation 23 shows the latent variable model that defined the utility (U^*) for a given individual (n), home zone (h), work zone (w) and transportation mode alternative (i).

$$U^*_{nhwi} = \alpha_{hwi} + \beta' x_{nhwi} + \varepsilon_{nhwi} \qquad \varepsilon_{nhwi} \sim i.i.d.\, EVI\left(0, \frac{\pi^2}{6\mu^2}\right) \tag{23}$$

This utility was assumed to equal an alternative specific intercept (α) for a home zone, work zone and alternative mode along with parameterized (β) values of independent variables (x) for individuals from a given home zone traveling to a work zone with a given transportation mode. The ε term is an i.i.d. error term from the extreme value type I distribution with typical variance estimate.

Equation 24 shows the macro-level model that feeds into the micro-level model (equation 23). The first term in the equation (γ) scales observed zonal-level attributes (z) into the alternative specific constant. The second term (τ_i) captures the average effects of unobserved variables on

[21] Scott and Shiell (1997) also employed a multi-level logit model to various dichotomous choices by physicians in Australia. However, these authors used general practitioner and patient characteristics rather than spatial scale levels.

alternative i (i.e., the τ_i are alternative specific constants). The remaining terms capture the unobserved variations across home (δ) and work zones (θ). Bhat assumed that the random variables δ and θ were normally distributed with mean of zero and variance equal to σ_i^2 and ω_i^2, respectively.

$$\alpha_{hwi} = \gamma z_{hwi} + \tau_i + \delta_{hi} + \theta_{wi}, \quad \delta_{hi} \sim N(0,\sigma_i^2),\ \theta_{wi} \sim N(0,\omega_i^2) \tag{24}$$

For identification purposes, the home (σ_i^2) and work (ω_i^2) zone error variances for one transportation mode alternative had to be restricted. In this case, the drive alone estimates were restricted to zero while the parameters for the shared ride and transit alternatives were estimated. The author found that the error variances for shared ride home and transit work zones were significantly different from zero. This finding implied that the between zone heterogeneity for the shared ride home zones and transit work zones was significantly greater than the heterogeneity between the drive alone work or home zones.

A later study by Bhat and Zhao (2002) provided additional improvements to multi-level models with limited dependent variable models. These authors used a mixed ordered logit (see equation 25) to study the number of stops individuals make for shopping from Boston residential zones. Equation 25 shows that the latent stop making propensity (s^*) that a household (n) from home zone (h) has during a typical mid-week day. The equation consists of a home zone constant (α_h), a parameterized (β_h) contribution of household exogenous variables from a zone (x_{nh}), and an error term (ε). The number of observed stops (s) equals r if the stop making propensity (s^*) falls between thresholds for one less stop (θ_{r-1}) and the current stop (θ_r).

$$s_{nh}^* = \alpha_h + \beta_h' x_{nh} + \varepsilon_{nh},\ \ s = r \ \ if\ \theta_{r-1} < s_{nh}^* \le \theta_r, \quad \varepsilon_{nh} \sim i.i.d.EVI\left(0, \frac{\pi^2}{6\mu^2}\right) \tag{25}$$

The macro-level model contained two parts. First, equation 26 shows that authors defined the home zone constant to consist of zone specific variables (z_h) plus an unobserved variable (δ_h). The unobserved variable was assumed to follow a normal distribution with a mean of zero and complex variance form. The variance form ($\exp(2\upsilon b_h)$) equalled an exponentiated parameterized weights (2υ) of zonal attributes (b_h) including a constant. The specification of the variance to include zonal attributes introduced heteroscedasticity in the model.

$$\alpha_h = z_h + \delta_h, \quad \delta_h \sim N\left(0, e^{2\upsilon b_h}\right) \tag{26}$$

The second part of the macro-level model focused on the g number of parameters (β_h) for the household exogenous variables from equation 25. Equation 27 shows a random parameter form that includes an average slope parameter (β_g) for each g variable plus a zone specific deviation (v_{hg}) from the area wide effect. The authors assumed that the v_{hg} terms were normally distributed random variables with mean zero and constant variance (σ_g^2).

$$\beta_{hg} = \beta_g + v_{hg}, \quad v_{hg} \sim N\left(0, \sigma_g^2\right) \tag{27}$$

In the application, the significant v_{hg} terms for the zones along with the υb_h terms captured spatial preference homogeneity within but not between zones. The significant υb_h (i.e., suburban and rural household locations) introduced spatial heteroscedasticity to the results.

Smith and LeSage (2002) extended the work on Bayesian probit models (LeSage, 2000) by employing an additive error component structure that included both regional and individual effects. In fact, one could interpret this model as a multi-level model. Equation 28 shows that the utility for alternative i by individual n from household zone h equals a parameterized (β) set of independent variables (x_{nhi}) plus a region specific error term (δ_{hi}) and an individual based error term (ε_{ni}). Equation 29 specifies the region specific error term (δ_{hi}) to have a spatial autoregressive structure. As usual, ρ is a spatial parameter and w_{hz} represents the spatial weight between regions h and z. The sum of w_{hm} terms row standardize the spatial weights. As well, the authors assumed that the variance (σ^2) of the region specific error term (δ_{hi}) was identical within but not between regions (i.e., the model accounts for regional heteroscedasticity).

$$U^*_{nhi} = \beta_h' x_{nhi} + \delta_{hi} + \varepsilon_{ni} \tag{28}$$

$$\delta_{hi} = \rho \sum_{z}^{M} \left(\frac{w_{hz} \delta_{hi}}{\sum_{m}^{M} w_{hm}} \right) + v_h, \quad v_h \sim i.i.d.\ N\left(0, \sigma_h^2\right) \tag{29}$$

The model was applied to presidential voting decisions for the 1996 United States election. The individuals were the 3,110 counties while the regions were the 48 states. The data was constrained to include only those votes for the Republican and Democratic candidates. The spatial probits with homoscedasticity and heteroscedasticity assumptions were much better than a probit with no spatial effects. A weak validity test (i.e., comparing county level model predictions greater than 0.5 with the actual outcomes) provided some evidence that the heteroscedastic spatial probit outperformed the homoscedastic spatial probit.

A final method to investigate spatial preference heterogeneity is the geographically weighted regression (GWR). Atkinson, German, Sear, & Clark (2003) focused on the presence or absence of erosion along a riverbank in Wales. The authors examined the importance of several factors (e.g., vegetation index) on erosion that were each employed in separate logit models. The extension of GWR was straightforward and involved calculating local level logit models with spatially weighted neighbouring observations. Although the local level parameter estimates exhibited great variability, there was no discussion whether these local level models captured any more than sampling variation from the global model. Furthermore, since the logit model cannot separate parameter estimates from error variance, one should not compare the local GWR logit estimates without accounting for possible variance differences. In fact, the variability found in the parameter estimates from Atkinson *et al.* (2003) may have arisen from parameter estimate differences, variance differences, or a combination of both.

2.5.2: Incorporating spatial effects from choice alternatives

Another general approach to incorporate spatial effects in choice models focuses on the spatial structure of the alternatives. These modelling efforts acknowledge that spatially near alternatives may be better substitutes for each other than are alternatives located farther away. Therefore, the IIA assumption of the MNL will likely be violated because of the complexity of space.

Three approaches dominate the choice model like applications that attempt to account for complex spatial substitution patterns among the alternatives. First, several researchers have adjusted the MNL to include a spatial measure into the systematic utility for the alternatives. Second, one application has examined the role of spatial dynamics. Finally, several studies have accounted for common unobserved utilities among spatially related alternatives.

2.5.2.1: Spatial effects in the systematic utilities of alternatives

One way to include spatial effects into a choice like model is to adjust the systematic utility for an alternative to account for space. While this simple adjustment appears to work within the confines of traditional choice models, it will be shown that this adjustment may affect the behavioural underpinnings of the choice model. This subsection reviews three different attempts to adjust the systematic utility to incorporate spatial effects.

Boots and Kanaroglou (1988) investigated the role of zone centrality on the inter-metropolitan migration decisions of Toronto residents. These authors measured the spatial centrality of zones by the primary eigenvector scores from a principal components analysis of the distance matrix among the alternatives. They included in the systematic utility function a similarity measure (s_{ij}) of the eigenvector scores (e) between neighbourhoods, i and j (see equation 30).

$$s_{ij} = \frac{100\left|e_i - e_j\right|}{\left(e_i + e_j\right)} \tag{30}$$

The parameter estimate for the centrality score captured the importance of moving to a neighbourhood with similar (or dissimilar) centrality. The destination choices of individuals were partially related to the centrality that existed between their past and chosen residences (i.e., *ceteris paribus*, people tended to move between areas with similar centrality measures).

The two remaining approaches included an accessibility measure to the systematic utility for each alternative. Researchers have used accessibility terms for some time to create different substitution patterns among alternatives than those produced by multinomial logit (MNL) and gravity models[22]. The accessibility terms measure a degree of similarity or dissimilarity of one alternative to all other alternatives. By including an accessibility measure in the systematic utility function for an alternative, an MNL choice model does not exhibit the IIA property. The inclusion of an accessibility term circumvents the IIA property since the utility for any alternative requires information about all other choice alternatives (i.e., the degree of similarity). However, the disadvantage of including an accessibility term is that the choice model may no longer be consistent with random utility theory[23]. Therefore, researchers who use these model adjustments must demonstrate either that their model is consistent with random utility theory or describe the different behavioural assumptions associated with their model. Otherwise, no foundation exists for the statistical model chosen by the researcher (i.e., there is no reason to favour one statistical model over any possible statistical model).

Borgers and Timmermans (1987a, 1987b) proposed adjusting the systematic utility for each alternative to include accessibility measures for both spatial structure and substitution. The spatial structure accessibility measure of alternative i (a_i) is shown in equation 31, where d_{ij} is the distance between alternatives i and j and $(J-1)$ is the number of relevant alternatives.

$$a_i = \ln\left(\frac{\sum_{j \neq i}^{J} d_{ij}}{(J-1)}\right) \tag{31}$$

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[22] Borgers and Timmermans (1987a, 1987b) provide reviews of choice modelling efforts that use accessibility like measures to account for different substitution possibilities.

[23] An accessibility term is simply a weighted average cross-effect. Cross-effects are measures of attributes from alternatives that are included in another alternative's systematic utility. This so-called mother logit model (McFadden, 1975) has not been proven to be consistent with random utility theory (Train, 1999).

In their 1987b paper, the authors compared the results of an MNL model versus several substitution and spatial structure models[24]. The authors simulated choice data for 12 alternatives from the substitution and spatial structure probit models. The results of these simulations showed that the MNL was very robust even with departures from IIA and error term distribution assumptions.

The final approach is the competing destinations model (Fotheringham, 1983). Fotheringham (1981, 1983, 1984) suggested that the spatial patterning found among distance decay parameters from origin specific production constrained gravity models arose from a systematic misspecification of the gravity model. Fotheringham argued that one could alleviate this model misspecification by including an accessibility term (a_i) that accounts for spatial structure (see equation 32), where W_j is a measure of the attractiveness of alternative j and d_{ij} is as defined above.

$$a_i = \ln\left(\frac{\sum_{j \neq 1}^{J} W_j}{(J-1)\sum_{j=1}^{J} d_{ij}}\right) \tag{32}$$

Fotheringham and others (Haynes, & Fotheringham, 1990; Fotheringham, 1986, 1988; Fotheringham, & O'Kelly, 1989; Pellegrini, & Fotheringham, 1999; Pellegrini *et al.*, 1997) later argued that researchers could view the competing destinations model as a general choice model that could rid the MNL of the IIA property.

Mechanically, the competing destinations model is similar to the approach of Borgers and Timmermans (1987a, 1987b). The competing destinations model, however, does differ from the two previously described approaches by its development and reliance on a behavioural theory of spatial information processing. The behavioural theory dictates that spatial structure is important to decision-makers. When confronted with many spatial choice alternatives, some researchers

[24] The spatial structure probit model is presented in section 2.5.2.3.

(Fotheringham, 1983, 1986) assume that individuals will follow a hierarchical decision-making process with individuals first choosing a region followed by an alternative from that region.

Researchers employing the competing destinations model now view the accessibility term as a weight of the likelihood that an individual will consider that alternative (Haynes, & Fotheringham, 1990; Fotheringham, 1988; Fotheringham, Nakaya, Yano, Openshaw, & Ishikawa, 2001; Fotheringham, & O'Kelly, 1989; Pellegrini, & Fotheringham, 2002; Pellegrini *et al.* 1999). The papers by Pellegrini and Fotheringham argue that a negative parameter estimate for the accessibility term provides evidence that individuals employ hierarchical decision-making processes and that individuals will underestimate the number of alternatives in regions containing many alternatives. Therefore, it is expected, *ceteris paribus*, that alternatives in areas with many nearby alternatives will receive fewer choices than will alternatives that are spatially dispersed.

In most competing destination applications, the accessibility term is significantly different from zero and negative in sign (see Pellegrini and Fotheringham (2002) for a review). This fact has led proponents of the model to suggest that the use of aspatial choice models such as MNL and nested logit may lead to biased and misleading results (Pellegrini, & Fotheringham, 1999, 2002; Pellegrini *et al.*, 1997). Furthermore, these proponents also suggest that problems exist with the estimation of a multinomial probit model, which potentially could account for a rich substitution pattern among choice alternatives. Advances to simulation techniques and additions to the family of generalized extreme value models as were described in Section 2.3 have overcome many criticisms that these authors levy against such models.

One major criticism with the competing destinations model relates to the behavioural theory upon which it rests. While the proponents of the model are convinced that a significant accessibility parameter estimate indicates hierarchical decision-making, the accessibility term may act as an unintended proxy for other substantive or nuisance effects in choice models. Furthermore, the proponents of this approach have not conducted detailed behavioural research on choice makers to validate the tenets of the behavioural theory.

The competing destinations model is a very restrictive implicit choice set model. These restrictions focus on three elements. First, the competing destinations model does not account for the shared unobserved factors that are likely to exist among alternatives in the implicit choice set modelling term. Second, the competing destinations model does not employ a variability term. Finally, the competing destination model assumes that spatial accessibility is the only factor that is important to the awareness of an alternative. Researchers could easily lessen each of these restrictions by using a general implicit choice set modelling approach such as the one advocated by Cascetta and Papola (2001).

Xue and Brown (2003) employed another implicit choice set model to account for space in a choice model of break and enters in Richmond, Virginia. The probability of an alternative belonging to an individual's choice set was based from a kernel density estimation approach that is used to detect areas of high spatial concentration of an event (i.e., a hot spot). Equation 32 describes the Gaussian functional form of the estimation with x and y as spatial coordinates, h_1 and h_2 being bandwidths, k being the chosen alternative on choice occasion n and i being the alternative in question.

$$P(i \mid C) = \frac{1}{N}\sum_{n}^{N}\frac{1}{2\pi h_1 h_2}e^{\left[-\frac{1}{2}\left(\left(\frac{x_i - x_k}{h_1}\right)^2 + \left(\frac{y_i - y_k}{h_2}\right)^2\right)\right]} \tag{32}$$

Several assumptions and problems exist that limit the usefulness of this approach. First, the model assumes that criminals have identical preferences and face only one choice set. The kernel density estimator also does not appear to correct for the population at risk. Therefore, the predicted choice set probabilities measure aspects related to preference and the availability of properties for break and enters. Finally, identifying choice set probabilities from a pattern rather than a process model may not be well suited to forecast scenarios that involve significant change. For example, if police increased enforcement efforts in areas identified as hot spots, criminals would likely shift their activities to new areas. Therefore, the spatial choice set model would likely overestimate crimes in the areas with enforcement (i.e., the choice set probabilities are not sensitive to this change).

2.5.2.2: Spatial dynamic effects from one decision-maker

Choices made at one time may impact future choices by individuals. This dynamic impact may involve a spatial component since past chosen alternatives may prime an individual's awareness of other nearby alternatives (e.g., because of travelling to the destination). While I am not aware of any study on this exact spatial dynamic process, Garrido and Mahmassani (2000) have employed a model that measured spatial dynamic effects that arise from one decision-maker.

Garrido and Mahmassani (2000) employed a spatial dynamic multinomial probit model to predict the freight pickup choices of a large truckload carrier in Texas. The authors simplified their analysis by: computing separate models for three seasons of shipments (three weeks of data for spring, summer and winter); aggregating the alternatives into 80 counties; using two time intervals each day; and simplifying the number of additional explanatory variables in the model.

The spatial dynamic choice model employed equations 33 and 34 to account for both spatial and temporal autoregressive errors in the model. By inserting equation 34 into equation 33, the spatial and temporal autoregressive structure of the model becomes apparent. The error terms (ε) at alternative i and time period t consist of three parts. The first part ($\rho \Sigma w_{ij} \varepsilon_{jt-1}$) is the spatially weighted (w_{ij}) errors from the previous time period at different alternatives (j). The second part ($\theta \mu_{it-1}$) equals some portion of the non-spatially autocorrelated errors from the previous time period at the same site. The final part (λ_{it}) is an i.i.d. error term. The parameters ρ and α, which relate to the spatial and temporal errors, respectively, are estimated from the model.

$$\varepsilon_{it} = \rho \sum_{j}^{J} w_{ij} \varepsilon_{jt-1} + \mu_{it} \tag{33}$$

$$\mu_{it} = \theta \mu_{it-1} + \lambda_{it}, \quad \lambda_{it} \sim i.i.d.N\left(0, \sigma^2\right) \tag{34}$$

The authors defined the spatial weights as dummy variables that equalled one if the borders of two counties were contiguous and zero otherwise. The authors found that the temporal error parameter (θ) was significantly different from zero and positive in sign. Therefore, if a pickup occurred in the previous time period at a site, the probability of pickup at that site in the current time period was greater, *ceteris paribus*. The spatial error parameter (ρ) was significantly different from zero for two of three seasons and this parameter was negative in sign. Therefore, an alternative in close proximity to other alternatives that received a pickup in the previous period was less likely to have a pickup in the current time period. The application demonstrates that researchers can use an open form choice model to study spatial dynamic behaviours.

2.5.2.3: General spatial effects in shared unobserved utilities

Another approach to account for spatial effects among the alternatives is to model the common unobserved utility among spatially near alternatives. Although this general approach can account for any type of spatial effect, the model's generality comes at a cost. Researchers using these models are unable to distinguish between behavioural and nuisance reasons for the spatial effects.

Generalized extreme value (GEV) models provide elegant closed form solutions for modelling choice behaviour. Numerous applications of the nested logit model have been used to account for common unobserved utility within regions. However, only one application has examined spatially related common unobserved utility with a more flexible generalized extreme value model.

Bhat and Guo (2004) employed a restricted generalized nested logit (Wen, & Koppelman, 2001) to examine the housing choices of residents from Dallas County, Texas. This restricted generalized nested logit differed from the one presented in equation 12 in two ways. First, the allocation parameters were fixed to equal w_{ij} divided by the sum of all w_{ij} for alternative i (see Equation 35), where w_{ij} was a dummy variable that equalled one if alternatives i and j were contiguous and zero otherwise. Second, all dissimilarity parameters (μ) were constrained to be equal for all pairwise nests (see Equation 36). The summations J_m and J_l in equation 36 refer to the two alternatives belonging to nests m and l, respectively.

$$\alpha_{im} = \frac{w_{ij}}{\sum_{j=1}^{J} w_{ij}} \tag{35}$$

$$P_n(i) = \sum_{m=1}^{M} \left[\frac{\left(\alpha_{im} e^{\beta_i' X_{in}}\right)^{\frac{1}{\mu}} \left(\sum_{j=1}^{J_m} \left(\alpha_{im} e^{\beta_i' X_{in}}\right)^{\frac{1}{\mu}} \right)^{\mu-1}}{\sum_{l=1}^{M} \left(\sum_{j=1}^{J_l} \left(\alpha_{jl} e^{\beta_i' X_{in}}\right)^{\frac{1}{\mu}} \right)^{\mu}} \right] \tag{36}$$

The model incorporated spatial effects by defining pairwise nests between contiguous neighbours for the 98 zones in the study. The authors showed that the number of contiguous neighbours in each zone along with the dissimilarity parameter conditioned the correlation of unobserved utilities among alternatives. The authors also calculated random parameters for the choice attributes by using the GEV model as a kernel for a mixing distribution. The study revealed a strong spatial relationship among the shared unobserved utilities of alternatives (i.e., the dissimilarity parameter μ was different from one). This application demonstrates that a researcher may employ a GEV model to account for complex patterns of substitution among the alternatives.

Borgers and Timmermans (1987b) were the first authors to estimate an open choice model with a form that incorporated spatial effects. The authors used simulated data to estimate a series of model forms including one that they termed a spatial structure probit model. The model updated the substitution model of Kamakura and Srivastava (1984) to account for space within a multinomial probit model.

The authors parameterized the covariance matrix of the error terms as a function of the distance between the two alternatives $f(d_{ij})$ and the standard deviations of the error terms for the alternatives in question (s_i) (see equation 37). The authors estimated the model with a now dated simulation approach and they tested the model with simulated data along with other model forms. The spatial structure probit did not appear to provide much improvement over the MNL, and I am not aware of any empirical application of this model. The model is, nevertheless, important as it represented a first step towards using an open form choice model to account for spatial effects in a choice model.

$$COV(i,j) = \mathbf{F_{in}TT'F_{in}}' = s_i s_j f(d_{ij}) \tag{37}$$

A second study that examined spatial effects within an open form choice model was conducted by Bolduc, Fortin, and Fournier (1996) who built upon the senior author's previous work on the generalized autoregressive choice model (Bolduc, 1992) and spatial autoregressive interaction models (Bolduc *et al.*, 1989; Bolduc, Laferriere, & Santarossa, 1995). Bolduc *et al.* (1996) developed their model to investigate the residency decisions of doctors in Quebec. The choice alternatives consisted of 18 regions in Quebec.

Bolduc *et al.* (1996) used a mixed logit approach to specify the spatial autoregressive (SAR) model. Equation 38 shows that the unobserved utility (ε) for individual n and alternative i equals a composite of terms. The σ term is the standard deviation for alternative i, ρ is a spatial parameter, w_{ij} is a spatial weight between alternatives i and j, ξ is an error tied to the spatial autoregressive structure, ζ is an i.i.d. normal error term, and v is an i.i.d. extreme value type I error term.

$$\varepsilon_{ni} = \sigma_i \rho \sum_j^J \left(\frac{w_{ij}\xi_{ni}}{\sum_k^J w_{ik}} \right) + \zeta_{ni} + v_{ni}, \quad \zeta_{ni} \sim i.i.d.N(0,1), \;\; v_{ni} \sim i.i.d.EVI\left(0, \frac{\pi^2}{6\mu^2}\right) \tag{38}$$

The spatial weights matrix was defined as a row standardized (i.e., W-coding scheme) inverse distance matrix. The spatial parameter ρ was statistically different from zero. This finding implied that a change to a spatial zone will impact near zones more than it will impact other zones.

A second paper by Bolduc, Fortin, and Gordon (1997) used a multinomial probit choice model on the same physician choice data as described above. This paper assessed whether maximum simulated likelihood (i.e., the GHK simulator) or Bayesian approaches led to different model estimates. The authors concluded that no real differences in parameter estimates existed between the SAR choice models. The authors also calculated the full error covariance matrix, with necessary identification restrictions, from Bayesian estimation and found that this model did not differ much from the Bayesian SAR choice model. Interestingly, the identification of the full error covariance matrix is analogous to a local level spatial modelling approach. While in this case, the authors concluded that a global spatial parameter adequately captured the local level covariance matrix, other researchers could exploit this avenue.

2.6: Accounting for spatial complexities in choice modelling approaches

Several developments have increased the generality and flexibility of choice models and have shed limitations associated with the multinomial logit. These general choice models now offer the potential to examine many issues including the complexities that space may present within a choice model. Furthermore, general choice models also now encompass spatially developed choice models such as the competing destinations model as special, albeit restrictive, cases.

The most interesting choice model developments from a geographer's viewpoint are the generalized extreme value (GEV) models, open form choice models and the implicit availability/perception random utility (IAPRU) model. The GEV models offer a convenient closed form model with sufficient flexibility to capture a wide array of substitution patterns among alternatives. Bhat and Guo (2004) showed this potential by developing a global like model that related substitution among alternatives to space.

Many complex open form choice models are now estimable because of advances to simulation approaches and increases to computing power and speed. The extreme flexibility of these models offers much potential to examine spatial patterns of substitution among alternatives (Bolduc *et al.*, 1996; Bolduc *et al.*, 1997), spatial dynamics (Garrido, & Mahmassani, 2000), and spatial relationships among individuals (Bhat, 2000; Bhat, & Zhao, 2002; Smith, & Lesage, 2002).

It should be straightforward to extend GEV and open form choice models to examine additional issues related to space and choice modelling. First, one may cast these models to study spatial heterogeneity at fine spatial scales. Choice model applications focusing on spatial heterogeneity are limited to date (Bhat, 2000; Bhat, & Zhao, 2002; Bolduc *et al.*, 1997; Smith, & LeSage, 2002) as researchers are still trying to develop global models to account for spatial dependence. Furthermore, the multi-level models conducted to date (Bhat, 2000; Bhat, & Zhao, 2002; Smith, & LeSage, 2002) only account for spatial heterogeneity in a limited fashion. In these models, it is assumed that behaviour is associated with an arbitrarily determined region rather than from a true local level model. Second, many models that account for spatial effects among individuals are dichotomous and/or focus on aspatial alternatives. Therefore, an active area for research is to develop choice models that link spatial choices of individuals to past spatial choices of other individuals. This leads to the final extension of creating spatial dynamic choice models. Many choice model developments have treated spatial effects without regard for the dynamic processes necessary to produce substantive effects. Again, the flexible choice models offer researchers the opportunity to assess spatial dynamics.

The issue of choice set development is difficult for spatial choice modellers. While random sampling, narrowing and aggregation approaches are available to limit the number of alternatives, these heuristics provide no guidance to processes of choice set development. Most modelling approaches of choice set development estimate a probability for every possible choice set. While this approach is tractable when the number of choice alternatives is small, the approach becomes unmanageable with even a medium number of choice sets that are likely to occur with spatial choice data (e.g., 50 fishing sites).

The open form IAPRU model abandons the need to evaluate all possible choice sets by assuming a fuzzy choice set membership for the alternatives. This model contains two features that add to its potential for studying spatial effects. First, a researcher can specify characteristics of individuals and alternatives including measures related to space as explanatory factors for choice set availability. One, therefore, could use the accessibility factor from a competing destinations model to explain the fuzziness of choice sets. Second, the IAPRU model correctly accounts for errors in any specification of a fuzzy choice set.

Chapter 3: Review of recreational fishing site choice models[25]

This chapter draws from past recreational fishing site choice model studies to assess the state of contemporary research on fishing site choice. This assessment includes a review of issues that complicate the design of fishing site choice models and of assumptions that researchers implicitly or explicitly employ to manage these issues.

Precedence provides some support for employing a choice modelling approach to examine the fishing site choices of northern Ontario anglers. These past recreational site choice model applications first appeared in the early 1980s (e.g., Feenberg, & Mills, 1980; Morey, 1981; Peterson, Anderson, & Lime, 1982; Peterson, Dwyer, & Darragh, 1983; Peterson, Stynes, & Arnold, 1985). However, not until several researchers (Bockstael, Hanemann, & Kling, 1987; Caulkins *et al.*, 1986; Kling, 1987) contrasted choice models and traditional statistical approaches such as gravity models did choice models became a mainstream method to examine recreational choices. Currently over 50 published choice model applications exist on recreational fishing.

The remainder of this chapter is organized as follows. Section 3.1 provides a conceptual model of fishing site choice. Within this section, efforts are spent discussing sources of choice data, relevant fishing site attributes and the concept of economic valuation. The basic conceptual model is enhanced in Section 3.2. This enhancement includes the discussion of four issues that are important to consider when conducting a fishing site choice model. Since Chapter 2 discussed the issues of substitution and choice sets, Section 3.2 only briefly describes these two issues. The issues related to varying preferences and participation and dynamic choices are described in detail in this section.

3.1: Conceptualizing the modelling of fishing site choice

Chapter 2 described a utility maximizing choice process whereby an individual selects the one alternative from a set of relevant alternatives that will provide him / her with greatest utility.

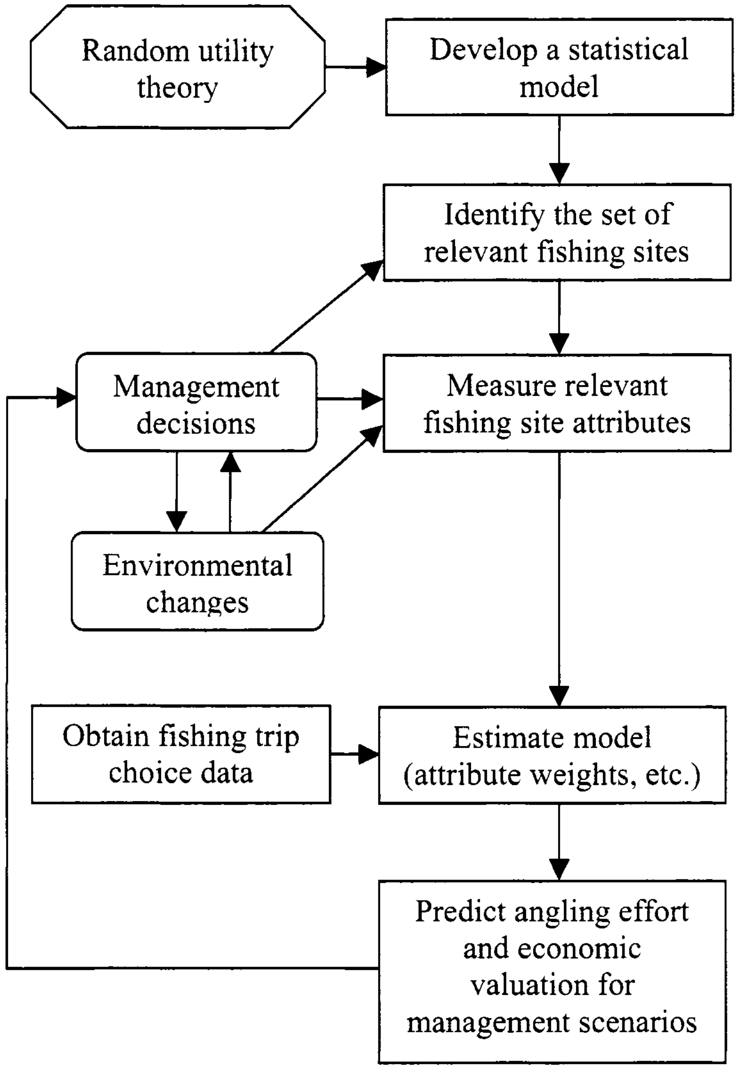
[25] Much of this chapter is similar to the review paper by Hunt (2005).

While this process is relatively straightforward, modelling this behavioural process may be complex. This complexity arises from the uncertainty that researchers have with the exact choice process used by every single choice maker. This uncertainty limits researchers to model the site choices probabilistically rather than deterministically. In this section, I create a conceptual model of site choice (see Figure 3.1.1) that captures the basic considerations for modelling fishing site choice.

The figure begins by using random utility theory to identify a statistical model. The statistical model estimation requires information on relevant and chosen fishing sites and measurements of salient attributes for all available fishing sites. As described in Chapter 2, these three data sources permit one to estimate parameters that are associated with the utility (i.e., preference) of a fishing site. With these parameter estimates, researchers or managers can develop forecasts for a wide range of management scenarios. These forecasts can predict how the scenarios may impact both the spatial pattern of fishing site choices and the economic value of recreational fishing. Resource managers may use these forecasts to make decisions that affect the set of fishing sites available to anglers (e.g., closure of a fishing site), relevant attributes at the fishing site (e.g., lake specific regulations), or the environment (e.g., stocking of a lake). Additionally, environmental changes such as climate change may impact the important attributes at fishing sites and/or influence management decisions.

The remainder of this section reviews and discusses three elements from Figure 3.1.1. First, I review the options available for individuals to obtain choice data from anglers. Second, a review of past fishing site choice model studies helps to identify salient attributes associated with site choice. Finally, I briefly discuss the economic value concept and describe an approach to estimate economic value from a choice model.

Figure 3.1.1: A basic model for predicting fishing site choice



3.1.1: Fishing site choice data

Researchers may gather fishing site choice data from reports of actual (i.e., revealed preference) or hypothetical (i.e., stated preference) fishing behaviours. Revealed preference choice models have the validity of using actual behaviours that permit one to assess directly the importance of contextual aspects such as space and habits within such models. The strengths of using actual behaviours are, however, often limited by collinearity among relevant attributes (e.g., sites with further travel distances from population centres may have good fishing quality), lack of variability among attributes (e.g., all fishing sites are governed by the same regulations), and the inability to forecast choices of alternatives that drastically differ from the current set of available alternatives (e.g., the effects of new regulations). The hypothetical nature of stated preference choice models (Louviere, & Woodworth, 1983) is both its greatest weakness and strength. Stated preference choice models must rely upon the tenuous connection of intentions to actual behaviours (Ben-Akiva, & Morikawa, 1990). However, the nature of stated preference choice models permits researchers to construct hypothetical fishing alternatives that facilitate the estimation of all model parameters (Hensher, Rose, & Greene, 2005; Louviere *et al.*, 2000). For example, one can create sets of hypothetical fishing sites that balance descriptions of management regulations and catch expectations. The result of such balancing permits researchers to estimate the effects of regulations and expectations independently from each other. Stated preference choice models also permit researchers to examine fishing sites or characteristics of fishing sites that do not currently exist (e.g., new fishing regulations).

To benefit from both data sources, some researchers have estimated choice models with stated and revealed preference data (e.g., Adamowicz, Louviere, & Williams, 1994; Ben-Akiva, & Morikawa, 1990). These joint models benefit from the validity of using some actual behaviours and the statistical efficiency of estimating independent model parameters. Searches through the literature suggest that no published study has employed a joint stated and revealed preference choice model on recreational fishing site choice[26]. Furthermore, this literature search revealed that there were only four published applications of stated preference compared to 48 published applications of revealed preference choice models on recreational fishing.

3.1.2: Relevant attributes of fishing site choice

A second data source required to estimate a choice model is measurements of fishing site attributes that are linked to the utility that individuals derive from fishing (see Figure 3.1.1).

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[26] The study by Adamowicz *et al.* (1994) focused on water based recreation, which included recreational fishing as one of several possible activities.

Appendix A summarizes the most common attributes employed in 31 unique data sets described in 48 separate published papers on fishing site choice using a revealed preference choice model[27].

Evidence from past recreational fishing site choice model studies and other recreational fishing literature suggests that: (1) costs; (2) fishing quality; (3) environmental quality; (4) facility development; (5) encounter levels; and (6) regulations may impact an angler's selection of a fishing site. The paragraphs below describe these general attributes, the measures that researchers have used for these attributes, and results from past research.

Every revealed preference fishing site choice model study has expressed costs through travel. These travel costs were typically transformed travel distance measures that incorporated vehicle operating costs and in some cases the travel time of the angler. The inclusion of these costs in a choice model makes it possible to estimate the dollar transfers that would be necessary to have anglers equally well off from a new management scenario (i.e., the compensating variation part of economic value).

While recreational fishing site choice models universally employ travel costs, almost no consideration exists for the different costs imposed on anglers by different qualities of roads. In fact, only Parsons' research (Hauber, & Parsons, 2000; Parsons, & Hauber, 1998; Parsons, & Kealy, 1992, 1994; Parsons, & Needleman, 1992) has employed any measure similar to road quality in a fishing site choice model. These authors employed different measures for remoteness as a choice attribute that included: (i) whether a site was accessible only off-road and/or on foot and (ii) whether anglers could reach the site by navigable water and/or public wilderness. In a study of Maine fishing trips in 1989, sites that were accessible only by off-road and/or foot were positively related to anglers' choices. This finding implied that anglers more often visited fishing sites in Maine with poor access than fishing sites with better access, *ceteris paribus*.

[27] A thorough attempt was made to identify all such studies in peer reviewed journals. Studies published in reports or books were excluded from this Appendix.

One expects that fishing quality is important to anglers when selecting a fishing site. While fishing quality is likely important, measuring fishing quality is not a simple matter. For example, limited data have led some researchers to use proxies for fishing quality including: waters that hold certain fish species (Hauber, & Parsons, 2000; Morey *et al.*, 1993; Parsons, & Hauber, 1998; Parsons, & Kealy, 1992); the presence of stocked water bodies (Montgomery, & Needleman, 1997); or the presence of waters that potentially hold certain fish species (Montgomery, & Needleman, 1997).

Researchers have also used numerous approaches to estimate the number of fish or expected catch of fish by anglers at the fishing sites. When detailed information about abundance is lacking, some researchers turn to simple approaches such as the average reported catches at a waterbody from the surveyed or other anglers (Adamowicz, 1994; Bockstael, McConnell, & Strand, 1989; Chen, & Cosslett, 1998; Greene, Moss, & Spreen, 1997; Jakus, Dadakas, & Fly, 1998; Jones, & Lupi, 1999; Kaoru, 1995; Kling, & Thomson, 1996; Lin, Adams, & Berrens, 1996; McConnell, & Tseng, 1999; Morey, Shaw, & Rowe, 1991; Whitehead, & Haab, 1999). A more formal approach to estimate fisheries abundance employs the survey-based data to estimate the expected catch at each site (Jakus *et al.*, 1997; Kaoru *et al.*, 1995; McConnell, Strand, & Blake-Hedges, 1995; Morey, & Waldman, 1998; Parsons *et al.,* 2000; Schuhmann, & Schwabe, 2004). Most studies using expected catch have employed a count-based limited dependent model (e.g., Poisson) to estimate the reported catch by anglers. These studies have used many different independent variables to explain catch including: years of fishing experience, age, season, hours of fishing at site, group size, horsepower of outboard motor, fishing technique, water quality, boat use, fishing skill, historical catch rates and past trips to a site. From this modelling approach, one may predict the expected catch of fish at each fishing site for each angler.

Morey and Waldman (1998) argued that the count model approach for estimating expected catch does not make efficient use of the trip information that is available to researchers. These authors offered a slightly different method that provides a weighted catch estimate from the catch and trip data that accounts for the low visitation at sites with lower expected catch rates. The method uses a shrinkage type estimator that incorporates information from the reported catch rates and reported trips. However, Train, McFadden and Johnson (2000) stated that Morey and Waldman's (MW) approach and the count model approach are both biased and MWs approach is inconsistent when site attributes are omitted whereas the count model approach is consistent. When the MW approach is consistent it is also efficient leading to a trade-off that researchers must make between an approach that is more efficient under specific conditions versus an approach that is consistent under more general conditions (Train *et al.*, 2000).

Researchers infrequently use information about fish size as an attribute for fishing quality. The few applications, however, that have employed a fish size measure (Adamowicz, 1994; Peters *et al.*, 1995; Watson, Adamowicz, & Boxall, 1994) or combined measure of expected pounds of fish (Ahn, DeSteiguer, Palmquist, & Holmes, 2000; Milon, 1988a, 1988b; Train, 1998) have found that these measures were positively related to fishing site choice. The results from stated preference choice model studies (Aas, Haider, & Hunt, 2000; Oh, Ditton, Gentner, & Riechers, 2005; Paulrud, & Latila, 2004) also suggest that fish size is an important attribute for fishing site choice.

Another attribute indirectly allied with fishing quality at freshwater fishing sites is the size of the water body. Larger water bodies have the potential to hold more fish species, larger sized fish, and offer anglers with a diversity of fishing opportunities. Studies using water body area have found that this attribute is positively related to freshwater fishing site choices made by anglers (see Appendix A).

Environmental quality is another important attribute since non-catch related aspects of fishing are important to anglers (e.g., Moeller, & Engelken, 1972). Environmental quality was employed in past fishing site choice models through either terrestrial aesthetics or water quality. Measures for terrestrial aesthetics have included ratings (Peters *et al.*, 1995; Train, 1998) and measures related to forested lands (Chen, & Cosslett, 1998; Jones, & Lupi, 1999; Tay *et al.*, 1996). These studies have found that terrestrial aesthetics positively influence anglers' fishing site choices.

Water quality may impact anglers' fishing experiences through effects on aesthetics and/or on the health of fish. Different measures have been employed for water and environmental quality measures including: perceptual ratings (Peters *et al.*, 1995; Watson *et al.*, 1994); fish advisories (Jakus *et al.*, 1997; Jones, & Lupi, 1999; Montgomery, & Needleman, 1997; Parsons, Jakus, & Tomasi, 1999b); water quality classifications (Ahn *et al.*, 2000); EPA standards (Parsons, & Hauber, 1998; Hauber, & Parsons, 2000); areas of concerns and impacts (Chen, & Cosslett, 1998; Hausman *et al.*, 1995; Jones, & Lupi, 1999); and secci depth (Feather, 1994; Feather, Hellerstein, & Tomasi, 1995; Lupi, & Feather, 1998). Some researchers have also used specific measures of dissolved oxygen, suspended solids, fecal coliform bacteria, acidity, phosphorous, lead, copper, pcbs, toxins and oil (see Kaoru (1995), Montgomery and Needleman (1997), Parsons and Kealy (1992, 1994), Parsons and Needleman (1992), Phaneuf, Kling, and Herriges (1998) ,Tay and McCarthy (1994), and Tay *et al.* (1996) for details). The findings generally suggest that fishing sites with better quality waters are preferred over other fishing waters.

Facility development is another potentially important attribute for anglers when choosing a fishing site. For example, the development of boat launches makes it easier for anglers to fish at certain sites. With the exception of studies from the 1978 Wisconsin data set (Parsons, & Kealy, 1992, 1994; Parsons, & Needleman, 1992), all other studies that used measures of the presence or the number of boat launches at a fishing site found positive relationships with fishing site choice (Jakus *et al.*, 1997; Jakus, & Shaw, 2003; Kaoru, 1995; Kaoru *et al.*, 1995; Montgomery, & Needleman, 1997; Parsons *et al.*, 1999b). The presence of campground facilities at freshwater fishing access points also positively influenced anglers' site choices (Adamowicz, 1994; MacNair, & Cox, 1999; Morey *et al.*, 2002; Morey, & Waldman, 1998; Peters *et al.,* 1995; Train, 1998). These campgrounds provide opportunities for anglers to conduct other recreational activities besides fishing at a site.

Encounters with other anglers may degrade an angling experience (e.g., Martinson, & Shelby, 1992). The attribute of encounter levels is, however, difficult to employ in revealed preference choice models since data typically do not exist and high encounter levels may be correlated with important, yet omitted, site-specific attributes[28]. This omission makes it difficult to isolate the expected negative effects of encounters from the positive effects of the omitted attributes on fishing site choice that lead to crowding at fishing sites[29]. The attribute of encounter levels is better suited to stated preference choice models where researchers can estimate the effect of encounters independent from any other attribute. The only study to employ encounters while fishing as an attribute in a stated preference choice model (Banzhaf, Johnson, & Mathews, 2001) found a negative relationship between encounters and site choice.

A final important attribute for fishing site choice is fishing regulations. Managers employ regulations to alter behaviours or the outcomes from behaviours (e.g., consumption of fish). The large suite of regulatory approaches available permits managers to search for approaches that achieve ecological targets while minimizing negative effects on anglers' experiences. Since regulations do not typically exhibit much variability over actual fishing sites, determining the effects of regulations on fishing site choice is best suited to a stated preference choice model. The few stated preference choice model applications in existence show that regulations are important aspects of site choice by anglers (Aas *et al.*, 2000; Oh *et al.*, 2005; Paulrud, & Latila, 2004).

3.1.3: Economic value of fishing

Measuring changes to economic value arising from resource management changes is a cogent reason for using choice models to examine outdoor recreation topics. This valuation information complements information about the redistribution of choices that may arise from such

[28] As an exception, Schuhmann and Schwabe (2004) estimated expected congestion from estimates of number of boats divided by the number of parking spots at an access point.

[29] For example, Lin *et al.* (1996) use total angler days in previous week divided by length of fishable waters as a proxy for congestion. The positive and significantly different from zero parameter estimate for this congestion attribute likely arises from a correlation between the congestion measure and unobserved factors that lead anglers to choose their fishing sites.

management changes. Consequently, resource managers can estimate how their management actions (e.g., a closure of a road) affect both the spatial redistribution of angling effort and the value of angling.

The discussion below, which draws from Varian (1987, Chapters 28 and 30) and Feenberg and Mills (1980, Chapters 1 and 2), provides a rudimentary overview of the concepts below. Economic welfare (or social economic welfare) involves some type of aggregation of individual level utilities to produce a societal estimate of welfare. Although many methods to aggregate individual utilities exist (see Varian (1987, Chapter 30) for a review), recreational choice model applications assume that the individual utilities are additive, which implies that the equity of the benefits and costs is unimportant. To determine economic welfare for a public good with the above assumption, a researcher only needs to determine and summate the utilities of each individual.

Economists often find it more instructive to translate utility measures into a metric that provides a monetary value for the welfare estimates. Researchers can use these monetary economic welfare estimates[30] to estimate the costs/benefits of a change to a public good.

Compensating and equivalent variation (CV and EV) are two measures for determining changes to economic welfare caused by changes to a public good. To illustrate the differences between CV and EV, assume that decision-makers are considering a change to fishing regulations. Further, assume that all individuals negatively view this potential change.

The change to economic welfare equals the summation of CV or EV estimates over all fishing trips. Compensating variation would measure the per trip monetary compensation required to adjust the utility of a trip <u>after</u> the regulation change to equal the utility of the same trip before the regulation change. Equivalent variation would measure the per trip income a trip maker would

[30] From this point forth, I use economic welfare to refer to monetary translated measures.

forgo to avoid having the regulation change instituted[31]. A sufficient, but not necessary, condition for CV and EV equivalence for models without income effects is a scalar that translates utility into monetary units. The discussion below uses CV since CV is the focus of most resource economists.

The above discussion begs the question as to how researchers convert utility measures into dollar metrics. Although market prices are unavailable for public goods, researchers can indirectly measure price from travel costs. In most studies, travel costs include vehicle related expenses (e.g., fuel costs) and an opportunity cost for travel time[32].

Researchers often calculate vehicle related expenses as the distance traveled by an individual multiplied by a preset mileage cost. As an exception, Hagerty and Moeltner (2005) examine different specifications for travel costs associated with jet ski site choice including preset mileage costs, preset mileage costs that accounted for vehicle type, weight and group size, and a parameterized version that accounts for preset mileage adjusted by estimates for vehicle type and weight. The results suggest that the first two models are virtually identical while the third model provides a significant improvement to the model.

Determining the opportunity cost of travel time is a source of much debate (Fletcher, Adamowicz, & Graham-Tomasi, 1990). Studies typically use a fraction of an individual's wage rate to determine travel costs. Researchers normally based this fraction from the results of transportation studies that have found that individuals value their commuting travel time as a fraction of their wages (usually between 25-40%). It is questionable whether these results provide accurate estimates of the value of recreational travel time. Another potential problem with using the fraction of an individual's wage rate is determining an individual's wage rate. Most studies ask an individual to select her or her household's annual income from a series of aggregated

[31] Although EV may seem implausible for the example I provide, one could argue that EV would measure the amount that individuals would use to lobby the decision-makers to abandon the regulation change. This scenario would also assume that the lobbying effort would have no risk of failure.
[32] Although most studies assume that on-site time is fixed at all sites, some researchers (e.g., Berman, & Kim, 1999) suggest that on-site recreational time may be endogenously determined.

income categories. To calculate a wage rate, researchers often divide the mid-point of an income category and assume that the individual works 40 hours per week, 52 weeks per year. These assumptions may distort the calculation of the true wage rate for an individual[33].

I now describe the utility translation process to determine per trip compensating variation (CV) with no income effects[34]. I first discuss the case for the multinomial logit provided by Small and Rosen (1982). In equation 39, the zero subscript represents the world before one makes a change to the sites while the subscript one represents the world after one makes the change (e.g., before and after fishing regulations are placed on some angling sites). The V terms are the systematic utilities of the choice model and the β_{cost} term is the parameter estimate for travel cost.

$$CV = -\frac{1}{\beta_{cost}}\left[\ln\sum_{i=1}^{J}V_{i0} - \ln\sum_{i=1}^{J}V_{i1}\right] \tag{39}$$

While equation 39 provides the most succinct notation for CV, I use equation 40 to demonstrate a few interesting features about the equation. In equation 40, I specify μ as the scale parameter and assume a linear in the parameters form for the deterministic utility (i.e., $\mathbf{X}\boldsymbol{\beta}$).

$$CV = -\frac{1}{\mu\beta_{cost}}\left[\frac{1}{\mu}\left(\ln\sum_{i=1}^{J}e^{\mu(X_o\beta)}\right) - \frac{1}{\mu}\left(\ln\sum_{i=1}^{J}e^{\mu(X_1\beta)}\right)\right] \tag{40}$$

A close examination of equation 40 shows its reliance on the expected maximum utility property from Ben-Akiva and Lerman (1985, p. 105). The two terms inside the bracket are the expected maximum utilities (i.e., inclusive values) of the sites before and after one makes a change. Since these expected maximum utilities are calculated from the same model estimates, one can drop the scale parameters (i.e., we can assume they equal one). The negative of the travel cost parameter estimate measures the marginal utility of income. In summary, CV for an MNL

[33] Since not all surveyed individuals provide income levels, some researchers (e.g. Whitehead, & Haab, 1999) also use imputation techniques to estimate missing income information.
[34] No income effects requires no relation between the parameter for cost and the income of the individual. This also requires that no distance decay function exists for travel costs.

model equals the differences between the per trip expected maximum utilities for the before and after change scaled into monetary units by the negative of the travel cost coefficient.

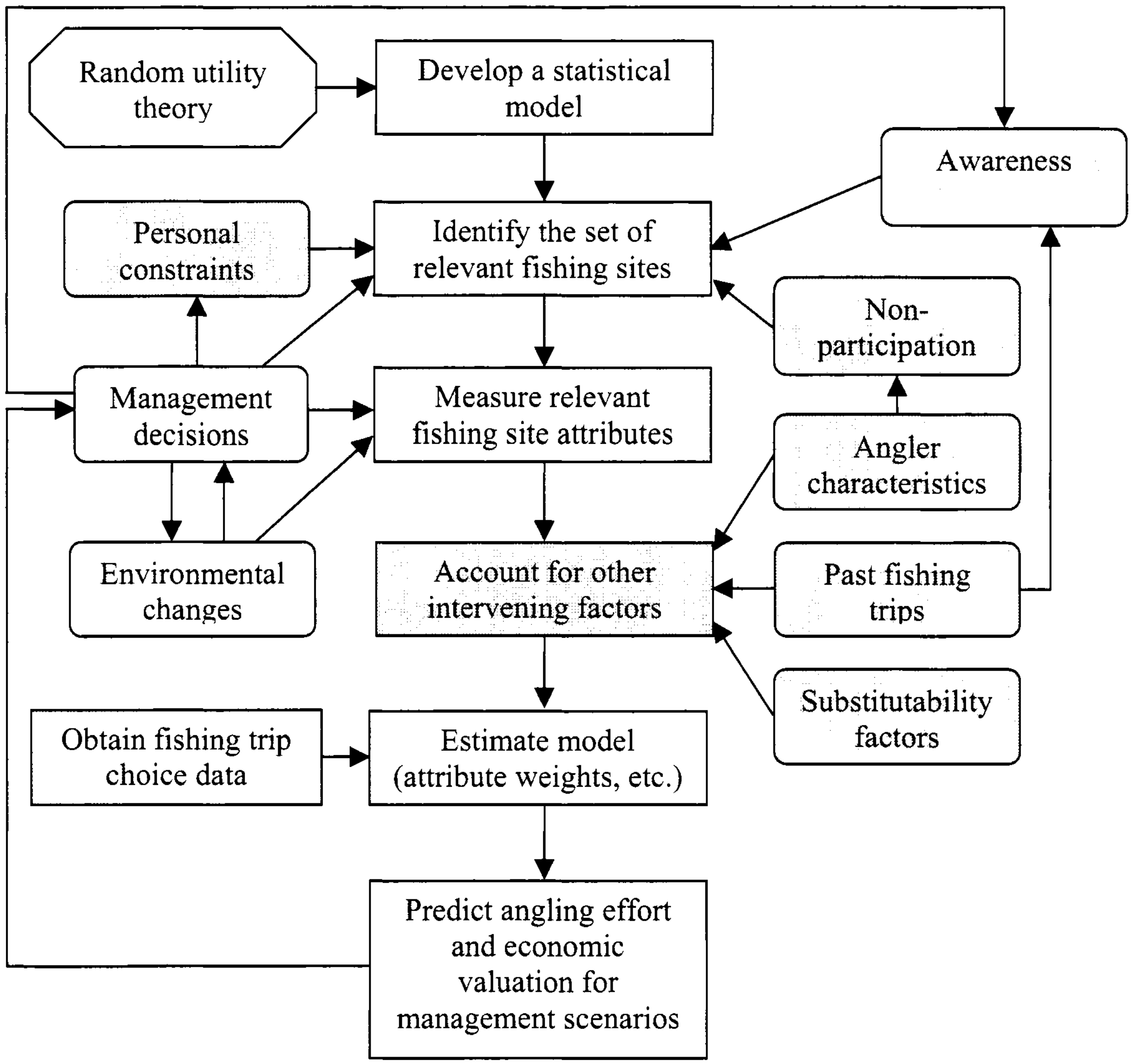
The CV estimate for the generalized nested logit is more complicated than that for the MNL. Equation 41 is a simple extension of the expected value and CV equations provided by Morey (1999) for the nested logit. As explained earlier, the allocation parameters (α_{im}) specify the proportion of an alternative (i) to a nest (m). One minus the dissimilarity parameters (μ_m) represents a statistic that is similar to the correlation among unobserved utilities in a nest.

$$CV = -\frac{1}{\beta_{\cos t}}\left[\begin{array}{l}\left(\ln\left(\sum_{m=1}^{M}\sum_{i=1}^{J}\left(\alpha_{im}e^{\mathbf{X}_0\boldsymbol{\beta}}\right)^{\frac{1}{\mu_m}}\left(\sum_{j=1}^{J}\left(\alpha_{jm}e^{\mathbf{X}_0\boldsymbol{\beta}}\right)^{\frac{1}{\mu_m}}\right)^{\mu_m-1}\right)\right)- \\ \left(\ln\left(\sum_{m=1}^{M}\sum_{i=1}^{J}\left(\alpha_{im}e^{\mathbf{X}_1\boldsymbol{\beta}}\right)^{\frac{1}{\mu_m}}\left(\sum_{j=1}^{J}\left(\alpha_{jm}e^{\mathbf{X}_1\boldsymbol{\beta}}\right)^{\frac{1}{\mu_m}}\right)^{\mu_m-1}\right)\right)\end{array}\right] \tag{41}$$

3.2: An enhanced model for predicting recreational fishing site choice

The basic fishing site choice model presented in Figure 3.1.1 is deficient for at least four reasons. First, factors were not included that may affect the ways that fishing sites act as substitutes for each other. Second, all anglers were assumed to choose fishing trips from the same set of fishing sites. Third, the model assumed that all anglers have identical preferences for the various attributes. Finally, no connection was drawn between site choice, participation level, and dynamic like choices. The following subsections describe the enhanced model of recreational fishing site choice shown in Figure 3.2.1. The subsections also describe the approaches taken by researchers to account for these deficiencies and any remaining problems from past research. Since Chapter 2 examined the topics of site substitution and choice sets, these topics receive less attention in this chapter than do the discussions of varying preferences and joint modelling of participation and site choice.

Figure 3.2.1: An enhanced model for predicting fishing site choice



3.2.1: Accounting for factors that affect fishing site substitutability

One important output from a recreational fishing site choice model is the prediction of how anglers redistribute their effort when confronted with environmental or management changes to a fishery. Despite the developments on spatial choice modelling described in Chapter 2, many researchers have used choice models that account for a very limited pattern of substitution among the sites. In particular, researchers still most often employ the multinomial logit model with its independence of irrelevant alternatives (IIA) property (see Appendix A). The restrictive pattern of substitution from IIA seems unlikely given that the similarities in fish species, fish abundance and spatial proximity should make some sites better substitutes than other sites (Shelby, & Vaske, 1991). Figure 3.2.1 shows that substitution factors may intervene in the normal estimation of the fishing site choice process.

Researchers who incorporate more flexible substitution patterns among fishing alternatives may make one of two assumptions. First, researchers may assume that fishing sites can be allocated into discrete groups or nests where sites within groups are better substitutes than are sites between groups. The nested logit model, which was described in Chapter 2, arises from the above assumption along with the assumptions that the researcher can identify these nests and that within a nest all sites have the same substitution pattern as imposed by the multinomial logit. Many fishing site choice model researchers have used this nested logit to permit greater flexibility in substitution patterns among alternatives than is provided by the MNL (Bockstael *et al.*, 1989; Hauber, & Parsons, 2000; Jones, & Lupi, 1999; Kaoru, 1995; Kling, & Thomson, 1996; Lupi, & Feather, 1998; MacNair, & Cox, 1999; Milon, 1988a, 1988b; Morey *et al.*, 2002; Morey *et al.*, 1993; Parsons, & Hauber, 1998; Parsons, & Kealy, 1992; Parsons *et al.*, 2000; Shaw, & Ozog, 1999).

The second assumption permits more flexible substitution patterns by allowing sites to be allocated among many overlapping nests. These more flexible generalized extreme value and mixed logit models (see Chapter 2) would allow for asymmetrical substitutability among sites as Shelby and Vaske (1991) identified for salmon fishing sites. No researcher studying fishing site choice, however, has used any of these more flexible choice models to account for substitution.

3.2.2: Accounting for differing choice sets in choice models

Chapter 2 discussed how each angler might have a different set of fishing sites (i.e., choice set) from which she makes a fishing site choice. The reason for such choice set differences among anglers relates to constraints faced by anglers (e.g., boat ownership) or the limited awareness that anglers may have for some fishing sites (see Figure 3.2.1). Researchers employing fishing site choice models, however, almost all implicitly assume that anglers select from the same universal set of fishing sites.

Only Peters *et al.* (1995) abandoned the universal choice set concept by asking anglers to record the fishing sites they would consider for a fishing trip. As discussed in Chapter 2, this approach requires one to decide whether consideration or awareness is the appropriate concept and to develop an appropriate question that will yield reliable information about the chosen concept (Parsons, *et al.* 1999a).

No researchers have yet embraced an assumption that would lead to a model of choice sets for anglers. However, as discussed in Chapter 2, researchers could employ one of two assumptions to produce such a choice set model. First, researchers could assume that anglers use a sequential approach whereby an angler first selects a subset of fishing alternatives and then selects one site from this subset. This assumption would produce Manski's (1977) explicit choice set modelling approach that would likely be intractable for most recreational fishing applications.

A researcher could make a different assumption to be consistent with the implicit choice set modelling approach of Cascetta and Papola (2001). In this instance, a researcher would assume that although anglers have knowledge about most fishing sites, some sites are better known than are others. This assumption is consistent with Meyer's (1980) notion that people have some awareness of how to access spatial alternatives but have limited awareness of what to expect at the sites.

Figure 3.2.1 shows that management decisions may indirectly impact choice sets through linkages to constraints and awareness[35]. Managers may affect constraints by banning certain equipment that anglers require to access fishing sites (e.g., an all terrain vehicle). Managers may affect awareness by producing information about fishing sites that anglers use to learn about fishing opportunities. In fact, managers may judiciously provide information on fishing sites to

[35] Managers can also directly affect choice sets through decisions to close fishing sites.

steer anglers' behaviours away from managerially undesirable sites and toward other fishing sites that are underutilized.

Past trips may also affect an angler's awareness of sites. Past fishing trips provide anglers with expectations about the attributes present at a given site (Meyer, 1980). During travel, anglers may also explore areas for other potential fishing sites leading to a greater likelihood that these sites will be chosen in the future (i.e., spatial habits are present).

3.2.3: Accounting for varying preferences among anglers

Most previous fishing site choice model studies have implicitly assumed that anglers have identical preferences. This implicit assumption is in conflict with most research that suggests that average based descriptions of outdoor recreationists are flawed (Shafer, 1969). Figure 3.2.1 abandons the preference homogeneity assumption by allowing the characteristics of anglers to influence an angler's commitment to fishing (i.e., non-participation) and to affect an angler's preference for fishing site attributes.

Researchers have implicitly accepted one of three assumptions when choosing an approach to account for different preferences for the attributes of fishing site choice among anglers. First, some researchers have assumed that all heterogeneity in angling preferences arises from observable characteristics of individuals. Through this assumption, a researcher may simply estimate parameters that measure the change in preferences for an attribute induced by the characteristics of the individual (e.g., older anglers may have less preference for catching fish than do other anglers). Many researchers who have used choice models to examine fishing site choice have employed this approach (Creel, & Loomis, 1992; Feather *et al.*, 1995; Greene *et al.*, 1997; Jakus *et al.*, 1998; Jakus, & Shaw, 2003; Milon, 1988a, 1988b; Morey *et al.*, 2002; Morey *et al.*, 1993; Morey, & Waldman, 1998; Parsons, & Kealy, 1994; Shaw, & Ozog, 1999; Tay, & McCarthy, 1994; Tay *et al.*, 1996).

A second assumption is that the heterogeneity source is completely unknown to the researcher. To account for this unknown source of heterogeneity, researchers treat the parameter estimates for each attribute as a random variable that follows a prespecified distribution (e.g., normal). This random parameters approach provides estimates of both the central tendency of a parameter estimate (i.e., a preference) along with the variation in the preferences according to the prespecified distribution. For encounters with other anglers, the random parameters approach would provide a mean preference estimate for encounters along with the crystallization of these preferences around this mean value (i.e., variance). Several researchers have used random parameters logit (Breffle, & Morey, 2000[36]; McConnell, & Tseng, 1999; Phaneuf *et al.*, 1998; Provencher, Baerenklau, & Bishop, 2002; Train, 1998) or random parameters probit (Chen, & Cosslett, 1998) models to estimate preference heterogeneity in fishing site choice models. All of these studies found significant model improvements when allowing preferences to vary over the different attributes. While the random parameters approach is useful to assess the extent of preference heterogeneity, the typical absence of an explanation for the source of preference heterogeneity limits the usefulness of the approach for managers (i.e., one typically assesses the extent and not the causes of the variability in preferences). As an exception, Hunt, Haider and Bottan (2005) used individual specific parameter estimates from a random parameters logit to examine the sources along with the extent of preference heterogeneity among moose hunters from northern Ontario.

The final assumption is that the variation in anglers' preferences arises from both observable characteristics of anglers and from sources unknown to the researcher. Since Chapter 2 did not describe this joint latent class and choice model approach (Swait, 1994), the following paragraphs describe this approach in some detail.

A latent class choice model assumes that several classes (segments) exist in the population. However, a researcher is not privy to the exact membership of an individual to a particular class since the class membership is unobserved or latent to the researcher. The researcher's task is to

[36] Breffle and Morey (2000) also show that it is possible to investigate heterogeneity through the scale utility parameter, which is inversely related to the variance of the unobserved utility scale.

determine different sets of parameter estimates for every class and the probabilities that individuals belong to each of these classes. Researchers have typically assumed that that the probabilities that individuals belong to each class arise from a multinomial logit form (Boxall, & Adamowicz, 2002; Gupta, & Chintagunta, 1994; Kamakura, & Russell, 1989; Louviere *et al.*, 2000; Provencher *et al.* 2002; Swait, 1994). This assumption allows researchers to determine inferentially whether respondent characteristics help to explain the class membership probabilities. For example, it is possible to examine whether measures related to recreationists are allied with the unobserved class membership probabilities. This marks a dramatic difference over market segmentation techniques that impose predetermined market segments on a choice model.

Equation 42 shows a latent class choice model with an implicit assumption that the scale factors (μ) are identical among the classes. The term after the multiplication in equation 42 takes an MNL form. The only difference is that the $\boldsymbol{\beta}$ terms have an extra subscript (l), which indicates that one must estimate a separate set of $\boldsymbol{\beta}$ for each of the L classes. The first summation in equation 42 suggests that a choice probability for alternative i for individual n equals the sum of choice probabilities for i for each latent class (l) weighted by the probability that individual n belongs to each class. This class membership probability immediately follows the first summation term, and it takes a multinomial logit form. In equation 42, $\mathbf{Z}$ is a vector of individual n's characteristics and the $\boldsymbol{\delta}$ term is a vector of parameter estimates that transforms the $\mathbf{Z}$ characteristics into a common metric. Since these $\mathbf{Z}$ characteristics do not vary among the classes for any given individual, one set of $\boldsymbol{\delta}$ must be restricted to a value (e.g., zero) for identification of the other L-1 sets of $\boldsymbol{\delta}$ parameter estimates.

$$P_n(i) = \sum_{l=1}^{L} \frac{e^{\mathbf{Z}_n \boldsymbol{\delta}_l}}{\sum_{k=1}^{L} e^{\mathbf{Z}_n \boldsymbol{\delta}_k}} * \frac{e^{\mathbf{X}_{in} \boldsymbol{\beta}_{il}}}{\sum_{j=1}^{J} e^{\mathbf{X}_{jn} \boldsymbol{\beta}_{jl}}}, i \in C_n, \forall j \in C_n \tag{42}$$

Latent class choice models suffer from a problem that also affects market segmentation schemes. The problem is that the researcher does not know the actual number of classes in the population. Researchers typically use two statistics to help identify the appropriate number of classes. Both statistics, examine the choice model performance through a log likelihood statistic that penalizes researchers for over specifying the model. Equations 43 and 44 show the formulas for the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). In the formulas, the *LL(β)* is the log likelihood of the latent class choice model, *k* is the number of parameters estimated by the model, and *n* is the number of individuals in the sample. A researcher calculates these statistics from models with differing numbers of latent classes. The model with the minimum BIC and AIC values indicate the appropriate number of classes.

$$AIC = -2 * (LL(\beta) - k) \tag{43}$$

$$BIC = -LL(\beta) + \frac{\ln(n) * k}{2} \tag{44}$$

Only Provencher *et al.* (2002) and Provencher and Bishop (2004) have employed this joint latent class and choice model approach to account for varying preferences among anglers. However, the choice of observable characteristics (i.e., age and years of fishing experience) used by both studies to explain participation decisions for salmon fishing in Lake Michigan appears to be guided by convenience rather than by behavioural theory.

3.2.4: Accounting for participation and dynamic like effects in choice models

While choice models are adequate for predicting the spatial distribution of angling trips, standard choice models cannot predict the number of fishing trips taken by an individual. This limitation is very important since choice models typically predict the consequences of actions that change the availability, quality or cost of at least one alternative. Without information on participation, the managerial usefulness of choice models is limited for activities such as recreational fishing.

A common approach to the participation dilemma is to assume that changes to alternatives have no affect on the total number of trips. This approach will lead to conservative forecasts, as impacts should affect both the total number and spatial pattern of fishing trips.

Researchers use one of two primary behavioural assumptions to develop models that account for both participation and site choice. First, a researcher may assume that anglers make fishing decisions on a periodic basis (e.g., daily). This assumption allows researchers to model site choice along with a no participation alternative throughout the fishing season. Several researchers have employed this repeated choice model approach to study both fishing site and fishing participation choices (Ahn *et al.*, 2000; Jakus *et al.*, 1997; Montgomery, & Needleman, 1997; Phaneuf *et al.*, 1998; Morey *et al.*, 1993). Figure 3.2.1 adopts this assumption by including non-participation as a valid choice set alternative.

A second assumption is that anglers decide upon the number and possibly the timing of trips before the start of the fishing year. Through this assumption, a researcher can model total participation through a count based limited dependent model such as Poisson and site choice through a choice model. The inclusion of the expected maximum utility from a set of fishing sites as an independent variable in the participation model links the site choice and participation models. As changes to the resource or management of the resource occur, the changing utilities of fishing sites may affect the forecasts of total fishing trips. Although some researchers have refined this approach by separating different parts of the expected maximum utility (Feather *et al.*, 1995; Hausman *et al.*, 1995; Parsons, & Kealy, 1995), Parsons *et al.* (1999b) showed that with a constant travel cost coefficient, all of these variants produce identical results. A few researchers have employed variants of this approach to study fishing site choices and participation decisions (Creel, & Loomis, 1992; Feather *et al.*, 1995; Hausman *et al.*, 1995; Lin *et al.*, 1996; Parsons *et al.*, 1999b).

Figure 3.2.1 shows that the participation decision for fishing should depend upon angler characteristics in addition to the expected utility from the fishing sites. The reviewed studies provide some evidence that the frequency of fishing participation is higher for individuals who are males (Greene *et al.*, 1997; Montgomery, & Needleman, 1997; Morey *et al.*, 2002), are older (Lin *et al.*, 1996; Montgomery, & Needleman, 1997; Morey *et al.*, 2002; Morey *et al.*, 1993;

Shaw, & Ozog, 1999)[37], live in rural residences (Jakus *et al.*, 1997), are Caucasians (Jakus *et al.*, 1997), are unemployed (Hausman *et al.*, 1995; Montgomery, & Needleman, 1997), and have children (Montgomery, & Needleman, 1997; Shaw, & Ozog, 1999). There is also evidence that individuals who own boats (Greene *et al.*, 1997; Lin *et al.*, 1996), have fished more years (Bergstrom, Dorfman, & Loomis, 2004; Lin *et al.*, 1996; Morey *et al.*, 2002; Morey *et al.*, 1993; Shaw, & Ozog, 1999), and take trips with their family (Kaoru, 1995) fish more often than do their counterparts.

Past experiences (Perdue, 1983) and the preferences that anglers develop for fish species or angling sites affect recreational fishing behaviours. These preferences may arise from an investment of time and money to develop skills necessary to catch a certain fish species or learn about the intricacies of a fishing area (e.g., areas with fish or areas to avoid) (Siemer, & Brown, 1994). The finding that the attachment of recreationists to a place increases with more visits (Williams, Patterson, Roggenbuck, & Watson, 1992) also implies that habits may be important when anglers choose fishing sites. Therefore, past fishing trips may partially influence an angler's choice for future fishing trips. For this reason, Figure 3.2.1 shows that past trips intervene in the normal estimation of a choice model.

Heckman (1981a, p.115) labelled the influence of past behaviours on future behaviours as state dependence[38]. However, measuring state dependence is not a simple task. Without knowing the first choice made (i.e., the initial conditions (Heckman, 1981b)), it is difficult to disentangle spurious from substantive state dependence. Choices in different time periods may display spurious dependence because of missing variables, incorrect functional forms for explanatory variables and unobserved taste heterogeneity in the population.

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[37] As an exception, Ahn *et al.* (2000) found that age was negatively related to participation in trout fishing in North Carolina.
[38] Heckman (1981a) also suggested that habit persistence may arise when previous preferences affect current preferences.

Substantive state dependence may arise for reasons such as habits whereby an individual continues to return to a fishing site because of their familiarity with that site and possibly other users of that site. I also believe that substantive state dependence may arise from a spatial perspective. For example, the trip to and from a fishing site by an angler may yield information about other nearby fishing sites to the angler. This information may lead an angler to select fishing sites in close proximity to the originally visited site leading to a type of spatial dynamic behaviour.

A few outdoor recreation researchers have attempted to develop choice models[39] that account for some dynamic like effects (Adamowicz, 1994; Adamowicz, Jennings, & Coyne, 1990; Moeltner, & Englin, 2004; Swait, Adamowicz, & van Bueren, 2004). Adamowicz *et al.* (1990) modelled Bighorn sheep (*Ovis canadensis*) hunting in Alberta. Although they only examined participation choices, their sequential choice model showed that hunters were less likely to take hunting trips after they successfully harvested an animal.

The study by Adamowicz (1994) on angling site choices of Albertans incorporated dynamic like effects into choice models. The author used a type of repeated choice model[40] on the weekly angling decisions of the sampled individuals. The author compared the results from a static model to results from two naïve models and one rational dynamic model. One naïve dynamic model included a generic attribute that measured the number of times an angler previously chose the current alternative, while the other naïve model interacted this generic attribute with the alternative specific constants for the 10 alternatives[41]. The rational dynamic model used a stock function to account for anglers' knowledge that current will influence their future choices. All dynamic models outperformed the static model. Although the naïve and rational models were not

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[39] McConnell *et al.* (1990) and Provencher and Bishop (1997) examine dynamics in outdoor recreation with travel demand models that differ from choice models.
[40] The model included the non-participation alternative as an alternative along with the nine fishing sites rather than nesting the participation and site choice decisions.
[41] From the results of the study, I am surprised that the author did not simply choose to separate the generic attribute into participation and non-participation interacted attributes rather than alternative specific attributes.

nested, the second naïve model performed as well if not better than did the rational dynamic model.

Swait *et al.* (2000) used a nested logit choice model to examine dynamic fishing site choices in Australia over 20 weeks of fishing by Perth residents[42]. The authors examined dynamic elements that included state dependence, habit persistence, future expectations, and initial utilities. The authors demonstrated that the inclusion of different aspects of dynamics greatly influenced parameter estimates in the model (e.g., after the initial utilities were included in the model, the parameter that measured the number of weeks without fishing moved towards zero). As with many GEV models, several models estimated by the authors violated random utility theory.

Finally, Moeltner and Englin (2001) examined state dependence of ski site choices in Nevada. The authors argued that by using a repeated random parameters logit with large samples of individuals and choice occasions the model bypasses the initial conditions problem. The authors examined ski site choices among eight different alternatives along with a no participation option over 151 choice occasions (i.e., days). The authors included state dependence measures for sites (i.e., the number of previous visits and the number of consecutive ski trips to the same site) and non-participation (i.e., number of previous non-participation days and the number of consecutive days without participation). The authors also employed time varying attributes of snow and weather and specified the time varying attributes and state dependence measures as random coefficients. The authors demonstrated that state dependence measures, other than the consecutive days without participation, were important attributes that varied over the sampled individuals. As well, the authors found a bias in the state dependence measures when the authors omitted the dynamic attributes of temperature and snow conditions from the analysis.

[42] Actually, the authors only used the last 19 weeks of the 20 recorded fishing weeks for their model estimation.

3.3: Overview of chapter contributions

A basic conceptual model for forecasting the fishing site choices of anglers was provided. The conceptual model makes explicit the need to collect information on chosen fishing sites, available fishing sites and attributes of available fishing sites. A review of over 50 previous fishing site choice applications suggests that six general attributes influence fishing site choice. These general attributes include cost, fishing quality, environmental quality, facility development, encounters, and regulations.

One reason for the prevalence of fishing site choice applications is the ability to estimate economic welfare changes from such choice models. While the formulas for estimating compensating variation are well established, many researchers estimate choice models without considering the consequences of incorrectly converting travel distances into travel costs.

The basic conceptual model was enhanced to include aspects relating to spatial substitution of fishing sites, heterogeneity in anglers' preferences for site attributes, choice sets, and participation and dynamic like decision-making. The various approaches and implicit assumptions associated with the approaches were discussed for each enhancement. While the various enhancements provide a fuller description of fishing site choice, limitations with data, computer memory, and statistical software often make it necessary to simplify the types of enhancements included in site choice models. The major contribution of this chapter is to make explicit the assumptions that researchers must make when using different approaches to account or not account for the various enhancements to fishing site choice models.

Chapter 4: Data and methods to collect data

The previous chapters described the types of data needed to conduct and to estimate a fishing site choice model. One can estimate a fishing site choice model with information on where people fish, where people could fish and what attributes are found at the sites where people could fish.

Researchers who estimate fishing site choice models typically employ data from secondary sources (e.g., researchers who rely upon state or provincial data collected by resource management agencies) that contain information on choices, available fishing sites and/or measures of relevant fishing site attributes. While those secondary data sources permit many researchers to benefit from the central data collection, the reliance on secondary data limits the abilities of researchers to capture the true behavioural site choice process (Fletcher *et al.*, 1990). For this reason, I decided to collect my own information on fishing site choices, available fishing sites and in some cases measures of fishing site attributes. Before collecting this data, efforts were also spent conducting interviews with resident northern Ontario anglers. The interviews were instrumental to assess the validity of a trade off approach for modelling fishing choice behaviours and to understand better those attributes that are likely to impact northern Ontario angler's choices of fishing sites.

The remainder of this chapter is organized as follows. Section 4.1 briefly describes the qualitative data collection approach. The following section discusses the data collected from angler diaries. Efforts to enumerate all available fishing sites and to identify potentially relevant site attributes are described in Section 4.3. Finally, Section 4.4 summarizes this chapter.

4.1: Qualitative interviews with anglers

Two information sources are beneficial when designing a fishing site choice model. First, a review of past research (see Chapter 3) greatly assists a researcher in formulating hypotheses among attributes and site choices. While this review is necessary, it is not sufficient to understand any peculiarities in angling behaviours that may arise from a specific context. Information from qualitative interviews can supplement literature reviews by identifying aspects of choice behaviours that are unique to a specific geography or time. In fact, qualitative interviews allow one to assess the suitability of a choice modelling approach for the specific choice context.

Qualitative interviews were conducted with resident anglers from the Thunder Bay and Wawa areas to better understand angling behaviours. During the summer of 2003, staff from the Ontario Ministry of Natural Resources conducted, taped and transcribed 72 qualitative interviews with resident anglers at inland fishing access points in areas north of Lake Superior. All interviewers employed a script of questions that guided their discussions with respondents (see Appendix B.1). Although only eight anglers refused to participate, the sampled anglers may over represent individuals who were fishing and camping as opposed to anglers who were only fishing. This potential bias arises since the interviewers contacted anglers on land near the fishing site access point rather than on the water. These interviews were conducted: to determine the validity of the compensatory/tradeoff nature espoused by choice models; to identify salient attributes for fishing site choices made by northern Ontario anglers; and to learn whether anglers believe that space impacts their fishing site choices. Details of this examination are presented in Chapter 5.

4.2: Data on angler choices

Information on the fishing sites actually visited by anglers from the Thunder Bay and Wawa areas were collected through an angling diary program. The diary program provided an opportunity to reduce recall bias (Dillman, 2000) and to collect information about the contexts that different anglers face when choosing a fishing trip.

A consultant recruited anglers into a diary program that was to run from April 1 to September 30, 2004. The consultant randomly called Thunder Bay and Wawa area residents in February and March of 2004. Before inviting an angler to participate in the diary program, these individuals were asked to complete a short telephone survey[43]. The telephone survey asked anglers about

[43] Anglers were given the option of communicating in English or French. Those respondents who preferred a French language correspondence were sent all subsequent materials in French.

their past fishing trips, fishing experiences, preferences for fish species, equipment and age. After completing the telephone survey, the individuals were asked if they would participate in an angling diary program. The responses to this short telephone survey provided an opportunity to assess the extent of non-response bias in the sample of diary participants. Table 4.2.1 highlights the efforts made by the consultant to contact anglers from the Thunder Bay and Wawa areas[44].

Table 4.2.1: Summary of telephone recruitment efforts

Description	Total Number	Response rate
Total Dials	23,937	
Total Answers	11,378	
Total Connects	10,381	
Sample (minus reschedules)	7,547	
Sample (minus non-anglers)	2,840	
Total completed surveys	1,454	14.01%[a]; 19.3%[b]; 51.2%[c]
Total recruits	1,005	69.1%[d]
Total survey respondent refusals	449	30.9%[d]

a –based from all connects
b –based from sample minus rescheduled calls never made
c –based from sample minus rescheduled calls and non-anglers
d –based from total completed surveys

The consultant completed 1,454 surveys with anglers including 932 in the Thunder Bay and 522 in the Wawa areas, respectively. From this set of 1,454 anglers, 1,005 agreed to participate in the angling diary program. The sample sizes from the Thunder Bay (654) and Wawa (351) areas were purposively different to reflect the disparate populations of these two areas.

In early April 2004, the 1,005 participants were mailed a package that included an angling diary for their April and May fishing trips, a covering letter that explained the project, and a fishing plug imprinted with the words 'Northern Ontario Angling Diary Participant'. At the end of May 2004, the anglers were sent a second mail package containing a covering letter that asked anglers to return their first diary, a business reply return envelope, a new diary for June and July, and a ballot for an entry to win one of ten $100 gift certificates from local sporting goods stores. About one-month later, the non-respondents were contacted by phone to remind them of the importance of the project. At the end of July, a third mail package was sent to all remaining

[44] The consultant did not separate the contact information by the origin of the respondent for initial contacts.

participants[45]. This mail package contained a covering letter asking participants to return their June and July diaries, a business reply return envelope, an entry ballot for ten new $100 gift certificates and the August and September diary. Two weeks after sending this package, a postcard reminder was mailed to all non-respondents.

The approach to collect the final set of diaries deviated slightly from the previous data collection approaches. First, all non-respondents were asked to complete an abridged telephone survey that contained the most crucial diary questions. Of the 568 original non-respondents, 132 responded to the telephone survey request[46]. All newly responding participants were included in a draw for the final set of ten $100 gift certificates for a local sporting goods store.

Participants who had returned at least one of the two previous diaries were contacted by mail. These participants were sent a covering letter, return envelope, a replacement diary, and a ballot for entry into the gift certificate draw. Two weeks after mailing this package, all non-respondents to this request were sent a postcard reminder. Finally, all remaining non-respondents from this group were contacted by phone and were asked to complete the diary by phone or by mail.

These efforts led us to obtain complete fishing information (i.e., from April 1 to September 30) from 498 of the 1005 anglers[47]. The response rate was greater for Thunder Bay (53.1%, n=347) than for Wawa area participants (43.0%, n=151). Another 89 anglers (8.9%) provided partial fishing trip details for the six-month diary period.

The diaries consisted of two different parts (see Appendix B). For the April and May and June and July diaries, the first part asked anglers about private cottage or commercial use of lakes or rivers, motivations for fishing, membership in fishing clubs and sex. For the August and

[45] Some anglers were removed from the study because they declined further participation or could not be contacted by mail.
[46] This does not include the many respondents who stated that they did not fish during April 1 to September 30. These individuals were not included as it was felt that many individuals may have provided this response to avoid the telephone survey.
[47] All numbers in this section refer to respondents who reported at least one fishing trip. Many other respondents completed or partially competed the diaries, but they reported that they had taken no trips from April 1 to September 30, 2004.

September diary, the first part asked anglers about awareness of fishing sites, place attachment, and the importance of different fishing site attributes. In all diaries, the second part asked detailed questions about each fishing trip taken by an angler. A fishing trip was defined as a trip taken for fishing to a specific waterbody. Therefore, a fishing trip could consist of multiple days or a single day could have multiple fishing trips.

The diary asked anglers to record the dates of the trip (see Appendix B.9), the origin and destination of the trip, the number of people who accompanied the individual while fishing and travelling to the fishing site, and the types of vehicles used to access the waterbody. Other information collected included: whether the person took the trip primarily for fishing; whether the person fished from a boat; the number of hours spent fishing; the number of other anglers seen while fishing; the species targeted; and the number of fish caught.

4.3: Inventorying fishing sites

The second data source required to estimate a fishing site choice model is an inventory of available fishing sites. The spatial scale for this inventory was determined primarily from the responses provided by the diary participants. The spatial scale, however, was slightly reduced in scope to reduce the number of fishing alternatives in the model (e.g., anglers took fishing trips as far away as British Columbia).

Figures 4.3.1 and 4.3.2 illustrate the study areas. For the Thunder Bay area, the spatial extent of the modelled area was slightly less than the area where site information was collected. The effective study area for Thunder Bay accounted for 96.6%, while the Wawa area accounted for 95.8% of modelled fishing trips.

Figure 4.3.1: Thunder Bay study area

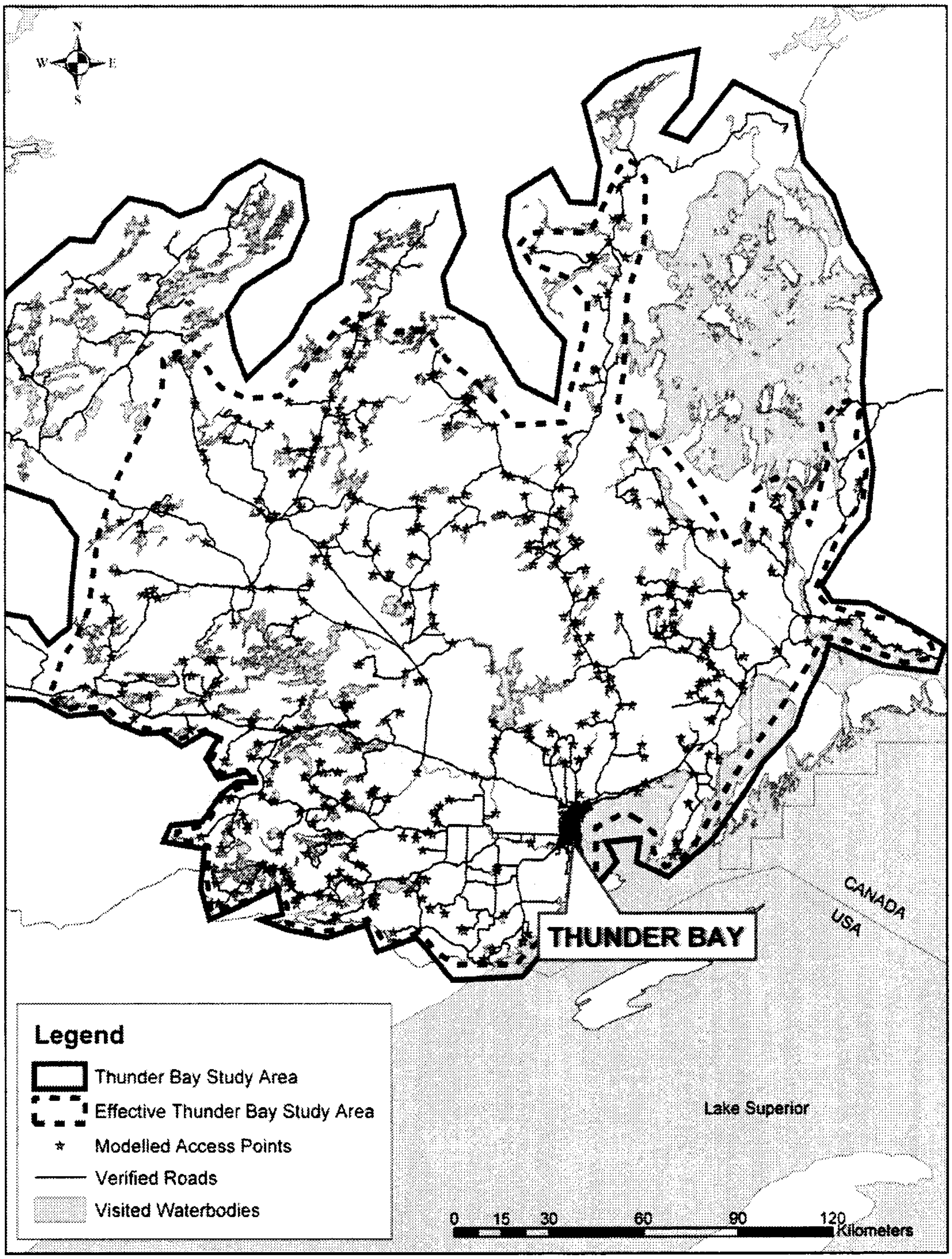
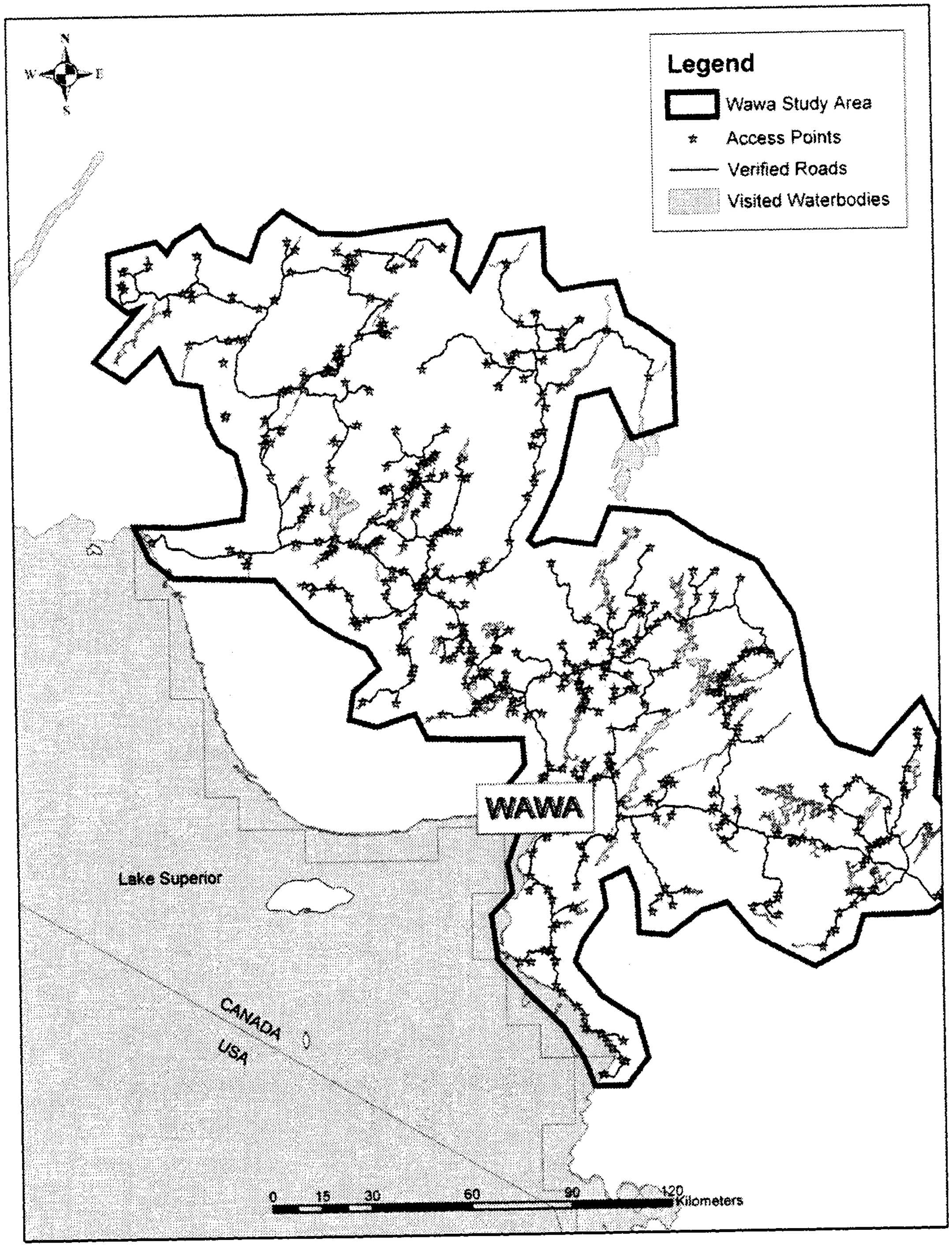


Figure 4.3.2: Wawa study area



Rather than relying on an *ad hoc* narrowing approach to limit the number of sites in the choice set (e.g., Parsons, & Hauber, 1998), the set of relevant sites included those that were directly or indirectly (i.e., boat navigation or popular portage routes) accessible from a road or trail. Several sources were used to identify a set of access points in both the Thunder Bay and Wawa areas. The sources included government databases, non-government fishing maps and local knowledge from OMNR Conservation Officers and resident anglers. While the inclusion of local knowledge and other inventory data greatly benefited the project, this data required field validation.

A field program was undertaken during the summers of 2003 and 2004 to visit every access point in the Thunder Bay and Wawa areas. Over 1,000 access points were visited over the course of the two summers with 629 in Thunder Bay and 406 in Wawa.

The field visits permitted validation of the access point database. The field visits also provided an opportunity to populate measurements for many attributes that may affect an angler's choice of a fishing site. Table 4.3.1 shows a list of the spatial and non-spatial information that was collected during each visit. Of most importance was information related to road quality, which was measured along a continuum including: paved roads; gravel highways, gravel roads, general trails and walking trails. It was anticipated that each road/trail type would induce a different cost to the anglers. Other potentially important information collected at the sites included: the presence and quality of boat launching facilities; the availability and size of campgrounds, the presence of outhouses, picnic tables, and garbage cans around the sites; information about the water and forested environment around the sites; presence of beaches; presence of litter; and use levels on the day of inspection. Spatial information related to the roads, campsites, access points and signs was also collected.

4.4: Summary

Three data sources are required to estimate a fishing site choice model. First, I collected information about where anglers fish through an angling diary program. This program focused on two populations of northern Ontario anglers and covered the period from April 1 to September 30, 2004. The diary data collection followed standard surveying principles. The diary also afforded the opportunity to collect much information about the context of the fishing trips that is typically lacking from studies of fishing site choice.

Table 4.3.1: Information collected during field visits to access points

Spatial Information	*Tabular information*
GPS coordinates for access point	Road quality measures
GPS tracking of camping area	Road type
GPS tracking of roads and trails	Presence of features indicating poor or no maintenance
GPS coordinates for signs	
	Campsite characteristics
Photographic information	Number of campsites
Access point	Campsite type
Campgrounds	Presence of litter
Signs	
Other (e.g., poor quality road)	*Access point characteristics*
	Boat launch type if any
	Presence of features (e.g., fire pits, tables, etc.)
	Types of signs
	Environmental characteristics
	Waterbody type (at access point)
	Waterbody depth (at access point)
	Water clarity (at access point)
	Forest type
	Forest age
	Use measures
	Number of day and overnight users
	Number of cached boats

The two-step process used to collect information on available fishing sites also is much different from most past fishing site choice applications. By relying on local knowledge from anglers and Conservation Officers, we were able to identify a nearly complete inventory of potential fishing sites. A field program helped to verify this local knowledge database and it provided an opportunity to collect information on potentially important attributes such as roads.

Finally, many potentially relevant attributes were collected during site visits or from other spatial and non-spatial databases. This inventory of potentially important attributes provides a starting point for the identification of relevant attributes that are described in Chapter 6.

Chapter 5: Highlights from the qualitative interview and diary program responses

The angling diaries were designed to collect information about fishing trips and anglers that would assist with the development of fishing site choice models. Before describing the fishing site choice models, it is necessary to highlight the key findings from the qualitative interviews with resident anglers. There is also need to acquaint readers with anglers' responses to the questions asked in the angling diary and during the diary recruitment.

Angler responses to diary and other questions serve several purposes. First, the responses provide an opportunity to assess whether differences exist between anglers from Thunder Bay and Wawa areas and between anglers who completed and did not complete the angling diary program. Second, the responses make it possible to understand better the general context faced by anglers when making choices about fishing. Third, an opportunity exists to investigate the specific contexts that affect the site choices made by anglers on each fishing occasion.

The chapter is organized as follows. Section 5.1 describes the key findings from the qualitative interviews conducted with resident anglers. This description focuses on support for a choice modelling approach, the expected importance of road access and the expected importance of space on fishing site choices.

The following section focuses on responses to a telephone survey that all anglers were asked to complete before being invited to the diary program. The telephone survey responses permit an assessment of non-response bias present among diary respondents and non-respondents. Non-response bias is assessed for questions that include fishing avidity, species preferences, equipment availability, age and other aspects.

Section 5.3 summarizes the diary participants' responses to questions about general aspects of fishing in northern Ontario. These questions included fishing related motivations, site awareness, place attachment, and importance of site attributes.

The final section summarizes some fishing trip information provided by the respondents. This fishing trip information answers questions such as when trips occurred; what fish species anglers targeted; and what types of roads and trails anglers used to arrive at their chosen fishing sites.

5.1: Summary from qualitative interviews

This section describes key results from the qualitative interviews that were conducted with resident northern Ontario anglers. First, there was a discussion of whether the interviews with anglers supported the trade off nature espoused by a choice model. Second, there was some discussion about the likely importance that road access has on anglers' fishing site choices. Finally, the potential importance of space on fishing site choices was explored.

5.1.1: Support for a choice modelling approach

Choice models assume that individuals make conscious trade offs among attributes when selecting an alternative (e.g., a fishing site). However, other competing approaches such as conjunctive, disjunctive, elimination by aspects (Tversky, 1972) all suggest that individuals use non-compensatory heuristics such as thresholds to make decisions. A conjunctive approach eliminates all alternatives that do not meet all threshold levels set by the decision-maker. By contrast, a disjunctive strategy only requires an alternative to meet one threshold. Finally, the elimination by aspects approach works by having the decision-maker identify the most important attribute and one eliminates all alternatives with values less than a preset threshold value. A decision-maker completes this process until only one alternative remains.

Less than a handful of respondents from the qualitative interviews provided any commentary that would support a threshold approach. In these instances, the respondents usually identified the thresholds on travel distance where the time and travel costs become prohibitive at some point for a fishing trip.

Much more evidence from the interviews supported the tenet that anglers make trade offs among attributes when selecting a fishing site. One particularly important trade off stated by respondents was between expected catch of fish and availability of other recreational opportunities. The quotations below suggest that the presence of settings conducive for participation in other recreational activities may attenuate the importance of expected fish catch in shaping angling effort.

> I don't usually come here, I usually go to Iron Range or Northern Light (Lakes) … but my daughter and her husband and my grandkids are here and it has a nice beach here for the kids. They do swimming … and the fishing here is not bad, you have got to fight to get them, but they are in there. (T1, Thunder Bay, resident angler)

> We go to the lake, and there is more than just the fishing. There is the swimming and being at the lake… (T2, Wawa area, resident angler)

Swimming is not the only tradeoff that anglers are willing to make related to non-catch factors. Some respondents provided commentary relating to the aesthetics of the fishing site. Again, anglers may be willing to trade-off better fishing opportunities for areas that are more pleasing.

> I like the scenery and getting a fish is (a) bonus. I just like enjoying the outdoors. (W1, Wawa area, resident angler)

> Well, we used to camp at Bouchard (Lake). I am sure you were there earlier; every time a truck rolls by you are tone deaf. Actually the fishing is way better there. Bouchard is a fantastic lake to fish on. This is nicer just because of the site. (W2, Wawa area, resident angler)

Readers should not conclude that fishing quality is unimportant to anglers. The quotations above provide evidence that fishing site choice is a complex behaviour. Anglers often demonstrated during the interviews that they would trade off undesirable attributes of sites for better fishing opportunities.

> Rough roads, well I'll pound my truck down the road if I have to, to get quality fish in it. (T3, Thunder Bay, resident angler)

> … I don't mind travelling, if I know the fish are biting. (W3, Wawa area, resident angler)

The overwhelming evidence from the interviews supports the use of a trade off decision-making process by anglers for selecting fishing sites. This result supports a choice modelling approach for examining angling site choices.

5.1.2: Importance of road access to anglers

Given the focus of the dissertation on road access, the qualitative interviews provided much information about the importance of road access to fishing site choice. Of the 63 comments related to road access, 34 (54%) respondents stated that poor access deterred them from some fishing sites. Many respondents stated that poor road access might lead to damages to their vehicles and fishing equipment as evidenced by the following excerpts from the interviews.

> … we would probably go to a lot more lakes but we can't get in. I mean we just don't want to abuse our truck. This lake is easy access. Yeah, that is why we like it here. (T4, Thunder Bay, resident angler)
>
> … if we weren't here, there are a lot of places we might try, but then again access, road conditions, stuff like that (is important). I am not going to destroy my equipment to go some place. (T5, Thunder Bay, resident angler)
>
> A lot of damage can get done if you haven't got a good road to go on. So, yeah, accessibility is big. (T2, Thunder Bay, resident angler)

The quotations show that some anglers are conscious of equipment repair costs that may arise from accessing a fishing site in an area with poor road accessibility. These real or perceived costs help to redirect angling effort away from areas with poor road accessibility and towards areas with better road accessibility. Therefore, the combination of both travel distance and road quality provides a more accurate accounting for travel costs than does travel distance alone. Almost all previous fishing site choice model applications have ignored this fact.

Despite most respondents stating that poor road access deterred their choice of fishing sites, 14% of respondents provided positive comments about poor road accessibility[48]. These comments do not necessarily suggest that some anglers prefer poor access. Instead, these anglers may be

[48] The remaining 32% of respondents stated their fishing site choices were unaffected by the quality of road access.

considering conscious tradeoffs between more difficult road access and the likely better fishing opportunities and lack of congestion at these fishing sites. The following quotations provide evidence of conscious tradeoffs made by anglers between road access and congestion and fisheries abundance.

> You start making the roads too good (and) you get every Tom, Dick and Harry in here and then there is no place to camp … (T1, Thunder Bay, resident angler)

> … when we go fishing, we go for the hardest (site) to get to because there are less people there; so we like that. (T6, Thunder Bay, resident angler)

> …the worse the road the better, because less people go in there fishing. (W4, resident angler)

> … I would rather have a rough road, then if I go in, I know that there is not that many people fishing. (W1, Wawa area, resident angler)

> This here is not too bad, I have been in worse. This here is a little bit rough, but it kind of keeps too many people (from) coming all at one time. (W5, Wawa area, resident angler)

The resonant theme above is that by acting to deter many anglers, poor access is desirable for some individuals who have invested the money in equipment (e.g., all terrain vehicles (ATVs)) and time to access these more remote fishing sites. From the above comments, different individuals desire different levels of accessibility at fishing sites.

Many anglers are willing to trade off more difficult access against the possibility of encountering other anglers. The preference for less congestion is likely important for at least two reasons. First, anglers are aware of human impacts to fisheries populations and, therefore, they may believe that areas with less fishing pressure should have more fish, *ceteris paribus*. Second, anglers may negatively view the act of encountering other anglers on a fishing trip as it may interfere with their attainment of recreational goals (e.g., escape, relaxation). This second reason is a very heavily studied area in recreational research (e.g., Manning, Valliere, Wang, & Jacobi, 1999; Shelby, & Heberlein, 1986; Shelby, Vaske, & Donnelly, 1996; Stewart, & Cole, 2001).

5.1.3: Importance of space for fishing site choice to anglers

As discussed in Chapter 2, space can influence both the behavioural process of fishing site selection and the estimation of a choice model in many ways. The interviews with resident anglers only explored spatial hierarchical decision-making and spatial insurance strategies. Section 5.3 discusses ways that space may impact fishing site choices through spatial awareness and place attachment considerations.

Most anglers who indicated that they used a hierarchical decision-making process viewed space as unimportant. Only five interviewees stated that they selected a fishing site by first choosing a region and then selecting one fishing site from that region. By contrast, 22 interviewees commented that they would first decide upon a fish species and then would select a fishing site that has that fish species.

A second way that space may influence site choice is through a strategic response on the behalf of anglers. Anglers may select a fishing site in close proximity to other fishing sites as a type of spatial insurance strategy. Under this hypothesis, anglers who are not satisfied with their chosen fishing opportunity (e.g., too congested) may incur minimal additional travel costs to a fish at a different site. If true, one would expect that anglers would over select from fishing sites that are located near other fishing opportunities and under select from more isolated fishing sites.

The responses from the interviews provided mixed support for the spatial insurance strategy. Of the forty comments relating to this strategy, 22 respondents stated nearby lakes were important while 18 respondents stated nearby lakes were unimportant when choosing a fishing site. Some excerpts supporting this strategy are included below.

> That's why we fish from here. If they're not biting we go to McGaughey or Tease Lake, and Burbidge is just up the road. (T7, Thunder Bay, resident angler)

> ... there is a lot of different accesses here. That means a lot. Just in case, like say you come in here and its packed, you don't really want to go back home... (W6, Wawa area, resident angler)

Other anglers were not convinced about the practicality of this spatial insurance strategy. These anglers see many costs associated with moving to a new location that may limit the usefulness of the strategy. The following quotation summarizes this aspect:

> That (strategy) does not matter. If I am going to get there, I am going to stay there. (There is) too much work to prepare to go somewhere else. (W5, Wawa area, resident angler)

The mixed support for this strategy shows that space may be important to some anglers. In these instances, anglers may choose fishing sites that are located near other fishing sites. For other anglers, the relative location of a fishing site is unimportant for insuring that they find a suitable fishing site.

5.2: Assessing differences among angler groups

The process for diary recruitment followed two steps. First, all anglers from the Thunder Bay and Wawa areas who intended to fish during the open water season of 2004 were asked to complete a short telephone survey. Second, after completing the telephone survey, the anglers were asked if they would participate in the angling diary program.

This two-stage process for recruitment was ideal to assess the non-response bias present in the sample of anglers that completed the diaries[49]. The assessment simply involved inferentially comparing whether the responses of anglers who completed the diary differed from responses of other anglers. A second assessment involving comparisons of differences in responses between anglers who accepted and those who declined the diary invitation was also undertaken (see Appendix C).

The following order is used to discuss the survey responses to each question. First, general comments about the overall pattern of responses are made. Second, statistical comparisons are made between the responses of all Wawa (n=521) and all Thunder Bay anglers (n=933). Finally, comparisons of non-response bias are made for both Wawa and Thunder Bay area anglers. The

[49] This non-response bias assessment only is valid for comparing anglers who agreed to the telephone survey. If differences between anglers who agreed and declined the telephone survey exist, they remain unknown.

sample sizes for the non-response bias tests include 151 and 347 anglers who completed the diary and 370 and 586 anglers who did not complete the diary for Wawa and Thunder Bay, samples respectively.

The telephone survey was designed to capture information about possible sources of response bias. One important set of questions related to the reported avidity of the anglers. Figures 5.2.1 and 5.2.2 show the results of questions on the reported number of fishing days spent in 2003 on open water and ice fishing, respectively. The stems on the charts represent plus or minus two times the standard errors from the mean while the boxes represent the area between plus and minus one standard error from the mean. Statistical inferential tests on differences in means were conducted via independent samples t-tests.

Figure 5.2.1: Reported number of days spent open water fishing by Wawa and Thunder Bay area anglers (separated by angling diary response)

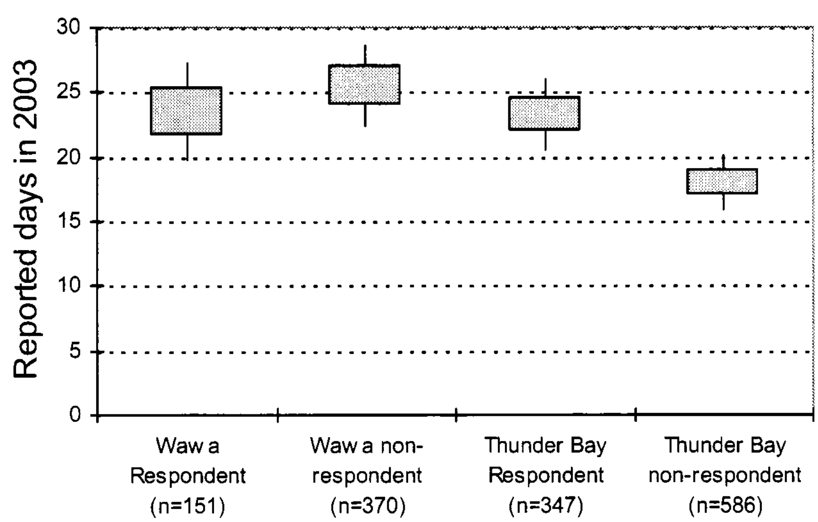
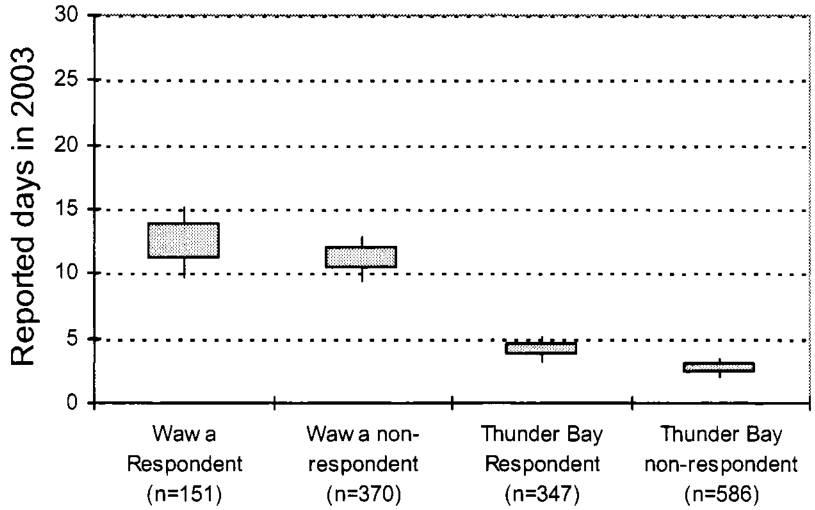


Figure 5.2.2: Reported number of days spent ice fishing in 2003 by Wawa and Thunder Bay area anglers (separated by angling diary response)



The reported number of open water fishing days was much greater than the reported number of ice fishing days. Wawa area anglers reported more days of fishing during the open water ($t=3.45$, $p=0.001$) and ice fishing ($t=10.67$, $p<0.001$) seasons than did Thunder Bay anglers.

The Thunder Bay diary respondents reported more fishing days spent on open water ($t=-3.13$, $p=0.002$) and ice fishing ($t=-2.51$, $p=0.001$) than did Thunder Bay area diary non-respondents. These findings suggest that results from the Thunder Bay diary respondents will contain an avidity bias (i.e., anglers in the diary sample pursue fishing more often than do other anglers). No statistically significant differences in number of fishing days existed between Wawa diary respondents and non-respondents for open water ($t=0.74$, $p=0.459$) or ice fishing ($t=-0.83$, $p=0.405$). Appendix C does show, however, that those Wawa area anglers who accepted the invitation to participate in the diary were more avid than were Wawa area anglers who declined this invitation.

Another question asked the anglers to state their most preferred fish species. Table 5.2.1 shows that walleye (*Stizostedion vitreum*) was by far the most important fish species to all anglers. Walleye was preferred as northern Ontario anglers consider it as a good food fish. Following walleye in preference were the various trout species (i.e., lake trout, brook trout (*Salvelinus fontinalis*) and rainbow trout (*Oncorhynchus mykiss*)).

Table 5.2.1: Reported favourite fish species among Wawa and Thunder Bay area anglers in 2003 (separated by angling diary response)

	Wawa Area (%)		Thunder Bay (%)	
Species	Respondent (n=151)	Non-respondent (n=370)	Respondent (n=347)	Non-respondent (n=586)
Walleye	75.5	74.1	78.4	79.0
Lake Trout	2.6	5.4	6.9	4.4
Brook Trout	4.6	5.9	3.2	4.9
Trout (not specified)	9.3	6.2	2.9	2.4
Northern Pike	5.3	5.7	2.0	1.2
Smallmouth Bass	0.0	0.3	1.4	3.2
Salmon	0.7	0.3	3.2	2.7
Walleye and Trout	2.0	0.8	0.6	0.2
Rainbow Trout	0.0	0.6	0.6	1.0
Other	0.0	0.8	0.9	0.8

The infrequent choice of some fish species makes a statistical comparison of the above table inappropriate. To enable statistical analyses, the fish species were aggregated into walleye, lake trout, other trout, and other categories. Wawa area anglers had less preference for walleye and greater preference for other trout species than did Thunder Bay area anglers (LR[50]=11.48, p=0.009).

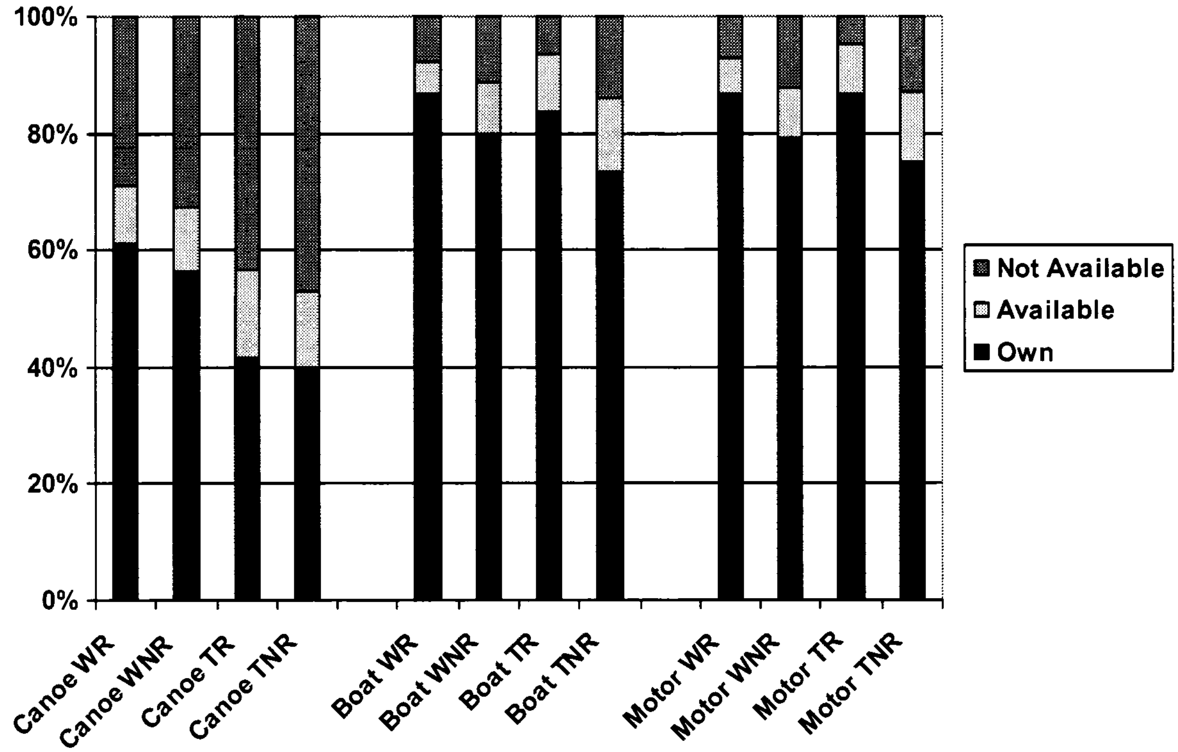
No statistical differences in fish species preference were found between diary and non-diary respondents for either the Thunder Bay (LR=4.27, p=0.234) or Wawa area (LR=2.37, p=0.499) samples. Any analyses based on the diary respondents, therefore, should not introduce any bias with respect to the fish species preferences.

Non-response bias was also assessed on the responses to the questions about ownership of boat and motorized vehicle equipment. Since people share equipment, each respondent was asked if he/she owned the equipment, had access to the equipment from someone else or had no access to the equipment. Figure 5.2.3 shows the percentages of the different samples that stated they had

[50] LR represents the likelihood ratio test statistic from cross tabulated results.

ownership or availability to different boat-based equipment. The figure shows that ownership of a boat and outboard motor is very common (about 80%) among Thunder Bay and Wawa area anglers.

Figure 5.2.3: Percentage of Wawa and Thunder Bay area anglers who owned or had access to boat equipment in 2004 (separated by angling diary response)



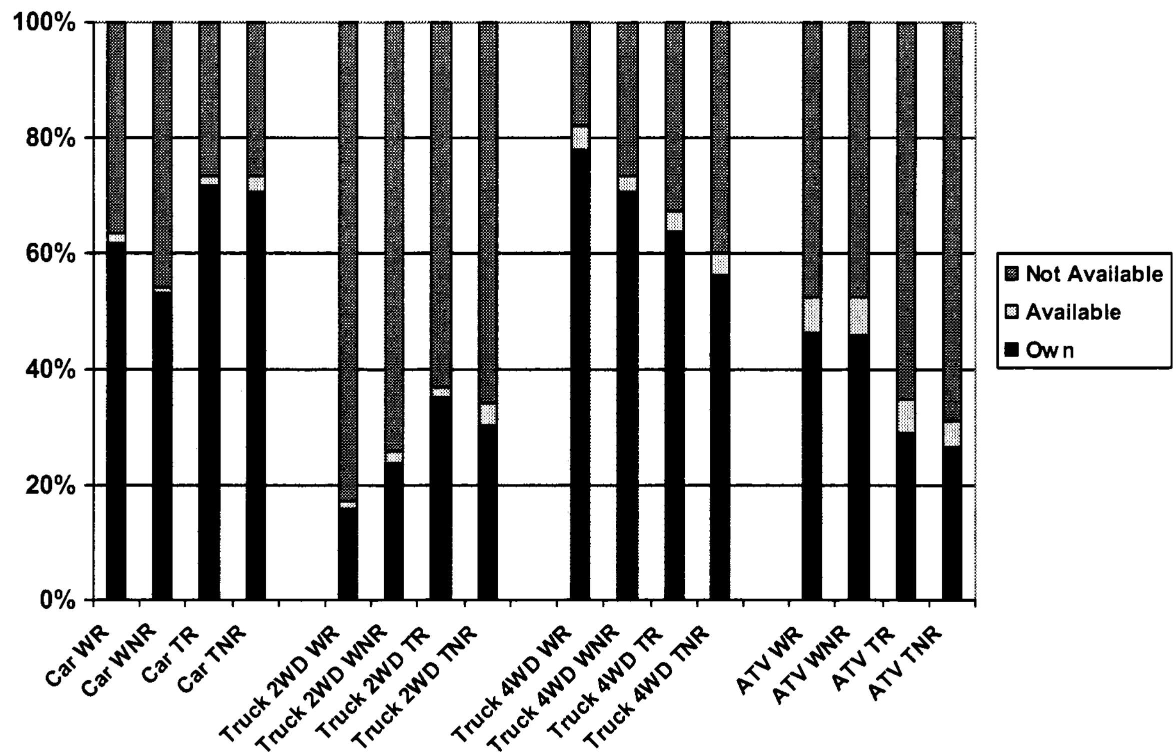
WR - Wawa area diary respondent (n=151)
WNR - Wawa area diary non-respondent (n=370)
TR - Thunder Bay area diary respondent (n=347)
TNR - Thunder Bay area diary non-respondent (n=586)

Wawa area anglers were much more likely to own a canoe (LR=39.2, $p<0.001$) than were Thunder Bay area anglers. No statistical difference in ownership or availability rates existed between Thunder Bay and Wawa anglers for either a boat (LR=5.52, p=0.063) or an outboard motor (LR=3.86, p=0.145).

No statistical differences in rates of ownership or availability of canoes (LR=9.79, p=0.613), boats (LR=3.84, p=0.147) and outboard motors (LR=4.42, p=0.110) were found between Wawa area diary respondents and non-respondents. Although canoe ownership rates were not different (LR=1.27, p=0.529), Thunder Bay diary respondents were much more likely to own a boat (LR=15.54, p<0.001) and outboard motor (LR=22.00, p<0.001) than were Thunder Bay area diary non-respondents.

Figure 5.2.4 shows the percentage of anglers who own or have access to various motorized vehicles. Thunder Bay and Wawa area anglers had very high ownership rates for four wheel drive trucks or sports utility vehicles (SUVs) and high ownership rates for all terrain vehicles (ATVs).

Figure 5.2.4: Percentage of Wawa and Thunder Bay area anglers who owned or had access to various motorized vehicles in 2004 (separated by angling diary response)



WR - Wawa area diary respondent (n=151)
WNR - Wawa area diary non-respondent (n=370)
TR - Thunder Bay area diary respondent (n=347)
TNR - Thunder Bay area diary non-respondent (n=586)

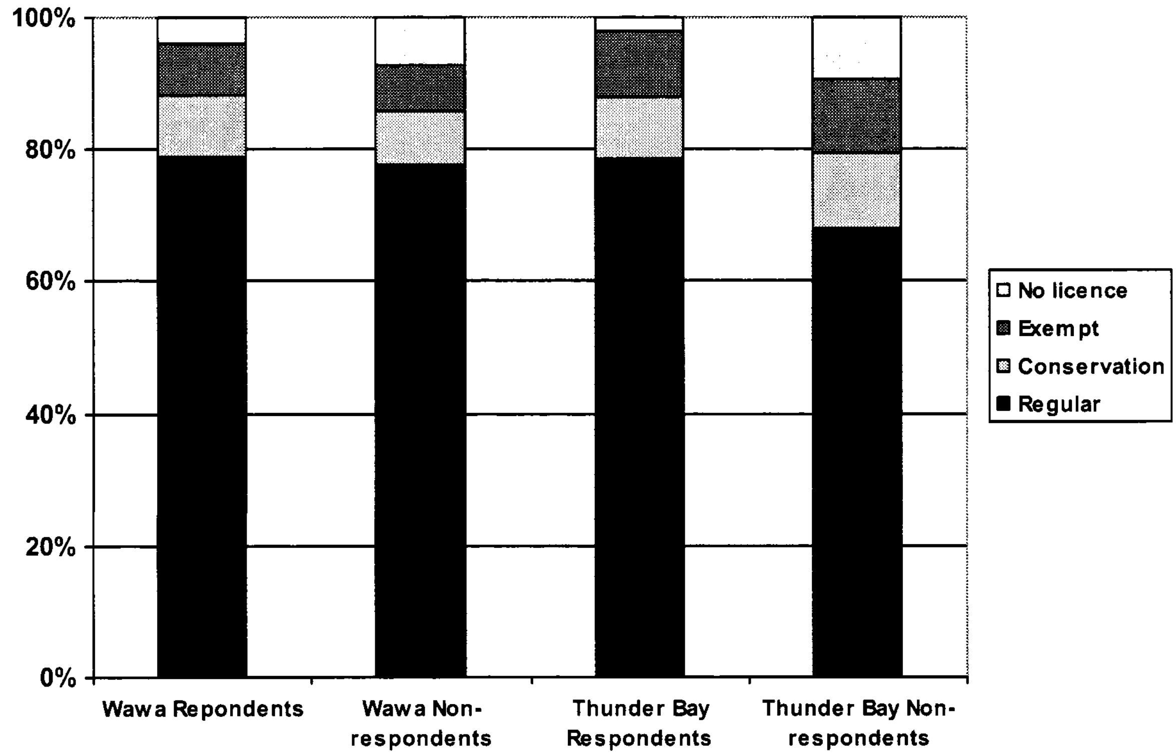
Wawa area anglers had higher rates of ownership for four wheel drive trucks and SUVs (LR=29.57, $P<0.001$) and ATVs (LR=56.12, $p<0.001$) than did Thunder Bay area anglers. Thunder Bay area anglers were more likely to own cars or minivans (LR=42.22, $p<0.001$) and two wheel drive trucks (LR=22.59, $p<0.001$) than were Wawa area anglers.

No statistical differences in ownership rates were found for cars or minivans (LR=4.81, p=0.090; LR=0.72, p=0.697), two wheel drive trucks or SUVs (LR=4.49, p=0.106; LR=4.62, p=0.099), four wheel drive trucks or SUVs (LR=4.83, p=0.090; LF=5.47, p=0.065) or ATVs (LR=0.05, p=0.974; LR=1.68, p=0.432) for either the Wawa or Thunder Bay area diary respondents and non-respondents, respectively. However, at a less restrictive probability of 0.10 or less, it appears that the Thunder Bay and Wawa diary respondents were more likely to own four wheel drive trucks or SUVs than were their counterparts.

Ontario residents have several different types of available fishing licences. For some anglers, Aboriginal status, disability or age leads to an exemption from requiring a fishing licence. For other anglers, they must be in possession of either a regular or conservation fishing licence. The less expensive conservation fishing licence limits anglers to possess fewer fish than the regular licence. Figure 5.2.5 shows the percentages of Wawa and Thunder Bay area anglers reporting different licence types.

Most Thunder Bay and Wawa area anglers held a regular fishing licence in 2004 with a much smaller percentage that held a conservation licence. The relatively high percentage of anglers stating that they had no fishing licence may arise for several reasons including: being exempt from a fishing licence; holding no licence but intending to obtain a licence before fishing; or holding no licence with no intention to obtain a licence before fishing.

Figure 5.2.5: Percentage of Wawa and Thunder Bay area anglers who held different fishing licences in 2004 (separated by angling diary response)



The difference in responses to the licence question approached significance between the Thunder Bay and Wawa area anglers (LR=7.54, p=0.056). This difference primarily arose since Thunder Bay anglers tended to possess conservation licences more often than did Wawa area anglers.

Thunder Bay diary respondents were more likely (LR=25.88, p<0.001) in possession of a fishing licence than were Thunder Bay diary non-respondents. No statistical difference existed between the licence types held by Wawa area diary respondents and non-respondents (LR=2.36, p=0.501).

Anglers were also asked about their fishing experience and age. Figures 5.2.6 and 5.2.7 provide the responses to these questions. As with the earlier figures, the stems represent plus or minus two times the standard error from the mean while the boxes represents the areas between plus and minus one standard error from the mean.

Figure 5.2.6: Reported years fished by Wawa and Thunder Bay area anglers (separated by angling diary response)

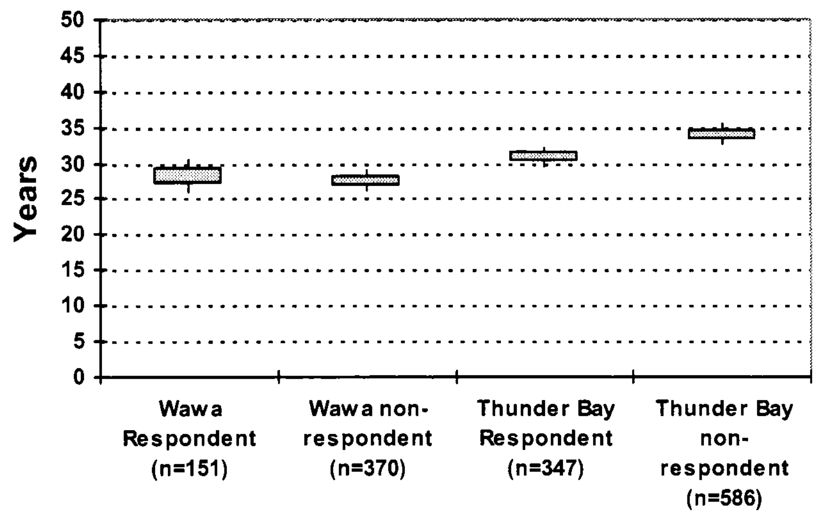
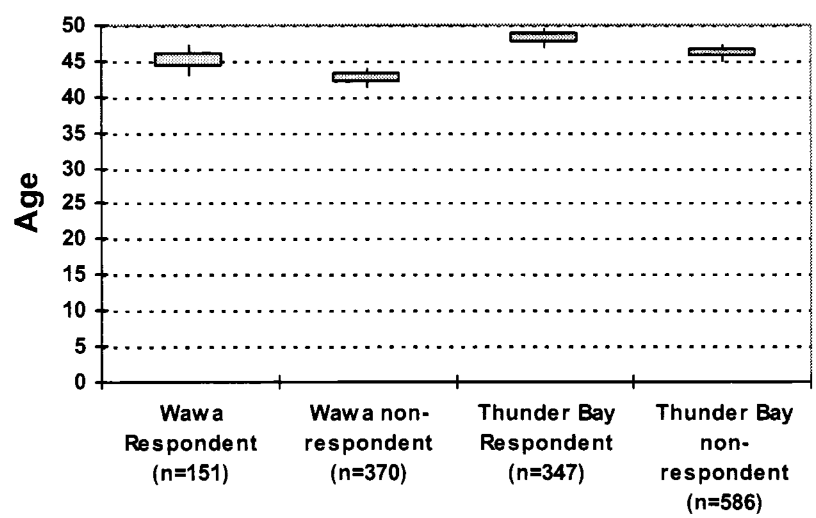


Figure 5.2.7: Reported age of Wawa and Thunder Bay area anglers in 2003 (separated by angling diary response)



The figures show that many anglers had between 25 and 35 years of fishing experience and were between 40 and 50 years of age. Thunder Bay area anglers had significantly more fishing experience ($t=-5.61$, $p<0.001$) and were older ($t=-4.90$, $p<0.001$) than were Wawa area anglers.

Thunder Bay diary respondents had fished more years ($t=-3.30$, $p=0.001$) and were older ($t=-2.50$, $p=0.013$) than were Thunder Bay diary non-respondents. While no statistical difference was found for reported years of fishing experience ($t=-0.35$, $p=0.725$), Wawa area diary respondents were older than were Wawa area diary non-respondents ($t=-2.04$, $p=0.042$).

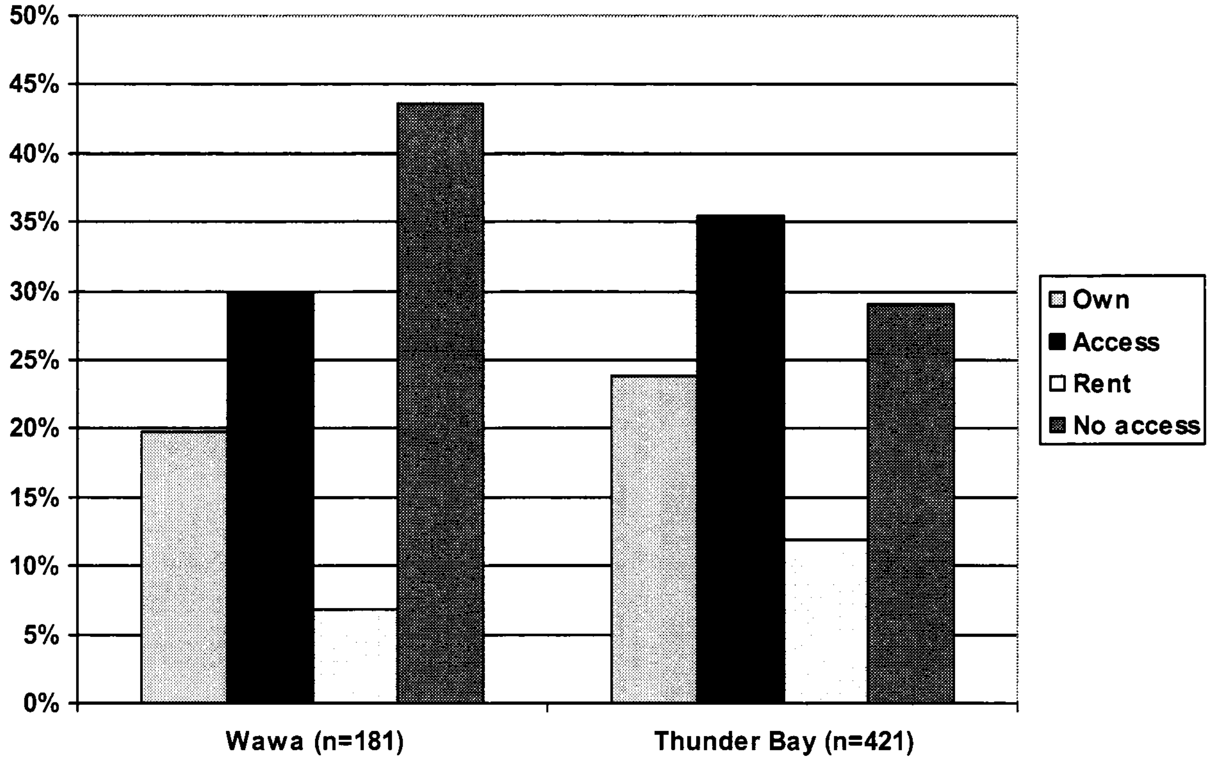
5.3: Understanding Thunder Bay and Wawa area anglers

The diaries sent to each participant contained two parts. The first part asked anglers to respond to questions related to items such as information sources, motivations, awareness of fishing sites, and attachment to fishing areas. The second part asked anglers to provide detailed information about their fishing trips. This section focuses on the responses to the first part of the diary. Besides highlighting the responses, statistical comparisons were made between the responses of Wawa and Thunder Bay area respondents.

The sample sizes for each question varied because of both item non-response and the data collection design. Item non-response occurs when a survey respondent chooses not to answer a question. As described in Chapter 4, some diary information was collected over the telephone. To reduce the interview time on the telephone, only a sub set of all questions found in part one of the diaries was asked. Therefore, the sample of anglers responding to any given question varied widely. Finally, the sample sizes were based from all valid responses to these questions regardless of whether the angler fully completed the angling diary program.

A simple set of questions asked diary respondents to indicate whether they owned, had access to, or typically rented private cottage or fixed trailer type accommodation in northern Ontario. This information along with the private cottage locations may be important for assessing any spatial habits underlying fishing site selection. Figure 5.3.1 summarizes the responses from the 181 Wawa and 421 Thunder Bay diary respondents.

Figure 5.3.1: Percentage of Wawa and Thunder Bay diary respondents who owned, accessed, or rented private cottages or tourist camps



The responses were compiled as follows when a respondent indicated that more than one category fit his/her accommodation situation. If a respondent owned a cottage, he/she would always be listed as a cottage owner regardless of whether he/she had access to other cottages or typically rented other cottages. If a respondent who did not own a cottage had access to a private cottage, they would be listed as having access to a cottage regardless of whether or not he/she rented a cottage or trailer.

The figure indicates that only a minority of the diary respondents stated they did not own, have access to or rent a private cottage or trailer. As well, over one in five respondents stated that they owned a private cottage. Thunder Bay area diary respondents were more likely to state they owned, rented or had access to a private cottage than were Wawa area diary respondents (LR=13.49, p=0.004).

Other sets of questions examined how anglers learned about fishing opportunities in northern Ontario. In this set of questions, respondents were asked to use a five-point scale, with five being most important, to rate the importance of various information sources. The results in Table 5.3.1, which are ordered by joint importance from both respondent groups, are based on approximately[51] 130 Wawa area and 330 Thunder Bay area diary respondents.

Table 5.3.1: Importance of information sources for learning about new fishing opportunities to Wawa and Thunder Bay area diary respondents (1=not at all important; 5= very important; standard deviations in parentheses)

Information Source	Wawa (n=130)	Thunder Bay (n=330)	Statistical inference (p value)
Other anglers I normally fish with	3.82 (1.15)	3.95 (1.15)	0.470
Driving and exploring in new areas	3.55 (1.13)	3.21 (1.28)	0.005
Other Maps	2.99 (1.28)	2.82 (1.27)	0.202
Ontario MNR maps	3.18 (1.30)	2.71 (1.28)	<0.001
Bait shops / sporting goods stores / licence issuers	3.01 (1.32)	2.74 (1.21)	0.034
Other anglers I don't normally fish with	2.68 (1.27)	2.84 (1.25)	0.213
Ontario's Fishing Summary	2.95 (1.46)	2.29 (1.28)	<0.001
Ontario MNR publications	2.76 (1.35)	2.26 (1.20)	<0.001
Outdoor magazines	2.68 (1.28)	2.28 (1.17)	0.001
Ontario MNR Conservation Officers	2.71 (1.36)	2.16 (1.26)	<0.001
Television fishing shows	2.62 (1.30)	2.06 (1.11)	<0.001
Ontario MNR District Offices	2.65 (1.33)	2.03 (1.20)	<0.001
Newspaper media	2.14 (1.16)	2.09 (1.08)	0.646
Internet sources	1.85 (1.05)	1.76 (1.04)	0.394

[51] The approximation is used to account for the variability in responses for any given information source.

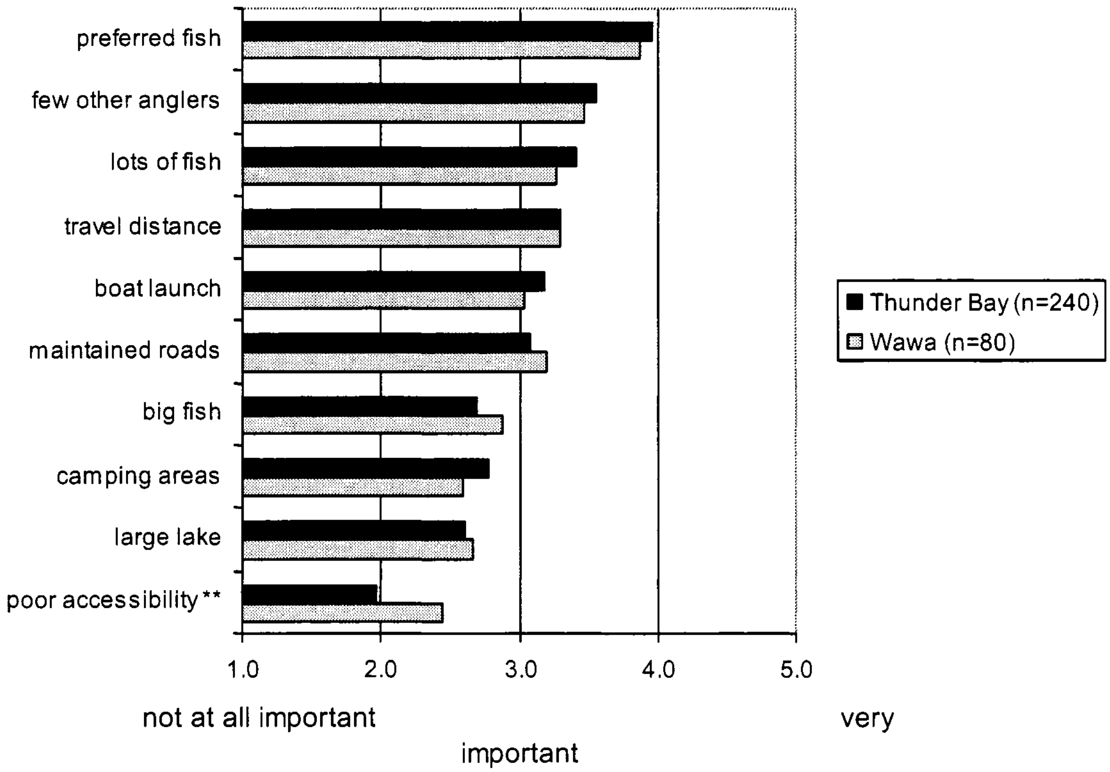
The most important source of information about fishing sites was other anglers with whom the individual fished. Respondents would obtain information about fishing opportunities either through word of mouth or from trips taken with these anglers into new areas. Exploration by the angler was the second most important source of information. Apparently, many resident anglers learn about new fishing opportunities by driving on roads into new areas. Maps were also an important source for information as different maps with marked locations of fishing sites exist for both the Thunder Bay and Wawa areas. Finally, bait shops, publications, media and MNR District Offices were important information sources to some anglers.

Wawa area diary respondents rated exploration, MNR sources, bait shops, and magazine and television media as more important information sources than did Thunder Bay area anglers. Thunder Bay area diary respondents did not rate any of the information sources as more important than did Wawa area diary respondents.

While the next chapter formally assesses the importance of attributes for fishing site choice, diary respondents were asked to state those attributes that they felt were important when choosing a fishing site. The anglers were asked to rate each attribute on a five-point importance scale that ranged from not at all important to very important. A total of 80 and 240 anglers from the Wawa and Thunder Bay samples, respectively provided the ratings that are summarized in Figure 5.3.2.

Respondents rated the presence of preferred fish species as the most important attribute. Since walleye is the most preferred fish species, one may assume that waters with walleye are more preferable to most anglers than are waters without walleye. Respondents rated the abundance of fish ("lots of fish") as slightly less important than the presence of preferred fish. Large fish ("big fish") was the least important attribute that focused on the fish.

Figure 5.3.2: Importance of attributes for selecting a fishing site by Wawa and Thunder Bay area diary respondents



** Significant difference in ratings among Thunder Bay and Wawa area residents ($p < 0.05$)

Anglers rated few encounters with other anglers as the second most important attribute when choosing a fishing site. Anglers, therefore, face an interesting dilemma when choosing a fishing site. Some lakes will be very popular because of the presence of desirable site attributes. However, anglers who want to avoid encountering other anglers when they fish, view the popularity of these lakes negatively. A choice model provides a much better approach for investigating this trade off issue than does a question that asks anglers to rate the importance of each site attribute.

Another set of important attributes focused on the roads and trails that lead anglers to the fishing sites. Travel distance was the most important of these attributes as anglers preferred fishing sites closer than farther from their homes. The presence of well maintained roads was also important to many anglers when choosing a fishing site. Finally, roads and trails that are accessible by four wheel drive vehicle or ATV were only important to a minority of anglers. This poor accessibility attribute produced the only significant difference in importance ratings between respondents as Wawa area respondents rated this attribute as more important than did Thunder Bay respondents ($t= 2.85$, $p=0.005$). This difference is likely due to the higher ownership rates for four wheel drive vehicles and ATVs among Wawa than Thunder Bay area diary respondents (see Figure 5.2.4).

The final attributes rated by respondents were the size of fishing waters and presence of facilities. For facility presence, boat launches were more important than were camping areas.

A frequently replicated scale (Fedler, & Ditton, 1994) designed to determine the importance of latent constructs of fishing motivations was employed in the diary. The scale was slightly modified to include the statements: "to teach others to fish"; "to catch a limit of fish" and "to catch and release fish". These statements were added to better identify anglers who have a consumptive orientation and to account for the importance of teaching skills to young anglers.

Each respondent was asked to rate each motivational statement on a five-point importance scale that ranged from not at all (1) to very important (5). A total of 180 and 400 anglers from the Wawa and Thunder Bay area samples, respectively provided the responses that are summarized in Table 5.3.2. The results are ordered by the average importance ratings for all respondents.

As is well established (Ditton, 2004), anglers rated the non-catch-related fishing motivations as more important than the catch-related fishing motivations. Many ratings for the catch-related fishing motivations were significantly higher for Wawa than for Thunder Bay area diary respondents. Therefore, Wawa area anglers were more attracted to catching and keeping fish than were Thunder Bay anglers.

Table 5.3.2: Importance of reasons for taking a fishing trip to Wawa and Thunder Bay area diary respondents (1=not at all important; 5=very important; standard deviations in parentheses)

Motivational Item	Wawa (n=180)	Thunder Bay (n=400)	Statistical inference (p)
To be outdoors	4.58 (0.69)	4.63 (0.66)	0.412
For relaxation	4.50 (0.74)	4.44 (0.81)	0.425
To experience natural surroundings	4.42 (0.80)	4.38 (0.88)	0.657
To get away from the daily routine	4.16 (1.06)	4.22 (1.00)	0.518
To be with friends	3.98 (1.06)	4.21 (0.93)	0.008
For family recreation	4.16 (1.08)	4.09 (1.11)	0.420
To be close to water	4.16 (1.04)	4.01 (1.13)	0.130
For the experience of the catch	3.85 (1.20)	3.82 (1.11)	0.728
For the challenge or the sport of fishing	3.95 (1.10)	3.75 (1.18)	0.047
To obtain fish for eating	3.73 (1.24)	3.46 (1.19)	0.011
To get away from other people	3.39 (1.41)	3.54 (1.41)	0.239
To experience new and different things	3.27 (1.30)	3.37 (1.27)	0.356
To teach others to fish	3.14 (1.39)	3.31 (1.32)	0.162
To catch and release fish	3.14 (1.37)	3.23 (1.27)	0.427
To develop my skills	3.03 (1.34)	2.83 (1.30)	0.086
For physical exercise	3.07 (1.30)	2.68 (1.30)	0.001
To catch a limit of fish	2.96 (1.45)	2.69 (1.37)	0.028
To test my equipment	2.68 (1.31)	2.42 (1.24)	0.023
To obtain a trophy fish	2.48 (1.42)	2.21 (1.35)	0.026

The most important motivations were non catch-related. These motivations focused on themes relating to outdoors, relaxation, escape, and affiliation. The importance of these non-catch-related motives seems to contradict the stated importance ratings for attributes when choosing a fishing site. While anglers stated that the species type and abundance of fish were very important attributes for fishing site choice, they also stated that catch-related motivations are less important than are non catch-related motivations. This apparent contradiction probably arises since many non catch-related motives will be achieved at most fishing sites. Therefore, fishing quality becomes paramount to site selection because fishing quality does vary over space.

The results of a principal components analysis of these motivational statements are provided since the site choice models employ these results. The principal components analysis extracted five latent components that accounted for 59.6% of data set variation. Table 5.3.3 shows the rotated loadings (greater than 0.400) for the various motivational statements. The skill component loaded highly with statements related to testing equipment and developing skills. The high loadings associated with being outdoors and in natural settings led me to label the second component as nature. The recreate component was labelled because of the importance of family recreation and teaching. The escape component loaded highly with statements such as getting away from the daily routine and experiencing new and different things. The high loadings associated with catching a limit of fish and keeping fish for eating led to the final component being labelled consume.

It is likely that an angler's choice of fishing sites results in a clustered spatial pattern of choices. This clustering of choices may arise from limited spatial awareness of fishing sites and/or a place attachment to a spatial area. The next two sets of questions explore the potential importance of each of these sources that may produce non-random spatial patterns of fishing site choices.

Table 5.3.3: Principal component loadings from importance ratings of reasons for taking a fishing trip for all diary respondents

Motivational Item	Skill	Nature	Recreate	Escape	Consume
To test my equipment	0.714				
To develop my skills	0.704				
For the challenge or the sport of fishing	0.675	0.404			
To obtain a trophy fish	0.648				
For the experience of the catch	0.589				
To catch and release fish	0.552				
To be outdoors		0.824			
To experience natural surroundings		0.687			
To be close to water		0.650			
To get away from other people		0.583		0.472	
For relaxation		0.515	0.468		
For family recreation			0.775		
To teach others to fish			0.663		
To be with friends			0.578		
To get away from the daily routine				0.722	
To experience new and different things				0.603	
For physical exercise				0.453	
To catch a limit of fish					0.827
To obtain fish for eating					0.788
Variance explained	16.8%	14.8%	10.0%	9.1%	8.9%

Space may affect the awareness of fishing sites. Given that anglers state that exploration is an important source they use to find information about new fishing sites, it is reasonable to assume that anglers' awareness of fishing opportunities is not uniform over space.

To understand the extent of awareness of fishing opportunities by Wawa and Thunder Bay area anglers, a question was included in the diary. The question asked respondents to rate on a four-point scale their level of awareness for fishing opportunities in the Wawa and Thunder Bay sub regions (see Figures 5.3.3 and 5.3.4). The four labels in the scale were: no fishing sites (1); only large lakes (2); large lakes and some smaller lakes (3); and almost every possible fishing site (4). Table 5.3.4 summarizes the ratings from the 100 Wawa and 300 Thunder Bay area diary respondents.

Figure 5.3.3: Sub-regions within the Wawa study area

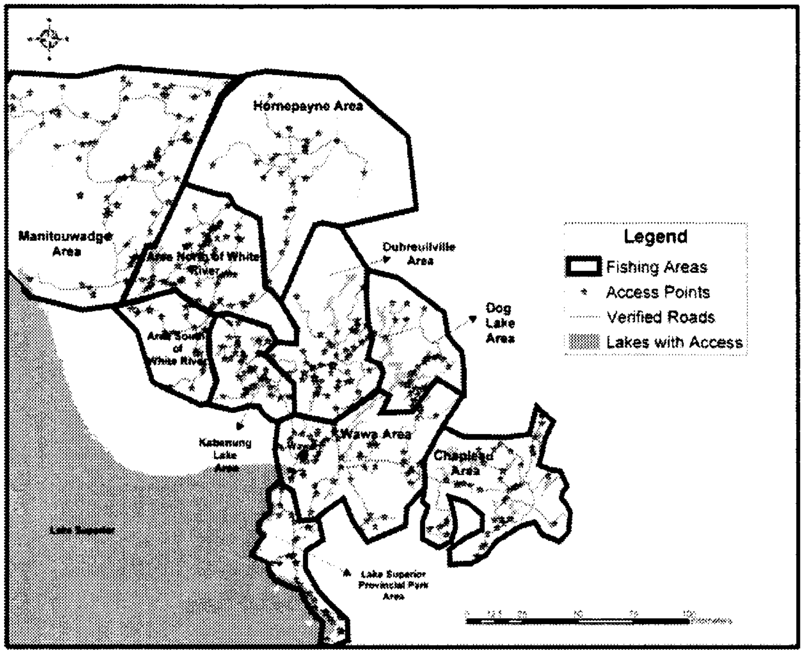


Figure 5.3.4: Sub-regions within the Thunder Bay study area

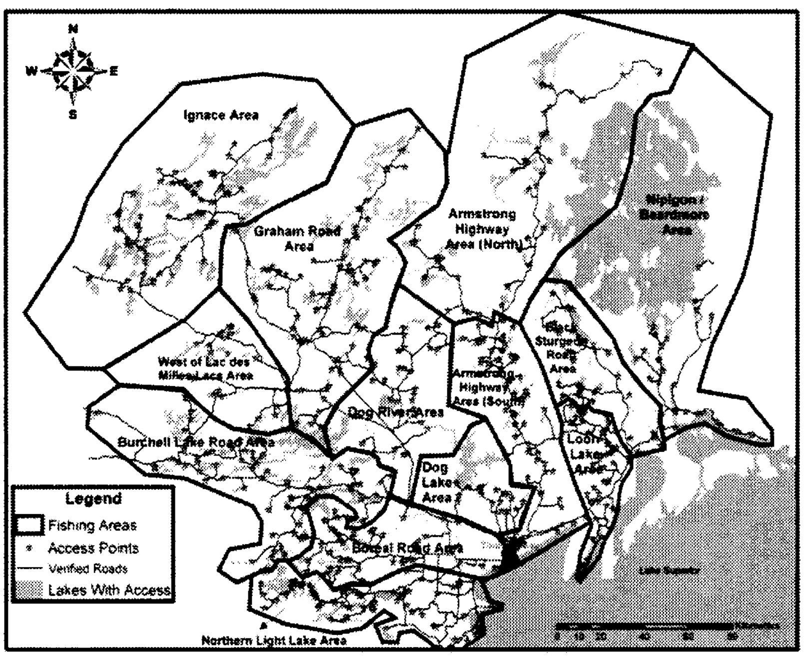


Table 5.3.4: Awareness ratings by Wawa and Thunder Bay diary respondents for fishing opportunities in sub regions (1=no fishing sites; 2=only large lakes; 3=large lakes and some smaller lakes; 4=almost every possible fishing site; standard deviations in parentheses)

Wawa Area (n=100)	Mean rating	Thunder Bay Area (n=300)	Mean rating
Area around Dubreuilville	2.73 (1.05)	Boreal Road	2.47 (1.04)
Area around Wawa	2.72 (1.07)	Northern Light Lake area	2.38 (1.05)
Area south of White river	2.25 (1.05)	Armstrong Highway (south)	2.18 (1.01)
Area north of White River	2.00 (1.05)	Dog Lake area	2.13 (0.89)
Kabenung Lake area	1.98 (1.08)	Dog River area	2.10 (0.99)
Lake Superior Provincial Park area	1.94 (1.10)	Graham Road	2.09 (1.06)
Dog Lake area	1.92 (1.07)	Black Sturgeon Road	2.00 (1.03)
Area west of Chapleau	1.74 (0.92)	Armstrong Highway (north)	1.94 (1.03)
Manitouwadge area	1.66 (1.03)	Burchell Lake Road	1.91 (1.03)
Area south of Hornepayne	1.62 (0.97)	Area west of Lacs des Milles Lacs	1.83 (0.97)
		Ignace area	1.83 (0.97)
		Nipigon River area	1.80 (0.95)
		Area north of Loon Lake	1.65 (0.96)
		Beardmore area	1.52 (0.85)

Awareness of fishing opportunities varied considerably over the sub regions. Typically, the awareness of fishing areas was highest around the origins of the anglers and dissipated with increasing distance from these origins. Many sub regions also received average ratings of less than two, which suggests that most respondents only know about fishing opportunities associated with large lakes.

This limited awareness of fishing opportunities may help to explain why large waters are important to anglers when choosing fishing sites. Instead of simply assuming that large waters are desirable to anglers as is typical with fishing site choice models, the importance of large waters for fishing site choice is likely to include both preference and awareness considerations. Indeed, the awareness ratings provided by Wawa and Thunder Bay area anglers supports the tenet that anglers choose large waters in part, because they are more aware of these than other fishing opportunities.

Another possibility for a non-random spatial pattern of fishing trips by individuals relates to the place attachment that individuals have with an area. Researchers typically define place attachment by two constructs relating to identity and dependence (Williams, Anderson, McDonald, & Patterson, 1995). Place identity refers to the connection that people have with a specific place. Place dependence refers to the ability of a place to provide the backdrop for activities pursued by the individual. To understand whether dependence and/or identity themes were important to these anglers, a frequently replicated scale (Williams *et al.*, 1995) on place attachment was used. The context for the question was the sub region from the awareness question that the angler stated he/she most often fished.

The question asked individuals to rate each statement on a five-point agreement scale that ranged from strongly disagree (1) to strongly agree (5). Table 5.3.5 shows the ratings provided by 80 Wawa and 230 Thunder Bay diary respondents.

Respondents typically rated the statements about place identity higher than the statements about place dependence. Therefore, anglers' are attached to areas because of their connection with an area than with an area's ability to support their fishing activities. From a management perspective, the result suggests that while other good substitute fishing sites may exist, anglers may not move from areas they most often fish because they have developed some connection with the surrounding environment.

Table 5.3.5: Agreement ratings by Wawa and Thunder Bay diary respondents for place attachment statements about typical fishing area (1= strongly disagree; 5= strongly agree; standard deviation in parentheses)

Statement	Identity or Dependence	Wawa (n=80)	Thunder Bay (n=230)	Statistical inference (p)
This area is very special to me	Identity	4.15 (0.92)	3.97 (0.91)	0.510
I feel like this area is part of me	Identity	4.05 (0.98)	3.86 (0.94)	0.120
I am very attached to this area	Identity	3.93 (0.99)	3.84 (1.00)	0.306
I identify strongly with this area	Identity	3.89 (0.93)	3.84 (0.90)	0.613
This area means a lot to me	Identity	3.85 (1.01)	3.79 (0.93)	0.528
I get more satisfaction out of visiting this area than from visiting any other area	Dependence	3.58 (1.02)	3.72 (1.04)	0.265
I would enjoy fishing in a different area just as much as I enjoy fishing here	Dependence	3.68 (0.76)	3.56 (0.94)	0.817
This area is the best place for fishing	Dependence	3.40 (1.05)	3.43 (0.90)	0.117
Visiting this area says a lot about who I am	Identity	3.40 (1.04)	3.20 (1.09)	0.155
Fishing in this area is more important than fishing in any other area	Dependence	3.24 (1.08)	3.21 (1.05)	0.787
No other area can compare with this area	Dependence	3.06 (1.07)	3.15 (1.02)	0.679
I would not substitute any other area for the fishing I do here	Dependence	2.92 (1.16)	2.86 (1.16)	0.701

5.4: Fishing trip characteristics

The primary reason for implementing the diary program with resident northern Ontario anglers was to obtain information about fishing site choices. This ability to design the diaries to support the estimation of fishing site choice models provided a great opportunity to understand the context of fishing trip choices made by anglers. The previous sections provide some findings about the general contexts faced by the anglers (e.g., awareness of fishing sites). However, anglers may be forced to choose fishing sites from many different contexts over the course of a fishing season (e.g., fishing trips taken while vacationing away from home). The questions asked to anglers about each fishing trip attempted to capture many different contexts that anglers faced when making fishing trip decisions.

This section highlights the different contexts that anglers faced on each trip occasion. This trip context review is especially useful for identifying a suitable set of fishing trips for estimating fishing site choice models. Besides the trip context, some other basic information is presented that highlights the effects of time on fishing trip decisions. Finally, a crude summary of the types of roads and trails that anglers used to access fishing sites is presented.

An often difficult problem with modelling fishing trips is that the trip context may differ substantially at each trip occasion. Besides the well known problem of modelling day and multiple day trips[52] (Fletcher *et al.*, 1990), trips to private cottages or part of longer trips away from home (e.g., from a private cottage to another lake) are likely different than are other fishing trips.

Table 5.4.1 summarizes the different trip contexts taken from May 1 to September 30, 2004. In addition to separating the trips by respondent origin and by those anglers who provided full and partial trip information in the diaries. The Wawa area diary respondents provided details on 996 trips that covered 1,474 days of fishing with an average of about four hours of fishing per day. The Thunder Bay area diary respondents provided information on 2,262 trips that covered 4,625 days of fishing with an average fishing day being about 3.6 hours of fishing. Anglers who provided partial compared to full trip information in the diaries reported many fewer trips and days of fishing. This difference simply reflects the very different sample sizes for these groups.

The first two rows from Table 5.4.1 contain information on trips that I used to estimate the fishing site choice models in Chapter 7. Both of these contexts focused on trips that were not to private cottages or tourist camps and that were not part of a longer trip away from home. Besides the above criteria, multiple day trips were only used to estimate the site choice models if the angler stated that the trip was for the primary purpose of fishing and the trips was less than one-

[52] While the problem is well known, it seems that many studies often avoid discussing this issue.

week long. These additional criteria for the multiple day trips ensured that the attributes important for day trips should be similar for multiple day trips. These two fishing contexts accounted for over 75% of trips by Wawa area diary respondents. However, the two contexts only accounted for about one-half of the fishing trips reported by Thunder Bay area diary respondents.

Thunder Bay area diary respondents were much more likely to take trips to private cottages or tourist lodges than were Wawa area diary respondents (about 30% compared to 15%). Thunder Bay area diary respondents were also much more likely to take a fishing trip as part of a longer trip from home than were Wawa area diary respondents. Finally, the respondents took a very small percentage of trips to tourist sites that were accessible by plane.

Table 5.4.1: Fishing trip types (%) and fishing effort by Wawa and Thunder Bay diary respondents for 2004 open water season (separated by anglers providing complete or partial information about their fishing trips)

	Wawa Full Sample (n=151)	Partial Sample (n=36)	Thunder Bay Full Sample (n=347)	Partial Sample (n=53)
Day trip, not to private accommodation, and not part of longer trip from home (%)	66.6	64.1	40.0	47.9
Two to six day trip, not to private accommodation, not part of longer trip from home, and for primary purpose of fishing (%)	11.0	10.6	11.0	8.6
Seven or more day trip, not to private accommodation, not part of longer trip from home, and for primary purpose of fishing (%)	0.3	0.0	0.4	1.2
Day trip to private accommodation (%)	6.1	9.4	8.3	7.0
Multi-day trip to private accommodation (%)	9.7	8.8	21.9	29.2
Day trip, not to private accommodation, but part of longer trip from home (%)	4.0	5.9	8.4	2.3
Multi-day trip, not to private accommodation, but part of longer trip from home (%)	1.5	0.00	2.4	1.6
Multi-day, not to private accommodation, not part of longer trip from home, but for some other purpose than fishing (%)	2.8	1.8	5.9	0.8
Air accessible fishing trip (%)	0.80	0.6	1.4	1.6
Unknown length of trip (%)	0.0	0.0	0.3	0.0
Total trips	*996*	*170*	*2,262*	*257*
Total days of fishing	*1,474*	*262*	*4,625*	*489*
Average hours fished per day	*3.98*	*4.73*	*3.56*	*3.68*

The diary responses also provide some data on the importance of time on angling behaviours. Figures 5.4.1 and 5.4.2 display the percentage of Wawa and Thunder Bay area diary respondents, respectively that reported fishing on a given day. While the figures summarize trips from April 1 to September 30, the site choice models only operate on the data from May 1 to September 30.

Figure 5.4.1 Percentage daily fishing effort from April 1, 2004 to September 30, 2004 by Wawa area diary respondents (n=151)

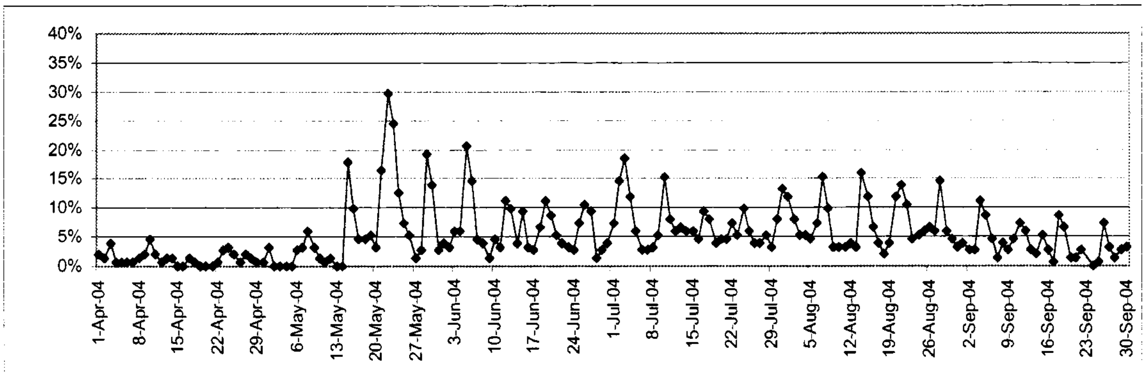
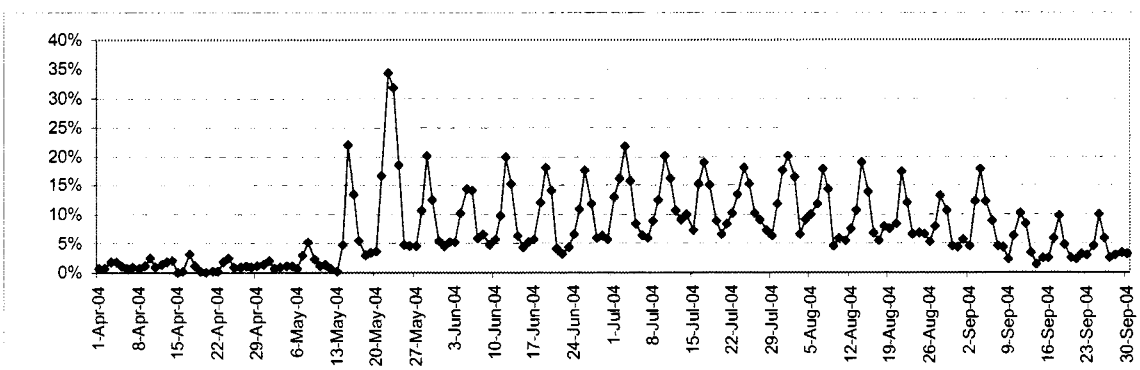


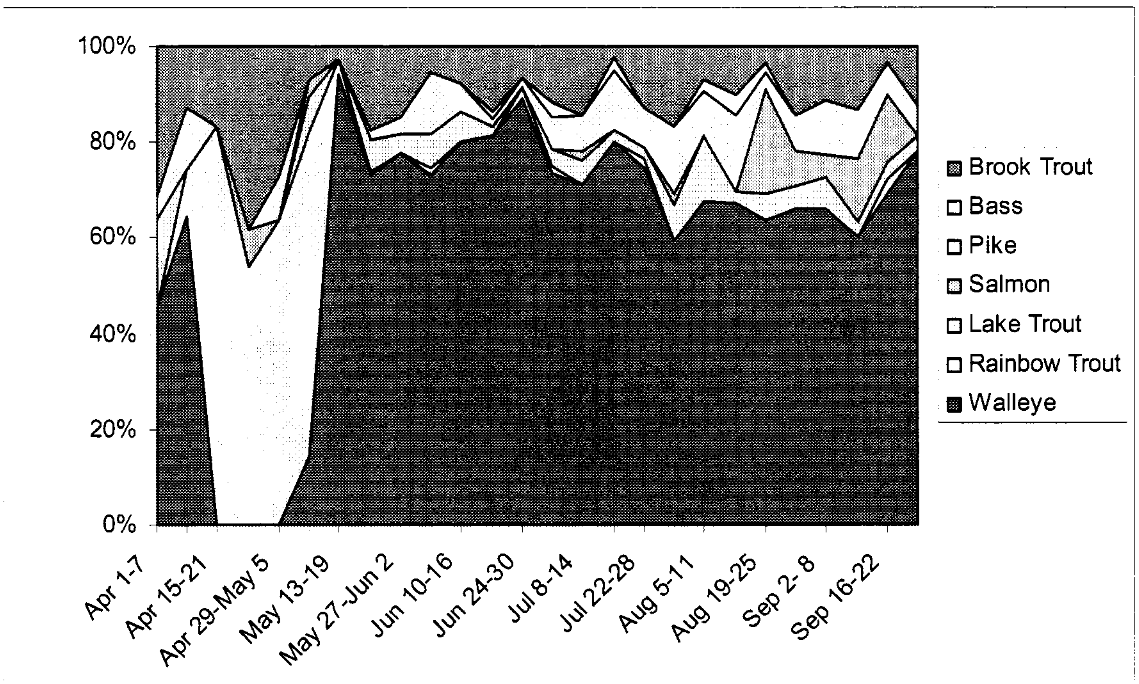
Figure 5.4.2 Percentage daily fishing effort from April 1, 2004 to September 30, 2004 by Thunder Bay area diary respondents (n=347)



The figures clearly show that fishing participation rates were very low until May 15, which was the start of the open water season for walleye in 2004. After May 15, the participation rates peaked on every weekend with the highest peak on the Victoria Day holiday weekend (May 22-24, 2004). After the Labour Day holiday weekend (September 4-6, 2004), the fishing participation rate took a noticeable decline. Fishing participation rates are clearly dependent on the day of the week and the availability of walleye.

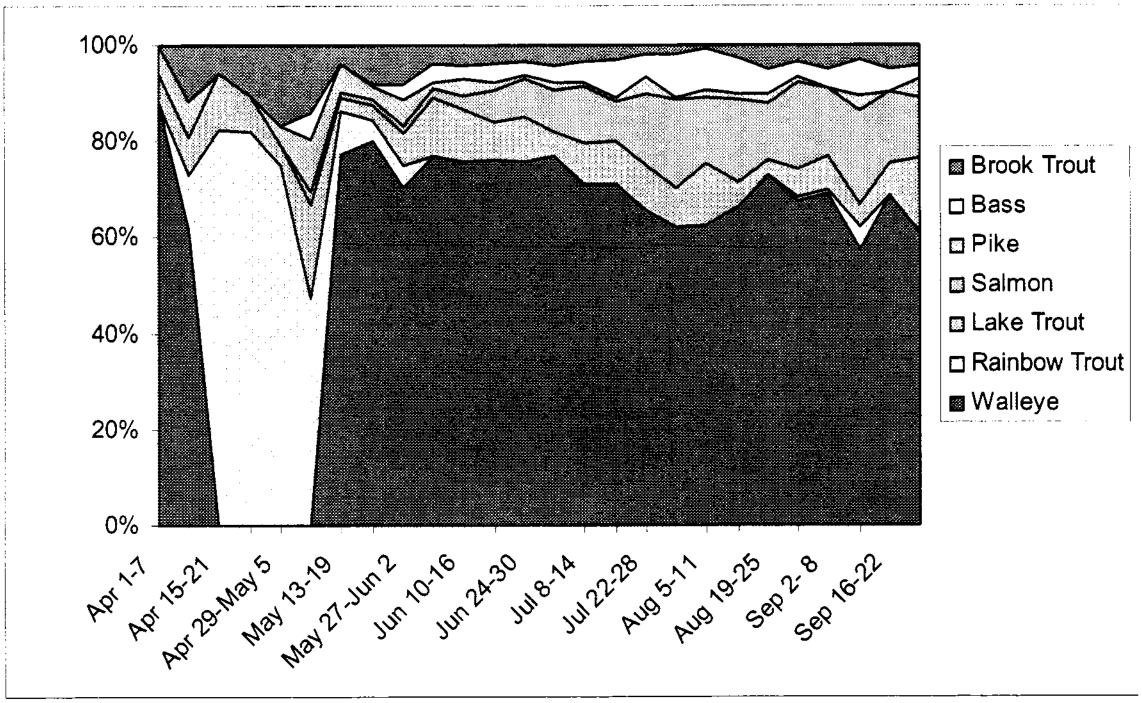
Another possible temporal trend in the data relates to targeted fish species. It is expected that the targeting of fish species will change over time as the catch vulnerability and availability (e.g., regulations) of different fish species change over time. Figures 5.4.3 and 5.4.4 show the percentage of fishing trips that Wawa and Thunder Bay area diary respondents targeted each week from April 1 to September 30, 2004.

Figure 5.4.3: Percentage of trips by week from Wawa area diary respondents that target various fish species



Both figures show that when it was legal to catch and keep walleye, most fishing trips targeted walleye. During the period that the walleye season was closed (i.e., April 16 until May 15, 2004), rainbow trout fishing trips dominated the sample. This fact reflects the increased vulnerability that rainbow trout have during the spring when they leave Lake Superior for tributaries that they use to spawn. Additionally, the conditions on many frozen lakes and roads change rapidly in April leaving many individuals to pursue rainbow trout fishing trips for safety concerns and convenience (i.e., important rainbow trout tributaries flow through the City of Thunder Bay and outlining areas).

Figure 5.4.4: Percentage of trips by week from Thunder Bay area diary respondents that target various fish species



Another major trend for the Thunder Bay anglers was the increasing attention that salmon species received in the late summer and early fall. This attention likely related to increased abilities to catch salmon at these times and to greater difficulties to catch walleye when temperatures peak (i.e., walleye are less active).

The trends in the Wawa data were similar to those from the Thunder Bay data with the following exceptions. First, brook trout received much more attention by Wawa area anglers early in the spring than it did from Thunder Bay anglers. As well, northern pike (*Esox lucius*) received more and salmon received less attention from Wawa area anglers than these species received from Thunder Bay area anglers.

The final summary of the diary responses focused on the use of different road types by anglers to access fishing waters. By matching the diary information with the road inventories, it was possible to investigate the use of different quality of roads by anglers when choosing a fishing site. Sites were assigned to access types if they met the criteria below and that the site did not meet the criteria for more remote access types (e.g., if a site met the paved road and poor quality gravel road criteria, the site was classified as a poor gravel road site).

Walking trail sites required a walk of more than 500m on a trail. If ATV and walking trails exceeded 500m, the site was considered an ATV site. Poor tertiary gravel road sites required a total of one km of trails and/or poor quality tertiary roads. Over one km of trails, tertiary roads and poor quality secondary roads led to a site being classified as an okay gravel road site. Good gravel road sites required trails and non-paved roads to exceed one km. Sites were defined as paved roads if all gravel roads and trails did not exceed one km. Finally, any site that required a portage was separated from the above classification system.

Table 5.4.2 shows that respondents took few fishing trips to sites accessible via portage or by walking or ATV trails when compared to the availability of these opportunities. The relative use of these trails and portage routes was less for Wawa area than Thunder Bay area diary respondents. Thunder Bay area diary respondents most often used paved roads sites followed by okay gravel roads, good gravel roads and poor gravel roads. Wawa area diary respondents most often used paved road sites followed by good gravel roads, poor gravel roads, and okay gravel roads.

Without accounting for other factors that influence site choice, the conclusions from Table 5.4.2 may be misleading. This again provides support for the use of a choice model instead of these more descriptive statistical analyses.

Table 5.4.2: Percentage of Wawa and Thunder Bay area diary fishing trips and fishing sites by road access

	Diary fishing trips		Fishing sites	
	Wawa (%)	Thunder Bay (%)	Wawa (%)	Thunder Bay (%)
Paved road site	31.6	41.9	22.1	12.8
Good gravel road site	28.1	18.6	27.3	32.2
Okay gravel road site	15.2	25.6	20.9	13.3
Poor gravel road site	20.6	12.1	13.5	24.0
ATV trail site	4.1	1.3	12.9	9.1
Walking trail site	2.3	0.3	1.8	2.6
Portage site	2.3	0.4	1.2	6.1

5.5: Summary

This chapter summarized basic information collected from the angling diary program. These summaries afforded opportunities to assess: non-response biases present in the data; differences between Wawa and Thunder Bay area anglers; issues important to site choice; and trip information. The chapter also served to explain many aspects of the data that are included in the next chapter on site choice models.

The qualitative interviews with the anglers provided support for the choice modelling approach. As well, it is anticipated that while road access is extremely important to some anglers, a smaller segment of anglers actually prefer poor access as it is often associated with low congestion and good quality fishing. The results from the qualitative interviews did not provide much support that anglers use a spatial hierarchical decision-making process when selecting a fishing site. Instead, it appears that anglers who used a hierarchical decision-making strategy focus on fish species rather than space. Mixed support was found for the notion that anglers may choose fishing sites in close proximity to other sites as part of a spatial insurance strategy. Responses to diary questions, however, do provide some support for the importance of space in the contexts of limited awareness of fishing opportunities and some attachment by anglers to fishing areas. Therefore, space should have some influence on site choice beyond a nuisance effect that would arise from model misspecification (e.g., omitting an important attribute that has a non-random spatial distribution of values).

The findings in Section 5.2 suggest that non-response bias is an issue with the sample of Thunder Bay area anglers. Thunder Bay anglers who completed the diary were more avid participants, more likely to own boat and outboard motor equipment, more often licenced anglers, and older more experienced anglers than were those anglers that did not complete the diary. For fish species preference and vehicle ownership or availability, no biases in responses were detected.

While non-response bias is an issue with the Thunder Bay diary respondents, it is not an issue with the Wawa area diary respondents. With the exception that Wawa area diary respondents were older than non-respondents, no other response biases were present. Therefore, the sample based on the Wawa diary respondents seems reflective of the population of Wawa area anglers.

Section 5.3 provided much important information for understanding site choice. The diary respondents were not aware of all available fishing opportunities and the respondents thought that word of mouth and exploration were the most important sources for learning about new fishing opportunities. The respondents also identified with sub regions that will likely make it difficult to move anglers from their current fishing areas. While anglers stated they were motivated to fish for many non-consumptive reasons, they did state that the presence of desirable fish species and an abundance of fish were very important reasons when choosing a fishing site. As well, anglers stated they preferred fishing waters that would have fewer encounters with other anglers.

The fourth section demonstrated the contextual nature of fishing trips taken by northern Ontario anglers. In particular, many Thunder Bay anglers fish while being accommodated at cottages or tourist camps. This heterogeneity in trip contexts makes it especially important to select a relatively homogeneous group of fishing trips when attempting to estimate a fishing site choice model.

Temporal examinations of fishing participation rates and targeting of different species provided some additional clues about angler behaviours. These results suggest that temporal considerations are important when modelling fishing trip site choice.

Chapter 6: Methods and assumptions employed to estimate the fishing site choice models

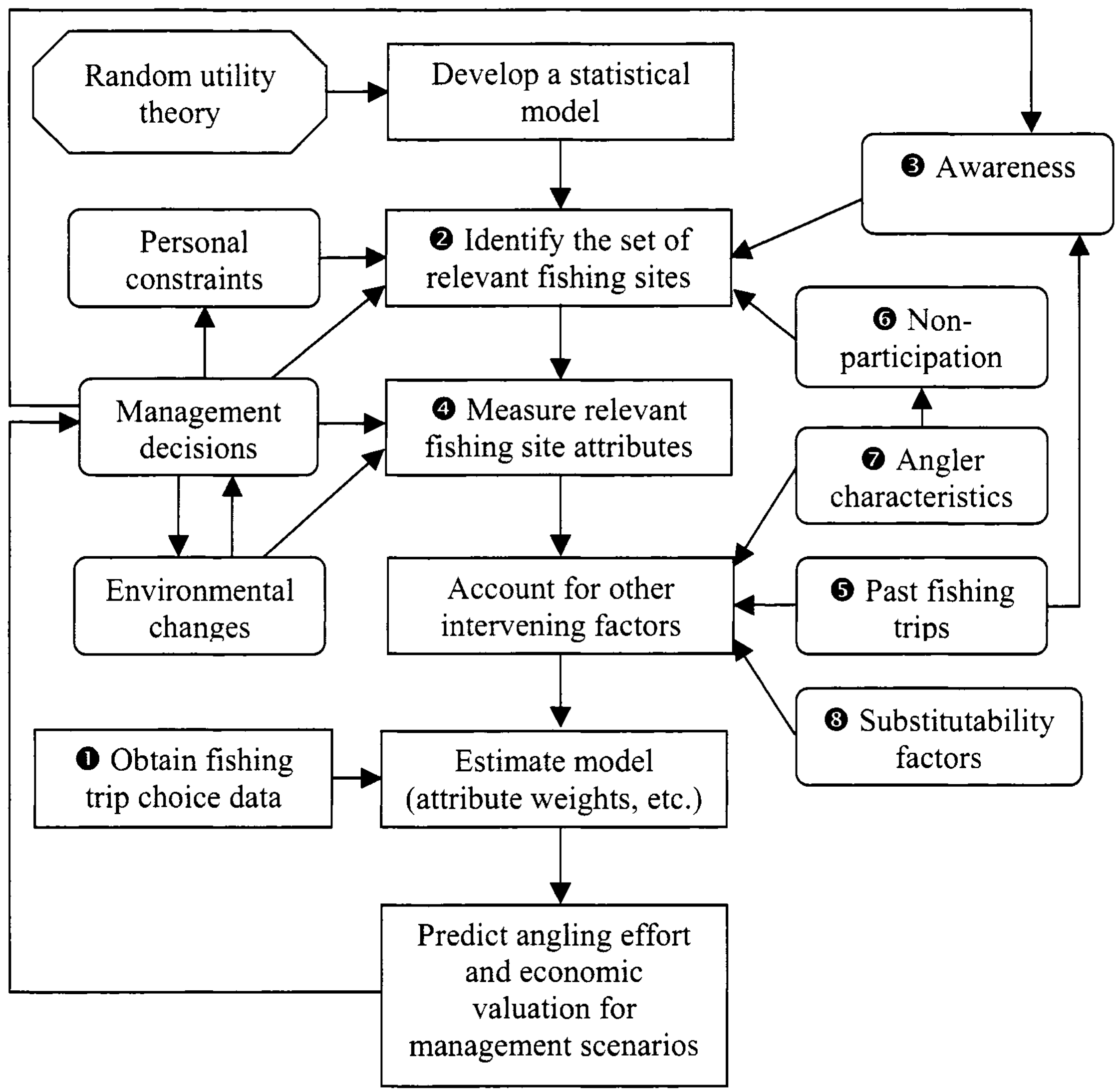
The literature reviews and analyses of qualitative interview and basic fishing trip diary information helped to shape the methods employed to estimate the site choice models. The conceptual models presented in Chapter 3 for predicting fishing site choice were particularly important for identifying suitable attributes and strategies to account for issues that complicate fishing site choice. The choice of a statistical model resulted from the strategies that were adopted to account for the site choice issues.

The next section discusses the fishing trip data, available fishing sites, and relevant attributes. This discussion also highlights the strategies that were employed to identify the choice sets of the anglers. The second section examines issues related to preference heterogeneity, dynamic-like effects and spatial substitution. The third section describes the statistical modelling approach and issues related to model estimation. The ways that this dissertation accounts for spatial complexities in fishing site choice models are summarized in the fourth section. The final section highlights some basic information about the attributes and other measures selected for estimating the fishing site choice models.

6.1: Basic information needs for estimating the fishing site choice models

The more general conceptual model from Chapter 3 is reproduced here to guide the discussion in the next three sections. Although Chapters 4 and 5 provided overviews of the fishing trip data, available fishing sites and site attributes, the discussion below describes the context of modelling fishing site choices of resident northern Ontario anglers in greater detail.

Figure 6.1.1: Predicting recreational fishing site choices



The fishing trip information (❶) was obtained from the angling diaries. While the diary collected information from April 1 to September 30, 2004, the trips used to estimate the site choice models only employed data from May 1 to September 30. The elimination of the April trips helped to avoid the problems of modelling ice fishing along with open water season fishing trips. Two trip contexts were used to reduce the heterogeneity in fishing trip types. First, the sample included all day trips that were not part of a longer trip from home and not taken to a private cottage or tourist camp or lodge. Multiple day trips of less than seven days and for the expressed primary purpose of fishing that met the criteria above were also included in the sample. As described in Chapter 5, the effective samples for model estimation were 1,152 and 749 trips for the Thunder Bay and Wawa area models, respectively.

The large areas and the thousands of potential fishing sites required the use of five criteria to reduce the burden of the universal choice set (❷). First, the waterbody had to be directly or indirectly (e.g., boat navigability or popular portage route) accessible from a road or trail. This criterion helped to reduce thousands of alternatives that were inaccessible from roads or trails. Second, the water body needed a desirable fish species available for anglers. These desirable fish species included walleye, smallmouth bass (*Micropterus dolomieu*), lake trout, brook trout, rainbow trout, splake (*Salvelinus fontinalis x Salvelinus namaycush*), northern pike, yellow perch (*Perca flavescens*), muskellunge (*Esox masquinongy*), and salmon species. Third, with a few exceptions, the choice alternative was based on a water body and not the access point or points to that water body. In cases where multiple access points existed on a water body, I selected the one access point that was easiest to reach (i.e., travel distance and road types) and had the best features for the site. This third criterion helped to reduce problems with the duplication of many alternatives (e.g., a lake with three access points would be considered as only one alternative). The few exceptions to this procedure (e.g., Lake Superior, Lake Nipigon and on large rivers) were made because of the large geography covered by these waters. Even in these exceptional cases, several access points that were in close proximity to one another were not considered as separate choice alternatives. The fourth criterion required the merger of water bodies that were connected via navigable waters to produce fewer but larger fishing alternatives. Finally, for the Thunder Bay fishing model, any alternative that exceeded 250km in road distance from Thunder Bay was removed to speed model estimation time. This removal resulted in a reduction in fishing alternatives from 500 to 431 sites. Given the number of unique starting points (i.e., five different communities) in the Wawa area, this narrowing of alternatives based on distance was not implemented. The number of alternatives for the Wawa area equalled 328.

The model only accounted for individual specific choice sets in a simplistic fashion that related to site awareness (❸). Measures related to site accessibility and the number of unique access points were included in the models. The number of unique access points equalled the frequency of access points that were a minimum of 250m apart on the same fishing alternative. This calculation was completed for the entire set of access points rather than those access points that survived the criteria that were used to reduce the number of alternatives. The minimum distance of 250m was chosen since the attribute was attempting to measure the importance that distinct access points had on site awareness. The choice models employed the log transformed value of this measure since past researchers have frequently used logarithmic transformations on attributes that relate to the size of the alternative (e.g., Jakus *et al.*, 1998).

An accessibility measure was included to measure the importance of anglers' spatial cognition on site choice. The composite measure shown in equation 45 sums the ratio of the size of a fishing alternative (i.e., water body in ha (WA_j)) to the Euclidean distance in meters (d_{ij}) separating fishing alternatives (i and j). The denominator $NN\text{-}1$ refers to the number of road, trail, or portage accessible fishing alternatives including lakes with unknown fish species less the alternative (i) in question. For the Thunder Bay data, the denominator also included those lakes that were beyond 250km in road distance, but were inventoried as part of the field data collection. The use of some sites outside of the modelled area to calculate equation 45 should help to reduce boundary effects. A natural logarithm transformed both attributes of accessibility and number of access points before including them into the site choice model.

$$a_i = \frac{\sum_{j=1}^{N} \frac{WA_j}{d_{ij}}}{NN-1}, \forall j \neq i \tag{45}$$

Chapter 3 described six general attributes (i.e., cost/distance, fishing quality, environmental quality, facility development, encounters, and regulations) that are likely important to anglers when choosing a fishing site (❹). The fishing site choice models attempted to account for most of these general attributes[53].

Cost was included in the fishing site choice models as the distance by road or trail that separates an angler's home from the destination lake. To simplify the number of unique starting points, all anglers from the same community were assumed to start from the same origin.

Other attributes under the general theme cost included the travel distances by different road and trail types and whether the fishing site was or was not accessible by a portage route. To reduce the number of categories, the roads and trails were aggregated into paved roads, good quality gravel roads, okay quality gravel roads, poor quality gravel roads, and general trails. Good quality gravel roads included all primary gravel roads and all maintained secondary roads. Okay gravel roads included all remaining secondary roads and all tertiary roads that were in good shape. A tertiary road was considered in good shape if it was not grown in, did not have severe potholes or washouts or did not require travel over large rocks as evaluated by field staff when they travelled the road. All remaining tertiary roads were classified as poor quality gravel roads. General trails included snowmobile, all terrain vehicle and walking trails.

Several different ways measured fishing quality. First, the availability of various fish species was used to capture anglers' preferences for different species of fish. The information for the presence of fish species for various water bodies was found from various databases, local fishing maps, angler diary responses, and local knowledge. Availability differed from presence of fish species by the inclusion of regulations. When it was illegal to catch and keep certain fish species, the species was considered unavailable regardless of whether the species was present in the fishing waters. The regulation information was obtained from a summary of fishing regulations published by the Ontario Ministry of Natural Resources. As such, the availability of fish species attribute captured both elements of fishing quality and regulations.

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[53] Limited availability of some data made it impossible to include all potentially relevant attributes into the choice models.

The variability estimates for the fish species were estimated from diary responses. Given the limited information on catch for most species, only the expected catch rate for walleye was estimated for all anglers and all fishing sites. For rainbow trout fishing in the Thunder Bay area, the reported average catch rates for three time periods and three geographies were used to capture the movement of these fish species into Lake Superior tributaries during the springtime. For the Wawa area, a rainbow trout availability attribute was included to capture the availability of this fish species in Lake Superior tributaries before June 1[54].

Finally, one may view water area as a measure of fishing quality (see Chapter 3). To account for this tenet, the natural logarithm of the water area in hectares of the fishing site was included as a separate attribute.

While information on the forested environment around access points was collected, this attribute was not allied with the site choices of anglers. Since information on water quality (e.g., secchi depth, lake depth, and total suspended solids) was only available for a very small subset of waters, no water quality attributes were included in the choice model.

Facility development was measured by the type of boat launch that existed at the access point. The boat launches were summarized into three groups that included concrete, gravel or sand boat launches, no boat launches, and all other remaining boat launch types. These attributes were interacted with whether an angler took the trip from a boat (+1) or not from a boat (-1). To identify these parameter estimates, the attribute for all other remaining boat launch types was fixed to zero.

For the Thunder Bay area, encounters were measured with a simple qualitative indicator of whether or not the water body had extensive cottage development. This indicator was based from my local knowledge of the study area. No similar measure for encounters was employed for the Wawa area model.

[54] Almost no fishing trips for rainbow trout in the Lake Superior tributaries in the Wawa area occurred after June 1. This fact leads me to believe that the rainbow trout were not available in these tributaries after June 1.

6.2: Enhancement to the fishing site choice models

While information on fishing site choices, available fishing sites and relevant site attributes are paramount for model estimation, other issues are important when estimating a fishing site choice model. As is described in Figure 6.1.1, these other issues include dynamic-like effects (❺), participation (❻), preference heterogeneity (❼), and spatial substitution (❽). I describe my course of action for addressing each of these issues that involved a careful trade off between model complexity and generality of the approach to address the issue.

Two approaches were used to incorporate dynamic-like effects (❺) into the choice models. First, a temporal attribute was included that represented whether or not the current fishing trip was taken to the same site as the previous fishing trip[55]. Second, a spatio-temporal attribute was included that approximated the propensity of anglers to take trips in close proximity to sites of previous trips. While this aspect is probably best captured through a measure of the road or trail distance from the site of the previous trip to the current site, such a measure would be highly collinear with the travel distance from an angler's home to the fishing site. To reduce this collinearity, the spatio-temporal attribute (*S_STATE*) was calculated as shown in equation 46.

$$S\_STATE_{in} = \frac{(d_{i,t-1})}{\min(d_{j,t-1})} \forall j \in C_n, j \neq t-1 \tag{46}$$

The *S_STATE* attribute equalled, for each angling site (i) in the choice set (C_n), the road distance (d) between the angling site (i) and the angling site chosen by angler n for the previous fishing trip (t-1) divided by the minimum distance between site t-1 and all other fishing sites. The *S_STATE* attribute equalled zero for the site that was the same as the site chosen on the previous trip. For all other sites, the *S_STATE* measure could range from one to infinity, where one equals the choice of a fishing site that is closest in road distance to the site previously chosen. While this spatio-temporal attribute does not directly appeal to angler behaviour (i.e., anglers are unlikely to

[55] To simplify model estimation, we only focused on the last and not other previous trips.

consider this measure when choosing a fishing site), it acts as a good proxy for measuring the propensity of anglers to fish in a constrained geographical space.

Non-participation (❻) was not included in the model for primarily pragmatic reasons. For example, an assessment of non-participation for each of the 347 anglers, 432[56] sites and 153 days would have created a data file of almost 23 million data records. A full information maximum likelihood estimation of this model would have exhausted all available computer memory and resulted in a very long time for estimation. While a sequentially estimated nested logit model could address this problem, I did not pursue this model.

Heterogeneity in preferences (❼) was estimated using interactions between the attributes and angler and trip characteristics. The market segmentation of anglers based on whether or not they fished during the winter fishing season was found to be important. This segment seems to measure two different aspects about anglers. First, anglers who fished year round likely view angling as a more central activity to their lifestyles than do anglers who fish only during the open water season. Second, anglers who fish during winter have the ability to travel by snowmobile to fishing sites that are difficult to reach during the open water season. This ability to travel easily in the winter may increase the awareness of available fishing sites for these anglers.

The trip duration had the potential to alter the context of the fishing trip. Multiple day trips are less constrained by time and thus, travel distance is likely less important for multiple day than day trips. During multiple day trips, some other aspects of recreation (e.g., camping or swimming) are likely more important than they are during day fishing trips. For this reason, interactions were calculated for the attributes and trip duration (i.e., whether the trip was for one or more days).

Substitution among fishing sites (❽) was expected to be partially dependent upon spatial considerations. To account for the potential complexity of space, nests that represented spatially

[56] The number of modelled alternatives in Thunder Bay is 431 plus one additional alternative for a no participation alternative.

close alternatives were constructed. These nests were based on spatial support points that were selected based on knowledge of different fishing areas (see Figures 6.2.1 and 6.2.2). Two different nesting approaches were employed. First, alternatives were assigned (i.e., $\alpha_{im} = 1$) to the nest having the closest spatial support point as measured by road distance. Otherwise, the allocation of an alternative to a nest equalled zero (i.e., $\alpha_{im} = 0$). Second, alternatives were partially allocated to nests by equation 47.

$$\alpha_{im} = \frac{\frac{1}{d_{im}}}{\sum_{l=1}^{M} \frac{1}{d_{il}}} \tag{47}$$

The allocation (α) of alternative i to nest m equals the inverse road distance from alternative i and spatial support point m divided by the sum of inverse road distances from alternative i and all M spatial support points. This equation ensured that the allocation of one alternative among the M nests equalled one (i.e., $\sum_{m=1}^{M} \alpha_{im} = 1$). The equation also represented a much different connectivity structure among the sites than would the use of discretely allocating an alternative to a nest.

6.3: Statistical model and estimation considerations

A hybrid generalized nested logit model (see equation 48) was chosen as the statistical model that could deliver on the complexities described above. Following the lead of Bhat and Guo (2004), the allocation parameters (α_{im}) for each alternative and each nest were specified by the researcher (i.e., equation 47) rather than estimated by the statistical model.

$$P_{in} = \sum_{m=1}^{M} \left[\frac{\left(\alpha_{im} e^{\boldsymbol{\beta}_i' \mathbf{X}_{in}}\right)^{\frac{1}{\mu_m}} \left(\sum_{j=1}^{J_m} \left(\alpha_{jm} e^{\boldsymbol{\beta}_j' \mathbf{X}_{jn}}\right)^{\frac{1}{\mu_m}} \right)^{\mu_m - 1}}{\sum_{l=1}^{M} \left(\sum_{j=1}^{J_l} \left(\alpha_{jl} e^{\boldsymbol{\beta}_j' \mathbf{X}_{jn}}\right)^{\frac{1}{\mu_l}} \right)^{\mu_l}} \right] \tag{48}$$

This generalized nested logit captures all models that are to be estimated. For example, when all dissimilarity parameters (μ_m) equal one, the model reverts to a multinomial logit model. The flexibility of this generalized nested logit allows one to test formally the different model forms that account for various model complexities.

Figure 6.2.1: Spatial support points for the Thunder Bay study area

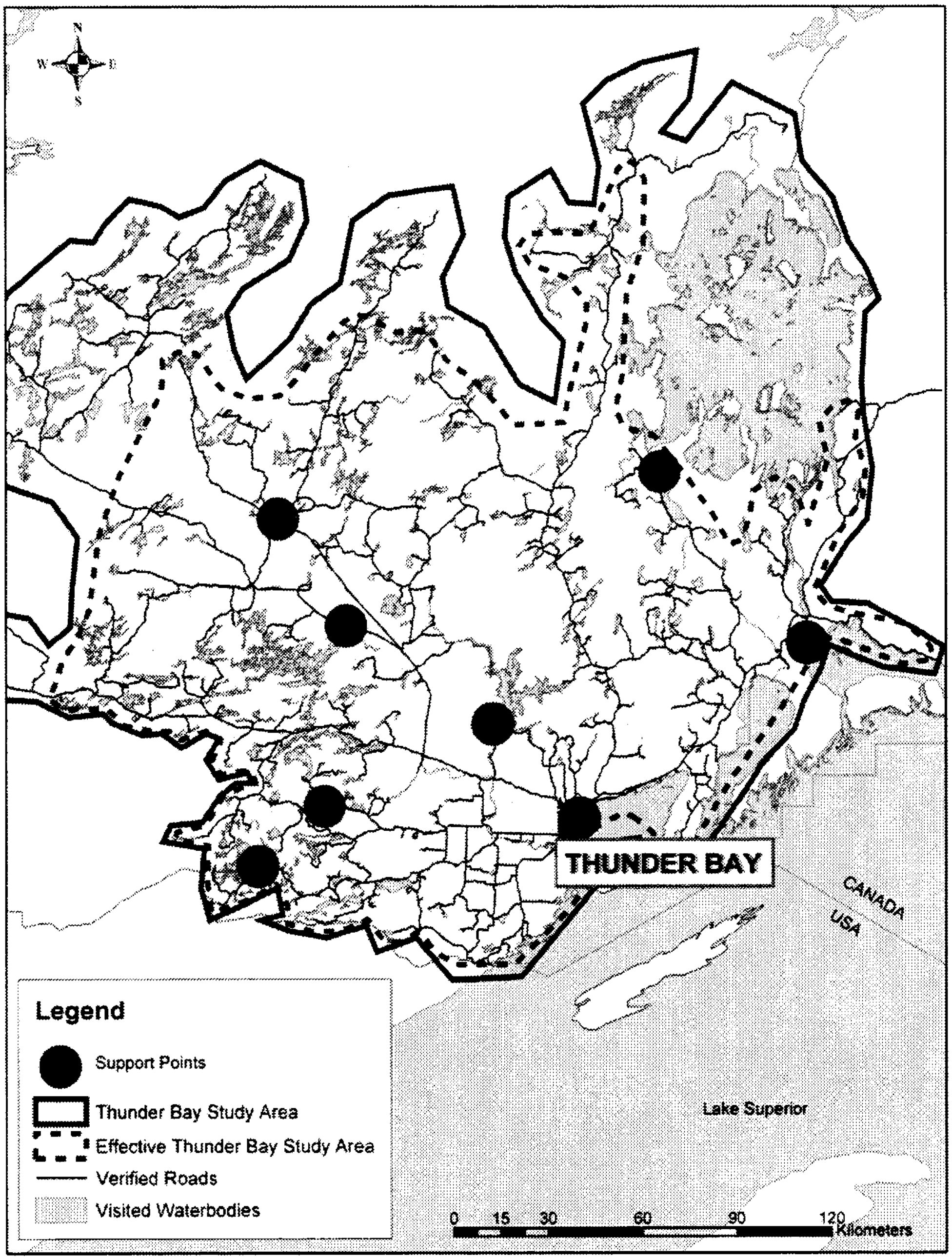
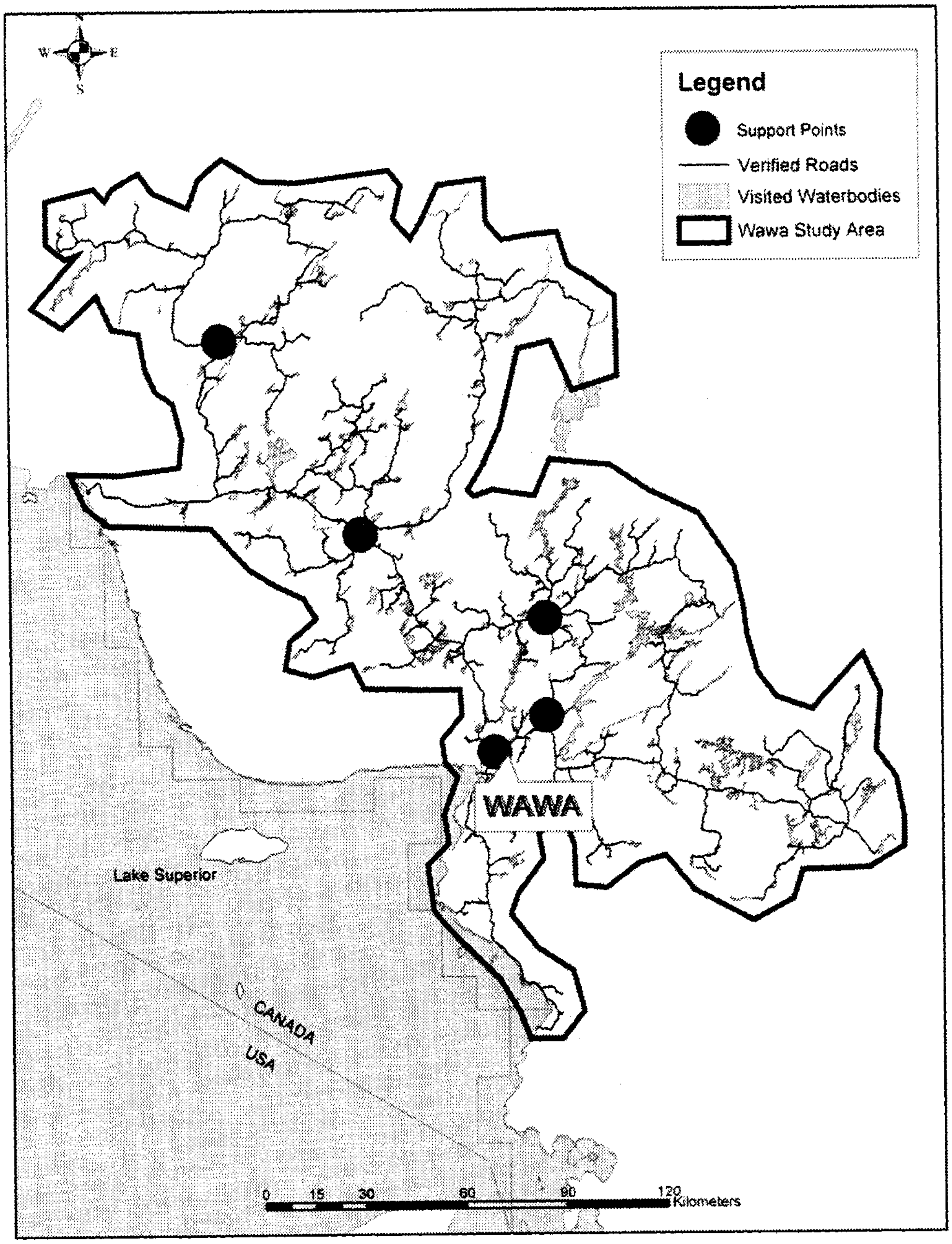


Figure 6.2.2: Spatial support points for the Wawa study area



Two different sets of dissimilarity parameters were estimated for the models with cross-nests. First, a single spatial dissimilarity parameter was estimated (i.e., $\mu_m = \mu$) for all nests. While this estimate is global, the specific pattern of substitution introduced in the model is dependent on the exact configuration of an alternative and the spatial support points. In another instance, nest specific dissimilarity parameters (μ_m) were estimated. These nest specific parameter estimates provided an opportunity to test whether the assumption of one global dissimilarity parameter was sufficient for the data. A rejection of the assumption of a global dissimilarity parameter implies that the spatial substitution process varies over space.

The models were all estimated with customized programs created for GAUSS 5.0 with the MAXLIK routine (see Appendix D). For the MNL models, the log likelihood function, gradient and Hessian matrix were all programmed. For the more sophisticated GEV models, only the log likelihood function was programmed and the MAXLIK routine was used to solve numerically the gradient vector and Hessian matrix. Model estimation used the BFGS secant method. Different sets of starting parameter values were used to estimate the GEV models to limit the possibility of finding a local rather than global maximum of the likelihood function.

6.4: Modelling the complexity of space

Three different approaches to account for the complexity of space are included in equation 48. First, the inclusion of an accessibility term (see equation 45) is consistent with the competing destinations model (Fotheringham, 1983). Following the results of other spatial choice model applications, the accessibility term should be significantly different from zero and negative in sign. This negative value would indicate that anglers fish more often at sites that are located far from other large sized fishing alternatives than would be predicted by an aspatial MNL model.

The spatial state dependence attribute (see equation 46) is included to determine whether anglers take trips in a small range of the possible available fishing area. This reduced range is likely to arise from both the limited awareness that anglers have for fishing sites and the place identity that anglers have for fishing areas. As such, the spatial state dependence measure should be significantly different from zero and negative in sign.

Finally, the use of discrete and cross-nests (i.e., equations 47 and 48) permits me to test for the existence of common elements of unobserved utilities among sites that are spatially close. If shared unobserved utility exists among spatially close sites, these sites will act as better substitutes than will other sites. It is expected that the use of cross-nests instead of discrete nests should better capture shared unobserved utility among the sites. Furthermore, it is expected that the degree of shared unobserved utility will vary over space and thus, there will be a rejection of a single parameter estimate to capture this sharing effect.

Chapter 2 discussed three issues arising from the spatial data properties that may affect any analyses of spatial data. The modifiable areal unit problem is thought to have little consequence on this research. While some aggregation of fishing alternatives was conducted, anecdotal discussions with anglers suggest that most anglers consider these aggregated alternatives as one fishing site. The boundary issue problem is also thought to be of minor importance as the spatial scale of the study was defined primarily by the observed choices made by anglers. Therefore, it is unlikely that the boundaries will truncate any spatial processes operating on the data. Finally, the spatial connectivity issue is relevant to the study. The results from all three approaches to account for space are likely contingent upon the chosen connectivity structure.

In all three instances, I chose connectivity structures that were very general. For the accessibility term in equation 45, a Euclidean distance was used since road distance should not affect anglers' spatial cognitions of mapped alternatives. The spatial state dependence connectivity structure in equation 46 was chosen to approximate the role of spatial state dependence while limiting the collinearity between the accessibility and the travel distance attributes. The connectivity structure used to allocate parts of alternatives into nests (equation 47) was chosen to provide a case that would drastically differ from the use of discrete nests. For this reason, all alternatives belonged to all nests with the exception of the alternatives located in unknown or outside of study area locales.

6.5: Summary of attribute information

This final section summarizes the various attribute measures for the Thunder Bay and Wawa area samples. Table 6.5.1 recaps the attributes that were employed in the site choice models and provides labels that are used for all subsequent analyses. To lessen the length of the table, I use XXX, YYY, and ZZZ as generic terms for attributes, alternatives and nests. The DS terms represent dissimilarity parameters, which negatively relate to the degree of correlation between the unobserved utilities among alternatives in the same nest.

Table 6.5.1: Description of attributes included in the fishing site choice models

Label	Description
T_DIST	Travel distance from origin to destination waters (km)
R_PAVE	Travel distance along a paved road (fixed to zero for identification purposes (km))
R_GDGR	Travel distance along a good (primary or maintained secondary) gravel road (km)
R_OKGR	Travel distance along an okay (other secondary or good tertiary) gravel road (km)
R_PRGR	Travel distance along a poor (other tertiary) gravel road (km)
R_TRAIL	Travel distance along a trail (km)
PORTAGE	Whether or not fishing alternative is accessed by a popular portage (0,1)
A_WALL	Availability of walleye (0, 1)
A_PIKE	Availability of northern pike (0, 1)
A_BASS	Availability of smallmouth bass (0, 1)
A_LTROUT	Availability of lake trout (0, 1)
A_BTROUT	Availability of brook trout (0, 1)
A_BSTR	Availability of smallmouth bass and any type of trout species (0,1)
A_ERRT	Availability of spring rainbow trout in Lake Superior tributaries (Wawa only) (0,1)
E(W_CUE)	Estimated walleye catch rate per one hour of fishing
RT_CUE	Average reported rainbow trout catch rate per one hour of fishing (Thunder Bay only)
LN_WAREA	Natural logarithm of area of fishing waters (ha)
M_SAND	Presence of sand beach (multiple day trips only) (0,1)
BT*GDLN	Presence of a good boat launch (0,1) times whether trip was taken from boat (1, -1)
BT*NOLN	Presence of no boat launch (0,1) times whether trip was taken from boat (1, -1)
COTTAGE	Presence of significant cottage development in Thunder Bay area (0,1)
LN_UNAC	Natural logarithm of unique access points
LN_ACC	Natural logarithm of accessibility measure
W**XXX*	Interaction between attribute *XXX* and whether the angler fished during the winter (1, -1)
MD**XXX*	Interaction between attribute *XXX* and whether the trip was a multiple or day trip (1, -1)
T_STATE	Temporal state dependence measure (yes=1, no=-1, other=0)
S_STATE	Spatio-temporal state dependence measure
ASC_*YYY*	Alternative specific constant for fishing alternative *YYY*
OUTSIDE	Trips taken outside of study area (1, 0)
UNKOWN	Trips taken to unknown locations within the study area (1, 0)
DS_*ZZZ*	Dissimilarity parameter estimate for nest *ZZZ*

Table 6.5.2: Attribute summary measures based on fishing alternatives

Label	Thunder Bay Mean	Std. Dev.	Wawa Mean	Std. Dev.
TDIST	124.2	56.4	108.4	58.9
R_PAVE	99.1	47.2	87.3	54.3
R_GDGR	20.4	24.0	14.2	19.6
R_OKGR	2.9	6.6	2.0	4.6
R_PRGR	1.5	3.3	0.7	1.9
R_TRAIL	0.4	1.5	0.6	2.0
PORTAGE	6.1%	NA	0.7%	NA
A_WALL*	53.1%	NA	60.5%	NA
A_PIKE*	68.1%	NA	65.9%	NA
A_BASS*	17.0%	NA	3.0%	NA
A_LTROUT*	17.5%	NA	14.0%	NA
A_BTROUT*	21.9%	NA	28.0%	NA
A_BSTR*	6.1%	NA	1.2%	NA
LN_WAREA+	1270.2	15695.7	251.8	68.6
M_SAND	7.5%	NA	12.3%	NA
GDLN	42.2%	NA	46.0%	NA
NOLN	19.6%	NA	15.3%	NA
COTTAGE	3.5%	NA	NA	NA
LN_UNAC+	1.4	1.7	1.2	0.8
LN_ACC+	8.0	1.3	3.90	1.1

* based on the presence and not availability of the fish species
\+ measured before the natural logarithmic transformation

The average total and road type travel distances were very similar between the models. The average fishing alternative was over 100km away from an angler's origin with much of the road being paved. Poor quality gravel roads and trails made up a very small portion of an average distance. More alternatives in the Thunder Bay than Wawa areas were accessible via popular portages. This difference in portage availability may simply relate to my greater knowledge of fishing opportunities around Thunder Bay than Wawa. The fishing alternatives most often had northern pike followed by walleye and trout species. Smallmouth bass was almost entirely absent from the Wawa area fishing sites. Even after removing Lake Superior and Lake Nipigon from the estimation, Thunder Bay area fishing areas were on average much larger than those in the Wawa area. Most fishing sites had some type of boat launch that was most often a good quality boat launch. The average fishing site had only one unique access point and accessibility measures were higher in the Thunder Bay area owing to the larger sized fishing waters[57].

Table 6.5.3 summarizes additional attributes and measures based on the chosen fishing trip for each choice occasion. Winter anglers from the Wawa area took a higher percentage of total fishing trips than did the Thunder Bay area anglers. However, multiple-day trips were more prevalent among Thunder Bay than among Wawa area anglers. Over four-fifths of all fishing trips involved the use of a boat by the respondents from Thunder Bay and Wawa. Anglers took few trips to areas outside of the study area or to sites of unknown location within the study area.

Table 6.5.3: Attribute summary measures based on trips

	Thunder Bay		Wawa	
Label	Mean	Std. Dev.	Mean	Std. Dev.
Winter	51.3%	NA	75.7%	NA
Multi Day	21.6%	NA	14.1%	NA
BOAT TRIP	84.2%	NA	81.0%	NA
T_STATE	24.2%	NA	39.6%	NA
S_STATE	34.1	97.9	16.3	29.2
UNKNOWN	2.6%	NA	6.3%	NA
OUTSIDE	3.4%	NA	4.2%	NA

A large percentage of trips taken by both Thunder Bay and Wawa area anglers were to the same site as their previous trip (T_STATE). This temporal state dependence measure was higher for Wawa than for Thunder Bay area anglers suggesting that Wawa area anglers are more likely to select the same fishing sites repeatedly. Finally, the spatial state dependence measure was lower for Wawa area anglers than for Thunder Bay area anglers. Wawa area anglers, therefore, were more likely to take fishing trips in close proximity[58] to past fishing trips than were Thunder Bay area anglers.

[57] To limit the effect of Lake Superior and Lake Nipigon on the accessibility measures, the water area for these alternatives were constrained to equal the next largest sized water in the Thunder Bay area.
[58] As explained, the S_STATE attribute is not actually a distance measure but a ratio that compares the distance between the locations for the current and past trip divided by the minimum distance that any site was to the location of the previous trip.

Chapter 7: Results and management implications

This chapter presents and discusses the fishing site choice models for the two study areas. The next section presents the results from the Thunder Bay data. This presentation begins with the basic MNL model followed by various enhancements that are designed to account for preference heterogeneity, site awareness, dynamic like effects and finally complex spatial substitution patterns among the alternatives.

This same progression from a basic MNL to more complex generalized extreme values (GEV) models is completed for the Wawa area data in section 7.2. The third section investigates the validity of the models by assessing how well the various models predict the fishing site choices from anglers whose trips were withheld from model estimation. The fourth section demonstrates the potential benefits of increasing the complexity of the models with management scenarios. The choice models are used to forecast the choices to fishing sites that arise from scenarios that include changes to road access, to walleye fishing, to the number of alternatives, and to road networks. The final section discusses the significance of this chapter to the dissertation.

7.1: Thunder Bay recreational fishing site choice models

Before describing the results from the fishing site choice model, one final set of attributes requires discussion. This set of attributes relates to the variability of catch rates for different fish species. As explained earlier, limited data only made it possible to estimate the walleye catch rate for each angler and each fishing site. For the Thunder Bay area data, the average reported catch rate for rainbow trout during their spawning run through the tributaries of Lake Superior was also employed as an attribute in the model.

Conversations with anglers and resource management agency staff revealed that rainbow trout catch varies over time and space in the Thunder Bay area. This variability arises from the timing of the spawning run of rainbow trout, which depends primarily upon the water temperature of the Lake Superior tributaries. The Thunder Bay study area was divided into three geographies and two time periods. The reported average catch rates per one hour of fishing in Table 7.1.1 suggest that rainbow trout first move into tributaries around Thunder Bay followed by the area to the northeast of Thunder Bay (Dorion) and finally to the area even further northeast (Nipigon) as the spring season progresses. This fact leads some anglers to follow the abundance of rainbow trout by fishing near Thunder Bay in April, fishing near Dorion in early May and finally fishing near Nipigon in late May. To capture this spatial and temporal fish catch attribute, the average reported catch rates based on survey responses were included in the model (see Table 7.1.1).

Table 7.1.1: Reported rainbow trout catch rates from diary respondents

	May 1 – May 15	May 16 – May 31
Thunder Bay	0.694	0.000
Dorion	0.910	0.961
Nipigon	0.694	1.143

Since walleye is important to many anglers (see Table 5.2.1), efforts were made to model the walleye catch rate from the characteristics of the fishing sites, anglers and aspects related to the separation of anglers from fishing sites. To account for censoring at zero, a tobit model was used to estimate the average walleye catch rate per one hour of fishing effort (see Table 7.1.2). The inclusion of variables in the tobit model led to a significant improvement in the log likelihood function over a model with only a constant (LR=319.3, df=19, $p<0.0001$).

Table 7.1.2: Tobit model estimates of reported walleye catch rates (standard errors in parentheses)

Parameter	Estimate
Intercept	-3.730863 **
	(1.607130)
Travel Distance from community (km)	0.002814 ***
	(0.000775)
Accessible via 500m or more ATV or walking trail	1.294412 ***
	(0.229560)
Water area (ha)	0.000027 ***
	(0.000006)
Presence of Lake Trout	-0.205739 **
	(0.091566)
Presence of Smallmouth Bass	-0.329513***
	(0.100342)
Primary or secondary targeted species	0.645917 ***
	(0.187651)
Fished from boat	0.744988 ***
	(0.139471)
Motivated to test equipment	0.129644 ***
	(0.037653)
Motivated to relax	0.186659 ***
	(0.037627)
Age	-0.073361 ***
	(0.034784)
Age (square root)	0.925761 ***
	(0.471559)
Own a four wheel drive vehicle	0.483427 ***
	(0.086743)
Area (Thunder Bay +1, Wawa -1)	-0.254461 ***
	(0.058401)
Intercept for Garden Lake (Thunder Bay)	1.304053 ***
	(0.468963)
Intercept for Bedivere Lake (Thunder Bay)	0.797121 **
	(0.348616)
Intercept for Dog River (Thunder Bay)	0.600684 ***
	(0.231843)
Intercept for Poshkokagan and Cheeseman Lakes (Thunder Bay)	0.625901 **
	(0.256800)
Intercept for Nelson, Swallow, and Batwing Lakes (Thunder Bay)	0.711230 ***
	(0.204525)
Intercept for Kagiano Lake (Wawa)	1.167368 ***
	(0.428302)
Sigma	1.448673 ***
	(0.027416)

* probability (<0.10)
** probability (<0.05)
*** probability (<0.01)

The model in Table 7.1.2 was based on the reported walleye catch rates by both Thunder Bay and Wawa area anglers. This pooling of the Thunder Bay and Wawa walleye catch data was conducted for several reasons. First, the pooled data helped to supply a large number of observations (1,783) from which to estimate the importance of different attributes. Second, the pooled data permitted an assessment of whether the importance of attributes related to walleye catch rates differed between the two populations. Finally, the pooling helped to ensure that the estimates for walleye catch rates in the Thunder Bay and Wawa areas were based on a general model that only differed if statistically significant interactions between the residence and the various attributes were present.

Larger bodies of water were more likely to produce higher walleye catch rates while waters with lake trout or smallmouth bass were associated with lower walleye catch rates. Lake trout presence was negatively associated with walleye rates since lake trout are typically present in deep lakes that have clear waters. Therefore, the significant negative effect of lake trout presence on walleye catch rates acts as a proxy for attributes related to water clarity and water depth. Indeed, exploratory analyses of walleye catch rates on lakes where more detailed information was available indicated that walleye are more abundant in waters that are shallow and murky. These shallow and murky waters seldom have lake trout populations. Two reasons are hypothesized for the lower walleye catch rates associated with the presence of smallmouth bass. First, smallmouth bass may compete for the same baitfish as walleye. Second, anglers may introduce smallmouth bass into lakes where walleye fishing is poor.

The separation of an angler from the fishing site was also an important determinant of walleye catch rates. The further that a waterbody was located from the communities of interest (e.g., Thunder Bay), the higher was the predicted catch rate for walleye. As well, waters that were accessible with a 500m or longer trail had higher walleye catch rates than did other waters. All else considered equal, walleye catch rates were higher around Wawa when compared to Thunder Bay locations.

Many characteristics of anglers or their equipment also helped to explain the reported walleye catch rates. First, anglers who were motivated to fish for testing equipment or for relaxation reported higher walleye catch rates than did other anglers. Second, the age of the angler had a non-linear association with reported walleye catch rates. Finally, if an angler owned a four-wheel drive vehicle, the reported catch rates were higher.

Two attributes specific to the fishing trip were also important. First, anglers who fished from a boat were more likely to report higher walleye catch rates than were other anglers. Second, walleye catch rates were higher for anglers who stated walleye was the primary rather than secondary fish species that they targeted.

The expected walleye catch rates for each alternative and each trip ($E(W\_CUE_{in})$) were estimated from the parameter estimates (γ), attribute measures ($\mathbf{Z}$), and sigma value (σ). These estimates also required some transformations based on the normal cumulative (Φ) and probability (φ) density functions (see equation 49). This estimation will introduce some bias since walleye catch rate estimates contain error (Morey, & Waldman, 1998). However, the difficulty of estimating a site choice model with 431 alternatives while accounting for complex substitution patterns required some simplification of other aspects of the choice model.

$$E(W\_CUE_{in}) = \Phi\left(\frac{\mathbf{Z}_{\mathbf{in}}\gamma}{\sigma}\right)\left[\mathbf{Z}_{\mathbf{in}}\gamma + \sigma\left(\frac{\phi\left(\frac{\mathbf{Z}_{\mathbf{in}}\gamma}{\sigma}\right)}{\Phi\left(\frac{\mathbf{Z}_{\mathbf{in}}\gamma}{\sigma}\right)}\right)\right] \tag{49}$$

The most basic spatial choice model (BASE MNL) presented in Table 7.1.3 describes a simplistic fishing site choice process used by Thunder Bay area anglers. This model only included attributes related to availability and variability of fish, road accessibility of the fishing site, water body area, boat launch type and congestion. The log likelihood improvement in the model (LL(B)) from the null model (LL(0)-chance) was significant ($LR = 3345.4$, $df=24$, $p<0.0001$).

The availability of brook trout (A_BTROUT), walleye (A_WALL), lake trout (A_LTROUT) and smallmouth bass (A_BASS) were all positively associated with the sites chosen by anglers. The negative interaction term between smallmouth bass and any trout species (A_BSTR) revealed that the utilities of fishing sites with bass and trout were less than that predicted by the individual parameters for these fish species.

A reason why the parameter estimate for walleye availability was lower than the estimate for brook trout availability was the presence of a significant walleye catch rate (*E(W_CUE)*) attribute. The expected walleye catch rate was positive and significant suggesting that anglers chose fishing sites in part because of the expected walleye catch rate. The average reported catch rate for rainbow trout (RT_CUE) was also positively associated with fishing site choice by anglers. The importance of rainbow trout during the spring time may also arise from the unavailability of walleye (i.e., walleye season was closed until May 15).

Table 7.1.3: Thunder Bay fishing site choice model estimates (standard errors in parentheses)

	BASE MNL	MNL Hetero	MNL Aware	MNL Dynamic	NL Dynamic	CNL Dynamic	GNL Dynamic
OUTSIDE	4.910***	5.335***	6.055***	5.216***	5.450***	3.978***	3.979***
	(0.262)	(0.314)	(0.772)	(0.806)	(0.870)	(0.763)	(0.770)
UNKNOWN	4.694***	5.300***	6.021***	5.189***	5.420***	3.953***	3.957***
	(0.274)	(0.303)	(0.767)	(0.802)	(0.867)	(0.758)	(0.765)
ASC_SUPL	4.721***	4.412***	2.176***	1.821***	1.889***	1.567***	1.546***
	(0.245)	(0.247)	(0.423)	(0.445)	(0.467)	(0.379)	(0.367)
ASC_NIPL	4.699***	4.170***	2.799***	2.224***	2.300***	1.947***	1.898***
	(0.371)	(0.391)	(0.458)	(0.484)	(0.511)	(0.413)	(0.402)
ASC_KAMR	-0.332**	-0.456***	-0.848***	-0.720***	-0.753***	-0.548***	-0.524***
	(0.168)	(0.168)	(0.177)	(0.191)	(0.201)	(0.167)	(0.163)
ASC_DOGR	1.125***	0.189	0.066	0.021	0.033	0.090	0.062
	(0.188)	(0.379)	(0.380)	(0.387)	(0.407)	(0.324)	(0.330)
ASC_DOGL	-1.095***	-1.063***	-1.021***	-0.838***	-0.854***	-0.634***	-0.552***
	(0.200)	(0.202)	(0.204)	(0.227)	(0.235)	(0.199)	(0.199)
MD*OUTSIDE		2.646***	4.727***	4.573***	4.588***	4.133***	4.174***
		(0.253)	(0.628)	(0.653)	(0.667)	(0.578)	(0.572)
MD*UNKNOWN		1.359***	3.439***	3.413***	3.427***	2.967***	3.008***
		(0.239)	(0.622)	(0.648)	(0.662)	(0.573)	(0.566)
MD*AC_DOGR		-1.223***	-1.297***	-1.152***	-1.202***	-0.941***	-0.901***
		(0.370)	(0.370)	(0.377)	(0.398)	(0.319)	(0.318)
A_WALL	0.981***	0.446**	0.529**	0.382	0.416	0.357**	0.461**
	(0.203)	(0.235)	(0.243)	(0.247)	(0.259)	(0.209)	(0.204)
A_BASS	0.498***	0.801***	0.794***	0.786***	0.810***	0.640***	0.589***

	BASE MNL	MNL Hetero	MNL Aware	MNL Dynamic	NL Dynamic	CNL Dynamic	GNL Dynamic
	(0.106)	(0.118)	(0.122)	(0.127)	(0.134)	(0.114)	(0.112)
A_LTROUT	0.841***	0.854***	0.925***	0.804***	0.834***	0.670***	0.613***
	(0.125)	(0.125)	(0.124)	(0.134)	(0.143)	(0.119)	(0.114)
A_BTROUT	1.543***	1.574***	1.401***	1.292***	1.356***	1.053***	0.978***
	(0.168)	(0.171)	(0.178)	(0.180)	(0.200)	(0.163)	(0.159)
A_BSTR	-0.628***	-0.568***	-0.627***	-0.574***	-0.592***	-0.481***	-0.458***
	(0.149)	(0.150)	(0.151)	(0.161)	(0.169)	(0.138)	(0.130)
MD*A_WALL		-0.588***	-0.601***	-0.645***	-0.668***	-0.556***	-0.501***
		(0.188)	(0.193)	(0.201)	(0.209)	(0.172)	(0.171)
MD*A_BASS		0.418***	0.497***	0.506***	0.524***	0.428***	0.388***
		(0.094)	(0.100)	(0.104)	(0.110)	(0.090)	(0.089)
E(W_CUE)	0.858***	1.427***	1.282***	1.206***	1.235***	0.995***	0.882***
	(0.128)	(0.149)	(0.154)	(0.161)	(0.168)	(0.148)	(0.145)
RT_CUE	4.631***	4.531***	4.194***	3.602***	3.747***	2.969***	2.763***
	(0.257)	(0.270)	(0.283)	(0.292)	(0.342)	(0.296)	(0.288)
*W*E(W_CUE)*		-0.288***	-0.257***	-0.196***	-0.202**	-0.172**	-0.171***
		(0.058)	(0.058)	(0.063)	(0.065)	(0.055)	(0.054)
W* RT_CUE		-0.764***	-0.710***	-0.520**	-0.535**	-0.443**	-0.479**
		(0.213)	(0.213)	(0.221)	(0.227)	(0.190)	(0.191)
*MD*E(W_CUE)*		0.570***	0.511***	0.443***	0.458***	0.383***	0.350***
		(0.133)	(0.136)	(0.143)	(0.149)	(0.123)	(0.121)
LN_WAREA	0.470***	0.441***	0.313***	0.270***	0.282***	0.215***	0.197***
	(0.027)	(0.027)	(0.033)	(0.034)	(0.037)	(0.032)	(0.031)
T_DIST	-0.023***	-0.018***	-0.017***	-0.013***	-0.013***	-0.010***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.125)	(0.001)	(0.001)
R_GDGR	0.002	0.001	0.001	0.000	0.000	-0.002	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
R_OKGR	-0.009	-0.006	-0.008	-0.008	-0.008	-0.003	0.002
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.008)	(0.007)
R_PRGR	-0.032**	-0.050***	-0.029*	-0.021	-0.023	-0.014	-0.012
	(0.015)	(0.017)	(0.017)	(0.017)	(0.018)	(0.014)	(0.014)
R_TRAIL	-0.261***	-1.903***	-1.676***	-1.506***	-1.564***	-1.186***	-1.227***
	(0.089)	(0.344)	(0.339)	(0.337)	(0.356)	(0.286)	(0.285)
PORTAGE	-1.468***	-1.426***	-1.334***	-1.279**	-1.326**	-1.039**	-1.039**
	(0.510)	(0.509)	(0.509)	(0.509)	(0.532)	(0.428)	(0.421)
W*R_PRGR		0.054***	0.049***	0.039**	0.040**	0.031**	0.028**
		(0.016)	(0.016)	(0.016)	(0.017)	(0.013)	(0.013)
W*R_TRAIL		1.789***	1.578	1.416***	1.471***	1.186***	1.163***
		(0.341)	(0.335)	(0.333)	(0.352)	(0.286)	(0.281)
MD*T_DIST		0.009***	0.010***	0.009***	0.009***	0.008***	0.008***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
BT*GDLN	0.668***	0.665***	0.656***	0.563***	0.583***	0.474***	0.475***
	(0.085)	(0.089)	(0.089)	(0.094)	(0.100)	(0.083)	(0.080)
BT* NOLN	-0.969***	-0.853***	-0.820***	-0.800***	-0.836***	-0.657***	-0.616***
	(0.160)	(0.159)	(0.156)	(0.162)	(0.171)	(0.141)	(0.137)
COTTAGE	-1.191***	-1.460***	-1.530***	-1.269***	-1.305***	-1.007***	-0.953***
	(0.173)	(0.218)	(0.220)	(0.224)	(0.236)	(0.200)	(0.194)
W*COTTAGE		-0.743***	-0.744***	-0.658***	-0.687***	-0.550***	-0.533***
		(0.212)	(0.212)	(0.216)	(0.226)	(0.183)	(0.174)
LN_ACC			0.535	0.338	0.322	0.336	0.430
			(0.341)	(0.358)	(0.368)	(0.305)	(0.315)
LN_UNAC			0.676***	0.590***	0.615***	0.448***	0.415***
			(0.097)	(0.101)	(0.108)	(0.093)	(0.090)
MD*LN_ACC			0.999***	0.995***	0.991***	0.862***	0.890***

	BASE MNL	MNL Hetero	MNL Aware	MNL Dynamic	NL Dynamic	CNL Dynamic	GNL Dynamic
			(0.271)	(0.285)	(0.293)	(0.245)	(0.242)
T_STATE				1.910***	1.968***	1.648***	1.572***
				(0.046)	(0.077)	(0.080)	(0.080)
S_STATE				-0.006***	-0.006***	-0.005***	-0.005***
				(0.001)	(0.002)	(0.001)	(0.001)
DS_ALL					1.043	0.833***	
					(0.046)	(0.043)	
DS_NIP_RIV							0.889**
							(0.065)
DS_BS_LAK							0.309***
							(0.096)
DS_NL_LAK							0.767**
							(0.070)
DS_LDML							0.855***
							(0.072)
DS_DOG_LAK							0.774***
							(0.084)
DS_SW_LAK							0.774***
							(0.084)
DS_GR_LAK							0.271***
							(0.132)
DS_TH_BAY							0.851***
							(0.058)
LL(B)	-5315.4	-5119.4	-5082.4	-4203.5	-4203.1	-4198.5	-4191.2
LL(0) – chance	-6988.2	-6988.2	-6988.2	-6988.2	-6988.2	-6988.2	-6988.2

* probability (<0.10)
** probability (<0.05)
*** probability (<0.01)

The road accessibility attributes suggest that travel distance (T_DIST) had a strong negative effect on the choice of a fishing site. Besides the main effect from travel distance, other attributes were included to contrast whether the type of road or trail had any influence on site choice. These four parameter estimates compared the cost of the specified road or trail type against the cost of travelling on a paved road. While no statistical difference existed among the estimates for paved, good (R_GDGR) and okay (R_OKGR) gravel roads, the estimates for poor gravel roads (R_PRGR) and trails (R_TRAIL) were both negative and significantly different from the effect of paved roads. This finding indicates that degradation of gravel roads and trails that lead to a fishing site would lower the likelihood that anglers would select this fishing site. This deterrent effect was greatest for trails and was non-existent for good or okay quality gravel roads. The

PORTAGE attribute also demonstrated the importance of road accessibility to anglers. The result indicated that anglers did not very often select fishing sites that were accessible through portages.

No attribute directly related to congestion at a fishing site was employed. A proxy for congestion, however, was included that indicated whether the fishing alternative was located on a water body with extensive cottage development (COTTAGE). This COTTAGE attribute, which was populated through expert judgement, had a significant and negative effect on site choice as anglers preferred to fish on water bodies that had less as opposed to more development.

Facility development was measured through attributes that interacted fishing trips with boat use and the types of boat launches. Fishing trips using boats were most likely to occur at sites with good quality boat launches (BT*GDLN) and least likely to occur at sites with no boat launch[59] (BT_NOLN).

Finally, several alternative specific constants (ASCs) were included in the model. One ASC simply captured the propensity of anglers to take fishing trips outside (OUTSIDE) of the study area. A second ASC accounted for fishing trips that anglers took within the study area but to unknown destinations (UNKNOWN). The remaining ASCs were specific to fishing waters and helped to account for very large fishing lakes (i.e., Lake Superior (ASC_SUPL) and Lake Nipigon (ASC_NIPL)) and for waters where the choice model poorly predicted fishing trips (i.e., Dog River (ASC_DOGR), Dog Lake (ASC_DOGL), and Kaministiquia River (ASC_KAMR)). The ASCs for Lake Superior and Lake Nipigon were positive and significantly different from zero. Consequently, more fishing trips occurred on these lakes than one would expect from the MNL model, ceteris paribus. The positive ASC for Dog River fishing trips also revealed that that model was under predicting the fishing trips taken to this river. Finally, the negative parameter estimates for the Kaministiquia River and Dog Lake accounted for over predictions of fishing site choice by the choice model.

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[59] Anglers could still fish from a boat at alternatives without a boat launch by carrying a boat to the water's edge.

The BASE MNL model implicitly assumed that all anglers have identical preferences for the various fishing site attributes. Past research on recreational fishing, which suggests that anglers have very heterogeneous preferences (e.g., Ditton, Loomis and Choi (1992)), does not support this implicit assumption. To account for preference heterogeneity in the model, interactions were estimated based on trip context (i.e., day or multiple day trip) and a measure of the centrality of fishing to the angler (i.e., year round or summer only fishing by the angler).

The MNL HETERO model presented in Table 7.1.3 included only significant interactions between the attributes and trip duration or year round fishing experience variables. Of the set of 12 new parameters included in the model, the interactions around road accessibility are probably the most interesting. One interaction (MD*T_DIST) suggested that travel cost was more important to anglers who were pursuing day as opposed to multiple day trips. The interactions also suggested that individuals who fished year round were less deterred by poor quality gravel roads or trails (W*_R_PRGR and W*_R_TRAIL) than were anglers who did not fish in the winter.

Preferences for the fishing quality attributes also differed among the groups. Year round anglers were less affected by walleye (*W*E(W_CUE)*) and rainbow trout (W*RT_CUE) catch rates than were summer only anglers. These differences likely arose since fish species other than walleye and rainbow trout were important to this group. While anglers taking multiple day trips were less influenced by walleye catch rates (*MD*E(W_CUE)*) and the availability of smallmouth bass (MD*A_BASS), they were more likely to have fished in lakes simply because walleye (MD*A_WALL) was available than were anglers taking day trips.

Year round anglers were less likely to fish at waters that had extensive cottage development (W*COTTAGE). Finally, anglers taking multiple day trips were more likely to fish at unknown sites (MD*UNKNOWN) and sites outside the study area (MD*OUTSIDE) and less likely to fish at Dog River (MD*ASC_DOGR) than were anglers who pursued day trips. The incorporation of heterogeneity in preferences for fishing site attributes led to a significant improvement to the log likelihood function (LR=392.2, df=12, p<0.0001).

The next generalization to the MNL (MNL AWARE) was to account for the awareness of fishing sites by anglers. Two attributes were included into the model that measured aspects of spatial cognition and opportunity. Spatial cognition was measured with an accessibility attribute as described in Chapter 6. Opportunity was measured as the logarithm of the number of unique access points at a fishing alternative.

For anglers who took a multiple day fishing trip, the logarithm of the accessibility measure was significant and positive (MD*LN_ACC). Therefore, these anglers tended to fish at sites surrounded by many other large sized fishing waters. For anglers who took day fishing trips, the combined effect of accessibility was negative, but it was not significantly different from zero. The logarithm of the number of unique access points (LN_UNAC) was positive and significant. Anglers were more likely to fish at sites with more access points than at fishing sites with fewer access points. The inclusion of these attributes related to site awareness led to a significant reduction in the log likelihood function (LR=74.0, df=3, p<0.0001).

Dynamic like attributes were next included in the fishing site choice model. The temporal state dependence (T_STATE) attribute was significant and positive. Many anglers, therefore, choose the same fishing site as they chose for their last fishing trip. The spatial state dependence (S_STATE) attribute was negative in sign and significantly different from zero. This significance revealed that anglers were more likely to choose fishing sites in close proximity to the site where they previously fished than to choose more distant fishing sites, *ceteris paribus*. The large improvement to the log likelihood of the fishing site choice model demonstrated the importance that dynamic like behaviours have on understanding site choice (LR=1757.7, df=2, p<0.001). Without an explicit treatment of the initial conditions, however, one cannot attribute these dynamic like effects to substantive or spurious state dependence.

The various model formulations have assumed independence among the unobserved utilities of the fishing sites. This independence of irrelevant alternatives (IIA) property of the MNL implies that any change to a fishing site will result in a rigid substitution pattern of fishing choices. To relax this assumption, a set of generalized extreme value (GEV) models were estimated.

The previously described spatial support points were used to allocate alternatives into one or more nests. While the choice of the spatial support points likely impacted the results of the nested logit, this choice less likely influenced the results from the more general GEV models that allowed cross-nesting of alternatives. This lower sensitivity for the generalized and cross-nested logit models arises since the alternatives are not discretely allocated to the nearest spatial support point.

The nested logit model was estimated with full information maximum likelihood and the dissimilarity parameter estimate was greater than one. While a value greater than one signals that random utility theory does not globally hold (Daly, & Zachary, 1978; McFadden, 1981), the estimate was not significantly different from one. This non-significance reveals that the NL model provided no improvement over the MNL model as is evidenced by the small change to the log likelihood value (LR=1.0, df=1, p=0.325). This rejection of the NL model usually leads researchers to conclude that the IIA property holds for the data. However, the non-significant result may arise from the use of discrete nests and/or the belief that a global process is sufficient to capture the correlations in unobserved utilities among the alternatives. Therefore, a single non-significant nested logit model is insufficient to conclude that the IIA property holds.

The cross-nested logit model permits alternatives to be allocated among many nests. As described in Chapter 6, this allocation was based on the inverse road distance separating two spatial sites divided by the sum of all inverse road distances. The dissimilarity parameter (DS_ALL) for the cross-nested logit model was significantly different from one suggesting that fishing sites in close proximity to one another were better substitutes than were fishing sites that were located further away. A useful but not entirely correct way (Train 2003) to interpret the model is that one minus the dissimilarity parameter for a nest (i.e., 0.167 for the cross-nested logit model) corresponds to the correlation in the unobserved utility among the alternatives within the nests. Since the scale of utility is arbitrary (Train, 2003), this deflation has no consequence on any choice probabilities that are estimated from the model.

The generalized nested logit model relaxed the assumption that one dissimilarity parameter was sufficient to account for the correlation among unobserved utilities for the alternatives. Eight dissimilarity parameters were estimated for each of the nests included in the model[60]. The likelihood ratio test statistic (LR=14.6, df =7, p=0.041) rejected the assumption that one dissimilarity parameter was sufficient for the data.

Figure 7.1.1 shows the dissimilarity parameters for the various nests and MNL, CNL, and GNL models. While one minus the dissimilarity parameter provides an approximation of the correlation among unobserved utilities within a nest, Bhat and Guo (2004) demonstrate that the actual correlation is more complex and can only be determined through numerical integration.

The MNL models exhibit the IIA property as all dissimilarity parameters are restricted to one. The CNL model shows that spatially near alternatives exhibit correlated unobserved utilities suggesting that a change to a site will result in a relatively larger impact in use to sites in close proximity. The GNL model abandoned the assumption of a single dissimilarity parameter for the nests. Strong correlation coefficients existed among unobserved utilities in alternatives nearby the Graham Lake (DS_GR_LAK) and Black Sturgeon (DS_BS_LAK) spatial support points. Therefore, a change to the deterministic utility of a fishing site in close proximity to one of these spatial support points would result in large relative change in predicted use at nearby fishing sites.

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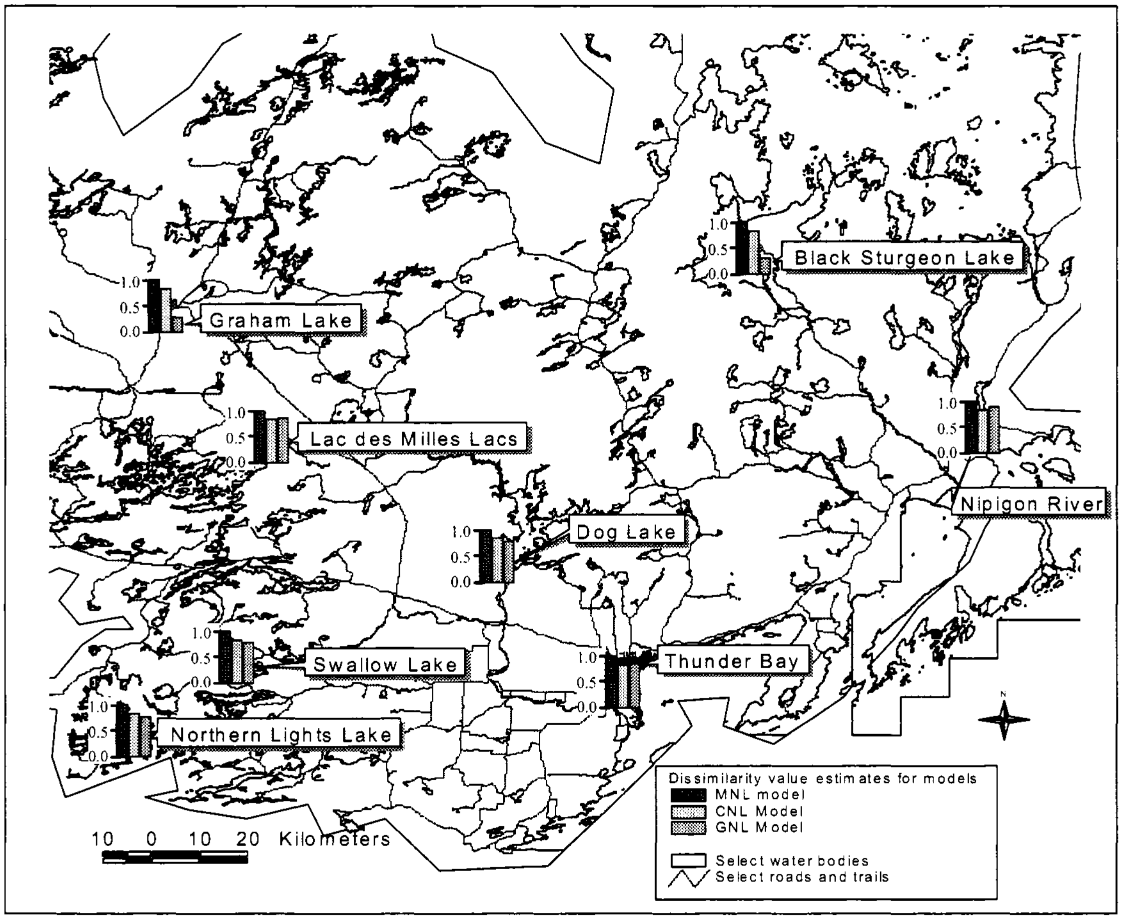
[60] The dissimilarity parameter for a ninth nest consisting of the alternatives of fishing outside the study area and to unknown sites was fixed to one.

Figure 7.1.1: Dissimilarity value estimates at spatial support points from various Thunder Bay choice models



7.2: Wawa area fishing site choice models

The same attributes from the Thunder Bay model were tested on the Wawa data with the following exceptions. First, no attribute for cottage development was available. While an alternative specific constant was included for a lake (Wawa Lake) where the community of Wawa is situated (ASC_WAWA), many other fishing areas with development around the waters probably affect the fishing site choices of Wawa area anglers. Second, an indicator attribute was used to capture the abundance of rainbow trout in Lake Superior tributaries during the spring. Unlike the Thunder Bay data, the few trips (30) that targeted rainbow trout were insufficient to calculate reliable average catch rates for rainbow trout over space and time. Finally, the expected walleye catch rate was removed from the analyses. Unexpectedly, the walleye catch rate was significant and negative in sign in the MNL models[61]. This highly counter intuitive result also captured much of the negative effect from trails on fishing site choice (i.e., since walleye catch is expected to be greater at ATV accessible sites, the walleye catch rate parameter estimate captured the low frequency of recorded fishing trips at these sites). Appendix E provides comparisons of whether the parameter estimates for the Wawa and Thunder Bay area data differ.

The basic MNL model (BASE MNL) produced a significant improvement (see Table 7.2.1) to the log likelihood function compared to a null model (LR=2812.0, df =20, $p<0.001$). As expected the availability of fish species, large waters, and travel distance were all important attributes aligned with anglers' fishing site choices. However, the effects of different types of roads on fishing site choices revealed an unexpected result. The effects of good quality and okay quality gravel roads were significantly different from paved roads and positive in sign. Consequently, Wawa area anglers travel more often on gravel than paved roads when accessing fishing sites. This aversion of paved roads may relate to encounters with non-local anglers, to familiarity with logging road networks, and/or to beliefs that catch rates are higher for sites that are more difficult to reach.

When one considers only the effects of the gravel roads on fishing site choice, the results make greater sense. Good and okay quality gravel roads were most preferred and poor quality gravel roads and trails were least preferred. While the effect of portage accessible sites was non-significant, this result likely arises from the very few portage accessible sites (four) among the fishing site alternatives.

[61] The attribute was not significantly different than zero in the more general MNL and GEV models.

Table 7.2.1: Wawa fishing site choice model estimates (standard errors in parentheses)

	BASE MNL	MNL Hetero	MNL Aware	MNL Dynamic	NL Dynamic	CNL Dynamic	GNL Dynamic
OUTSIDE	2.449***	3.161***	0.380	0.439	-0.357	-0.850	-1.144**
	(0.291)	(0.336)	(0.616)	(0.633)	(0.655)	(0.530)	(0.533)
UNKNOWN	3.385***	3.874***	1.092*	1.152*	0.360	-0.138	-0.431
	(0.233)	(0.303)	(0.599)	(0.616)	(0.638)	(0.510)	(0.509)
ASC_SUPL	2.759***	2.769***	0.783	0.698	0.572	0.551	0.383
	(0.385)	(0.383)	(0.520)	(0.530)	(0.466)	(0.365)	(0.358)
ASC_WAWA	-0.814***	-0.837***	-1.057***	-0.932***	-0.810***	-0.767***	-0.739***
	(0.270)	(0.271)	(0.272)	(0.312)	(0.274)	(0.215)	(0.211)
ASC_MGPIE	0.798***	0.825***	0.212	0.225	0.237	0.171	0.167
	(0.180)	(0.180)	(0.226)	(0.254)	(0.218)	(0.169)	(0.164)
MD*OUTSIDE		1.114***	-0.480	-0.384	-0.318	-0.073	-0.020
		(0.301)	(0.336)	(0.502)	(0.460)	(0.388)	(0.421)
MD*UNKNOWN		0.654**	0.809***	-0.845*	-0.784*	-0.533	-0.481
		(0.264)	(0.458)	(0.480)	(0.437)	(0.361)	(0.370)
A_WALL	1.235***	1.270***	1.368***	1.226***	1.066***	0.818***	0.814***
	(0.140)	(0.205)	(0.237)	(0.240)	(0.218)	(0.180)	(0.178)
A_BASS	0.781***	0.322	0.374	0.393	0.329	0.281	0.253
	(0.198)	(0.334)	(0.336)	(0.353)	(0.301)	(0.235)	(0.234)
A_LTROUT	0.402***	0.397***	0.471***	0.374***	0.297**	0.211**	0.196**
	(0.123)	(0.124)	(0.126)	(0.134)	(0.120)	(0.095)	(0.093)
A_BTROUT	0.422***	0.403***	0.130	0.230	0.201	0.178*	0.155
	(0.118)	(0.119)	(0.135)	(0.143)	(0.124)	(0.097)	(0.096)
A_BSTR	-0.567**	-0.633**	-0.357	-0.458	-0.364	-0.266	-0.217
	(0.282)	(0.284)	(0.289)	(0.325)	(0.282)	(0.222)	(0.219)
MD*A_WALL		0.042	0.279	0.284	0.252	0.204	0.206
		(0.188)	(0.217)	(0.217)	(0.190)	(0.150)	(0.147)
MD*A_BASS		-0.558*	-0.562*	-0.459	-0.379	-0.293	-0.296
		(0.307)	(0.307)	(0.321)	(0.275)	(0.215)	(0.213)
A_ERRT	1.036***	1.400***	1.054***	0.893**	0.762**	0.585**	0.585**
	(0.309)	(0.358)	(0.350)	(0.365)	(0.323)	(0.253)	(0.245)
W* A_ERRT		-0.554*	-0.481	-0.352	-0.340	-0.261	-0.270
		(0.332)	(0.324)	(0.336)	(0.295)	(0.230)	(0.217)
LN_WAREA	0.370***	0.371***	0.270***	0.226***	0.196***	0.165***	0.154***
	(0.034)	(0.034)	(0.038)	(0.038)	(0.035)	(0.028)	(0.027)
T_DIST	-0.043***	-0.037***	-0.039***	-0.034***	-0.032***	-0.024***	-0.024***
	(0.02)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R_GDGR	0.012***	0.012***	0.011***	0.010***	0.010***	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
R_OKGR	0.069***	0.069***	0.066***	0.060***	0.056***	0.047***	0.046***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)	(0.008)	(0.008)
R_PRGR	-0.022	-0.011	0.014	0.032	0.029	0.025	0.025
	(0.028)	(0.029)	(0.029)	(0.029)	(0.025)	(0.019)	(0.019)
R_TRAIL	-0.099***	-0.124***	-0.096**	-0.065	-0.055	-0.043	-0.040
	(0.036)	(0.048)	(0.047)	(0.044)	(0.038)	(0.030)	(0.029)
PORTAGE	-0.800	-0.784	-0.697	-0.645	-0.526	-0.402	-0.393
	(0.715)	(0.713)	(0.713)	(0.718)	(0.608)	(0.476)	(0.464)
W*R_PRGR		-0.037	-0.034	-0.044	-0.037	-0.027	-0.024
		(0.028)	(0.028)	(0.028)	(0.024)	(0.019)	(0.018)
W*R_TRAIL		0.053	0.050	0.039	0.034	0.028	0.024
		(0.046)	(0.045)	(0.042)	(0.036)	(0.028)	(0.027)
MD*T_DIST		0.008***	0.006***	0.004**	0.003**	0.003*	0.003*
		(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)

	BASE MNL	MNL Hetero	MNL Aware	MNL Dynamic	NL Dynamic	CNL Dynamic	GNL Dynamic
BT*GDLN	-0.257*** (0.081)	-0.246*** (0.081)	-0.243*** (0.082)	-0.072 (0.084)	-0.063 (0.074)	-0.043 (0.060)	-0.025 (0.057)
BT* NOLN	-0.836*** (0.200)	-0.832*** (0.200)	-0.797*** (0.199)	-0.729*** (0.210)	-0.630*** (0.185)	-0.486*** (0.150)	-0.465*** (0.146)
LN_ACC			-1.696*** (0.362)	-1.752*** (0.372)	-1.729*** (0.333)	-1.309*** (0.269)	-1.414*** (0.273)
LN_UNAC			0.615*** (0.130)	0.401*** (0.141)	0.329*** (0.125)	0.221** (0.100)	0.238** (0.097)
MD*LN_ACC			-1.100*** (0.309)	-1.023*** (0.320)	-0.956*** (0.284)	-0.734*** (0.225)	-0.707*** (0.230)
T_STATE				1.653*** (0.054)	1.430*** (0.099)	1.152*** (0.098)	1.052*** (0.093)
S_STATE				-0.001 (0.002)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.002)
DS_ALL					0.849*** (0.058)	0.660*** (0.057)	
DS_WAWA							0.6453*** (0.090)
DS_MANIT							0.430*** (0.092)
DS_DUBR							0.652*** (0.066)
DS_WRIVER							0.665*** (0.065)
DS_HAWK							0.690*** (0.070)
LL(B)	-2943.0	-2923.9	-2902.3	-2513.4	-2510.6	-2505.9	-2498.8
LL(0) – chance	-4339.0	-4339.0	-4339.0	-4339.0	-4339.0	-4339.0	-4339.0

* probability (<0.10)
** probability (<0.05)
*** probability (<0.01)

Wawa area anglers who fished from boats often chose sites with a middle level of boat launch quality rather than sites with either good quality boat launches or no boat launches. The estimates for the alternative specific constants showed that more fishing trips occurred outside (OUTSIDE) the study area, to unknown sites (UNKNOWN), to Lake Superior (ASC_SUPL), and to the Magpie River (ASC_MGPIE) than otherwise predicted by the model. Finally, the significant and negative estimate for the alternative specific constant for Wawa Lake (ASC_WAWA) results from an over prediction by the model for trips to this lake. This over prediction likely arose from the extensive development around Wawa Lake.

The inclusion of significant interactions based on angler type (i.e., year round and summer only fishing) and trip context (i.e., day and multiple day trips) improved the model (LR=38.2, df

=8, p<0.001). As with the Thunder Bay model, anglers who took multiple day trips were less influenced by travel distance than were anglers who took day trips (MD*T_DIST). The interactions of trip duration and outside (MD*OUTSIDE) and to unknown (MD*UNKNOWN) sites were significantly different from zero and positive in sign. As with the Thunder Bay model, these interactions suggested that individuals who took multiple day trips were more likely to fish at sites outside the study area or to unknown sites than were anglers who pursued day fishing trips. The interaction of trip length on smallmouth bass (MD*A_BASS) availability also approached significance. Unlike the Thunder Bay data, the negative sign suggests that the availability of bass had less influence on anglers who took multiple as opposed to day trips. The interaction between winter fishing and the availability of rainbow trout early in the season (W*A_ERRT) was negative and approached significance. As with the Thunder Bay data, the availability of rainbow trout in the Lake Superior tributaries had less influence on site choices by anglers who fished year round as opposed to only fishing during the summer season.

Unlike the results from the Thunder Bay data, the three remaining interactions were not significant. These results suggest that less (or a different form of) preference heterogeneity existed among Wawa area anglers for walleye availability (MD*A_WALL) and the different types of poor gravel roads (W*A_ERRT) and trails (W*R_TRAIL). The different finding from the Thunder Bay models for the roads and trails may relate to the much higher propensity that Wawa area anglers had for fishing during the winter than did Thunder Bay area anglers (see Figure 5.2.2).

The inclusion of awareness attributes related to accessibility and unique access points led to a significant reduction in the log likelihood (LR=43.2, df =3, p<0.001). As expected, the number of unique access points (LN_UNAC) on a water body was positively associated with fishing site choice. The significant and negative parameter estimate for accessibility (LN_ACC) and the interaction estimate of day and accessibility (MD*LN_ACC) were different from those observed from the Thunder Bay area. The negative effect implies that these anglers do not typically select fishing alternatives in close proximity to other large sized fishing alternatives. This effect was especially pronounced for anglers who took multiple day fishing trips. By contrast, the result for the Thunder Bay area anglers was completely opposite as Thunder Bay area anglers appeared to select fishing sites in close proximity to other large waters.

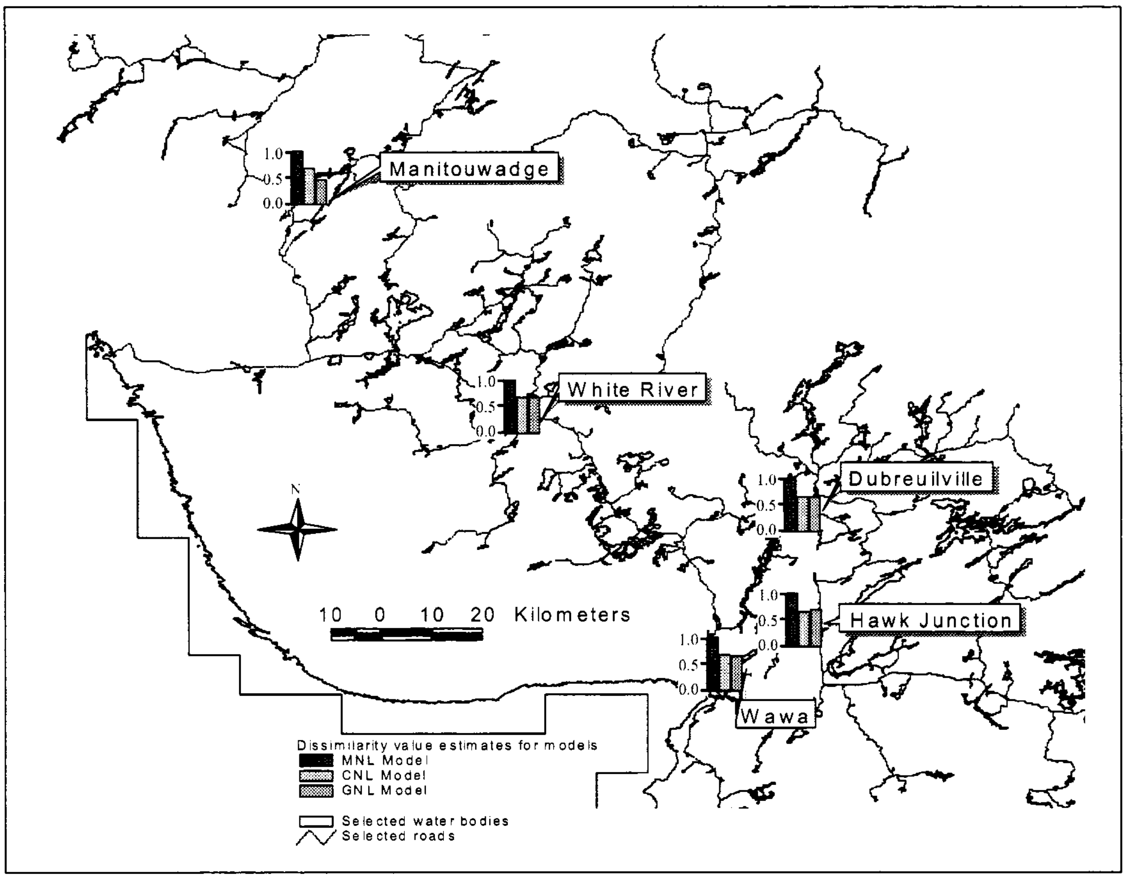
The inclusion of the state dependence and spatial state dependence measures greatly improved the log likelihood function (LR=777.8, df =2, $p<0.001$). The state dependence measure (T_STATE) implied that anglers' choices of fishing sites were often the same as the sites chosen on previous trips. The non-significant result for the spatial state dependence attribute (S_STATE) differed from the Thunder Bay data. Therefore, Wawa area anglers were not any more likely to fish at sites located close to their previously chosen fishing site than they were to choose a more distant site.

Unlike the Thunder Bay model, the use of discrete nests resulted in a significant improvement in the log likelihood of the site choice model (LR=5.6, df =1, $p=0.018$). The significantly different from one dissimilarity parameter (DS_ALL) revealed that sites within a nest were better substitutes than were sites outside of nests. This significance of the NL model for the Wawa area may relate to omitted attributes of cottage development and fish catch in the Wawa area site choice model.

The cross-nested logit model also produced a significant improvement over the MNL dynamic model (LR=24.4, df =1, $p<0.001$). Since the nested logit and cross-nested logit models are not nested, a likelihood ratio test comparison of these models was inappropriate. When competing models have the same number of observations and parameters, the Akaike Information Criterion (see equation 43) always suggests that the model with the lower log likelihood is preferred. Since the nested and cross-nested logit models had the same number of parameters and observations, the lower log likelihood for the cross-nested logit made it a more preferable model to the nested logit. The cross-nested logit also had greater face validity, as one would suspect that spatial substitution would not be restricted to arbitrary nests but would vary over space.

The generalized nested logit represented a significant improvement to the cross-nested logit (LR=14.2, df =4, p=0.007). Figure 7.2.1 illustrates the dissimilarity parameters from the MNL, CNL, and GNL models associated with the various nests. The graphs correspond to the spatial support point from which the allocation of each fishing site to each nest was determined.

Figure 7.2.1: Dissimilarity value estimates at spatial support points from various Wawa area choice models



The MNL model exhibited no correlation among the unobserved utilities because of the IIA property. While the CNL model relaxed the IIA property, the GNL model allowed for a more complex pattern of correlations among the various fishing sites. In particular, the dissimilarity parameter estimate for the Manitouwadge area (DS_MANIT) was very much lower than were the other dissimilarity parameter estimates. Fishing sites near the town of Manitouwadge, therefore, were better substitutes for each other than were sites located nearer to the other spatial support points

7.3: Validity assessments of fishing site choice models

Not all anglers who began the diary program provided complete trip information from May 1 to September 30, 2005. While these partially completed diaries were not used to estimate the models, I used this trip data to assess the validity of the choice models. While this approach made effective use of all data provided by anglers, the use of incomplete diary data introduces some biases. For example, these anglers were more likely to provide some fishing trip information when the diary program first began (i.e., April and May) than when the diary program was finishing (i.e., August and September). Therefore, more trips in the holdout sample were taken during the closure of the walleye fishing season than would actually occur with a representative sample of fishing trips. This fact led to many more trips on rainbow trout than one would expect by chance.

Following Haener, Boxall, and Adamowicz (2001), measures relating to the sum of absolute errors and the correlation between the vectors of observed and predicted choices were used to evaluate the validity of the aggregate model predictions[62]. The sum of absolute errors (SAE) simply measures the sum of absolute differences between observed and expected choices from the hold out data. The SAE measures are positive and higher predictive validity is associated with smaller values. For the correlation coefficients, values closer to one suggest better concordance between predicted and expected choices.

For the Thunder Bay data, 144 trips were used to assess the validity of the models. The results in Table 7.3.1 show that all choice models predict fishing trips better than chance. The most significant enhancement to the validity of the models was the inclusion of the dynamic like attributes. In fact, the correlation coefficient increased from 0.49 to 0.81 by simply including the

[62] No assessment at the individual level was conducted because of the vast number of alternatives that were modelled.

state dependence and spatial state dependence attributes. The SAE measures and correlation coefficients were unexpectedly better for models without heterogeneity or the site awareness related attributes.

Table 7.3.1: Validity assessments of the Thunder Bay site choice models

	CHANCE	BASE MNL	MNL Hetero	MNL Aware	MNL Dynamic	NL Dynamic	CNL Dynamic	GNL Dynamic
SAE	253.25	169.45	174.54	175.51	132.52	132.41	132.09	132.04
Correlation coefficient	<0.01	0.55	0.48	0.49	0.81	0.81	0.80	0.79

No improvement to the SAE measure or correlation coefficients was observed for the more generalized extreme value (GEV) models. However, based on face validity, these GEV models invoke a less rigid substitution pattern than do the MNL models. Furthermore, the assessment of predictive validity is based on an unchanged fishing world. An assessment of choices made by anglers after changing fishing sites (e.g., closure of sites) may provide different conclusions about model validity.

The results from the validity tests of the 124 Wawa area trips were very similar as were the results from the Thunder Bay models (see Table 7.3.2). All Wawa area choice models provided much better forecasts than did chance. Again, the inclusion of dynamic like elements provided the greatest improvement to the predictive quality of the models. The inclusion of preference heterogeneity, awareness and the various GEV models did not provide much benefit in predictive validity.

Table 7.3.2: Validity assessments of the Wawa area site choice models

	CHANCE	BASE MNL	MNL Hetero	MNL Aware	MNL Dynamic	NL Dynamic	CNL Dynamic	GNL Dynamic
SAE	348.00	153.60	153.43	153.90	128.71	129.06	128.24	127.87
Correlation coefficient	0.00	0.48	0.47	0.48	0.59	0.59	0.59	0.59

7.4: Management scenarios

A great strength of a choice model is its ability to forecast how changes to the resource or management of the resource are likely to impact use at affected and non-affected sites. This section highlights four different scenarios that help to demonstrate the benefits of this modelling approach. The forecasts from the site choice models required some consideration of dynamic like effects (i.e., knowledge of the actual trips chosen). Therefore, simulations were used to identify the trips that anglers would take from the forecast probabilities. The simulations used uniform random number draws that were compared to the cumulative density function of the estimated probabilities for the sites. The parameter estimates were also randomly drawn to account for the average (i.e., mean estimate), the variability (i.e., the standard errors) and the correlation among the various estimates (i.e., the covariance matrix of the parameter estimates). Since the decision to participate in fishing was not modelled, I used the observed distribution of trips from the angling diaries as a representative set of trips for anglers. The use of simulations and the observed distribution of trips allowed me to include dynamic like elements into fishing site choice (i.e., the influence of past trips on the choice of a current fishing trip).

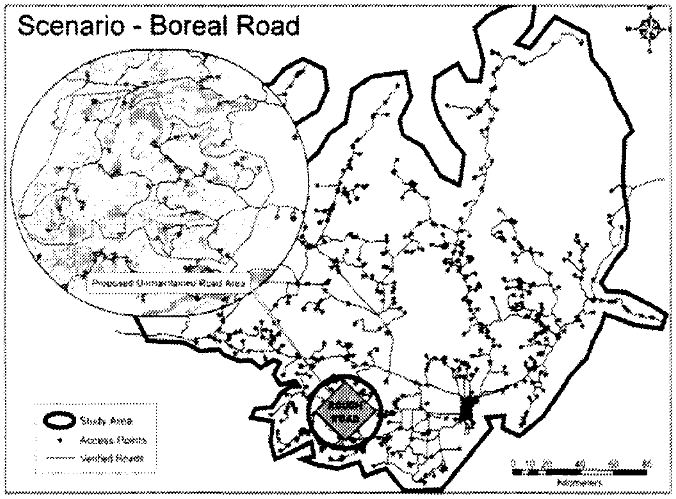
The simulations were conducted for the dynamic like MNL, the CNL and the GNL models for all four scenarios. The forecasts, which were based on 2000 simulations, included information on the predicted pattern of use and the change to the economic value of recreational fishing. Changes to economic value, which were based on compensating variation with no income effects, employed equation 40 for the MNL model and equation 41 for the CNL and GNL models. A value of \$1.09 per return km transformed the distance parameter into cost. This value comes from the average operating expenses for a Dodge Caravan in 2004 that an individual drove 18,000km annually with fuel costs \$0.744/litre (Canadian Automobile Association, 2004). This estimate appears to be inflated given that most anglers do not travel alone when fishing. However, the travel cost value is downwardly biased given that gasoline prices were often above \$0.744 during the summer of 2004, that anglers often own four wheel drive trucks that have higher operating costs than do minivans and that no attempt was made to include a value of travel time into the costs. As such, I believe that the $1.09 travel cost per km is a reasonable approximation for the costs faced by northern Ontario anglers during the summer of 2004. Following the lead of Hagerty and Moeltner (2005), the bootstrapped mean and 90% confidence intervals were calculated for the compensating variation median value based on each of the 2000 replications.

7.4.1: Scenario 1: Major road degradation to some Thunder Bay fishing sites

This scenario demonstrates the importance of road access to the fishing site choices by Thunder Bay area anglers. The scenario works by assuming that all good and okay quality gravel roads in Figure 7.4.1 are degraded to poor quality gravel roads. It is also assumed that all poor quality gravel roads are degraded to trails. As with all scenarios, the forecasts are naïve in the sense that they do not account for any changes to fishing participation and they do not account for impacts to resource quality (e.g., walleye catch) resulting from changing patterns of angling behaviours.

Figure 7.4.2 presents a subset of forecasts for the dynamic like MNL, CNL and GNL models. The MNL model predicted a large relative change in use of fishing sites in the affected area. All three models predicted that sites that are accessible by travel on long trails would have almost no remaining use. However, one should realize that the poor accessibility at these sites would eventually lead to better expectations for catching fish that could increase use at these sites. For sites that would be accessible by poor quality gravel roads, the models predicted different effects on use. The MNL model predicted that the use of these sites would decline by approximately 50 to 60%. Conversely, the CNL model predicted that use would decline only by about 25 to 50%. The GNL model predictions had a slightly lesser impact on use than did the CNL model predictions.

Figure 7.4.1: Degradation of logging roads in area west of Thunder Bay

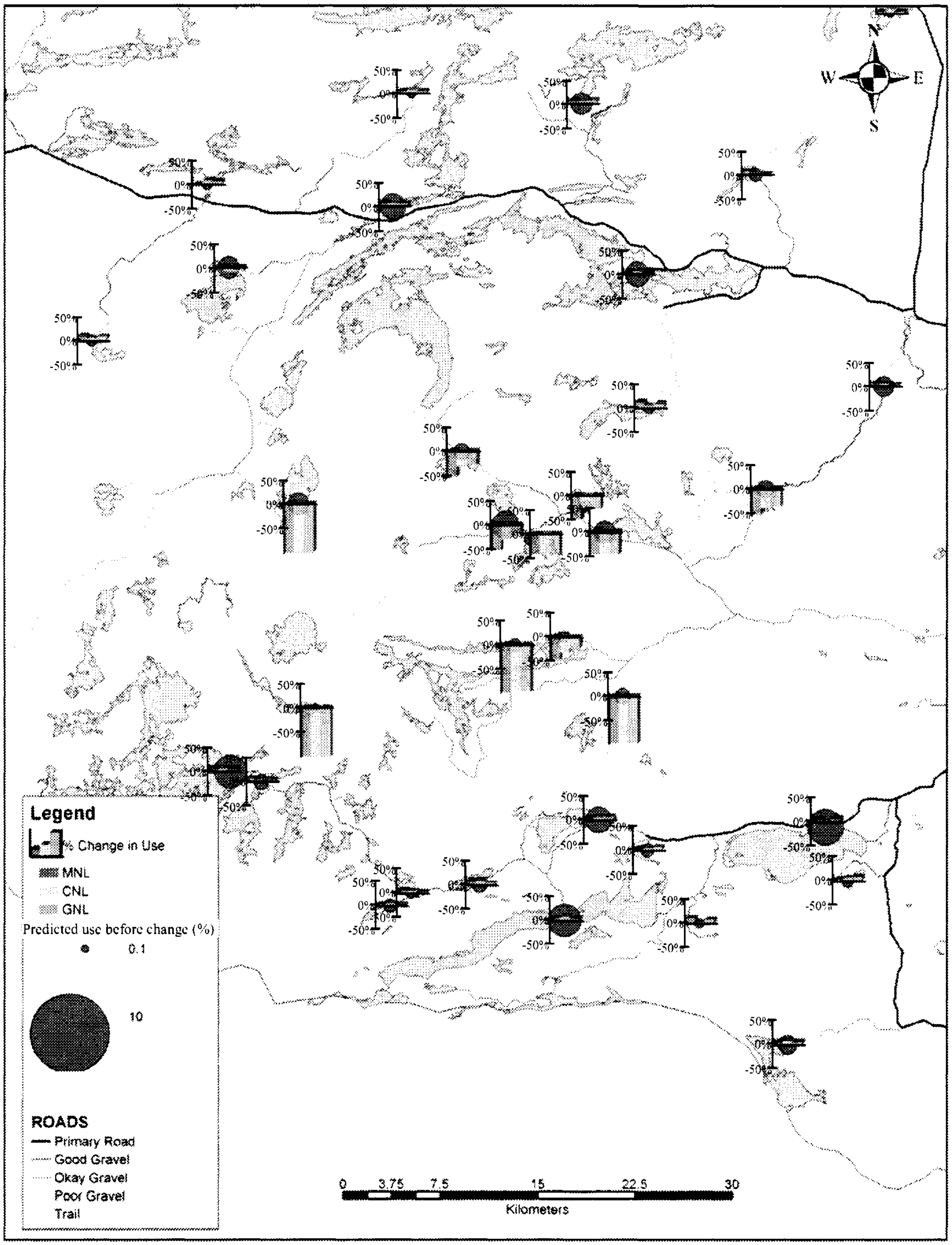


A reason for the lower percentage change in use predicted by the CNL and GNL models compared to the MNL model arises from the different substitution patterns implied by the models. Whereas space has little affect on the MNL model[63], the CNL and GNL models explicitly account for space among the fishing sites. In essence, the CNL and GNL models predict that some use that would have occurred at the new trail accessible sites would shift to nearby fishing alternatives (i.e., these nearby sites are better substitutes than are more distant sites).

The changing pattern of fishing effort in the study area would also likely affect the value of recreational fishing to anglers. With the previously discussed assumptions, the MNL predicts an average median loss in the economic value of a fishing trip of $2.99 with a range of $1.17 to $4.17 at the 90 percent confidence interval. The CNL and GNL models have lower average median losses of $2.60 and $2.98 and larger confidence intervals $0.27 to $4.10 and $0.13 to $4.92, respectively than the MNL model. Regardless, the models all suggest that the degradation of logging roads in this scenario would result in a large impact on the economic value of recreational fishing.

[63] The presence of the accessibility and the spatial state dependence attributes make substitution patterns in the MNL partially dependent upon space.

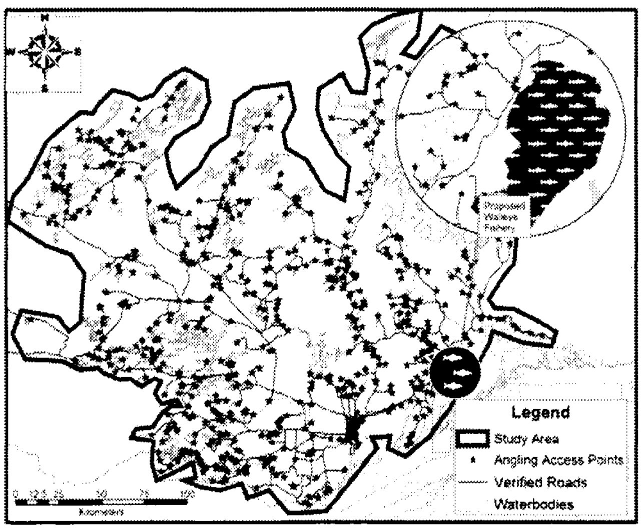
Figure 7.4.2 Forecasted changes in angling site use (%) resulting from degradation of logging roads



7.4.2: Scenario 2: Restoration of walleye into Black Bay (Lake Superior)

A change some individuals are currently contemplating around the Thunder Bay area relates to the restoration of walleye into Black Bay in Lake Superior (see Figure 7.4.3). Many questions remain related to this proposed restoration including whether managers should allocate walleye to recreational or commercial fishing interests and whether the restoration costs are justified by the likely benefits that anglers would receive. To provide some answers to these questions, the fishing site choice model forecasted changing use patterns and benefits associated with this recreational walleye fishery in Black Bay.

Figure 7.4.3: Restoration of walleye fishery to Black Bay, Lake Superior



The MNL model predicted a 580% increase in fishing trips to Black Bay. This increase would result in Black Bay accounting for over 9% of all modelled angling trips taken by resident anglers. The CNL and GNL models predicted slightly lower percentage changes in use at Black Bay of 550% and 487%, respectively. The lower percentage changes for the GNL and CNL models reflect the substitutability of nearby alternatives to Black Bay.

Figure 7.4.4 Forecasted changes in angling site use (%) resulting from walleye restoration in Black Bay

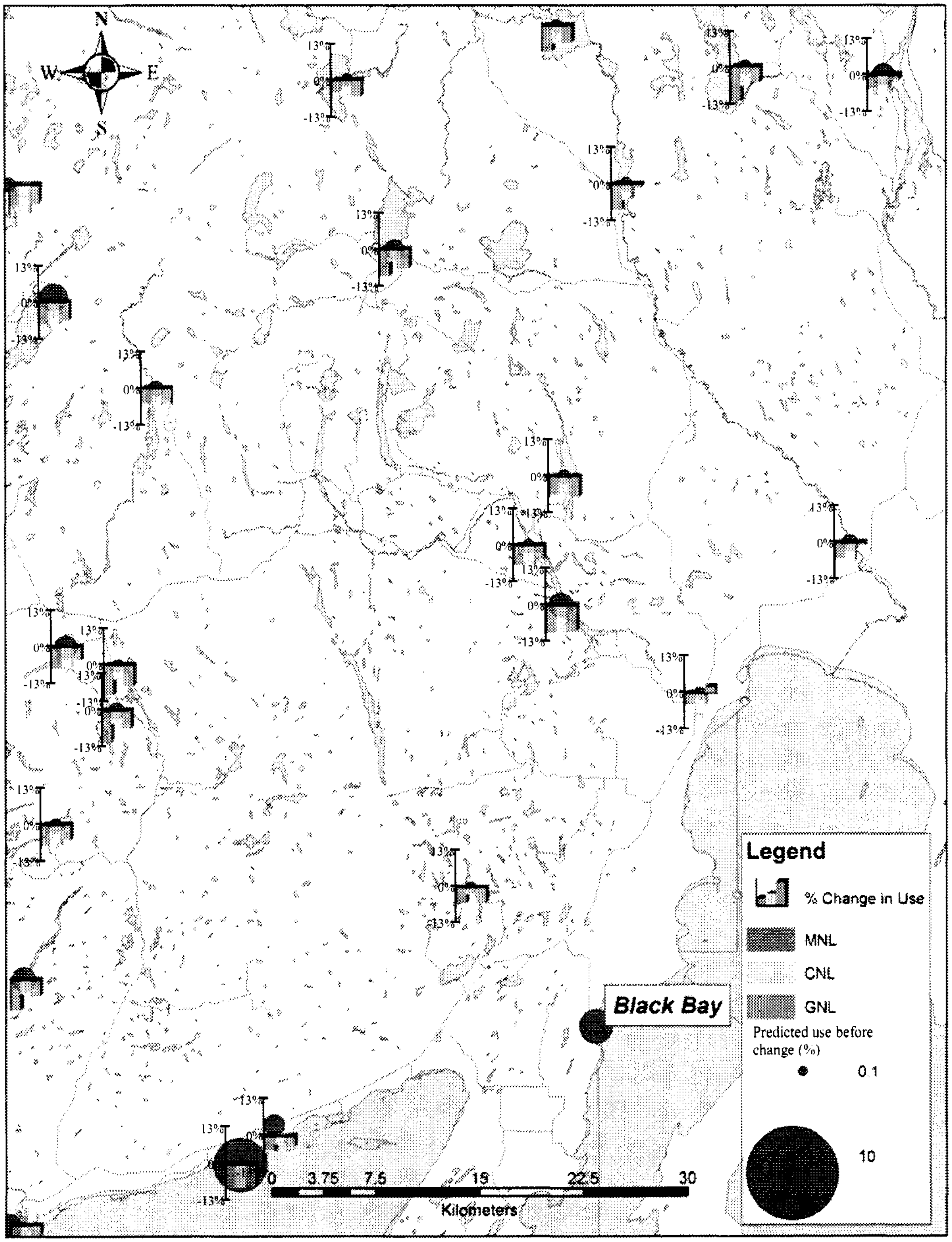


Figure 7.4.4 shows the percentage change in fishing site choice near Black Bay. The MNL model predicted an almost constant pattern of change at nearby sites. By contrast, the CNL and GNL

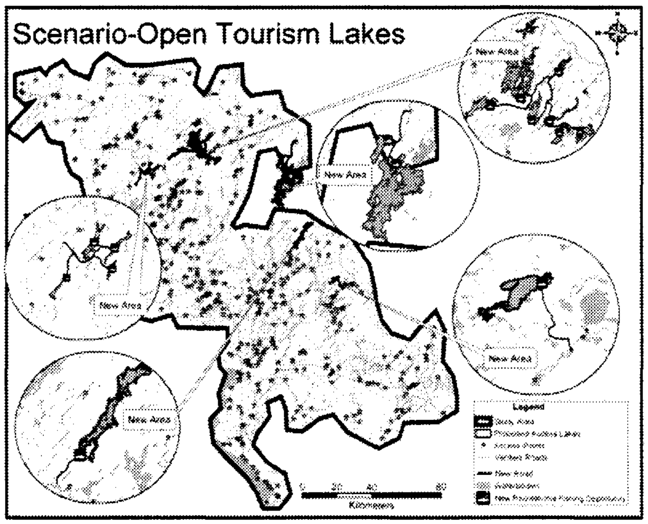
models exhibited more variability in predicted use at the fishing sites. The MNL model also predicted that the successful restoration of walleye into Black Bay would result in an average median increase in value of \$3.28 per fishing trip with a range of \$2.00 to \$4.92 at the 90^{th} percentile. Again, the CNL and GNL models predicted lower average medians of \$2.82 and \$2.67, respectively than did the MNL model. The ranges of \$1.64 to \$4.21 and \$1.41 to \$4.10 for the CNL and GNL models, respectively did not differ much from the range for the MNL model. All models suggest that the restoration of walleye into the Black Bay of Lake Superior would result in a strong increase to the economic value of recreational fishing.

7.4.3: Scenario 3: Opening up road access on resource based tourism lakes in Wawa

A contentious issue for resource management in northern Ontario is the conflict between recreational anglers and resource based tourism operators. Some lakes in northern Ontario are currently managed to provide remote and inaccessible experiences to both tourists and recreational anglers. While no plan exists to change the remote character of these lakes, one should still assess whether these lakes are best suited for remote tourism and recreation or for road accessible recreation. A scenario whereby managers create roads to 15 fly-in accessible tourism lakes in the Wawa study area was examined (see Figure 7.4.5). Since the Wawa area choice models did not include the abundance of walleye as a factor in site choice, one should assume that the forecasts represent the average effect over many years (i.e., the model will under predict initial use when walleye populations are high, but will likely over predict use if walleye populations decline from angler exploitation).

The scenario involves the construction of logging roads from the existing road network to the water bodies with the tourism establishments. These newly created logging roads were classified as okay quality gravel roads. Figure 7.4.6 demonstrates the forecasted changes in use resulting from these new road accessible fishing opportunities. Note that the expected use at the new tourism sites is based on a proportion rather than percentage. The figure shows that the relative change in use among alternatives predicted from the GNL model was much more variable than it was for predictions from the other models. Therefore, the GNL model predicted a much more complex substitution pattern among the sites than did the other models.

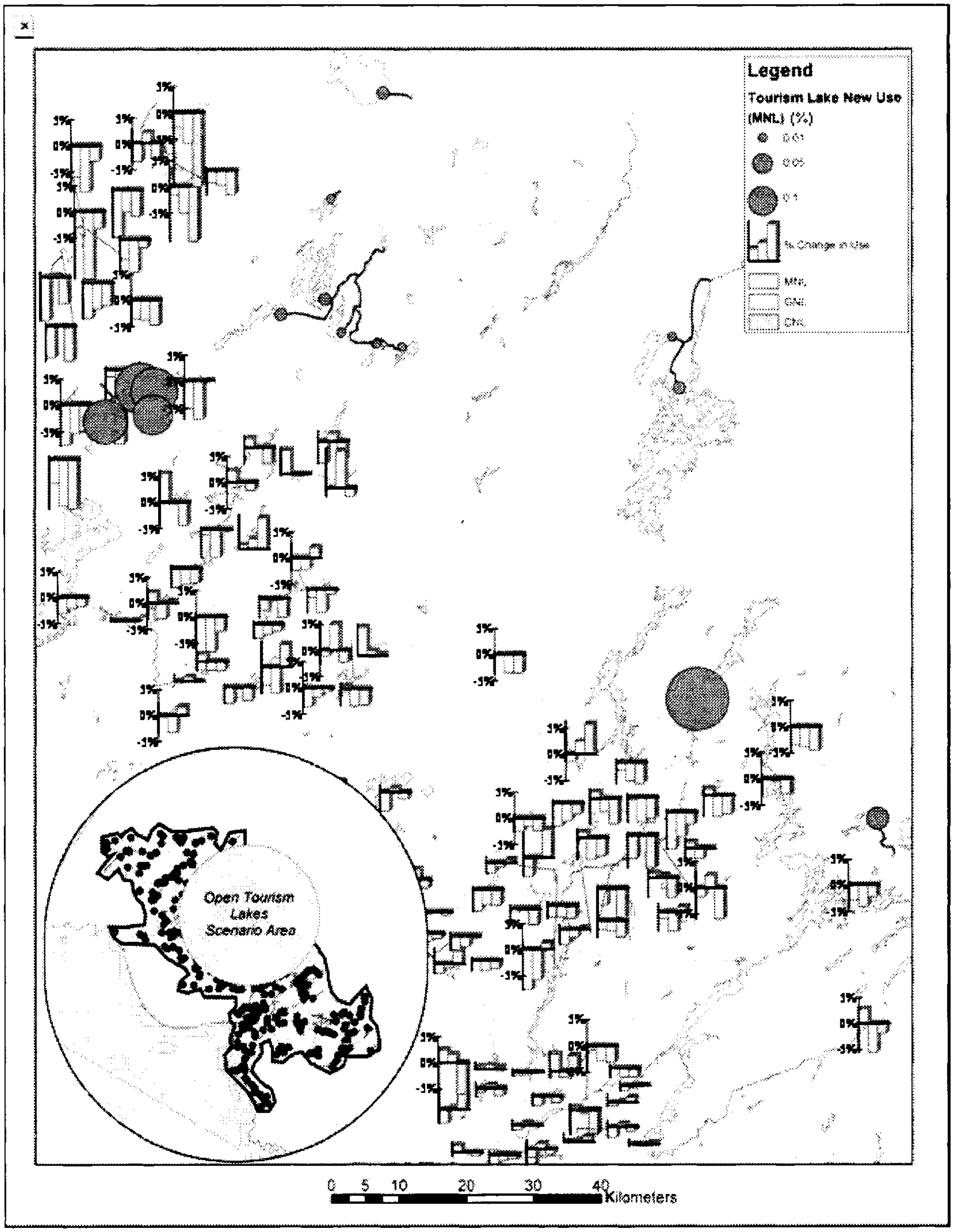
Figure 7.4.5 Conversion of Wawa area remote tourism lakes to road accessible angling opportunities



Besides changes in the spatial pattern of choices resulting from the new road accessible opportunities, one should assess how the new opportunities may affect the economic value of recreational fishing[64]. The MNL model predicted that the average median per trip change to economic value was $0.12 with a range from $0.08 to $0.18 at a 90% confidence interval. This change was noticeably smaller than the predicted changes for the Thunder Bay scenarios partially since the parameter estimate for travel is about two times the size of the travel parameter estimate for the Thunder Bay model. The CNL and GNL models predicted similar changes to the economic value of fishing with averages of $0.08 and $0.10 and 90% confidence intervals of $0.02 to $0.14 and $0.03 to $0.17, respectively.

[64] Since the accessibility term will change with the addition of new alternatives, I recalculated the accessibility measures to keep a common base for evaluating changes to the expected maximum utility of fishing.

Figure 7.4.6 Forecasted changes in angling site use (%) resulting from new road accessible opportunities in Wawa area



7.4.4: Scenario 4: Expansion of logging road network in Wawa area

As with the first scenario, many people believe that the presence of logging roads provides benefits to recreationists. While scenario one focused on changes to the quality of logging roads, this scenario focuses on the creation of new linkages among the logging road networks in the Wawa area. Figure 7.4.7 shows this scenario with the inclusion of a new good quality logging road that connects logging road networks between Manitouwadge and Dubreuilville and Dubreuilville and roads connecting to Hawk Junction. The question from this scenario is what benefit, if any, does the construction of good quality logging roads constructed for forestry and not for recreational fishing (scenario #3) provide to resident anglers of the Wawa area.

Figure 7.4.7 Additions to logging road networks in the Wawa area

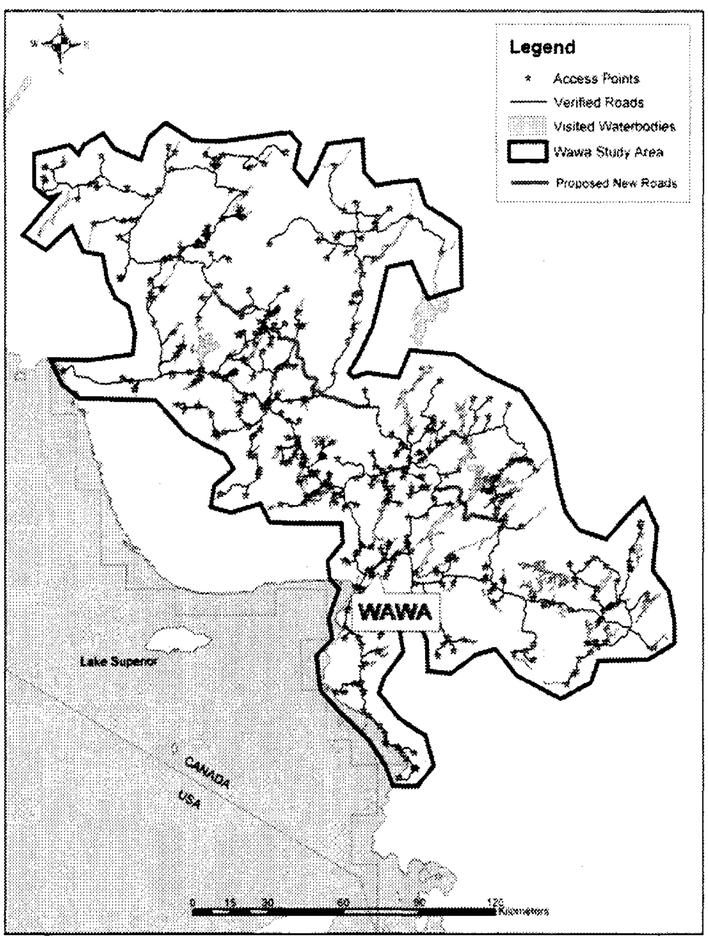


Figure 7.4.8 Forecasted changes in angling site use (%) resulting from changes to the logging road network in Wawa area

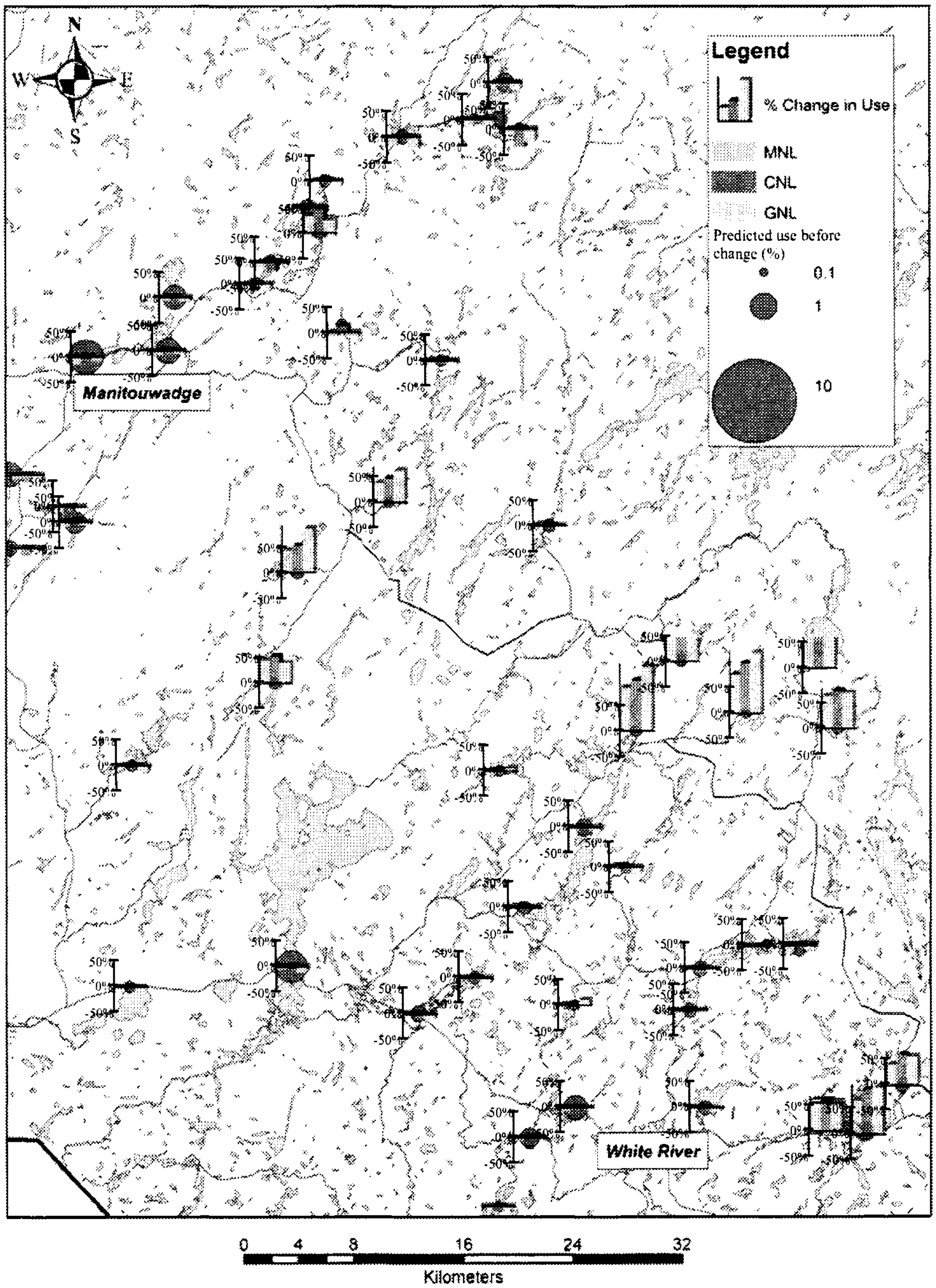


Figure 7.4.8 shows the percentage change in use predicted by the three choice models. Fishing alternatives located in near proximity to these roads were predicted to have large relative

increases in use. On average, the percentage changes for sites in close proximity to these new roads appear largest from the GNL model predictions.

The forecasted changes to fishing site use resulting from these logging roads are provided in Figure 7.4.8. There was almost no noticeable change to the economic value of fishing as the average median value for the MNL model was \$0.26 with a range from -\$0.05 to \$1.10 at the 90% confidence level. Similar results were found for the predictions from the CNL and GNL models with averages of \$0.16 and \$0.15 and 90% confidence intervals of -\$0.23 to \$1.03 and -\$0.32 to \$1.13, respectively. Anglers would apparently receive little benefit to their recreational fishing activity from the construction of these roads.

7.5 Conclusion

The site choice models provided much information about the effects of road access on site choice. For Thunder Bay area anglers who fish only during the summer, the effects of poor quality gravel roads and trails were strong and negative on fishing site choice. For Thunder Bay area anglers who fish year round, the effects of poor quality gravel roads and trails on fishing site choice were much less important. The impact of poorer quality gravel roads and trails on fishing site choice was also much lower for Wawa area than for Thunder Bay area anglers.

The models were presented to assess whether increases to the complexity and flexibility of the site choice models resulted in significant statistical improvements to the choice models. The *BASE MNL* model was abandoned in favour of a model that accounted for different preferences among the anglers. This model was followed by considerations of how spatial cognition and site awareness affect angler's choices of fishing sites. The remaining models were provided to account for increasingly complex substitution patterns among the alternatives.

Space was an important factor of fishing site choice in several ways. First, the accessibility attributes were significant in the choice models. However, the sign for the accessibility attribute was different for the Thunder Bay and Wawa area models. The spatial state dependence attribute was negative for both models. While this affect was significantly different from zero for the

Thunder Bay model, there was no reason to conclude that this spatial state dependence measure was important to the fishing site choices made by Wawa area anglers.

Unlike the spatial cognition and spatial state dependence attributes, the generalized nested logit models revealed significant and similar effects from space. For both areas, the models found that sites in close proximity to one another were better substitutes than were sites located further away. As well, the strength of this substitution process varied over the landscape. This fact indicates that a global parameter estimate was not capable of accounting for the spatial heterogeneity present in both data sets.

Predictive validity assessments of the various models did not provide much support for the various treatments of space in the choice models. In fact, only the models that incorporated both state dependence and spatial state dependence attributes provided a significant change in the predictive power of the models. Readers, however, are cautioned that these predictive validity assessments were based on an unchanging world. These assessments may be different if one was able to change aspects of some fishing alternatives and observe the changes to the spatial pattern of fishing site choices.

Four different scenarios were used to illustrate the managerial usefulness of the results from the choice models. The two Thunder Bay scenarios helped to display the importance to the economic welfare of anglers and to describe the complex substitution patterns predicted by several choice models. The scenarios for the Wawa area showed much smaller changes to the economic value of recreational fishing than did the Thunder Bay area scenarios. While this different finding partially arose from the different types of scenarios examined, the change also arose from the relatively larger impact of travel distance on Wawa than Thunder Bay area respondents. By being more deterred by travel distance than were anglers from Thunder Bay, any change to another attribute (e.g., new alternatives added) would result in less compensation for Wawa area anglers in terms of travel distance and thus economic value.

Chapter 8: Discussion and conclusions

A most contentious issue for resource management in Ontario is road access (Hunt, unpublished manuscript). The provision of road access has the potential to lead to ecological impacts (e.g., Gunn, & Sein, 2000) and to conflicts among different types of tourists and recreationists who use public lands to pursue various activities (e.g., McKercher, 1992). These potential negative impacts associated with the provision of roads have led some to call for greater scrutiny of methods to control road access (Henschel, 2003).

While many negative impacts associated with road access are understood, little attention has been spent on trying to understand how, if at all, road access provides benefits to outdoor recreationists. This information on the potential benefits of road access to recreationists is paramount if one is to make decisions about the creation, removal, or maintenance of roads.

To answer partially the question of benefits about road access to recreationists, a study of the relationships between road access and fishing site choices of resident northern Ontario anglers during the open water fishing season was conducted. The two study areas chosen for the investigation permitted an assessment of whether the fishing site choices by resident northern Ontario anglers were affected differently by changes to the quality of road access. A choice modelling approach was used because of the strong precedence of choice model applications to study recreational fishing site choice (see Chapter 3) and since qualitative interviews suggested that trade offs are important to anglers when they choose their fishing sites (see Section 5.1).

The choice models suggested that the effects of roads on angling behaviours differed among anglers. Poor quality logging roads and trails negatively influenced the fishing site choices of Thunder Bay area anglers who only fish during the open water season. Conversely, Thunder Bay anglers who fish year round were less likely to have their fishing site choices affected by varying qualities of roads and trails. This difference between these two angler types was hypothesized to arise for at least two reasons. First, anglers who fish year round likely view angling as a more central activity to their lifestyles than do anglers who fish only during the open water season. Second, anglers who fish during winter have the ability to travel by snowmobile to fishing sites that are difficult to reach during the open water season. This ability to travel easily in the winter may increase the awareness of available fishing sites by these anglers.

The results do not suggest that anglers who fish year round were indifferent between travelling on different quality roads and trails. Rather, an equilibrium exists whereby trade offs among road quality, congestion, and fishing quality already existed. The comparative rather than experimental approach used to examine fishing site choice likely masked some trade offs among road quality, encounters and fishing quality. In fact, the finding that sites with greater than a 500m trail had much higher expected catch rates for walleye (see Table 7.1.2) provided evidence for the existence of these trade offs.

The Wawa area choice model results differed from the results of the Thunder Bay area choice models (see Appendix E). The parameter estimates from the Wawa data for the good and okay quality gravel roads actually exceeded the value for the paved roads. This does not suggest that these anglers preferred travelling on gravel roads. Instead, this result more likely arose since Wawa area anglers use gravel logging roads to access fishing sites because: they were more aware of fishing opportunities along these logging roads; and they expected fewer encounters with other anglers when avoiding easily accessible lakes. Results from questions within the angling diary (see Tables 5.3.1 and 5.3.4) supported the notion that the awareness of fishing opportunities by anglers was limited. This limited awareness implied that anglers should know about better fishing opportunities near their communities even if these opportunities were less accessible than were other opportunities that were located further away.

While the Wawa area estimates for the poor quality gravel roads and trails were not significantly different from paved roads, these estimates were significantly different and more negative than were the estimates for good and okay gravel roads. This finding supported the view that Wawa area anglers were negatively impacted by the presence of poor quality gravel roads and trails. Appendix E, however, revealed that impacts of road quality were much more pronounced on the site choices of Thunder Bay than on Wawa area anglers.

Three different management scenarios that focused on aspects of road access were examined. For the Thunder Bay area, degrading a large network of logging roads into poor quality gravel roads and trails result in significant changes to both the spatial pattern of angling effort and the economic value of recreational fishing. A second scenario showed that adding road access to Wawa area lakes that currently have remote tourism operations would result in a positive yet small increase to the economic value of recreational fishing. Finally, while the creation of logging roads that create greater connectivity among existing Wawa area, logging roads would result in some shift in use patterns by anglers, the economic value of these connecting roads was not significantly different from zero. These management scenarios highlighted the utility of the fishing site choice models to answer the question about the benefits of road access to recreational anglers.

One may use the information related to changes in the economic value of recreational fishing to assist managers in decision-making. For example, anglers were predicted to receive a benefit of approximately \$3 per trip from a successful restoration of walleye into Black Bay, Lake Superior. This restoration will likely only be successful if costs are incurred to remove barriers on tributaries that walleye would likely use for spawning. By estimating changes to fishing participation (i.e., the number of trips) in addition to the change in the value of recreational fishing per trip, one may begin assessing the costs and benefits of this restoration effort. Obviously, managers would require information about benefits and costs to various users and non-users of Black Bay when conducting their cost benefit analysis.

The fishing site choice models revealed many other interesting aspects of angling behaviours. Chapters 3 and 4 described six general attributes related to recreational fishing site choice. The fishing site choice models provided some support for the importance of including many of these attributes.

Travel costs acted a deterrent to anglers when choosing a fishing site. This effect was strongest for anglers who were pursuing day as opposed to multiple day trips. This difference in effect between trip duration reflected both the reduction of time constraints associated with multiple day trips and the willingness of individuals to pursue other activities besides fishing on multiple day excursions. Consequently, travel costs were more important to anglers who took day as opposed to multiple day trips. This was especially true of fishing sites near urban centres that most anglers avoided when taking multiple day fishing trips.

Fishing quality was also an important general attribute for anglers when choosing fishing sites. The availability of desirable fish species at a fishing site was important to anglers. Since walleye is highly preferred by anglers (see Table 5.2.1), it was not surprising that the availability of walleye was important to anglers when selecting a fishing site. The availability of other fish species such as smallmouth bass and trout were also important to many anglers when selecting fishing sites. For Thunder Bay area anglers, the average reported catch rate for rainbow trout and the expected catch rate for walleye were also strongly related to the fishing site choices made by these anglers. The water body area was important for fishing site choice as large sized waters received more trips than did smaller sized waters, *ceteris paribus*. While one may assume that water body size is an indicator of fishing quality, the answers to questions on fishing site awareness (see Table 5.3.4) suggested a different effect. Large sized water bodies may be important to anglers since anglers were more aware of these water bodies than smaller sized water bodies. As such, the water body size attribute was probably more indicative of awareness than a true expression of preference for a fishing quality attribute.

Facility development as measured by types of boat launching facilities was important to anglers. Anglers who fished from boats desired better quality boat launches while anglers who fished from shore tended to fish in areas void of boat launches. For the Wawa area anglers this result was slightly different as those anglers who fished from boats preferred any type of boat launch to sites where no boat launch was available. No measures for environmental quality were included in the model.

Expected encounters with other anglers were assessed in the Thunder Bay model through a proxy variable that measured cottage development (i.e., lakes with high development will likely have many recreationists). Thunder Bay anglers preferred fishing sites that were not located in areas with extensive cottage development, *ceteris paribus*. Finally, the importance of regulations was considered through the availability of fish species. These availability attributes were developed by considering the presence and the legality of keeping caught fish in the different water bodies. The significant availability estimates show that resource managers have the great potential to influence fishing effort by using regulations that prohibit the retention of some fish species in certain areas.

The fishing site choice models were very elaborate as they included many alternatives and accounted for spatial complexities in several ways. To accommodate these complexities, other aspects of the model were simplified. One simplification involved attempts to account for preference heterogeneity. Instead of more complex random parameters or latent class choice models, the models employed simple interactions between observable angler characteristics and the site choice attributes. This simplification may have hidden some variability in anglers' preferences for the different attributes.

Many geographers have criticized choice models for failing to incorporate the complexity of space (Fotheringham, & O'Kelly, 1989; Pellegrini, & Fotheringham, 1999, 2002; Pellegrini *et al.*, 1997). Therefore, a secondary purpose of the dissertation was to investigate three different approaches to account for space in a choice model. In all three instances, the results were partially conditional upon the spatial connectivity matrices employed to link the fishing site information (see Section 6.4).

Like the vast number of competing destinations model applications, an accessibility measure was included in the fishing site choice models to account for limitations in the spatial cognition of anglers. Although many spatial choice model applications have used these accessibility measures, little if any attention has focused on whether the accessibility parameter varies in importance for different choice makers. This omission is surprising given that one would expect heterogeneity in the spatial cognitive abilities of decision-makers.

The accessibility measure, which was a composite measure of water area and Euclidean distance separating fishing sites, provided mixed results in the models. For the Wawa area anglers, the accessibility term was significant and negative in sign as is typically found in spatial choice model applications (Pellegrini, & Fotheringham, 2002).

The results for Thunder Bay area anglers suggested that the accessibility term was positive in sign and significant for anglers who took multiple day trips. Therefore, Thunder Bay anglers who took multiple day trips often chose fishing sites that were located near other water bodies, *ceteris paribus*. The summary of the qualitative interviews (see Section 5.1.3) implied that some anglers would choose their fishing sites in close proximity to other sites. This insurance strategy would provide nearby alternatives in case the conditions at the initially chosen site were not as expected (e.g., a campsite is full).

The results from the fishing site choice models suggested that some anglers are affected differently by this spatial cognitive attribute. For the Wawa area anglers, the effect of the accessibility measure was significant and negative. However, Wawa area anglers who took multiple day fishing trips were much more heavily influenced by the accessibility measure than were anglers who took day fishing trips. Consequently, multiple day trips by Wawa area anglers often occurred at water bodies that were isolated from other waters.

A second spatial measure included in the choice models attempted to capture dynamic like decision-making. The spatial state dependence measure was included as the spatial alternative to the traditional state dependence measure employed to handle dynamic like behaviours. A relative measure for spatial state dependence was chosen to avoid high collinearity between this measure and the effect of travel distance.

The spatial state dependence measure was not significant for the Wawa area model. However, the measure was significant and negative in sign for the Thunder Bay area model. The significant finding suggested that anglers' trips were often taken in close proximity to their past trips. Since the initial conditions (Heckman, 1981b) were not assessed, one cannot conclude that the significant finding arose from a nuisance or substantive perspective. Responses to the diary questions, however, suggest that anglers have limited awareness of fishing opportunities and often identify with specific fishing areas (see Tables 5.3.4 and 5.3.5). The limited awareness of fishing opportunities and place attachment to fishing areas suggested that one cannot explain the significance of the spatial state dependence measure from solely a nuisance perspective.

The differences in results for the accessibility and spatial state dependence attributes for Wawa and Thunder Bay area anglers likely arose for two reasons. These reasons included behavioural differences between Wawa and Thunder Bay area anglers (see Sections 5.2 and 5.3) and the different spatial structure (e.g., number and locations) of fishing alternatives.

The final spatial measure included in the choice models was designed to capture correlations among the unobserved utilities of the sites. While a nested logit offers one method to account for shared unobserved utilities, researchers (Pellegrini, & Fotheringham, 1999, 2002; Pellegrini *et al.*, 1997) often criticize the nested logit since it requires researchers to *a priori* partition space into non-overlapping discrete nests. A cross-nested logit model was estimated that permitted alternatives to be allocated among many different nests. Following Bhat and Guo (2004), a deterministic approach was used to allocate the alternatives into the various nests. This deterministic allocation was based on the inverse road distances that separated the site from various spatial support points (i.e., the nests). These spatial support points were strategically chosen to test whether spatial heterogeneity existed without excessively burdening model estimation[65]. To provide a maximal contrast to the nested logit, the allocation of each alternative to each nest was based on the inverse distance between the site and the spatial support point

[65] It is feasible to have nests for every pair of alternatives.

divided by the sum of inverse distances between the site and all spatial support points. This allocation resulted in all alternatives partially belonging to all nests.

Akiake Information Criterion tests favoured the cross-nested logit over the nested logit model. For both the Thunder Bay and Wawa area models, fishing sites in close proximity acted as much better substitutes than were fishing sites that were located further away. This finding was present even with the inclusion of the spatial state dependence and spatial accessibility measures in the models.

A final generalization to the choice models involved relaxing the assumption that a global dissimilarity parameter was sufficient to capture the spatial substitution process among the alternatives. Results from generalized nested logit (GNL) models from the Thunder Bay and Wawa data rejected the assumption of a global dissimilarity parameter. The GNL found interesting spatial pockets whereby the correlation in unobserved utility among sites was much different than it was for other areas. While not truly a local estimate, the GNL approach provided a convenient method to account for some spatial heterogeneity in the spatial substitution process among the fishing sites. The management scenarios helped to demonstrate the flexible patterns of substitution that are possible with a GNL or even cross-nested logit.

The choice set was also simplified. A naive implicit choice set modelling approach was employed that weighted the likelihood of choosing a fishing site by aspects related to spatial cognition and site awareness. While the spatial cognition aspects are typically included with these naïve implicit choice set models, the importance of the site awareness attribute demonstrates that the fuzziness of choice alternatives is affected by more than space. Consequently, the choice model estimates were likely impacted by not fully specifying the awareness of fishing alternatives.

The decision to participate in fishing was not included in the analyses. While the inclusion of a participation model would link changes to environmental quality to trip taking, the dissertation focused on fishing site choice and ways to account for spatial complexities in choice models.

Other simplifications to the models were undertaken to reduce the complexity of model estimation. First, the fishing quality attributes likely introduce some problems to model estimation. These problems arise from using reported average catch rates for rainbow trout instead of expected catch rates and for not accounting for the errors associated with estimates for expected walleye catch rates. No explicit treatment of the initial conditions was conducted along with the estimates of the state dependence and spatial state dependence attributes. By not formally accounting for the initial conditions, one cannot state with certainty that these dynamic like measures captured substantive processes or statistical nuisances (e.g., model misspecification, variation in tastes for attributes, etc.).

The treatment of space within the fishing site choice models may be enhanced in future efforts. For example, one could use a random parameters approach to account for the expected heterogeneity in spatial cognitive abilities among anglers. This random parameters treatment would allow one to investigate the extent of heterogeneity within the accessibility measures. The limited evidence from this study indicates that the effects of spatial cognition of fishing site choice vary over the population of anglers. Future research could also enhance the spatial state dependence measure by considering whether the previous trip is a sufficient lag for identifying spatial habit like behaviour (i.e., should additional attributes be included for lags beyond the most recent trip). Finally, researchers could enhance the GNL model by estimating the allocation of alternatives to the various nests rather than deterministically allocating portions of alternatives to the nests. This statistical allocation would avoid many concerns over the sensitivity of the results to the spatial connectivity matrix chosen (see Sections 2.1.1 and 6.4).

The dissertation began by emphasizing that change, complexity, conflict and uncertainty affect many problems in resource management (Mitchell, 2002). This study has provided new information that can help to reduce some uncertainties associated with understanding the benefits of road access to northern Ontario resident anglers. The choice models, which embrace the uncertainty of the researcher (i.e., random utility theory), provide a convenient tool to forecast how change may influence both the spatial pattern of angling behaviours and the economic value of recreational fishing. Decision-makers may use this information to help alleviate conflicts among anglers and other competing users of resources (e.g., resource based tourists, commercial fishers, etc.).

Appendix A: Review of recreational fishing site choice model applications

Authors	*Data set*	*Fishery*	*Model*	*Alternatives*	*Travel Cost*	*Fishing Quality*	*Water Area*	*Water Quality*	*Aesthetics*	*Boat Ramp*
Milon (1988a)	Florida 1985	Marine	NL	13 zones	-	+				
Milon (1988b)	Florida 1985	Marine	NL	13 zones	-	+				
Bockstael *et al.* (1989)	Florida 1987	Marine	NL	9 zones	-					
Morey *et al.* (1991)	Oregon 1981	Marine	NL	7 zones	-	NS				
Creel & Loomis (1992)	California 1988	Unsure	MNL	14 sites	-	+				
Parsons & Kealy (1992)	Wisconsin 1978	Fresh	MNL	1133 sites	-	+		+		-
Parsons & Needleman (1992)	Wisconsin 1978	Fresh	MNL	1133 sites	-	+		+		-
Parsons & Kealy (1994)	Wisconsin 1978	Fresh	MNL	1133 sites	NLin	+	+	+		-
McConnell *et al.* (1995)	Maryland 1987	Marine	MNL	7 zones	-	+				
Morey *et al.* (1993)	Maine 1988	Fresh	NL	8 zones	NLin	NLin				
Shaw & Ozog (1999)	Maine 1988	Fresh	NL	8 zones	NLin	NLin				
Adamowicz (1994)	Alberta 1990	Fresh	MNL	9 sites	-	VS				
Feather (1994)	Minnesota 1989	Fresh	MNL	3500 sites	-		+	+		
Feather *et al.* (1995)	Minnesota 1989	Fresh	NL	3500 sites	-		+	+		
Lupi & Feather (1998)	Minnesota 1989	Fresh	NL	1667 sites	-		+	+		
Tay & McCarthy (1994)	Indiana 1985	Fresh	MNL	366 zones	-		+	+		
Tay *et al.* (1996)	Indiana 1985	Fresh	MNL	9 zones	-		+	+	+	
Watson *et al.* (1994)	Alberta 1991	Fresh	MNL	19 sites	NLin	+	+	+		
Peters *et al.* (1995)	Alberta 1991	Fresh	MNL	67 sites	-	+	+	+	+	
Hausman *et al.* (1995)	Alaska 1989	Both	NL	9 zones	-	-		+		
Kaoru (1995)	North Carolina 1981	Marine	NL	35 sites	-	+		VS		+
Kaoru *et al.* (1995)	North Carolina 1981	Marine	MNL	35 sites	-	+				+
Ahn *et al.* (2000)	North Carolina 1996	Fresh	NL	97 streams	-	+	+	+		
Kling & Thomson (1996)	California 1989	Marine	NL	8 zones	-	+				
Lin *et al.* (1996)	Oregon 1988	Fresh	MNL	4 zones	-	+				
Greene *et al.* (1997)	Florida 1991	Both	NL	7 zones	-					
Jakus *et al.* (1997)	Tennessee 1994	Fresh	NL	31 sites	-	VS		+		+
Parsons *et al.* (1999)	Tennessee 1994	Fresh	NL	14 Reservoirs	-	+		+		+
Montgomery & Needleman (1997)	New York 1989	Fresh	NL	3100 sites	-	+		+		+
Chen & Cosslett (1998)	Michigan 1983	Fresh	MNP	41 sites	-	+		+	+	
Jones & Lupi (1999)	Michigan 1983	Fresh	NL	41 sites	-	VS	+	VS	+	

Authors	*Data set*	*Fishery*	*Model*	*Alternatives*	*Travel Cost*	*Fishing Quality*	*Water Area*	*Water Quality*	*Aesthetics*	*Boat Ramp*
Jakus *et al.* (1998)	Tennessee 1997	Fresh	MNL	14 Reservoirs	-	+				NS
Jakus & Shaw (2003)	Tennessee 1997	Fresh	MNL	14 Reservoirs	-	+		+		+
Morey & Waldman (1998)	Montana 1992	Fresh	NL	26 rivers	NLin	+			+	
Train (1998)	Montana 1992	Fresh	RPL	59 rivers	-	+	+		+	
MacNair & Cox (1999)	Montana 1992	Fresh	NL	253 sites	-	+	+		+	
Morey *et al.* (2002)	Montana 1992	Fresh	NL	26 rivers	NLin	+			+	
Parsons & Hauber (1998)	Maine 1989	Fresh	NL	1899 sites	-	+	+	VS		
Breffle & Morey (2000)	Maine 1989	Fresh	RPL	8 areas	-	+				
Hauber & Parsons (2000)	Maine 1989	Fresh	NL	1899 sites	-	+	+	VS		
Pendelton & Mendelsohn (1998)	Northeast US 1989	Fresh	MNL	513 lakes	-	+				
Phaneuf *et al.* (1998)	Wisconsin 1990	Fresh	RPL	22 aggregates	-	+		+		
Whitehead & Haab (1999)	Southeast US	Marine	MNL	70 Counties	-	+				
McConnell & Tseng (2000)	Northeast US 1994	Marine	RPL	63 sites	-	+				
Parsons *et al.* (2000)	Maine 1994	Fresh	NL	814 sites	-	+				
Provencher *et al.* (2002)	L. Michigan 1996	Fresh	LCM	1 site	-	+				
Schuhmann & Schwabe (2004)	North Carolina 1998	Fresh	MNL	10 sites	-	+				
Swait *et al.* (2004)	Australia no date	Marine	GEV	3 zones	-	VS				

MNL Multinomial logit model
NL Nested Logit model
RPL Random parameters logit model
LCM Latent class choice model
GEV Other generalized extreme value model
\+ positive relationship
\- negative relationship
NLin non-linear
VS varies

Appendix B: Communications with anglers

B.1: Qualitative interview script (used as a guide by interviewers)

BACKGROUND

- How long have they fished?
- Who do they normally fish with?
- How serious of an angler are they?

DECIDING ON FISHING SITES

- How do they go about deciding whether or not to fish? (if necessary provide prompts of past fishing trips, season, weather, weekend vs. week day)
- How do they go about deciding where to fish? (what do they decide first (species, region, other); what next?
- If necessary, what factors are important in determining where to fish? (special emphasis on the accessibility of the water body)
- How important are the locations of nearby fishing sites to their choice?
- How important are the locations of other amenities such as stores to their choices?
- How do (have) they learn(ed) about new fishing sites?

PAST FISHING TRIP

- Where did they last go fishing?
- What species did they target?
- How many fish did they and others catch by species (how many others)?
- How many hours and days did they and others spend fishing?
- About how many other anglers did they see while fishing?
- What did they like about their fishing experience?
- What didn't they like about their fishing experience?

B.2: Telephone survey script and questions

Hi my name is ___________ from Northern Ontario On-call and I am phoning on behalf of Len Hunt who is a Ph.D. candidate at Wilfrid Laurier University in the Department of Geography and Environmental Studies. Len is examining residential recreational fishing behaviours in northern Ontario to better understand the factors that are important to anglers when and where deciding to fish. This research will provide much needed information to resource managers and to angling stakeholders about the importance and value of recreational fishing in northern Ontario. We would like to ask you a few basic questions about fishing and determine your willingness to assist this study by completing an angling diary for this upcoming year. Both of these tasks will take less than five minutes. Your responses will remain confidential as we will provide Len with the data and we will delete our records. Your participation in the telephone survey and angling diary is strictly voluntary and you may terminate the survey or diary at any time. The research has been approved by the Wilfrid Laurier University Ethics Board and you may contact Bill Marr @ (519) 884-0710 (Ext. 2468) if you have any questions about the ethics of the research. If you are interested in learning more about the study or obtaining copies of the study results, you may contact Len Hunt at (807) 343-4007 (hunt5510@wlu.ca). May we proceed by asking you a few questions about fishing?

B.3: Telephone interview questions

1. **Do you intend to fish in northern Ontario during the upcoming summer season this year (2004)?**

   - ❑ no →*(Thank individual for time and terminate interview)*
   - ❑ yes

2. **Did you fish last year?**

   - ❑ no →*(skip to question 5)*
   - ❑ yes

3. **About how many days did you fish last summer?** ________

4. **About how many days did you fish last winter?** ________

5. **About how many years have you fished anywhere?** ________

6. **Which of the following equipment do you own or have access to for fishing?**

Equipment	*Own*	*Have access to*	*Neither*
Canoe	❑	❑	❑
Boat	❑	❑	❑
Outboard Motor	❑	❑	❑
Car/ Minivan	❑	❑	❑
2 wheeled drive truck/SUV	❑	❑	❑
4 wheeled drive truck/SUV	❑	❑	❑
All terrain vehicle	❑	❑	❑

7. **Did you purchase a fishing licence last year?**

   - ❑ no →*(skip to question 9)*
   - ❑ yes

8. **What type of licence did you purchase?**

   - ❑ Conservation
   - ❑ Regular

9. **What northern Ontario fish species do you fish for most often?** ________________

10. **What is your age?** ________________

11. **What is your postal code** ________________

12. **As stated earlier, we would like to know if you are willing to further assist this study by agreeing to participate in an angler diary program? Your participation would involve completing an angling diary that describes aspects about your fishing trips for the upcoming open water season (April until September). The research is a joint effort by the Ontario Ministry of Natural Resources and Wilfrid Laurier University. The funding for this research**

comes from the Living Legacy Trust, the Ontario Ministry of Natural Resources, the Ontario Federation of Anglers and Hunters and the Northwestern Ontario Sportsmen's Alliance. As tokens of appreciation, we will provide you with a small gift when we mail the diary and opportunities to participate in lotteries for additional prizes.

- ☐ no →*(Thank individual for time and terminate interview)*
- ☐ yes

13. **Thank you. You will receive a diary in the mail over the next few weeks. Therefore, let me make sure I have your correct name and address** *(Legibly print the following information and ask the individual to spell her/his name)*.

Name ______________________

Street Address ______________________

City ______________________

Postal Code ______________________

Phone Number ______________________

B.4: Initial mail covering letter

April 8, 2004

Re: Participation in the northern Ontario Angling Diary Program

Thank you once again for agreeing to participate in this angling diary study. The information you provide will allow us to identify those aspects of fishing sites that are important to anglers like yourself. Furthermore, the information will allow us to develop predictive models of angling behaviours and to assess the changes in the value of fishing arising from changes to either the resource or management of the resource. The predictive models will provide managers with a better understanding of how the decisions made at one fishing site are likely to affect recreational fishing at all fishing sites. The estimation of the value of recreational fishing will also permit fisheries managers to assess how their decisions are likely to impact the economic benefits that anglers like yourself realize from fishing. In fact, managers can assess both of the above aspects before drafting a management change. This fact should help to lessen conflicts between resource managers and anglers like yourself.

The study is supported by angling stakeholder organizations (Ontario Federation of Anglers and Hunters and Northwestern Ontario Sportsmen's Alliance, Michipicoten Rod & Gun Club), the Ontario Ministry of Natural Resources, and the Northern Ontario Tourism Outfitters Association. All of these groups recognize the potential benefits that this study has for anglers like you.

We ask that you complete your diary during or as soon as possible after each fishing trip (i.e., a trip to a different lake or river). I promise to you that any information you provide will be held in strict confidence. Your information will not be shared with anyone with exception of my research assistant and possibly my academic supervisory committee at Wilfrid Laurier University (my advisor is Dr. Barry Boots with the Department of Geography and Environmental Studies at Wilfrid Laurier University). Although there is an identification number on the diary, this number is only used to reduce our costs of mailing reminders only to individuals who have not returned a diary. Only I have access to the database that links your diary and name, and I will sever this link after the data collection is complete. Furthermore, only results based on aggregated data will appear in products arising from the study that will include my thesis, journal papers, and presentations.

Although the study time frame covers the period from April to the end of September, this diary corresponds only to your fishing trips in April and May. Towards the end of May we will send you a diary for the second two month time period along with a self addressed return envelope with paid postage for this completed first diary.

Your response is very important as only 1000 individuals from across northern Ontario are participating in this study. As a small token of appreciation, we have included a fishing lure that we hope brings you good luck for the upcoming season. As well, we will be conducting raffle draws for ten $100 gift certificates from Canadian Tire after we collect each of the three two month diaries. Your participation in the study is voluntary and at any time you may withdraw from the study or refuse to answer any questions you do not wish to answer.

If you have any questions about the study, would like to obtain a copy of the results, or if you would like us to collect the diary information from you via telephone, please contact Len Hunt through one of the modes below. If you have any questions about the ethics of this research that has been approved by the Wilfrid Laurier Ethics Research Board, please contact Bill Marr at (519) 884-0710 (Ext. 2468).

Happy fishing,

Len Hunt
e-mail: **hunt5510@wlu.ca** OR **len.hunt@mnr.gov.on.ca**
phone: (807) 343-4007
fax: (807) 343-4001

B.5: Follow-up covering letter (same for June and August contacts)

August 3, 2004

Re: Participation in the northern Ontario Angling Diary Program

Thank you once again for agreeing to participate in this angling diary program. The information you provide will help to ensure that recreational angling values are better understood by decision-makers and stakeholders who seek to represent your angling interests.

This mail package should contain an entry ballot, the third and final diary (August and September), and a return envelope. The entry ballot provides you with an opportunity to win one of ten $100 gift certificates from Canadian Tire or Superior Sportsmen. To enter the draw, simply complete the ballot, fold in half your completed second fishing diary for your June and July trips (even if you took no trips) and return the ballot and diary in the enclosed self addressed return envelope (no postage is necessary). The ten randomly selected winners will be notified by the end of August. We will also be holding other draws for ten additional $100 gift certificates when the final diary is returned.

If you have not yet submitted your first diary covering your April and May trips, please include these trip details in your June and July diary. If you have misplaced your June and July diary, please complete your information for June and July on the diary that is included in this package.

Please be assured that any information you provide will be treated confidentially. Only myself and one other assistant will have access to your diary data. Your individual data will not be shared with anyone else.

If you have any questions about the study, would like to obtain a copy of the results, or if you would like us to collect the diary information from you via telephone, please contact Len Hunt. If you have any questions about the ethics of this research that has been approved by the Wilfrid Laurier Ethics Research Board, please contact Bill Marr at (519) 884-0710 (Ext. 2468).

Happy fishing,

Len Hunt
e-mail: **hunt5510@wlu.ca** OR **len.hunt@mnr.gov.on.ca**
phone: (807) 343-4007
fax: (807) 343-4001

B.6: Final mail covering letter

September 23, 2004

Re: Participation in the northern Ontario Angling Diary Program

Thank you for your participation and cooperation with the northern Ontario angling diary program. Without your assistance, the study would be unsuccessful. Your diary information will allow us to identify those aspects of fishing sites that are important to anglers like yourself.

The study is supported by angling stakeholder organizations (Ontario Federation of Anglers and Hunters and Northwestern Ontario Sportsmen's Alliance, Michipicoten Rod & Gun Club), the Ontario Ministry of Natural Resources, and the Northern Ontario Tourism Outfitters Association. All of these groups recognize the potential benefits that this study has for anglers like you.

Please find a postage paid self-addressed return envelope and ballot enclosed. <u>We ask that you return your August and September diary by folding the diary and placing it into the self-addressed return envelope</u>. To enter the draws for ten $100 gift certificates from either Canadian Tire or D&R Sporting goods, simply complete the ballot and place it with your completed diary in the return envelope. The winners of the draws will be notified in early November.

In terms of fairness, here are some details of my two fishing trips from 2004. One trip was to Sioux Lookout (June 11-13) where I fished on Abram and Minnitaki Lakes and Lac Seul for walleye (pickerel). The fishing on Lac Seul was very good (45 walleye in six hours). The only other trip I took (August 6) was to Arrow Lake (near Sandstone Lake) where I fished for walleye and was skunked.

If you have any questions about the study, would like to obtain a copy of the results, or if you would like us to collect the diary information from you via telephone, please contact Len Hunt through one of the modes below. If you have any questions about the ethics of this research that has been approved by the Wilfrid Laurier Ethics Research Board, please contact Bill Marr at (519) 884-0710 (Ext. 2468).

Sincerely,

Len Hunt
e-mail: **hunt5510@wlu.ca** OR **len.hunt@mnr.gov.on.ca**
phone: (807) 343-4007
fax: (807) 343-4001

B.7: Front questions for April/May and June/July Northern Ontario Angling Diary

1. Do you own a private camp/cottage?

- ❑ no
- ❑ yes (please specify the nearest lake/river ________________________________)

2. Do you have access to someone else's private camp/cottage?

- ❑ no
- ❑ yes (please specify the nearest lake/river ________________________________)

3. Do you typically rent a camp/cottage or trailer site?

- ❑ no
- ❑ yes (please specify the nearest lake/river ________________________________)

4) How important are the following information sources to you for learning about __new fishing__ opportunities in northern Ontario? *(please circle a number for each statement)*

I learn from	*not at all important*		*somewhat important*		*very important*
...other anglers I normally fish with	1	2	3	4	5
...other anglers I don't normally fish with	1	2	3	4	5
...Ontario MNR maps	1	2	3	4	5
...other maps	1	2	3	4	5
...Ontario's Fishing Summary	1	2	3	4	5
...Ontario MNR publications	1	2	3	4	5
...Ontario MNR District Offices	1	2	3	4	5
...Ontario MNR Conservation Officers	1	2	3	4	5
...driving and exploring in new areas	1	2	3	4	5
... bait shops/ sporting goods stores/ licence issuers	1	2	3	4	5
...television fishing shows	1	2	3	4	5
...newspaper media	1	2	3	4	5
...outdoor magazines	1	2	3	4	5
...internet sources	1	2	3	4	5
...other sources *(please specify below)*	1	2	3	4	5

____

5. Below is a list of reasons why people fish. How important is each item for you as a reason for fishing in Ontario. *(please circle the appropriate number for each reason)*

Reasons	*Not at all important*		*Somewhat important*		*Very important*
For relaxation	1	2	3	4	5
For family recreation	1	2	3	4	5
For the experience of the catch	1	2	3	4	5
For physical exercise	1	2	3	4	5
For the challenge or the sport of fishing	1	2	3	4	5
To obtain fish for eating	1	2	3	4	5
To get away from other people	1	2	3	4	5
To experience new and different things	1	2	3	4	5
To test my equipment	1	2	3	4	5
To catch a limit of fish	1	2	3	4	5
To be with friends	1	2	3	4	5
To experience natural surroundings	1	2	3	4	5
To obtain a trophy fish	1	2	3	4	5
To develop my skills	1	2	3	4	5
To get away from the daily routine	1	2	3	4	5
To be outdoors	1	2	3	4	5
To be close to water	1	2	3	4	5
To catch and release fish	1	2	3	4	5
To teach others to fish	1	2	3	4	5

Some questions about you:

6. You are:

- ❑ female
- ❑ male

7. Are you a member of a fishing club?

- ❑ No
- ❑ Yes (please specify ______________________________)

B.8: Front questions for August/September Northern Ontario Angling Diary

1) Where did you take your first ever fishing trip in the Thunder Bay (Wawa) area?

Lake/River name ____________________

Please name a close Landmark ____________________

2) For each of the following areas around Thunder Bay, how many fishing opportunities do you feel you know how to access ...? *(please circle a number for each area)*

	No fishing sites	*Only Large lakes*	*Large lakes and some smaller lakes*	*Almost every possible fishing site*
Ignace area (Highway 599)	1	2	3	4
Area west of Lac des Mille Lacs (e.g., Bedivere Lake)	1	2	3	4
Graham Road	1	2	3	4
Burchell Lake Road	1	2	3	4
Boreal Road	1	2	3	4
Dog River area	1	2	3	4
Dog Lake area	1	2	3	4
Northern Light Lake area (Hwy 588)	1	2	3	4
Armstrong Highway (south end of Hwy 527)	1	2	3	4
Armstrong Highway (north end of Hwy 527)	1	2	3	4
Area north of Loon Lake	1	2	3	4
Black Sturgeon Road	1	2	3	4
Nipgon River area (Hwy 585)	1	2	3	4
Beardmore area	1	2	3	4

3) Of the above areas, which area do you most often fish during the spring and summer *(please use a name from the list above)*

____

4) For the area that you most often fish, please state your agreement/disagreement with the following statements? *(please circle a number for each statement)*

	Strongly Disagree	*Disagree*	*Neutral*	*Agree*	*Strongly Agree*
I feel like this area is part of me	1	2	3	4	5
This area is the best place for fishing	1	2	3	4	5

This area is very special to me	1	2	3	4	5
No other area can compare to this area	1	2	3	4	5
I identify strongly with this area	1	2	3	4	5
I get more satisfaction out of visiting this area than from visiting any other area	1	2	3	4	5
I am very attached to this area	1	2	3	4	5
Fishing in this area is more important than fishing in any other area	1	2	3	4	5
Visiting this area says a lot about who I am	1	2	3	4	5
I would enjoy fishing in a different area just as much as I enjoy fishing here	1	2	3	4	5
This area means a lot to me	1	2	3	4	5
I would not substitute any other area for the fishing I do here	1	2	3	4	5

5) How important are the following aspects of fishing to you when choosing a fishing site?
(please circle the number that best reflects your level of importance)

	Not at all important		*Somewhat Important*		*Very Important*
Travel distance	1	2	3	4	5
Preferred fish species	1	2	3	4	5
Lots of fish	1	2	3	4	5
Big fish	1	2	3	4	5
Few other anglers	1	2	3	4	5
Well maintained roads	1	2	3	4	5
Areas accessible only by four wheeled drive vehicle or ATV	1	2	3	4	5
Camping areas	1	2	3	4	5
Large lake or river	1	2	3	4	5
Boat launching facilities	1	2	3	4	5

B.9: Trip questions from the Northern Ontario Angling Diary

Northern Ontario Fishing Diary

Starting date for the fishing trip to this site *(Day/Month/Year)*

____

Duration of trip at this fishing site *(# of days)*

____

Lake / River Name *(if on a river/ large lake, please also specify the access point)*

____

Name a close landmark to this fishing site *(e.g., large lake, community or a store)*

____

Was this trip <u>to</u> a private or commercial camp/cottage?	❑ *Yes*	❑ *No*
Is this fishing trip part of a longer trip from home?	❑ *Yes*	❑ *No*

If YES, where was this fishing trip taken from? *(please be specific)*

____

What was the approximate driving <u>time</u> to site *(1-way driving time in hours)*

____

How many individuals including you were ...

	Children 17 years or less	Females 18 years or older	Males 18 years or older
on this fishing trip			
fished during this trip			

Which of the following vehicles did YOU use to access this fishing site?

Yes	*No*	
❑	❑	*Car or van*
❑	❑	*Recreational Vehicle (RV)*
❑	❑	*Truck or sports utility vehicle in two-wheeled drive*
❑	❑	*Truck or sports utility vehicle in four-wheeled drive*
❑	❑	*All Terrain Vehicle (ATV)*
❑	❑	*Other (please specify)* ________________

Was fishing the primary purpose	❑ *Yes*	❑ *No*	**of <u>YOUR</u> trip?**
Did <u>YOU</u> fish from a boat/canoe	❑ *Yes*	❑ *No*	**on this trip?**

About how much time did <u>YOU</u> spend fishing during this trip *(total hours)* ________________

What fish species did <u>YOU</u> try and catch on this trip?

____

How many fish by species did <u>YOU</u> (not your party) catch *(include those released)* **during this trip?**

Number

________ *Pickerel (Walleye)*
________ *Northern Pike*
________ *Smallmouth Bass*
________ *Lake Trout*
________ *Speckled Trout (Brook Trout)*
________ *Other (please specify)*____

Appendix C: Telephone survey response comparisons between anglers who accepted and declined the angling diary invitation

Table C.1: Comparison of Thunder Bay anglers who accepted and declined diary invitation

Fishing Avidity

		Accepted (%)	*Declined (%)*	*Inferential Test*
Fished last year	*Yes*	93.4	90.3	χ^2: p=0.095

Days Fished		*Accepted (Mean (Std. Dev.))*	*Declined (Mean (Std. Dev.))*	*Inferential Test*
	Summer 2003	21.9 (26.2)	15.4 (21.0)	t-test: p=0.001
	Winter 2003	3.8 (9.5)	2.0 (5.4)	t-test: p<0.001

	Accepted (Mean (Std. Dev.))	*Declined (Mean (Std. Dev.))*	*Inferential Test*
Years Fished	32.4 (13.7)	31.2 (14.8)	t-test: p=0.235

Favourite Fish Species		*Accepted (%)*	*Declined (%)*	*Inferential Test*
	Walleye	79.4	77.3	χ^2: p=0.481*
	Lake Trout	5.6	4.7	* reduced groups
	Brook Trout	4.1	4.7	(walleye, lake trout
	Trout (not specified)	2.4	2.9	other trout, other)
	Northern Pike	1.5	1.4	
	Bass	2.0	4.0	
	Salmon	2.7	3.2	
	Walleye & Trout	0.5	0.0	
	Rainbow Trout	0.9	0.7	
	Others	0.9	1.1	

Fishing Licence		*Accepted (%)*	*Declined (%)*	*Inferential Test*
	None	5.8	8.6	χ^2: p=0.063
	Exempt	9.6	13.3	
	Conservation	10.1	11.9	
	Regular	74.5	66.2	

Equipment

		Accepted (%)	*Declined (%)*	*Inferential Test*
Canoe	No access	45.0	47.5	χ^2: p=.261
	Can access	14.8	10.8	
	Own	40.2	41.7	

		Accepted (%)	*Declined (%)*	*Inferential Test*
Boat	No access	9.8	14.7	χ^2: p=0.074
	Can access	12.1	10.1	
	Own	78.2	75.2	

		Accepted (%)	*Declined (%)*	*Inferential Test*
Outboard Motor	No access	7.5	15.5	χ^2: p=0.001
	Can access	10.7	10.8	
	Own	81.8	73.7	

		Accepted (%)	*Declined (%)*	*Inferential Test*
Car/Minivan	No access	27.5	24.5	χ^2: p=0.497
	Can access	2.4	1.8	
	Own	70.1	73.7	

		Accepted (%)	*Declined (%)*	*Inferential Test*
Truck/SUV (2wd)	No access	65.0	64.7	χ^2: p=0.996
	Can access	2.9	2.9	
	Own	32.1	32.4	

		Accepted (%)	*Declined (%)*	*Inferential Test*
Truck/SUV (4wd)	No access	34.8	43.2	χ^2: p=0.013
	Can access	4.6	1.8	
	Own	60.6	55.0	

		Accepted (%)	*Declined (%)*	*Inferential Test*
ATV	No access	66.9	68.7	χ^2: p=0.720
	Can access	5.5	4.3	
	Own	27.6	27.0	

Angler Characteristics

		Accepted (Mean (Std. Dev.))	*Declined (Mean (Std. Dev.))*	*Inferential Test*
	Age	46.7 (12.9)	47.2 (14.3)	t-test: p<0.001

	Accepted	*Declined*
Sample Size	655	278

Table C.2: Comparison of Wawa area anglers who accepted and declined diary invitation

Fishing Avidity

		Accepted (%)	*Declined (%)*	*Inferential Test*
Fished last year	*Yes*	96.9	95.9	χ^2: p=0.577

Days Fished		*Accepted (Mean (Std. Dev.))*	*Declined (Mean (Std. Dev.))*	*Inferential Test*
	Summer 2003	26.2 (26.8)	22.3 (30.2)	t-test: p=0.141
	Winter 2003	12.7 (17.1)	9.2 (15.1)	t-test: p=0.025

	Accepted (Mean (Std. Dev.))	*Declined (Mean (Std. Dev.))*	*Inferential Test*
Years Fished	27.5 (13.3)	28.3 (14.1)	t-test: p=0.816

Favourite Fish Species		*Accepted (%)*	*Declined (%)*	*Inferential Test*
	Walleye	74.6	74.3	χ^2: p=0.697*
	Lake Trout	4.3	5.3	* reduced groups
	Brook Trout	5.4	5.8	(walleye, lake trout
	Trout (not specified)	7.7	5.8	other trout, other)
	Northern Pike	5.1	6.4	
	Bass	0.0	0.6	
	Salmon	0.3	0.6	
	Walleye & Trout	1.4	0.6	
	Rainbow Trout	0.6	0.0	
	Others	0.6	0.6	

Fishing Licence		*Accepted (%)*	*Declined (%)*	*Inferential Test*
	None	4.0	11.1	χ^2: p=0.010
	Exempt	6.6	8.8	
	Conservation	9.1	7.0	
	Regular	80.3	73.1	

Equipment

		Accepted (%)	*Declined (%)*	*Inferential Test*
Canoe	No access	29.4	36.3	χ^2: p=.290
	Can access	11.1	9.9	
	Own	59.4	53.8	

		Accepted (%)	*Declined (%)*	*Inferential Test*
Boat	No access	9.1	12.9	χ^2: p=0.051
	Can access	6.3	11.1	
	Own	84.6	76.0	

		Accepted (%)	*Declined (%)*	*Inferential Test*
Outboard Motor	No access	8.6	15.8	χ^2: p=0.021
	Can access	6.9	9.4	
	Own	84.6	74.9	

		Accepted (%)	*Declined (%)*	*Inferential Test*
Car/Minivan	No access	42.9	43.9	χ^2: p=0.976
	Can access	1.1	1.2	
	Own	56.0	55.0	

		Accepted (%)	*Declined (%)*	*Inferential Test*
Truck/SUV (2wd)	No access	79.1	71.9	χ^2: p=0.171
	Can access	1.7	1.8	
	Own	19.1	26.3	

		Accepted (%)	*Declined (%)*	*Inferential Test*
Truck/SUV (4wd)	No access	21.1	29.8	χ^2: p=0.084
	Can access	3.4	2.3	
	Own	75.4	67.8	

		Accepted (%)	*Declined (%)*	*Inferential Test*
ATV	No access	45.1	52.6	χ^2: p=0.262
	Can access	6.9	5.3	
	Own	48.0	42.1	

Angler Characteristics

		Accepted (Mean (Std. Dev.))	*Declined (Mean (Std. Dev.))*	*Inferential Test*
	Age	43.2 (12.8)	43.7 (12.7)	t-test: p=0.654

	Accepted	*Declined*
Sample Size	350	171

Appendix D: GAUSS choice model programs

D.1: GAUSS program for estimating a MNL site choice model

```
/*                  MULTINOMIAL LOGIT APPLICATION FOR GAUSS

                     Requires MaxLik routine for estimation

                                Len Hunt

                              June 6, 2003 */


/* User defined values
    NOBS      = number of observations
    NVAR      = number of variables
    NALT      = number of choice alternatives
    BBB       = starting values for the parameters */


screen on;
NOBS   = 1152 ;
OVAR   = 47;
NALT   = 431;
NOBS2  = NALT * NOBS;

/* READ IN THE CHOICE DATA

The data should be organized as follows:

Each row should contain NVAR measures (attributes) for one individual
and one alternative and the final attribute must represent whether that
individual has chosen this alternative. The next rows must represent
the other NALT-1 alternatives that are faced by this individual. In
total, there must be NALT times NOBS rows in the data set and NVAR
variables
*/

load XX[NOBS2, OVAR] = c:\len\thbay\tballXB.dat;


/* PROVIDE INFORMATION ON WHICH VARIABLES WILL (1) AND WILL NOT (0) BE
INCLUDED AS INDEPENDENT VARIABLES FOR THE SITE CHOICE MODEL */

INC    =
{ 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
  1, 1, 1, 1, 1, 1, 1,
  1, 0, 1, 1, 1, 1,
  1,
  1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
  1, 1, 0,
  1, 1,
  1, 1, 1, 1, 1, 0, 0,
```

```
  0} ;


/*PROVIDE VALUES FOR SCALING THE ATTRIBUTES ~ NOTE THAT CONVERGENCE IS
MUCH FASTER IF ALL ELEMENTS IN THE HESSIAN ARE OF ABOUT THE SAME
MAGNITUDE */

SCL    =
{ 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
  1, 1, 1, 1, 1, 1, 1,
  1, 1, 1, 1, 1, 1,
  1,
  100, 100, 100, 10, 10, 1, 1, 10, 1, 100,
  1, 1, 1,
  1, 1,
  1, 1, 1, 100, 1, 1, 100,
  1} ;

/* PROVIDE A LIST OF PARAMETER NAMES */

PARNAMES = {"I_OUTSID", "I_UNKNOW", "LK_SUP","LK_NIP", "KAM RIV", "DOG
RIV",                   "DOG_LAKE", "D_OUTSID", "D_UNKN", "D_DRIV",
            "F_WALL", "F_BASS", "F_LTROUT", "F_BTROUT", "TRT*BASS",
"D_WALL",         "D_BASS", "W_CUE", "RT_CUE", "W_WCUE", "W_SPRT",
"D_WCUE",
            "LN_LKAR",
            "RD_ALL", "RD_GDGR", "RD_OKGR", "RD_PRGR", "RD_TRAIL",
"PORTAGE",        "W_RDPRGR", "W_RDTRL", "D_RDALL",
            "B*LN_CON",  "B*LN_NON",
            "COTTAGE", "W_COTT",
            "LN_CD", "LN_ACCPT", "T_HABITS", "S_HABITS", "DLNCD"};


NVAR = sumc(inc);
yMAT   = zeros(NOBS,NALT);
XREAL  = zeros(NOBS2,NVAR);
X      = zeros(NOBS,NALT*NVAR);

/* SPECIFY A SET OF STARTING VALUES FOR THE PARAMETERS */

BBB = ones(NVAR,1) * 0.1;

/* SHORTEN THE DATA SET TO INCLUDE ONLY RELEVANT VARIABLES*/
C = 1;
for I (1,OVAR,1);
      if INC[I,1] == 1;
            XREAL[.,C] = XX[.,I] / SCL[I];
      C = C + 1;
      endif;
Endfor;

/* RESHAPE THE INDEPENDENT AND DEPENDENT VARIABLE MATRICES */
for I (1, NOBS, 1);
      for j (1, NALT, 1);
      YMAT[I,J] = XX[J+(I-1)*NALT, OVAR];
            for k (1, NVAR, 1);
                  X[I,(J-1)*NVAR+K] = XREAL[(I-1)*NALT+J,K];
```

```
            Endfor;
      Endfor;
Endfor;

/* CLEAR MATRICES THAT ARE NOT USED */

clear XX;
clear XREAL;


/* CALCULATE THE LOG LIKELIHOOD
   USES GLOBALS NOBS NALT NVAR X YMAT */

proc ll(BB,X);
local p_util, J, p_ll, BASC;

p_util  = zeros(NOBS,NALT);
p_ll    = zeros(NOBS,1);
BASC    = BB;

for j (1,NALT,1);
    p_util[.,J] = exp(X[.,1+((J-1)*NVAR):NVAR*(J)]*BASC[1:NVAR,1]);
endfor;

p_ll = ln(sumc((p_util .* ymat)') ./ sumc(p_util'));
retp(p_ll);
endp;

/* CALCULATE THE GRADIENT
   USES GLOBALS NOBS NALT NVAR X YMAT */
proc GRAD(BB,X);
local J, resid, p_grad, BASC, p_util;

RESID   = zeros(NOBS,NALT);
P_GRAD  = zeros(NOBS,NVAR);
P_UTIL  = zeros(NOBS,NALT);
BASC    = BB;

for j (1,NALT,1);
    P_UTIL[.,J] = exp(X[.,1+((J-1)*NVAR):NVAR*(J)]*BASC[1:NVAR,1]);
endfor;

RESID = YMAT - (P_UTIL ./ sumc(P_UTIL'));
for j (1,NALT,1);
    P_GRAD[.,1:NVAR] = P_GRAD[.,1:NVAR] + (RESID[.,j] .* X[.,1+(J-
1)*NVAR:J*NVAR]);
endfor;
retp(P_GRAD);
endp;

/* CALCULATE THE HESSIAN
   USES GLOBALS NOBS NALT NVAR X YMAT */
proc HESN(BB,X);
local J, PROB, ALL, BASC, P_UTIL, KK, LL, STORE;

PROB   = zeros(NOBS,NALT);
ALL    = zeros(NVAR,NVAR);
```

```
P_UTIL = zeros(NOBS,NALT);
STORE  = zeros(NOBS,NVAR);
BASC   = BB;

for j (1,NALT,1);
    P_UTIL[.,J] = exp(X[.,1+((J-1)*NVAR):NVAR*(J)]*BASC[1:NVAR,1]);
endfor;

PROB = P_UTIL ./ sumc(P_UTIL');

for J (1,NALT,1);
    STORE[.,1:NVAR] = STORE[.,1:NVAR] + X[.,1+((J-1)*NVAR):NVAR*(J)] .*
PROB[.,J];
endfor;

for KK (1,NVAR,1);
    for LL (KK,NVAR,1);
        for J (1,NALT,1);
           ALL[KK,LL] = ALL[KK,LL] - sumc(PROB[.,J] .* (X[.,KK+((J-
1)*NVAR)] - STORE[.,KK]) .* (X[.,LL+((J-1)*NVAR)] - STORE[.,LL]));
        endfor;
        ALL[LL,KK] = ALL[KK,LL];
    endfor;
endfor;

retp(ALL);
endp;


/* MAXIMIZE THE LIKELIHOOD WITH THE MAXLIK LIBRARY ROUTINE */
library maxlik,pgraph;
maxset;
_max_GradProc = &GRAD;
_max_HessProc = &HESN;
_max_Parnames = PARNAMES;
{bb,f,g,cov,ret}=maxlik(X,0,&ll,BBB);
call maxprt(bb,f,g,cov,ret);

print _MAX_FINALHESS;

end;
```

D.2: GAUSS program for estimating nested, cross-nested and generalized nested logit models

```
/*              GENERALIZED NESTED LOGIT APPLICATION FOR GAUSS

                     Requires MaxLik routine for estimation

                              Len Hunt

                          NOVEMBER 12, 2004
*/

/* User defined values
    NOBS      = number of observations
    NVAR      = number of variables
    NALT      = number of choice alternatives
    BBB       = starting values for the parameters */

new;
screen on;
NOBS   = 1152 ;
OVAR   = 47;
NALT   = 431;
NOBS2  = NALT * NOBS;
NNEST   = 9;

/* ADD IN DETERMINISTIC ALLOCATIONS (0,1 for nested logit and decimals
for cross and generalized nested logit models) OF THE ALTERNATIVES TO
THE NESTS example

NNMEM = {
0.069709746 0.058714363 0.180592994 0.095503557 0.157744149 0.181477677
      0.064686402 0.191571112 0         ,
…
0     0     0     0     0     0     0     0     1
}; */

/* READ IN THE CHOICE DATA

The data should be organized as follows:

Each row should contain NVAR measures (attributes) for one individual
and one alternative and the final attribute must represent whether that
individual has chosen this alternative. The next rows must represent
the other NALT-1 alternatives that are faced by this individual. In
total, there must be NALT times NOBS rows in the data set and NVAR
variables
*/

load XX[NOBS2, OVAR] = c:\len\thbay\tballXB.dat;


/* PROVIDE INFORMATION ON WHICH VARIABLES WILL (1) AND WILL NOT (0) BE
INCLUDED AS INDEPENDENT VARIABLES FOR THE SITE CHOICE MODEL */
```

```
INC     =
{ 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
  1, 1, 1, 1, 1, 1, 1,
  1, 0, 1, 1, 1, 1,
  1,
  1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
  1, 1, 0,
  1, 1,
  1, 1, 1, 1, 1, 0, 0,
  0} ;

/*PROVIDE VALUES FOR SCALING THE ATTRIBUTES ~ NOTE THAT CONVERGENCE IS
MUCH FASTER IF ALL ELEMENTS IN THE HESSIAN ARE OF ABOUT THE SAME
MAGNITUDE */

SCL     =
{ 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
  1, 1, 1, 1, 1, 1, 1,
  1, 1, 1, 1, 1, 1,
  1,
  100, 100, 100, 10, 10, 1, 1, 10, 1, 100,
  1, 1, 1,
  1, 1,
  1, 1, 1, 100, 1, 1, 100,
  1} ;

/* PROVIDE A LIST OF PARAMETER NAMES (EXAMPLE FOR THE CROSS-NESTED
LOGIT)*/
Parnames = {"IV_ALL", "IV_OTH",
            "I_OUTSID", "I_UNKNOW", "LK_SUP","LK_NIP", "KAM RIV", "DOG
RIV", "DOG_LAKE", "D_OUTSID", "D_UNKN", "D_DRIV",
            "F_WALL", "F_BASS", "F_LTROUT", "F_BTROUT", "TRT*BASS",
"D_WALL", "D_BASS",
            "W_CUE", "RT_CUE", "W_WCUE", "W_SPRT", "D_WCUE",
            "LN_LKAR",
            "RD_ALL", "RD_GDGR", "RD_OKGR", "RD_PRGR", "RD_TRAIL",
"PORTAGE", "W_RDPRGR", "W_RDTRL", "D_RDALL",
            "B*LN_CON",  "B*LN_NON",
            "COTTAGE", "W_COTT",
            "LN_CD", "LN_ACCPT", "T_STATE", "S_STATE", "DLNCD"};


NVAR    = sumc(INC);
YMAT    = zeros(NOBS,NALT);
XREAL   = zeros(NOBS2,NVAR);
X       = zeros(NOBS,NALT*NVAR);

/* SPECIFY A SET OF STARTING VALUES FOR THE PARAMETERS (EXAMPLE BELOW
USES THE MNL MODEL ESTIMATES ~NOTE MORE THAN ONE STARTING VALUES SHOULD
BE USED TO AVOID FINDING A LOCAL MAXIMUM OF THE LOG LIKELIHOOD FUNCTION
*/

bbb     =
{
1,
1.000,
5.253,
```

```
5.222,
1.840,
2.263,
-0.708,
-0.005,
-0.855,
4.584,
3.422,
-1.177,
0.470,
0.768,
0.802,
1.280,
-0.568,
-0.658,
0.500,
0.886,
3.601,
-0.125,
-0.496,
0.363,
0.272,
-1.283,
-0.004,
-0.069,
-0.217,
-1.369,
-1.282,
0.370,
1.301,
0.868,
0.550,
-0.804,
-1.266,
-0.661,
0.351,
0.588,
1.912,
-0.593,
1.002
};

/* SHORTEN THE DATA SET TO INCLUDE ONLY RELEVANT VARIABLES*/

C = 1;
for I (1,OVAR,1);
      if INC[I,1] == 1;
            XREAL[.,C] = XX[.,I] / SCL[I];
      C = c + 1;
      endif;
endfor;

/* RESHAPE THE INDEPENDENT AND DEPENDENT VARIABLE MATRICES */

for I (1, NOBS, 1);
      for j (1, NALT, 1);
      YMAT[I,J] = XX[J+(I-1)*NALT, OVAR];
```

```
            for k (1, NVAR, 1);
                  X[I,(J-1)*NVAR+K] = XREAL[(I-1)*NALT+J,K];
            endfor;
      endfor;
endfor;

/* CLEAR MATRICES THAT ARE NOT USED */

clear XX;
clear xreal;



/* CALCULATE THE LOG LIKELIHOOD
   USES GLOBALS NOBS NALT NVAR X YMAT NNEST*/


proc ll(BB,X);
local part1, part2, J, K, store, BASC, numer;

store = zeros(NOBS,1);

/* USE THE FOLLOWING LINE FOR THE NESTED AND CROSS-NESTED LOGIT MODELS
*/
BASC  = BB[1,1] .* ones(NNEST-1,1)|BB[2:2+NVAR,1];

/* USE THE FOLLOWING LINE FOR THE GENERALIZED NESTED LOGIT MODEL */
/*BASC  = BB;*/

PART1 = zeros(NOBS,NALT*NNEST);
PART2 = zeros(NOBS,NNEST);
NUMER = zeros(NOBS,NALT);

for j (1,NALT,1);
    for k (1,NNEST,1);
        PART1[.,J+(K-1)*NALT] = (NNMEM[J,K] .* exp(X[.,1+((J-
1)*NVAR):NVAR*(J)]*BASC[NNEST+1:NNEST+NVAR,1]))^(1/BASC[K]);
        PART2[.,K] = PART2[.,K] + PART1[.,J+(K-1)*NALT];
    endfor;
endfor;

part2 = part2 .^ (ONES(NOBS,NNEST) .* (BASC[1:NNEST,1] -
ONES(NNEST,1))');

for j (1,NALT,1);
    for k (1,NNEST,1);
        NUMER[.,J] = NUMER[.,J] + PART1[.,J+(K-1)*NALT] .* PART 2[.,K];
    endfor;
endfor;

store = ln(sumc(YMAT' .* NUMER') ./ sumc(NUMER'));

retp(store);
endp;
```

```
/* MAXIMIZE THE LIKELIHOOD WITH THE MAXLIK LIBRARY ROUTINE ~NOTE THAT
MAXLIK ESTIMATES THE GRADIENT AND HESSIAN */

library maxlik,pgraph;
maxset;
/* FOR THE FISH SITE CHOICE APPLICATION ONE NEST (UNKNOWN AND OUTSIDE)
WAS FIXED TO ONE */

/*USE THE FOLLOWING FOR THE NESTED AND CROSS-NESTED LOGIT MODELS. THE
ZERO REPRESENTS THE ONE DISSIMILARITY PARAMETER THAT IS FIXED TO ITS
STARTING VALUE */

_Max_Active = {1, 0,
                1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 1, 1, 1, 1, 1, 1,
                1, 1, 1, 1, 1,
                1,
                1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 1,
                1, 1,
                1, 1, 1, 1, 1};

/*USE THE FOLLOWING FOR THE GENERALIZED NESTED LOGIT MODEL THE ZERO
REPRESENTS THE ONE DISSIMILARITY PARAMETER THAT IS FIXED TO ITS
STARTING VALUE */
/*_Max_Active =  {1, 1, 1, 1, 1, 1, 1, 1, 0,
                1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 1, 1, 1, 1, 1, 1,
                1, 1, 1, 1, 1,
                1,
                1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 1,
                1, 1,
                1, 1, 1, 1, 1};*/

_max_GradTol = 5e-5;
_Max_Parnames = PARNAMES;
{bb,f,g,cov,ret}=maxlik(X,0,&ll,BBB);
call maxprt(bb,f,g,cov,ret);

print _MAX_FINALHESS;

end;
```

Appendix E: Comparisons of Thunder Bay and Wawa area fishing site choice models

The table below compares the estimates between the Thunder Bay and Wawa area models. Only the MNL DYNAMIC model was assessed since the IIA property associated with this model permits me to use a random sample of alternatives to estimate the choice model (McFadden, 1978). Three separate random draws of 49 alternatives plus the chosen alternative were selected for each of the modelled trips from the Thunder Bay and Wawa data (1901 trips in total). Parameter estimates for interactions between residency (Thunder Bay = 1 and Wawa = -1) and common attributes are included in the table (identified by R*). Please note that the ASC terms are heavily impacted by both the reduced set of alternatives and the sampling of alternatives that is used to estimate the model.

Table E.1 Joint fishing site choice models with estimates from a MNL Dynamic with random sampling of alternatives (standard errors in parentheses)

	MNL DYNAMIC 1	MNL DYNAMIC 2	MNL DYNAMIC 3
OUTSIDE	3.376*** (0.566)	3.347*** (0.573)	3.389*** (0.564)
UNKNOWN	3.711*** (0.563)	3.814*** (0.570)	3.598*** (0.557)
ASC_SUPL	1.508*** (0.384)	1.326*** (0.384)	1.300*** (0.382)
ASC_NIPL	2.470*** (0.522)	2.503*** (0.534)	2.543*** (0.537)
ASC_KAMR	-0.646*** (0.219)	-0.863*** (0.220)	-0.760*** (0.219)
ASC_DOGR	0.104 (0.395)	0.179 (0.397)	0.115 (0.399)
ASC_DOGL	-0.789*** (0.266)	-0.738*** (0.264)	-0.599*** (0.270)
ASC_WAWA	-0.768* (0.399)	-1.098*** (0.390)	-0.725* (0.386)
ASC_MAGPIE	0.639** (0.306)	0.503 (0.309)	0.499* (0.301)
MD*OUTSIDE	2.192*** (0.452)	1.978*** (0.464)	2.034*** (0.453)
MD*UNKNO	1.330*** (0.448)	1.578*** (0.461)	1.320*** (0.445)
MD*AC_DRIV	-1.030*** (0.383)	-1.118*** (0.385)	-1.114*** (0.386)
A_WALL	0.846***	0.827***	0.780***

	(0.186)	(0.193)	(0.187)
A_BASS	0.808***	0.747***	0.744***
	(0.200)	(0.198)	(0.190)
A_LTROUT	0.600***	0.635***	0.554***
	(0.105)	(0.106)	(0.107)
A_BTROUT	0.892***	0.854***	0.844***
	(0.125)	(0.125)	(0.124)
A_BSTR	-0.401*	-0.489**	-0.403*
	(0.213)	(0.212)	(0.213)
MD*A_WALL	-0.113	-0.237	-0.150
	(0.162)	(0.171)	(0.163)
MD*A_BASS	0.148	0.165	0.086
	(0.180)	(0.178)	(0.177)
W_CUE	1.196***	1.268***	1.385***
	(0.177)	(0.181)	(0.176)
RT_CUE	3.690***	3.550***	3.711***
	(0.333)	(0.340)	(0.334)
W*W_CUE	-0.199**	-0.207**	-0.254***
	(0.073)	(0.074)	(0.074)
W* RT_CUE	-0.626**	-0.632*	-0.507*
	(0.270)	(0.278)	(0.267)
MD*W_CUE	0.296**	0.549***	0.433***
	(0.161)	(0.163)	(0.159)
A_ERRT	1.401***	1.488***	1.178**
	(0.434)	(0.425)	(0.469)
W* A_ERRT	-0.420	-0.140	-0.245
	(0.397)	(0.396)	(0.434)
LN_WAREA	0.286***	0.277***	0.262***
	(0.028)	(0.029)	(0.028)
T_DIST	-0.023***	-0.024***	-0.024***
	(0.001)	(0.001)	(0.001)
R_GDGR	0.005**	0.006***	0.005**
	(0.002)	(0.002)	(0.002)
R_OKGR	0.033***	0.027***	0.031***
	(0.008)	(0.008)	(0.008)
R_PRGR	0.008	0.009	0.003
	(0.019)	(0.019)	(0.019)
R_TRAIL	-0.754***	-0.893***	-0.884***
	(0.177)	(0.194)	(0.186)
PORTAGE	-0.736*	-0.877*	-0.757*
	(0.445)	(0.455)	(0.444)
W*R_PRGR	-0.007	-0.010	0.014
	(0.019)	(0.018)	(0.018)
W*R_TRAIL	0.706***	0.836***	0.821***
	(0.175)	(0.191)	(0.184)
MD*TDIST	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)
BT*GDLN	0.301***	0.310***	0.313***
	(0.072)	(0.072)	(0.070)
BT* NOLN	-0.756***	-0.781***	-0.773***
	(0.148)	(0.149)	(0.148)
COTTAGE	-1.545***	-1.600***	-1.468***
	(0.241)	(0.247)	(0.243)
W*COTTAGE	-0.473**	-0.557**	-0.451*
	(0.232)	(0.238)	(0.235)
LN_ACC	-0.690**	-0.683**	-0.613**

	(0.282)	(0.289)	(0.281)
LN_UNAC	0.441***	0.481***	0.486***
	(0.098)	(0.098)	(0.098)
MD*LN_ACC	-0.063	-0.059	-0.041
	(0.232)	(0.242)	(0.233)
T_STATE	1.946***	1.970***	1.874***
	(0.063)	(0.063)	(0.060)
S_STATE	-0.006***	-0.003*	-0.004***
	(0.002)	(0.001)	(0.001)
R*OUTSIDE	2.243***	2.342***	2.658***
	(0.566)	(0.573)	(0.564)
R*UNKNOWN	1.807***	1.771***	2.139***
	(0.563)	(0.570)	(0.557)
R*ASC_SUPL	0.293	0.338	0.286
	(0.384)	(0.384)	(0.382)
R*MD*OUTSIDE	2.634***	2.578***	2.617***
	(0.452)	(0.464)	(0.453)
R*MD*UNKNO	2.131***	1.992***	2.264***
	(0.448)	(0.461)	(0.445)
R*A_WALL	-0.502**	-0.590***	-0.610***
	(0.186)	(0.193)	(0.187)
R*A_BASS	0.078	0.108	0.102
	(0.200)	(0.198)	(0.190)
R*A_LTROUT	0.163	0.128	0.184
	(0.105)	(0.106)	(0.107)
R*A_BTROUT	0.420***	0.425***	0.431**
	(0.125)	(0.125)	(0.124)
R*A_BSTR	-0.108	-0.051	-0.040
	(0.213)	(0.212)	(0.213)
R*MD*A_WALL	-0.447***	-0.600***	-0.511***
	(0.162)	(0.171)	(0.163)
R*MD*A_BASS	0.339*	0.315*	0.421**
	(0.180)	(0.178)	(0.177)
	0.013	0.018	0.037
R*LN_WAREA	(0.028)	(0.029)	(0.028)
R*T_DIST	0.010***	0.010***	0.010***
	(0.013)	(0.013)	(0.013)
R*R_GDGR	-0.005**	-0.005**	-0.004**
	(0.002)	(0.002)	(0.002)
R*R_OKGR	-0.039***	-0.040***	-0.037***
	(0.008)	(0.008)	(0.008)
R*R_PRGR	-0.031	-0.034*	-0.024
	(0.019)	(0.019)	(0.019)
R*R_TRAIL	-0.714***	-0.828***	-0.838***
	(0.177)	(0.194)	(0.186)
R*PORTAGE	-0.454	-0.299	-0.451
	(0.445)	(0.455)	(0.444)
R*W*R_PRGR	0.042**	0.044**	0.030
	(0.019)	(0.018)	(0.018)
R*W*R_TRAIL	0.679***	0.798***	0.795***
	(0.175)	(0.191)	(0.184)
R*MD*TDIST	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)
R*BT*GDLN	0.229***	0.262***	0.217***
	(0.072)	(0.072)	(0.070)
R*BT* NOLN	-0.139	-0.093	-0.075

	(0.148)	(0.149)	(0.148)
R*LN_ACC	1.010***	1.163***	1.117***
	(0.282)	(0.289)	(0.281)
R*LN_UNAC	0.209**	0.129	0.173*
	(0.098)	(0.098)	(0.098)
R*MD*LN_ACC	1.112***	1.150***	1.099***
	(0.232)	(0.242)	(0.233)
R*T_STATE	0.039	0.149**	0.099*
	(0.063)	(0.063)	(0.060)
R*S_STATE	-0.002	-0.003**	-0.003**
	(0.002)	(0.001)	(0.001)
LL(B)	-3447.5	-3440.0	-3490.9
LL(0)	-7436.8	-7436.8	-7436.8

* probability (<0.10)
** probability (<0.05)
*** probability (<0.01)

References

Aas, O., Haider, W., & Hunt, L. M. (2000). Angler responses to potential harvest regulations in Engerdal, Norway: A conjoint based choice modeling approach. *North American Journal of Fisheries Management, 20*, 940-950.

Ahn, S., DeSteiguer, J. E., Palmquist, R. B., & Holmes, T. P. (2000). Economic analysis of the potential impact of climate change on recreational trout fishing in the southern Appalachian Mountains: An application of a nested multinomial logit model. *Climatic Change, 45*, 493-509.

Adamowicz, W. L. (1994). Habit formation and variety seeking in a discrete choice model of recreation demand. *Journal of Agricultural and Resource Economics, 19*, 19-31.

Adamowicz, W. L., Jennings, S., & Coyne, A. G. (1990). A sequential choice model of recreation behavior. *Western Journal of Agricultural Economics, 15*, 91-99.

Adamowicz, W. L., Louviere, J. J., & Williams, M. (1994). Combining stated and revealed preference methods for valuing environmental amenities. *Journal of Environmental Economics and Management, 26*, 271-292.

Adamowicz, W. L., Swait, J. F., Boxall, P. C., Louviere, J. J., & Williams, M. (1997). Perceptions versus objective measures of environmental quality in combined revealed and stated preference models of environmental valuation. *Journal of Environmental Economics and Management, 32*, 65-84.

Albert, J. H., & Chib, S. (1993). Bayesian analysis of binary and polychotomous response data. *Journal of the American Statistical Association, 88*(422), 669-679.

Allenby, G. M., & Lenk, P. J. (1994). Modeling household purchase behavior with logistic normal regression. *Journal of the American Statistical Association, 89*(428), 1218-1231.

Andrews, R. L., & Srinivisan, T. C. (1995). Studying consideration effects in empirical choice models using scanner panel data. *Journal of Marketing Research, 32*, 30-41.

Anselin, L. (1988). *Spatial econometrics: Methods and models*. Boston, MA: Kluwer Academic Publishers.

Anselin, L. (1995). Local indicators of spatial association - LISA. *Geographical Analysis, 27*, 93-115.

Anselin, L., Bera, M., Florax, R. J. G. M., & Yoon, M. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics, 26*, 77-104.

Anselin, L., & Florax, R. J. G. M. (1995a). New directions in spatial econometrics. L. Anselin, & R. J. G. M. Florax (Editors), *New directions in spatial econometrics* (pp. 3-18). New York: Springer.

Anselin, L., & Florax, R. J. G. M. (1995b). Small sample properties of tests for spatial dependence in regression models: Some further results. L. Anselin, & R. J. G. M. Florax (Editors), *New Directions in spatial econometrics* (pp. 21-74). New York: Springer.

Anselin, L., Rey, S. (1991). Properties of tests for spatial dependence in linear regression models. *Geographical Analysis, 23*, 112-131.

Arbia, G. (1989). *Spatial data configuration in statistical analysis of regional economic and related problems*. Boston, MA: Kluwer Academic Publishers.

Atkinson, P. M., German, S. E., Sear, D. A., & Clark, M. J. (2003). Exploring the relations between riverbank erosion and geomorphological controls using geographically weighted logistic regression. *Geographical Analysis, 35*, 58-82.

Baltagi, B. H., & Li, D. (2001). Double length artificial regressions for testing spatial dependence. *Econometric Reviews, 20*, 31-40.

Banzhaf, M. R., Johnson, F. R., & Mathews, K. E. (2001). Opt-out alternatives and anglers' stated preferences. J. Bennett, & R. Blamey (Editors), *The choice modelling approach to environmental valuation* (pp. 157-177). Northampton, MA: Edward Elgar.

Ben-Akiva, M. E., & Boccara, B. (1995). Discrete choice models with latent choice sets. *International Journal of Research in Marketing, 12*, 9-24.

Ben-Akiva, M. E., Bolduc, D., & Walker, J. (2001). Specification, identification, & estimation of the logit kernel (or continuous mixed logit) model. Retrieved August 25, 2005 from http://www.mit.edu/jwalker/www/JW_LK.pdf .

Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete choice analysis: Theory and application to travel demand.* Cambridge, MA: MIT Press.

Ben-Akiva, M. E., McFadden, D., Train, K. E., Walker, J., Bhat, C. R., Bierlaire, M., et al. (2002). Hybrid choice models: Progress and challenges. *Marketing Letters, 13*, 163-175.

Ben-Akiva, M. E., & Morikawa, T. (1990). Estimation of switching models from revealed preferences and stated intentions. *Transportation Research, Part A, 24*, 485-495.

Bergstrom, J.C., Dorfman, J.H., & Loomis, J.B. (2004) Estuary management and recreational fishing benefits. *Coastal Management, 32*, 417-432.

Berman, M. D., & Kim, H. J. (1999). Endogenous on-site time in recreation demand model. *Land Economics, 75*, 603-619.

Beron, K. J., & Vijverberg, W. P. M. (2004). Probit in a spatial context: A Monte Carlo analysis. L. Anselin (Editor), *Advances in spatial econometrics: Methodology, tools and* *applications*. (pp. 169-195). Berlin: Springer.

Bhat, C. R. (1997). Covariance heterogeneity in nested logit models: Econometric structure and application to intercity travel. *Transportation Research, Part B, 31*, 11-21.

Bhat, C. R. (1998). An analysis of travel mode and departure time choice for urban shopping trips. *Transportation Research, Part B, 32*, 361-371.

Bhat, C. R. (2000). A multi-level cross-classified model for discrete response variables. *Transportation Research, Part B, 34*, 567-582.

Bhat, C. R. (2001). Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. *Transportation Research, Part B, 35*, 677-693.

Bhat, C. R. (2002). Recent methodological advances relevant to activity and travel behaviour analysis. H. S. Mahmassani (Editor), *In perpetual motion: Travel behavior research opportunities and application challenges* (pp. 381-414). New York: Pergamon.

Bhat, C. R. (2003). Econometric choice formulation: Alternative model structures, estimation techniques, and emerging directions. *Resource paper for workshop entitled "Econometric models of choice: Formulation and estimation" 2003 IATBR Conference, Lucerne, Switzerland.*

Bhat, C. R. (2003). Random utility-based discrete choice models for travel demand analysis. K. Goulias (Editor), *Transportation system planning: Methods and application* (Chapter 10, pp. 1-30). New York: CRC Press.

Bhat, C. R., & Guo, J. (2004). A mixed spatially correlated logit model: Formulation and application to residential choice modeling. *Transportation Research, Part B, 38*, 147-168.

Bhat, C. R., & Zhao, H. (2002). The spatial analysis of activity stop generation. *Transportation Research Part B, 36*, 557-575.

Bierlaire, M. (forthcoming). A theoretical analysis of the cross-nested logit. *Annals of Operations Research*.

Bockstael, N. E., Hanemann, W. M., & Kling, C. L. (1987). Estimating the value of water quality improvements in a recreational demand framework. *Water Resources Research, 23*, 951-960.

Bockstael, N. E., McConnell, K. E., & Strand, I. E. (1989). A random utility model for sportfishing: Some preliminary results for Florida. *Marine Resource Economics, 6*, 245-260.

Bolduc, D. (1992). Generalized autoregressive errors in the multinomial probit model. *Transportation Research, Part B, 26*, 155-170.

Bolduc, D., Dagenais, M. G., & Gaudry, M. J. I. (1989). Spatially autocorrelated errors in origin-destination models: A new specification applied to aggregate mode choice. *Transportation Research Part B, 23*, 361-372.

Bolduc, D., Fortin, B., & Fournier, M. (1996). The effect of incentive policies on the practice location of doctors: A multinomial probit analysis. *Journal of Labor Economics, 14*, 703-732.

Bolduc, D., Fortin, B., & Gordon, S. (1997). Multinomial probit estimation of spatially interdependent choices: An empirical comparison of two new techniques. *International Regional Science Review, 20*, 77-101.

Bolduc, D., Laferriere, R., & Santarossa, G. (1995). Spatial autoregressive error components in travel flow models: An application to aggregate mode choice. L. Anselin, & R. J. G. M. Florax (Editors), *New directions in spatial econometrics* (pp. 96-108). New York: Springer.

Boots, B. N. (2001). Local measures of spatial association. *Ecoscience, 9*, 168-176.

Boots, B. N., & Kanaroglou, P. S. (1988). Incorporating the effects of spatial structure in discrete choice models of migration. *Journal of Regional Science, 28*, 495-509.

Borgers, A., & Timmermans, H. J. P. (1987a). A context-sensitive model of spatial choice behaviour. R. G. Golledge, & H. Timmermans (Editors), *Behavioural modelling in geography and planning* (pp. 159-178). London: Croom Helm.

Borgers, A., & Timmermans, H. J. P. (1987b). Choice model specification, substitution and spatial structure effects. *Regional Science and Urban Economics, 17*, 29-47.

Boxall, P. C., & Adamowicz, W. L. (2002). Understanding heterogeneous preferences in random utility models: A latent class approach. *Environmental and Resource Economics, 23*, 421-446.

Boyd, J. H., & Mellman, R. E. (1980). The effect of fuel economy standards on the U.S. automotive market: An hedonic demand analysis. *Transportation Research, Part A, 14*, 367-378.

Breffle, W. S., & Morey, E. R. (2000). Investigating preference heterogeneity in a repeated discrete-choice recreation demand model of Atlantic Salmon fishing. *Marine Resource Economics, 15*, 1-20.

Bresnahan, T. F., Stern, S., & Trajtenberg, M. (1997). Market segmentation and the sources of rents from innovation: Personal computers in the late 1980s . *RAND Journal of*

Economics, 28(0), S17-S44.

Brunsdon, C., Fotheringham, A. S., & Charlton, M. E. (1996). Geographically weighted regression: A method for exploring spatial nonstationarity. *Geographical Analysis, 28*, 281-298.

Brunsdon, C., Fotheringham, A. S., & Charlton, M. E. (1998). Spatial nonstationarity and autoregressive models. *Environment and Planning A, 30*, 957-973.

Canadian Automobile Association. (2004). *Driving costs: 2004 edition.* World wide web publication http://www.caa.ca/e/automotive/pdf/driving-costs-04.pdf accessed July 15 2005.

Cardell, N., & Dunbar, F. C. (1980). Measuring the societal impacts of automobile downsizing. *Transportation Research, Part A, 14*, 423-434.

Cascetta, E., & Papola, A. (2001). Random utility models with implicit availability/perception of choice alternatives for the simulation of travel demand. *Transportation Research, Part C, 9*, 249-263.

Case, A. (1992). Neighborhood influence and technological change. *Regional Science and Urban Economics, 22*, 491-508.

Casetti, E. (1972). Generating models by the expansion method: Applications to geographical research. *Geographical Analysis, 4*, 81-91.

Caulkins, P. P., Bishop, R. C., & Bouwes, Sr., N. W. (1986). The travel cost model for lake recreation: A comparison of two methods for incorporating site quality and substitution effects. *American Journal of Agricultural Economics, 68*, 291-297.

Chen, H. Z., & Cosslett, S. R. (1998). Environmental quality preference and benefit estimation in multinomial probit models: A simulation approach. *American Journal of Agricultural Economics, 80*, 512-520.

Chiang, J., Chib, S., & Narasimhan, C. (1999). Markov chain Monte Carlo and models of consideration set and parameter heterogeneity. *Journal of Econometrics, 89*, 223-248.

Cliff, A. D., & Ord, J. K. (1973). *Spatial autocorrelation.* London: Pion.

Cliff, A. D., & Ord, J. K. (1981). *Spatial processes: Models and applications.* London, UK: Pion.

Cox, S. P., & Walters, C. J. (2002). Modeling exploitation in recreational fisheries and implications for effort management on British Columbia rainbow trout lakes. *North American Journal of Fisheries Management, 22*, 21-34.

Creel, M., & Loomis, J. (1992). Recreation value of water to wetlands in the San Joaquin Valley: Linked multinomial logit and count data trip frequency models. *Water Resources Research, 28*, 2597-2606.

Daganzo, C. (1979). *Multinomial probit: The theory and its application to demand forecasting.* New York: Academic Press.

Daly, A. J., & Zachary, S. (1978). Improved choice models. D. A. Hensher, & Q. Dalvi (Editors), *Determinant of travel choice* (pp. 335-357). Sussex, UK: Saxon House.

Dillman, D. A. (2000). *Mail and internet surveys: The tailored design method.* Toronto, ON: John Wiley & Sons.

Ditton, R.B. (2004). Human dimensions of fisheries. M. J. Manfredo, J. J. Vaske, B. L. Bruyere, D. R. Field, & P. J. Brown (Editors), Society and natural resources: A summary of knowledge (pp. 199-208) Jefferson, MO: Modern Litho.

Ditton, R.B., Loomis, D.K., & Choi, S. (1992). Recreation specialization: Re-conceptualization from a social worlds perspective. *Journal of Leisure Research, 24*, 33-51.

Domencich, T. A., & McFadden, D. (1975). *Urban travel demand: A behavioral analysis.* A Charles River Associates research study (Contributions to economic analysis No. 93). Amsterdam, Netherlands: North-Holland Publishing.

Dubin, R. A. (1995). Estimating logit models with spatial dependence. L. Anselin, & R. J. G. M. Florax (Editors), *New directions in spatial econometrics* (pp. 229-242). New York: Springer.

Dubin, R. A. (1998). Spatial autocorrelation: A primer. *Journal of Housing Economics, 7*, 304-327.

Duncan, C., & Jones, K. (2000). Using multilevel models to model heterogeneity: Potential and pitfalls. *Geographical Analysis, 32*, 279-305.

DuWors, E., Villeneuve, M., Filion, F.L., Reid, R., Bouchard, P., Legg, D., et al. (1999). *The importance of nature to Canadians: Survey highlights*. Ottawa, ON: Environment Canada.

Feather, P. M. (1994). Sampling and aggregation issues in random utility model estimation. *American Journal of Agricultural Economics, 76*, 772-780.

Feather, P. M., Hellerstein, D., & Tomasi, T. (1995). A discrete-count model of recreational demand. *Journal of Environmental Economics and Management, 29*, 214-227.

Fedler, A. J., & Ditton, R. B. (1994). Understanding angler motivations in fisheries management. *Environmental Management, 19*, 6-13.

Feenberg, D., & Mills, E. S. (1980). *Measuring the benefits of water pollution abatement*. New

York: Academic Press.

Ferguson, M. R. (1995). *The aggregated spatial logit model: Theory, estimation and application.* Unpublished doctoral dissertation, McMaster University, Hamilton, ON.

Ferguson, M. R., & Kanaroglou, P. S. (1997). An empirical evaluation of the aggregated spatial choice model. *International Regional Science Review, 20*, 53-75.

Fleming, M. M. (2004). Techniques for estimating spatially dependent discrete choice models. L. Anselin (Editor), A*dvances in spatial econometrics: Methodology, tools and applications*. (pp. 145-167). Berlin: Springer.

Fletcher, J. J., Adamowicz, W. L., & Graham-Tomasi, T. (1990). The travel cost model of recreation demand: Theoretical and empirical issues. *Leisure Sciences, 12*, 119-147.

Florax, R. J. G. M., & Rey, S. (1995). The impacts of misspecified spatial interaction in linear regression models. L. Anselin, & R. J. G. M. Florax (Editors), *New directions in spatial econometrics* (pp. 112-135). New York: Springer.

Forest Management Branch. (2001). Management guidelines for forestry and resource-based tourism. Toronto, Ontario Ministry of Natural Resources, Queen's Printer for Ontario.

Fotheringham, A. S. (1981). Spatial structure and distance-decay parameters. *Annals of the Association of American Geographers, 71*, 425-436.

Fotheringham, A. S. (1983). A new set of spatial-interaction models: The theory of competing destinations. *Environment and Planning A, 15*, 15-36.

Fotheringham, A. S. (1984). Spatial flows and spatial patterns. *Environment and Planning A, 16*, 529-543.

Fotheringham, A. S. (1986). Modelling hierarchical destination choice. *Environment and Planning A, 18*, 401-418.

Fotheringham, A. S. (1988). Consumer store choice and choice set definition. *Marketing Science, 7*, 299-310.

Fotheringham, A. S. (1997). Trends in quantitative methods I: Stressing the local. *Progress in Human Geography, 21*, 88-96.

Fotheringham, A. S., & Brunsdon, C. (1999). Local forms of spatial analysis. *Geographical Analysis, 31*, 340-358.

Fotheringham, A. S., Nakaya, T., Yano, K., Openshaw, S., & Ishikawa, Y. (2001). Hierarchical destination choice and spatial interaction modelling: A simulation experiment. *Environment and Planning A, 33*, 901-920.

Fotheringham, A. S., & O'Kelly, M. E. (1989). *Spatial interaction models: Formulations and applications*. Amsterdam: Kluwer Academic.

Garrido, R. A., & Mahmassani, H. S. (2000). Forecasting freight transportation demand with the space-time multinomial probit model. *Transportation Research, Part B, 34*, 403-418.

Geary, R. C. (1954). The contiguity ratio and statistical mapping. *The Incorporated Statistician,5*, 115-145.

Gehlke, C. E., & Biehl, K. (1934). Certain effects of grouping upon the size of the correlation coefficient in census tract material. *Journal of the American Statistical Association, 29*, 169-170.

Getis, A., & Aldstadt, J. (1992). On the specification of the spatial weights matrix. *Geographical Analysis, 36*, 90-104.

Getis, A., & Ord, J. K. (1992). The analysis of spatial association by use of distance statistics. *Geographical Analysis, 24*, 189-206.

Greene, G., Moss, C. B., & Spreen, T. H. (1997). Demand for recreational fishing in Tampa Bay, Florida: A random utility approach. *Marine Resource Economics, 12*, 293-305.

Griffith, D. A. (1996). Some guidelines for specifying the geographic weights matrix contained in spatial statistical models. S. L. Arlinghaus, D. A. Griffith, W. C. Arlinghaus, W. D. Drake, & J. D. Nystuen *Practical Handbook of Statistics* (pp. 65-82). New York: CRC Press.

Gunn, J. M., & Sein, R. (2000). Effects of forestry roads on reproductive habitat and exploitation of lake trout (*Salvelinus namaycush*) in three experimental lakes. *Canadian Journal of Aquatic Sciences, 57* ((Supplement #2)), 97-104.

Gupta, S., & Chintagunta, P. K. (1994). On using demographic variables to determine segment membership in logit mixture models. *Journal of Marketing Research, 31*, 128-136.

Haab, T. C., & Hicks, R. L. (1997). Accounting for choice set endogeneity in random utility models of recreation demand. *Journal of Environmental Economics and Management, 34*, 127-147.

Haab, T. C., & Hicks, R. L. (1999). Choice set considerations in models of recreation demand: History and current state of the art. *Marine Resource Economics, 14*, 271-281.

Haegerty, P., & Lele, S. R. (1998). A composite likelihood approach to binary spatial data. *Journal of the American Statistical Association, 93*(443), 1099-1111.

Haener, M., Boxall, P. C., & Adamowicz, W. L. (2001). Modeling recreation site choice: Do hypothetical choices reflect actual behavior? *American Journal of Agricultural*

Economics, 83, 629-642.

Haener, M., Boxall, P.C., Adamowicz, W. L., & Kuhnke, D.H. (2004). Aggregation bias in recreation site choice models: Resolving the resolution problem. *Land Economics 80,* 561-574.

Haider, W., & Hunt, L. M. (1997). Remote tourism in northern Ontario: Patterns of supply and a motivational segmentation of clients. *Journal of Applied Recreation Research, 22*, 49-78.

Haining, R. (1990). *Spatial data analysis in the social and environmental sciences*. New York: Cambridge University Press.

Hagerty, D., & Moeltner, K. (2005). Specification of driving costs in models of recreation demand. *Land Economics, 81*, 127-143.

Hauber, A. B., & Parsons, G. R. (2000). The effect of nesting structure specification on welfare estimation in a random utility model of recreation demand: An application to the demand for recreational fishing. *American Journal of Agricultural Economics, 82*, 501-514.

Hauser, J. R., & Wernerfelt, B. (1990). An evaluation cost model of consideration sets. *Journal of Consumer Research, 16*, 393-408.

Hausman, J. A., Leonard, G. K., & McFadden, D. (1995). A utility-consistent, combined discrete choice and count data model: Assessing recreational losses due to natural resource damage. *Journal of Public Economics, 56*, 1-30.

Hausman, J. A., & Wise, D. A. (1978). A conditional probit model for qualitative choice: Discrete decisions recognizing interdependence and heterogeneous preferences. *Econometrica, 46*, 403-426.

Hautsch, N., & Klotz, S. (2003). Estimating the neighborhood influence on decision-makers:

Theory and an application on the analysis of innovation decisions. *Journal of Economic Behavior & Organization, 52*, 97-113.

Haynes, K. E., & Fotheringham, A. S. (1990). The impact of space on the application of discrete choice models. *The Review of Regional Studies, 20*, 39-49.

Heckman, J. J. (1981a). Statistical models for discrete panel data. C. F. Manski, & D. McFadden (Editors), *Structural analysis of discrete data with econometric applications* (pp. 114-175). Cambridge, MA: MIT Press.

Heckman, J. J. (1981b). The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic approach. C. F. Manski, & D. McFadden (Editors), *Structural analysis of discrete data with econometric applications* (pp. 190-195). Cambridge, MA: MIT Press.

Henschel, C. (2003). *The road less travelled: A report on the effectiveness of controlling motorized access in remote areas of Ontario.* Toronto, ON: Wildlands League and Sierra Legal Defence Fund.

Hensher, D. A., & Greene, W. H. (2003). The mixed logit model: The state practice. *Transportation, 30*, 133-176.

Hensher, D. A., Rose, J.M., & Greene, W. H. (2005). *Applied choice analysis: A primer.* New York: Cambridge University Press.

Hess, S., Train, K., & Polak, J. (forthcoming). On the use of a modified Latin hypercube sampling (MLHS) method in the estimation of a mixed logit for vehicle choice. *Transportation Research, Part B.*

Hicks, R. L., & Strand, I. E. (2000). The extent of information: Its relevance for random utility models. *Land Economics, 76*, 374-385.

Holt, D., Steel, D. G., Tranmer, M., & Wrigley, N. (1996). Aggregation and ecological effects in geographically based data. *Geographical Analysis, 28*, 244-261.

Horowitz, J. L., & Louviere, J. J. (1995). What is the role of consideration sets in choice modeling? *International Journal of Research in Marketing, 12*, 39-54.

Hunt, L. M. (unpublished manuscript). Highlights of the workshops on tourism research and future social science needs in resource management. *(August 16, 2002),* p.6.

Hunt, L. M. (2005). Choice models and recreational fishing site choice: Insights and future opportunities. *Human Dimensions of Wildlife, 10,* 153-172.

Hunt, L. M., Boots, B. N., & Kanaroglou, P. S. (2004). Spatial choice modelling: New opportunities to incorporate space into substitution patterns. *Progress in Human Geography, 28*: 746-766.

Hunt, L. M., Haider, W., & Bottan, B. (2005). Accounting for varying setting preferences among moose hunters. *Leisure Sciences,* 27: 297-314.

Hunt, L.M., Haider, W., & Johnson, M. (2000) *Ontario resource based tourism operators and forest management: Highlights of an operator survey*. Ont. Min. Natur. Resour. Centre for Northern Forest Ecosystem Research, Thunder Bay, ON. CNFER Technical Report TR-005. 88 pp + append.

Jakus, P. M., Dadakas, D., & Fly, J. M. (1998). Fish consumption advisories: Incorporating angler-specific knowledge, habits, and catch rates in a site choice model. *American Journal of Agricultural Economics, 80*, 1019-1024.

Jakus, P. M., Downing, M., Bevelhimer, M. S., & Fly, J. M. (1997). Do sportfishing consumption advisories affect reservoir anglers' site choice? *Agricultural and Resource Economics Review, 26*, 196-204.

Jakus, P. M., & Shaw, W. D. (2003). Perceived hazard and product choice: An application to recreational site choice. *The Journal of Risk and Uncertainty, 26*, 77-92.

Jones, C. A., & Lupi, F. (1999). The effect of modeling substitute activities on recreational benefit estimates. *Marine Resource Economics, 14*, 357-374.

Jones, K. (1991). Specifying and estimating multi-level models for geographical research. *Transactions of the Institute of British Geographers, 16*, 148-159.

Kamakura, W. A., & Russell, G. J. (1989). A probabilistic choice model for market segmentation and elasticity structure. *Journal of Marketing Research, 26*, 379-390.

Kamakura, W. A., & Srivastava, R. K. (1984). Predicting choice shares under conditions of brand interdependence. *Journal of Marketing Research, 21*, 420-434.

Kanaroglou, P. S., & Ferguson, M. R. (1996). A discrete spatial choice model for aggregate destinations. *Journal of Regional Science, 36*, 271-290.

Kanaroglou, M.R., & Ferguson, M. R. (1998). Representing the shape and orientation of destinations in spatial choice models. *Geographical Analysis, 30*, 119-137.

Kaoru, Y. (1995). Measuring marine recreation benefits of water quality improvements by the nested random utility model. *Resource and Energy Economics, 17*, 119-136.

Kaoru, Y., Smith, V. K., & Liu, J. L. (1995). Using random utility models to estimate the recreational value of estuarine resources. *American Journal of Agricultural Economics, 77*, 141-151.

Kelejian, H. H., & Robinson, D. P. (1998). A suggested test for spatial autocorrelation and/or heteroskedasticity and corresponding Monte Carlo results. *Regional Science and Urban Economics, 28*, 389-417.

Kitamura, R., Kostyniuk, L., & Ting, K. (1979). Aggregation in spatial choice modeling. *Transportation Science, 13*, 325-342.

Klein, N. M., & Bither, S. W. (1987). An investigation of utility-directed cutoff selection. *Journal of Consumer Research, 14*, 240-256.

Kling, C. L. (1987). A simulation approach to comparing multiple site recreation demand models using Chesapeake Bay survey data. *Marine Resource Economics, 4*, 95-109.

Kling, C. L., & Thomson, C. J. (1996). The implications of model specification for welfare estimation in nested logit models. *American Journal of Agricultural Economics, 78*, 103-114.

Koppelman, F. S., & Sethi, V. (2000). Closed form discrete choice models. D. A. Hensher, & K. J. Button (Editors), *Handbook of transport modeling* (Vol. Volume I: Transport Modeling. (pp. 211-222). Oxford: Pergamon Press.

Koppelman, F. S., & Wen, C. - H. (2000). The paired combinatorial logit model: Properties, estimation and application. *Transportation Research Part B, 34*, 75-89.

LeSage, J. P. (2000). Bayesian estimation of limited dependent variable spatial autoregressive models. *Geographical Analysis, 32*, 19-35.

Lin, P. C., Adams, R. M., & Berrens, R. P. (1996). Welfare effects of fishery policies: Native America treaty rights ad recreational salmon fishing. *Journal of Agricultural and Resource Economics, 21*, 263-276.

Lin, Y., Peterson, G. L., & Rogerson, P. A. (1988). A nested urban recreation site choice model. *Leisure Sciences, 10*, 1-15.

Lo, L. (1990). A translog approach to consumer spatial behavior. *Journal of Regional Science, 30*, 393-413.

Lo, L. (1991). Spatial structure and spatial interaction: A simulation approach. *Environment and Planning A, 23*, 1279-1300.

Louviere, J. J., Hensher, D. A., & Swait, J. F. (2000). *Stated choice methods: Analysis and applications*. New York: Cambridge University Press.

Louviere, J. J., Street, D., Carson, R., Ainslie, A., Deshazo, J. R., Cameron, T., et al. (2002). Dissecting the random component of utility. *Marketing Letters, 13*, 177-193.

Louviere, J. J., & Woodworth, G. (1983). Design and analysis of simulated consumer choice or allocation experiments: An approach based on aggregated data. *Journal of Marketing Research, 20*, 350-367.

Luce, R. (1959). *Individual choice behavior: A theoretical analysis*. New York: Wiley.

Lupi, F., & Feather, P. M. (1998). Using partial site aggregation to reduce bias in random utility travel cost models. *Water Resources Research, 34*(, 3595-3603.

MacNair, D. J., & Cox, S. D. (1999). A heteroscedastic nested RUM of freshwater fishing. *Marine Resource Economics, 14*, 333-341.

Manski, C. F. (1973). *The analysis of qualitative choice*. Unpublished doctoral dissertation, Department of Economics, Massachusetts Institute of Technology, Cambridge, MA.

Manski, C. F. (1977). The structure of random utility models. *Theory and Decision, 8*, 229-254.

Manski, C. F., & Lerman, S. R. (1981). On the use of simulated frequencies to approximate choice probabilities. C. F. Manski, & D. McFadden (Editors), *Structural analysis of discrete data* (pp. 305-319). Cambridge, MA: The MIT Press.

Manning, R., Valliere, W., Wang, B., & Jacobi, C. (1999). Crowding norms: Alternative measurement approaches. *Leisure Sciences, 21*, 97-115.

Martinson, K. S., & Shelby, B. (1992). Encounters and proximity norms for salmon anglers in California and New Zealand. *North American Journal of Fisheries Management, 12*, 559-567.

McConnell, K. E., Strand, I. E., & Blake-Hedges, L. (1995). Random utility models of recreational fishing: Catching fish using a Poisson process. *Marine Resource Economics, 10*, 247-261.

McConnell, K. E., & Tseng, W. (1999). Some preliminary evidence on sampling of alternatives with random parameters logit. *Marine Resource Economics, 14*, 317-332.

McCulloch, R., & Rossi, P. E. (1994). An exact likelihood analysis of the multinomial probit model. *Journal of Econometrics, 64*, 207-240.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. P. Zarembka (Editor), *Frontiers in econometrics* (pp. 105-142). New York: Academic Press.

McFadden, D. (1975). *On independence structure and simultaneity in transportation demand analysis*. Berkley, CA: Working paper No. 7511, Urban Travel Demand Forecasting Project, Department of Economics, University of California.

McFadden, D. (1978). Modelling the choice of residential location. A. Karlqvist, L. Lundqvist, F. Snickars, & J. W. Weibull (Editors), *Spatial interaction theory and planning models*

(Vol. 3pp. 75-96). Amsterdam: North Holland Publishing.

McFadden, D. (1981). Econometric models of probabilistic choice. C. F. Manski, & D. McFadden (Editors), *Structural analysis of discrete data* (pp. 199-272). Cambridge, MA: The MIT Press.

McFadden, D. (1989). A method of simulated moments for estimation of discrete response models without numerical integration. *Econometrica, 57*, 995-1026.

McFadden, D., & Train, K. E. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics, 15*, 447-470.

McKercher, B. (1992). Tourism as a conflicting land use: Northern Ontario's outfitting industry. *Annals of Tourism Research, 19*, 467-481.

McMillen, D. P. (1992). Probit with spatial autocorrelation. *Journal of Regional Science, 32*, 335-348.

McMillen, D. P. (1995). Selection bias in spatial econometric models. *Journal of Regional Science, 35*, 417-436.

Meyer, R. J. (1980). A descriptive model of constrained residential search. *Geographical Analysis, 12*, 21-32.

Milon, J. W. (1988a). A nested demand shares model of artificial marine habitat choice by sport anglers. *Marine Resource Economics, 5*, 191-213.

Milon, J. W. (1988b). Travel cost methods for estimating the recreational use benefits of artificial marine habitat. *Southern Journal of Agricultural Economics, 20*, 87-101.

Mitchell, B. (2002). *Resource and environmental management, 2nd Edition*. New York: Prentice

Hall.

Moeller, G. H., & Engelken, J. H. (1972). What fishermen look for in a fishing experience. *Journal of Wildlife Management, 36*, 1253-1257.

Moeltner, K., & Englin, J. (2004). Choice behavior under time-variant quality: State dependence versus "play-it-by-ear" in selecting ski resorts. *Journal of Business and Economic Statistics, 22*, 214-224.

Mohammadian, A., Kanaroglou, P. S., & Haider, M. (2003). *Spatial multinomial logit model: A housing type choice model considering spatial dependencies.* Unpublished Working Paper.

Montgomery, M., & Needleman, M. S. (1997). The welfare effects of toxic contamination in freshwater fish. *Land Economics, 73*, 211-223.

Moran, P. A. P. (1948). The interpretation of statistical maps. *Journal of the Royal Statistical Society, B 10*, 243-251.

Morey, E. R. (1981). The demand for site-specific recreational activities: A characteristics approach. *Journal of Environmental Economics and Management, 8*, 345-371.

Morey, E. R. (1999). Two RUMs uncloaked: Nested logit models of site choice and nested-logit models of participation and site choice. Herriges, J. A., & Kling, C. L. (Editors), *Valuing recreation and the environment: Revealed preference methods in theory and practice* (pp. 65-120). Northhampton, MA: Edward Elgar.

Morey, E. R., Breffle, W. S., Rowe, R. D., & Waldman, D. M. (2002). Estimating recreational trout fishing damages in Montana's Clark Fork River basin: Summary of a natural resource damage assessment. *Journal of Environmental Management, 66*, 159-170.

Morey, E. R., Rowe, R. D., & Watson, M. (1993). A repeated nested-logit model of Atlantic salmon fishing. *American Journal of Agricultural Economics, 75*, 578-592.

Morey, E. R., Shaw, W. D., & Rowe, R. D. (1991). A discrete-choice model of recreational participation, site choice, and activity valuation when complete trip data are not available. *Journal of Environmental Economics and Management, 20*, 181-201.

Morey, E. R., & Waldman, D. M. (1998). Measurement error in recreation demand models: The joint estimation of participation, site choice, and site characteristics. *Journal of Environmental Economics and Management, 35*, 262-276.

Mur, J. (1999). Testing for spatial autocorrelation: Moving average versus autoregressive processes. *Environment and Planning A, 31*, 1371-1382.

Nedungadi, P. (1990). Recall and consumer consideration sets: Influencing choice without altering brand evaluations. *Journal of Consumer Research, 17*, 263-276.

Needleman, M. S., & Kealy, M. J. (1995). Recreational swimming benefits of New Hampshire lake water quality policies: An application of a repeated discrete choice model. *Agricultural and Resource Economics Review, 24*, 78-87.

Oh, C.-O., Ditton, R. B., Gentner, B., & Riechers, R. (2005). A stated preference choice approach to understanding angler preferences for management options. *Human Dimensions of Wildlife, 10,* 173-186.

Ontario Government. *Crown Forest Sustainability Act, 1994: Statues of Ontario, 1994, Chapter 25*. Toronto, ON: Queen's Printer for Ontario.

Ontario Ministry of Natural Resources. (2002). *A review by the Ministry of Natural Resources regarding the Class Environmental Assessment for Timber Management on Crown Lands* *in Ontario "MNR's Timber Class EA Review"*. Toronto, ON: Queen's Printer for Ontario.

Openshaw, S. (1977). A geographical solution to scale and aggregation problems in region-building, partitioning, and spatial modelling. *Transactions of the Institute of British Geographers, NS 2*, 459-472.

Openshaw, S. (1978). An empirical study of some zone-design criteria. *Environment and Planning A 10*: 781-794.

Openshaw, S. (1984). The modifiable areal unit problem. *Concepts and techniques in modern geography, 38*. Norwich: Geo Books.

Openshaw, S., & Taylor, P. J. (1979). A million or so correlated coefficients: Three experiments on the modifiable areal unit problem. N. Wrigley (Editor), *Statistical applications in spatial sciences* (pp. 127-144). London, UK: Pion.

Openshaw, S., & Taylor, P. J. (1981). The modifiable areal unit problem. N. Wrigley, & R. J. Bennett (Editors), *Quantitative geography: A British view* (pp. 60-70). London, UK: Routledge & Kegan Paul.

Ord, J. K., & Getis, A. (1995). Local spatial autocorrelation statistics: Distributional issues and an application. *Geographical Analysis, 27*, 286-305.

Paez, A., Uchida, T., & Miyamoto, K. (2002a). A general framework for estimation and inference of geographically weighted regression models: 2. Spatial association and model specification tests. *Environment and Planning A, 34*, 883-904.

Paez, A., Uchida, T., & Miyamoto, K. (2002b). A general framework for estimation and inference of geographically weighted regression models: 1. Location-specific kernel bandwidths and a test for locational heterogeneity. *Environment and Planning A, 34*, 733-754.

Parsons, G. R., & Hauber, A. B. (1998). Spatial boundaries and choice set definition in a random utility model of recreation demand. *Land Economics, 74*, 32-48.

Parsons, G. R., Jakus, P. M., & Tomasi, T. (1999b). A comparison of welfare estimates from four models for linking seasonal recreational trips to multinomial logit models of site choice. *Journal of Environmental Economics and Management, 38*, 143-157.

Parsons, G. R., & Kealy, M. J. (1992). Randomly drawn opportunity sets in a random utility model of lake recreation. *Land Economics, 68*, 93-106.

Parsons, G. R., & Kealy, M. J. (1994). Benefits transfer in a random utility model of recreation. *Water Resources Research, 30*, 2477-2484.

Parsons, G. R., & Kealy, M. J. (1995). A demand theory for number of trips in a random utility model of recreation. *Journal of Environmental Economics and Management, 29*, 357-367.

Parsons, G. R., Massey, D. M., & Tomasi, T. (1999a). Familiar and favorite sites in a random utility model of beach recreation. *Marine Resource Economics, 14*, 299-315.

Parsons, G. R., & Needleman, M. S. (1992). Site aggregation in a random utility model of recreation. *Land Economics, 68*, 418-433.

Parsons, G. R., Plantinga, A. J., & Boyle, K. J. (2000). Narrow choice sets in a random utility model of recreation demand. *Land Economics, 76*, 86-99.

Paulrud, A. & Latila, T. (2004). Valuation of management policies for sport-fishing on Sweden's Kaitum River, *Journal of Environmental Planning and Management, 47*, 863-879.

Pellegrini, P. A., & Fotheringham, A. S. (1999). Intermetropolitan migration and hierarchical destination choice: A disaggregate analysis from the US public use microdata samples.

Environment and Planning A, 31, 1093-1118.

Pellegrini, P. A., & Fotheringham, A. S. (2002). Modelling spatial choice: A review and synthesis in a migration context. *Progress in Human Geography, 26*, 487-510.

Pellegrini, P. A., Fotheringham, A. S., & Lin, G. (1997). An empirical evaluation of parameter sensitivity to choice set definition in shopping destination choice models. *Papers in Regional Science, 76*, 257-284.

Pendleton, L. H., & Mendelsohn, R. (1998). Estimating the economic impact of climate change on the freshwater sportsfisheries of the northeastern U.S. *Land Economics, 74*, 483-496.

Perdue, R. R. (1983). External information search in marine recreational fishing. *Leisure Sciences, 15*, 169-187.

Peters, T., Adamowicz, W. L., & Boxall, P. C. (1995). Influence of choice set considerations in modeling the benefits from improved water quality. *Water Resources Research, 31*, 1781-1787.

Peterson, G. L., Anderson, D. H., & Lime, D. W. (1982). Multiple-use site demand analysis: An application to the Boundary Waters Canoe Area Wilderness. *Journal of Leisure Research, 14*, 27-36.

Peterson, G. L., Dwyer, J. F., & Darragh, A. J. (1983). A behavioral urban recreation site choice model. *Leisure Sciences, 6*, 61-81.

Peterson, G. L., Stynes, D. J., & Arnold, J. R. (1985). The stability of a recreation demand model over time. *Journal of Leisure Research, 17*, 121-132.

Phaneuf, D. J., & Herriges, J. A. (1999). Choice set definition issues in a Kuhn-Tucker model of recreation demand. *Marine Resource Economics, 14*, 343-355.

Phaneuf, D. J., Kling, C. L., & Herriges, J. A. (1998). Valuing water quality improvements using revealed preference methods when corner solutions are present. *American Journal of Agricultural Economics, 80*, 1025-1031.

Pinske, J., & Slade, M. E. (1998). Contracting in space: An application of spatial statistics to discrete-choice models. *Journal of Econometrics, 85*, 125-154.

Post, J. R., Sullivan, M., Cox, S., Lester, N. P., Walters, C. J., Parkinson, E. A., *et al.* (2002). Canada's recreational fisheries: The invisible collapse? *Fisheries, 27*, 6-17.

Provencher, W., Baerenklau, K. A., & Bishop, R. C. (2002). A finite mixture logit model of recreational angling with serially correlated random utility. *American Journal of Agricultural Economics, 84*, 1066-1075.

Provencher, W., & Bishop, R. C. (2004). Does accounting for preference heterogeneity improve the forecasting of a random utility model? A case study. *Journal of Environmental Economics and Management, 48*, 793-810.

Ratchford, B. (1980). The value of information for selected appliances. *Journal of Marketing Research, 17*, 14-25.

Rempel, R. S., Elkie, P. C., Rodgers, A. R., & Gluck, M. J. (1997). Timber-management and natural-disturbance effects on moose habitat: Landscape evaluation. *Journal of Wildlife Management, 61*, 517-524.

Richardson, A. (1982). Search models and choice set generation. *Transportation Research, Part A, 16*, 403-419.

Roberts, J. H., & Lattin, J. M. (1991). Development and testing of a model of consideration set composition. *Journal of Marketing Research, 28*, 429-440.

Robinson, W. S. (1950). Ecological correlations and the behavior of individuals. *American Sociological Review, 15*, 351-357.

Romano, D., Scarpa, R., Spalatro, F., & Vigano, L. (2000). Modelling determinants of participation, number of trips and site choice for outdoor recreation in protected areas. *Journal of Agricultural Economics, 51*, 224-238.

Schuhmann, P. W., & Schwabe, K. A. (2004). An analysis of congestion measures and heterogeneous angler preferences in a random utility model of recreational fishing. *Environmental and Resource Economics, 27*, 429-450.

Scott, A., & Shiell, A. (1997). Do fee descriptors influence treatment choices in general practice? a multilevel discrete choice model. *Journal of Health Economics, 16*, 323-342.

Shafer, E., Jr. (1969). *The average camper who doesn't exist*. Upper Darby, PA: US Department of Agriculture, Forest Service, Northeastern Forest Experiment Station.

Shaw, W. D., & Ozog, M. T. (1999). Modeling overnight recreation trip choice: Application of a repeated nested multinomial logit model. *Environmental and Resource Economics, 13*, 397-414.

Shelby, B., & Heberlein, T. A. (1986). *Carrying capacity in recreation settings*. Corvallis, OR: Oregon State University Press.

Shelby, B., & Vaske, J. J. (1991). Resource and activity substitutes for recreational salmon fishing in New Zealand. *Leisure Sciences, 13*, 21-32.

Shelby, B., Vaske, J. J., & Donnelly, M. (1996). Norms, standards, and natural resources. *Leisure Sciences, 18*, 103-123.

Shugan, S. M. (1980). The cost of thinking. *Journal of Consumer Research, 7*, 99-111.

Siemer, W. F., & Brown, T. L. (1994). Motivations and satisfactions of Lake Ontario boating salmonid anglers. *Journal of Great Lakes Research, 20*, 457-470.

Small, K. A. (1987). A discrete choice model for ordered alternatives. *Econometrica, 55*, 409-424.

Small, K. A., & Rosen, H. S. (1981). Applied welfare economics with discrete choice models. *Econometrica, 49*, 105-130.

Smith, T. E., & LeSage, J. P. (2002). A Bayesian probit model with spatial dependencies. J. P. Leagage, & R. K. Pace (Editors). *Advances in econometrics: Volume 18: Spatial and spatiotemporal econometrics*. (pp. 127-160). Oxford: Elsevier Ltd.

Sokal, R. R., Oden, N. L., & Thomson, B. A. (1998). Local spatial autocorrelation in a biological model. *Geographical Analysis, 30*, 331-354.

Stewart, W., & Cole, D. (2001). Number of encounters and experience quality in Grand Canyon backcountry: Consistently negative and weak relationships. *Journal of Leisure Research, 33*, 106-120.

Stetzer, F. (1982). Specifying weights in spatial forecasting models: The results of some experiments. *Environment and Planning A, 14*, 571-584.

Stigler, G. J. (1961). The economics of information. *The Journal of Political Economy, 69*, 213-225.

Swait, J. F. (1994). A structural equation model of latent segmentation and product choice for cross-sectional revealed preference choice data. *Journal of Retailing and Consumer Services, 1*, 77-89.

Swait, J. F. (2001a). Choice set generation within the generalized extreme value family of discrete choice models. *Transportation Research, Part B, 35*, 643-666.

Swait, J. F. (2001b). A non-compensatory choice model incorporating attribute cutoffs. *Transportation Research Part B, 35*, 903-928.

Swait, J. F., Adamowicz, W. L., & van Bueren, M. (2004). Choice and temporal welfare impacts: Incorporating history into discrete choice models. *Journal of Environmental Economics and Management, 47*, 94-116.

Swait, J. F., & Ben-Akiva, M. E. (1987a). Empirical test of a constrained choice discrete model: Mode choice in Sao Paulo, Brazil. *Transportation Research, Part B, 21*, 103-115.

Swait, J. F., & Ben-Akiva, M. E. (1987b). Incorporating random constraints in discrete models of choice set generation. *Transportation Research, Part B, 21*, 91-102.

Tay, R. S., & McCarthy, P. S. (1994). Benefits of improved water quality: A discrete choice analysis of freshwater recreational demands. *Environment and Planning A, 26*, 1625-1638.

Tay, R. S., McCarthy, P. S., & Fletcher, J. J. (1996). A portfolio choice model of the demand for recreational trips. *Transportation Research, Part B, 30*, 325-337.

Thill, J. C. (1992). Choice set formation for destination choice modelling. *Progress in Human Geography, 16*, 361-382.

Thill, J. C., & Horowitz, J. L. (1997a). Travel-time constraints on destination-choice sets. *Geographical Analysis, 29*, 108-123.

Thill, J. C., & Horowitz, J. L. (1997b). Modeling non-work destination choices with choice sets defined by travel time constraints. A. Getis, & M. M. Fischer (Editors). *Recent developments in spatial analysis – spatial statistics, behavioural modelling and* *neurocomputing*. (pp. 186-208). Heidelberg: Springer.

Thurstone, L. (1927). A law of comparative judgment. *Psychological Review, 34*, 273-286.

Tiefelsdorf, M. (2000). *Modelling spatial processes: The identification and analysis of spatial relationships in regression residuals by means of Moran's I.* New York: Springer.

Tiefelsdorf, M., Griffith, D. A., & Boots, B. N. (1998). A variance stabilizing coding scheme for spatial link matrices. *Environment and Planning A, 31*, 165-180.

Train, K. E. (1998). Recreation demand models with taste differences over people. *Land Economics, 74*, 230-239.

Train, K. E. (1999). Mixed logit models for recreation demand. J. A. Herriges, & C. L. Kling (Editors), *Valuing recreation and the environment* (pp. 121-140). Northampton, MA: Edward Elgar.

Train, K. E. (2001). A comparison of hierarchical Bayes and maximum simulated likelihood for mixed logit. Berkley, CA: Working paper, Department of Economics, University of California, Berkley.

Train, K. E. (2003). *Discrete choice methods with simulation.* New York: Cambridge University Press.

Train, K. E., McFadden, D., & Johnson, R. (2000). Discussion of Morey and Waldman's "Measurement error in recreation demand models". *Journal of Environmental Economics and Management, 40*, 76-81.

Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review, 79*, 281-299.

Upton, G., & Fingelton, B. (1985). *Spatial data analysis by example. Volume 1 - point pattern and quantitative data.* New York: Wiley.

Vaughan, W. J., & Russell, C. S. (1982). Valuing a fishing day: An application of a systematic varying parameter model. *Land Economics, 58*, 450-463.

Vovsha, P. (1997). *The cross-nested logit model: Application to mode choice in the Tel-Aviv metropolitan area.* Washington, D.C.: presented at the 1997 Annual Transportation Research Board Meeting.

Walker, J. (2001). *Extended discrete choice models: Integrated framework, flexible error structures, and latent variables.* Unpublished doctoral dissertation, Massachusetts Institute of Technology, Cambridge, MA.

Walker, J. (2002). The mixed logit (or logit kernel) model: Dispelling misconceptions of identification. *Transportation Research Record, 1805,* 86-98.

Walker, J., & Ben-Akiva, M. E. (2002). Generalized random utility model. *Mathematical Social Sciences, 43*, 303-343.

Walters, C. J., & Cox, S. P. (1999). Maintaining quality in recreational fisheries: How success breeds failure in the management of open-access sport fisheries. T. J. Pitcher (Editor). *Evaluating the benefits of recreational fishing.* (pp. 22-29). Vancouver, BC: Fisheries Centre, University of British Columbia.

Watson, D. O., Adamowicz, W. L., & Boxall, P. C. (1994). An economic analysis of recreational fishing and environmental quality changes in the upper Oldman River. *Canadian Water Resources Journal, 19*, 203-225.

Wen, C.-H., & Koppelman, F. S. (2001). The generalized nested logit model. *Transportation*

Research, Part B, 35, 627-641.

Whitehead, J. C., & Haab, T. C. (1999). Southeast marine recreational fishery statistical survey: Distance and catch based choice sets. *Marine Resource Economics, 14*, 283-298.

Williams, D. R., Anderson, B. S., McDonald, C. D., & Patterson, M. E. (1995). Measuring place attachment: More preliminary results. V. Freysinger, & P. Stokowski (Editors) *Abstracts - 1995 Symposium on Leisure Research*, (p. 78), Arlington, VA: National Recreation and Park Association.

Williams, D. R., Patterson, M. E., Roggenbuck, J. W., & Watson, A.E. (1992). Beyond the commodity metaphor: Examining emotional and symbolic attachment to place. *Leisure Sciences, 14*, 29-46.

Williams, H. C. W. L. (1977). On the formation of travel demand models and economic evaluation measures of user benefit. *Environment and Planning A, 9*, 285-344.

Williams, H. C. W. L., & Ortuzar, J. D. (1982). Behavioural theories of dispersion and the mis-specification of travel demand models. *Transportation Research, Part B, 16b*, 167-219.

Yule, G. U., & Kendall, M. G. (1950). *An introduction to the theory of statistics*. London, UK: Griffin