Cumulative attraction and spatial dependence in a destination choice model for beach recreation

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Acknowledgements

We are very grateful for research funding contributed by Waikato Regional Council and Waikato Management School

Highlights

- The beach destination choices of domestic tourists in New Zealand are analysed
- The spatial distribution of beach amenities is an important consideration in choice
- We include complement and substitute accessibility parameters for each attribute
- The implications of two site changes are compared for different models

Abstract

The destination choices of individual recreationalists are dependent on the spatial distribution of sites and attractions. An important issue in destination choice modelling is how to account for the effects of cumulative attraction from multiple sites and hierarchical processing of potential destinations. This study is concerned with recreational visits to beaches on the Coromandel Peninsula of New Zealand. Each beach has a different combination of attractions with potentially complex substitution patterns. We find that an Agglomerating and Competing Destination Choice model, with differentiated accessibility parameters for each attribute, offers the best fit. It is flexible enough to model different levels of substitutability for different attraction types, yet is tractable in estimation. We compare response predictions of different models for two site-specific changes - closure of a campground and construction of a sea wall. Allowing for more complex substitution patterns results in different predictions for visitation in the wider area.

1. Introduction

Destination choices of individual recreationists collectively determine the demand for beach recreation and the welfare effect they experience from changes to the coastal environment. A common approach to modelling determinants of recreation site choice is by means of random utility models (RUM). This allows the estimation of demand for multiple sites, substitution across sites, and is consistent with utility maximisation theory (Phaneuf & Smith, 2005). Recent applications include domestic tourism in Spain (Bujosa, Riera, & Torres, 2015), Japan (Wu, Zhang, & Fujiwara, 2011) and China (Yang, Fik, & Zhang, 2013), angling in New Zealand (Mkwara, Marsh, & Scarpa, 2015) and lake recreation in Iowa (Smirnov & Egan, 2012).

An important issue in destination choice models is how to account for the effects of the spatial distribution of sites and attractions. There can be spatial dependencies (e.g. when site attractiveness is enhanced or diminished by attractiveness of a nearby site) and/or spatial correlation of errors (e.g. when the attractiveness of multiple sites is affected by an unobserved feature of the area) (Griffith, 2007). Spatially correlated errors violate the assumption of the travel cost method that sites must be substitutes. When sites share unobserved attributes that influence choice behaviour this also violates the assumption of independence of error terms in the widely-used multinomial logit model for discrete choices. Spatial heterogeneity, if ignored, may cause substantial bias in model parameters (Bhat, Dubey, Alam, & Khushefati, 2015).

For this study we analyse destination choices of recreational visitors to beaches on the Coromandel Peninsula of New Zealand. There is a dearth of quantitative studies about beach recreation in New Zealand, despite the fact that the coast is an important part of New

Zealand cultural identity (Kearns & Collins, 2012). The Peninsula has many attractive beaches within close proximity, each with a unique set of features and services. The values people hold for these beaches may be significantly affected by coastal policy and management decisions.

We first review modelling approaches for spatial correlation and multiple destination trips. We estimate an Agglomerating and Competing Destination Choice (ACDC) model that extends previous research (Bernardin, Koppelman, & Boyce, 2009). By using not just one, but multiple dissimilarity measures, we estimate spatial interaction effects for each type of observed beach attribute. We demonstrate that the expanded model allows the simulation of more complex response effects than alternative models. Yet, this model retains a computationally simple closed form, which makes it mathematically tractable in estimation.

2. Theoretical framework

2.1 Travel cost method

The consumption of beach recreation requires the user to incur the costs of travel and access to the site. These costs serve as the implicit price of the trip. An individual can visit only one site at a time and is assumed to choose the site that maximises his or her unobserved utility function for recreation benefits (Phaneuf & Smith, 2005). Multiple-destination trips complicate travel cost analysis because there is the potential for value to be attributed to the wrong site. The most direct solution is to discard multiple-site visitors from the sample. A less drastic approach is to include a dummy variable and price interaction for multiple destination trips (Parsons & Wilson, 1997) or use nested models for additional or “follow on” destinations (Taylor, McKean, & Johnson, 2010). Mendelsohn (1992) treats combinations of sites as additional sites, but this is only practical if there are small numbers of possible combinations. Lue, Crompton and Fesenmaier (1993) argue that the most appropriate way to allocate costs largely depends on which travel pattern the individual visitor is using. However, in practice it is difficult to distinguish between different patterns such as en-route, base-camp, regional tour or trip chaining. We use the approach proposed by Yeh, Haab and Sohngen (2006) who allocate travel cost by the proportion of time spent at each site. The assumption is that people spend more time at more highly valued sites.

2.2 Spatial random utility models

The multinomial logit (MNL) model was shown to be consistent with RUM by McFadden (1974) and is the most widely used structure within random utility modelling. However, the independent and identical distribution of the error term results in the property called Independence of Irrelevant Alternatives (IIA). IIA is undesirable when patterns of substitution vary across different types or spatial clusters of alternatives. As McFadden (1978) noted, “there may be a structure of perceived similarities among alternatives” that invalidate this assumption of the model. Early applications of discrete choice models included spatial choices (for example, residential location in McFadden (1978)) but the added complexity of spatial dependence was not often recognised (Pellegrini & Fotheringham, 2002). There are two concepts that help explain the reasons for spatial dependence in destination choices: cumulative attraction (Nelson, 1958) and hierarchical processing.

2.2.1 Cumulative Attraction

The theory of cumulative attraction (Nelson, 1958) implies that multiple attractions in an area will draw more visitors than if such attractions were widely scattered. A key component is the principle of compatibility in which total attractiveness depends not only on geographic proximity but also on how complementary the sites are. Complementary sites must be dissimilar in some way, providing different experiences or services. This allows visitors to satisfy a diverse range of objectives and reduce the risk of unrealised expected benefits (Lue, Crompton, & Stewart, 1996). Applications of Cumulative Attraction to tourism research have corroborated empirically the importance of the principle of compatibility (Lue et al., 1996; Weidenfeld, Butler, & Williams, 2010).

2.2.2 Hierarchical processing

Destination choices can involve a large number of destination options. Limited substitutability or hierarchical behaviour is therefore more appropriate than the MNL assumption of unlimited substitutability, typical of fully compensatory random utility models (Drakopoulos, 1994). The role of hierarchical processing has been explored in detail in the area of choice set formation (Decrop, 2010; Pagliara & Timmermans, 2009; Thiene, Swait, & Scarpa, 2017) and also used to explain spatial dependence in destination choice (Schüssler & Axhausen, 2009). The assumption is that destinations are evaluated in spatial or typological clusters.

There are various alternatives, generalisations or extensions to MNL that can be used to model hierarchical choice processes. The multinomial probit (MNP) model is very flexible with joint multivariate normal error terms, rather than the independent and identically distributed (i.i.d.) extreme values in MNL. However, the calculation of a single choice probability requires integration with as many dimensions as there are alternatives, which is not feasible without substantial investment in programming purpose-specific code and simulation techniques. The mixed logit model (Train, 1998) can also capture complex correlation patterns, using random parameters or error components. Thiene and Scarpa (2008), for example, used joint error components for two or more alpine sites that were believed to give sites a higher degree of substitutability, resulting in correlated choice. The limitation is that the number of random parameters required increases with the number of correlations modelled. Again, simulation techniques are required in estimation, which are slow and give estimates prone to simulation error (Klaiber & von Haefen, 2008). Simulation variance which adds to the unavoidable sampling variance. The challenge is to specify a computationally tractable model that accommodates the important spatial effects and has a firm foundation in economic theory. We therefore turn our attention to models with closed-form probabilities, which do not require computationally expensive simulation techniques.

2.2.3 GEV models

Hierarchical choice processes can be modelled using the Generalized Extreme Value (GEV) class of models, of which MNL is a special case (McFadden, 1978). GEV models remove the IIA property of MNL by allowing the random components of alternatives to be correlated, while maintaining the assumption that they are identically distributed. The set of alternatives are partitioned into subsets (called nests), which correspond to similarity of influence. Nests may be non-overlapping, as in the nested logit (Daly, 1987), or overlapping, as in the cross-nested logit (Vovsha, 1997), paired combinatorial logit (Chu, 1989), generalized nested logit (Wen & Koppelman, 2001), spatially correlated logit (Bhat & Guo, 2004), generalized spatially correlated logit (Sener, Pendyala, & Bhat, 2011), or the network GEV (Daly & Bierlaire, 2006). Multiple-level hierarchies have also been used in destination choice (Bekhor & Prashker, 2008).

GEV models are very flexible and maintain closed-form expressions for choice probabilities. However, this flexibility can require estimating a large number of dissimilarity or allocation parameters (Bhat & Guo, 2004). Another limitation of GEV models is that the hierarchical structure must be exogenously specified, which can be a somewhat arbitrary division of continuous space (Pellegrini & Fotheringham, 2002). Ishaq, Bekhor & Shiftan (2013) used "fuzzy segmentation" to assign individuals to different structures, but the structures were still specified exogenously rather than emerging endogenously from the data.

2.2.4 Competing Destinations models

Another closed-form model free of the IIA property is the Competing Destinations (CD) model introduced by Fotheringham (1983). CD is similar to MNL but the utility function is amended to reflect the probability that an alternative is evaluated. The rationale for this approach is that people do not evaluate every alternative and are more likely to be aware of sites that are large and close. Accessibility affects the likelihood that alternative *j* is in the cluster of awareness for individual *n*. There are different ways to evaluate accessibility, which has been defined as "reflects the ease of reaching needed or desired activities" (Handy & Clifton, 2001). Fotheringham (1983) used a Hansen accessibility variable of the form:

$$A_j = \frac{1}{K-1} \sum_{\substack{k \\ k \neq j}}^{K} \frac{W_k}{{d_{jk}}^{\theta}} \tag{1}$$

where K is the set of all alternatives, W is an attraction measure, d_{jk} is the distance between alternatives j and k, and θ is a distance decay parameter. Attraction measures can reflect cumulative opportunities (Handy & Niemeier, 1997) or a calculation of similarity/dissimilarity (Schüssler & Axhausen, 2009). The impedance parameter (distance) may also take other forms. The distance decay parameter is often omitted to simplify estimation, which implicitly constrains it to one (Bernardin et al., 2009). If the estimated parameter for *A* is negative then competition effects dominate. A positive parameter indicates that agglomeration effects dominate. A limitation of the CD model is that it only measures the net effect of competition and agglomeration. Which of the two effects prevails and for whom remains an empirical question.

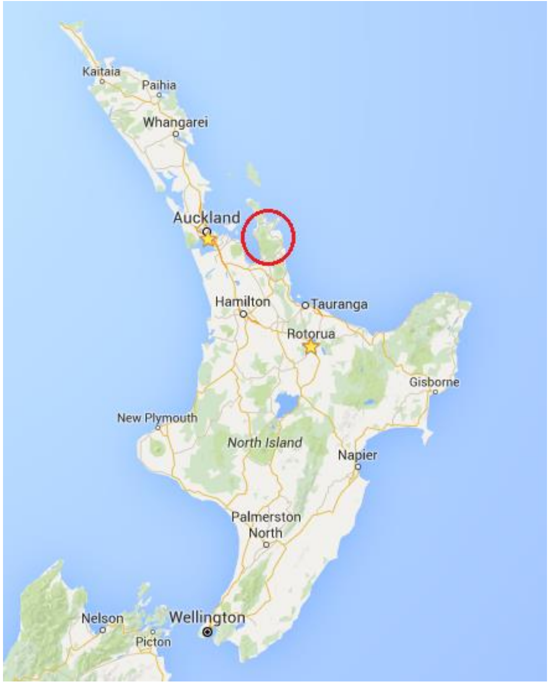
2.2.5 Agglomerating and Competing Destination Choice model

Bernardin et al. (2009) included two adjustment terms in the utility function to separately measure spatial competition and agglomeration effects and named this model Agglomerating and Competing Destination Choice (ACDC). Using a dissimilarity statistic based on business types, Bernardin et al. (2009) calculated the number of complement and substitute urban zones available to every other zone. In their application the ACDC model outperformed the CD model and was more useful for analysing trip chaining effects. Although Bernardin et al. (2009) and other ACDC model users (e.g. Ho & Hensher, 2016) had separate measures of competition and agglomeration, they still used only a single measure of dissimilarity to calculate both variables. This does not allow for differentiation of competition or agglomeration effects for different types of attractions.

The beach sites in our study each have a different set of attraction characteristics and do not fit into neat non-overlapping typologies. If two sites have sandy beaches they are substitutes for people who like sand. If one site has a motel and the other has no motel, but is undeveloped and peaceful, these may be complementary attributes. A single nest structure or dissimilarity measure may therefore be inadequate to capture complex substitution effects. For this study we expand on the ACDC model concept and estimate complement and substitute parameters for a range of site attributes.

3. Empirical context

The Coromandel Peninsula is steep and hilly and lies across the Hauraki Gulf from Auckland, the largest city in New Zealand. Most of the Peninsula interior is forest park and settlements of varying sizes are dotted along the coastline. Coromandel beaches are popular holiday destinations for residents of the nearby urban areas of Auckland and Hamilton, and to a lesser extent, international tourists. There are many beaches with high scenic and recreational appeal. Coastal areas in New Zealand are highly valued for wildness, accessibility and contribution to identity (Kearns & Collins, 2012) . Administratively, it comprises five Community Board areas (Figure 2). The Thames area is named for the town at the southern corner of the Gulf and it is the entry point for the majority of visitors who come from Auckland or Hamilton. There is a road going east to Tairua and another winding road that heads north along the relatively homogenous shingle-covered West coast. We further divide the Coromandel-Colville area into West (popular for fishing) and East coast. Mercury Bay has the largest population and many exceptionally scenic white sand beaches. The Tairua-Pauanui area is the gateway to Mercury Bay and provides a wide range of services. The Whangamata area contains a large town and popular surf beach of the same name, and is the main route for people travelling from the Bay of Plenty region that lies to the south.



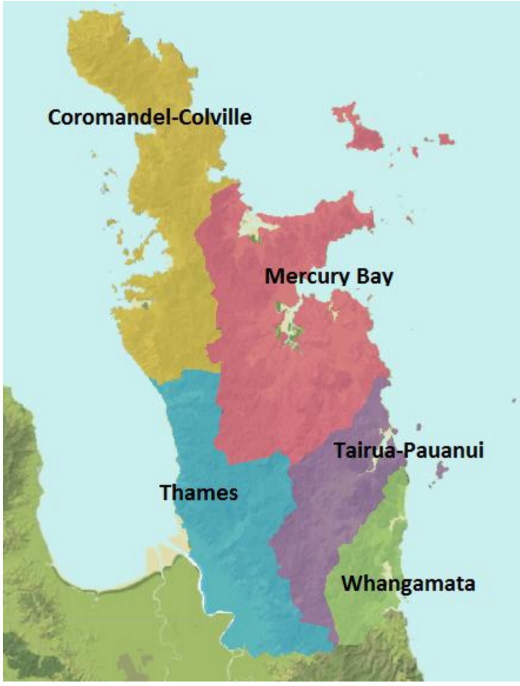


Figure 1 - Coromandel Peninsula (circled)

Figure 2 - Community Board Areas

For this study the Coromandel Peninsula coast is divided into 109 discrete beach "sites" based on geographically distinct bays or harbours, most of which have existing names. Some longer bays are divided into two sites, such as Hot Water Beach, which has a settlement at the southern end and undeveloped dunes at the northern end and separate access points. The west coast has long stretches of relatively homogenous coast with few distinct inlets, so some beach sites are defined by the nearest settlement instead.

The destination choice analysis is simplified somewhat because the vast majority of visitors travel by car, every urban area is on the coast, and the main road forms a loop around the Peninsula. It is a simple matter to determine a visitor's probable route to any beach, and which other beaches they would have passed along the way.

There is a forthcoming Regional Coastal Plan review[1] that will address issues such as coastal erosion, development, conservation, contaminants and location of infrastructure. One

[1] https://www.waikatoregion.govt.nz/community/whats-happening/waikato-regional-plan-review/

objective of this study is to help inform the review about possible effects on recreational users of the beaches.

4. Data Collection

The data were collected via a web-based panel survey from October 2013 to April 2014 designed to gather information about beach preferences of domestic visitors to the Coromandel Peninsula. We primarily sourced participants from a panel of New Zealanders pre-recruited by a market research company. The use of a pre-recruited panel restricts multiple participations by the same individuals and is an increasingly popular collection mode (Windle & Rolfe, 2011). The survey included questions about previous and planned Coromandel Peninsula visits, environmental attitudes, socio-economic variables and choice experiment questions. In this paper we only report the revealed preference results. Respondents were asked to report only trips where beach recreation was the primary purpose of the trip. They indicated the location of their beach visit(s) using a Google Maps™ API tool, which provided the latitude and longitude of each visit. The beach markers were assigned to a beach site based on proximity. We excluded markers that were outside the Coromandel Peninsula, too far off shore or too far inland.

No data were collected about trips to other regions or recreational activities near home that might be substitutes for visiting a beach (e.g. swimming in a pool). The destination choices we analyse are conditional on the fact that the respondent has already decided to visit the Coromandel Peninsula for the purpose of beach recreation.

4.1 Definition of variables

The value of coastal recreation is highly dependent on the physical appearance of the coastal zone (Coombes, Jones, & Sutherland, 2008). A large number of variables were calculated for each site including length, width, surrounding land cover, type of sand/shingle, the presence of a stream, suitability for surfing, length of dune, length of seawalls, headland elevation, presence of boating facilities, public toilets, campgrounds, playgrounds, motels, food retailers, usual population and overall development level. There was no water quality data to include in the model as monitoring is sporadic and limited to a few estuaries. Many biophysical variables were highly correlated or just not useful explanatory variables. For example, almost all beaches are in close proximity to the forest park that covers the interior of the Peninsula. Development level of each site is determined by adjacency to an urban area and the significance of that urban area. See Table V in the appendix for list of variables included in the final models and their data sources.

The travel distance and time by car between each origin and destination was calculated using Google© Distance Matrix API[2]. A standard fuel cost of 20 cents per kilometre was assumed, based on the assumption of $2 per litre of petrol and 10 kilometres to the litre[3]. For sites with no road access to the foreshore we added additional walking time, also calculated by the Google API. The opportunity cost of travel time was defined as 33 per cent of hourly household income, which is a typical approach without introducing the additional complexities of a “noisy” wage fraction (Larson & Lew, 2013). For the distance weighting of accessibility variables we used travel time rather than distance, because many stretches of road on the Peninsula are narrow, windy or unsealed and travel speed is variable. For multiple-destination visits the total trip cost is apportioned based on the proportion of time spent at each site. Travel cost *C* for individual *n* to site *j* in trip *t* is therefore defined as:

$$C_{njt} = \rho_{njt} \sum_{k=1}^{K_t} \left(0.2 d_{ntk} + 1/3\, \omega_n m_{ntk} \right) \tag{2}$$

[2] https://developers.google.com/maps/documentation/distance-matrix/

[3] Data were not collected about the vehicle type or whether it was towing a boat.

where ρ_{njt} is the proportion of time in trip t that is spent at site j; K_t is the set of destinations in the trip (including home as the final destination); d_{ntk} is distance in kilometres; m_{ntk} is travel time in minutes from origin k-1 (0 is home) to destination k; and ω_n is household wage per minute. By factoring in the structure of multiple-destination trip-chaining, we avoid the downward bias from ignoring multi-day trips and the upward bias from attributing all trips costs to a single site.

5. Model Formulation

We estimate and compare MNL, CNL, CD and ACDC models. The formulations are presented below.

5.1 MNL

The utility or net benefit that person n expects to obtain from site j is specified as:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{3}$$

where V_{nj} is a deterministic, linear-in-parameters component and ε_{nj} is an unobserved utility component with an i.i.d. Type I Extreme Value distribution. The probability that person n chooses site j is therefore:

$$P_{nj} = \frac{e^{V_{nj}}}{\sum_k (e^{V_{nk}})} \tag{4}$$

V_{nj} includes site-specific parameters (listed in appendix), travel cost, and a wage-travel cost interaction variable.

$$V_{nj} = \sum_g \beta_g B_{jg} + \beta_c\, c_{njt} + \beta_{cw}\, c_{njt}\omega_{\boldsymbol{n}} \tag{5}$$

B_{jg} indicates the value of attribute g at site j. The β parameters are estimated by maximum likelihood.

5.2 CNL

The CNL specification is given by the generator function (Michel Bierlaire, 2006):

$$G(y) = \sum_{m=1} \left(\sum_{j \in K} \left({\alpha_{jm}}^{1/\mu} y_j \right)^{\mu_m} \right)^{\mu/\mu_m} \tag{6}$$

where y is the deterministic part of the utility function; j refers to an alternative in the set of all sites K; m is a nest; μ is a scale parameter; μ_m is a nest-specific coefficient; and α_{jm} are the parameters allocating sites to nests. There is one nest for site attribute type[4], which are defined in Table V in the appendix. Every site that possesses the attribute is a member of the nest, weighted by the number of other attributes the site also possesses:

$$\alpha_{jm} = \frac{B_{jm}}{\sum_k B_{km}} \tag{7}$$

where B_{jm} = 1 if the site has the feature and 0 if it does not. The sum of the allocation variables for each site is one.

5.3 CD model with single accessibility variable

In the model labelled "CD1", the MNL choice probability is modified by the addition of an accessibility variable A_j.

$$P_{nj} = \frac{e^{V_{nj} + \beta_A A_j}}{\sum_k \left(e^{V_{nk} + \beta_A A_k} \right)} \tag{8}$$

The accessibility variable is specified as:

$$A_j = ln \sum_{\substack{k \\ k \neq j}} \frac{W_k}{d_{jk}} \tag{9}$$

where d_{jk} is the travel time in minutes between alternatives j and k; and W is an attraction measure that adds the attributes at site k and weights them by f_g, the frequency of visits to all sites with that attraction type.

[4] We tested several GEV nested and cross-nested logit structures including area, trip duration, development level, paired distance, en-route availability, and attribute-based nests. For brevity we only report the specification and results for the attribute-based CNL because it significantly outperformed any other nest structure in terms of AIC/BIC measures.

$$W_k = \frac{\sum_g f_g B_{kg}}{\sum_g f_g}$$

(10)

5.4 CD model with multiple accessibility variables

In the model labelled "CD2", the single accessibility variable is replaced by a vector of 14 variables measuring the access to every attribute in the utility function except for estuary (which is excluded because there is no variation - every estuary is beside a non-estuary site).

$$A_{jg} = \frac{1}{K-1} \sum_{\substack{k \\ k \neq j}}^{K} \frac{B_{kg}}{d_{jk}}$$

(11)

5.5 Simple ACDC model

In the model labelled "ACDC1" we estimate the number of complement and substitute attributes at each site using Lierberson's D dissimilarity statistic (Lieberson, 1969). *D* is based on the probability of randomly selecting different attribute types (*g)* from a pair of sites *j* and *k*. It is weighted by the frequency of visit for each attribute type (f_g).

$$D_{jk} = 1 - \sum_g f_g \frac{B_{jg} B_{kg}}{\sum_{g'} B_{jg} \sum_{g'} B_{kg}}$$

(12)

The two accessibility variables A^C (complements) and $A^S A^S$ (substitutes) are:

$$A_j^C = \ln\left(\sum_k D_{jk} \frac{\sum_g B_{kg}}{d_{jk}}\right)$$

(13)

$$A_j^S = \ln\left(\sum_k (2 - D_{jk}) \frac{\sum_g B_{kg}}{d_{jk}}\right)$$

(14)

5.6 Expanded ACDC model

In the model labelled "ACDC2" there are complement and substitute accessibility variables for every attribute except estuary. If site *j* has attribute *g* the accessibility variable is specified as a substitute. If it does not, it is a complement.

$$A_{jg}^{C} = \begin{cases} \frac{1}{K-1} \sum_{k \neq j}^{K} \frac{B_{kg}}{d_{jk}} & \text{for } B_{jg} = 0 \\ 0 & \text{for } B_{jg} > 0 \end{cases}$$

(15)

$$A_{jg}^{S} = \begin{cases} \frac{1}{K-1} \sum_{k \neq j}^{K} \frac{B_{kg}}{d_{jk}} & \text{for } B_{jg} > 0 \\ 0 & \text{for } B_{jg} = 0 \end{cases}$$

(16)

6. Results

A total of 2,447 trips and 3,946 beach visits by 1,137 unique respondents are in the final data set. The following table shows a selection of descriptive statistics. Women and people with degrees are over-represented when compared with the New Zealand census. However, the sampling frame of Coromandel Peninsula visitors do not necessarily have the same characteristics as the general population. On-site surveys have also found beach visitors were more likely to have a degree than the general population (Thomson, 2003).

Table I - Descriptive statistics

Measure	
Count of respondents	1,137
Count of trips	2,447
Count of beach visits	3,946
Average travel time to site (hours)	2.33
Average age of respondent	43
Proportion of female respondents	0.59
Proportion of university-educated respondents	0.47
Proportion from Waikato region	0.41

Proportion from Auckland region	0.38
Proportion from Bay of Plenty region	0.21
Proportion of visits with an overnight stay	0.39

Figure 3 shows the relative intensity of beach visits around the Peninsula with hotspots around urban areas and the Mercury Bay area (each additional overlapping point changes the colour towards red). It also illustrates how close the sites are to each other. Within a 15 minute travel time radius of each beach there are an average of six other beaches. Almost three quarters of beaches have an urban area less than 15 minutes away. Visiting multiple sites on one trip is therefore a practical way to fulfill a variety of needs. In our sample, 31 percent of trips included multiple beach sites.

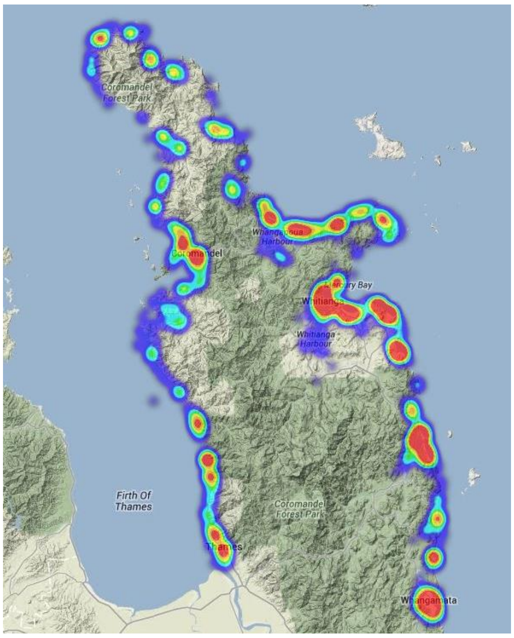


Figure 3 – Heat map of beach visits

6.1 Site compatibility

Compatibility is defined as the proportion of visitors to site A that also visit site B (Nelson, 1958)[5]. We fit a logistic regression to see how well compatibility can be explained by site characteristics and site differences. The dependent variable equals one if a visitor to site A also visits site B, otherwise zero. The independent variables include visitor counts to each site, travel time, site B attributes and "dissimilarity" variables to indicate site B has the attribute while site A does not. Results are reported in Table VI in the appendix. The model fit is high with a McFadden pseudo R-square of 0.63.

The model implies that compatibility is higher if site A has few visitors or site B has many visitors. Travel time has a negative effect and being en-route a positive one. Some site B attributes are positive and significant regardless of whether site A has them or not (i.e. boat ramps, campground, dune, food, public road and toilet). Negative site B attributes are estuary, seawall, undeveloped, and all sizes of urban area. To summarise the dissimilarity variables: if site B is in a different area or has a different scale of urban development to site A, it is less compatible. If site B has a natural dune, non-estuarine sandy beach, or is urban or undeveloped while site A is not, it is more compatible. The results imply that a one-dimensional site typology such as "urban" versus "rural" would be inadequate for modelling complex substitution patterns in site choice. In the next section we show the destination choice model results.

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[5] We restrict site combinations to pairs because only 11 per cent of people visited more than two beaches and the large number of possible three-site combinations results in miniscule compatibility measures for trios.

6.2 Model results

We used Biogeme (Bierlaire, 2003) to estimate the multinomial logit (MNL), cross-nested logit (CNL), Competing Destinations (CD1 and CD2) and Agglomerating and Competing Destination Choice (ACDC1 and ACDC2) models[6]. Results are reported in Table II.

The basic MNL model has a relatively good fit to the data, with an adjusted (for the number of parameters) McFadden pseudo r-squared of 0.18. The travel cost parameter is negative and significant in all models. The travel cost times wage interaction variable is positive, which means that high income individuals are willing to travel further. The area dummy variables are all positive, which means every other area is preferred to Thames area. Site characteristics associated with a higher probability of visit are boat ramp, campground, motel, playground, public road, public toilet, sandy (as opposed to shingle or pebble) beach and a large urban area. The negative variables are estuary sites (which tend to be silty and colonised by mangroves), undeveloped sites, and the presence of seawalls. The presence of food retailers is positive only in the ACDC model. Tourists cannot have motels and playgrounds without the associated urban areas, but after controlling for these amenities small and medium urban areas have a residual negative effect. The parameter for large urban areas is positive and significant in all models except ACDC2.

The CNL model with attribute-based nests offers an improvement in model fit over the basic MNL with an r-squared of 0.209[7]. Eight out of the fifteen nests had Inclusive Value (IV) variables significantly larger than one, which means that variance is different across sites with different attributes. Models CD1 and CD2 fit slightly worse fit than the CNL in terms of

[6] Various mixed logit and error components models were also tested but not reported because they were either unstable (with enormous standard errors) and/or did not fit as well as the CNL/CD/ACDC models.

[7] We also tested models nested by distance, area or development level (not reported here) but these did not fit as well. This is consistent with the compatibility analysis that implied beach characteristics are an important determinant of substitutability.

r-squared and AIC/BIC statistics. The addition of multiple accessibility variables in CD2 improved fit slightly. Campground, public road and medium urban are positive, implying agglomeration effects dominate. Boat ramp, playground, sandy and toilet are negative, implying competition effects dominate.

The model ACDC1, which has one complement and one substitute variable, fits only marginally better than CD1. ACDC2, with complement and substitute variables for each attribute, is the preferred model in terms of AIC/BIC and offers more insight into competition and agglomeration effects of different attributes. The complement accessibility variables are almost all positive and larger than the substitution variables. The exception is the large urban variable. Perhaps large urban areas have negative spill-overs that mean close proximity is undesirable, all else being equal. A medium urban area has a negative effect when on-site but the complement accessibility variable is positive and larger than any other accessibility parameter. Campground, food retail, motels, sandy beach, public toilet also have significant positive complement effects for sites without these attributes. The significant substitute variables are boat ramp, food retail, public road, and small urban area. Substitute food retail is positive, which implies there is value in having access to other food establishments even when there is one at the site. This is probably because different types of food retailers (e.g. a convenience store versus a café) are not perfect substitutes. The other substitute variables are all negative; implying the close proximity of substitutes reduces the likelihood of visitation. This is consistent with the conjecture that similarity results in lower visibility and reduced attractiveness (Schüssler & Axhausen, 2009).

Table II - Estimated models

	Variable	MNL	CNL	CD1	CD2	ACDC1	ACDC2
Model fit	Log-likelihood	-15158	-14604	-14724	-14626	-14706	-14428
	Psuedo-r2	0.180	0.209	0.203	0.208	0.204	0.218
	No. Parameters	22	37	23	36	24	50
	AIC	30359	29282	29495	29324	29461	28956
	BIC	30497	29208	29639	29509	29413	28856
Individual attributes	Travel cost	-0.0775***	-0.0509***	-0.078***	-0.077***	-0.077***	-0.079***
	Travel cost x wage	0.0007***	0.0005***	0.0007***	0.0007***	0.0007***	0.0007***
Site attributes	Area CE	1.6900	1.1000*	0.904***	1.530***	0.918***	1.460***
	Area CW	0.9130*	0.6310*	1.690***	1.520***	1.430***	1.060***
	Area M	2.2000	1.4000*	2.200***	2.050***	2.090***	1.980***
	Area TP	0.9590	0.6680*	0.964***	0.391*	0.815***	0.176
	Area W	1.0700	0.7150*	1.080***	0.720***	0.968***	0.389
	Boat ramp	0.3540*	0.3370**	0.354***	0.406***	0.330***	0.545**
	Campground	0.3730**	0.1510**	0.372***	0.335***	0.350***	1.110***
	Natural dune	0.0486*	0.2090*	0.050	0.519***	0.010	0.191
	Estuary	-1.8800	-1.7100*	-1.880***	-1.280***	-1.870***	-0.726***
	Food retailer	-0.2040*	-0.1400**	-0.206***	-0.302*	-0.262***	1.150***
	Motel	0.2240*	0.0239**	0.229***	0.042	0.229***	0.270
	Playground	0.2650*	0.2910**	0.265***	1.520***	0.323***	1.330***
	Public road	1.0300*	0.6550*	1.030***	1.040***	0.969***	1.380***
	Public toilet	0.2480*	0.2130*	0.248***	0.079	0.258***	0.165
	Sandy beach	0.4930*	0.6740**	0.492***	0.335***	0.539***	1.460***
	Undeveloped	-0.2860*	-0.0172**	-0.288***	-0.054	-0.310***	-0.132
	Small urban	-0.3200*	-0.3900**	-0.321***	0.288**	-0.333***	-0.951***
	Medium urban	-0.3290*	-0.1120**	-0.330***	0.170*	-0.271***	-0.923***
	Large urban	0.4680*	0.2330**	0.469***	0.862***	0.526***	0.293

	Seawall	-0.4220*	-0.1340*	-0.420***	-0.326	-0.253***	-0.257
Accessibility (complements, substitutes)	Boat ramp				-52.300***		27.500, -84.300***
	Campground				140.000***		106.000***, 11.300
	Natural dune				-32.500		37.900, -20.200
	Food retailer				34.300		343.000***, 155.000**
	Motel				67.800		204.000**, -172.000
	No seawall				0.132		16.100, -0.785
	Playground				-105.000***		84.900, -63.700
	Public road				46.200**		20.400, -46.800**
	Sandy beach				-37.300***		61.900***, -12.700
	Toilet				-69.700***		179.000***, -22.100
	Undeveloped				14.200		39.900*, -5.020
	Urban small				0.677		-3.020, -213.000***
	Urban medium				114.000***		433.000***, 48.900
	Urban large				2.860		-199.000**, -121.000
	Composite			0.019		22.100***, -22.400***	

6.3 Model response properties

The differences in model fit are small. However, the ACDC2 model has the potential to capture more complex spatial effects. We examine two hypothetical scenarios to illustrate the different response properties of each model. The first scenario (A) involves the closure of a popular campground at Hahei. As coastal property values increase it is common for camping grounds to be sold and developed with houses or apartments (Collins & Kearns, 2010). Hahei has a few small, boutique accommodation options but campgrounds provide a unique, low cost experience enjoyed by families and backpackers and can accommodate many more people than a low-rise residential development on the same site. Accessibility variables for all other sites were re-calculated and choice probabilities were simulated using the Biosim function provided with Biogeme. Simulation results for the MNL model are not reported because the IIA property means there will simply be equal allocation across sites. Nor is model CD1 used, since the accessibility parameter is insignificant.

Table III shows a selection of the most affected sites (which are all in Mercury Bay area) as well as total changes for each area. The CNL model predicts the smallest effect on visitation share of the Hahei site, with a 20.3% decrease from 0.047 to 0.0375. Just over half of the visits are redistributed within the Mercury Bay area and there are small increases (0.6% - 0.9%) in each of the other areas. However, the CNL model ignores the fact that many visitors to undeveloped sites will want low-cost accommodation nearby. Similarly, model ACDC1 also redistributes visitors mostly to sites closest to Hahei with no regard for the reduced accessibility to campgrounds.

The CD2 model has a positive and significant parameter on campground accessibility, which means that sites close to Hahei (such as Cathedral Cove and Hot Water Beach) lose visitors also. Similarly, ACDC2 also predicts a decline in visitors to most beaches near Hahei. A difference arises from the fact that the campground substitute parameter in ACDC2 is close to zero. Cooks Beach and Whitianga both have campgrounds, so they gain rather than lose visitors in the ACDC2 model.

Table III – Change in site and area visitation for scenario A

			% Change in share			
	Site Name	Current share	CNL	CD2	ACDC1	ACDC2
Individual sites	Hahei	0.047	-20.3%	-23.0%	-24.3%	-31.1%
	Cathedral cove	0.020	2.0%	-29.5%	9.2%	-22.8%
	Hot Water Beach South	0.009	1.6%	-10.7%	4.2%	-7.9%
	Cooks beach	0.043	1.5%	-2.6%	0.5%	5.1%
	Whitianga	0.084	0.8%	2.3%	1.3%	4.4%
Areas	Coro-Colville East	0.147	0.7%	3.4%	2.6%	2.6%
	Coro-Colville West	0.042	0.6%	3.4%	0.0%	2.6%
	Mercury Bay	0.469	-0.9%	-3.6%	-1.6%	-2.5%
	Tairua-Pauanui	0.118	0.9%	2.3%	2.2%	3.9%
	Thames	0.084	0.7%	3.6%	1.5%	2.9%
	Whangamata	0.140	0.8%	3.4%	1.8%	3.5%

A second scenario (B) involves the construction of a seawall at Tairua ocean beach to protect properties from coastal erosion. This would result in the loss of sand dune, so it affects two attributes (seawall and dune) and the associated accessibility variables. The CNL model predicts a 14.7 percent decrease in the probability of visiting Tairua ocean beach and some variation in redistribution to other sites due to the heterogeneous substitution patterns imposed by the nesting structure. The CD2 model has larger coefficients for dune and seawall, so it predicts a larger decline at Tairua (-20.8 percent). Because the accessibility parameters on “natural dune” and “no seawall” are small, the redistribution of visits is relatively even across all other sites. The ACDC1 model again predicts most visitors will be redistributed to the closest sites. The ACDC2 predicts that near sites without a dune (such as Tairua harbour) will also lose visitors because complementary dune accessibility decreases.

Similarly, sites with seawalls are negatively affected by the reduced accessibility to beaches with no seawalls. Seawalls are predominantly located in Mercury Bay area (Whitianga and Cooks Beach), Coromandel-Colville West and Thames.

Table IV – Change in site and area visitation for scenario B

			% Change in share			
	Site Name	Current share	CNL	CD	ACDC1	ACDC2
Individual sites	Tairua	0.057	-14.7%	-20.8%	-16.5%	-17.7%
	Pauanui	0.042	1.5%	2.6%	5.6%	2.9%
	Hahei	0.047	-0.4%	2.3%	4.5%	2.7%
	Tairua harbour	0.008	0.6%	2.6%	6.0%	-2.6%
	Whitianga	0.084	0.5%	1.8%	1.6%	-0.1%
Areas	Coromandel-Colville East	0.147	1.1%	1.4%	0.5%	1.6%
	Coromandel-Colville West	0.042	0.8%	1.9%	0.0%	0.5%
	Mercury Bay	0.469	1.1%	2.0%	0.9%	1.1%
	Tairua-Pauanui	0.118	-9.4%	-15.4%	-5.3%	-6.8%
	Thames	0.084	2.0%	2.5%	0.3%	0.7%
	Whangamata	0.140	1.9%	2.5%	1.1%	1.3%

7. Management implications

Our preferred model, ACDC2, is more useful than the alternatives for analysing policy options such as campground development and coastal erosion protection. It captures not only the on-site effects but also the effects on other sites that are specific to the type and location of the change.

In addition, the model highlights the importance of site diversity in a context where multiple-destination visits are common. Undeveloped sites have a lower probability of being visited, but the model shows they increase the attractiveness of nearby developed sites, which visitors could use as a base for a visit to the undeveloped site. If an undeveloped site is the last in the area, then the ACDC2 model implies development would have a detrimental effect on surrounding areas that would lose accessibility to an undeveloped beach. Conversely, in more remote areas such as the northern end of the Peninsula, general development could provide food, accommodation, and boating facilities that are currently unavailable, and therefore have positive value to visitors in the wider area. Development decisions require consideration of the existing spatial distribution of services and site attributes.

8. Limitations

Data limitations of this study meant that we could only analyse choices conditional on the decision to visit the Peninsula. We could not model substitutions between alternative regions or other types of recreation. Nor could we model state-dependent effects such as resistance to change, since there were no changes to observed beach attributes during the data collection period. Emotional attachment to place can generate mobilisation against coastal change (Kearns & Collins, 2012). This status-quo bias could manifest as support for seawalls in erosion prone areas, or intense opposition to new development even if it provides additional services. The model allows a preliminary assessment of where certain changes might be more or less favourable but to analyse specific changes would require more detailed data from stated preference studies or qualitative research.

Nor do we model heterogeneity of visitor preferences beyond including an income-interaction variable for cost[8]. There are innumerable possibilities to create discrete distributions from demographics, trip motivation, residence location, group composition, or activities. Heterogeneous response to change is an issue we leave for future research about site-specific management issues.

[8] An individual-specific randomly-distributed error-component was tested but the resulting model was unstable.

9. Conclusion

With this study we have demonstrated that including multiple accessibility variables in a destination choice model allows for complex substitution patterns and avoids the need to exogenously specify a hierarchical structure as in GEV models. Our preferred model does not impose the restrictive IIA property and is more computationally tractable than multinomial probit models or mixed logit with large numbers of random parameters. The use of separate complement and substitute accessibility variables for each attribute captures the complex spatial dimensions of agglomeration and competition and hence makes the model attractive for spatial planning and policy processes.

10. References

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11. Appendix

Table V – Site variable definition and sources

Variable name	Average	Definition	Source
Area CE	0.15	1 if site is in Coromandel-Colville East area, otherwise 0	Community Boards GIS layer (WRC)
Area CW	0.34	1 if site is in Coromandel-Colville West area, otherwise 0	Community Boards GIS layer (WRC)
Area M	0.31	1 if site is in Mercury Bay area, otherwise 0	Community Boards GIS layer (WRC)
Area TP	0.06	1 if site is in Tairua-Pauanu area, otherwise 0	Community Boards GIS layer (WRC)
Area W	0.08	1 if site is in Whangamata area, otherwise 0	Community Boards GIS layer (WRC)
Boat ramp	0.06	1 if site includes boat launch facilities, otherwise 0	Coastal structures GIS layer (WRC)
Campground	0.24	1 if site has a campground, otherwise 0	Inspection of Google Map
Natural dune	0.32	Proportion of beach length with a sand dune	"TOE_OF_DUNE" GIS feature (WRC)
Estuary	0.06	1 if site is a harbour or estuary, otherwise 0	Visual inspection of map
Food retailer	0.16	1 if site has a convenience store, café or restaurant	Inspection of business names on Google Maps and Streetview
Motel	0.07	1 if site motel, hotel or other serviced accommodation	Inspection of business names on Google Maps and Streetview
Playground	0.21	1 if site has a public playground, otherwise 0	GIS point data (TCDC)
Public road	0.36	1 if site has a public road within 200m of the foreshore	Visual inspection of map
Public toilet	0.39	1 if site has a public toilet, otherwise 0	GIS point data (TCDC)
Sandy beach	0.65	1 if beach is sandy, 0 if it is predominantly shingle, silt or rock	Landcover database V3 (MfE) and visual inspection
Undeveloped	0.46	1 if there are no buildings at the site, otherwise 0	Properties GIS layer (LINZ)
Small urban	0.13	1 if site overlaps a "local" scale urban area	Urban boundaries GIS layer (WRC)
Medium urban	0.09	1 if site overlaps a "district" scale urban area	Urban boundaries GIS layer (WRC)
Large urban	0.10	1 if site overlaps a "regional" scale urban area	Urban boundaries GIS layer (WRC)
Seawall	0.20	1 if site overlaps a "local" scale urban area	Coastal structures GIS layer (WRC)

Table VI – Compatibility Logistic Regression

Dependent variable = 1 if site A visitor also visits site B, otherwise 0	Coefficient
Intercept	-4.2584***
Site A visitors	-0.0005**
Travel time between sites	-0.0380***
Site B Characteristics	
Site B visitors	0.0058***
Site B is on-route to site A	0.4706***
Mercury Bay area	1.1896***
Tairua-Pauanui area	-0.1466
Coromandel-Colville East	0.1958**
Coromandel-Colville West	1.0234***
Whangamata Area	0.2615**
Boat ramp	0.3710***
Campground	0.2191***
Natural dune	0.5546***
Estuary	-0.9835***
Food retailer	0.1237**
Sandy beach	-0.0061
Motel	-0.1553
Playground	0.0523
Public road access	0.9287***
Public toilet	0.1833***
Seawall	-0.2736***
Undeveloped	-0.2835***
Small urban	-0.1750***
Medium urban	-0.3274***
Large urban	-0.2286***
Differences - characteristics possessed by site B but not site A	
Different area	-0.2536***
Boat ramp	-0.0267
Campground	0.0599
Natural dune	0.4101***
Food retailer	-0.0852
Not on an estuary	0.2747***
Sandy beach	0.2468***
Motel	0.0972
Playground	0.1013*
Public road access	- 0.1117
Public toilet	0.2211***
No wall	0.0228
Undeveloped	0.5147***
Urban	0.2134***
Larger urban	-0.2284***
Smaller urban	-0.6041***

Observations	11881
Null deviance	21850.9
Residual deviance	7881.3

* significant at 10%, ** significant at 5%, *** significant at 1%

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Yvonne Matthews has recently completed a PhD at the University of Waikato, New Zealand. Her research interests include realism and reliability in choice experiments, and how make environmental economics useful for policy decision-making. She has published results in the Journal of Environmental Economics and Management, and Ecological Economics.

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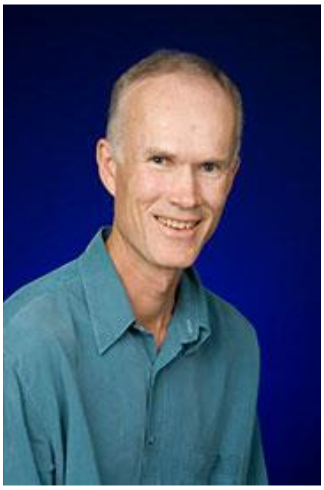

Dan Marsh was awarded his MA from Oxford University, MSc from the University of Reading and PhD (Factors affecting innovation in biotechnology) from the University of Waikato. He has worked on development projects in Nepal, Botswana, Ghana, Pakistan, Oman, Bangladesh, Cambodia, India, Kazakhstan and Bosnia.

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