Issues in the non-market valuation of Coromandel coastal recreation: realism, permanence and spatial distribution

A thesis

submitted in fulfilment

of the requirements for the degree

of

Doctor of Philosophy in Economics

at

The University of Waikato

by

Yvonne Sharon Matthews

THE UNIVERSITY OF
WAIKATO
Te Whare Wānanga o Waikato

2017

Abstract

The purpose of this thesis is to apply non-market valuation techniques to estimate the effect of coastal development and erosion protection on beach recreation values. The study area is the Coromandel Peninsula in New Zealand. The peninsula is a popular holiday destination and the coastal landscape generates strong feelings of attachment in many New Zealanders. However, twin pressures of rising coastal land values and shoreline fluctuations have led to conflict between people who want to protect or develop built environments and those who want to conserve or restore natural landscapes. The recreation amenity values which are under threat are difficult to include in a cost-benefit analysis of coastal policy because they have no explicit market price.

I review the issues and limitations associated with non-market valuation methods and apply advanced visualisation and spatially-referenced data collection techniques to estimate the non-market values. This thesis comprises four papers which are either published or in the process of being published. A particular focus is whether 3D visualisations or "virtual environments" can improve the reliability and validity of stated preference results. The first paper describes the rationale and method for developing the virtual environments for use in a choice experiment about erosion protection and headland development. I find the virtual environments reduced bias, improved choice consistency and made respondents more likely to complete the survey. In the second paper I report the results of a choice experiment about development options for a specific undeveloped beach. I find that the virtual environment presentation format more strongly influences stated preferences amongst respondents with no direct experience of the site. The additional information provided by 3D visualisations may therefore be useful when people have to make decisions about the unfamiliar.

In the third paper I report the results of tests of stability of stated preferences over time. A novel feature of this study is the use of two re-tests over time rather than just one. I find that stability at an individual level is positively associated

with choice certainty. The virtual environments have a positive effect on respondent confidence but respondent education level has a larger effect. The large variation in stated value over time is consistent with the constructed preference viewpoint. However, the results are not necessarily incompatible with the alternative discovered preference hypothesis because there may have been too little consequential feedback to facilitate any preference learning.

In the fourth paper I report the results of a destination choice analysis for beach recreation on the Coromandel Peninsula, using data collected in the same survey as the choice experiments. The focus of the fourth paper is the issue of spatially correlated errors caused by the spatial distribution of sites. Visitors are influenced by opportunities available at other sites and many visit multiple beaches in one trip, which violates the conventional assumption that sites are substitutes. I analyse the cumulative attraction of each pairwise combination of sites and review modelling approaches that allow for flexible patterns of substitutions but are also computationally efficient. I find that an Agglomerating and Competing Destination Choice (ACDC) model with differentiated accessibility parameters for each attribute offers the best fit. It has complex response properties for specific site changes yet retains a computationally feasible closed form. I use the model to examine the implications of two site-specific changes. The results highlight the importance of preserving coastal camping grounds and natural sand dunes because these attributes increase the diversity and attractiveness of the wider area as well as the individual site .

The findings of these four papers and the data collected for this thesis make a significant contribution to knowledge about the recreation value of Coromandel beaches. This research is of particular relevance to the local policy issues of coastal erosion and development.

Acknowledgements

This research would not have been possible without funding provided by the Waikato Doctoral Scholarship and the Department of Economics. I am very grateful to my supervisors Professor Riccardo Scarpa and Dr Dan Marsh for their guidance and my manager Ruth Buckingham for being so supportive of my studies. In addition, Waikato Regional Council helped with survey expenses. Thanks also to everyone who reviewed or proof-read the papers or listened to me complain about having to write my thesis. Finally, I dedicate this thesis to my daughters Zara and Ashley who taught me advanced time management skills and helped me keep things in perspective.

Table of Contents

1. INTRODUCTION

The coastal environment of the Coromandel Peninsula of New Zealand is highly valued for recreation and relaxation. It is close to the cities Auckland, Tauranga and Hamilton but the rugged geography and forested interior has historically limited the scale and scope of human development. However, twin pressures of rising coastal land values and shoreline fluctuations have created conflict between natural and built environments, conservation versus protection and public versus private property. The recreation amenity values which are under threat are difficult to include in a cost-benefit analysis of coastal policy because they have no explicit market price. Environmental non-market valuation techniques are therefore required. The purpose of this thesis is dual-edged. First, I aim to provide robust estimates of the effects of Coromandel coastal development and erosion protection on non-market amenity values. Second, I review the issues and limitations associated with the non-market valuation methods I use. I apply state-of-the-art techniques in visualisation and spatially-referenced data collection. A particular focus is on whether 3D visualisations can improve the reliability and validity of stated preference results.

The remainder of this chapter is organised as follows. First, I outline a history of non-market valuation and choice modelling methods. This section explains the current methodological issues and challenges for practitioners. I explain the motivation for focussing on improving realism through visualisations, analysis of stability and spatial dependencies. The specific models and equations used in each paper are included in the method section within that paper and are not repeated in this introduction. In the second section I provide more detail about the Coromandel Peninsula and why non-market valuation of coastal recreation is important for local policy and strategy. In the third section I describe the survey instrument and sample recruitment because these are not explained in detail in included papers due to publishing space limits. In the final section I provide an

overview of each paper, contribution to the literature and current status in terms of publication.

1.1 MOTIVATION AND METHODOLOGY OVERVIEW

1.1.1 A BRIEF HISTORY OF NON-MARKET VALUATION AND CHOICE MODELLING

Non-market valuation refers to methods used to estimate the economic value of goods or services which are not traded in markets. These methods are particularly important to the field of environmental economics which is concerned with the costs and benefits of environmental policies. In a review of the history of environmental economics, Pearce (2002) explains that the idea that policies could be evaluated in terms of costs and benefits, individual preferences and willingness-to-pay (WTP) can be attributed to Dupuit (1853). The theory of an externality such as environmental pollution was formalized by Pigou in the 1920s and welfare economics developed in the 1930s to 40s (e.g. Hicks, 1939; Kaldor, 1939) provided the analytical formulations to account for these externalities in cost-benefit analysis. The concepts of option and non-use values, which can comprise a large proportion of environmental values were identified in the 1960s (Krutilla, 1967; Weisbrod, 1964). Mäler (1974) showed that the welfare measure concepts of compensating and equivalent variation could be extended from analysis of price changes to quantity changes and also discussed the elicitation of willingness-to-pay (WTP) or willingness-to-accept (WTA) from questionnaires.

The process of using surveys and questionnaires to ask questions about preferences and WTP became known as Stated Preference (SP) methods. This is in contrast to Revealed Preference (RP) methods in which preferences are revealed through the inspection of other markets, such as travel or housing. However, as noted by Carson and Louviere (2011), both SP and RP methods require inference to estimate actual preferences and the statistical methods are often identical. With the increasing availability of microeconomic data from 1960's, economists began to focus on individual behaviour and WTP. Data

collected at the level of the individual decision do not suffer from the same problems that occur when attempting to infer response elasticities from the behaviour of heterogeneous groups (McFadden, 1974). However, new theories were required to explain and model these variations as part of consumer theory.

Random utility modelling (RUM) is an important theoretical framework for choice analysis. McFadden (2001) attributes the beginnings of random utility to Thurstone's (1927) *law of comparative judgement* which specifies a normal error component involved in choices between paired alternatives. Luce (1959) introduced the *independence from irrelevant alternatives* (IIA) axiom that allowed random utility theory to be extended to multinomial choices because it means the ratio of choice probabilities for two alternatives is the same regardless of how many other alternatives there are. Marschak (1960) introduced the concept of randomness in choices to economics and rational consumer theory and called it r*andom utility maximisation*. McFadden (1974) showed that a multinomial logit (MNL) model is consistent with RUM. The independently and identically distributed Type I extreme value error terms in MNL make computation far simpler than the normally distributed errors of a multinomial probit model. McFadden provided a direct connection to consumer theory and used MNL to calculate marginal WTP for characteristics of shopping destinations. This type of study became known as discrete choice analysis (Carson & Louviere, 2011). Lancaster's (1966) theory of consumer behaviour is also relevant to choice analysis because it states a good can be defined as a bundle of characteristics. Choices between these bundles can yield insights into the relative value of each characteristic. If the choices are between alternatives devised by the researcher (SP) rather than measurement of real-world choices (RP), it is a "discrete choice experiment" (Carson & Louviere, 2011).

Subsequent developments in discrete choice analysis included nested logit and GEV models with hierarchical choice structures (McFadden, 1978), mixed logit models with random taste or error parameters (Train, 1998) and WTP-space models (Train & Weeks, 2005). Simulation methods have also been developed to

approximate the multi-dimensional integration required to fit multinomial probit models (Bhat, 2011). The discrete choice experiment (DCE) is now a popular method in stated preference non-market environmental valuation literature (Adamowicz, Glenk, & Meyerhoff, 2014). It is well suited to the analysis of environmental policies with multiple effects and can be used to estimate marginal WTP or WTA for each effect or attribute. Choices may be less prone to biased responses than other elicitation methods such as open-ended contingent valuation where respondents are asked to specify a dollar value (Braga & Starmer, 2005).

1.1.2 Issues in stated preference methods

Stated preference techniques including DCEs are important in environmental economics because they can elicit all kinds of economic value relevant to a policy or project decision. However, they have always been controversial. In perhaps the first discussion of stated preference techniques, Mäler (1974) was concerned about whether respondents would be motivated to tell the truth. The potential for incongruence between stated and actual WTP is known as hypothetical bias and has been a criticism of SP methods ever since. There are many studies in the literature devoted to measuring, minimising and controlling for hypothetical bias. See, for example, a meta-analysis by Murphy, Allen, Stevens and Weatherhead (2005). Due to the extensive coverage of hypothetical bias in the existing literature, this topic is not an area of focus in my investigation of Coromandel non-market values.

The other major issue with SP methods is a range of "anomalies" (Braga & Starmer, 2005) reported in decision behaviour research that are inconsistent with expected utility theory. The theory of consumer behaviour was "shorn of all irrelevant postulates" (Lancaster, 1966) but perhaps it was shorn too closely. The anomalies found in environmental valuation studies include scope insensitivity and dependence on other options in the choice set (Tversky & Kahneman, 1991), preference reversals due to different response mode (Slovic, Griffin, & Tversky, 1990), gain/loss asymmetry (Horowitz & McConnell, 2002) and other

presentation-dependent effects, such as framing. These results and the importance of the situational component they imply have been taken as evidence that preferences are often constructed, rather than merely revealed, in response to an elicitation question (Gregory, Lichtenstein, & Slovic, 1993).

The constructed preference perspective acknowledges that individuals have limits on their ability (and motivation) to process complex information (Simon, 1955). This bounded rationality means that people may use simplifying strategies such as satisficing to construct preferences, rather than a consistent and invariant algorithm such as expected value calculation. There can be multiple, potentially conflicting processing goals such as maximising accuracy, minimising effort, minimising negative emotion or maximising ease of justification (Payne, Bettman, & Schkade, 1999). These strategies may vary depending on the method of elicitation, causing procedural variance (Gregory et al., 1993). Even when people have strong pre-existing preferences for the environment, they may be unaccustomed to making trade-offs between environmental quality and allocation of government funding. This lack of compatibility between stimulus and response (Slovic et al., 1990) is believed to contribute to processing pitfalls.

Plott (1996) criticises the constructed preference perspective for undermining the foundations of rational choice theory, which assumes stable and context-free preferences exist independently of the elicitation process. However, Payne et al. (1999) argues that constructed preferences do not necessarily mean there is no "true" value. Rather, "truth ultimately resides in the process" (Slovic, 1995) of the decision. The role of the non-market valuation researcher is to ensure respondents have all the relevant information and make decisions with a high standard of reasoning. The decisions of boundedly rational individuals can be improved if information provided is all salient and easy to process. Respondents who have difficulty evaluating information make larger and more frequent errors of judgement (Bateman, Jones, Lovett, Lake, & Day, 2002). An effective way to improve comprehension of information is the use of visualisation techniques and this is a central area of contribution of this thesis to the literature.

1.1.3 VISUALISATIONS AND VIRTUAL ENVIRONMENTS IN CHOICE EXPERIMENTS

In choice experiments the attributes of non-market goods are typically presented as a table of data, sometimes with images. Visualisations such as photographs, maps and diagrams have been found to both standardise and aid respondents' comprehension in many studies (Mathews, Freeman, & Desvousges, 2006). For example, MacGregor and Slovic (1986) report that visual displays helped respondents integrate information cues into a correct overall judgement. Lipkus and Hollands (1999) report that visual information outperformed numeric data when it came to understanding risk, and Epstein and Pacini (2001) report that visualization of a description of a game of chance reproduced a response that otherwise only occurred in real situations.

Advances in computing power and geographically-referenced modelling software have opened up the possibility of visualising choice experiment alternatives in 3 dimensions. 3D rendering software, combined with geographic information system (GIS) data allows the generation of realistic, accurate and evaluable representations of real-world environments. If the models are interactive they are referred to as virtual reality (VR). Otherwise, the term virtual environment (VE) is more correct. 3D visualisations are reported to be more engaging that static images (Harrison, Haruvy, & Rutström, 2011; Jude, 2008), help respondents generate more accurate beliefs (Fiore, Harrison, Hughes, & Rutström, 2009) and help respondents make decisions more consistent with their verbalised preferences (Bishop, Wherrett, & Miller, 2001). Some researchers developed 3D models to illustrate environmental scenarios, but presented these to respondents as static images (Davies, Laing, & Scott, 2002; Madureira, Nunes, Borges, & Falcão, 2011; Olschewski, Bebi, Teich, Wissen Hayek, & Grêt-Regamey, 2012). I.e. they did not make full use of the dynamic nature of 3D visualisations. In perhaps the first use of VEs in environmental valuation, Bateman et al. (2009) report that the 3D visualisations improved the evaluability of unfamiliar land-use change scenarios and reduced anomalous gain/loss asymmetry.

Despite the apparent benefits, use of 3D visualisation has been extremely limited in environmental valuation. This could be because creating virtual environments was traditionally a complicated and expensive undertaking, requiring access to a GIS database and specialised software such as AutoCAD, Arcview or Terra Vista. However, digital elevation maps and satellite imagery are now freely available in Google Earth™. This data may be imported and manipulated at low-cost, by means of relatively intuitive software such as Sketchup™ [1]. The increasing pervasiveness of high-speed internet in homes is another important technological development because it means VE experiments are no longer necessarily restricted to the exclusive settings of expensive computer labs. It follows that now is an ideal time to bring virtual environments into the mainstream environmental valuation toolkit. This point motivates one methodological contribution of this thesis.

1.1.4 STABILITY OF PREFERENCES

Another important issue in the area of stated preferences is stability over time. Results may be used from studies conducted years ago in both policy design and benefit transfer. In these cases a fundamental maintained assumption is that these values are robust over time (Brouwer, 2006). The implication of the constructed preference perspective is that preferences for the unfamiliar may be transient (Simon, Krawczyk, Bleicher, & Holyoak, 2008) and therefore variable over time. Conversely, the discovered preference hypothesis (Plott, 1996) implies that stability will improve with repetition. Most environmental valuation studies use data collected at a single point in time, so the assumption of temporal stability cannot be tested. At the time of planning this research there were no environmental choice experiments in the literature with delayed retests using the same respondents. There are now some recent examples (Czajkowski, Barczak, Budziński, Giergiczny, & Hanley, 2016; Liebe, Meyerhoff, & Hartje, 2012; Lienhoop & Volker, 2016; Schaafsma & Brouwer, 2013) which all report rejection

[1] The Sketchup motto is “3D modelling for everyone” http://www.sketchup.com/

of strict tests of preference equality, but varying levels of stability in mean WTP. Some important empirical questions remain, such as whether and to what degree choice consistency can be explained by individual characteristics or study design. This study about Coromandel beaches has a relatively unique aspect, which is the use of a second retest three months after the first retest. This additional data point allows the examination of whether stability improves with repetition as the discovered preference hypothesis predicts.

1.1.5 ISSUES IN REVEALED PREFERENCE METHODS

The travel cost method is most often used to estimate the benefits of outdoor recreation such as beach visits (Whitehead 2008, Pattanayak et al. 2008). It begins with the realization, attributed to Hotelling (1947), that the major cost of outdoor recreation is the travel and time costs incurred to get to the recreation site. Random utility maximisation is the predominant modelling approach in non-market valuation based on travel cost (Phaneuf & Smith, 2005). The discrete site choice random utility framework incorporates travel costs and site qualities and allows the estimation of demand and substitution patterns across multiple sites. Analysis of site choice and trade-offs between travel cost and site characteristics allows the inference of the marginal value of these characteristics.

A disadvantage of RP methods is that they rely on existing combinations of site attributes (which may be collinear) and can only be used to analyse environmental quality levels within the realm of previous experience. RP may be prone to bias because functional form and choice of variables can greatly affect welfare estimates from hedonic and travel cost data (Azevedo, Herriges et al. 2003). Methodological issues in destination choice analysis include the definition of the destination set (Thiene, Swait & Scarpa, 2017), recall error (Whitehead et al., 2010), the appropriate opportunity cost of time (Fezzi, Bateman, & Ferrini, 2014), value allocation in multiple destination trips (Lue, Crompton, & Fesenmaier, 1993) and spatially correlated errors (Anselin, 2001).

GIS data and trip data for this research is limited by the research sponsor to the Coromandel Peninsula, New Zealand. This limits the scope of the destination set. Nevertheless the study includes a large number of distinct beach sites (109). I test a model specification that allows for different probabilities of evaluation by respondents for destinations that are small and remote. Using three separate instances of data collection over the period from spring to autumn is expected to reduce the risk of recall error compared with the standard approach of asking once about all trips in the previous year. I also test the effects of different assumptions about allocation of travel cost among multiple-beach-destination trips. However, the main focus of my RP analysis is testing modelling approaches to address spatially correlated errors in the trip data. This research is meaningful within the New Zealand environment because the Coromandel Peninsula has some unique geographic and sociographic characteristics. The effects of these characteristics on destination choice, and the resulting policy implications, have not previously been studied.

1.2 Empirical Context – The Coromandel Peninsula

I explore the above issues in non-market value in the empirical context of recreation and non-use values of coastal landscapes on the Coromandel Peninsula of New Zealand. Coastal landscapes, such as those on the Coromandel Peninsula, generate strong feelings of attachment among New Zealanders (Collins & Kearns, 2010a). The Coromandel Peninsula is a relatively small geographic land area of approximately 2,300 square kilometres and with a usual resident population of 27,000. It has a diverse range of landscapes from undeveloped beaches and native forest cover to towns and coastal protection structures. Thames-Coromandel is one of the fastest-growing districts in the country and tourism causes the population to fluctuate dramatically, as much as tripling during the summer. The geography is also dynamic, with sand movement and storms causing noticeable changes in some shorelines from year to year.

In the nineteenth century the economy on the Peninsula was dominated by gold mining and kauri logging. Farming and commercial fishing became more common in the twentieth century, but poor roading and lack of a deep harbour meant the area remained geographically isolated. The population began to grow from the 1960s with the rise in popularity of coastal beaches and holiday accommodation. The Peninsula is a significant tourism destination for both domestic and international tourists, although the majority of visitors are domestic (Thomson 2003). Although it is close to two large population centres, Auckland to the west and Tauranga to the southeast, its rugged nature means that much of the relatively isolated interior and northern tip are both largely undeveloped and sparsely inhabited. Coromandel Forest Park covers much of the peninsula's interior. It is also a centre for environmental tourism and various environmental projects such as kauri planting and habitat protection for native birds and aquatic life.

Figure 1-1 - Map of the Coromandel Peninsula

1.2.1 POPULATION

There were approximately 26,200 usual residents and 11,500 occupied dwellings in the Thames-Coromandel district as at the 2013 census (Table 1-1). A large proportion of property on the Peninsula are secondary or holiday homes and not occupied all year round, which explains the large discrepancy between residential properties and dwellings occupied on census night (Tuesday, March 7). The difference is largest in the Tairua-Pauanui community where only 25 per cent of residential properties were occupied on census night.

The final column shows average socioeconomic deprivation for each area. The deprivation index[2] ranges from one to ten, with ten being the most deprived. The average for Thames-Coromandel is 6.8 while the Waikato region is 6.0. Thames-Coromandel district had less deprivation in 2006, but the change may be partly due to the fact that lack of a home internet connection now contributes to the deprivation measure. The Coromandel-Colville area has the highest level of social deprivation (8.1) and Tairua-Paunui the lowest (5.1).

Table 1-1 - Population and occupied dwellings by community board area

Community	2013 Residents	2013 Occupied dwellings	Per-cent occupied	2013 Deprivation
Coromandel-Colville	2823	1218	89%	8.1
Mercury Bay	7182	3126	41%	6.3
Tairua-Pauanui	2289	1032	25%	5.1
Thames	10047	4395	94%	6.9
Whangamata	3873	1746	34%	7.2
Coromandel Total	**26214**	**11517**	**49%**	**6.8**

1.2.2 COROMANDEL LAND VALUES

Figure 1-2 shows the distribution of rateable land values on the Peninsula, excluding Department of Conservation land. Land value per square metre ranges from less than $1 in rugged rural areas to over a thousand dollars for prime locations. Higher land values are positively associated with population density, accessibility, and access to urban services such as water and electricity. The value of natural landscape features is reflected in the premium values for beachfront or elevated properties with coastal views. While population density provides services that add to the value of properties, it is also a result of historical choices of which areas to develop. So, it is difficult to disentangle the marginal value of the coastal landscape by looking only at property values.

[2] A combination of 9 variables which reflect different dimensions of deprivation. Includes income, benefits, unemployment, access to communication and transport, single parent status, qualifications, living space and home ownership (Atkinson, Salmond & Crampton, 2014).

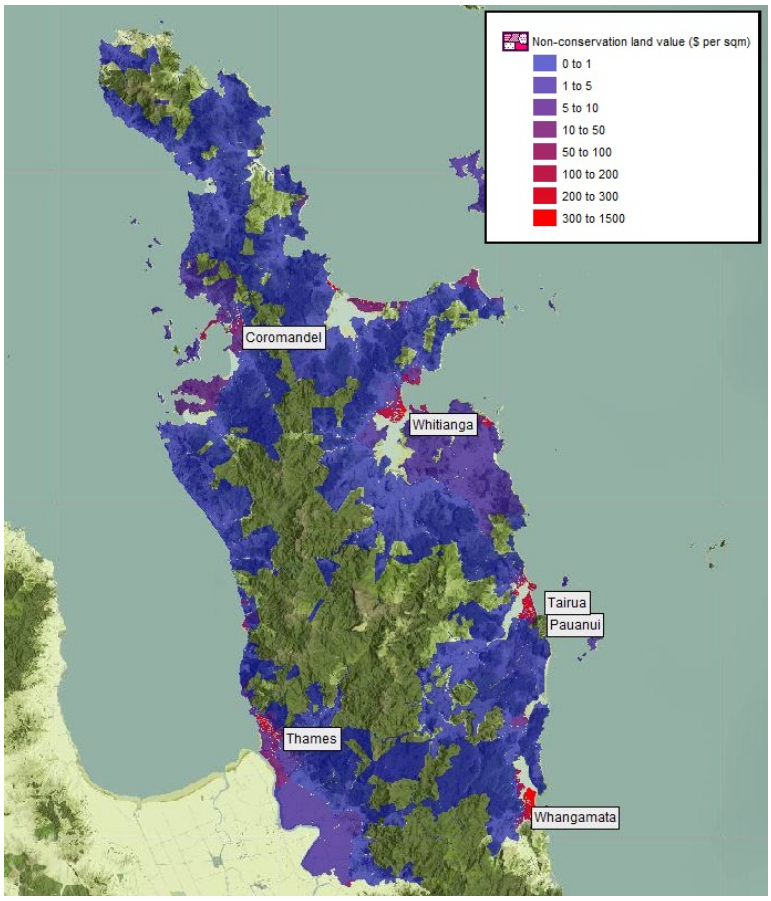


Figure 1-2 - Land value per square metre of non-conservation land[3]

There were approximately 22,200 residential properties[4] in the Thames-Coromandel district, with a total capital value of $10.6 billion and land value $7.2 billion in 2013. Residential property values tend to be higher on the east coast. Whangamata has the highest average capital value and land value per square metre of residential property at $691 and $477 respectively. Thames-Coromandel district residential property values are significantly higher than average for the Waikato region.

[3] Cadastral information derived from Land Information New Zealand's Landonline Cadastral Database". CROWN COPYRIGHT RESERVED. Valuation Data Sourced from Territorial Authority District Valuation Roll

[4] Includes properties where either zone code or land use code begin with '9'

Table 1-2 - Number and rateable value of residential properties by community board area (2013)

Community Board Area	Residential Properties	Capital value ($M)	Land value ($M)	Capital value per m2	Land value per m2	Avg area (sqm)
Coromandel-Colville	1364	$508	$313	$210	$129	1776
Mercury Bay	7542	$3,934	$2,749	$493	$345	1058
Tairua-Pauanui	4142	$2,342	$1,617	$558	$385	1013
Thames	4672	$1,230	$653	$212	$113	1425
Whangamata	5104	$2,601	$1,794	$691	$477	738
Coromandel Total	22219	$10,616	$7,126	$439	$295	1087
Waikato region Total	143,117	$48,083	$24,577	$300	$153	1119

1.2.3 TOURISM

In the year ended March 2014 there were 376,700 guest arrivals and 729,000 guest nights spent in commercial accommodation in the Coromandel Regional Tourism Organisation (RTO) area. Domestic visitors accounted for 210,400 arrivals and 488,000 guest nights[5].

Data from the MBIE Domestic Travel Survey (DTS) from 2006 to 2011[6] show that only a fifth of visitor nights to the Peninsula are spent in commercial accommodation, which comprises hotels, motels, backpackers and campgrounds. Bed and breakfasts, free camping and private holiday homes are excluded. Including these other types of accommodation, there were approximately 1,026,000 overnight (one or more nights) visits by New Zealanders in total.

Overnight visits comprise 39 percent of all domestic visits to the Peninsula so there are around 2.7 million trips per year including day trips[7]. Two thirds of these are for the purpose of beach recreation, which implies a total of 1.8 million

[5] http://www.med.govt.nz/sectors-industries/tourism/tourism-research-data/commercial-accommodation-monitor-data

[6] http://www.mbie.govt.nz/info-services/sectors-industries/tourism/tourism-research-data/domestic-travel-survey

[7] MBIE Regional Tourism Estimates 2006-2011

trips for beach recreation per year (which may include visits to multiple beaches).

The following Figure 1-3 shows the origin of visitors for all visits to the Coromandel Peninsula[8]. Aucklanders have the largest share at 43 percent, followed by Waikato residents (27 percent). Only 15 percent of visitors are international, with a third of these from Australia.

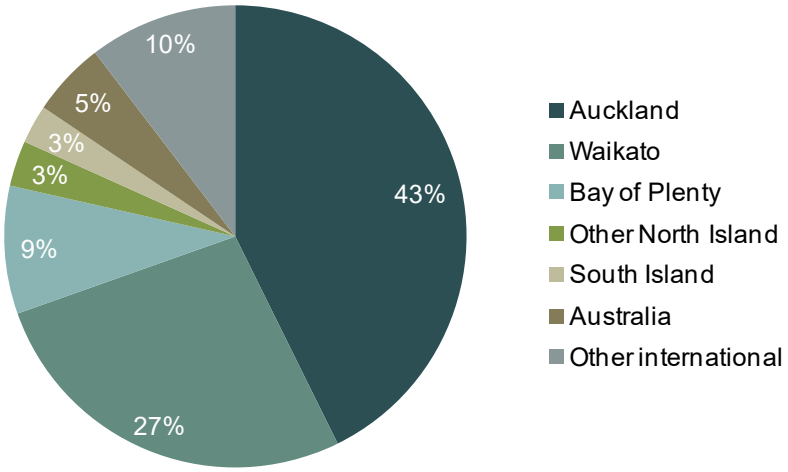


Figure 1-3 - Origin of visitors to the Coromandel Peninsula

The Ministry of Business, Innovation and Employment (MBIE) estimated spending by visitors to the Coromandel RTO to be $204 million in 2014, of which $145 million is domestic (Figure 1-4). Total gross output of the Thames-Coromandel district economy is estimated at $1,860 million for 2014[9]. So, tourism is a significant part of the local economy. The limitation of visitor spending data is that it does not take into account fuel bought in other regions for the trip or the opportunity cost of travel time. Nor does the data allow any further spatial disaggregation.

[8] MBIE Regional Tourism Estimates 2006-2011

[9] Estimated using Waikato Spatial Economic Futures Model V.2011.01 (Doc #2135477) and adjusted for inflation

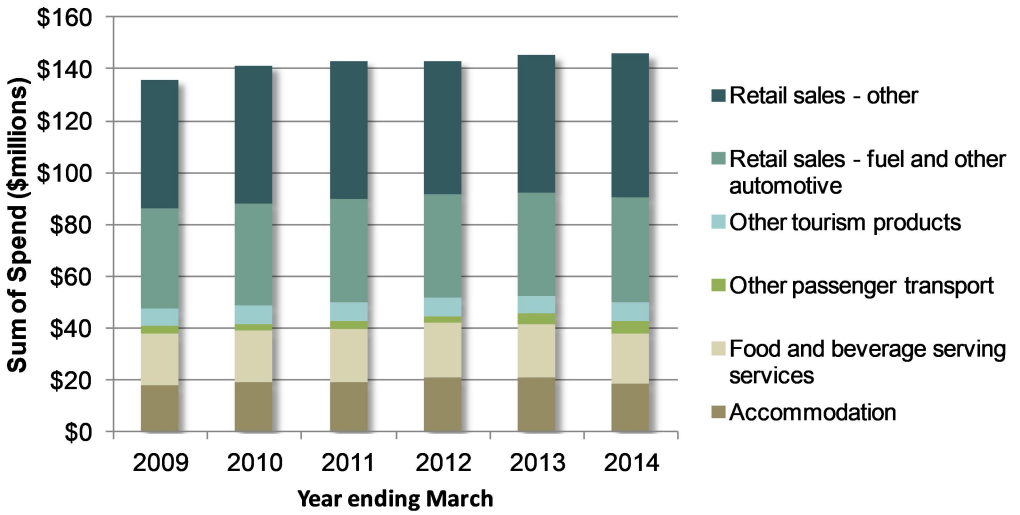


Figure 1-4 - Total spending by domestic visitors in Coromandel RTO[10]

1.2.4 Coromandel Coastal Policy Issues

The Waikato Regional Council and Thames-Coromandel District Council are responsible for coastal management of the Coromandel Peninsula. Coastal management is concerned with protecting, conserving and managing coasts and coastal resources. The New Zealand Town and Country Planning Act 1953 first recognised that unspoiled coastal areas are a scarce resource. The 1991 Resource Management Act (RMA), which replaced the Town and Country Planning Act, requires regional coastal plans to control the following activities:

- the occupation of space on the foreshore and seabed,
- the allocation of sand and shingle resources,
- navigation structures (buoys, markers, lights, lighthouses),
- natural hazards, hazardous substances,
- surface water activities,
- discharges of wastewater, contaminants
- and management of coastal habitats.

[10] http://www.rtonz.org.nz/coromandel.html

Regional and local policy statements and plans are also required to give effect to the New Zealand Coastal Policy Statement (NZCPS). The NZCPS took effect in 1994 and was revised in 2010. It states policies in order to achieve the sustainable management purpose of the RMA in relation to the coastal environment of New Zealand. The objectives of the NZCPS are to:

1. safeguard the integrity, form, functioning and resilience of the coastal environment and sustain its ecosystems, including marine and intertidal areas, estuaries, dunes and land;
2. preserve the natural character of the coastal environment and protect natural features and landscape;
3. take account of the principles of the Treaty of Waitangi, recognise the role of tangata whenua as kaitiaki and provide for tangata whenua involvement in management of the coastal environment;
4. maintain and enhance the public open space qualities and recreation opportunities of the coastal environment;
5. ensure that coastal hazard risks taking account of climate change, are managed;
6. enable people and communities to provide for their social, economic, and cultural wellbeing and their health and safety, through subdivision, use, and development, recognising;
7. ensure that management of the coastal environment recognises and provides for New Zealand's international obligations regarding the coastal environment, including the coastal marine area.

In deciding how to achieve these objectives, councils must take account of local issues and priorities and balance the competing economic, cultural, and environmental interests. Beaches and other natural assets provide flows of services to the public, such as recreation, economic impacts, landscape amenity, public access, natural character, conservation and heritage, which generate

consumer welfare for the recipients. Coastal management policies can have significant effects on the provision and quality of these services.

Coastal development and management of natural hazards can detract from natural character, reduce public access and affect recreation and other values. Coastal management decision-making will become increasingly difficult with the expected sea level rise from global warming and increased storm frequency and strength due to climate change, especially where on-going economic activities, such as subdivision and development, place increasing pressure on coastal resources. Often developers will attempt (either actively or passively) to externalise as many costs as possible (especially those with a longer timeframe) and put these onto communities and individuals. The economic choices available to communities need to be more clearly identified and debated at times of decision-making in order to avoid or minimise any inappropriate transfer of costs into the future.

Monetary impacts are relatively easily identified and measured, but there is little information on non-market values affected by coastal management. Non-market values include:

- use values which arise from utilization of the environment for recreational, social and cultural activities. Boating, fishing, swimming, and landscape appreciation are prominent non-market uses of the coastal environment;
- existence values, which arise from knowing that a beach exists in a certain state (existence values are typically associated with “natural” environments);
- option values, which arise from wanting to retain the option to visit a natural beach if the opportunity arises, a response to uncertainty about future demand for and supply of beach amenities.

The application of economic valuation techniques provides an alternative to qualitative evaluation of non-market effects. Without non-market valuation

these effects are either excluded from consideration, since they cannot be included in cost-benefit analysis, or are left for political consideration, which may not accurately reflect the values of those affected. Coastal landscape non-market values have both use and non-use components, and are geo-spatially referenced. These values are therefore suitable for a wide range of stated preference and revealed preference techniques, including spatial econometrics. Visual aspects are typically of foremost importance to coastal landscape values (Collins & Kearns, 2010a). There are two public policy issues affecting (or with potential to affect) Coromandel coastal landscape values. These are foreshore erosion and new development.

1.2.4.1 Erosion

Some beach development over the past few decades has occurred very close to the foreshore. In some areas property or roads are within a zone of natural beach erosion and accretion, which can be as much as thirty metres for dune beach systems (Environment Waikato, 2002). Natural protection provided by different zones of dune vegetation has been removed in many cases. In some of the worst affected areas structures such as rock armour or seawalls have been built to protect beachfront property. These structures adversely affect the landscape and recreation values of the beach and cause a loss of useable sandy foreshore. There is conflict between protection of private property and public amenity values. The prospect of rising sea levels places even more properties at risk and more hard structures may be built. Better information about the trade-offs between public and private, market and non-market values are required in order to improve the quality of long-term decision making and planning.

1.2.4.2 Development

Similar to many coastal areas in New Zealand, there is considerable development pressure and strong demand for holiday housing on the Coromandel Peninsula. There are few beaches remaining on the Peninsula that do not have buildings visible from the foreshore and most of these are in areas accessible only by boat.

Accessible undeveloped beaches are doubly valuable as natural landscapes and as sites that generate human emotions such as "nostalgia, freedom and belonging" (Collins & Kearns, 2010a). Some undeveloped beaches, such as Cathedral Cove, are adjacent to crown-owned land managed by the Department of Conservation so are at low risk of development. Others are adjacent to privately owned farmland which may be subdivided for development subject to a successful resource consent application.

One such beach at risk of private development is New Chums in Wainuioto Bay. It is approximately one kilometre long, with white sand characteristic of the east coast of the Peninsula. The surrounding hills are clad with native forest and large pohutukawa trees. Access to New Chums requires a thirty minute walk from nearby Whangapoua so it is relatively accessible. In 2010 an application was made to the local authority to develop a twenty-lot residential development on privately owned farmland adjacent to the beach. The application received high public interest in New Zealand and protection of the beach was strongly advocated by community groups[11]. People value not only the recreational use of New Chums but also option, bequest and existence values of this increasingly rare undeveloped beach resource. In June 2015 the latest application for consent was withdrawn, but there may be further applications in the future unless the land is purchased by the government for conservation or legally protected in other ways.

Development is also an issue for beaches that already have beachfront housing, but retain headlands that are relatively natural in appearance. While steep and difficult building sites, there is strong demand for houses on headlands and ridgelines where views may be maximised. Building on elevated sites only would allow the preservation of trees on the foreshore, but elevated houses have the potential to disrupt natural contours and dominate the landscape. They also need access roads, which might cut across the homogeneous forest cover,

[11] http://www.nzherald.co.nz/nz/news/article.cfm?c_id=1&objectid=10671323

scarring the natural landscape with artificial elements. Coastal landscapes are degraded when houses on high "look down" over people on the beach (Collins & Kearns, 2010a).

1.2.5 COASTAL RECREATION IN THE LITERATURE

Despite the importance of the coastal environment to New Zealanders, there has been limited application of environmental valuation techniques. Kaval and Yao (2007) conducted a meta-analysis of New Zealand studies relating to outdoor recreation. The only studies pertaining to salt water recreation were about marine fishing. They report the average value of outdoor recreation in general is $71 per day, with wide variation for different activities, environments and valuation techniques. However, there have been some qualitative studies about beach preferences and attitudes. Thomson (2003) reports that Coromandel beach visitors prefer natural beaches all else being equal, but also value proximity to facilities and accommodation. "Retention of some undeveloped, natural beaches" was rated most highly. Protecting existing property was rated the lowest. Collins and Kearns (2010b) analyse the social and emotional significance of campground closures at New Zealand beaches. They also explore how landscape values are articulated in Hawke's Bay (Collins & Kearns 2010a).

In the absence of coastal valuation studies in New Zealand I briefly review some international studies. Australian beaches are facing similar development pressure (Collins & Kearns, 2010a) and beach recreation is similarly ingrained in the national psyche. Windle and Rolfe (2014) used a choice experiment to evaluate toilets, picnic areas, beach cleaning and lifeguard service and a contingent valuation experiment to elicit WTP for beach erosion protection in Brisbane. They report that services and access to beaches are important to Brisbane residents, although there is significant heterogeneity in WTP. Maguire, Miller, Weston and Young (2011) analysed what visitors valued about south-eastern Australian beaches. They also found people valued natural features such as wildlife, but also facilities. There was a dichotomy between beaches favoured by locals and those popular with non-locals. Blackwell (2007) reports that the

passive-use values of beaches in Mooloolaba, Australia are higher than those of Australian national parks or forests.

In the USA, Lindsay, Halstad and Tupper (1992) analysed WTP for a beach erosion control program in Maine and New Hampshire. They report that significant explanatory factors include experience of the beach and familiarity with beach protection laws. Also in Maine and New Hampshire, Huang, Poor and Zhao (2007) use a discrete choice experiment to value beach erosion control impacts. They warn that values are highly dependent on the specifics of the negative effects such as visibility, restriction of access, effect on wildlife and erosion of neighbouring beaches. In contrast to Lindsay et al.(1992) they find that frequency of beach use is not a significant predictor of WTP. Using hedonic analysis based on house price in Georgia, Landry, Keeler and Kriesel (2003) report that shoreline armouring (seawalls) with beach nourishment is less economically efficient than nourishment alone or managed retreat. Using surveys of visitors to East Anglia beaches in the UK, Coombes et al.(2008) report that tourists are highly sensitive to changes to the environments they visit. Whitehead et al.(2009) report that sea level rise and associated beach width reductions in New Carolina may reduce recreation values by up to a third. Ghermandi and Nunes (2013) conducted a spatially explicit meta-analysis of coastal recreation and report that low human development is associated with higher value, after controlling for population size. Penn, Hu, Cox, and Kozloff (2016) report that water quality is the most important attribute for beach visitors in Hawaii, while residents place greater value on avoiding congestion.

To summarise, there are some general findings that are consistent across the literature. A preference for natural, uncrowded beaches with good access and facilities appears typical. However, specific values for recreation, erosion protection and development are highly dependent on the context in which they are analysed. It is highly unlikely that any existing study is similar enough in site-or-population specific factors (Johnston, Rolfe, Rosenberger, & Brouwer, 2015) to be useful for transfer of benefit functions to the Coromandel Peninsula. The

collection of data specifically about Coromandel Peninsula beaches makes this research significant in a New Zealand context.

1.3 The Survey Instrument

A web-based survey was developed to gather information about revealed and stated preferences for coastal landscapes amongst domestic visitors to the Coromandel Peninsula. The survey is in Appendix A. The first wave of data collection was in October/November 2013, with subsequence waves at the end of January and April 2014. The survey included questions about previous and planned beach visits, environmental attitudes, socio-economic variables and choice experiment questions about erosion protection and development options at beaches that already have suburban development. The third wave of the survey also included a choice experiment about an undeveloped beach, New Chums.

Each participant was randomly assigned to a video or no-video treatment group for the choice experiments. The video treatment group had the option of playing a video of a virtual reality representation of the beaches before and after modification.

1.3.1 Sample recruitment

For this research the target population is defined as individuals who live in New Zealand and have visited the Coromandel Peninsula for the purpose of beach recreation within the past 12 months. Because the survey is delivered via the web the frame population consists only of people with access to the internet and the technical skills to use it. In 2012, 82 percent of individuals in New Zealand were classified as “recent internet users” (Statistics New Zealand, 2012). Some demographic groups (the elderly, low income, Maori ethnicity) have lower rates of internet usage so there is potential for coverage error by excluding these people. A screening question was used at the start of the survey to screen out individuals who did not fit the criteria for the target population. This was obfuscated so that individuals did not know which option would get them

selected; to minimise the likelihood of people pretending to fit the criteria just to receive the incentive.

Probability-based sampling was not an option for this study due to the high cost and very low response rate from panels pre-recruited by telephone (based on my previous experience). The proportion of individuals who meet the criteria of being Coromandel Peninsula beach users decreases with geographic distance from the Peninsula, and it would be particularly expensive to pre-recruit by phone or mail enough qualifying individuals from more distant regions.

Participants for this survey were recruited using both web advertisements with Google Adwords and Facebook, and a pre-recruited volunteer panel from the market research company Research Now Ltd., which has one of the largest databases of survey sources in New Zealand. Panel participants were rewarded with points that may be redeemed for cash when enough points are accumulated.

Facebook advertisements

The process of advertising on Facebook requires you to create a "page" to interact with people. One can then create advertisements linking to that page (paid on a per-click basis). This study had an associated Facebook page with details about the survey[12] and used advertisements targeting all Facebook users in New Zealand. People who "like" a page can receive messages from the page. Paying for a "sponsored story" means the message will be visible to their friends as well. I used a sponsored post inviting people to participate in the survey.

Adwords advertisements

The Google Adwords service allows the placement of ads on the Google website or with any of thousands of websites in the Google Display Network. For the target criteria I specified a geographic location of all New Zealand and excluded mobile browsers because the choice card text was too small to read on a

[12] https://www.facebook.com/coromandelsurvey

smartphone. Advertisements were paid for on a per-click basis. The advertisement text specifically asked for people who met the criteria of visiting the Peninsula in the past year in order to minimise the cost of non-qualifying clicks. A third of Adwords respondents nonetheless failed the screening question.

Four concurrent advertisement campaigns were conducted to test the effects of different incentives. Campaign #1 offered the chance to win an iPad or Galaxy Note tablet worth approximately $1000. Campaign #2 offered the same prize but stated 1 in 500 odds of winning a prize. Campaign #3 stated 1 in 200 odds. Campaign #4 offered a $5 electronic Amazon voucher to every participant. Those who completed the survey had the option of entering the prize draw, receiving a voucher or donating $5 to the Dune Restoration Trust, a charity with the goal of restoring coastal environments. The ads involved some deception about the chance of winning a prize but the actual odds ended up being better than people were told.

Figure 1-5 - Example display ad

Online panel

I purchased a sample of 750 participants from Research Now, evenly split between Waikato, Auckland and Bay of Plenty regions. The vast majority of domestic Coromandel visitors come from these three regions (Thomson, 2003). It would have been more expensive to purchase samples from other regions with lower expected qualifying rates. A small number of panel participants (3 percent) said they reside in a region different to that recorded by Research Now. These people were included.

1.4 THESIS STRUCTURE

This thesis comprises six chapters, which include two published papers and a further two papers still in the publication process at the time of thesis submission.

1.4.1 PAPER 1 - USING VIRTUAL ENVIRONMENTS TO IMPROVE THE REALISM OF CHOICE EXPERIMENTS

This paper reports the results of a choice experiment designed to estimate WTP for coastal erosion management and headland development on the Coromandel Peninsula of New Zealand. It contributes to choice experiment literature in two ways. First, by describing the method by which virtual landscapes can be generated using free software and satellite imagery and presented to respondents via a web survey. Second, by adding to the limited pool of experimental economics studies about virtual environments by reporting the effect of randomised VE treatment on choice consistency and bias reduction. This paper has been published in the Journal of Environmental Economics and Management (Matthews, Scarpa, & Marsh, 2017a).

1.4.2 PAPER 2 - VIRTUAL ENVIRONMENTS FOR THE UNEXPERIENCED

This paper reports the results of another VE choice experiment, this time about development scenarios for a Coromandel beach that is currently undeveloped and highly valued in its current state. The beach had only been visited by a minority of respondents and individuals who are unfamiliar with a site may have unreliable or imprecise WTP estimates (Diamond & Hausman, 1993). Hypothesizing that VE would be more useful to inexperienced respondents, there are tests for systematic differences between the VE treatment and control groups amongst visitors and non-visitors. This paper has been submitted to the Journal of Outdoor Recreation and Tourism for a special edition in memory of Dr. Wolfgang Haider and is awaiting review.

1.4.3 Paper 3 - Stability of willingness-to-pay for coastal management

The focus of this paper is the temporal stability of WTP for the beach management options. The choice experiment described in "Using virtual environments to improve the realism of choice experiments: a case study about coastal erosion management" was repeated in retests three and six months after the original survey. I investigate the stability of WTP in this specific context and whether it is consistent with other test-retest studies. I also investigate whether stability improves between the first and second re-test. If so, it would be consistent with the concept of learning and preference discovery. If not, the results would be consistent with the transience of preferences constructed on the spot. I also investigate to what degree choice consistency can be explained by individual-specific factors and whether the VE treatment has a systematic effect on stability. If preference stability is predictable this could lead to design improvements or calibration options to improve confidence in one-shot experiments where retest is not an option. This paper has been published in Ecological Economics (Matthews, Scarpa & Marsh, 2017b).

1.4.4 Paper 4 - Attribute-based agglomeration and competition in beach recreation site choice

In this paper I present the results of a destination choice travel cost analysis of Coromandel beach visitors. This analysis uses data about actual beach visits collected in the same survey as the choice experiment questions covered by previous chapters. In stated preference methods, information processing limitations can lead to biased or unreliable responses. In contrast, in revealed preferences it tends to manifest as hierarchical processing of alternative sites. Hierarchical processing, along with the potential for multiple-destination trips, can result in complex substitution patterns and spatially correlated errors.

The purpose of this paper is to identify a random utility modelling approach that is flexible enough to capture these patterns but also computationally simple

enough to allow estimation of a model with large numbers of sites and attributes.

The Theory of Cumulative Attraction is applied to analyse site compatibility and help guide model formulation. Different random utility models are reviewed and I estimate and compare cross-nested logit, Competing Destinations (CD) and Agglomerating and Competing Destination Choice (ACDC) models. I find that including multiple measures of accessibility for different attributes improves model fit and results in more sophisticated model response properties. In contrast, previous studies used only a single dissimilarity measure. Two scenarios for site-specific changes are analysed using the preferred and alternative models. This paper has been submitted to the journal of Tourism Management. It has been reviewed and revised and is awaiting further decision from the editorial office.

1.5 References

Adamowicz, W. L., Glenk, F., & Meyerhoff, J. (2014). Choice modelling research in environmental and resource economics. In S. Hess & A. Daly (Eds.) *Handbook of choice modelling* (pp. 661–674). Edward Elgar Publishing.

Anselin, L. (2001). Spatial Effects in Econometric Practice in Environmental and Resource Economics. *American Journal of Agricultural Economics*, *83*(3), 705–710.

Atkinson, J., Salmond, C., & Crampton, P. (2014). *NZDep2013 Index of Deprivation*. Dunedin, New Zealand: University of Otago. Retrieved from http://www.health.govt.nz/publication/nzdep2013-index-deprivation

Bateman, I. J., Day, B. H., Jones, A. P., & Jude, S. (2009). Reducing gain–loss asymmetry: a virtual reality choice experiment valuing land use change. *Journal of Environmental Economics and Management*, *58*(1), 106–118.

Bateman, I. J., Jones, A. P., Lovett, A. A., Lake, I. R., & Day, B. H. (2002). Applying Geographical Information Systems (GIS) to Environmental and Resource

Economics. *Environmental and Resource Economics*, *22*, 219–269. http://doi.org/10.1023/a:1015575214292

Bhat, C. R. (2011). The maximum approximate composite marginal likelihood (MACML) estimation of multinomial probit-based unordered response choice models. *Transportation Research Part B: Methodological*, *45*(7), 923–939.

Bishop, I. D., Wherrett, J. R., & Miller, D. R. (2001). Assessment of path choices on a country walk using a virtual environment. *Landscape and Urban Planning*, *52*(4), 225–237. http://doi.org/10.1016/S0169-2046(00)00118-3

Blackwell, B. (2007). The Value of a Recreational Beach Visit: an Application to Mooloolaba Beach and Comparisons With Other Outdoor Recreation Sites *Economic Analysis and Policy*, *37*(1), 77–98. http://doi.org/10.1016/S0313-5926(07)50005-6

Braga, J., & Starmer, C. (2005). Preference anomalies, preference elicitation and the discovered preference hypothesis. *Environmental and Resource Economics*, *32*(1), 55–89.

Brouwer, R. (2006). Do stated preference methods stand the test of time? A test of the stability of contingent values and models for health risks when facing an extreme event. *Ecological Economics*, *60*(2), 399–406. http://doi.org/10.1016/j.ecolecon.2006.04.001

Carson, R. T., & Louviere, J. J. (2011). A common nomenclature for stated preference elicitation approaches. *Environmental and Resource Economics*, *49*(4), 539–559.

Collins, D., & Kearns, R. (2010a). “It’s a gestalt experience”: Landscape values and development pressure in Hawke’s Bay, New Zealand. *Geoforum*, *41*(3), 435–446. http://doi.org/10.1016/j.geoforum.2009.11.010

Collins, D., & Kearns, R. (2010b). “Pulling up the Tent Pegs?” The Significance and changing status of coastal campgrounds in New Zealand. *Tourism Geographies*, *12*(1), 53–76. http://doi.org/10.1080/14616680903493647

Coombes, E. G., Jones, A. P., & Sutherland, W. J. (2008). The biodiversity implications of changes in coastal tourism due to climate change. *Environmental Conservation*, *35*(4), 319–330.

Czajkowski, M., Barczak, A., Budziński, W., Giergiczny, M., & Hanley, N. (2016). Preference and WTP stability for public forest management. *Forest Policy and Economics*, *71*, 11–22.

Davies, A.-M., Laing, R., & Scott, S. (2002). Combining visualisation and choice experiments in built environment research. In *Information Visualisation, 2002. Proceedings. Sixth International Conference on* (pp. 785–790). http://doi.org/10.1109/IV.2002.1028870

Diamond, P., A., & Hausman, J. A. (1993). Chapter I - On Contingent Valuation Measurement of Nonuse Values. In Jerry A. Hausman (Ed.), *Contributions to Economic Analysis* (Vol. Volume 220, pp. 3–38). Elsevier. Retrieved from http://www.sciencedirect.com/science/article/pii/B9780444814692500079

Dupuit, A. (1853). On Utility and its Measure–On Public Utility. *Journal Des Économistes*, *36*, 1–27.

Environment Waikato. (2002). *Coromandel Beaches. Coastal Hazards & Development Setback Recommendations Summary Report* (Environment Waikato Technical Report).

Epstein, S., & Pacini, R. (2001). The Influence of Visualization on Intuitive and Analytical Information Processing. *Imagination, Cognition and Personality*, *20*(3), 195–216. http://doi.org/10.2190/G4VG-AKQP-2Q91-JQHP

Fezzi, C., Bateman, I. J., & Ferrini, S. (2014). Using revealed preferences to estimate the Value of Travel Time to recreation sites. *Journal of Environmental Economics and Management*, *67*(1), 58–70.

Fiore, S. M., Harrison, G. W., Hughes, C. E., & Rutström, E. E. (2009). Virtual experiments and environmental policy. *Frontiers of Environmental and*

Resource Economics, *57*(1), 65–86. http://doi.org/10.1016/j.jeem.2008.08.002

Ghermandi, A., & Nunes, P. A. L. D. (2013). A global map of coastal recreation values: Results from a spatially explicit meta-analysis. *Sustainable Urbanisation: A Resilient Future*, *86*, 1–15. http://doi.org/10.1016/j.ecolecon.2012.11.006

Gregory, R., Lichtenstein, S., & Slovic, P. (1993). Valuing environmental resources: a constructive approach. *Journal of Risk and Uncertainty*, *7*(2), 177–197.

Johnston, R. J., Rolfe, J., Rosenberger, R. S., & Brouwer, R. (2015*). Benefit transfer of environmental and resource values (Vol. 14)*. Springer.

Harrison, G. W., Haruvy, E., & Rutstrom, E. E. (2011). Remarks on Virtual World and Virtual Reality Experiments. *Southern Economic Journal*, *78*(1), 87–94.

Horowitz, J. K., & McConnell, K. E. (2002). A Review of WTA/WTP Studies. *Journal of Environmental Economics and Management*, *44*, 426–447. http://doi.org/10.1006/jeem.2001.1215

Hotelling, H. (1947). The economics of public recreation. *The Prewitt Report*.

Huang, J.-C., Poor, P. J., & Zhao, M. Q. (2007). Economic valuation of beach erosion control. *Marine Resource Economics*, *22*(3), 221.

Jude, S. (2008). Investigating the Potential Role of Visualization Techniques in Participatory Coastal Management. *Coastal Management*, *36*(4), 331–349. http://doi.org/10.1080/08920750802266346

Kaldor, N. (1939). Welfare propositions of economics and interpersonal comparisons of utility. *The Economic Journal*, 549–552.

Krutilla, J. V. (1967). Conservation reconsidered. *The American Economic Review*, *57*(4), 777–786.

Lancaster, K. J. (1966). A New Approach to Consumer Theory. *Journal of Political Economy*, *74*(2), 132–157. http://doi.org/10.1086/259131

Landry, C. E., Keeler, A. G., & Kriesel, W. (2003). An Economic Evaluation of Beach Erosion Management Alternatives. *Marine Resource Economics*, *18*(2), 105–127. http://doi.org/10.1086/mre.18.2.42629388

Liebe, U., Meyerhoff, J., & Hartje, V. (2012). Test-Retest Reliability of Choice Experiments in Environmental Valuation. *Environmental and Resource Economics*, *53*(3), 389. http://doi.org/10.1007/s10640-012-9567-1

Lienhoop, N., & Volker, M. (2016). Preference Refinement in Deliberative Choice Experiments for Ecosystem Service Valuation. *Land Economics*, *92*(3), 555–577. http://doi.org/10.3368/le.92.3.555

Lindsay, B. E., Halstad, J. M., & Tupper, H. C. (1992). Factors influencing the willingness to pay for coastal beach protection. *Coastal Management*, *20*, 11.

Lue, C.-C., Crompton, J. L., & Fesenmaier, D. R. (1993). Conceptualization of multi-destination pleasure trips. *Annals of Tourism Research*, *20*(2), 289–301.

MacGregor, D., & Slovic, P. (1986). Graphic representation of judgmental information. *Human-Computer Interaction*, *2*(3), 179–200.

Madureira, L., Nunes, L. C., Borges, J. G., & Falcão, A. O. (2011). Assessing forest management strategies using a contingent valuation approach and advanced visualisation techniques: A Portuguese case study. *Journal of Forest Economics*, *17*(4), 399–414. http://doi.org/10.1016/j.jfe.2011.04.001

Maguire, G. S., Miller, K. K., Weston, M. A., & Young, K. (2011). Being beside the seaside: Beach use and preferences among coastal residents of south-eastern Australia. *Ocean & Coastal Management*, *54*(10), 781–788.

Mäler, K.-G. (1974). *Environmental Economics: A Theoretical Enquiry*. Johns Hopkins University Press.

Marschak, J. (1960). Binary Choice Constraints on Random Utility Indicators. In *Stanford symposium on mathematical methods in the social sciences* (pp.

312–29). Stanford, CA: Stanford University Press. Retrieved from http://cowles.yale.edu/sites/default/files/files/pub/d00/d0074.pdf

Mathews, K. E., Freeman, M. L., & Desvousges, W. H. (2006). How and how much? The role of information in stated choice questionnaires. In B. J. Kanninen (Ed.), *Valuing environmental amenities using stated choice studies: a common sense approach to theory and practice* (Vol. 8, pp. 111–133). Dordrecht: Kluwer Academic Pub.

Matthews, Y., Scarpa, R., & Marsh, D. (2017a). Using virtual environments to improve the realism of choice experiments: A case study about coastal erosion management. *Journal of Environmental Economics and Management*, *81*, 193–208.

Matthews, Y., Scarpa, R., & Marsh, D. (2017b). Stability of Willingness-to-Pay for Coastal Management: A Choice Experiment Across Three Time Periods. *Ecological Economics, 138,* 64-73.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics*. New York: Academic Press.

McFadden, D. (1978). *Modelling the choice of residential location*. Institute of Transportation Studies, University of California.

McFadden, D. (2001). Economic Choices. *The American Economic Review*, *91*(3), 351–378. http://doi.org/10.1257/aer.91.3.351

Murphy, J., Allen, P., Stevens, T., & Weatherhead, D. (2005). A Meta-analysis of Hypothetical Bias in Stated Preference Valuation. *Environmental and Resource Economics*, *30*, 313–325. http://doi.org/10.1007/s10640-004-3332-z

Olschewski, R., Bebi, P., Teich, M., Wissen Hayek, U., & Grêt-Regamey, A. (2012). Avalanche protection by forests — A choice experiment in the Swiss Alps. *Integrating Forest Products with Ecosystem Services*, *17*, 19–24. http://doi.org/10.1016/j.forpol.2012.02.016

Payne, J. W., Bettman, J. R., & Schkade, D. A. (1999). Measuring Constructed Preferences: Towards a Building Code. *Journal of Risk and Uncertainty*, *19*(1), 243–270. http://doi.org/10.1023/A:1007843931054

Pearce, D. (2002). An intellectual history of environmental economics. *Annual Review of Energy and the Environment*, *27*(1), 57–81.

Penn, J., Hu, W., Cox, L., & Kozloff, L. (2016). Values for Recreational Beach Quality in Oahu, Hawaii. *Marine Resource Economics*, *31*(1), 47–62. http://doi.org/10.1086/683795

Phaneuf, D. J., & Smith, V. K. (2005). Chapter 15 Recreation Demand Models. In Karl-Gran Mler and Jeffrey R. Vincent (Ed.), *Handbook of Environmental Economics* (Vol. Volume 2, pp. 671–761). Elsevier. Retrieved from http://www.sciencedirect.com/science/article/pii/S1574009905020152

Plott, C. R. (1996). Rational Individual Behavior in Markets and Social Choice Processes: the Discovered Preference Hypothesis. In *K. J. Arrow, E. Colombatto, M. Perleman & C. Schmidt (Eds.) The Rational Foundations of Economic Behaviour,* (pp. 225–250). London: Macmillan. Retrieved from https://books.google.co.nz/books?id=wsO7QgAACAAJ

Luce, R. D. (1959). *Individual Choice Behavior a Theoretical Analysis*. John Wiley and sons.

Schaafsma, M., & Brouwer, R. (2013). Testing geographical framing and substitution effects in spatial choice experiments. *Journal of Choice Modelling*, *8*, 32–48. http://doi.org/10.1016/j.jocm.2013.04.007

Simon, D., Krawczyk, D. C., Bleicher, A., & Holyoak, K. J. (2008). The transience of constructed preferences. *Journal of Behavioral Decision Making*, *21*(1), 1–14.

Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 99–118.

Slovic, P. (1995). The construction of preference. *American Psychologist*, *50*(5), 364–371. http://doi.org/10.1037/0003-066X.50.5.364

Slovic, P., Griffin, D., & Tversky, A. (1990). Compatibility effects in judgment and choice. *In R. Hogath (Ed.) Insights in Decision Making: A Tribute to Hillel J. Einhorn*, 5–27.

Statistics New Zealand. (2012). *Household Use of Information and Communication Technology* (Statistics New Zealand data release). Wellington, New Zealand. Retrieved from http://www.stats.govt.nz/browse_for_stats/industry_sectors/information_technology_and_communications/hhold-use-of-ict.aspx

Thiene, M., Swait, J., & Scarpa, R. (2017). Choice set formation for outdoor destinations: The role of motivations and preference discrimination in site selection for the management of public expenditures on protected areas. *Journal of Environmental Economics and Management*, *81*, 152–173. http://doi.org/10.1016/j.jeem.2016.08.002

Thomson, J. (2003). *Coastal values and beach use survey report* (Technical Report No. 2003/09). Waikato Regional Council. Retrieved from http://www.waikatoregion.govt.nz/Services/Publications/Technical-reports/2003-technical-reports/

Thurstone, L. L. (1927). A law of comparative judgment. *Psychological Review*, *34*(4), 273.

Train, K. E. (1998). Recreation demand models with taste differences over people. *Land Economics, 74(2)*, 230–239.

Train, K., & Weeks, M. (2005). Discrete choice models in preference space and willingness-to-pay space. In *R.Scarpa & A. Alberini, eds, "Applications of simulation methods in environmental and resource economics."* Springer, Dordrecht, The Netherlands.

Tversky, A., & Kahneman, D. (1991). Loss Aversion in Riskless Choice: A Reference-Dependent Model. *The Quarterly Journal of Economics*, *106*, 1039–1061. http://doi.org/10.2307/2937956

Weisbrod, B. A. (1964). Collective-consumption services of individual-consumption goods. *The Quarterly Journal of Economics*, *78*(3), 471–477.

Whitehead, J. C., Phaneuf, D. J., Dumas, C. F., Herstine, J., Hill, J., & Buerger, B. (2010). Convergent Validity of Revealed and Stated Recreation Behavior with Quality Change: A Comparison of Multiple and Single Site Demands. *Environmental and Resource Economics*, *45*, 91–112.

Whitehead, J. C., Poulter, B., Dumas, C. F., & Bin, O. (2009). Measuring the Economic Effects of Sea Level Rise on Beach Recreation. *Working Papers*.

Windle, J., & Rolfe, J. (2014). Estimating the nonmarket economic benefits of beach resource management in southeast Queensland, Australia. *Australasian Journal of Environmental Management*, *21*(1), 65–82. http://doi.org/10.1080/14486563.2013.875953

2. USING VIRTUAL ENVIRONMENTS TO IMPROVE THE REALISM OF CHOICE EXPERIMENTS: A CASE STUDY ABOUT COASTAL EROSION MANAGEMENT

2.1 ABSTRACT

Choice experiment surveys are commonly used to assess the general public's willingness to pay for different levels of environmental quality. However, respondents need to understand what they are valuing or they will make potentially wrong assumptions based on different experiences and frames of reference. Three-dimensional computer generated models or Virtual Environments (VE) have so far seen little use in economics research, probably due to the complexity and cost of developing and delivering them to study participants. The few studies that have used them find that VE are superior to static image presentations in helping people evaluate complex data. For this study we developed virtual environments for a choice experiment about coastal erosion management using free, easy-to-use software and Google Earth© satellite imagery and presented these to respondents as video tours. Our results indicate that the VE treatment reduced choice error, reduced left-right bias and improved respondent engagement and retention when compared with static images. There were also differences in WTP between the two groups.

Keywords

Virtual environment, videos, choice experiment, coastal erosion, scale factor

2.2 INTRODUCTION

In choice experiments, survey respondents are presented with a series of alternative non-market goods and are asked to make trade-offs (state their preference), based on the attributes of the goods which may include environmental quality and cost. For stated preference non-market valuation results to have external validity, participants must be able to comprehend how the changes would affect them in real life and evaluate the alternatives accordingly. Visualisations, such as images, diagrams and maps are usually helpful for conveying complex information to participants (Mathews, Freeman, & Desvousges, 2006). Most visualisations are static, but an alternative is to use dynamic computer-generated 3D environments to convey information about scenarios. Sometimes referred to as virtual environments, the added value of 3-dimensional visualization for the 'evaluability' of unfamiliar scenarios was persuasively argued by Bateman, Day, Jones and Jude (2009). However, virtual environments have rarely been used in non-market valuation - perhaps due to the cost and complexity of developing them. In this paper we describe a relatively cheap and easy method we used to create videos of virtual environments for a choice experiment about coastal development. We use a split-sample and report the differences in models and WTP between the treatment and control group.

2.3 LITERATURE

It is a well-documented fact that preferences for goods are determined not only by the attributes of a good, but also by the context in which the decision is made. The goal of environmental valuation studies is to determine human response to real environments. Stated preference estimates, however, are based on responses to the information provided by the researcher. Respondent familiarity with an environmental good under valuation is a highly significant predictor of response reliability (Loomis & Ekstrand, 1998) and the information provided is often an inadequate substitute. The choice experiment is an artefactual context

that can lack many of the cues that being physically present at the site provides (Fiore, Harrison, Hughes, & Rutström, 2009).

Decision framing effects have been demonstrated in many experimental settings, an early example being the famous study by Tversky and Kahneman (1981). Swait et al. (2002) decomposed the different ways in which context can affect the decision structure: in choice set formation, constraints, evaluation rules and decision rules. Information in a choice task should ideally be presented in a way that minimises "perception confounds" or participant life experiences that influence how they perceive a task (Harrison, Haruvy, & Rutstrom, 2011). Choice experiments often use numerical tables to present information about the alternatives, but these can be either difficult for respondents to comprehend or they may be used in different frames of reference to evaluate them. If the complexity of a task exceeds respondents' median cognitive ability the majority of respondents will make larger errors of judgement than when this is not the case. Consequently, observed choices will appear less consistent (DeShazo & Fermo, 2002). People may also use simplifying strategies to ease choice task execution and not completely process all alternatives and attributes. In addition to having the cognitive abilities to process the task, respondents must also be engaged enough to use their abilities (Bonsall & Lythgoe, 2009). Degrees of engagement, as a broad construct of multiple individual factors, were found by Hess and Stathopoulos (2013) to significantly influence choice consistency.

2.3.1 VISUALISATIONS

Visualisations such as photographs, maps and diagrams were found to both standardise and aid respondent's comprehension in many studies (Mathews et al., 2006). For example, Corso (2001) found that WTP sensitivity to the magnitude of a risk reduction was improved using visual aids rather than just text. Landscapes are particularly difficult to evaluate and even photographs may be inadequate representations for scenic beauty judgements (Daniel & Meitner, 2001). A computer-generated virtual environment is more immersive than static images because visual fields are generated dynamically depending on the

simulated viewpoint (Harrison et al., 2011). If the virtual environments are interactive they are referred to as virtual reality (VR). While virtual environments have been used for decades in games and building design, their use in non-market valuation is extremely limited and more recent.

3D visualisations have been developed for several studies (Davies, Laing, & Scott, 2002; Madureira, Nunes, Borges, & Falcão, 2011; Olschewski, Bebi, Teich, Wissen Hayek, & Grêt-Regamey, 2012). However, these were only shown to participants as static images. Jude (2008) found that a combination of 3D visualisation and GIS stimulated more meaningful discussions about coastal planning among planners than did 2D maps, thus improving engagement. Fiore et al. (2009) introduced the use of virtual environments for quantitative analysis of preferences. They found the 3D visualisation generated more accurate beliefs about forest fire risks and recommended it as a way to bring natural field cues into a lab setting. Virtual representation techniques in an area of market research called "information acceleration" have also proven useful for forecasting demand for unfamiliar goods (Urban et al., 1997). Perhaps the first systematic use of virtual environment in a choice experiment was Bateman et al. (2009). Bateman et al. used a fixed flight path so it was not true virtual reality (which is interactive) but they report that the treatment reduced choice error and gain-loss asymmetry in a study of preferences for coastal land-use change.

Creating virtual environments can be a complicated and expensive undertaking. Some researchers such as Davies et al. (2002) used AutoCAD while Olschewski et al. (2012) used Visual Nature Studio. If the virtual environment is to be based on a real location it requires software that integrates with GIS data, such as Arcview© or MapInfo© plugins. Bateman et al. (2009) used a modelling and simulation package called "Terra Vista", while Fiore et al. (2009) used specialised forest fire simulation software. These are all expensive software packages that require specialised skills to use, making their affordability a potential barrier to adoption. However, the effectiveness of visualisation depends more upon their

"application in support of communicating the 'concept' and its 'value' to the user" (Hughes, 2004) than the use of state-of-the-art photorealism technology.

The contribution to the literature of this paper is twofold. First, we report a method by which virtual landscapes can be generated using free, easy-to-use software and satellite imagery. We discuss options for delivering the virtual environments to experiment participants via a web survey so that virtual experiments are no longer necessarily restricted to the exclusive settings of expensive computer labs. Second, we contribute to the limited literature about virtual environments in choice experiments by analysing the effect on choice consistency and anomaly reduction.

2.4 EMPIRICAL CONTEXT

Our study area is beaches of the Coromandel Peninsula in the Waikato region of New Zealand. The Coromandel is a steep and hilly peninsula that lies across the Hauraki Gulf from Auckland city. The Peninsula is sparsely populated but is a popular holiday destination for residents of the nearby urban areas of Auckland and Hamilton, and to a lesser extent, international tourists. The local population more than doubles during the summer season. There are many coastal landscapes on the Peninsula that are considered "Significant Natural Areas" (Graeme, Dahm, & Kendal, 2010) due to their scenic beauty. However, since the 1950s, these coastal areas have been subject to considerable development pressure for holiday accommodation.

Some of the older beachfront developments are now at risk from foreshore erosion and the problem is expected to worsen as sea levels rise. There is conflict between property owners, who want to build seawalls to protect their properties and the council, who have a mandate under the Resource management Act and Coastal Policy Statement to protect natural landscapes and recreation opportunities. Hard coastal defence structures reduce the natural character of a beach, resulting in a loss of sandy foreshore. While there are some short-term options, such as beach nourishment (adding sand), in the long term the main

alternative to seawalls is to retreat from the foreshore (remove properties and infrastructure) combined with restoration of the natural dune system.

A qualitative study (Thomson, 2003) found that visitors to the Coromandel Peninsula value the natural coastal landscape and recreation opportunities provided. Coromandel tourism expenditure totaled $310 million NZD in the year ended March 2014[13]. However, there is a distinct lack of quantitative non-market valuation studies for New Zealand beaches. Some non-New Zealand studies have examined the effects of erosion or sea level rise on beach amenity value including Windle & Rolfe (2014), Whitehead, Poulter, Dumas, & Bin (2009) and Huang, Poor & Zhao (2007). One motivation for the present study is the need to estimate non-market values for the different options for future erosion management on Coromandel beaches, so that both market and non-market costs and benefits can be included in assessments of these options.

2.5 METHOD

2.5.1 MODELLING FRAMEWORK

We develop a choice experiment survey to elicit preferences for Coromandel coastal development and estimate marginal utilities. As per random utility theory (RUT McFadden, 1974) we assume the probability of a respondent choosing a scenario is a function of deterministic and random or unobserved components of utility. For reasons of computational tractability we use the logit discrete choice model to develop our analysis. Alternative RUT specifications, such as multivariate probit, would also be possible but are outside the scope of this paper.

To reduce the number of choice cards required to achieve statistical significance we require respondents to fully rank alternatives by sequentially selecting their preferred option. These choices are modelled using an exploded logit

[13]http://www.med.govt.nz/sectors-industries/tourism/tourism-research-data/regional-tourism-estimates/regional-summaries

specification (Lancsar & Louviere, 2008). The utility that person *n* obtains from alternative beach *j* is specified as follows:

$$U_{nj} = \left(ASC_j + \beta_n \mathrm{X_j} + \varepsilon_{\mathrm{nj}}\right) \times \delta_j \qquad (2\text{-}1)$$

Where ASC_j is an alternative-specific constant, X_j denotes the attribute vector (cost, headland development and erosion protection), β_n is a vector of taste parameters specific to each *n* respondent, ε_{nj} is an i.*i.d* extreme value type one error term, *j* are the alternatives and δ_j denotes whether alternative *j* is available or was already ranked. The β parameters are specified as random with normally distributed density. The unconditional probability of choosing alternative *i* is therefore:

$$P(i) = \int \prod_t \frac{e^{\lambda(\beta' X_i)}}{\sum_j e^{\lambda(\beta' X_j)}} \varphi(\beta|b, W) d\beta \qquad (2\text{-}2)$$

Where $\varphi(\beta|b, W)$ is, in our case, a normal density with mean *b* and covariance W. Known as a panel (over *t* choices) mixed (over random β) logit specification, this form allows for taste variation across individuals, unrestricted substitution patterns and correlations in unobserved components across the *t* choices by the same respondent (Train, 2003). The model also includes a scale parameter λ, which cannot be uniquely identified and is inversely related to the variance of the error term in the utility function.

2.5.2 MEASURING THE IMPACT ON EVALUABILITY

Information that is easier to evaluate should reduce "anomalies" in stated preferences or results that conflict with rational choice theory (Bateman et al., 2009). In this study we examine four different indicators of relative evaluability of the alternative scenarios: idiosyncratic choice error, stated choice certainty, frequency of status-quo choices and left-right bias.

2.5.2.1 *Idiosyncratic choice error*

RUT includes both random and deterministic components. The random component is a combination of unobserved factors affecting preferences and judgement errors that people make when evaluating the utility of each alternative (Blavatskyy, 2007).

The random or idiosyncratic choice error ε_{nj} can be systematically larger for some individuals and choice situations than others. Choices which are more deterministic have a higher relative scale factor and it is possible to compare the relative scale of pooled datasets such as the VE treatment and control groups (Swait & Louviere, 1993).

The scale factor in stated choice studies is systematically affected by design and respondent-specific factors. In general terms, the greater the gap between choice complexity and respondent's cognitive ability, the higher the idiosyncratic choice error (Caussade, Ortúzar, Rizzi, & Hensher, 2005). In ranking tasks the choice error increases with lower ranks (Ben-Akiva, Morikawa, & Shiroishi, 1992).There is a scarcity of literature about the effects of presentation specifically on choice error. Arentze, Borgers, Timmermans, & DelMistro (2003) found that a presentation with images had no impact on scale factor. On the other hand, Bateman et al. (2009) found that choice variability was lower in the VE treatment group. This paper adds to the limited literature on the effect of presentation formats on scale factor.

Our hypothesis is that the treatment group will have a higher scale factor relative to the control group because the virtual environments make the alternatives easier to evaluate. Using the terms of Swait and Erdem (2007), the videos should increase preference 'discrimination' and reduce the confounding of the preference signal with random error. We parameterise the scale factor and include a treatment dummy variable to test this hypothesis.

2.5.2.2 Stated Choice Certainty

One way of explicitly accounting for preference uncertainty is to ask people how certain they are about their choice in a follow-up question. An example of this is the Exxon Valdez oil spill study (Carson et al., 1992) in which respondents were asked how strongly they favoured the program. Certainty or follow-up questions in contingent valuation literature appear in several forms and include continuous ratings (Li & Mattsson, 1995), 10-point scales (Champ et al., 1997), 5-point scales (Lundhede, Olsen, Jacobsen, & Thorsen, 2009; Ready, Whitehead, & Blomquist, 1995) or two options "definitely sure" and "probably sure" (Blomquist, Blumenschein, & Johannesson, 2009). The certainty responses may be incorporated directly in the likelihood function (Brouwer, Dekker, Rolfe, & Windle, 2010; Li & Mattsson, 1995) or used to exclude the WTP of uncertain respondents as non-compliant with the assumed fully compensatory behaviour and mitigate hypothetical bias (Champ, Bishop, Brown, & McCollum, 1997)

Similar to idiosyncratic choice error, self-reported certainty has been found to be related to design and individual factors (Lundhede et al., 2009) but individuals with high idiosyncratic error may be more likely to misreport their own certainty (Beck, Rose, & Hensher, 2013). Individuals may also interpret certainty rating scales differently (Loomis & Ekstrand, 1998). So, it is worthwhile examining both the implicit scale factor and stated certainty.

In this study each choice card was followed by a question in which the participant was reminded of their first selection for the card and asked "Do you think this would be your preferred alternative if you really did have to pay?" The response format was a five-point scale comprising "definitely not", "probably not", "maybe", "probably" and "definitely". We test the hypothesis that the VE treatment group will have higher stated certainty on average. We do not include stated certainty as a scale parameter in the logit models because it would be confounded with the VE dummy variable if the hypothesis were correct.

2.5.2.3 *Frequency of status-quo choices*

People tend to disproportionately favour an alternative framed as the current situation or status quo (Samuelson & Zeckhauser, 1988). This can be a rational strategy when there are transition costs or the benefits of change are uncertain. Cognitive costs can also cause individuals to favour the status quo because they undertake only partial analysis of the available alternatives. The status quo alternative is advantaged because respondents are familiar with it and understand it better than the alternatives (Scarpa, Willis, & Acutt, 2007). Boxall, Adamowicz, & Moon (2009) found that increased choice complexity leads to increased frequency of the status quo choice, presumably because the analysis costs are higher. Our third hypothesis is that the VE treatment reduces the cognitive cost of alternative evaluation and therefore the magnitude of the status quo advantage. We test this by including a VE times status quo interaction variable in the logit model.

2.5.2.4 *Left-right bias in choice experiments*

When alternatives are difficult to evaluate, choices may be influenced more by design factors, such as order of presentation of items, than by the attributes characterizing choice alternatives. Heiner (1983) explained that uncertainty can induce choice behaviour to simple, less sophisticated patterns by the adoption of decision heuristics.

Left-right bias is a systematic result relating to presentation that can arise in choice experiments (Chrzan, 1994). Visually presented items are subject to primacy effects because the first items examined are subject to deeper cognitive processing and establish a standard of comparison (Krosnick, 1999). This implies a left-to-right bias in cultures where individuals read from left to right, and has been reported as an effect (Campbell & Erdem, 2015; Scarpa, Notaro, Louviere, & Raffaelli, 2011). This can be tested, as we do here, by randomising choice profile order and interacting order variables with individual or design-specific parameters such as the VE treatment.

2.5.3 EQUALITY OF WILLINGNESS-TO-PAY

Willingness-to-pay (WTP) for a marginal change is the ratio of the attribute coefficient to price coefficient. We use the variance-covariance matrices at convergence and Monte Carlo simulation (Krinsky & Robb, 1986) to approximate the asymptotic sampling distribution of WTP for the video treatment and control groups. Because simulated WTP is not necessarily normally distributed we use the non-parametric Mann-Whitney U test (Mann & Whitney, 1947) to test for equality of mean WTP between both groups.

2.5.4 EXPERIMENTAL DESIGN

The design was kept simple because a virtual environment model and video had to be created for every combination of attributes and levels that affect the visual landscape. The attributes comprise erosion protection, headland development and cost in terms of a tax increase. Headland development is a binary variable, it either occurs or it does not. Thomson (2003) suggests that the number of houses on a headland is irrelevant – if they can be seen from the beach then the natural landscape loses appeal. The erosion options are do nothing, build a seawall or property removal and dune restoration along a specified length of foreshore at risk from erosion. WTP for seawalls may be non-linear with increasing length because of the attitude that any hard protection compromises the natural character of the beach. We use different beach lengths and "at risk" lengths in the design and test for non-linearity in the results for seawalls and dune restoration. Table I shows the attribute descriptions and levels.

Table 2-1 - Choice experiment attributes and levels

Attribute	Description	Levels
Erosion protection	The beach is *x* km long and *y* km of this has properties at risk from erosion and high waves during storms. The options are to do nothing, remove the front row of properties and restore the nature dune system or build a seawall.	0 = None 1 = Restore dune 2 = Sea wall
Headland	The headland is currently undeveloped and covered with native bush. If development is	0 = No development

	allowed then houses will be visible in future	1 = Development allowed
Household taxes	Protection of the headland and foreshore require public funding so some of these options will increase your annual rates or taxes by the amount shown	$10 increments from $0 to $100

The status quo option or "current condition" was defined as no erosion protection, development allowed and zero cost. The five other combinations of erosion protection and headland development also appeared on each choice card[14] but in random order to allow for testing of left-right bias. Cost ranged from $0 to $100 per household per year. There were three beaches of different lengths 0.5, 0.8 and 1.2 kilometres and most popular Coromandel beaches fall within this size range. The "the length at risk" to become seawall or restored dune (or neither) was also expressed in kilometres and varied from approximately 30 to 70 per cent of the length of the beach (200 to 800 metres). We tested an orthogonal design in a focus group and obtained prior values with which to generate a Bayesian D-efficient design (Ferrini & Scarpa, 2007) by swapping the cost attribute. This means that cost is no longer orthogonal to the other attributes but this is a more efficient design with which to discern the value of attributes with non-zero priors (Rose, Bliemer, Hensher, & Collins, 2008).

Respondents each received three choice cards, one for each beach of a different length and were asked to rank the six alternatives on each card sequentially. The choice data were modelled as a sequence of five choices from a decreasing set of remaining alternatives, as in Scarpa, Notaro, Louviere and Raffaelli (2011). Respondents were also randomly assigned to a video treatment group or control group. Both groups were presented choice cards with text descriptions of the attribute levels and small images for each alternative. The video group got a

[14] Choice cards with fewer alternatives were tested in a focus group but participants disliked not having all the combinations to choose from, even though it made the choice task more complex.

button to play a video for each alternative while the control group did not. An example of the beach description and choice card can be found in the appendix.

2.5.4.1 Development of virtual environments

The virtual beach visualisations were developed using Sketchup Make©, a free 3D drawing tool published by Trimble[15]. The first step was to import the terrain and land-cover imagery of a real Coromandel beach from Google Earth©. Realistic yet simple models of houses were added to urban areas by raising building footprints from satellite imagery and draping them with images from Google Streetview©. Sketchup provides a tutorial on how to do this and it only takes a few clicks depending on how many faces the building has.

The study sponsor required that the beaches be unlabelled and did not depict real properties to avoid upsetting property owners about (at this stage) purely hypothetical coastal development. This was not ideal when the goal was to make the experiment as realistic as possible, but we disguised the beaches by draping generic land-cover imagery over easily recognisable landmarks in Google Earth©. The models of buildings were not in their real-world locations and were generic examples of the typical architecture of the region. Participants were informed the beaches were hypothetical, but meant to be representative of beaches in the area. Low-polygon trees and models of people available from the Sketchup 3D Warehouse were dropped into the scene to improve realism of scenarios and provide a sense of scale.

[15] http://www.sketchup.com

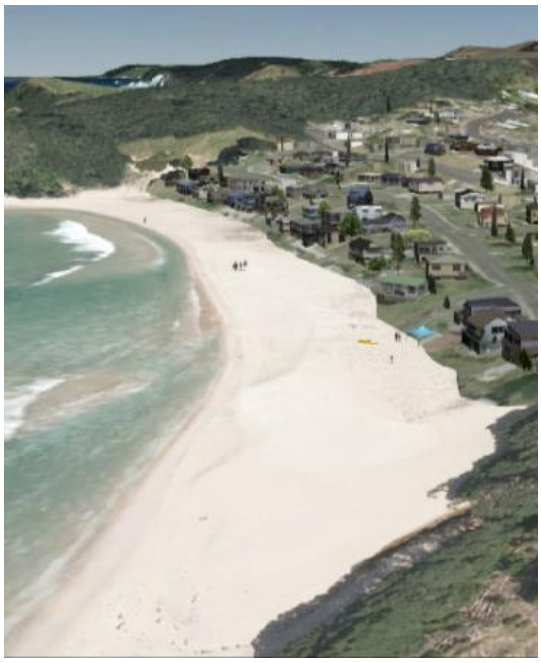


Figure 2-1 - Bird's eye view of beach with model buildings and props

Seawall models for seawall scenarios were created with a similar height and concrete block texture to that of an existing wall in the Mercury Bay area of the Peninsula. For the managed retreat and dune restoration scenarios, the front row of properties was removed and the terrain was raised to form a dune shape. The dune models were draped with a texture from a typical vegetated Coromandel dune. Figure 2-2 shows still images of the same beach with a seawall or restored dune.

Figure 2-2 – Beach with status quo, seawall model and restored dune model

For the headland development scenarios, additional buildings were added to the headland at heights such that they appear to be nestled in the herbaceous

vegetation. Figure 2-3 shows a virtual headland with and without houses and a photo of a real headland for comparison.

Figure 2-3 – Two virtual headlands and a real headland

The virtual beaches were exported as geo-referenced KML files for Google Earth. The Google Earth application or a browser plug-in can be used to view and virtually walk around these models. Interactive virtual environments could be provided to survey participants using the browser plugin but there are three complications: high data usage, compatibility problems with older versions of browsers and difficulty in controlling what participants see. Like Bateman et al. (2009) we traded interactiveness for simplicity and control and recorded pre-defined tours. Each tour lasted 30 seconds, began with a bird's eye view and traversed the length of the beach at the height of a person walking[16]. Tours were embedded in the web survey using the Youtube© API for javascript[17]. The advantage of the Youtube© API is that it provides excellent cross-browser support and the ability to capture events, such as the user starting and stopping the video.

2.5.5 THE SURVEY INSTRUMENT AND RECRUITMENT

The choice experiment was part of a web-based survey developed to gather information about the revealed and stated preferences of domestic visitors to the Coromandel Peninsula for features of coastal landscapes. The survey was repeated three times over six months and included questions about their previous and planned beach visits, environmental attitudes, socio-economic

[16] A selection of videos may be viewed at https://youtu.be/1YuvGW4FOSs

[17] https://developers.google.com/youtube/js_api_reference

variables and the choice experiment questions. In this paper we only report the stated preference choice experiment results from the first wave of the survey. Participants were randomly assigned to the virtual environment video treatment group or no-video control group. Participants in the video group could not reasonably be forced to watch every video for every alternative so they had to click on a video icon to make it start playing. There were three beaches each with a "current state" video and five alternative videos.

Participants were recruited from October to November 2013 from a pre-recruited panel of participants provided by a market research company and a smaller, self-selected sample from online advertisements on Facebook and Google[18]. To take part in the survey respondents had to live in New Zealand and have visited the Coromandel Peninsula in the past year. People who completed the survey were offered either $5 worth of rewards points for panel members, or a $5 Amazon voucher or prize draw for other participants. We advised respondents we would provide aggregate results to a local authority which implied some degree of consequentiality (Vossler, Doyon, & Rondeau, 2012).

Although face-to-face interviews have long been considered the gold standard of stated preference surveys (Arrow & Solow, 1993), this was simply not practical when the sampling frame included the whole of New Zealand. Web surveys exclude households without internet from the sampling frame but this is less of an issue now that 93 per cent of New Zealand households have an internet connection[19]. The use of a pre-recruited panel restricts multiple participations by the same individuals and is an increasingly popular collection mode (Windle & Rolfe, 2011). Other survey modes have different response biases such as that towards older respondents in face-to-face or telephone interviews (Versus Research, 2012).

[18] There were demographic and attitudinal differences between the panel and advertisement samples which are discussed in more detail in a forthcoming technical report.

[19] http://www.stats.govt.nz/browse_for_stats/snapshots-of-nz/yearbook/society/technology/connection.aspx

The survey collection mode may affect responses due to normative or cognitive factors (Dillman, 2011). The physical presence of an interviewer may induce a "social desirability bias" on stated WTP (Groves, Presser, & Dipko, 2004) and provide motivation to put more effort into processing the information. Lindhjem and Navrud (2011) found no evidence of a significant difference in WTP or the degree of satisficing between face-to-face and internet surveys. There may be counterfactual examples, but the fact remains that web surveys are increasingly popular. If virtual environments increase the interest of respondents or reduce the cognitive burden they may be useful for both web surveys and computer-assisted face-to-face interviews.

2.6 RESULTS

2.6.1 DESCRIPTIVE STATISTICS

The sample for the choice experiment comprised 1,062 individuals. Table 2-2 shows a selection of demographic variables for the samples. The majority of respondents lived in the Waikato or Auckland regions and less than ten per cent were permanent residents of the Peninsula. Respondents tended to be older and more highly educated than the general population. Thomson (2003a) also found in on-site surveys that visitors to Coromandel beaches were more highly educated than the general population.

Table 2-2 - Descriptive statistics

Variable	
Count of respondents	1062
Average age	42
Coromandel resident	0.09
Waikato resident	0.39
Auckland resident	0.36
Female	0.58
Maori ethnicity	0.09
University educated	0.47
Employed full-time	0.48
Preschool children	0.11
Income over $100k	0.33

The average participant made 2.25 trips to visit a Coromandel beach during the six month survey period and spent 6.7 days there in total. The average reported cost of accommodation per night was $11, or $79 excluding people who stayed for free in a private property.

2.6.2 VIRTUAL ENVIRONMENT TREATMENT EFFECTS

The majority (81 percent) of respondents in the VE treatment group watched at least one video. The average time spent watching videos was 73 seconds. Figure 2-4 shows the distribution of the number of videos watched by people in the VE treatment group. There were 18 videos available across the three choice cards but no-one watched more than 6 videos. The number of videos watched declined after the first choice card, perhaps because the scenarios were similar for each beach. Respondents watched an average of 1.4 videos for the first beach, 0.7 for the second and 0.6 for the third.

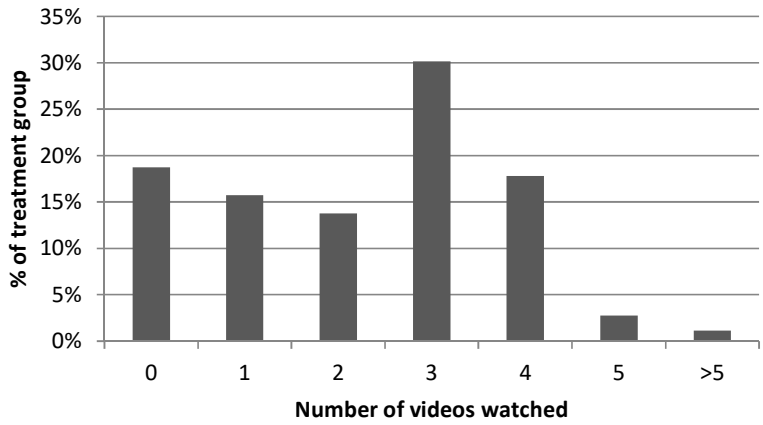


Figure 2-4 - Number of videos watched by participants in VE treatment group

Respondents in the pilot launch of the survey (n = 136) were asked to give feedback about their survey experience. On a five-point scale of progressively higher enjoyment, the video group gave an average score of 3.8 versus 3.5 for the control group (t-test p = 0.002). The video group were also more likely to agree the survey was "interesting" (82 percent compared with 68 percent for the control group, p = 0.03).

We test whether the video treatment affected stated choice certainty and survey completion rates using Pearson's Chi-squared tests. Table 2-3 shows the proportion of respondents in each group who were uncertain of their choices (did not answer "probably" or "definitely" certain), the proportion who completed the post-choice survey questions and retest surveys, as well as odds ratios and Chi-square statistics. The video treatment group had a lower rate of stated uncertainty but this was significant only at ten per cent. Differences in survey completion and retest participation, however, are all significant at less than one per cent. The video treatment group were 2.61 times more likely to complete the first survey, 1.83 times more likely to complete the three-month retest and 1.54 times more likely to complete the six-month retest. The virtual environments apparently reduced panel attrition by making the experience more engaging.

Table 2-3 – Video treatment effect on stated choice certainty, survey completion and participation

	Uncertain of choice	Completed survey	3mth retest participation	6mth retest participation
Treatment mean	0.22	0.97	0.536	0.403
Control mean	0.26	0.93	0.387	0.304
Odds ratio	0.77	2.61	1.83	1.54
χ_2 statistic	1.86*	9.37***	24.62***	11.63***

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

2.6.3 Model results

We used maximum simulated likelihood in Biogeme (Bierlaire, 2003) to estimate random parameter logit (RPL) models for the data. The random parameters are normally distributed. There are dummy variables for headland development, dune restoration and seawall. There are also continuous variables for dune and seawall length. In Table 2-5 we present the model results for the video and control groups separately and three pooled models. Pooled model A has a scale parameter for video treatment and interaction variables for video treatment with left-most position, status quo, dune and seawall. Pooled model B only has the scale parameter and pooled model C assumes equal scale.

2.6.3.1 Log-likelihood ratio tests for pooled models

To test the equality of the pooled and separate models for the video treatment group and control group we use a likelihood ratio (LR) test (Swait & Louviere, 1993). The LR test statistic is calculated as follows:

$$LR = -2\left(LL_{pooled} - (LL_1 + LL_2)\right) \tag{2-3}$$

Where LL_1 is the final log-likelihood of the model for video treatment sub-sample, LL_2 is that for the control sub-sample, and LL_{pooled} is for the pooled model. The LR statistic has a Chi-square distribution with degrees of freedom equal to the difference in number of parameters. Table 2-4 shows that the LR statistics for pooled models B and C with equal scale exceed the 1 percent critical value so do not explain the data as well as the separate models even after controlling for scale effects. The test statistic for model A is insignificant because the addition of treatment interaction terms sufficiently improves the explanatory power of the pooled model. On the basis of these test results we conclude that results for the two groups are different and the interaction terms discussed in the next section help clarify where they are different.

Table 2-4 - Log-likelihood ratio tests

	Pooled A (λ1 ≠ λ2)	Pooled B (λ1 ≠ λ2)	Pooled C (λ1 = λ2)
LR test statistic	14.51	50.16	88.78
Degrees of freedom	10	16	18
P-value	0.151	<0.001	<0.001

2.6.3.2 Parameter estimates

The first five parameters account for the effect of position (left-right bias) on participant choice. The choice card is relatively complex with six alternatives and the significant positive coefficients on positions one to five show the right-most item is least likely to be chosen for both groups. The position parameters are relatively smaller for the video group and the VIDEO × POSITION1 parameter in the pooled model is negative, indicating that the video group exhibit less left-

right bias. The STATUSQUO mean parameter is not significantly different from zero in either group although the random parameter is.

The cost parameter is fixed, rather than random, to avoid the issue of an untenably long upper tail caused by draws that are close to zero (Scarpa, Thiene, & Train, 2008). It is negative and significant for both groups. The HEADLAND parameter – which denotes development is permitted – is also negative and significant for both groups. There is significant taste heterogeneity in the sample as evidenced by the random parameter STDEV_HEADLAND. DUNE, which denotes a restored and planted dune, is significant and positive as is the random parameter STDEV_DUNEDUMMY. DUNELENGTH is not significant but its random parameter is, implying many respondents were insensitive to the size of the restored area.

Preferences for seawalls to protect existing properties are more complicated because some people have positive attitudes towards them and some negative. On average people have a positive WTP but the mean is not significantly different from zero for the video sub-sample. The random parameter STDEV_WALL is significant and slightly larger than the other random parameters indicating wide variation in preferences for seawalls. We tested an alternative latent class specification for seawalls but the overall model fit was poor. Again, the SEAWALLLENGTH mean parameter is insignificant which means people were insensitive to the length of the seawall.

Models A and B have a scale parameter SCALE_VIDEO to test for a systematic difference in scale between the video treatment and control groups. This parameter is positive and significant, which means that the video treatment group exhibits more deterministic choices. This is consistent with the finding that the video sub-sample model has a higher McFadden r-square (0.17 verus 0.11 for the control sample). Model A also has interaction variables for headland, dune, seawall and status quo to test whether the video treatment shifted preferences but none of these are significant.

Table 2-5 –Panel mixed logit models

	Pooled A (λ1 ≠ λ2)		Pooled B (λ1 ≠ λ2)		Pooled C (λ1 = λ2)		Video sub-sample		Control sub-sample	
Variable	Coefficient	Z-value	Coefficient	Z-value	Coefficient	Z-value	Coefficient	Z-value	Coefficient	Z-value
POSITION1	0.2980***	9.35	0.5170***	8.63	0.6150***	9.23	0.5060***	5.33	0.7090***	7.60
POSITION2	0.3490***	5.99	0.3510***	6.01	0.4180***	6.30	0.3440***	3.64	0.4950***	5.34
POSITION3	0.2900***	4.97	0.2910***	4.97	0.3440***	5.16	0.2920***	3.06	0.4030***	4.32
POSITION4	0.2450***	4.18	0.2480***	4.21	0.2930***	4.34	0.2710***	2.82	0.3120***	3.28
POSITION5	0.1630**	2.68	0.1640**	2.69	0.1950**	2.78	0.1840*	1.84	0.2170**	2.19
STATUSQUO	0.0199	0.28	-0.0123	-0.26	-0.0077	-0.14	-0.0577	-0.73	0.0584	0.79
COST	-0.0083***	-8.51	-0.0083***	-8.52	-0.0093***	-8.47	-0.0110***	-7.00	-0.0069***	-4.62
HEADLAND	-0.9230***	-12.42	-0.9690***	-17.47	-1.1200***	-18.97	-1.3200***	-13.90	-0.8960***	-11.97
DUNE	0.5100***	4.75	0.5520***	7.62	0.6400***	7.86	0.8210***	6.44	0.5370***	4.89
DUNELENGTH	0.1910	1.01	0.1950	1.59	0.1260	0.90	0.3850*	1.87	0.2030	1.04
SEAWALL	0.2720**	2.34	0.1550**	2.02	0.1710*	1.94	-0.0420	-0.31	0.3090**	2.68
SEAWALLLENGTH	-0.0700	-0.35	0.0791	0.60	0.0663	0.44	0.1090	0.49	-0.0145	-0.08
STDEV_HEADLAND	1.5800***	26.29	1.5900***	26.58	1.8200***	32.82	2.0100***	23.25	1.5500***	21.80
STDEV_DUNEDUMMY	-1.3600***	-22.19	1.3700***	22.45	1.5800***	26.08	1.8100***	18.91	1.3800***	16.32
STDEV_DUNELENGTH	1.1000***	7.10	1.1200***	7.40	1.2500***	6.77	1.2800***	3.87	1.1800***	4.10
STDEV_WALLDUMMY	-1.6500***	-23.11	1.6500***	23.67	1.8800***	27.31	2.3000***	21.32	1.6700***	17.48
STDEV_WALLLENGTH	1.5800***	8.47	1.6300***	9.07	1.8500***	8.84	1.7400***	5.90	1.0600*	1.84

STDEV_STATUSQUO	0.8180***	12.98	0.8160***	12.95	0.9380***	13.95	0.8960***	8.80	0.8530***	9.66
SCALE_VIDEO	1.3100***	5.37	1.3000***	5.44						
VIDEO x POSITION1	-0.1390***	-3.33								
VIDEO x STATUSQUO	-0.0563	-0.63								
VIDEO x HEADLAND	-0.0843	-0.83								
VIDEO x DUNE	0.0747	0.51								
VIDEO x DUNEKM	0.1710	0.70								
VIDEO x WALL	-0.2120	-1.36								
VIDEO x WALLKM	0.2580	0.98								
Observations		16,230		16,230		16230		8135		8095
Log-likelihood		-18,340		-18,358		-18,377		-8875		-9458
Pseudo-R^2		0.141		0.140		0.139		0.170		0.110

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

2.6.3.3 Choice probabilities

Figure 7 reports choice probabilities for the video treatment and control sub-samples. The left bar chart shows how often each alternative is chosen first, when all six alternatives are available. If there were no left-right bias each position would have an equal probability 0.167 of being selected. The video treatment group have a flatter slope and less left-right bias. The second figure shows small differences in the propensity of the video and control groups to different management options.

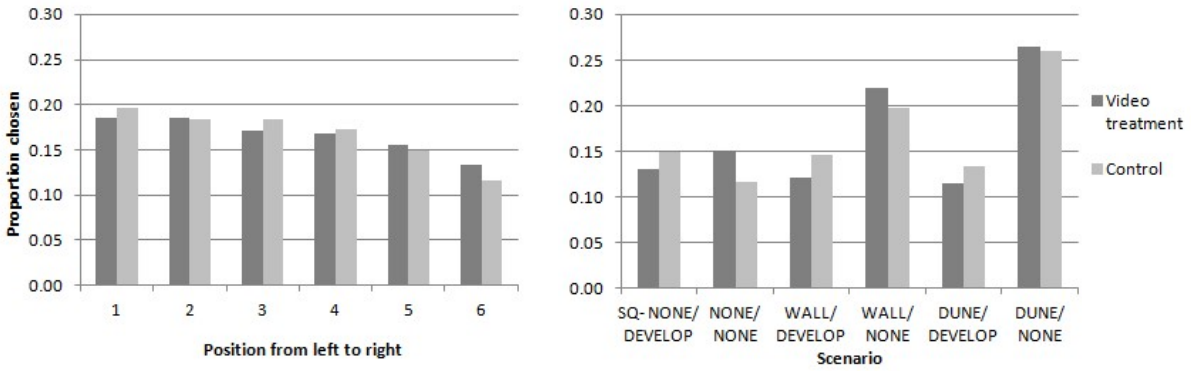


Figure 2-5 - Choice probabilities for first rank by position and scenario

The model for the video treatment group has slightly better in-sample predictive power and correctly predicts 40 percent of choices across all ranks versus 38 percent for the control group model. By chance alone, we would expect 29 percent correct.

2.6.3.4 Willingness to pay results

Figure 2-4 shows box plots of the WTP distributions for headland development and average-length dune and seawall. Visual inspection reveals a large degree of overlap in the distributions for the treatment and the control group with the control group having slightly wider distributions.

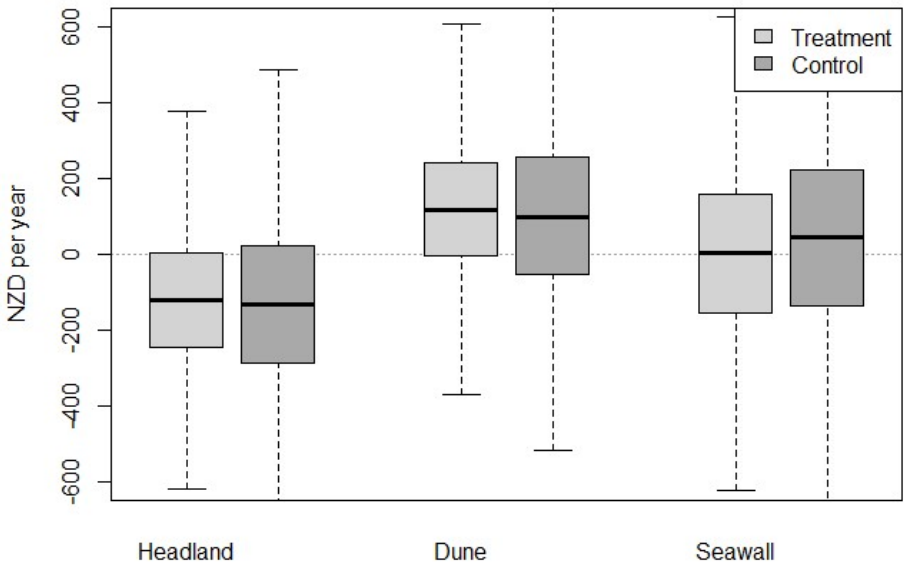


Figure 2-6 - Boxplot of simulated WTP for video treatment and control groups at mean lengths

In Table 2-6 we present mean WTP, confidence intervals and results of the equality tests for different length dunes and seawalls. Headland development has a mean value of minus $124 for the video group versus minus $138 for the control group. The difference is not significant according to a Mann-Whitney U or Kolmogorov-Smirnov test. The difference in WTP for an 800 metre restored dune versus a 200m restored dune is not large: $43 (47 per cent increase) for the video group and $19 (22 per cent increase) for the control group. Mean WTP for the smallest length of dune restoration is similar for both groups ($91 versus $88) but the video group has a significantly higher WTP for the longest 800m dune. WTP for seawalls is even less sensitive to length and varies by only a few dollars for both groups. The video group has significantly lower mean WTP for seawalls of each length.

Table 2-6 - WTP mean, confidence intervals and tests for differences

		Video treatment		Control		Mann-Whitney	K-S
	Length	Mean	90% C.I.	Mean	90% C.I.	U Z-score	Adj D
Headland	N/A	-124	(-364,114)	-138	(-445,163)	-0.49	1.41
Dune	200m	91	(-126,309)	88	(-186,366)	-1.20	1.62
	400m	106	(-118,332)	96	(-188,387)	0.28	1.68*
	600m	120	(-113,357)	103	(-199,410)	-0.87	2.15**
	800m	134	(-115,387)	107	(-220,441)	-2.25**	2.27**
Seawall	200m	-3	(-278,275)	47	(-281,376)	3.34***	2.95***
	400m	2	(-284,288)	47	(-292,389)	2.54**	2.30**
	600m	2	(-298,304)	46	(-308,401)	2.21**	1.96**
	800m	5	(-316,329)	46	(-330,423)	2.53**	2.21**

2.7 DISCUSSION

Our finding that WTP is not very sensitive to the length of the dune restoration or seawall is not uncommon in stated preference studies. Also known as embedding or part-whole bias, many researchers have reported evidence of scope insensitivity since it was first demonstrated by Kahneman (1986) and was blamed on the "purchase of moral satisfaction" rather than an economic choice (Kahneman & Knetsch, 1992). Scope insensitivity can be consistent with rational choice theory in situations such as when there are diminishing marginal values for larger area (Rollins & Lyke, 1998), income effects (Randall & Hoehn, 1996) or a lower perceived probability of provision for the larger good (Powe & Bateman, 2004). In the case of seawalls the scope insensitivity may be a result of a perception that any structure on the foreshore reduces the natural character of the whole beach.

In contrast, Carson and Mitchell (1993) argue that scope insensitivity commonly arises when the good or scope are not fully understood by the respondent, referred to as "amenity misspecification" bias. Utility is context-specific (Wilcox, 2011) and choice tasks may define the context imperfectly. If the VE treatment reduces the potential for amenity misspecification it may also increase scope sensitivity. We find a significant difference in

WTP for dune restoration for the longest dune in the VE group but this is not strictly speaking a test of scope sensitivity so we are unable to draw any conclusions on the issue.

In section 2.5.2 we discussed four measures that are affected by respondent difficulties in processing complex information. We use a split sample to investigate whether a VE presentation format affects these measures and present a summary in Table 2-7. The effect on idiosyncratic error is clear – the scale parameter was higher in both choice experiments in the group with VE treatment. However, it did not appear to make respondents significantly more confident about their choices in terms of stated certainty. The treatment group show less left-right bias, as evidenced by a significant interaction term in pooled model A. The status quo parameter was slightly lower for the treatment group, but the interaction term was insignificant.

We estimated separate and pooled models for the virtual environment treatment and control groups and find that the models are not sufficiently similar even after correcting for scale. The difference is most evident in WTP for seawalls, with the treatment group having a significantly lower mean and a higher proportion with negative values.

Table 2-7 - Summary of video treatment effect

Measure	Test	Result
Survey enjoyment (pilot only)	T-test	Higher
Retest participation	Pearson's Chi-squared	Higher
Stated choice certainty	Pearson's Chi-squared	No significant effect
Idiosyncratic error variance	T-test on scale parameter	Lower
Frequency of status quo	T-test on interaction term	No significant effect
Left-right bias	T-test on interaction term	Lower
Willingness-to-pay	Mann-Whitney U, K-S	Lower for seawalls

When there are differences in parameter estimates the question arises as to which values are "right"? Could the videos in fact *alter* preferences rather than elicit them more accurately? It is common knowledge that stated preferences are strongly influenced by framing and presentation effects. However, the literature on stated preference surveys shows that visualisations generally help individuals make more accurate and consistent

responses (Mathews et al., 2006). So long as the virtual environment is a fair representation of landscape change then it seems reasonable to assume it will improve the accuracy of elicited values. When respondents can view the landscape from different angles and experience it in a more natural way it reduces the number of potentially wrong assumptions they have to make. The lower choice error variance might also have been due to improved respondent engagement in the VE treatment group. In a climate where people are constantly being asked to do web surveys and response rates are declining, the value of a more engaging survey experience must not be underestimated.

2.8 AREAS FOR FUTURE RESEARCH

This study has shown that a virtual environment can improve the reliability of choice responses in terms of lowering choice error variance. A useful avenue of further research would be to test the effect of VE on external validity, for example by comparing stated preferences for sites with subsequent visits. Virtual environments developed using the tools we describe can be as simple or as complex as the researcher desires. Scenarios of land use change can be represented simply by draping Google Earth terrain with images of a different type of land cover. For a more engaging environment the researcher can add models of buildings, trees, people or other elements from the 3D Warehouse[20]. A VE can also include sound and simple animations created in Sketchup such as a day/night cycle or moving water. The presentation of the virtual environments is not limited to videos of fixed flight paths. Future research could investigate interactive options using the Google Earth browser plugin and API library. This would allow users to freely move around the model while their viewpoints are recorded. Providing an interactive experience does introduce additional technological[21] and methodological complications. More research is required to confirm whether more realistic or interactive virtual environments outperform simple ones, and to

[20] https://3dwarehouse.sketchup.com

[21] Cross-browser compatibility was an issue we encountered when testing the Google Earth plugin and API

what extent and under what circumstances the extra development effort is a worthwhile investment.

2.9 Conclusion

In this paper we demonstrate a method of developing virtual environments that does not require proprietary GIS data or expensive and complicated modelling and rendering software packages. Nor is the experiment confined to a computer lab setting. The virtual environment can be delivered to web survey participants using free Application Programming Interfaces (APIs) for Google Earth or embedded videos. The treatment has small but statistically significant effects in parameter results and a significant effect on respondent retention. Based on our findings we feel that virtual environments should seriously be considered for use in any non-market valuation study of visible changes to the landscape.

2.10 References

Arentze, T., Borgers, A., Timmermans, H., & DelMistro, R. (2003). Transport stated choice responses: effects of task complexity, presentation format and literacy. *Transportation Research Part E*, *39*, 229–244. http://doi.org/10.1016/s1366-5545(02)00047-9

Arrow, K., & Solow, R. (1993). *Report of the NOAA panel on contingent valuation* (Vol. 58). Retrieved from http://www.cbe.csueastbay.edu/~alima/courses/4306/articles/NOAA%20on%20contingent%20valuation%201993.pdf

Bateman, I. J., Day, B. H., Jones, A. P., & Jude, S. (2009). Reducing gain-loss asymmetry: A virtual reality choice experiment valuing land use change. JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT, 58, 106–118.

Bateman, I. J., Day, B. H., Jones, A. P., & Jude, S. (2009b). Reducing gain-loss asymmetry: A virtual reality choice experiment valuing land use change. *JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT*, *58*, 106–118.

Beck, M. J., Rose, J. M., & Hensher, D. A. (2013). Consistently inconsistent: The role of certainty, acceptability and scale in choice. *Transportation Research. Part E, Logistics & Transportation Review*, *56*, 81. http://doi.org/10.1016/j.tre.2013.05.001

Ben-Akiva, M., Morikawa, T., & Shiroishi, F. (1992). Analysis of the reliability of preference ranking data. *Journal of Business Research*, *24*, 149–164. http://doi.org/10.1016/0148-2963(92)90058-j

Bierlaire, M. (2003). BIOGEME: a free package for the estimation of discrete choice models.

Blavatskyy, P. (2007). Stochastic expected utility theory. *Journal of Risk and Uncertainty*, *34*(3), 259–286. http://doi.org/10.1007/s11166-007-9009-6

Blomquist, G. C., Blumenschein, K., & Johannesson, M. (2009). Eliciting Willingness to Pay without Bias using Follow-up Certainty Statements: Comparisons between Probably/Definitely and a 10-point Certainty Scale. *Environmental and Resource Economics*, *43*(4), 473–502. http://doi.org/10.1007/s10640-008-9242-8

Bonsall, P., & Lythgoe, B. (2009). Factors affecting the amount of effort expended in responding to questions in behavioural choice experiments. *Journal of Choice Modelling*, *2*(2), 216–236. http://doi.org/10.1016/S1755-5345(13)70011-3

Boxall, P., Adamowicz, W. L. (Vic), & Moon, A. (2009). Complexity in choice experiments: choice of the status quo alternative and implications for welfare measurement. *The Australian Journal of Agricultural and Resource Economics*, *53*(4), 503–519. http://doi.org/10.1111/j.1467-8489.2009.00469.x

Brouwer, R., Dekker, T., Rolfe, J., & Windle, J. (2010). Choice Certainty and Consistency in Repeated Choice Experiments. *Environmental and Resource Economics*, *46*(1), 93–109. http://doi.org/10.1007/s10640-009-9337-x

Campbell, D., & Erdem, S. (2015). Position bias in best-worst scaling surveys: a case study on trust in institutions. *American Journal of Agricultural Economics*, *97*(2), 526–545. http://doi.org/10.1093/ajae/aau112

Carson, R. T., & Mitchell, R. C. (1993). The issue of scope in contingent valuation studies. *American Journal of Agricultural Economics*, *75*(5), 1263–1267.

Carson, R. T., Mitchell, R. C., Hanemann, W. M., Kopp, R. J., Presser, S., & Ruud, P. A. (1992). *A contingent valuation study of lost passive use values resulting from the Exxon Valdez oil spill*. University Library of Munich, Germany.

Caussade, S., Ortúzar, J. de D., Rizzi, L. I., & Hensher, D. A. (2005). Assessing the influence of design dimensions on stated choice experiment estimates. *Transportation Research Part B: Methodological*, *39*, 621–640. http://doi.org/10.1016/j.trb.2004.07.006

Champ, P. A., Bishop, R. C., Brown, T. C., & McCollum, D. W. (1997). Using Donation Mechanisms to Value Nonuse Benefits from Public Goods. *Journal of Environmental Economics and Management*, *33*(2), 151–162. http://doi.org/10.1006/jeem.1997.0988

Chrzan, K. (1994). Three kinds of order effects in choice-based conjoint analysis. *Marketing Letters*, *5*(2), 165–172. http://doi.org/10.1007/BF00994106

Corso, P. S., Hammitt, J. K., & Graham, J. D. (2001). Valuing mortality-risk reduction: using visual aids to improve the validity of contingent valuation. *Journal of Risk and Uncertainty*, *23*(2), 165–184.

Daniel, T. C., & Meitner, M. M. (2001). Representational validity of landscape visualizations: the effects of graphical realism on perceived scenic beauty of forest vistas. *Journal of Environmental Psychology*, *21*(1), 61–72.

Davies, A.-M., Laing, R., & Scott, S. (2002). Combining visualisation and choice experiments in built environment research. In *Information Visualisation, 2002. Proceedings. Sixth International Conference on* (pp. 785–790). http://doi.org/10.1109/IV.2002.1028870

Day, B., Bateman, I. J., Carson, R. T., Dupont, D., Louviere, J. J., Morimoto, S., … Wang, P. (2012). Ordering effects and choice set awareness in repeat-response stated preference studies. *Journal of Environmental Economics and Management*, *63*(1), 73–91. http://doi.org/10.1016/j.jeem.2011.09.001

DeShazo, J. R., & Fermo, G. (2002). Designing Choice Sets for Stated Preference Methods: The Effects of Complexity on Choice Consistency. *Journal of Environmental Economics and Management*, *44*, 123–143. http://doi.org/10.1006/jeem.2001.1199

Dillman, D. A. (2011). *Mail and Internet Surveys: The Tailored Design Method -- 2007 Update with New Internet, Visual, and Mixed-Mode Guide*. Wiley. Retrieved from http://books.google.co.nz/books?id=d_VpiiWp51gC

Ferrini, S., & Scarpa, R. (2007). Designs with< i> a priori information for nonmarket valuation with choice experiments: A Monte Carlo study. *Journal of Environmental Economics and Management*, *53*(3), 342–363.

Fiore, S. M., Harrison, G. W., Hughes, C. E., & Rutström, E. E. (2009). Virtual experiments and environmental policy. *Frontiers of Environmental and Resource Economics*, *57*(1), 65–86. http://doi.org/10.1016/j.jeem.2008.08.002

Graeme, M., Dahm, J., & Kendal, H. (2010). *Coromandel Peninsula - Ecological Assessment of Natural Character* (Report prepared for Thames-Coromandel Distric Council).

Groves, R. M., Presser, S., & Dipko, S. (2004). The Role of Topic Interest in Survey Participation Decisions. http://doi.org/10.1093/poq/nfh002

Harrison, G. W., Haruvy, E., & Rutstrom, E. E. (2011). Remarks on Virtual World and Virtual Reality Experiments. *Southern Economic Journal*, *78*(1), 87–94.

Heiner, R. A. (1983). The Origin of Predictable Behavior. *The American Economic Review*, *73*(4), 560–595.

Hess, S., & Stathopoulos, A. (2013). Linking response quality to survey engagement: A combined random scale and latent variable approach. *Journal of Choice Modelling*, *7*, 1–12. http://doi.org/10.1016/j.jocm.2013.03.005

Huang, A., & Levinson, D. (2016). A model of two-destination choice in trip chains with GPS data. *Journal of Choice Modelling*. http://doi.org/10.1016/j.jocm.2016.04.002

Huang, J.-C., Poor, P. J., & Zhao, M. Q. (2007). Economic valuation of beach erosion control. *Marine Resource Economics*, *22*(3), 221.

Hughes, R. (2004). Visualization in transportation: Current practice and future directions. *Transportation Research Record: Journal of the Transportation Research Board*, (1899), 167–174.

Johnston, R. J., Besedin, E. Y., & Stapler, R. (2016). Enhanced geospatial validity for meta-analysis and environmental benefit transfer: an application to water quality improvements. *Environmental and Resource Economics*, 1–33.

Jude, S. (2008). Investigating the Potential Role of Visualization Techniques in Participatory Coastal Management. *Coastal Management*, *36*(4), 331–349. http://doi.org/10.1080/08920750802266346

Kahneman, D. (1986). Comments by Professor Daniel Kahneman. In D. S. B. R.G. Cummings (Ed.), *Valuing Environmental Goods: A State of the art Assessment of the Contingent Valuation Method* (pp. 185–194). New Jersey: Rowman and Allanheld.

Kahneman, D., & Knetsch, J. L. (1992). Valuing public goods: The purchase of moral satisfaction. *JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT*, *22*, 57–70. http://doi.org/10.1016/0095-0696(92)90019-s

Krinsky, I., & Robb, A. L. (1986). On Approximating the Statistical Properties of Elasticities. *The Review of Economics and Statistics*, *68*, 715–719.

Krosnick, J. A. (1999). Survey Research. *Annual Review of Psychology*, *50*(1), 537–567. http://doi.org/10.1146/annurev.psych.50.1.537

Lancsar, E., & Louviere, J. (2008). Estimating individual level discrete choice models and welfare measures using best-worst choice experiments and sequential best-worst MNL. *University of Technology, Centre for the Study of Choice (Censoc)*, 8–4.

Li, C.-Z., & Mattsson, L. (1995). Discrete Choice under Preference Uncertainty: An Improved Structural Model for Contingent Valuation. *Journal of Environmental Economics and Management*, *28*(2), 256–269. http://doi.org/10.1006/jeem.1995.1017

Lindhjem, H., & Navrud, S. (2011). Are Internet surveys an alternative to face-to-face interviews in contingent valuation? *Ecological Economics*, *70*(9), 1628–1637. http://doi.org/10.1016/j.ecolecon.2011.04.002

Loomis, J., & Ekstrand, E. (1998). Alternative approaches for incorporating respondent uncertainty when estimating willingness to pay: the case of the Mexican spotted owl. *Ecological Economics*, *27*(1), 29–41. http://doi.org/10.1016/S0921-8009(97)00126-2

Lundhede, T. H., Olsen, S. B., Jacobsen, J. B., & Thorsen, B. J. (2009). Handling respondent uncertainty in Choice Experiments: Evaluating recoding approaches against explicit modelling of uncertainty. *Journal of Choice Modelling*, *2*(2), 118–147. http://doi.org/10.1016/S1755-5345(13)70007-1

Madureira, L., Nunes, L. C., Borges, J. G., & Falcão, A. O. (2011). Assessing forest management strategies using a contingent valuation approach and advanced visualisation techniques: A Portuguese case study. *Journal of Forest Economics*, *17*(4), 399–414. http://doi.org/10.1016/j.jfe.2011.04.001

Mann, H. B., & Whitney, D. R. (1947). On a test of whether one of two random variables is stochastically larger than the other. *The Annals of Mathematical Statistics*, 50–60.

Mathews, K. E., Freeman, M. L., & Desvousges, W. H. (2006). How and how much? The role of information in stated choice questionnaires. In B. J. Kanninen (Ed.), *Valuing environmental amenities using stated choice studies: a common sense approach to theory and practice* (Vol. 8, pp. 111–133). Dordrecht: Kluwer Academic Pub.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics*. New York: Academic Press.

Olschewski, R., Bebi, P., Teich, M., Wissen Hayek, U., & Grêt-Regamey, A. (2012). Avalanche protection by forests — A choice experiment in the Swiss Alps. *Integrating Forest Products with Ecosystem Services*, *17*, 19–24. http://doi.org/10.1016/j.forpol.2012.02.016

Powe, N. A., & Bateman, I. J. (2004). Investigating insensitivity to scope: a split-sample test of perceived scheme realism. *Land Economics*, *80*(2), 258–271.

Randall, A., & Hoehn, J. P. (1996). Embedding in market demand systems. *Journal of Environmental Economics and Management*, *30*(3), 369–380.

Ready, R. C., Whitehead, J. C., & Blomquist, G. C. (1995). Contingent Valuation When Respondents Are Ambivalent. *Journal of Environmental Economics and Management*, *29*(2), 181–196. http://doi.org/10.1006/jeem.1995.1040

Rollins, K., & Lyke, A. (1998). The case for diminishing marginal existence values. *Journal of Environmental Economics and Management*, *36*(3), 324–344.

Rose, J. M., Bliemer, M. C. J., Hensher, D. A., & Collins, A. T. (2008). Designing efficient stated choice experiments in the presence of reference alternatives. *Transportation Research Part B*, *42*, 395–406. http://doi.org/10.1016/j.trb.2007.09.002

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty*, *1*(1), 7–59. http://doi.org/10.1007/BF00055564

Scarpa, R., Notaro, S., Louviere, J., & Raffaelli, R. (2011). Exploring Scale Effects of Best/Worst Rank Ordered Choice Data to Estimate Benefits of Tourism in Alpine Grazing Commons. *American Journal of Agricultural Economics*, *93*, 809–824. http://doi.org/10.1093/ajae/aaq174

Scarpa, R., Thiene, M., & Train, K. (2008). Utility in Willingness to Pay Space: A Tool to Address Confounding Random Scale Effects in Destination Choice to the Alps. *American Journal of Agricultural Economics*, *90*, 994–1010. http://doi.org/10.1111/j.1467-8276.2008.01155.x

Scarpa, R., Willis, K. G., & Acutt, M. (2007). Valuing externalities from water supply: Status quo, choice complexity and individual random effects in panel kernel logit analysis of choice experiments. *Journal of Environmental Planning and Management*, *50*, 449–466. http://doi.org/10.1080/09640560701401861

Swait, J., Adamowicz, W., Hanemann, M., Diederich, A., Krosnick, J., Layton, D., … Tourangeau, R. (2002). Context Dependence and Aggregation in Disaggregate Choice Analysis. *Marketing Letters*, *13*(3), 195–205. http://doi.org/10.1023/A:1020262503119

Swait, J., & Erdem, T. (2007). Brand effects on choice and choice set formation under uncertainty. *Marketing Science*, *26*(5), 679–697.

Swait, J., & Louviere, J. (1993). The Role of the Scale Parameter in the Estimation and Comparison of Multinomial Logit Models. \iJournal of Marketing Research, \i30, 305–314.

Thomson, J. (2003). Coastal values and beach use survey report (Technical Report No. TR2003/09). Waikato Regional Council. Retrieved from http://www.waikatoregion.govt.nz/Services/Publications/Technical-reports/2003-technical-reports/

Thomson, J. (2003b). *Coastal values and beach use survey report* (Technical Report No. 2003/09). Waikato Regional Council. Retrieved from http://www.waikatoregion.govt.nz/Services/Publications/Technical-reports/2003-technical-reports/

Train, K. (2003). *Discrete choice methods with simulation*. Cambridge Univ Pr.

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, *211*(4481), 453–458. http://doi.org/10.1126/science.7455683

Urban, G. L., Hauser, J. R., Qualls, W. J., Weinberg, B. D., Bohlmann, J. D., & Chicos, R. A. (1997). Information acceleration: validation and lessons from the field. *Journal of Marketing Research*, 143–153.

Versus Research. (2012). Community held values of Waikato rivers, lakes and streams in the Waikato and Waipā catchments. *Waikato Regional Council Technical Report*, *2013*(31), 160.

Vossler, C. A., Doyon, M., & Rondeau, D. (2012). Truth in consequentiality: theory and field evidence on discrete choice experiments. *American Economic Journal: Microeconomics*, *4*(4), 145–171.

Whitehead, J. C., Poulter, B., Dumas, C. F., & Bin, O. (2009). Measuring the Economic Effects of Sea Level Rise on Beach Recreation. *Working Papers*.

Wilcox, N. T. (2011). “Stochastically more risk averse:” A contextual theory of stochastic discrete choice under risk. *The Economics and Econometrics of Risk*, *162*(1), 89–104. http://doi.org/10.1016/j.jeconom.2009.10.012

Windle, J., & Rolfe, J. (2014). Estimating the nonmarket economic benefits of beach resource management in southeast Queensland, Australia. *Australasian Journal of Environmental Management*, *21*(1), 65–82. http://doi.org/10.1080/14486563.2013.875953

Windle, & Rolfe, J. (2011). Comparing Responses from Internet and Paper-Based Collection Methods in more Complex Stated Preference Environmental Valuation Surveys. *Economic Analysis and Policy*, *41*(1), 83–97. http://doi.org/10.1016/S0313-5926(11)50006-2

2.11 APPENDIX

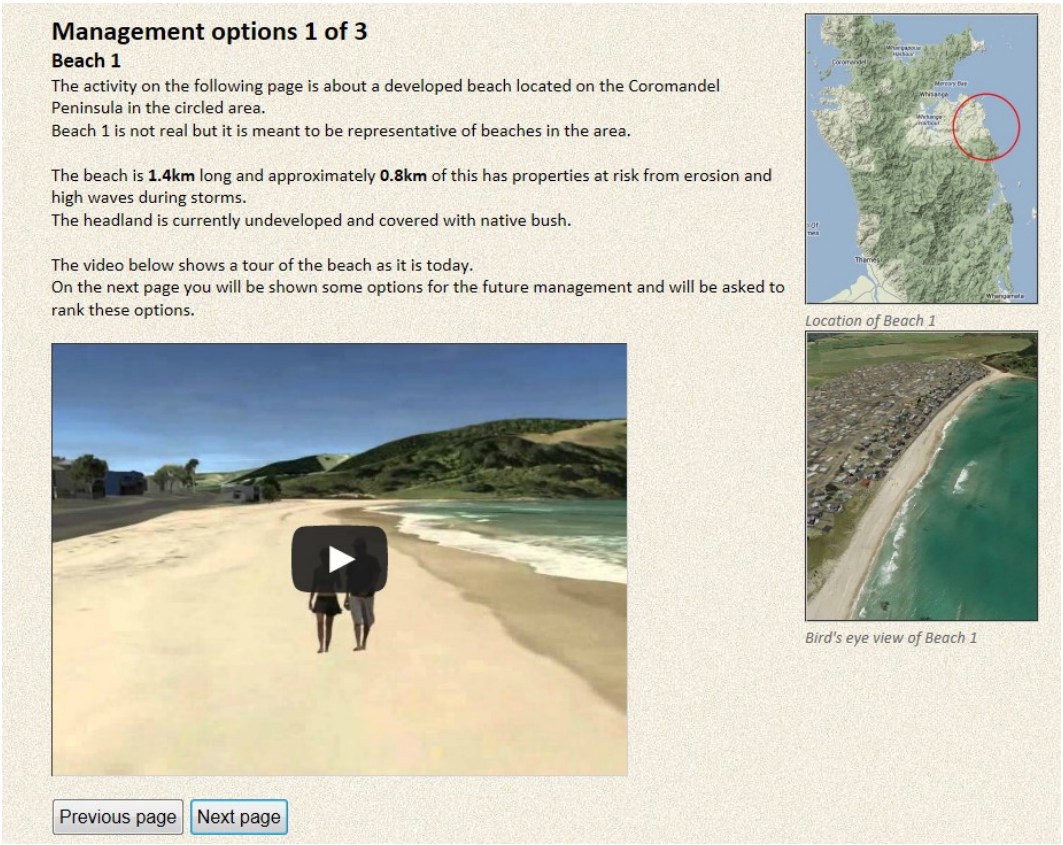


Figure 2-7 - Choice experiment beach introduction page

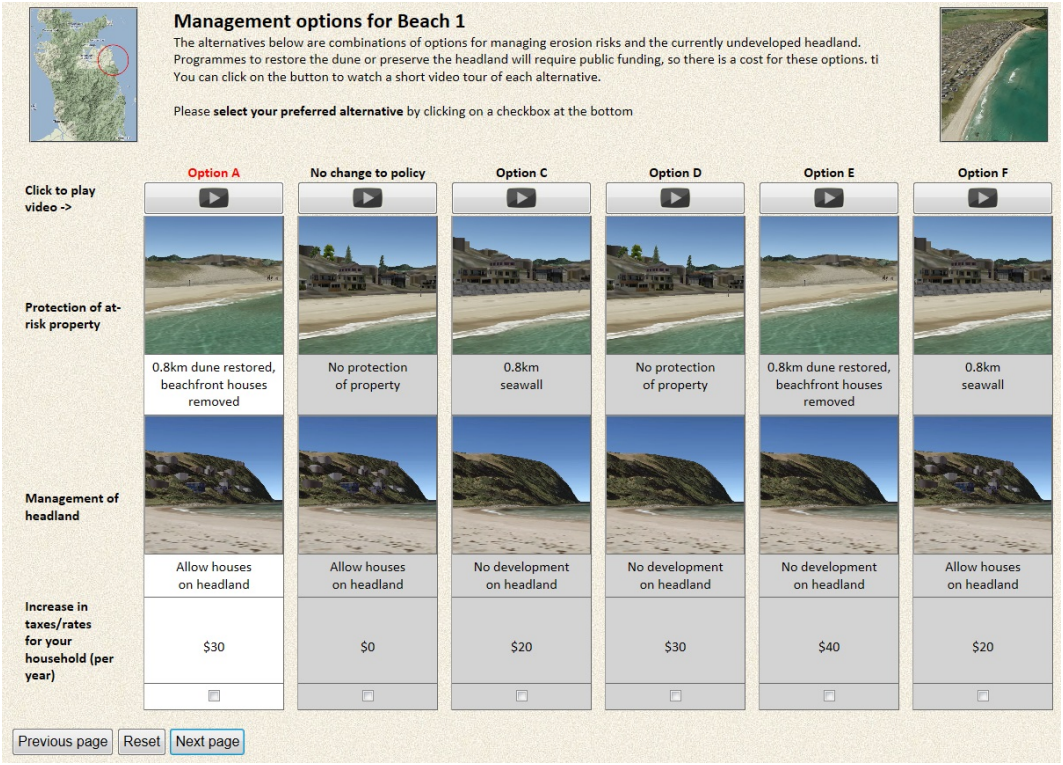


Figure 2-8 - Example choice card showing mouse-over highlight

3. VIRTUAL ENVIRONMENTS FOR THE UNEXPERIENCED: A CHOICE EXPERIMENT ABOUT COASTAL CONSERVATION

3.1 ABSTRACT

Non-market valuation researchers sometimes ask individuals to express preferences for environments they have never directly experienced. We conduct a choice experiment about some development or conservation options for a particularly scenic undeveloped beach in New Zealand that only a minority of New Zealanders have visited. This is problematic because stated preferences for unfamiliar locations or issues tend to be constructed on the spot and can be unreliable and prone to departures from the tenets of rational choice theory. However, many New Zealanders have pre-existing preferences about beach conservation in a more general sense. Salient and easy-to-process information can help survey respondents construct or discover their preferences for an unfamiliar site. We develop 3D virtual environments illustrating each development scenario to help respondents understand the effects on the coastal landscape. Using a split-sample where the control group see only static images, we test for systematic differences in preferences, choice error and willingness-to-accept values for development. We find that for people who have not visited the site, the VE treatment is associated with significantly different preferences and reduced choice error. We find no evidence that the VE affected stated preferences of respondents with direct experience of the site.

Keywords

Choice experiment, virtual environment, beach conservation, coastal development

3.2 INTRODUCTION

Modification of the coastal landscape has the potential to damage not only the functioning of ecosystems but also degrade the quality of recreation opportunities, passive use, and other social and cultural values. Choice experiments are a popular technique for quantifying the expected effect on public welfare resulting from changes in environmental quality by eliciting structured preferences of recreationists. Some applications of choice experiments in the literature include: preferences for tourist facilities at Caribean beaches (Haider & Ewing, 1990); beach management in Australia (Windle & Rolfe, 2014); beach erosion control in New Hampshire and Maine (Huang, Poor, & Zhao, 2007); coastal water quality in Tobago (Beharry-Borg, Hensher, & Scarpa, 2009); and seawalls and headland development in New Zealand (Matthews, Scarpa, & Marsh, 2017)

3.2.1 FAMILIARITY

An assumption of stated preference methods such as choice experiments is that stable and well-defined preferences exist for the good being valued. If well-defined preferences do exist the task is to uncover them like archaeologists (Gregory, Lichtenstein, & Slovic, 1993), making sure the good is correctly defined and respondents are motivated to respond truthfully. Choice experiments should be less prone to bias than directly asking people to place a dollar value on a resource they may not have thought about in dollar terms before (Braga & Starmer, 2005)

However, it is unrealistic to assume people will have well-articulated and well-defined stable preferences for an environment they have not directly experienced, such as a future development scenario, for example. Our study is about an undeveloped beach site that only a minority of New Zealanders have visited and we were concerned about potential lack of well-defined preferences for the site amongst non-visitors. New Zealanders in general place high value on unspoiled coastal environments (Collins & Kearns, 2010a) so it is not unrealistic

for non-visitors to have high option or existence values for the beach. However, lack of familiarity can lead to unreliable, inaccurate or imprecise WTP estimates (Diamond & Hausman, 1993). Unfamiliarity makes users more susceptible to ordering effects, part-whole bias (Boyle, Desvousges, Johnson, Dunford, & Hudson, 1994) and hypothetical bias (Paradiso & Trisorio, 2001). These findings are all consistent with the constructive perspective that says that when an issue is unfamiliar, complex, or not directly experienced; people may use a wide variety of heuristics instead of strict utility maximisation to make decisions (Payne, Bettman, & Schkade, 1999). This problem is not limited to the area of environmental valuation. People frequently have to make real-life decisions about unfamiliar issues such as new products and services. Unfamiliarity or lack of pre-existing preferences therefore does not invalidate stated preference techniques – the challenge is to help people discover or construct their preferences using all relevant information and with a high standard of reasoning (Payne et al., 1999). The goal of environmental valuation studies is to predict human response to real environments.

The term "familiarity" may include knowledge of an issue in a general, wider context (Diamond & Hausman, 1993). It seems reasonable to assume that most New Zealanders are aware of the effects of coastal development since clusters of new holiday homes are a common sight in every coastal area (Collins & Kearns, 2010b). What many respondents in our study lacked was direct experience of the study site and a way to anticipate what development might do to the landscape. We therefore use previous visitation as a proxy for familiarity with the site.

Respondents who lack "exogenous" knowledge of a site from direct experience can instead rely on "endogenously" provided information from the survey instrument (Cameron & Englin, 1997). The information provided in surveys can affect WTP estimates in a theoretically plausible manner and is important for accurate environmental valuation (Bergstrom, Stoll, & Randall, 1990). Visual impacts are generally the issue of primary importance in coastal development

(Collins & Kearns, 2010a), so it was important to convey detailed visual information about the scenarios in our choice experiment.

3.2.2 VISUALISATIONS

Visualisations such as photographs, maps and diagrams are reported to both standardise and aid respondent comprehension in many studies (Mathews, Freeman, & Desvousges, 2006). Landscapes are particularly difficult to evaluate and even photographs may be inadequate representations for scenic beauty judgements (Daniel & Meitner, 2001). A relatively new tool in the toolbox of non-market valuation researchers is the use of a computer generated virtual environment (VE) or interactive virtual reality (VR) to communicate landscape changes. If a picture tells a thousand words then a 3D model can tell a great many more, since the visual field is generated dynamically depending on the simulated viewpoint. VE can provide a "decision context supported by more intuitive information" (Bishop, Stock, & Williams, 2009). Jude (2008), for example, reported that a combination of 3D visualisation and GIS stimulated more meaningful discussions about coastal planning among planners than did 2D maps. Fiore et al. (2009) reported that virtual reality generated more accurate beliefs about forest fire risks.

There are very few examples of choice experiments with virtual environments in the literature. Bateman et al.(2009) persuasively argued that 3D visualisations improved the evaluability of unfamiliar scenarios and reduced anomalous gain/loss asymmetry. Some researchers (Davies, Laing, & Scott, 2002; Madureira, Nunes, Borges, & Falcão, 2011; Olschewski, Bebi, Teich, Wissen Hayek, & Grêt-Regamey, 2012) developed 3D models but presented these to participants as static images. In another paper (Matthews et al., 2017) we describe the method by which we created virtual environments depicting erosion management options using free, easy-to-use software and Google Earth© satellite imagery and presented these to respondents as video tours. We found the VE treatment reduced choice error, left-right bias and improved respondent engagement and retention when compared with static images.

The question then arises; would virtual environments provide the same benefits to information evaluability to respondents who have direct experience of the site? On one hand, we might expect direct users to have well-formed opinions about the benefits they obtain visiting the beach, and how those benefits might be degraded (or perhaps enhanced) by coastal development. We might suppose that these preferences would be invariant to any elaborate presentation method. On the other hand, even experienced visitors may benefit from 3D visualisations to help them understand the impact on the landscape of hypothetical development options.

For this study we created new virtual environments for an undeveloped beach using the same method as detailed in Matthews et al.(2017) and use a split-sample treatment to test for systematic effects on stated preferences of people with and without direct site experience. Our contributions to the literature are to add to the very small pool of literature about virtual environments in non-market valuation, by testing both whether the treatment effects are consistent with previous findings and whether the VE treatment has the same effect on users and non-users.

3.3 EMPIRICAL CONTEXT

The study area is a beach called New Chums in Wainuioto Bay on the Coromandel Peninsula, New Zealand. It is approximately one kilometre long, with white sand characteristic of the east coast of the Peninsula. The surrounding hills are clad with native forest and large, iconic pohutukawa trees. Steep slopes and forest are important components of the aesthetic quality of shorelines, particularly large trees and hardwoods (Haider & Hunt, 2002) such as those found in pohutukawa forest. In the summer months there is a mass exodus of city-dwelling New Zealanders to coastal communities such as the Coromandel Peninsula. New Zealanders commonly have strong feelings about, and attachment to, natural coastal landscapes (Collins & Kearns, 2010a). This is partly

due to recreation values but also cultural values of food gathering, connecting with nature and “familial landscapes”.

New Chums is one of few remaining undeveloped beaches on the Peninsula that is relatively accessible. While the access track is not wheelchair or stroller-friendly, it is only a thirty minute walk from nearby Whangapoua. The character and accessibility of this beach is important for visitors because visits to near-natural landscapes promote psychological and physical health. The quality of the environment is an important condition for these benefits (Buchecker & Degenhardt, 2015).

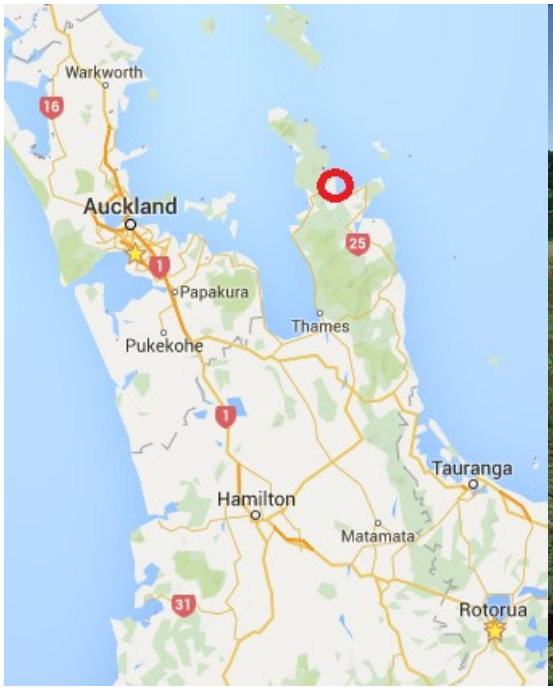


Figure 3-1 - Location of study area (circled)

Figure 3-2 – Google Earth image of New Chums

However, there is strong demand for holiday housing on the Coromandel Peninsula and the natural landscape at New Chums is at risk from this development pressure. In 2010 an application was made to the local authority to develop a twenty-lot residential development on privately owned farmland adjacent to the beach. The application received high public interest in New Zealand and protection of the beach was strongly advocated by community

groups[22]. People value not only the recreational use of New Chums but also option, bequest and existence values of this increasingly rare undeveloped beach resource. Twenty houses may be a small-scale development but small-scale land use decisions in the coastal environmental have cumulative impacts on both environmental processes and visual intrusiveness (Collins & Kearns, 2010a). In June 2015 the latest application for consent was withdrawn, but there may be further applications in the future unless the land is purchased by the government or covenanted[23] for conservation.

Beachfront sites are highly desirable for developers but there is also strong demand for houses on headlands and ridgelines, built to maximise views. Building on elevated sites only would allow the preservation of trees on the foreshore, but elevated houses have the potential to disrupt natural contours and dominate the landscape. They also need access roads, which might cut across the homogeneous forest cover, scarring the natural landscape with artificial elements. Coastal landscapes are degraded when houses on high "look down" over people on the beach (Collins & Kearns, 2010a). We therefore designed this study to obtain separate value estimates for foreshore and hilltop development to estimate which would have the greater impact on welfare.

If subdivision of the land adjacent to New Chums beach were allowed, public accessibility may be improved with the provision of a public road and parking and toilet facilities. Improved accessibility would probably lead to an increase in visitor numbers. The downside is that growth in visitor numbers may very well degrade the recreation value for visitors who seek solitude and a natural environment, as reported by Cságoly et al.(2017) in a study of areas located at the border of wilderness and urban environments.

The New Zealand Coastal Policy Statement (2010) and Resource Management Act (1991) require decision makers to take account of economic, environmental,

[22] http://www.nzherald.co.nz/nz/news/article.cfm?c_id=1&objectid=10671323

[23] http://www.doc.govt.nz/about-us/science-publications/conservation-publications/protecting-and-restoring-our-natural-heritage-a-practical-guide/legal-protection/

social and cultural effects of policies relating to the coastal environment. The motivation for studying New Chums beach is to improve understanding of social and cultural values associated with the site and quantify the public welfare impacts of both private housing and public facility development.

3.4 METHOD

3.4.1 RANDOM UTILITY MODELLING FRAMEWORK

The underlying theory of discrete choice experiments is Lancaster's theory of consumer behaviour (Lancaster, 1966) in which a good is defined as a bundle of characteristics. In this case the "good" is alternative future states of New Chums. As per random utility theory (Manski, 1977) we assume the probability of a consumer choosing a state is a function of deterministic and random or unobserved components of utility. The utility that person *n* obtains from alternative *j* is specified as follows:

$$U_{nj} = ASC_{left} + \beta_n \mathrm{X_j} + \varepsilon_{\mathrm{nj}} \quad \textbf{(3-1)}$$

Where ASC is an alternative-specific constant for the option displayed on the left (to control for left-right bias in the presentation of scenarios to respondent (Scarpa, Notaro, Louviere, & Raffaelli, 2011; Campbell & Erdem, 2015), X_j denotes the attributes (cost and development type), β_n is a vector of taste parameters specific to each individual, *n* are individual respondents, and *j* are the alternative states. The error term ε_{nj} is assumed to have an *i.i.d.* extreme value type 1 distribution, consistent with the widely used MNL specification. Alternative error structures such as multivariate normal are of course possible, but far less computationally tractable and require purpose-specific programming to estimate.

Since human values toward natural resources are variable across time and space (McCool, Nkhata, Breen, & Freimund, 2013) we model this unobserved heterogeneity using random parameters for β. The unconditional probability of choosing alternative *i* is therefore:

$$P(i) = \int \prod_t \frac{e^{\lambda(\beta' x_{it})}}{\sum_j e^{\lambda(\beta' x_{jt})}} \varphi(\beta|b,W)d\beta \qquad \textbf{(3-2)}$$

Where $\varphi(\beta|b,W)$ is, in our case, a normal density with mean b and covariance W. This is known as a panel (over t choices) mixed (over random β) logit (RPL) specification and allows for taste variation across individuals, unrestricted substitution patterns and correlations in unobserved components across the t choices by the same respondent (Train, 2003). The model also includes a scale parameter λ which is inversely related to the variance of the error term in the utility function. The latter cannot be uniquely identified but it is possible to compare its relative scale from pooled datasets (Swait & Louviere, 1993). We estimate RPL models with alternative choice probabilities as the dependent variables, with the objective of maximising the likelihood of observing the choices that we did in fact observe. This was achieved using maximum simulated likelihood estimation in Biogeme (Bierlaire, 2003).

3.4.2 WELFARE MEASURES

The purpose of the choice analysis is to obtain monetary measures of the welfare changes due to changes to the public good that is New Chums. For a desirable change the compensating variation welfare measure is the maximum amount an individual would be willing to pay (WTP) to secure the change. For an undesirable change it is the minimum amount they would require in order to accept it (WTA). WTA tends to be higher in absolute terms than WTP, particularly for public goods with few close substitutes (Hanemann, 1991). Marginal WTP/WTA for a particular attribute is calculated by dividing the negative of the attribute parameter by the cost parameter. We also tested models estimated directly in "WTP-space" (Scarpa, Thiene, & Train, 2008) which would have allowed more direct comparison of WTP/WTA. However, the WTP-space models had significantly worse fit, so we opted for the historically more conventional preference-space models. We used the variance-covariance matrix at

convergence and Monte Carlo simulation (Krinsky & Robb, 1986) to approximate the asymptotic sampling distribution of WTP/WTA.

3.4.3 HYPOTHESES AND TESTS

The motivation for using 3D virtual environments in this study was to help respondents better understand the effect of development on the landscape and user experience of the beach. We wanted to know whether the VE would affect stated preferences in a systematic way so as to test three important hypotheses: equality of utility functions, equality of scale and equality of marginal WTA distributions.

3.4.3.1 Test of preference equality

The null hypothesis is for equal utility functions for treatment and control groups. To test this we follow the likelihood ratio (LR) test procedure described by Swait and Louviere (1993) in which the data from test and retest is stacked and a pooled model is estimated. The LR test is an asymptotic test of global goodness of fit and it tells us whether the variables explain the same amount of variance before or after the equality restriction. The LR test statistic is calculated as follows:

$$LR = -2\left(LL_{pooled} - (LL_{control} + LL_{treatment})\right) \quad \textbf{(3-3)}$$

where *LL* is the final log-likelihood of the RPL models for the pooled, control and treatment samples, respectively. It has a chi-square distribution with degrees of freedom equal to the number of parameters in the utility function subject to restriction. If the LR test does not reject the pooled model we conclude that the models for the treatment and control groups are sufficiently similar. We also estimate separate models for New Chums visitors and non-visitors to test whether the treatment and control models are sufficiently similar for these sub-samples.

We also report the results of Wald tests of joint parameter equality. The Wald test statistic, W is:

$$W = (\hat{b}_1 - \hat{b}_2)'\widehat{V}_1^{-1}(\hat{b}_1 - \hat{b}_2) \quad \textbf{(3-4)}$$

where $\hat{b}_1$ and $\hat{b}_2$ are the vectors of parameter estimates from models one and two and $\widehat{V}_1$ is the variance-covariance matrix of model one. Similar to the LR test, this statistic also has a sampling distribution that is asymptotically chi-square. If the LR or Wald tests reject model equality they do not identify which utility coefficients vary significantly from the restricted and unrestricted specification. So, we also test for equality of scale and marginal WTA for each attribute.

3.4.3.2 Test for equality of scale

The second null hypothesis is for equal scale for the treatment and control groups. The scale factor λ in equation 2 is inversely proportional to the variance of the idiosyncratic choice error. Choices which are more deterministic have a higher relative scale factor. Scale has been shown to be systematically affected by experimental design and respondent-specific factors (Bradley & Daly, 1994; Louviere et al., 1999). Design features which reduce choice complexity tend to reduce choice error and therefore increase the scale factor (Caussade, Ortúzar, Rizzi, & Hensher, 2005). 3D visualisations have been reported to have significant positive scale effect in previous studies (Bateman et al., 2009; Matthews et al., 2017). To test whether this is also the case here, we estimate a pooled model where scale is normalised to one for the control group and estimated by maximum likelihood for the video treatment group. If the scale parameter is positive and significant it is evidence that the treatment reduced choice error. We also conduct a LR test with the pooled model with unequal scale to test whether parameters are equal after allowing for scale differences.

3.4.3.3 Test of WTP/WTA equality

The third null hypothesis is for equal WTA between treatment and control groups. Simulated WTP/WTA is not necessarily normally distributed so we use a

non-parametric Mann-Whitney U test[24] (Brouwer & Spaninks, 1999) to test for equality of WTP means. We also use the Kolmogorov-Smirnov (K-S) two-sample test of equality of the WTP distributions because it is not reliant on normality and is sensitive to differences in both location and shape of the empirical cumulative distribution function of the two samples[25]. We generate the WTP/WTA distributions with a million parameter draws and then draw samples from these distributions the same size as our observed samples. For both tests we calculate the average test statistic from a thousand such drawn samples.

3.4.4 EXPERIMENTAL DESIGN

A motivation for this study was to discover whether and by how much the location of private development affects WTA values. The choice experiment alternatives therefore included two options for private housing development - either on the foreshore or on the hill behind the beach where they are not visible from the shore, or both. The number of houses is a dozen in both locations. The attribute for public facilities is either "none" or public road, car park and toilet. There is no need to value these facilities separately since they tend to be provided together in practice. The cost attribute is defined as the up-front cost per taxpaying household for the government to buy the land for public use and manage it in perpetuity. Alternatives with private housing and no public facilities

[24] The Mann-Whitney U test (also known as Wilcoxon rank-sum) involves ranking the pooled WTP and then adding up the ranks for test and re-test datasets. The statistic $U = R_1 - \frac{n_1(n_2+1)}{2}$ where R_1 is the smaller sum of ranks of the two samples and n_1 and n_2 the sample sizes. For large samples U is approximately normally distributed with mean $\frac{n_1 n_2}{2}$ and standard deviation $\sqrt{\frac{n_1 n_2 (n_1+n_2+1)}{12}}$.

[25] The K-S test statistic *D* is based on the maximum absolute difference between the two CDFs $S_{N_1}(x)$ and $S_{N_2}(x)$. The null hypothesis of equal distributions is rejected at level α if: where *m* and *n* are the sample sizes and $c(0.05)$ equals 1.36 for sufficiently large samples

provided are defined as the zero cost, do-nothing option. Table 3-1 shows the attribute descriptions and levels.

Table 3-1 - Attributes and levels used in choice experiment

Attribute	Description	Levels
Public facilities	Public road access, carpark and toilet	0 = No 1 = Yes
Housing	How many private houses will be built, and where	0 = No development 1 = A dozen houses on the shore 2 = A dozen houses on the hill 3 = A dozen houses each on the shore and hill
Household taxes	One-off cost to your household (total cost for government to buy and manage the land, averaged over taxpaying households)	$0 or $10 increments from $50 to $200

Each choice card has three alternatives and each respondent completed three cards. We tested an orthogonal design in a focus group and obtained prior values with which to generate a Bayesian D-efficient design (Ferrini & Scarpa, 2007) by swapping the cost attribute. This means that cost is no longer orthogonal to the other attributes but this is a more efficient design with which to discern the value of attributes with non-zero priors (Rose, Bliemer, Hensher, & Collins, 2008). There were six blocks required in order to use all the cost levels (which were in $10 increments) and respondents were randomly assigned a block. Respondents were also randomly assigned to a video treatment group or control group. Both groups were presented choice cards with text descriptions of the attribute levels and small images for each alternative. The video group had a button to play a video for each alternative while the control group did not. An example of the choice card presentation can be found in the appendix.

3.4.4.1 Development of virtual beaches

With four options for housing development (none, foreshore, hill or both) and two options for public facilities we needed eight virtual environments to show every combination. The 3D models were developed using Sketchup Make©, a free 3D drawing tool originally developed by Google and now published by

Trimble[26]. We imported a digital elevation model and land-cover imagery of New Chums beach from Google Earth©. For the car park we copied satellite imagery of a car park (complete with cars) from a different beach and placed it near the middle of the New Chums beach, over an existing private vehicle track.

To create the houses we located properties around the Peninsula from post-2000 housing developments to represent typical architecture of the era and locality. Simple yet photo-realistic 3D models were created by raising the building's footprint from satellite imagery and draping the sides with images of the house from Google Streetview©. The house models were then transplanted to New Chums beach to nestle in the forest by the foreshore or perch on the hill behind the beach. There are plenty of models of trees, people and other objects available to download from the 3D warehouse[27] but we deemed the satellite imagery provided sufficient realism. We could have added people to the beach but would have had to make explicit judgements about the effects of development on visitor numbers, which are also highly variable by season and time of day. Crowding certainly has the potential to negatively affect visitor experiences, especially for crowd-averse individuals with a preference for solitude and stress relief (Arnberger & Haider, 2005), but with no data to forecast visitor numbers we had to let respondents form their own expectations.

Figure 3-3 – Image of the virtual road, car park and toilet block

[26] http://www.sketchup.com

[27] https://3dwarehouse.sketchup.com/

Figure 3-4 – Images of 3D model with no houses, houses on the foreshore and on the hill

The 3D beach models were exported as geo-referenced KML files for Google Earth. The Google Earth application or a browser plug-in can be used to view and virtually "walk around" these development scenarios. In order to provide control over what participants see—and avoid browser compatibility problems—we presented the virtual environments to respondents as pre-recorded tours, rather than interactive models. The "tour" lasted 20 seconds, began above the headland one end of the beach, traversed the length of the beach at the height of a person walking and finished with a view from the other headland[28]. Tours were embedded in the web survey using the Youtube© API for javascript[29] because it provides excellent cross-browser support, does not require the user to install any additional software, and allows the recording of start/stop events.

3.4.5 THE SURVEY INSTRUMENT AND RECRUITMENT

The data were collected via a web-based survey in February 2014. Respondents were sourced from a pre-recruited panel of participants provided by a market research company. To take part in the survey respondents had to live in New Zealand and have visited the Coromandel Peninsula in the past year. The qualifying criteria were obfuscated by asking about outdoor recreation in general, in case people were motivated to lie about qualifying simply to receive survey rewards. People who completed the survey were given rewards points by

[28] A sample video may be viewed here: https://www.youtube.com/watch?v=bb8ay6McCFA

[29] https://developers.google.com/youtube/js_api_reference

the market research company. The survey was pilot-tested in focus groups but face-to-face interviews were not feasible for main data collection given how geographically spread-out the target population was. The use of a pre-recruited panel restricts the undesirable multiple participations by the same individuals and is an increasingly popular collection mode, especially in New Zealand. The sampling frame may be biased towards a certain type of person (web-savvy and motivated by small financial rewards) but other survey modes have different response biases such as overrepresentation of older respondents in face-to-face or telephone interviews (Versus Research, 2012).

3.4.5.1 Mapping of likes/dislikes

The survey also included an interactive mapping tool using an embedded Google Maps API to discover what New Chums visitors liked and disliked about the beach in a spatially explicit way. Participatory mapping techniques are an increasingly popular method to produce spatially explicit information about outdoor recreation experiences (Pietilä & Kangas, 2015) or environmental planning (Brown, 2012)

3.5 RESULTS

3.5.1 DESCRIPTIVE STATISTICS

A total of 551 individuals completed the survey. Table 3-2 shows a selection of demographic variables for the sample. The majority of participants live in the Waikato or Auckland regions and less than ten percent are permanent residents of the Peninsula. Respondents tended to be older and more highly educated than the general population. This may be due in part to some degree of sample selection bias, but Thomson (2003) also found that visitors to Coromandel beaches were more highly educated than non-visitors. The average respondent made 2.57 trips to the Peninsula for beach recreation in the previous 12 months, and lived 2.33 hours away from New Chums beach. Only 38 percent of respondents said they knew of the existence of New Chums beach and 83 respondents (15 percent) indicated they had visited the beach before. This small

proportion reflects the fact that there are many attractive beaches on the Peninsula and the secluded, undeveloped nature of New Chums appeals more to some types of people than others. Many people who visit the Peninsula return to the same beach(es) year after year (Collins & Kearns, 2010b)

Table 3-2 - Descriptive statistics

Variable	Sample mean
Count	551
Age	42
Coromandel resident	0.09
Waikato resident	0.39
Auckland resident	0.36
Female	0.63
Post-school education	0.71
Employed full-time	0.48
Income over $100k	0.33
Holiday home owned by family	0.24
Travel time from home to site (hours)	2.33
Number of visits to peninsula last year (non-residents only)	2.57
Have heard of New Chums	0.38
Have visited New Chums	0.15
Video treatment group	0.51

3.5.2 VIRTUAL ENVIRONMENT VIDEO TREATMENT

Participants were randomly assigned to the videos-plus-static-images treatment group or static-images-only control group. Those in the video treatment group could not reasonably be forced to watch every video for every alternative, so they had to click on a video icon to make it start playing. Of the 281 respondents in the treatment group, 238 watched at least one video. Out of these, the average number of videos watched was 2.54, or 58 seconds of total video play time.

3.5.3 LIKED AND DISLIKED FEATURES

The 83 respondents who said they had ever visited New Chums beach were asked to place markers on an interactive map to show what features they liked or disliked. Many people liked the scenic views, white sandy beach, trees on the foreshore and the peacefulness of New Chums. Only three respondents indicated

they dislike the difficult access. However, there may be people who do not visit the beach because of the difficult access (the track is uneven and requires a certain level of mobility and fitness – or a boat). People who have visited the site may value it more highly since they have direct use as well as some passive and non-use values (Carson, Flores, & Meade, 2001). We include interaction variables in the following models to allow for a systematic difference in mean WA for visitors.

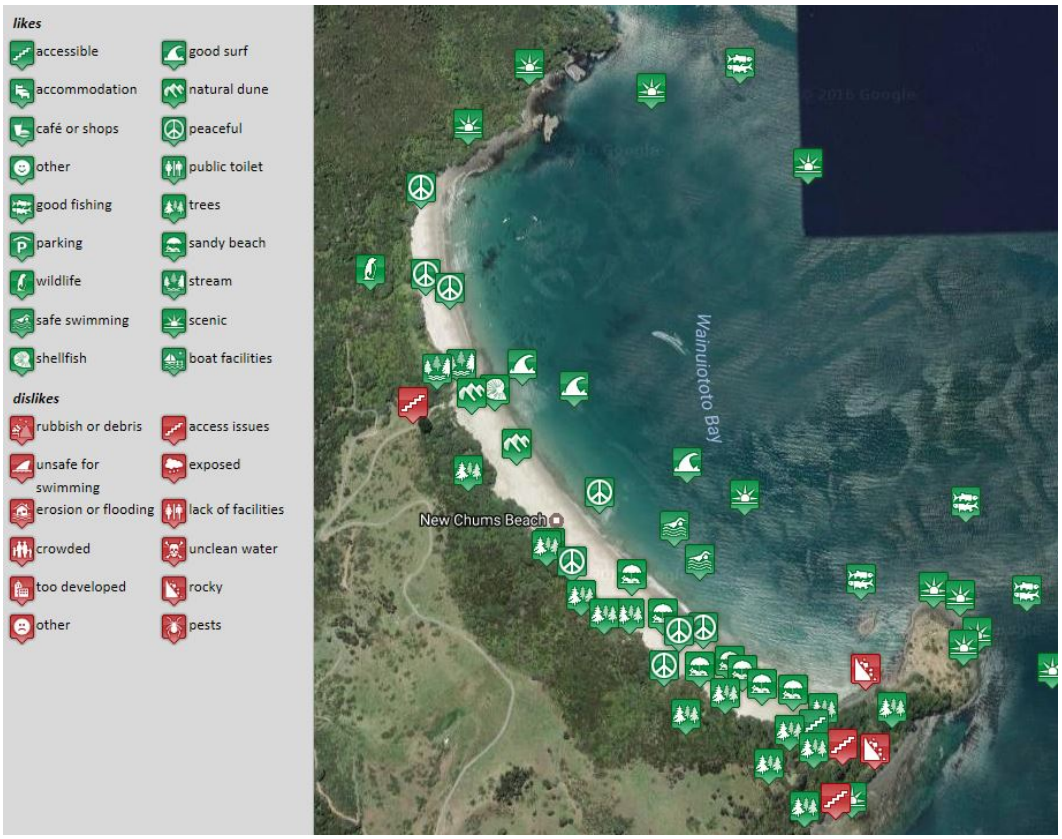


Figure 3-5 - Satellite image with visitor like/dislike marker overlay

3.5.4 ESTIMATION RESULTS

3.5.4.1 Results for preference equality between VE and control

Table 3-3 presents the results of the likelihood ratio (LR) tests of equality of pooled versus separate RPL models for the VE treatment and control groups[30].

[30] We also tested model equality for non-visitors who stated they "know of" of New Chums beach and found no evidence to suggest these people had different preferences to people who were

We also undertook a LR test for pooling visitors and non-visitors and this was rejected, as expected. Visitors and non-visitors have different utility functions. For the visitor-only sample, the LR statistic for pooling treatment and control groups is not significant at five percent so we do not reject model equality. However, for non-visitors the LR statistic greatly exceeds the critical chi-squared values even when allowing for difference of scale. When we combine visitors and non-visitors the LR test similarly rejects model equality. The Wald test results are similar – *W* equals 21.7 for visitors and 199.5 for non-visitors. The Wald test rejects joint parameter equality for non-visitors but not for visitors.

When we relax the restriction of equal scale, the scale parameter for the VE treatment group is greater than one (the normalised value for the control group) for both visitors and non-visitors. However, the difference is insignificant for visitors. We conclude that the VE treatment did reduce choice error for non-visitors but had no significant effect on choice error for visitors.

Table 3-3 - Likelihood ratio tests for pooled versus separate treatment and control group models

Pooled vs separate treatment/control groups	Visitors		Non-visitors	
	(λ1 = λ2)	(λ1 ≠ λ2)	(λ1 = λ2)	(λ1 ≠ λ2)
LR test statistic	19.64	15.90	92.06	71.00
Degrees of freedom	12	13	12	13
P-value	0.07	0.25	<0.001	<0.001
VE scale parameter		1.08		5.48*

3.5.4.2 RPL parameter estimates

In Table 3-4we show the panel mixed logit models for VE and control groups, visitors, non-visitors. Overall model fit as measured by McFadden pseudo r-squared is higher for the video treatment group than the control group (0.203 versus 0.13 in the combined visitor/non-visitor model) and higher for visitors than non-visitors. The constant for left-most position is positive and significant only for the non-visitor control group. This is consistent with the theory that

previously unaware of the beach. Visitors and non-visitors, on the other hand, are significantly different.

people are more influenced by framing effects when the issue is unfamiliar (Payne et al., 1999). The statistical significance of the bias is reduced by the VE treatment, consistent with previous findings (Matthews et al., 2017). The status quo parameter does not reach five percent significance in any model. It could alternatively be named a "do nothing" constant, since the zero cost option is to concede to private development.

The cost parameter is negative, as expected, although it does not achieve five percent significance in every model. The public facilities and private housing attributes all have negative means, although again not all are significant in every model. The visitors sample is relatively small with only 129 and 132 observations in the control and VE treatment groups respectively. The result is that few parameters in the visitor models are statistically significant despite the high overall model fit.

The interaction variable for houses on the hill and the shore is insignificant[31]. The implication is that there are no diminishing marginal effects to having both areas developed. The high income times cost interaction is positive and significant, which means high income people are willing to pay more. The effect disappears when separating visitors and non-visitors but this could be explained by the fact that New Chums visitors had higher average incomes. In the models which combine visitors and non-visitors the interaction variable (visited times cost) is also positive and significant, which means people who have visited New Chums have higher average WTA values. This is consistent with the finding that WTP estimates tend to increase with site experience (Cameron & Englin, 1997), presumably because these people have direct use values.

[31] We also tested a model with a random parameter for the hill and shore interaction but that was also insignificant.

Table 3-4 –Panel mixed logit models

		Visitors		Non-visitors	
Variable	Measure	Control group	VE Group	Control group	VE Group
Left-most position	μ	0.679	0.521	0.715***	2.120
Status quo	μ	2.290*	0.285	-0.321	-5.220
Cost	μ	-0.035**	-0.015*	-0.029**	-0.123*
	σ	0.002	-0.015	0.014	-0.144
Facilities	μ	-0.964	-1.850*	-0.504	-22.400**
	σ	-2.310	-1.750	-1.780	-27.600
Houses on hill	μ	-0.243	-0.064	-0.681	-3.390*
	σ	0.410	-0.495	1.170	10.700
Houses on shore	μ	-1.260*	-2.280*	-1.700**	-19.500**
	σ	1.450	-1.080	-0.186	-3.610
Hill and shore houses	μ	0.733	2.400	-0.224	11.500
High income * cost	μ	0.026	0.022	0.010*	0.142
Visited * cost	μ				
Observations		129	132	690	720
Log-likelihood		-87.00	-99.93	-668.64	-640.043
Pseudo-R^2		0.39	0.311	0.118	0.191
BIC		237	263	1422	1366

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

3.5.4.3 WTP/WTA results

We present the simulated WTP/WTA distributions for all respondents (visitors and non-visitors combined) as boxplots in Figure 3-6. The VE treatment group has more negative values for public facilities and houses on the shore but the distributions for houses on the hill appear similar. Almost half of the control group demonstrate positive values for public facilities, while the majority of the treatment group are negative.

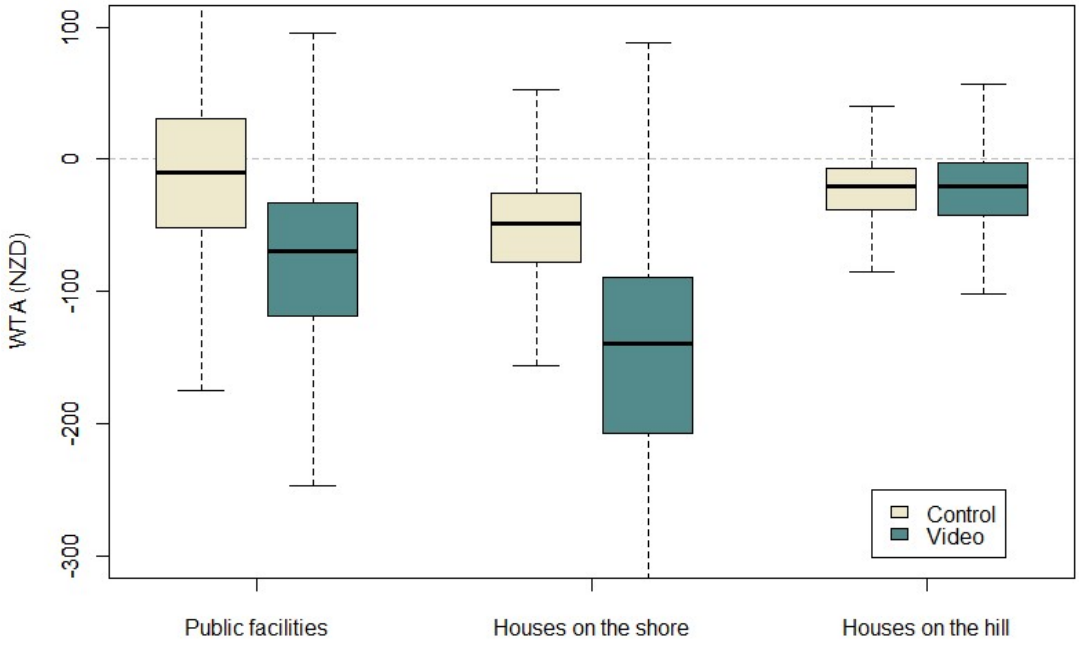


Figure 3-6 - Boxplot of control versus VE treatment simulated WTP/WTA for all respondents

In Table 3-5 we present the median values, ninety percent confidence intervals and equality tests for visitors, non-visitors and both combined. For the combined models of visitors and non-visitors (which include visit-cost interaction terms) the U-test and K-S test both reject WTA equality for public facilities and houses on the shore. For houses on the hill, the test statistics are only significant at ten percent. Similarly, for the non-visitor group we find that mean WTA in the treatment group is significantly more negative for public facilities and houses on the shore, and that there is no difference in means for houses on the hill.

The visitor-only models have wider WTA ranges, perhaps partly due to the small sample size and lack of statistical significance of several variables. The U-test results do not reject mean WTA equality, but the stricter K-S tests reject distribution equality. There is no strong evidence that the VE treatment systematically affected WTA for people with site experience, but with the small sample we might be unable to detect an effect even if it did exist.

Table 3-5 - WTP/WTA confidence intervals and equality tests

	Control		VE treatment		U-test	K-S
	Median	90% C.I.	Median	90% C.I.	Z-score	D
Visitors						
Public facilities	-25	(-354,255)	-61	(-883,665)	-0.98	0.20**
Houses on shore	-33	(-387,266)	-74	(-1118,851)	-0.85	0.24**
Houses on hill	-6	(-95,70)	-2	(-349,342)	-0.33	0.25***
Non-Visitors						
Public facilities	-13	(-261,211)	-51	(-380,267)	-6.51***	0.28***
Houses on shore	-46	(-297,149)	-81	(-390,204)	-9.03***	0.35***
Houses on hill	-17	(-261,240)	-12	(-183,144)	-0.62	0.15***

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

3.6 DISCUSSION

In the introduction we discussed how lack of familiarity may make stated preferences unreliable and susceptible to framing effects and other biases. In this study we ask respondents to make decisions about the future of a beach most of them have never visited. It is reasonable to assume even non-visitors will have non-zero WTA for development at New Chums beach because coastal landscapes are an important part of New Zealanders' identities. When a similarly undeveloped beach in the South Island was threatened with development in 2015, people from all over New Zealand successfully raised the money to purchase the beach for conservation in a crowdfunding campaign[32]. The challenge of this study was therefore to assist people to understand and evaluate the hypothetical alternative futures for New Chums beach and map their pre-existing general preferences for coastal landscapes onto the specific choice task.

[32] nzherald.co.nz/nz/news/article.cfm?c_id=1&objectid=11671959

We decided to create virtual environments for the survey because in previous studies they have been associated with improved evaluability and anomaly reduction.

We used a split sample to test for systematic effects of the VE presentation format. We find evidence that the utility functions of the treatment and control groups are dissimilar for non-visitors but not for visitors. The VE treatment appeared to have little effect on the choices of people who have direct experience of New Chums beach. A caveat, however, is that the sample of visitors was quite small with only 87 individuals and 261 choice observations. So, a small effect might not be detectable. The VE treatment improved model fit and reduced choice error (as evidenced by a scale parameter greater than one), but the effect was statistically insignificant for visitors.

We estimated WTP/WTA distributions and confidence intervals with simulation for visitors and non-visitors, treatment and control groups. The VE treatment group had significantly more negative WTA for the public facilities and houses on the shore. Apparently, the carpark and houses looked worse in the 3D visualisations when people were able to see them from different angles but the difference was only significant for non-visitors. For the visitor sub-sample there was no evidence to reject equality of means, although the distribution shapes were different. Again, the small sample size and large standard errors would have made detection of a small difference in means difficult.

We have demonstrated that the VE presentation systematically affected stated preferences. The ability of different presentation formats to systematically affect stated preferences is well-known (Slovic, 1995). However, the virtual environments provided additional information to respondents to help them evaluate the effect of potential development on the landscape so it is not merely a framing effect. When respondents can view the landscape from different angles it reduces the number of potentially wrong assumptions they have to make about physical scale, visibility and landscape dominance etcetera. More

information leads to better (more reliable) decisions, so long as that information is in a format that is salient and easy to process (Payne et al., 1999)

We found no evidence to suggest the VE treatment affected the preferences of people who had direct experience of New Chums. The small sample size might have made detection of an effect difficult, but this result lends some support to our hypothesis that the information provided in the virtual environment would be more informative to people who have not seen the site in person.

The implications for coastal policy are that houses located near the foreshore are perceived more negatively than those on the hill behind New Chums. Public road access and parking was viewed quite negatively by both users and non-users. It is possible that a more discrete car park tucked behind the hill would be more acceptable, although the inevitable increase in visitors would probably still degrade the quality of peacefulness that visitors appreciate.

Future studies could reveal more about the effects of crowding on outdoor recreation by adding varying numbers of model people (or wildlife) to a VE; similar to the multivariate visual approach used by Arnberger and Haider (2007) but three dimensional. Virtual environments could also easily incorporate sounds such as waves, birdsong or the hubbub of voices in a crowded environment. Virtual environments are an imperfect substitute for direct site experience but non-market valuation researchers should make experiments as realistic as is reasonably practical.

3.7 References

Arentze, T., Borgers, A., Timmermans, H., & DelMistro, R. (2003). Transport stated choice responses: effects of task complexity, presentation format and literacy. *Transportation Research Part E*, *39*, 229–244. http://doi.org/10.1016/s1366-5545(02)00047-9

Arrow, K., & Solow, R. (1993). *Report of the NOAA panel on contingent valuation* (Vol. 58). Retrieved from

http://www.cbe.csueastbay.edu/~alima/courses/4306/articles/NOAA%20on%20contingent%20valuation%201993.pdf

Bateman, I. J., Day, B. H., Jones, A. P., & Jude, S. (2009). Reducing gain-loss asymmetry: A virtual reality choice experiment valuing land use change. JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT, 58, 106–118.

Bateman, I. J., Day, B. H., Jones, A. P., & Jude, S. (2009b). Reducing gain-loss asymmetry: A virtual reality choice experiment valuing land use change. *JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT*, *58*, 106–118.

Beck, M. J., Rose, J. M., & Hensher, D. A. (2013). Consistently inconsistent: The role of certainty, acceptability and scale in choice. *Transportation Research. Part E, Logistics & Transportation Review*, *56*, 81. http://doi.org/10.1016/j.tre.2013.05.001

Ben-Akiva, M., Morikawa, T., & Shiroishi, F. (1992). Analysis of the reliability of preference ranking data. *Journal of Business Research*, *24*, 149–164. http://doi.org/10.1016/0148-2963(92)90058-j

Bierlaire, M. (2003). BIOGEME: a free package for the estimation of discrete choice models.

Blavatskyy, P. (2007). Stochastic expected utility theory. *Journal of Risk and Uncertainty*, *34*(3), 259–286. http://doi.org/10.1007/s11166-007-9009-6

Blomquist, G. C., Blumenschein, K., & Johannesson, M. (2009). Eliciting Willingness to Pay without Bias using Follow-up Certainty Statements: Comparisons between Probably/Definitely and a 10-point Certainty Scale. *Environmental and Resource Economics*, *43*(4), 473–502. http://doi.org/10.1007/s10640-008-9242-8

Bonsall, P., & Lythgoe, B. (2009). Factors affecting the amount of effort expended in responding to questions in behavioural choice experiments. *Journal of Choice Modelling*, *2*(2), 216–236. http://doi.org/10.1016/S1755-5345(13)70011-3

Boxall, P., Adamowicz, W. L. (Vic), & Moon, A. (2009). Complexity in choice experiments: choice of the status quo alternative and implications for welfare measurement. *The Australian Journal of Agricultural and Resource Economics*, *53*(4), 503–519. http://doi.org/10.1111/j.1467-8489.2009.00469.x

Brouwer, R., Dekker, T., Rolfe, J., & Windle, J. (2010). Choice Certainty and Consistency in Repeated Choice Experiments. *Environmental and Resource Economics*, *46*(1), 93–109. http://doi.org/10.1007/s10640-009-9337-x

Campbell, D., & Erdem, S. (2015). Position bias in best-worst scaling surveys: a case study on trust in institutions. *American Journal of Agricultural Economics*, *97*(2), 526–545. http://doi.org/10.1093/ajae/aau112

Carson, R. T., & Mitchell, R. C. (1993). The issue of scope in contingent valuation studies. *American Journal of Agricultural Economics*, *75*(5), 1263–1267.

Carson, R. T., Mitchell, R. C., Hanemann, W. M., Kopp, R. J., Presser, S., & Ruud, P. A. (1992). *A contingent valuation study of lost passive use values resulting from the Exxon Valdez oil spill*. University Library of Munich, Germany.

Caussade, S., Ortúzar, J. de D., Rizzi, L. I., & Hensher, D. A. (2005). Assessing the influence of design dimensions on stated choice experiment estimates. *Transportation Research Part B: Methodological*, *39*, 621–640. http://doi.org/10.1016/j.trb.2004.07.006

Champ, P. A., Bishop, R. C., Brown, T. C., & McCollum, D. W. (1997). Using Donation Mechanisms to Value Nonuse Benefits from Public Goods. *Journal of Environmental Economics and Management*, *33*(2), 151–162. http://doi.org/10.1006/jeem.1997.0988

Chrzan, K. (1994). Three kinds of order effects in choice-based conjoint analysis. *Marketing Letters*, *5*(2), 165–172. http://doi.org/10.1007/BF00994106

Corso, P. S., Hammitt, J. K., & Graham, J. D. (2001). Valuing mortality-risk reduction: using visual aids to improve the validity of contingent valuation. *Journal of Risk and Uncertainty*, *23*(2), 165–184.

Daniel, T. C., & Meitner, M. M. (2001). Representational validity of landscape visualizations: the effects of graphical realism on perceived scenic beauty of forest vistas. *Journal of Environmental Psychology*, *21*(1), 61–72.

Davies, A.-M., Laing, R., & Scott, S. (2002). Combining visualisation and choice experiments in built environment research. In *Information Visualisation, 2002. Proceedings. Sixth International Conference on* (pp. 785–790). http://doi.org/10.1109/IV.2002.1028870

Day, B., Bateman, I. J., Carson, R. T., Dupont, D., Louviere, J. J., Morimoto, S., … Wang, P. (2012). Ordering effects and choice set awareness in repeat-response stated preference studies. *Journal of Environmental Economics and Management*, *63*(1), 73–91. http://doi.org/10.1016/j.jeem.2011.09.001

DeShazo, J. R., & Fermo, G. (2002). Designing Choice Sets for Stated Preference Methods: The Effects of Complexity on Choice Consistency. *JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT*, *44*, 123–143. http://doi.org/10.1006/jeem.2001.1199

Dillman, D. A. (2011). *Mail and Internet Surveys: The Tailored Design Method -- 2007 Update with New Internet, Visual, and Mixed-Mode Guide*. Wiley. Retrieved from http://books.google.co.nz/books?id=d_VpiiWp51gC

Ferrini, S., & Scarpa, R. (2007). Designs with< i> a priori information for nonmarket valuation with choice experiments: A Monte Carlo study. *Journal of Environmental Economics and Management*, *53*(3), 342–363.

Fiore, S. M., Harrison, G. W., Hughes, C. E., & Rutström, E. E. (2009). Virtual experiments and environmental policy. *Frontiers of Environmental and Resource Economics*, *57*(1), 65–86. http://doi.org/10.1016/j.jeem.2008.08.002

Graeme, M., Dahm, J., & Kendal, H. (2010). *Coromandel Peninsula - Ecological Assessment of Natural Character* (Report prepared for Thames-Coromandel Distric Council).

Groves, R. M., Presser, S., & Dipko, S. (2004). The Role of Topic Interest in Survey Participation Decisions. http://doi.org/10.1093/poq/nfh002

Harrison, G. W., Haruvy, E., & Rutstrom, E. E. (2011). Remarks on Virtual World and Virtual Reality Experiments. *Southern Economic Journal*, *78*(1), 87–94.

Heiner, R. A. (1983). The Origin of Predictable Behavior. *The American Economic Review*, *73*(4), 560–595.

Hess, S., & Stathopoulos, A. (2013). Linking response quality to survey engagement: A combined random scale and latent variable approach. *Journal of Choice Modelling*, *7*, 1–12. http://doi.org/10.1016/j.jocm.2013.03.005

Huang, A., & Levinson, D. (2016). A model of two-destination choice in trip chains with GPS data. *Journal of Choice Modelling*. http://doi.org/10.1016/j.jocm.2016.04.002

Huang, J.-C., Poor, P. J., & Zhao, M. Q. (2007). Economic valuation of beach erosion control. *Marine Resource Economics*, *22*(3), 221.

Hughes, R. (2004). Visualization in transportation: Current practice and future directions. *Transportation Research Record: Journal of the Transportation Research Board*, (1899), 167–174.

Johnston, R. J., Besedin, E. Y., & Stapler, R. (2016). Enhanced geospatial validity for meta-analysis and environmental benefit transfer: an application to water quality improvements. *Environmental and Resource Economics*, 1–33.

Jude, S. (2008). Investigating the Potential Role of Visualization Techniques in Participatory Coastal Management. *Coastal Management*, *36*(4), 331–349. http://doi.org/10.1080/08920750802266346

Kahneman, D. (1986). Comments by Professor Daniel Kahneman. In D. S. B. R.G. Cummings (Ed.), *Valuing Environmental Goods: A State of the art Assessment of the Contingent Valuation Method* (pp. 185–194). New Jersey: Rowman and Allanheld.

Kahneman, D., & Knetsch, J. L. (1992). Valuing public goods: The purchase of moral satisfaction. *JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT*, *22*, 57–70. http://doi.org/10.1016/0095-0696(92)90019-s

Krinsky, I., & Robb, A. L. (1986). On Approximating the Statistical Properties of Elasticities. *The Review of Economics and Statistics*, *68*, 715–719.

Krosnick, J. A. (1999). Survey Research. *Annual Review of Psychology*, *50*(1), 537–567. http://doi.org/10.1146/annurev.psych.50.1.537

Lancsar, E., & Louviere, J. (2008). Estimating individual level discrete choice models and welfare measures using best-worst choice experiments and sequential best-worst MNL. *University of Technology, Centre for the Study of Choice (Censoc)*, 8–4.

Li, C.-Z., & Mattsson, L. (1995). Discrete Choice under Preference Uncertainty: An Improved Structural Model for Contingent Valuation. *Journal of Environmental Economics and Management*, *28*(2), 256–269. http://doi.org/10.1006/jeem.1995.1017

Lindhjem, H., & Navrud, S. (2011). Are Internet surveys an alternative to face-to-face interviews in contingent valuation? *Ecological Economics*, *70*(9), 1628–1637. http://doi.org/10.1016/j.ecolecon.2011.04.002

Loomis, J., & Ekstrand, E. (1998). Alternative approaches for incorporating respondent uncertainty when estimating willingness to pay: the case of the Mexican spotted owl. *Ecological Economics*, *27*(1), 29–41. http://doi.org/10.1016/S0921-8009(97)00126-2

Lundhede, T. H., Olsen, S. B., Jacobsen, J. B., & Thorsen, B. J. (2009). Handling respondent uncertainty in Choice Experiments: Evaluating recoding approaches against explicit modelling of uncertainty. *Journal of Choice Modelling*, *2*(2), 118–147. http://doi.org/10.1016/S1755-5345(13)70007-1

Madureira, L., Nunes, L. C., Borges, J. G., & Falcão, A. O. (2011). Assessing forest management strategies using a contingent valuation approach and

advanced visualisation techniques: A Portuguese case study. *Journal of Forest Economics*, *17*(4), 399–414. http://doi.org/10.1016/j.jfe.2011.04.001

Mann, H. B., & Whitney, D. R. (1947). On a test of whether one of two random variables is stochastically larger than the other. *The Annals of Mathematical Statistics*, 50–60.

Mathews, K. E., Freeman, M. L., & Desvousges, W. H. (2006). How and how much? The role of information in stated choice questionnaires. In B. J. Kanninen (Ed.), *Valuing environmental amenities using stated choice studies: a common sense approach to theory and practice* (Vol. 8, pp. 111–133). Dordrecht: Kluwer Academic Pub.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics*. New York: Academic Press.

Olschewski, R., Bebi, P., Teich, M., Wissen Hayek, U., & Grêt-Regamey, A. (2012). Avalanche protection by forests — A choice experiment in the Swiss Alps. *Integrating Forest Products with Ecosystem Services*, *17*, 19–24. http://doi.org/10.1016/j.forpol.2012.02.016

Powe, N. A., & Bateman, I. J. (2004). Investigating insensitivity to scope: a split-sample test of perceived scheme realism. *Land Economics*, *80*(2), 258–271.

Randall, A., & Hoehn, J. P. (1996). Embedding in market demand systems. *Journal of Environmental Economics and Management*, *30*(3), 369–380.

Ready, R. C., Whitehead, J. C., & Blomquist, G. C. (1995). Contingent Valuation When Respondents Are Ambivalent. *Journal of Environmental Economics and Management*, *29*(2), 181–196. http://doi.org/10.1006/jeem.1995.1040

Rollins, K., & Lyke, A. (1998). The case for diminishing marginal existence values. *Journal of Environmental Economics and Management*, *36*(3), 324–344.

Rose, J. M., Bliemer, M. C. J., Hensher, D. A., & Collins, A. T. (2008). Designing efficient stated choice experiments in the presence of reference

alternatives. *Transportation Research Part B*, *42*, 395–406. http://doi.org/10.1016/j.trb.2007.09.002

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty*, *1*(1), 7–59. http://doi.org/10.1007/BF00055564

Scarpa, R., Notaro, S., Louviere, J., & Raffaelli, R. (2011). Exploring Scale Effects of Best/Worst Rank Ordered Choice Data to Estimate Benefits of Tourism in Alpine Grazing Commons. *American Journal of Agricultural Economics*, *93*, 809–824. http://doi.org/10.1093/ajae/aaq174

Scarpa, R., Thiene, M., & Train, K. (2008). Utility in Willingness to Pay Space: A Tool to Address Confounding Random Scale Effects in Destination Choice to the Alps. *American Journal of Agricultural Economics*, *90*, 994–1010. http://doi.org/10.1111/j.1467-8276.2008.01155.x

Scarpa, R., Willis, K. G., & Acutt, M. (2007). Valuing externalities from water supply: Status quo, choice complexity and individual random effects in panel kernel logit analysis of choice experiments. *Journal of Environmental Planning and Management*, *50*, 449–466. http://doi.org/10.1080/09640560701401861

Swait, J., Adamowicz, W., Hanemann, M., Diederich, A., Krosnick, J., Layton, D., … Tourangeau, R. (2002). Context Dependence and Aggregation in Disaggregate Choice Analysis. *Marketing Letters*, *13*(3), 195–205. http://doi.org/10.1023/A:1020262503119

Swait, J., & Erdem, T. (2007). Brand effects on choice and choice set formation under uncertainty. *Marketing Science*, *26*(5), 679–697.

Swait, J., & Louviere, J. (1993). The Role of the Scale Parameter in the Estimation and Comparison of Multinomial Logit Models. \iJournal of Marketing Research, \i30, 305–314.

Thomson, J. (2003). Coastal values and beach use survey report (Technical Report No. TR2003/09). Waikato Regional Council. Retrieved from

http://www.waikatoregion.govt.nz/Services/Publications/Technical-reports/2003-technical-reports/

Thomson, J. (2003b). *Coastal values and beach use survey report* (Technical Report No. 2003/09). Waikato Regional Council. Retrieved from http://www.waikatoregion.govt.nz/Services/Publications/Technical-reports/2003-technical-reports/

Train, K. (2003). *Discrete choice methods with simulation*. Cambridge Univ Pr.

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, *211*(4481), 453–458. http://doi.org/10.1126/science.7455683

Urban, G. L., Hauser, J. R., Qualls, W. J., Weinberg, B. D., Bohlmann, J. D., & Chicos, R. A. (1997). Information acceleration: validation and lessons from the field. *Journal of Marketing Research*, 143–153.

Versus Research. (2012). Community held values of Waikato rivers, lakes and streams in the Waikato and Waipā catchments. *Waikato Regional Council Technical Report*, *2013*(31), 160.

Vossler, C. A., Doyon, M., & Rondeau, D. (2012). Truth in consequentiality: theory and field evidence on discrete choice experiments. *American Economic Journal: Microeconomics*, *4*(4), 145–171.

Whitehead, J. C., Poulter, B., Dumas, C. F., & Bin, O. (2009). Measuring the Economic Effects of Sea Level Rise on Beach Recreation. *Working Papers*.

Wilcox, N. T. (2011). “Stochastically more risk averse:” A contextual theory of stochastic discrete choice under risk. *The Economics and Econometrics of Risk*, *162*(1), 89–104. http://doi.org/10.1016/j.jeconom.2009.10.012

Windle, J., & Rolfe, J. (2014). Estimating the nonmarket economic benefits of beach resource management in southeast Queensland, Australia. *Australasian Journal of Environmental Management*, *21*(1), 65–82. http://doi.org/10.1080/14486563.2013.875953

Windle, & Rolfe, J. (2011). Comparing Responses from Internet and Paper-Based Collection Methods in more Complex Stated Preference Environmental

Valuation Surveys. *Economic Analysis and Policy*, *41*(1), 83–97. http://doi.org/10.1016/S0313-5926(11)50006-2

3.8 APPENDIX

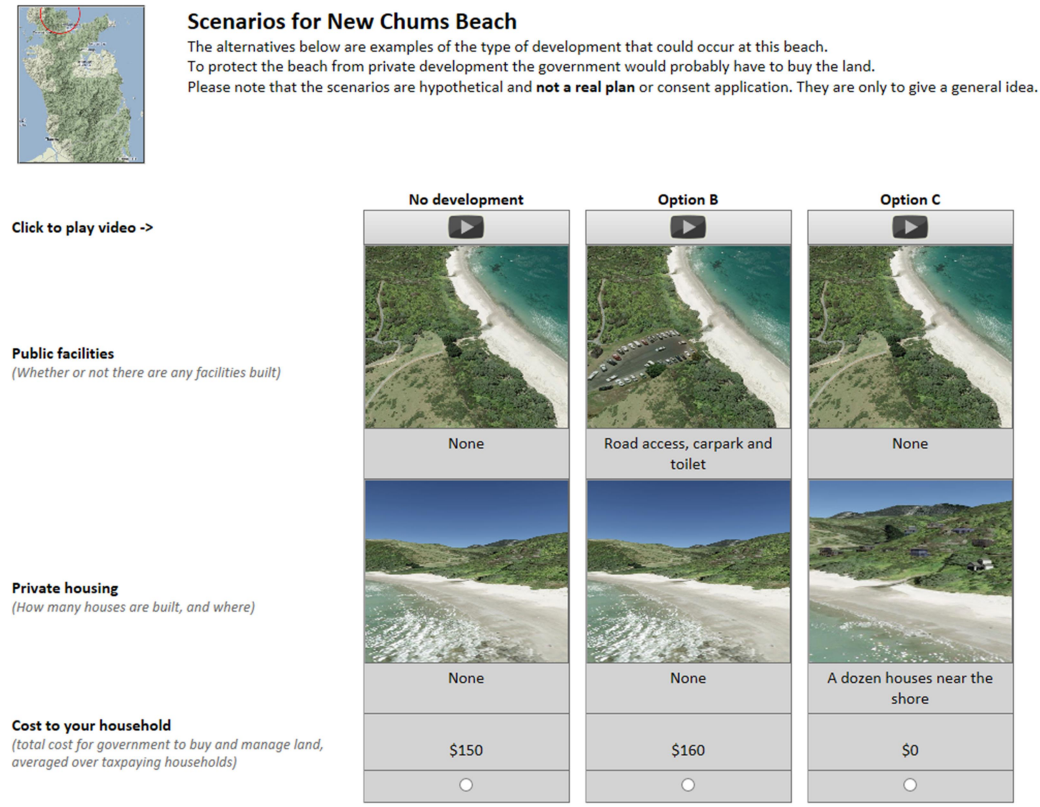


Figure 3-7 – Sample choice card

4. STABILITY OF WILLINGNESS-TO-PAY FOR COASTAL MANAGEMENT: A CHOICE EXPERIMENT ACROSS THREE TIME PERIODS

4.1 ABSTRACT

A key assumption of stated preference methods is that individuals have well-formed preferences that are robust over time. Both the discovered and constructed preference perspectives imply this is not necessarily the case. There can be a large situational component to expressed preferences that add to the uncertainty of sampling error. Most non-market valuation studies collect data from only one point in time so the degree of temporal variability cannot be tested. Test-retest studies that provide data from two points in time generally find significant differences in preference structure and willingness-to-pay (WTP). In this study we test stability of WTP for beach erosion management using a fully ranked discrete choice experiment survey with not one but two retests over a six month period. We find that stability does not improve with the additional repetition as the preference discovery hypothesis implies it might. WTP confidence intervals overlap but the models are significantly different at each point in time, even after allowing for variation in choice error. Either the survey did not facilitate sufficient preference discovery, preferences were reconstructed, or preferences changed for other reasons. However, respondents with high scores of self-reported certainty in their choices in the first survey had significantly more stable WTP estimates.

Keywords

Preference stability, choice experiment, coastal erosion management, New Zealand

4.2 INTRODUCTION

When using stated preference methods to learn about preferences for the environment we ask people to explore and state their willingness-to-pay (WTP) for hypothetical alternatives. An important issue in stated preference research is whether these decisions are reliable. Results may be used today from studies conducted years ago in both policy design and benefit transfer. In these cases a fundamental maintained assumption is that these values are robust over time (Brouwer, 2006). It is important for decision makers and practitioners to know to what degree this is the case. Rational choice theory allows WTP to vary for reasons such as changes in the choice context or changes in individual circumstances. Individuals who gain new consumptive experience such as experiencing a change in environmental quality may alter their preferences (McConnell, Strand, & Valdés, 1998). Shared experiences such as a natural disaster can cause preferences to change in aggregate. However, individual preferences may also change due to unobserved or random effects in the process of constructing a response to the valuation question (Gregory, Lichtenstein, & Slovic, 1993)

4.2.1 EVIDENCE ON STABILITY

Discrete choice experiments (DCEs) allow explicit testing of the stability of the utility function and choice consistency. There does not appear to be any difference in reliability compared with other stated preference elicitation methods such as contingent valuation (Liebe, Meyerhoff, & Hartje, 2012). Some DCE studies use repeated choice questions within the same survey which provide clues about choice reliability in the very short term. Choices have been shown to vary over the duration of a single survey due to learning (about the choice task) or fatigue (Hess, Hensher, & Daly, 2012) , but in other cases due to strategies (Day et al.2012). Most stated preference studies merely provide information from one point in time due to attrition in longitudinal panels, or the need to meet a short timeframe. Some retests use different samples (e.g. Bliem, Getzner,

& Rodiga-Laßnig, 2012), but it is then impossible to control for unobservable sample differences. However, there are examples in the literature where a re-test using the same sample was conducted either weeks or months after the original survey.

Several DCE studies report 60-80 percent congruent choices for same-sample retests within weeks or months of the first test in the area of health economics (Bryan, Gold, Sheldon, & Buxton, 2000; Ryan, Netten, Skåtun, & Smith, 2006; Skjoldborg, Lauridsen, & Junker, 2009) and food preferences (Carlsson, Mørkbak, & Olsen, 2012; Rigby & Burton, 2011). Unlike healthcare or food, environmental quality is typically a public good with components of non-use value and may have greater WTP variability (Carlsson, 2010). Bliem, Getzner and Rodiga-Laßnig (2012) report that WTP for water quality varied by up to 39 percent using two independent samples a year apart. Liebe, Meyerhoff and Hartje (2012) find preferences for wind farms are significantly different after eleven months, but assert WTP reliability is "fair to moderate" based on a complete combinatorial test of means. Schaafsma et al.(2014) report 57 percent choice congruency for land use changes after a year and "very good agreement" for WTP based on overlapping confidence intervals, but mean WTP varied by minus 527 to plus 160 percent for some attributes. Lienhoop and Volker (2016) found that WTP for German forests did not vary significantly after a delay of one week. Czajkowski, Barczak, Budziński, Giergiczny, & Hanley (2016) report that WTP distributions for public forest management were significantly different after a 6 month delay, but that means were "relatively" stable. In contrast, Lew & Wallmo (2017) found no significant change in WTP for endangered species after 17 months. To summarise, stability of stated WTP for the environment appears to be the exception rather than the norm.

4.2.2 CONSTRUCTED VERSUS DISCOVERED PREFERENCES

There are two perspectives in behavioural decision research that can provide insight into apparent preference instability: discovered versus constructed preferences. The discovered preference hypothesis (DPH) was proposed by Plott

(1996), who stated that when people have to make decisions about an unfamiliar issue or in an unfamiliar environment, their initial responses may be impulsive. As they learn about the decision environment (institutional learning) and their own attitudes (value learning), their decisions begin to exhibit less randomness and greater rationality. Preference discovery requires repetition, feedback on consequences and belief that those consequences are real. The requirement for feedback is important and some systematic biases have been reported to persist unless people experience a loss as a result of their choice (Braga & Starmer, 2005). However, it is problematic to provide feedback on consequences for environmental changes that may take years to eventuate. Lienhoop and Volker (2016) suggest that group discussion and reflection time may provide feedback and lead to more preference discovery than simple repetition, although they were not able to detect a statistically significant increase in preference adjustment. In our study about beach management preferences, DPH implies we might expect some institutional learning and a corresponding decrease in choice error in retests similar to that found in within-survey choice task repetition (Hess et al., 2012). On the other hand we may not find any increase in value learning because our experiment did not include any mechanism by which respondents could gain feedback on the implications of their choices.

The alternative constructed preference perspective is that preferences for the unfamiliar are often constructed, not merely revealed, when a decision is required (Gregory, Lichtenstein, & Slovic, 1993). This view rejects the usual presumption that stable and context-free preferences exist independently of the elicitation process, and has been criticized for undermining the foundations of rational choice theory (Plott, 1996). However, consumers and voters make real-life decisions about unfamiliar products and issues regularly. Unfamiliarity, complex information, and public good character can cause instability in real-world choices as well as stated preferences (Carlsson, 2010) so a lack of pre-existing preferences does not necessarily invalidate SP methods. Similar to the ways by which authorities attempt to educate stakeholders during a policy

consultation process; the role of the non-market valuation researcher is to ensure respondents have all the relevant information and make decisions with a high standard of reasoning (Gregory et al., 1993). When preferences are constructed rather than pre-existing they tend to be more strongly influenced by situational and framing effects such as presentation order (Krosnick & Alwin, 1987) or arbitrary anchors (Ariely, Loewenstein, & Prelec, 2003). Preferences may be constructed using a variety of simplifying strategies rather than expected utility maximisation. The result is that constructed preferences may be confined in scope (e.g. to a specific elicitation format) and transient – soon to be forgotten (Simon, Krawczyk, Bleicher, & Holyoak, 2008). The Constructed Preferences perspective implies that preferences may not necessarily stabilise with repetition, especially if a time delay means that respondents don't remember their exact choices from the previous task.

The work presented in this paper is based on a fully-ranked choice experiment for erosion management options for beaches on the Coromandel Peninsula of New Zealand. We conduct not one but two identical re-tests each spaced three months apart. Having three points in time allows a more robust assessment of individual stability of stated WTP estimates in a manner that, as far as we are aware, no other study of environmental WTP has reported. Coastal landscapes are an important part of New Zealanders' identities (Collins & Kearns, 2010) and it is reasonable to assume respondents have pre-existing general preferences for coastal features and experience of beaches with the management options described. However, they have probably never been asked to make a specific trade-off between beach management and taxes so it is difficult to say whether the discovered or constructed viewpoint is likely to be more applicable. Our first research question is how stable is WTP in our specific context, and is this consistent with other test-retest studies? But the more interesting and unique question is does stability improve between the first and second re-test? If so, it would be consistent with the concept of learning and preference discovery. If not, the results would be more consistent with the transience of preferences

constructed on the spot. We also investigate to what degree choice consistency can be explained by individual-specific factors. If preference stability could be predicted this could improve confidence in one-shot experiments where retest is not an option.

4.3 METHOD

4.3.1 RANDOM UTILITY MODELS

Management options for Coromandel beaches may be thought of as a bundle of characteristics that affect the aesthetics and use of the beach. As per random utility theory (McFadden, 1974) we assume the probability of a consumer choosing their preferred future state of a beach is a function of deterministic and random or unobserved components of utility. Since the purpose of this study is to test for stability of WTP over time, we use a random utility model specified directly in "WTP-space" (Train & Weeks, 2005) such that the attribute parameters are interpretable as marginal WTP for each attribute. This is in contrast to the historically more common utility specification in "preference space" by which one first estimates preference parameters for attributes and cost (marginal utility of income) and then combines these to derive marginal WTP estimates. A model with utility specified in WTP-space is a more efficient estimator of WTP distributions and in random parameter models tends to produce spreads of marginal WTPs that are more plausible (Scarpa, Thiene, & Train, 2008). WTP-space models have previously been applied to outdoor recreation (e.g. in mountains by Scarpa et al., 2008 and in public forests by Czajkowski et al., 2016), as well as in other nonmarket valuation fields (e.g. in food choice by Balcombe et al. 2009 and in energy (Scarpa and Willis 2010).

In this study we obtained full rankings of six alternatives in each choice card. The choice probabilities are modelled using the standard exploded logit model (Lancsar & Louviere, 2008). The utility in WTP space that person *n* obtains from the alternative state *j* and measured in time period *t* is specified as follows:

$$U_{njt} = \lambda_{nt}(ASC_j + \omega_{nt}'\mathbf{x}_j - p_j) + \varepsilon_{njt} \quad (4\text{-}1)$$

Where ASC is an alternative-specific constant for position on the choice card, $\mathbf{x}_j$ denotes the non-price attribute levels, p_j is price, ε_{njt} is an i.i.d. extreme value type 1 error term, *n* are individual respondents, and *j* are the alternatives. ω_{nt} is a vector of marginal WTP parameters specific to each individual *n* and assumed to be normally-distributed. λ_{nt} is a mixture of scale and cost coefficient with an assumed log-normal distribution to ensure the expected positive sign. Any unobserved variation in scale is also captured by this parameter. If we re-write indirect utility as$V_{nit}(\beta_{nt})$, with β_{nt} denoting the vector of random coefficients in equation 8, then the unconditional probability of person *n* set of choices in her sequence of *k* ranking over *t* repetitions is therefore the integral of the product of standard logit formulas over all values ofβ_{nt}:

$$P(i,t) = \int_{\beta} \prod_{t} \prod_{k} L_k(V_{nit}(\beta_{nt}))\, \varphi(\beta | b_{nt}, W_{nt}) d\beta \quad (4\text{-}2)$$

Where $\varphi(\beta|b_{nt}, W_{nt})$ is, in our case, normal densities with mean b_{nt} and var-covariance W_{nt}. This is known as a panel rank-exploded mixed logit specification and allows for taste variation across individuals, unrestricted substitution patterns and correlations in unobserved components across the choices by the same respondent (Train, 2002).

4.3.2 RE-TEST SELECTION BIAS

If the decision to participate in the re-test is not independent of preference stability[33] then there is potential for selection bias in the results. As per a standard sample selection model (Winship & Mare, 1992) we specify that continuous latent variables Y_{1n}^* and Y_{2n}^* affects whether the choices of individual *n* are observed in retest 1 and 2. We fit binary logit models such that

[33] Selection bias may also affect average WTP in retests but this paper is concerned with consistency at an individual level

$$Y_1 = 1 \text{ if } Y_{1n}^* > 0 \quad (4\text{-}3)$$

$$Y_1 = 0 \text{ if } Y_{1n}^* \leq 0 \quad (4\text{-}4)$$

to test whether there is a strong relationship between demographic variables and re-test participation. For respondents who complete the first retest we also test whether choice consistency is a significant explanatory variable for participation in the second retest. If choice consistency is related to participation, or there are variables that explain both consistency and participation, then a correction for selection bias is needed.

4.3.3 TESTS OF STABILITY

We test reliability of a DCE at three levels: (*i*) the proportion of identical choices, (*ii*) equality of the utility function and (*iii*) equality of marginal willingness-to-pay (WTP) for attributes, which is a less restrictive test of the equality of utility function.

4.3.3.1 Choice congruency

Comparison of choices is possible only when the same individuals are sampled in both the test and re-test. The measure of stability is the proportion of choice situations in which the same choice was made (congruency). Respondents may select the same alternative purely by chance so we correct this using Cohen's κ (Cohen, 1968), which acts as a correction factor for random matching:

$$\kappa = \frac{p_o - p_c}{1 - p_c} \quad (4\text{-}5)$$

where p_o is the observed probability and p_c is the probability that we would expect by chance.

We estimate panel binary logistic regressions with random effects using R (R Core Team, 2012) to explore the relationships between choice and individual characteristics and choice consistency in both retests. The dependent variable is one if the retest rank is the same as the rank in the first survey, otherwise it is zero. The set of binary outcomes can be written as:

$$P(Y_i = 1|\eta_i) = \frac{\exp(\eta_i)}{1+\exp(\eta_i)}, \qquad \eta_i = x_i\alpha + z_i u \tag{4-6}$$

where x_i are the fixed effects, α are the fixed effects parameters, z_i are the random effects and μ is the unobserved portion of heterogeneity. We include parameters for rank level, demographics and individual-specific variables that we expect to be related to emotional involvement or consumptive experience in the study area—travel distance, number of days visited in the previous year, and Coromandel holiday home ownership. Changes in individual circumstances might also cause people to adjust their preferences for beach recreation. We asked respondents if their household composition, income, labour force status or education level changed in each retest (waves 2 and 3) and included dummy variables for changed circumstances. Changes that might affect aggregate results (such as environmental quality changes) cannot be tested due to a lack of data about such events. Nor can seasonal effects be measured since they are confounded with results.

How restrictive choice congruency is becomes apparent when considering it would be difficult for someone to rank six alternatives in exactly the same order each time. It ignores the unobserved component of utility, which means that at least some degree of random error is expected even if preferences are indeed stable. A change of one position is less inconsistent than a complete reversal of ranks so we also report the absolute difference in ranks for both waves. However, we do not estimate a linear regression for difference in rank because rank is an ordinal, not a lineal variable and it would be incorrect to treat it as such. Another issue with using choice congruency as a measure of reliability is the risk that respondents may simply be remembering previous choices and selecting the same alternative rather than processing the information again, which would bias reliability upwards. Mørkbak and Olsen (2014) found no evidence of a memory effect on reliability after just two weeks so there is unlikely to be one in our case since the two waves were taken three months apart. However, we did not ask respondents whether they remembered their

previous choices, so we are unable to specifically test this instance, which we expect to be quite remote.

4.3.3.2 Stability of parameter estimates

Testing for equality of the random utility function allows for random error in responses. We include only respondents who completed all three waves so that sample differences are not confounded with stability measures. We follow the LR procedure detailed by Swait and Louviere (1993) in which the data from test and retest is stacked and a pooled model is estimated. The likelihood ratio (LR) test statistic is calculated as follows:

$$LR = -2\left(LL_{pooled} - (LL_1 + LL_2)\right) \tag{4-7}$$

where $LL_1$is the final log-likelihood of the model for the first test, LL_2 is for a retest, and LL_{pooled} is for the pooled model. The LR statistic has a Chi-square distribution with degrees of freedom equal to the number of parameters in the utility function. The LR statistic is an asymptotic test of global goodness of fit and it tests whether the variables with restricted (to be equal across waves) coefficients explain the same amount of variance before or after the restriction (Brouwer, 2006; Brouwer & Spaninks, 1999). If LR statistic does not exceed the five percent critical value, the models for test and retest are not statistically dissimilar. The less restrictive LR test involves including explicit scale parameters in the pooled model to allow for differences in relative scale across waves. In a WTP-space model the scale parameter (λ) is in fact a combination of scale and the marginal utility of money. If the additional parameter is significant it is impossible to know whether one or both are different across waves, but a difference in λ does not affect WTP.

We also use Wald tests of joint asymptotic parameter equality between each pairwise combination of waves. The Wald test statistic, *W* is:

$$W = (\hat{b}_1 - \hat{b}_2)'\hat{V}_1^{-1}(\hat{b}_1 - \hat{b}_2) \tag{4-8}$$

where $\hat{b}_1$ and $\hat{b}_2$ are the vectors of parameter estimates from models one and two and $\widehat{V}_1$ is the variance-covariance matrix of model one. The same as the LR test, this statistic also has a sampling distribution that is asymptotically Chi-square distributed with degrees of freedom equal to the number of restricted parameters.

4.3.3.3 Stability of WTP

The joint tests do not identify which utility coefficients vary significantly from the restricted and unrestricted specification so we also perform equality tests on each WTP parameter. We use the variance-covariance matrix at convergence and Monte Carlo simulation (Krinsky & Robb, 1986) to approximate the asymptotic sampling distribution of WTP and use the non-parametric Mann-Whitney U test[34] (Brouwer & Spaninks, 1999) to test for equality of WTP means between each wave. We also examine the distributions of WTP using the Kolmogorov-Smirnov two-sample test because this is a more restrictive null hypothesis than equality of means (Brouwer & Spaninks, 1999). The K-S test statistic *D* is sensitive to differences in both location and shape, is not reliant on normality and is based on the maximum absolute difference between the two cumulative distribution functions $S_{N_1}(x)$ and $S_{N_2}(x)$:

$$D = \max_{-\infty<x<\infty} \left| S_{N_1}(x) - S_{N_2}(x) \right| \tag{4-9}$$

The null hypothesis of equal distributions is rejected at level α if:

---

[34] The Mann-Whitney U test (also known as Wilcoxon rank-sum) involves ranking the pooled WTP and then adding up the ranks for test and re-test datasets. The statistic U is given by:

$$U_1 = R_1 - \frac{n_1(n_2+1)}{2}$$

where R_1 is the smaller sum of ranks of the two samples and n_1 and n_2 the sample sizes. For large samples U is approximately normally distributed with mean $\frac{n_1 n_2}{2}$ and standard deviation $\sqrt{\frac{n_1 n_2 (n_1+n_2+1)}{12}}$.

$$D_{mn} > c(\alpha)\sqrt{\frac{m+n}{mn}} \quad \text{(4-10)}$$

where *m* and *n* are the sample sizes and $c(0.05)$ equals 1.36 (Pearson & Hartley, 1972).

4.4 STUDY DESIGN

4.4.1 THE SURVEY INSTRUMENT

The data were collected in a web-based survey developed to gather information about preferences for beach management among domestic visitors to the Coromandel Peninsula, New Zealand. The Coromandel is a steep and hilly peninsula that lies across the Hauraki Gulf from Auckland city. The Peninsula is sparsely populated but is a popular holiday destination 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. Since the 1950s there has been considerable development pressure for holiday accommodation and some of the older developed areas are now at risk from coastal erosion. The primary purpose of the survey was to estimate the effect of different erosion management and headland development options on non-market value.

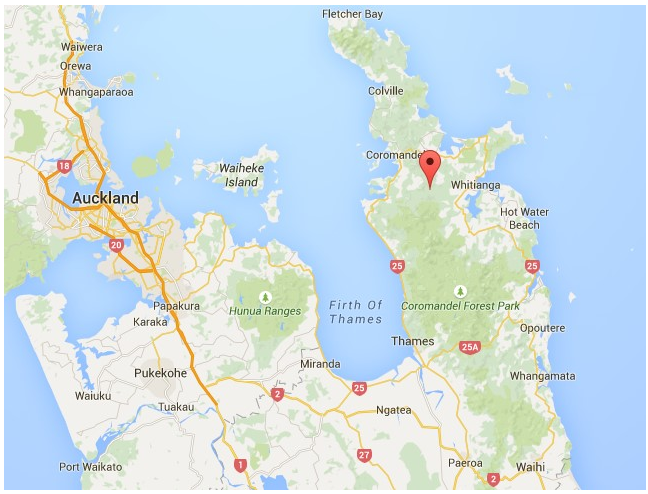


Figure 4-1 - Map showing the location of Coromandel Peninsula relative to Auckland (Source: Google Maps)

The survey included questions about participants' previous and planned beach visits, location of residence, environmental attitudes, socio-economic variables, and the choice experiment questions. Respondents were selected from a pre-recruited panel of New Zealand residents provided by a market research company and a smaller, self-selected sample from online advertisements on Facebook and Google. To qualify for the survey, respondent had to have visited the Peninsula in the previous twelve months. Data collection was conducted in three separate waves in October 2013, January 2014 and April 2014 to gather additional information about recent beach trips and preference stability.

4.4.2 EXPERIMENTAL DESIGN

The choice experiment design was relatively simple with only three attributes—erosion protection, headland and cost—because virtual 3D models had to be created for each combination of attribute levels. Respondents were randomly assigned to a treatment group—which received videos, static images and text for the scenarios—and a control group which saw only static images and text. The video presentation format and impact is discussed in more detail in Matthews, Scarpa, & Marsh (2017). Table 4-1 shows the attribute levels and descriptions.

Table 4-1- Attributes and levels used in the choice experiment

Attribute	Description	Levels
Erosion protection	The beach is *x* km long and *y* km of this has properties at risk from erosion and high waves during storms. The options are to do nothing, remove the front row of properties and restore the nature dune system or build a seawall.	• None • Restored dune • Sea wall
Headland	The headland is currently undeveloped and covered with native bush. If development is allowed then houses will be visible in future	• No development • Development allowed
Household taxes	Protection of the headland and foreshore require public funding so some of these options will increase your annual rates or taxes by the amount shown	$10 increments from $0 to $100

Respondents were given descriptions for three similar beaches of varying lengths with the current condition being no erosion protection and an undeveloped headland. Each choice card presented the respondent with six alternatives in random order so that every combination of headland and erosion protection appeared. This layout was tested with participants of a focus group who strongly preferred this to the alternative design of pair-wise alternatives where their preferred combination might not appear, even though it made their choice more complex. We generated a Bayesian-efficient design (Scarpa, Campbell, & Hutchinson, 2007) by swapping and cycling the cost attribute to minimise the average D-error across the distribution of prior values obtained from a focus group. The choice cards show thumbnail images of the attributes and, for the treatment group, a play button to play a video tour of the beach in a pop-up window. A sample choice card is provided in Appendix 4.8. When survey respondents selected their preferred alternative it disappeared and they were asked to select the next preferred and so on until all six alternatives were ranked. We use an exploded logit format (Lancsar & Louviere, 2008) to model the ranks as repeated choices from sets with a decreasing number of alternatives. Respondents completed one choice card for each of the four beaches and one of these was selected at random to be used in the re-tests.

The choice questions were followed by a "stated certainty" question (Beck, Rose, & Hensher, 2013) in which the respondent was asked if they were sure they would have the same preference in real life if their preferred scenario was implemented in policy with the associated real local tax increase. The response format was a five-point scale comprising "definitely not", "probably not", "maybe", "probably" and "definitely". Self-reported stated certainty measures have been found to be a function of several individual characteristics and tend to be inversely correlated with choice error (Beck et al., 2013).

4.5 RESULTS

4.5.1 DESCRIPTIVE STATISTICS

The sample for the first survey comprised 1059 individuals. There was considerable attrition over the six month period and only 551 completed the second wave and 426 completed the third wave. The final sample of individuals who completed all three waves was 387. Attrition is a major problem in panel studies: a drop-out rate of around 50% after the first survey is typical (Fitzmaurice, Heath, & Clifford, 1996). Table 4-2 shows a selection of demographic variables for the samples. Respondents tended to be older and more highly educated than the general population. There are small differences in means across waves for several variables (female, school children, high income, holiday house, travel distance and video treatment).

Table 4-2 - Descriptive statistics for each survey wave

Measure	Completed Wave 1	Completed Wave 2	Completed Wave 3	Completed all waves
Count of respondents	1059	551	426	387
Age (in years)	43	44	44	44
Degree	0.46	0.49	0.51	0.50
Female	0.59	0.63	0.63	0.63
Preschool children in household	0.17	0.16	0.17	0.17
School children in household	0.28	0.31	0.29	0.29
Annual household income < $50k	0.30	0.32	0.31	0.31
Annual household income > $100k	0.30	0.29	0.27	0.28
Holiday house owned by family	0.26	0.24	0.21	0.21
Travel time to site (hours)	2.33	2.27	2.19	2.20

Number of peninsula visits	2.36	2.57	2.29	2.31
Video treatment	0.52	0.56	0.61	0.60
Certain of choices	0.38	0.53	0.50	0.47^
Uncertain of choices	0.20	0.19	0.13	0.23^

^as measured in wave 1

4.5.1.1 Re-test selection bias

We fit two binary logistic regression models for retest participation (

Table 4-9 in the appendix) in retests one and two. The models have low explanatory power with pseudo R-squares of around 0.03, but there are some statistically significant effects. Women, respondents with school-age children, and people in the video treatment group were more likely to re-participate. For second retest participation we include a variable for choice congruency from the first retest and it is insignificant. The lack of significance of this variable combined with the fact that there is no overlap between significant variables for retest participation and those explaining choice congruency (Table 4-10 in the appendix) implies consistency results are unlikely to be affected by selection bias.

4.5.1.2 Choice congruency

Under a third (29 percent) of alternatives in the second wave were ranked identically to the first wave. While this is lower than the 57-59 percent congruency reported by Schaafsma et al. (2014) and Liebe et al. (2012), there are six fully ranked alternatives on the choice cards in this study rather than a single choice between three alternatives as in the other studies. If respondents selected randomly we would expect only 1/6 (17 percent) rank congruency. After adjusting for chance we calculate a Cohen's κ of 15 percent or "slight agreement" (Landis & Koch, 1977). There is higher rank congruency for the first rank (42 percent) and last rank (34 percent) than in the middle ranks (22 to 27 percent). This is consistent with the finding that choice error is lower for the best and worst alternatives (Ben-Akiva, Morikawa, & Shiroishi, 1992). Congruency between waves one and three is slightly lower at 26 percent, while the average

for waves two versus three is 28 percent. The cumulative frequency graph (Figure 4-2) shows that half of the observations differ by only one position in waves two and three. Randomly simulated choices resulted in a median difference of two ranks. The rank difference is marginally larger in wave 1 versus 3 compared with 1 versus 2 and 2 versus 3.

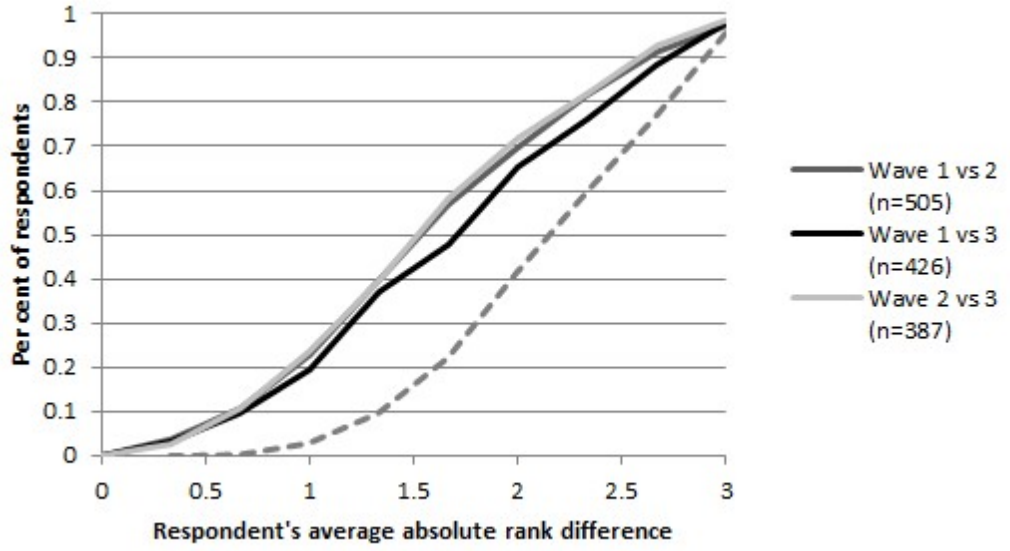


Figure 4-2 - CDF of absolute difference in ranks

Many respondents reported a change in household composition, income, labour force status or education level and these are reported in Table 4-3. Some people refused to answer a demographic question in one or more retests. The proportion of missing observations is high (up to 34 percent for household composition) which may attenuate any explanatory effect on choice congruency.

Table 4-3 - Changes to individual characteristics

	Retest 1		Retest 2	
Measure	Count	Missing	Count	Missing
Household change	99 (18%)	189 (34%)	99 (23%)	84 (20%)
Income increase	57 (10%)	136 (25%)	59 (14%)	77 (18%)
Income decrease	49 (9%)	136 (25%)	37 (9%)	77 (18%)
Labour force status change	71 (13%)	148 (27%)	68 (16%)	75 (18%)
Education level change	55 (10%)	144 (26%)	47 (11%)	60 (14%)

The logistic regressions for congruency (Table 4-10 in the appendix) have relatively poor overall model fit, indicating a large unobserved component to consistency. Education tends to be associated with lower within-survey choice error (Mazzotta & Opaluch, 1995) and also has a positive effect on choice consistency over time in our results. Ranks two to six have negative parameters so are less consistent than rank one. It is generally easier to choose the most preferred alternative (Ben-Akiva et al., 1992). Liebe et al. (2012) found choice consistency to be higher for the status quo alternative, but our status quo parameter is insignificant.

People with more experience with the good being valued tend to have better formed and more stable preferences (Brouwer, Dekker, Rolfe, & Windle, 2010; LaRiviere et al., 2014; McConnell et al., 1998). To test this hypothesis we include variables for ownership of a holiday house on the Peninsula, travel distance and days spent visiting the Peninsula in the previous year as measures of experience. We find that ownership of a holiday house is associated with higher choice congruency only for the first retest.

The video treatment effect on choice consistency is positive but insignificant. The video treatment is, however, positively correlated with stated certainty (people who answered “definitely” or “probably”) which is strongly positive and significant. This is in contrast to Mørkbak and Olsen (2014) who found a positive but insignificant relationship between stated certainty and retest consistency. We also test a variety of variables measuring a change in personal circumstances including income increase/decrease, gain/loss of employment, a change from single-person household to partnered to a family with children (and vice-versa), but find none of these to be significant predictors of choice congruency, similar to previous environmental test-retest choice experiments (Liebe et al., 2012; Schaafsma et al., 2014). Measurement error was perhaps too high to detect any effect even if it did exist.

4.5.2 MODELS AND PARAMETER EQUALITY

We estimated pooled and separate (for each wave) WTP-space random parameter logit models for respondents who completed all three waves using maximum simulated likelihood estimation in Biogeme (Bierlaire, 2003). Dune restoration, headland development, seawall and status quo alternative all have normally distributed random parameters while the cost/scale parameter (λ) is log-normal. We also estimated similar separate and pooled models for the sub-sample of respondents who claimed to be certain ("definitely" or "probably") of their choices in wave one.

Table 4-4 shows the values for the simulated log-likelihoods at convergence and the likelihood ratio (LR) test statistics. When including all respondents who completed all three waves, the LR test is significant at one percent even when allowing for scale/price coefficient differences. This means that the preference structure is significantly different across waves, not an uncommon finding in time-delayed test-retest surveys (Liebe et al., 2012; Schaafsma et al., 2014). However, using only "certain" respondents, the LR test statistic B is insignificant. This means that "certain" respondents did not significantly alter their preferences after allowing for variation in scale or marginal utility of money.

Table 4-4 - Pooled and separate model likelihood ratio tests for respondents who completed all 3 waves

Sample	Separate Models (LL1 + LL2 + LL3)	Pooled A (λ1 = λ2 = λ3)	Pooled B (λ1 ≠ λ2 ≠ λ3)	LR test A	LR test B	Model equality rejected?
All respondents	-6836	-7063	-6896	454.94***	120.55***	Yes
"Certain" respondents	-3130	-3195	-3143	129.32***	25.98	No

Table 4-5 shows the results of Wald tests of joint parameter equality between each pair of waves. The tests reject joint parameter equality even for "certain" respondents. However, the tests are insignificant if only parameter means and

not the random parameter standard deviations are considered. This implies means but not variances are stable for “certain” respondents.

Table 4-5 – Pairwise Wald test statistics for respondents in all 3 waves

Sample	Parameters	Wave 1 vs 2	Wave 1 vs 3	Wave 2 vs 3
All respondents	All parameters	149.17***	691.85***	1084.47***
	Means only	17.44***	202.40***	96.60***
"Certain" respondents	All parameters	92.81***	77.37***	131.56***
	Means only	10.98	7.38	8.94

Table 4-6 reports the parameter estimates and their significance levels for the separate waves, pooled model A with equal scale, pooled model B with unrestricted scale, and pooled model C with “certain” respondents only and unrestricted scale. It is encouraging that almost all parameters have stable signs and similar orders of magnitude. The exception is the status quo coefficient estimate, which has a mean insignificantly different from zero in most cases, but often significant standard deviations. This simply suggests a large variation of the status-quo effect around zero across respondents and it is plausible. The alternative specific constants to control for position are significant in all models and do not decrease in significance in waves two or three. There is an enduring left-right bias that repetition does not erode, which is well documented in ranked and other choice data (Campbell & Erdem, 2015; Scarpa, Notaro, Louviere, & Raffaelli, 2011). The mean for dune restoration and seawalls are positive and headland development is negative, although the random parameter standard deviations are wide enough that a large area of the distributions are on the positive side of zero. We expected significant heterogeneity in taste over attributes because people have different attitudes towards erosion protection and this is reflected in the significance of the random parameters. The relative importance of the scenario attributes does not vary across waves. The mean for headland development is always the largest in absolute terms, and the mean for seawalls the lowest.

Table 4-6 – Panel Random Parameter Logit models

Variable		Wave 1	Wave 2	Wave 3	Pooled A λ1 = λ2 = λ3	Pooled B λ1 ≠ λ2 ≠ λ3	Pooled C "Certain" λ1 ≠ λ2 ≠ λ3
Position 1 (left-most)		63.20*	19.00*	30.50***	57.80***	26.40**	59.30**
Position 2		72.60*	21.40*	46.20***	61.10***	26.40**	56.70**
Position 3		54.30*	18.60	43.00**	50.60**	22.90**	39.30*
Position 4		43.50	21.90*	36.50*	48.20**	22.90**	46.40*
Position 5		1.80	15.80	8.50*	26.30*	15.30	48.90*
Ln(λ)	μ	-4.73***	-4.26***	-5.32***	-4.97***	-8.19***	-6.48***
	σ	0.49***	1.76***	2.46***	0.48***	0.94***	-0.51***
Restored dune	μ	87.80**	32.00***	61.00***	55.30***	34.90***	56.50**
	σ	117.00**	72.30***	95.50***	63.10***	83.60***	81.90**
Headland development	μ	-84.20**	-76.40***	-155.00***	-88.70***	-85.80***	-84.80**
	σ	211.00**	95.10***	207.00***	81.40***	108.00***	95.90***
Seawall	μ	49.90*	10.40*	13.85*	32.40***	19.10***	41.60**
	σ	-204.00**	-78.80***	-148.00***	-84.10***	-72.60***	-116.00**
Status quo	μ	3.50	9.36	6.33	7.72	5.94	5.55
	σ	51.20	-11.60**	-80.90***	-13.90	-21.70**	51.40**
Scale parameter wave 2						3.85***	2.25***
Scale parameter wave 3						3.87***	1.94***
Observations (individuals)		1960 (387)	1965 (387)	1965 (387)	5890 (387)	5890 (387)	2685 (180)
Log-likelihood		-2295	-2304	-2299	-7141	-6976	-3143
Pseudo-R2		0.110	0.109	0.111	0.079	0.100	0.110
BIC		4704	4721	4711	14411	14100	6421

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

4.5.3 WILLINGNESS TO PAY

We present the results of the marginal WTP simulations as box plots in Figure 4-3 and in tabular format in Table 4-7. WTP variance is higher in the sub-sample of certain respondents, perhaps due to the difficulty of achieving statistical precision in a smaller sample size (180 versus 387 individuals in the full sample).

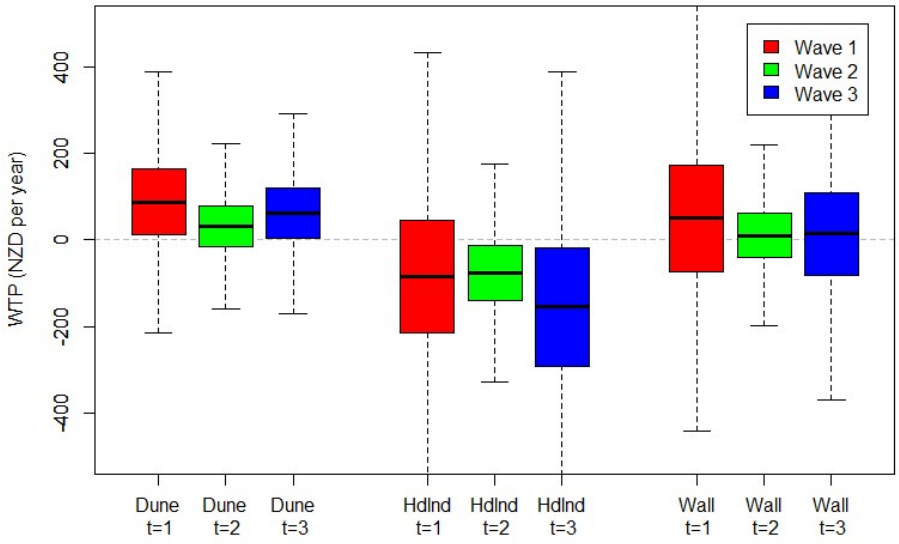


Figure 4-3 - Boxplot of WTP for respondents who completed all 3 waves

Table 4-7 - Mean WTP and confidence intervals for individuals who completed all 3 waves

	All respondents		"Certain" respondents	
	Mean	90% C.I.	Mean	90% C.I.
Wave 1				
Dune restoration	88	(-132,307)	70	(-265,404)
Headland developed	-84	(-467,299)	-88	(-473,295)
Seawall	50	(-317,417)	78	(-1024,1185)
Wave 2				
Dune restoration	32	(-89,153)	83	(-162,329)
Headland developed	-76	(-238,85)	-149	(-551,254)
Seawall	10	(-121,142)	47	(-320,411)
Wave 3				
Dune restoration	61	(-110,232)	59	(-122,241)
Headland developed	-155	(-503,194)	-96	(-310,119)
Seawall	14	(-235,263)	16	(-166,197)

Table 4-8 shows the results of the formal tests for mean and distribution equality as outlined in section 2. The Mann-Whitney U test is significant at five percent in seven out of nine cases and the Kolmogorov-Smirnov test in every case. It follows that distributions of marginal WTPs are significantly different. For "certain" respondents we find some significant differences in mean WTP for headland development and in the variance of WTP for seawalls but WTP is otherwise stable.

Table 4-8 - Tests of equality of WTP means and distributions[35]

		All respondents		"Certain" respondents	
Attribute	Wave comparison	U-test (Z score)	K-S (D score)	U-test (Z score)	K-S (D score)
Dune restoration	1 vs 2	-6.20***	0.30***	-0.33	0.12
	1 vs 3	-1.98**	0.16***	-0.26	0.15*
	2 vs 3	-3.52***	0.19***	-1.00	0.14
Headland developed	1 vs 2	-0.12	0.19***	-1.58*	0.18*
	1 vs 3	-2.96***	0.17***	-0.09	0.14*
	2 vs 3	-4.96***	0.33***	-1.64*	0.22***
Seawall	1 vs 2	-2.33***	0.27***	-0.43	0.25***
	1 vs 3	-1.80**	0.14***	-0.77	0.35***
	2 vs 3	0.01	0.17***	-0.99	0.18**

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

4.6 DISCUSSION AND CONCLUSION

This paper presents a study on temporal stability of WTP for beach development management. The study contributes to the limited research on temporal reliability in non-market valuation of environmental goods and has the unique feature of reporting on not only one but two retests and fully ranked choice cards. We find there is sufficient evidence to reject equality of joint and individual parameters in the WTP-space models in different time periods. Choice

[35] The number of draws used equals the comparison sample size in each case

congruency is significantly higher than would be expected by chance alone, but there was little difference in congruency between waves one and two (29 percent), one and three (26 percent) and two and three (28 percent). Stability did not improve with the additional re-test, nor did left-right bias diminish. This implies that the tasks either lacked sufficient feedback to stimulate preference discovery, or that WTP was constructed on the spot as per the constructed preferences point of view. What we find to remain consistent is the relative importance of the attributes. The negative perception of headland development outweighed values for seawalls or dune restoration.

The implication for policy decision-makers is to be particularly cautious of stated preference values for goods that require complex and unfamiliar trade-offs, such as environmental quality. If values are to be used in a cost-benefit analysis we should focus on the order of magnitude of the values and the relative importance of the attributes. If the difference between cost and benefit is small, a high margin of error around the non-market costs or benefits will make it difficult to justify a decision.

On an encouraging note, we find there is a subset of respondents who exhibit more stable preferences. These respondents rated highly on scores of self-reported stated certainty. The use of certainty scores to measure a respondent's confidence in his or her choices originated from research on hypothetical bias (Beck et al., 2013) but our results suggest it may also be useful for predicting stability of preferences. Further research will be required to find out if this result is generalizable. Stated preference practitioners need to design experiments that maximise the likelihood of eliciting well-formed preferences (see Payne et al.1999 for a review of common faults in preference construction). Providing opportunity for deliberation might be useful (Lienhoop & Volker, 2016). Alternatively, researchers could attempt to make the consequences seem more real – for example, by providing virtual reality representation of the chosen scenario or personalised hypothetical rates invoices showing the cost. Certainty

scaling questions could be used as a measure of relative success in this endeavour.

4.7 References

Ariely, D., Loewenstein, G., & Prelec, D. (2003). "Coherent Arbitrariness": Stable Demand Curves Without Stable Preferences. *The Quarterly Journal of Economics*, *118*(1), 73–106.

Beck, M. J., Rose, J. M., & Hensher, D. A. (2013). Consistently inconsistent: The role of certainty, acceptability and scale in choice. *Transportation Research. Part E, Logistics & Transportation Review*, *56*, 81. https://doi.org/10.1016/j.tre.2013.05.001

Ben-Akiva, M., Morikawa, T., & Shiroishi, F. (1992). Analysis of the reliability of preference ranking data. *Journal of Business Research*, *24*, 149–164. https://doi.org/10.1016/0148-2963(92)90058-j

Bierlaire, M. (2003). BIOGEME: a free package for the estimation of discrete choice models.

Bliem, M., Getzner, M., & Rodiga-Laßnig, P. (2012). Temporal stability of individual preferences for river restoration in Austria using a choice experiment. *Journal of Environmental Management*, *103*, 65–73. https://doi.org/10.1016/j.jenvman.2012.02.029

Braga, J., & Starmer, C. (2005). Preference anomalies, preference elicitation and the discovered preference hypothesis. *Environmental and Resource Economics*, *32*(1), 55–89.

Brouwer, R. (2006). Do stated preference methods stand the test of time? A test of the stability of contingent values and models for health risks when facing an extreme event. *Ecological Economics*, *60*(2), 399–406. https://doi.org/10.1016/j.ecolecon.2006.04.001

Brouwer, R., Dekker, T., Rolfe, J., & Windle, J. (2010). Choice Certainty and Consistency in Repeated Choice Experiments. *Environmental and Resource Economics*, *46*(1), 93–109. https://doi.org/10.1007/s10640-009-9337-x

Brouwer, R., & Spaninks, F. (1999). The Validity of Environmental Benefits Transfer: Further Empirical Testing. *Environmental and Resource Economics*, *14*(1), 95–117. https://doi.org/10.1023/A:1008377604893

Bryan, S., Gold, L., Sheldon, R., & Buxton, M. (2000). Preference measurement using conjoint methods: an empirical investigation of reliability. *Health Economics*, *9*(5), 385–395.

Campbell, D., & Erdem, S. (2015). Position bias in best-worst scaling surveys: a case study on trust in institutions. *American Journal of Agricultural Economics*, *97*(2), 526–545. https://doi.org/10.1093/ajae/aau112

Carlsson, F. (2010). Design of Stated Preference Surveys: Is There More to Learn from Behavioral Economics? *Environmental and Resource Economics*, *46*(2), 167–177. https://doi.org/10.1007/s10640-010-9359-4

Carlsson, F., Mørkbak, M. R., & Olsen, S. B. (2012). The first time is the hardest: A test of ordering effects in choice experiments. *Journal of Choice Modelling*, *5*(2), 19–37.

Cohen, J. (1968). Weighted kappa: Nominal scale agreement provision for scaled disagreement or partial credit. *Psychological Bulletin*, *70*(4), 213.

Collins, D., & Kearns, R. (2010). "It's a gestalt experience": Landscape values and development pressure in Hawke's Bay, New Zealand. *Geoforum*, *41*(3), 435–446. https://doi.org/10.1016/j.geoforum.2009.11.010

Czajkowski, M., Barczak, A., Budziński, W., Giergiczny, M., & Hanley, N. (2016). Preference and WTP stability for public forest management. *Integrating Ecosystem Service Concepts into Valuation and Management Decisions*, *71*, 11–22. https://doi.org/10.1016/j.forpol.2016.06.027

Fitzmaurice, G. M., Heath, A. F., & Clifford, P. (1996). Logistic Regression Models for Binary Panel Data with Attrition. *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, *159*(2), 249–263. https://doi.org/10.2307/2983172

Gregory, R., Lichtenstein, S., & Slovic, P. (1993). Valuing environmental resources: a constructive approach. *Journal of Risk and Uncertainty*, *7*(2), 177–197.

Hess, S., Hensher, D. A., & Daly, A. (2012). Not bored yet – Revisiting respondent fatigue in stated choice experiments. *Transportation Research Part A: Policy and Practice*, *46*(3), 626–644. https://doi.org/10.1016/j.tra.2011.11.008

Krinsky, I., & Robb, A. L. (1986). On Approximating the Statistical Properties of Elasticities. *The Review of Economics and Statistics*, *68*, 715–719.

Krosnick, J. A., & Alwin, D. F. (1987). An Evaluation of a Cognitive Theory of Response-Order Effects in Survey Measurement. *The Public Opinion Quarterly*, *51*(2), 201–219. https://doi.org/10.1086/269029

Lancsar, E., & Louviere, J. (2008). Estimating individual level discrete choice models and welfare measures using best-worst choice experiments and sequential best-worst MNL. *University of Technology, Centre for the Study of Choice (Censoc)*, 8–4.

Landis, J., & Koch, G. (1977). The Measurement of Observer Agreement for Categorical Data. *Biometrics*, *33*(1), 159-174. doi:10.2307/2529310LaRiviere, J., Czajkowski, M., Hanley, N., Aanesen, M., Falk-Petersen, J., & Tinch, D. (2014). The value of familiarity: Effects of knowledge and objective signals on willingness to pay for a public good. *Journal of Environmental Economics and Management*, *68*(2), 376–389. https://doi.org/10.1016/j.jeem.2014.07.004

Lew, D. K., & Wallmo, K. (2017). Temporal stability of stated preferences for endangered species protection from choice experiments. *Ecological Economics*, *131*, 87–97.

Liebe, U., Meyerhoff, J., & Hartje, V. (2012). Test-Retest Reliability of Choice Experiments in Environmental Valuation. *Environmental and Resource Economics*, *53*(3), 389. https://doi.org/10.1007/s10640-012-9567-1

Lienhoop, N., & Volker, M. (2016). Preference Refinement in Deliberative Choice Experiments for Ecosystem Service Valuation. *Land Economics*, *92*(3), 555–577. https://doi.org/10.3368/le.92.3.555

Matthews, Y., Scarpa, R., & Marsh, D. (2017). Using virtual environments to improve the realism of choice experiments: A case study about coastal erosion management. *Journal of Environmental Economics and Management*, *81*, 193–208. https://doi.org/10.1016/j.jeem.2016.08.001

Mazzotta, M. J., & Opaluch, J. J. (1995). Decision making when choices are complex: a test of Heiner's hypothesis. *Land Economics*, *71*(4), 500–515.

McConnell, K. E., Strand, I. E., & Valdés, S. (1998). Testing Temporal Reliability and Carry-over Effect: The Role of Correlated Responses in Test-retest Reliability Studies. *Environmental and Resource Economics*, *12*(3), 357–374. https://doi.org/10.1023/A:1008264922331

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics*. New York: Academic Press.

Mørkbak, M. R., & Olsen, S. B. (2014). A within-sample investigation of test–retest reliability in choice experiment surveys with real economic incentives. *Australian Journal of Agricultural and Resource Economics*.

Pearson, E. S. and Hartley, H. O., eds. (1972). *Biometrika Tables for Statisticians. 2. Cambridge University Press. pp. 117–123, Tables 54, 55*

Plott, C. R. (1996). Rational Individual Behavior in Markets and Social Choice Processes: the Discovered Preference Hypothesis. In *The Rational Foundations of Economic Behaviour, ed. K. J. Arrow, E. Colombatto, M. Perleman, & C. Schmidt* (pp. 225–250). London: Macmillan. Retrieved from https://books.google.co.nz/books?id=wsO7QgAACAAJ

R Core Team. (2012). R: a language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing; 2012.

Rigby, D., & Burton, M. (2011). Intertemporal choice consistency and the information sensitivity of welfare estimates in stated preference studies. Presented at the EAERE 18th annual conference, Rome.

Ryan, M., Netten, A., Skåtun, D., & Smith, P. (2006). Using discrete choice experiments to estimate a preference-based measure of outcome—an application to social care for older people. *Journal of Health Economics*, *25*(5), 927–944.

Scarpa, R., Campbell, D., & Hutchinson, W. G. (2007). Benefit estimates for landscape improvements: sequential Bayesian design and respondents' rationality in a choice experiment. *Land Economics*, *83*(4), 617–634.

Scarpa, R., Notaro, S., Louviere, J., & Raffaelli, R. (2011). Exploring Scale Effects of Best/Worst Rank Ordered Choice Data to Estimate Benefits of Tourism in Alpine Grazing Commons. *American Journal of Agricultural Economics*, *93*, 809–824. https://doi.org/10.1093/ajae/aaq174

Scarpa, R., Thiene, M., & Train, K. (2008). Utility in Willingness to Pay Space: A Tool to Address Confounding Random Scale Effects in Destination Choice to the Alps. *American Journal of Agricultural Economics*, *90*, 994–1010. https://doi.org/10.1111/j.1467-8276.2008.01155.x

Schaafsma, M., Brouwer, R., Liekens, I., & De Nocker, L. (2014). Temporal stability of preferences and willingness to pay for natural areas in choice experiments: A test–retest. *Resource and Energy Economics*, *38*, 243–260.

Simon, D., Krawczyk, D. C., Bleicher, A., & Holyoak, K. J. (2008). The transience of constructed preferences. *Journal of Behavioral Decision Making*, *21*(1), 1–14.

Skjoldborg, U. S., Lauridsen, J., & Junker, P. (2009). Reliability of the discrete choice experiment at the input and output level in patients with rheumatoid arthritis. *Value in Health*, *12*(1), 153–158.

Swait, J., & Louviere, J. (1993). The Role of the Scale Parameter in the Estimation and Comparison of Multinomial Logit Models. *Journal of Marketing Research*, *30*, 305–314.

Train, K. (2002). Discrete choice methods with simulation. Cambridge Univ Pr.

Train, K., & Weeks, M. (2005). Discrete choice models in preference space and willingness-to-pay space. In *R.Scarpa & A. Alberini, eds, "Applications of*

simulation methods in environmental and resource economics." Springer Publisher, Dordrecht, The Netherlands.

Winship, C., & Mare, R. D. (1992). Models for Sample Selection Bias. *Annual Review of Sociology*, *18*, 327–350.

4.8 APPENDIX

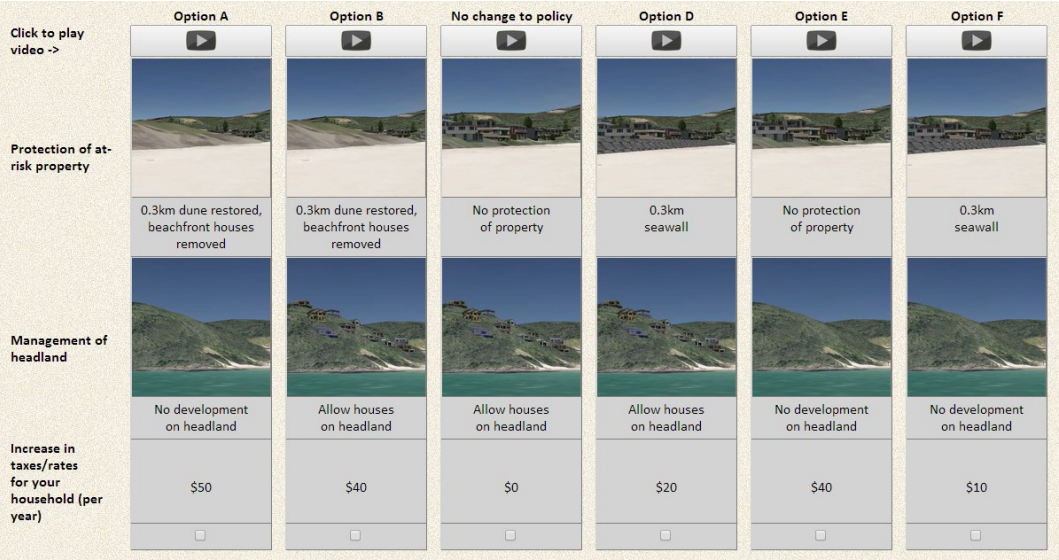


Figure 4-4 - Example beach choice card

Table 4-9 – Binary logit model results for retest participation

Dependent variable = retest participation	1st retest		2nd retest | 1st retest	
Variable	Coefficient	Z score	Coefficient	Z score
Constant	-0.335	-0.61	-0.735	-1.25
Age (in years)	-0.0244	-0.96	-0.0029	-0.11
Age squared	0.0004	1.46	0.0002	0.56
Degree	0.2363*	1.73	0.3540**	2.49
Female	0.2981**	2.18	0.2175	1.52
Preschool children in household	-0.0366	-0.20	0.1447	0.77
School children in household	0.4397***	2.91	0.1043	0.66
Annual household income< $100k	0.0255	0.15	-0.1865	-1.05
Annual household income > $100k	-0.0113	-0.07	-0.3028*	-1.67
Bach owned by family	-0.1747	-1.15	-0.3999**	-2.45
Travel time to site (hours)	-0.0451	-1.13	-0.1182**	-2.17
Peninsula visits duration (days)	-0.0157	-1.18	-0.0374**	-2.37
Video treatment	0.4175***	2.94	0.3925***	2.61
Certain of choice	-0.0929	-0.64	0.1002	0.66
Choice congruency 1st retest				
Number of individuals		1059		505
Log-likelihood		-1423		-651
Pseudo-R^2		0.029		0.036
Bayesian information criteria		2953		1389

Table 4-10 - Logistic regression for rank congruency

Dependent variable = 1 if ranks are the same as first wave, otherwise = 0

	Wave 2		Wave 3	
Variable	Coefficient	Z -value	Coefficient	Z -value
Intercept	-0.982***	-3.07	-1.575***	-3.06
Rank 2	-0.778***	-5.25	-0.785***	-3.86
Rank 3	-1.078***	-7.01	-0.581***	-2.93
Rank 4	-0.858***	-5.72	-0.676***	-3.38
Rank 5	-1.128***	-7.27	-0.463**	-2.37
Rank 6	-0.413***	-2.85	-0.241	-1.26
Status quo alternative	0.090	0.75	0.118	0.76
Age (years)	-0.006	-1.31	0.010	1.63
Degree	0.300**	2.37	0.151	0.86
Female	-0.056	-0.43	0.327*	1.78
Preschool children in household	-0.157	-0.92	-0.012	-0.05
School children in household	0.046	0.35	0.126	0.69
Annual household income < $50k	-0.064	-0.41	-0.236	-1.09
Annual household income > $100k	-0.174	-1.11	-0.197	-0.93
Holiday home owned by family	0.295**	2.10	-0.036	-0.17
Travel time to site (hours)	0.014	0.27	-0.097	-0.71
Days visited peninsula	-0.002	-0.24	-0.015	-1.46
Video treatment	0.200*	1.68	0.171	1.39
Certain of choices	1.058***	8.12	0.450***	2.62
Change in income	-0.254*	-1.71	0.337	1.64
Change in labour force status	0.062	0.36	-0.340	-1.35
Change in household composition	-0.055	-0.36	0.347	1.57
Sigma (panel variance)	1.188***	10.92	1.344***	9.74
Number of individuals		551		426
Log-likelihood		-1659		-999
Pseudo-R2		0.087		0.062
Bayesian information criteria		3470		2142

5. CUMULATIVE ATTRACTION AND SPATIAL DEPENDENCE IN A DESTINATION CHOICE MODEL FOR BEACH RECREATION

5.1 ABSTRACT

The destination choices of individual recreationalists are often 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. For this study we use a random utility model to analyse recreational beach visits on the Coromandel Peninsula in New Zealand. Each beach site has a different combination of attraction variables with potentially complex substitution patterns. We estimate and compare types of Generalized Extreme Value and Competing Destinations models. 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 its mathematical form is tractable in estimation. We use the model to examine the implications of two site-specific changes: closure of a campground and construction of a sea wall. The model estimates predict that these changes would affect visitation in the wider area, and the overall effect depends on the spatial distribution of sites and associated attractions.

5.2 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.

5.3 THEORETICAL FRAMEWORK

5.3.1 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.

5.3.2 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.

5.3.2.1 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).

5.3.2.2 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 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.

5.3.2.3 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.

5.3.2.4 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:

$$A_j = \frac{1}{K-1} \sum_{k \neq j}^{K} \frac{W_k}{{d_{jk}}^{\theta}} \qquad (5\text{-}1)$$

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.

5.3.2.5 *Agglomerating and Competing Destination Choice model*

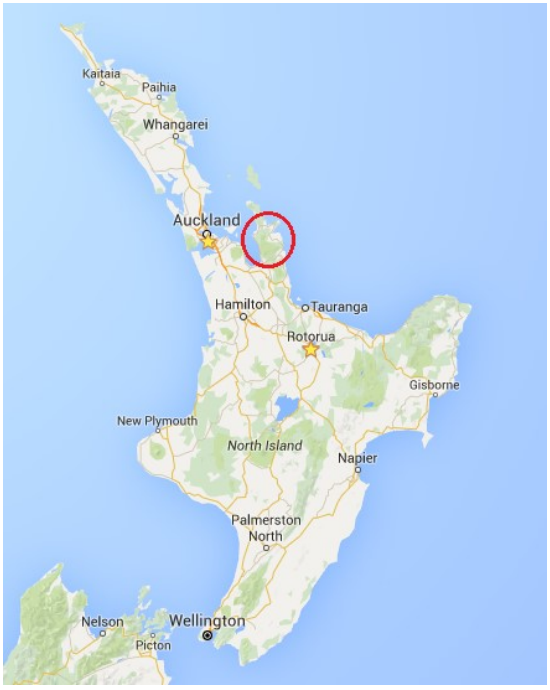
Bernardin et al. (2009) included two adjustment terms in the utility function to separately measure spatial competition and agglomeration effects and named this model Agglomerating and Competing Destination Choice (ACDC). Using a dissimilarity statistic based on business types, Bernardin et al. (2009) 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.

5.4 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 5-2). 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.



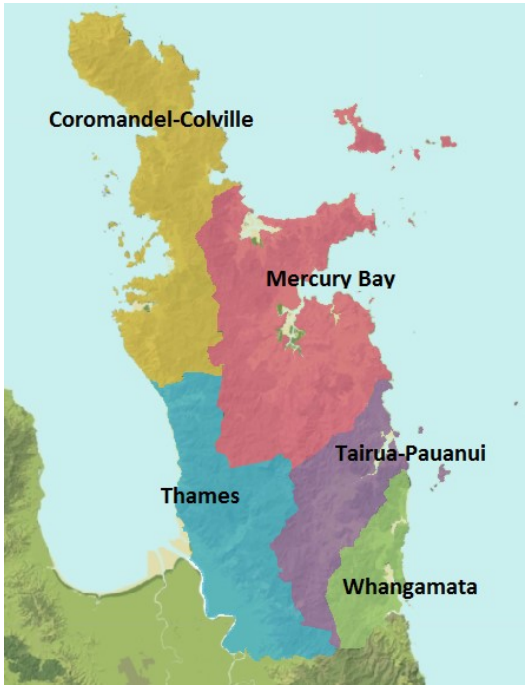


Figure 5-1 - Coromandel Peninsula (circled) **Figure 5-2 - Community Board Areas**

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[36] that will address issues such as coastal erosion, development, conservation, contaminants and location of infrastructure. One objective of this study is to help inform the review about possible effects on recreational users of the beaches.

5.5 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.

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

5.5.1 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 5-5 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[37]. 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[38]. 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:

$$C_{njt} = \rho_{njt} \sum_{k=1}^{K_t} (0.2 d_{ntk} + 1/3 \, \omega_n m_{ntk}) \qquad (5\text{-}2)$$

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

[38] 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.

5.6 Model Formulation

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

5.6.1 MNL

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

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{5-3}$$

where V_{nj} is a deterministic, linear-in-parameters component and ε_{ni} 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:

$$P_{nj} = \frac{e^{V_{nj}}}{\sum_k (e^{V_{nk}})} \tag{5-4}$$

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

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

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

5.6.2 CNL

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

$$G(y) = \sum_{m=1} \left(\sum_{j \in K} \left({\alpha_{jm}}^{1/\mu} y_j \right)^{\mu_m} \right)^{\mu/\mu_m} \tag{5-6}$$

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[39], which are defined in Table 5-5 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:

$$\alpha_{jm} = \frac{B_{jm}}{\sum_k B_{km}} \tag{5-7}$$

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.

5.6.3 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.

$$P_{nj} = \frac{e^{V_{nj}+\beta_A A_j}}{\sum_k (e^{V_{nk}+\beta_A A_k})} \tag{5-8}$$

The accessibility variable is specified as:

$$A_j = ln \sum_{\substack{k \\ k \neq j}} \frac{W_k}{d_{jk}} \tag{5-9}$$

where d_{ik} 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.

$$W_k = \frac{\sum_g f_g B_{kg}}{\sum_g f_g} \tag{5-10}$$

5.6.4 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).

[39] 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.

$$A_{jg} = \frac{1}{K-1} \sum_{\substack{k \\ k \neq j}}^{K} \frac{B_{kg}}{d_{jk}} \quad (5\text{-}11)$$

5.6.5 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).

$$D_{jk} = 1 - \sum_g f_g \frac{B_{jg} B_{kg}}{\sum_{g'} B_{jg} \sum_{g'} B_{kg}} \quad (5\text{-}12)$$

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

$$A_j^C = ln \sum_k D_{jk} \frac{\sum_g B_{kg}}{d_{jk}} \quad (5\text{-}13)$$

$$A_j^S = ln \sum_k \left(2 - D_{jk}\right) \frac{\sum_g B_{kg}}{d_{jk}} \quad (5\text{-}14)$$

5.6.6 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.

$$A_{jg}^C = \begin{cases} \frac{1}{K-1} \sum_{\substack{k \\ k \neq j}}^{K} \frac{B_{kg}}{d_{jk}} & \text{for } B_{jg} = 0 \\ 0 & \text{for } B_{jg} > 0 \end{cases} \quad (5\text{-}15)$$

$$A_{jg}^S = \begin{cases} \frac{1}{K-1} \sum_{\substack{k \\ k \neq j}}^{K} \frac{B_{kg}}{d_{jk}} & \text{for } B_{jg} > 0 \\ 0 & \text{for } B_{jg} = 0 \end{cases} \quad (5\text{-}16)$$

5.7 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 5-1 - 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 5-3 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.

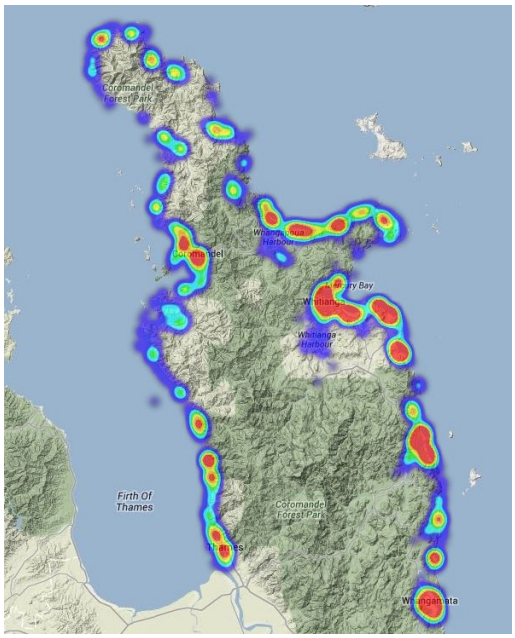


Figure 5-3 – Heat map of beach visits

5.7.1 SITE COMPATIBILITY

Compatibility is defined as the proportion of visitors to site A that also visit site B (Nelson, 1958)[40]. 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 the appendix Table 5-6Table . The model fit is high with a McFadden pseudo R-square of 0.63.

[40] 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.

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.

5.7.2 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[41]. Results are reported in Table 5-2.

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

[41] 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.

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[42]. 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 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).

[42] 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.

Table 5-2 - 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***	

5.7.3 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 5-3 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% decrease from 0.047 to 0.038. 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 5-3 – 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 affects two attributes (seawall and dune) and 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 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 5-4 – 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%

5.8 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.

5.9 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[43]. 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.

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

5.10 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.

5.11 References

Bekhor, S., & Prashker, J. N. (2008). GEV-based destination choice models that account for unobserved similarities among alternatives. *Transportation Research Part B*, *42*(3), 243–262. http://doi.org/10.1016/j.trb.2007.08.003

Bernardin, V., Koppelman, F., & Boyce, D. (2009). Enhanced Destination Choice Models Incorporating Agglomeration Related to Trip Chaining While Controlling for Spatial Competition. *Transportation Research Record: Journal of the Transportation Research Board*, *2132*, 143–151. http://doi.org/10.3141/2132-16

Bhat, C. R., Dubey, S. K., Alam, M. J. B., & Khushefati, W. H. (2015). A New Spatial Multiple Discrete-Continuous Modeling Approach to Land Use Change Analysis. *Journal of Regional Science*, *55*(5), 801–841.

Bhat, C. R., & Guo, J. (2004). A mixed spatially correlated logit model: formulation and application to residential choice modeling. *Transportation Research Part B: Methodological*, *38*(2), 147–168. http://doi.org/10.1016/S0191-2615(03)00005-5

Bierlaire, M. (2003). BIOGEME: a free package for the estimation of discrete choice models.

Bierlaire, M. (2006). A theoretical analysis of the cross-nested logit model. *Annals of Operations Research*, *144*(1), 287–300.

Bujosa, A., Riera, A., & Torres, C. M. (2015). Valuing tourism demand attributes to guide climate change adaptation measures efficiently: The case of the Spanish domestic travel market. *Tourism Management*, *47*, 233–239. http://doi.org/10.1016/j.tourman.2014.09.023

Chu, C. (1989). A paired combinatorial logit model for travel demand analysis. In *Transport Policy, Management & Technology Towards 2001: Selected Proceedings of the Fifth World Conference on Transport Research* (Vol. 4).

Collins, D., & Kearns, R. (2010). "Pulling up the Tent Pegs?" The Significance and Changing Status of Coastal Campgrounds in New Zealand. *Tourism Geographies*, *12*(1), 53–76. http://doi.org/10.1080/14616680903493647

Coombes, E. G., Jones, A. P., & Sutherland, W. J. (2008). The biodiversity implications of changes in coastal tourism due to climate change. *Environmental Conservation*, *35*(4), 319–330.

Daly, A. (1987). Estimating "tree" logit models. *Transportation Research Part B: Methodological*, *21*(4), 251–267. http://doi.org/10.1016/0191-2615(87)90026-9

Daly, A., & Bierlaire, M. (2006). A general and operational representation of generalised extreme value models. *Transportation Research Part B: Methodological*, *40*(4), 285–305.

Decrop, A. (2010). Destination Choice Sets. *Annals of Tourism Research*, *37*, 93–115.

Drakopoulos, S. A. (1994). HIERARCHICAL CHOICE IN ECONOMICS. *Journal of Economic Surveys*, *8*(2), 133–153. http://doi.org/10.1111/j.1467-6419.1994.tb00097.x

Fotheringham, S. (1983). A new set of spatial-interaction models: the theory of competing destinations. *Environment & Planning A*, *15*, 15–36.

Griffith, D. A. (2007). Spatial Structure and Spatial Interaction: 25 Years Later. *The Review of Regional Studies*, *37*(1), 28–38.

Handy, S. L., & Clifton, K. J. (2001). Evaluating neighborhood accessibility: Possibilities and practicalities. *Journal of Transportation and Statistics*, *4*(2/3), 67–78.

Handy, S. L., & Niemeier, D. A. (1997). Measuring Accessibility: An Exploration of Issues and Alternatives. *Environment and Planning A*, *29*(7), 1175–1194. http://doi.org/10.1068/a291175

Ho, C. Q., & Hensher, D. A. (2016). A workplace choice model accounting for spatial competition and agglomeration effects. *Journal of Transport Geography*, *51*, 193–203. http://doi.org/10.1016/j.jtrangeo.2016.01.005

Ishaq, R., Bekhor, S., & Shiftan, Y. (2013). A flexible model structure approach for discrete choice models. *Transportation*, *40*(3), 609–624. http://doi.org/10.1007/s11116-012-9431-8

Kearns, R., & Collins, D. (2012). Feeling for the coast: the place of emotion in resistance to residential development. *Social & Cultural Geography*, *13*(8), 937–955. http://doi.org/10.1080/14649365.2012.730150

Klaiber, H. A., & von Haefen, R. H. (2008). Incorporating random coefficients and alternative specific constants into discrete choice models: implications for in-sample fit and welfare estimates. *WESTERN REGIONAL RESEARCH*, 200.

Larson, D. M., & Lew, D. K. (2013). The Opportunity Cost of Travel Time as a Noisy Wage Fraction. *American Journal of Agricultural Economics*, *96*(2), 420. http://doi.org/10.1093/ajae/aat093

Lieberson, S. (1969). Measuring population diversity. *American Sociological Review*, 850–862.

Lue, C.-C., Crompton, J. L., & Fesenmaier, D. R. (1993). Conceptualization of multi-destination pleasure trips. *Annals of Tourism Research*, *20*(2), 289–301.

Lue, C.-C., Crompton, J. L., & Stewart, W. P. (1996). Evidence of Cumulative Attraction in Multidestination Recreational Trip Decisions. *Journal of Travel Research*, *35*(1), 41–49. http://doi.org/10.1177/004728759603500107

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics*. New York: Academic Press.

McFadden, D. (1978). *Modelling the choice of residential location*. Institute of Transportation Studies, University of California.

Mendelsohn, R., Hof, J., Peterson, G., & Johnson, R. (1992). Measuring Recreation Values with Multiple Destination Trips. *American Journal of Agricultural Economics*, *74*(4), 926–933. http://doi.org/10.2307/1243190

Mkwara, L., Marsh, D., & Scarpa, R. (2015). The effect of within-season variability on estimates of recreational value for trout anglers in New Zealand. *Ecological Economics*, *119*, 338–345. http://doi.org/10.1016/j.ecolecon.2015.09.012

Nelson, R. (1958). The selection of retail locations (Dodge, New York).

Pagliara, F., & Timmermans, H. (2009). Choice set generation in spatial contexts: a review. *Transportation Letters*, *1*(3), 181–196. http://doi.org/10.3328/TL.2009.01.03.181-196

Parsons, G. R., & Wilson, A. J. (1997). Incidental and joint consumption in recreation demand. *Agricultural and Resource Economics Review*, *26*, 1–6.

Pellegrini, P. A., & Fotheringham, A. S. (2002). Modelling spatial choice: a review and synthesis in a migration context. *Progress in Human Geography*, *26*(4), 487–510.

Phaneuf, D. J., & Smith, V. K. (2005). Chapter 15 Recreation Demand Models. In Karl-Gran Mler and Jeffrey R. Vincent (Ed.), *Handbook of Environmental Economics* (Vol. Volume 2, pp. 671–761). Elsevier. Retrieved from http://www.sciencedirect.com/science/article/pii/S1574009905020152

Schüssler, N., & Axhausen, K. W. (2009). *Accounting for similarities in destination choice modelling: A concept*. ETH, Eidgenössische Technische Hochschule Zürich, IVT, Institut für Verkehrsplanung und Transportsysteme.

Sener, I. N., Pendyala, R. M., & Bhat, C. R. (2011). Accommodating spatial correlation across choice alternatives in discrete choice models: an application to modeling residential location choice behavior. *Journal of*

Transport Geography, *19*(2), 294–303. http://doi.org/10.1016/j.jtrangeo.2010.03.013

Smirnov, O. A., & Egan, K. J. (2012). Spatial random utility model with an application to recreation demand. *Frontiers in Spatial Econometrics Modelling*, *29*(1), 72–78. http://doi.org/10.1016/j.econmod.2010.09.026

Taylor, R. G., McKean, J. R., & Johnson, D. (2010). Measuring the Location Value of a Recreation Site. *Journal of Agricultural and Resource Economics*, *35*(1), 87–104.

Thiene, M., & Scarpa, R. (2008). Hiking in the Alps: exploring substitution patterns of hiking destinations. *Tourism Economics*, *14*(2), 263–282.

Thiene, M., Swait, J., & Scarpa, R. (2017). Choice set formation for outdoor destinations: The role of motivations and preference discrimination in site selection for the management of public expenditures on protected areas. *Journal of Environmental Economics and Management*, *81*, 152–173. http://doi.org/10.1016/j.jeem.2016.08.002

Thomson, J. (2003). *Coastal values and beach use survey report* (Technical Report No. 2003/09). Waikato Regional Council. Retrieved from http://www.waikatoregion.govt.nz/Services/Publications/Technical-reports/2003-technical-reports/

Train, K. E. (1998). Recreation demand models with taste differences over people. *Land Economics*, *74*(2), 230–239.

Vovsha, P. (1997). Application of cross-nested logit model to mode choice in Tel Aviv, Israel, metropolitan area. *Transportation Research Record: Journal of the Transportation Research Board*, (1607), 6–15.

Weidenfeld, A., Butler, R. W., & Williams, A. M. (2010). Clustering and compatibility between tourism attractions. *International Journal of Tourism Research*, *12*(1), 1–16.

Wen, C.-H., & Koppelman, F. S. (2001). The generalized nested logit model. *Transportation Research Part B: Methodological*, *35*(7), 627–641.

Wu, L., Zhang, J., & Fujiwara, A. (2011). Representing tourists' heterogeneous choices of destination and travel party with an integrated latent class and nested logit model. *Tourism Management*, *32*(6), 1407–1413. http://doi.org/10.1016/j.tourman.2011.01.017

Yang, Y., Fik, T., & Zhang, J. (2013). MODELING SEQUENTIAL TOURIST FLOWS: WHERE IS THE NEXT DESTINATION? *Annals of Tourism Research*, *43*, 297–320. http://doi.org/10.1016/j.annals.2013.07.005

Yeh, C.-Y., Haab, T. C., & Sohngen, B. L. (2006). Modeling Multiple-Objective Recreation Trips with Choices Over Trip Duration and Alternative Sites. *Environmental & Resource Economics*, *34*, 189–209.

5.12 Appendix

Table 5-5 – 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 5-6 – 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%

6. CONCLUSION

This research focussed on non-market values affected by the issues of coastal erosion protection and coastal development on the Coromandel Peninsula, New Zealand. Property owners who are detrimentally affected by coastal erosion are naturally motivated to build armoured seawalls to protect their investments. Beachfront property values are often upwards of a million dollars so the benefits significantly outweigh the costs from a private point of view, even if the seawall is only delaying the inevitable loss. What is more difficult to quantify is the loss of amenity value that seawalls cause to other beach users. In most cases they are non-locals and therefore have no strong voice in local decision-making. In the absence of quantitative values these public effects are either ignored or relegated to political debate. The debate on the issue of coastal development is similarly conflicted. Greenfield development can be lucrative for developers and existing landowners, as well as providing additional rates revenue to local government. Local residents are often the staunchest opponents of new development (Collins and Kearns 2010) but non-locals can also have high use, option and existence values for the preservation of remaining natural coastal features. Non-market valuation techniques are important because they provide quantitative estimates of value that can then be compared with the private costs and benefits.

In this research I applied random utility theory to analyse both stated preferences for hypothetical erosion protection and development scenarios and revealed preferences for beach destination choice. However, there are criticisms of non-market valuation methods that have potential to limit confidence in results. One issue is the claim that preferences are often constructed, rather than revealed, in response to an unfamiliar task such as making trade-offs between the coastal environment and taxes. Even if all the relevant information is provided by the researcher, these decisions may be reached without complete processing and consideration of this information. People may use simplifying

heuristics rather than play the part of a fully rational consumer. A significant contribution of the research is investigating whether choice reliability can be improved by providing respondents with 3D visualisations (virtual environments) depicting the alternatives. Another novelty of this research is that data were collected at three different times across a 6-month period, allowing the testing of preference stability over time. Revealed preference analysis is similarly fraught with issues. A major weakness is caused by the fact that random utility theory was originally developed for non-spatial choices so does not account for spatial distribution or spatial dependence. I reviewed different model specifications to account for spatial dependencies and include spatial variables to account for the effects of amenities available at nearby sites.

6.1 SUMMARY OF RESULTS

6.1.1 USING VIRTUAL ENVIRONMENTS TO IMPROVE THE REALISM OF CHOICE EXPERIMENTS

In Chapter Two I reported the results of a choice experiment about coastal erosion protection and headland develop. A split-sample treatment was used to test a novel technique of using virtual environment (VE) tours to present the alternatives to web survey respondents. Tests of the effect of the treatment on left-right bias, frequency of status quo choices and idiosyncratic error variance were conducted. All of these indicators are associated with the relative ease (or difficulty) of assimilating and processing the information provided in the choice experiment. The results showed that idiosyncratic choice error and left-right bias are lower for the video treatment group but there was no significant effect on status quo choice frequency. The virtual environment videos appeared to improve respondents' abilities to evaluate the information and make consistent choices. Perhaps an equally important finding is that the VE treatment was associated with improved re-test participation and higher survey enjoyment ratings. An engaging survey experience is important in the current era when

consumers are frequently bombarded with web surveys and response rates are declining.

The final model included random parameters to allow for taste heterogeneity across respondents. The marginal effect of headland development was negative for most respondents, although a 90 percent confidence interval included positive values. Mean willingness-to-accept (WTA) was $124 for the VE treatment group and $138 for the control group. Dune restoration was perceived positively, with VE-group WTP ranging from $91 for the shortest dune (200m) and $134 for the longest (800m). The treatment group dune WTP ranged from $88 to $107. The mean values for seawall erosion protection were significantly different for the VE group ($2) and control groups ($47). Neither group exhibited significant sensitivity to the length of the seawall. The significantly lower mean for the VE group implies that the treatment affected stated preferences as well as reducing left-right bias. The potency of presentation effects is a well-researched issue within decision research and is consistent with the constructed preferences perspective. The question then arises as to which preferences are true, if either? If we accept the recommendation that more weight should be given to decisions that are reached with a higher standard of reasoning (Payne, Bettman, & Schkade, 1999) then there is good reason to believe the VE preferences are more valid. When respondents can view the landscape from different angles and experience it in a more natural way it reduces the number of potentially wrong assumptions they have to make. The assertion of improved validity is predicated on the assumption that the virtual environment is an accurate portrayal of the scenario. In this choice experiment the scenarios were hypothetical, generic, and the seawall models were based on an existing seawall at nearby Whitianga. For a detailed consent proposal at a specific site, for a seawall different in appearance, WTP would probably be quite different. But that does not change the implication that elicited WTP is probably more accurate with an elicitation format incorporating 3D visualisations. Virtual environments can now be constructed relatively easily

and cheaply using the method described in this paper. They can be presented to respondents in a web survey or on a tablet for in-person surveys. The findings of bias reduction and improved engagement imply that virtual environments should be seriously considered for any non-market valuation study of visible changes to real environments.

6.1.2 VIRTUAL ENVIRONMENTS FOR THE UNEXPERIENCED

Chapter Three presented the results of the choice experiment about development options for an undeveloped beach named New Chums. I discussed how lack of familiarity with the decision context may make preferences less reliable and susceptible to framing effects. The issue of familiarity was particularly relevant to this choice task because just over a third of respondents had heard of the beach and only fifteen percent had visited it. There is reason to believe even non-visitors would have non-zero WTP for conservation of the beach because coastal landscapes are an important part of New Zealand culture. This study was an opportunity to test whether virtual environments could compensate for lack of site experience and help respondents make more consistent choices. The study used a randomised split-sample treatment where half of respondents saw static images and text, while the other half also had the option to see a video tour.

We estimated pooled and separate models for treatment and control groups, visitors and non-visitors. Visitation was associated with higher average WTA, as expected. For New Chums visitors there was no significant difference in the utility functions between treatment and control groups. For non-visitors the models were significantly different and the treatment group had higher scale factor which meant choice error was lower. We simulated willingness-to-avoid (WTA) distributions and found that VE treatment was associated with larger mean WTA for visitors but the difference was not statistically different. For non-visitors, mean WTA was significantly larger for public facilities and houses on the shore. It follows that non-visitors were more strongly influenced by the VE treatment than visitors were. One limitation of this study was the relatively small

sample size of New Chums visitors which made it difficult to achieve statistical significance in all attribute parameters. Nonetheless, the results support the hypothesis that 3D visualisations are a particularly useful tool to describe landscape changes to the inexperienced respondent.

6.1.3 Stability of willingness-to-pay for coastal management

Chapter Four presented an analysis of preference stability across the different waves of the survey, with a model estimated in WTP-space rather than the traditional preference-space. This simplified the comparison of WTP across time because the parameters are scale-neutral. Similar to other findings in the literature, we found evidence to reject joint equality of parameters at different points in time. The relative importance of each attribute remained constant, with WTA for headland development being larger than WTP for seawalls or dune restoration. However, mean WTP/WTA variance was as high as 85 percent for some comparisons.

A novel feature of this study was the use of two retests which allowed the examination of three points in time rather than the usual two in the literature. I discussed the theories of constructed versus discovered preferences and the implications for unfamiliar or complex decision-making. The discovered preference view implies that reliability should improve with repetition as people learn about their preferences and receive feedback on their decisions. This study found that stability did not improve between the second and third waves compared with the first and second waves. This could be because respondents did not receive feedback about the consequences of their decisions. The results are also consistent with the constructed preference view that preferences for the unfamiliar are transient - constructed to suit the task at hand and then forgotten.

I investigated potential explanatory factors for choice consistency and found the virtual environment treatment was positively associated with stability but the effect was statistically insignificant when a variable for stated certainty was also included. Higher education was also associated with more stable choices. I

estimated separate models for people who answered “definitely” or “probably” to the certainty question and found the preference structure was sufficiently similar across waves. WTP/WTA means were statistically similar across different waves for this group, although variance was higher in wave two. This result implies that if the goal is reliable estimates of WTP, then researchers need to ensure respondents are confident about their choices. Lack of confidence could signal a lack of understanding of the issues or incomplete processing of the information.

6.1.4 Attribute-based agglomeration and competition in beach recreation site choice

Chapter Five reports the results of a destination choice analysis of recreational visitors to beaches on the Coromandel Peninsula. A typical approach in the literature is to use random utility models to analyse disaggregate choices. Literature about cumulative attraction and hierarchical processing both imply that the spatial distribution of alternatives will affect site choice. The research question was how to capture these complex substitution patterns in a computationally feasible random utility model.

I reviewed the modelling options to account for the spatial errors caused by cumulative attraction or other spatial effects. These include multinomial probit, hierarchical processing or generalised extreme value (GEV), mixed logit, and Competing Destinations (CD) type models. With 109 different sites, 14 attributes and almost 4,000 observations it was impractical to use multinomial probit or a mixed logit with random parameters for each attribute or every site pair. An extension of the CD model with separate variables for complements and substitutes (Agglomerating and Competing Destination Choice) was a more feasible option.

Multiple-beach-destination trips are common amongst Coromandel visitors, rather than an inconvenient minority to be ignored as in other studies. I discussed the relevance of the theory of cumulative attraction and calculated

compatibility ratings between each pair of beaches. A logistic regression for compatibility showed that highly compatible sites tend to be close, on the same route, or within the same area. If beaches are different in terms of some attributes (developed versus undeveloped, natural dune versus no dune, sandy versus pebble or shingle, ocean versus estuary) they tend to have higher compatibility.

I estimated and compared GEV, CD and ACDC models using the beach visitation data. The GEV model that provided the best fit in terms of AIC and BIC was a cross-nested logit (CNL) with nests defined by attribute availability.

In every model, the seawall dummy variable was negative and significant which implies that people prefer not to visit beaches with seawalls, all else being equal. This is in contrast to the stated preference results in earlier chapters in which a large proportion of people apparently had positive WTP for seawall erosion protection. This may reflect a preference by some of the population to preserve the status quo and existing shoreline, even if it reduces amenity value.

The preferred model as identified by AIC and BIC measures was an ACDC model with complement and substitute accessibility measures for every attribute ("ACDC2"). Previous studies using ACDC models only had a single dissimilarity measure to determine complements and substitutes. The significantly improved fit from adding multiple accessibility measures in this study implies that substitution patterns are more complex than can be capture by a single dissimilarity measure.

The response properties of the different models were compared for two different scenarios. The first scenario involved the closure of a campground at Hahei, and the second was the construction of a sea wall at Tairua ocean beach. Only the preferred model ACDC2 captured both the effects of reduced accessibility to these attributes for nearby sites, and the intuitively likely increase in visitors for other sites that still have a campground (scenario one) or natural dune (scenario two).

The preferred model is more attractive for policy analysis than alternative models because it captures the complex spatial interaction effects of changes to specific beach attributes. This recognition of the importance of complementary differences between sites is apparently rare in a literature that appears to be more focussed on unobserved similarities.

6.2 WHERE THE FIELD IS NOW

The validity and reliability of environmental valuation is currently a topic of considerable interest in the literature. In perhaps the most systematic review to date, Rakotonarivo, Schaafsma, and Hockley (2016) summarise the results of 107 environmental discrete choice experiments (DCEs) from 2003 to 2016. These studies all tested one or more aspects of validity and reliability of results. Rakotonarivo et al.(2016) report that large proportions of choices were inconsistent with utility axioms. In many studies a large proportion of respondents found the tasks confusing, inconsequential, and were easily swayed by "modest" changes to survey designs. However, the authors also note that stated preference methods are still the only valuation method available in many environmental contexts, and they expects DCEs will continue to be used.

Within-sample retests after time delay are one way to assess the reliability of preferences. Environmental DCE retests have become more popular in recent years. Publications in this area appear sparse or even non-existent prior to 2012 but there are several recent examples not including this study (Bliem, Getzner, & Rodiga-Laßnig, 2012; Czajkowski, Barczak, Budziński, Giergiczny, & Hanley, 2016; Liebe, Meyerhoff, & Hartje, 2012; Lienhoop & Volker, 2016; Schaafsma, Brouwer, Liekens, & De Nocker, 2014). Some researchers are investigating the benefits of deliberation in choice experiments (Lienhoop & Volker, 2016) and suggest it could facilitate preference discovery. In another study, Sandorf, Aanesen, and Navrud (2016) compare the reliability of a DCE conducted in workshops versus internet survey. They investigate the use of video to replace face-to-face presentations from the workshop. They report significantly more internet

respondents viewed the survey as inconsequential and recommend internet surveys should be made “more engaging”.

The psychology of decision-making is a hot topic within stated preference methods and has also received recent attention in revealed preference literature. Masatlioglu, Nakajima, and Ozbay (2016) investigate the issue of limited attention in real-world choices and how both attention and preference can be deduced from observed behaviour. Another area of ongoing methodological research is combining stated and revealed preferences (Bigerna, Bollino, Micheli, & Polinori, 2017; Grisolía & Willis, 2016; Qiao, Huang, Yang, Zhang, & Chen, 2016; Whitehead & Lew, 2016).

The importance of spatial distribution in non-market values is receiving more attention in recent literature. Johnston, Besedin, and Stapler (2016) report that stated WTP values for water quality are sensitive to geospatial factors including scale, market extent and availability of substitutes and complements. Research into modelling spatial effects in revealed preference studies also continues. Data availability is improving and some researchers are using real-time GPS data to gain new insights (Huang & Levinson, 2016). Bhat, Dubey, Alam and Khushefati (2015) apply maximum approximate composite marginal likelihood (MACML) techniques to the estimation of a multiple discrete-continuous probit land use model. Advances in computer processing power and improving the accessibility of simulation methods such as MACML may increase the popularity of multinomial probit models in the future. These models could be expanded to include attribute-based interaction effects similar to how I included multiple attribute accessibility measures in an ACDC model in Chapter 5.

6.3 FUTURE RESEARCH

Validity and reliability are still important avenues for future research. In this thesis I investigated whether 3D visualisation could reduce left-right bias, an aspect of theoretical validity (Day et al., 2012). Reliability was also analysed in terms of within-survey choice consistency and between-survey stability. What

was not carried out, however, were tests for external validity or content validity. Tests of external validity require a criterion measure, which is considered to be true. It can be difficult to find criterion measures for environmental valuation but one could compare stated preferences for a recreational site versus actual visitation behaviour, or hypothetical willingness to pay a donation versus actual donations. Future research could investigate whether virtual environments can improve external validity, by comparing stated choices with actual destinations visited.

Content validity can be measured by protest attitudes, comprehension, and perceptions of consequentiality. Other studies have shown that 3D visualisations can improve respondent comprehension (Bateman, Day, Jones, & Jude, 2009; Fiore, Harrison, Hughes, & Rutström, 2009). Perceived consequentiality is also important because without it, respondents have no incentive to respond accurately or carefully (Vossler, Doyon, & Rondeau, 2012). Consequences are also important to preference discovery. Preferences are more accurately revealed when subjects learn from the consequences of their decisions, and believe those consequences to be real (Braga & Starmer, 2005). Deliberation has been suggested as one way to provide feedback about choices (Lienhoop & Volker, 2016). Another option is to give respondents feedback analogous to that provided by repeated markets (Sugden, 2005). Virtual environments could be useful for this purpose, to show the chosen alternative in greater detail and make it seem more real. Payment mechanisms could also be made to seem more real by presenting a personalised rates bill showing the associated public cost.

The virtual environments used in this thesis were relatively simple and low resolution to minimise internet bandwidth use. The realism of virtual environments is limited only by how much time and effort the researcher is willing to put in. The software (Sketchup) used in this study has the capability to include sound and simple animations such as moving water or day/night cycles. Future research could also investigate the use of interactive virtual realities in which allow users to freely move around the model rather than following a fixed

path. Virtual reality headsets could also be used in a lab setting. More research is required to confirm whether more realistic or interactive virtual environments outperform simple ones, and whether they have a systematic effect on perceived consequentiality.

6.4 References

Bateman, I. J., Day, B. H., Jones, A. P., & Jude, S. (2009). Reducing gain–loss asymmetry: a virtual reality choice experiment valuing land use change. *Journal of Environmental Economics and Management*, *58*(1), 106–118.

Bhat, C. R., Dubey, S. K., Alam, M. J. B., & Khushefati, W. H. (2015). A New Spatial Multiple Discrete-Continuous Modeling Approach to Land Use Change Analysis. *Journal of Regional Science*, *55*(5), 801–841.

Bigerna, S., Bollino, C. A., Micheli, S., & Polinori, P. (2017). Revealed and stated preferences for CO2 emissions reduction: The missing link. *Renewable and Sustainable Energy Reviews*, *68*, *Part 2*, 1213–1221. http://doi.org/10.1016/j.rser.2016.02.020

Bliem, M., Getzner, M., & Rodiga-Laßnig, P. (2012). Temporal stability of individual preferences for river restoration in Austria using a choice experiment. *Journal of Environmental Management*, *103*, 65–73.

Braga, J., & Starmer, C. (2005). Preference anomalies, preference elicitation and the discovered preference hypothesis. *Environmental and Resource Economics*, *32*(1), 55–89.

Collins, D., & Kearns, R. (2010). "It's a gestalt experience": Landscape values and development pressure in Hawke's Bay, New Zealand. *Geoforum*, *41*(3), 435–446. http://doi.org/10.1016/j.geoforum.2009.11.010

Czajkowski, M., Barczak, A., Budziński, W., Giergiczny, M., & Hanley, N. (2016). Preference and WTP stability for public forest management. *Integrating Ecosystem Service Concepts into Valuation and Management Decisions*, *71*, 11–22. http://doi.org/10.1016/j.forpol.2016.06.027

Day, B., Bateman, I. J., Carson, R. T., Dupont, D., Louviere, J. J., Morimoto, S., … Wang, P. (2012). Ordering effects and choice set awareness in repeat-

response stated preference studies. *Journal of Environmental Economics and Management*, *63*(1), 73–91. http://doi.org/10.1016/j.jeem.2011.09.001

Fiore, S. M., Harrison, G. W., Hughes, C. E., & Rutström, E. E. (2009). Virtual experiments and environmental policy. *Frontiers of Environmental and Resource Economics*, *57*(1), 65–86. http://doi.org/10.1016/j.jeem.2008.08.002

Grisolía, J. M., & Willis, K. G. (2016). Consumer choice of theatrical productions: a combined revealed preference–stated preference approach. *Empirical Economics*, *50*(3), 933–957. http://doi.org/10.1007/s00181-015-0948-5

Huang, A., & Levinson, D. (2016). A model of two-destination choice in trip chains with GPS data. *Journal of Choice Modelling*. http://doi.org/10.1016/j.jocm.2016.04.002

Johnston, R. J., Besedin, E. Y., & Stapler, R. (2016). Enhanced geospatial validity for meta-analysis and environmental benefit transfer: an application to water quality improvements. *Environmental and Resource Economics*, 1–33.

Liebe, U., Meyerhoff, J., & Hartje, V. (2012). Test-Retest Reliability of Choice Experiments in Environmental Valuation. *Environmental and Resource Economics*, *53*(3), 389. http://doi.org/10.1007/s10640-012-9567-1

Lienhoop, N., & Volker, M. (2016). Preference Refinement in Deliberative Choice Experiments for Ecosystem Service Valuation. *Land Economics*, *92*(3), 555–577. http://doi.org/10.3368/le.92.3.555

Masatlioglu, Y., Nakajima, D., & Ozbay, E. Y. (2016). Revealed Attention. In S. Ikeda, H. K. Kato, F. Ohtake, & Y. Tsutsui (Eds.), *Behavioral Economics of Preferences, Choices, and Happiness* (pp. 495–522). Tokyo: Springer Japan. Retrieved from http://dx.doi.org/10.1007/978-4-431-55402-8_19

Payne, J. W., Bettman, J. R., & Schkade, D. A. (1999). Measuring Constructed Preferences: Towards a Building Code. *Journal of Risk and Uncertainty*, *19*(1), 243–270. http://doi.org/10.1023/A:1007843931054

Qiao, Y., Huang, Y., Yang, F., Zhang, M., & Chen, L. (2016). Empirical study of travel mode forecasting improvement for the combined revealed preference/stated preference data–based discrete choice model. *Advances in Mechanical Engineering*, *8*(1), 1687814015624836.

Rakotonarivo, O. S., Schaafsma, M., & Hockley, N. (2016). A systematic review of the reliability and validity of discrete choice experiments in valuing non-market environmental goods. *Journal of Environmental Management*, *183*, *Part 1*, 98–109. http://doi.org/10.1016/j.jenvman.2016.08.032

Sandorf, E. D., Aanesen, M., & Navrud, S. (2016). Valuing unfamiliar and complex environmental goods: A comparison of valuation workshops and internet panel surveys with videos. *Ecological Economics*, *129*, 50–61. http://doi.org/10.1016/j.ecolecon.2016.06.008

Schaafsma, M., Brouwer, R., Liekens, I., & De Nocker, L. (2014). Temporal stability of preferences and willingness to pay for natural areas in choice experiments: A test–retest. *Resource and Energy Economics*, *38*, 243–260.

Sugden, R. (2005). Anomalies and Stated Preference Techniques: A Framework for a Discussion of Coping Strategies. *Environmental and Resource Economics*, *32*(1), 1–12. http://doi.org/10.1007/s10640-005-6025-3

Vossler, C. A., Doyon, M., & Rondeau, D. (2012). Truth in consequentiality: theory and field evidence on discrete choice experiments. *American Economic Journal: Microeconomics*, *4*(4), 145–171.

Whitehead, J. C., & Lew, D. K. (2016). *Estimating Recreation Benefits through Joint Estimation of Revealed and Stated Preference Discrete Choice Data*.

7. APPENDIX A: SURVEY

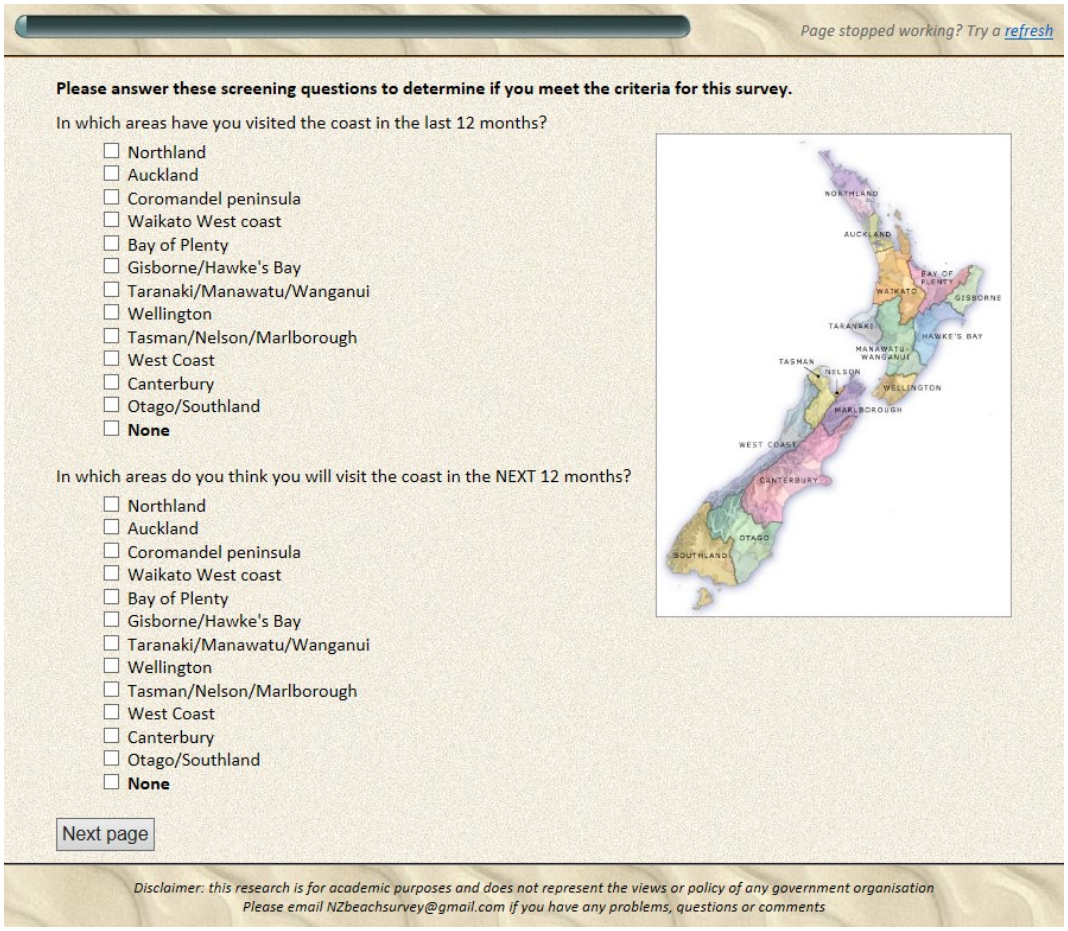


Figure 7-1 - Screening question for first survey

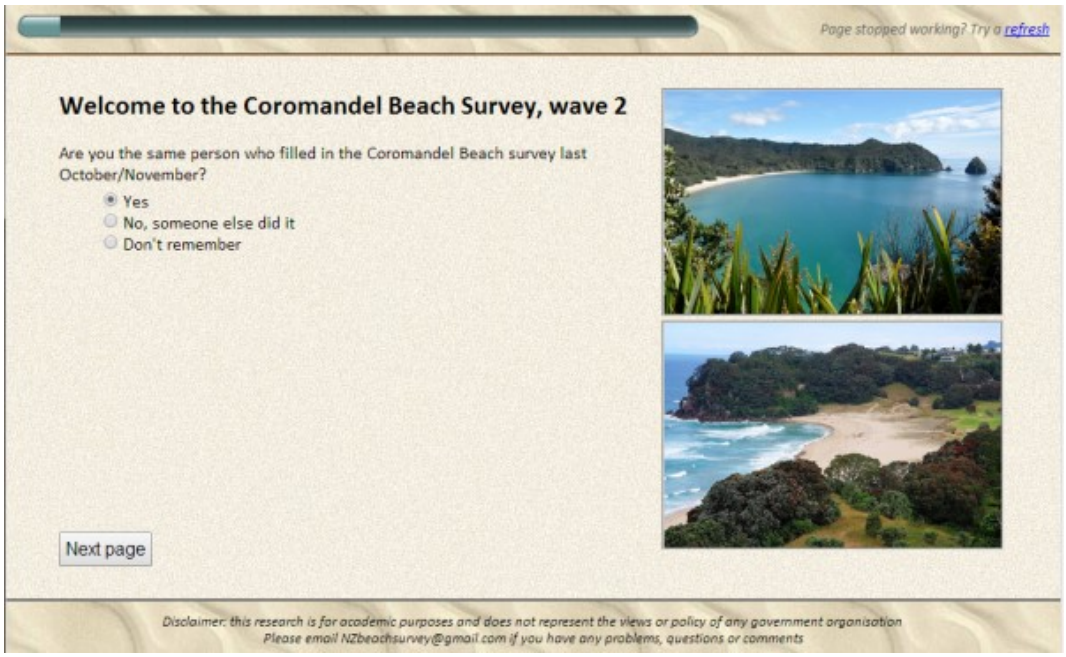


Figure 7-2 - First page for subsequent waves

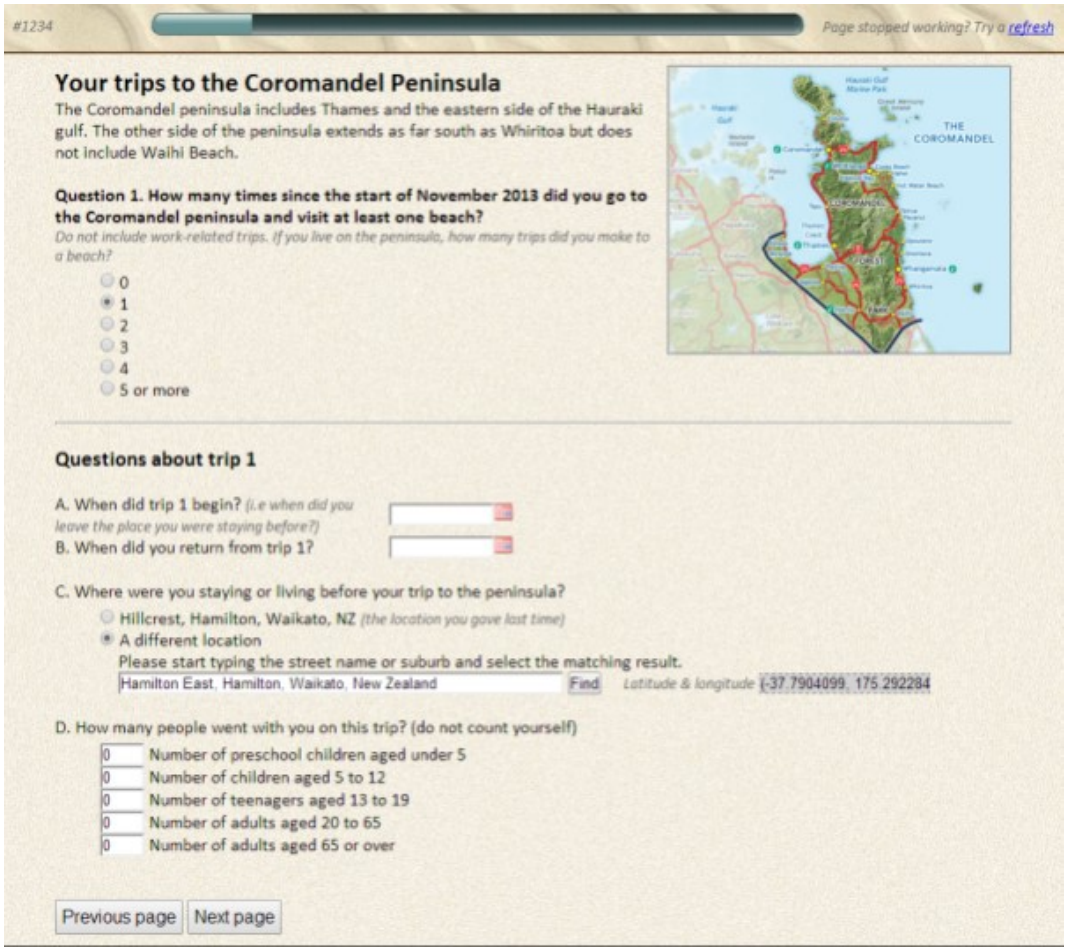


Figure 7-3 - Trip details

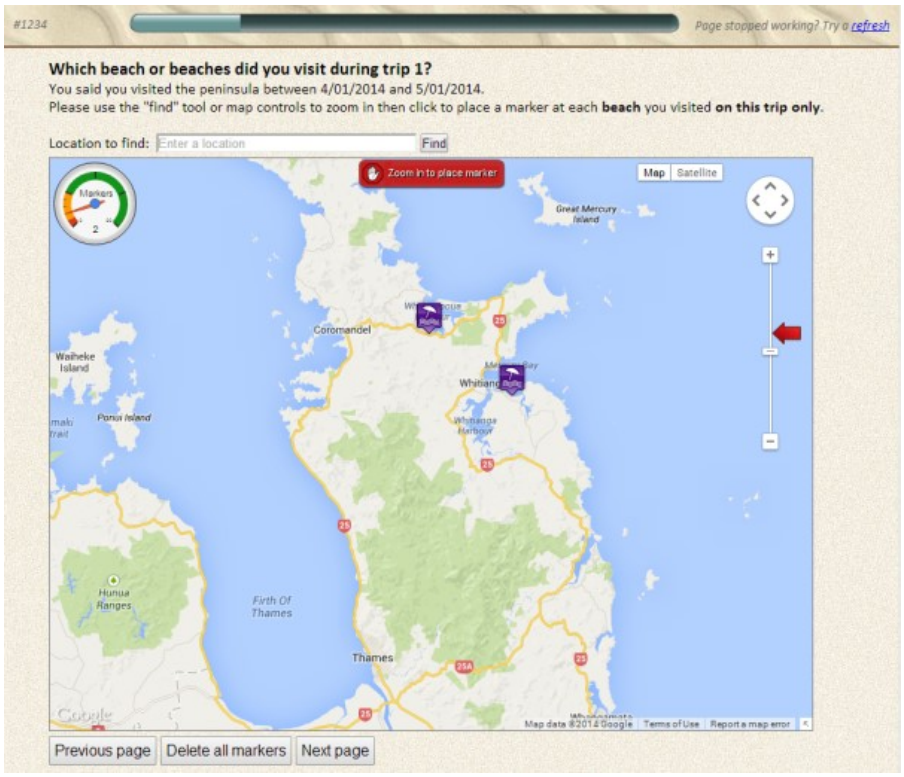


Figure 7-4 - Beach visit details repeated for each trip

When a marker is placed there is a pop-up window asking about activities.

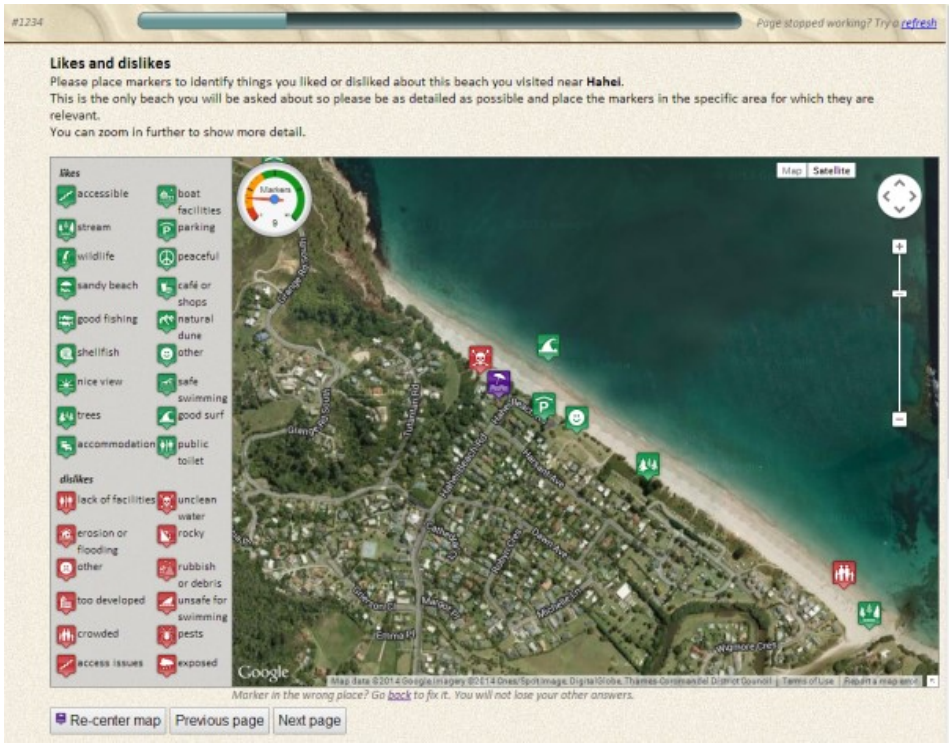


Figure 7-5 - Likes and dislikes repeated for each beach visited

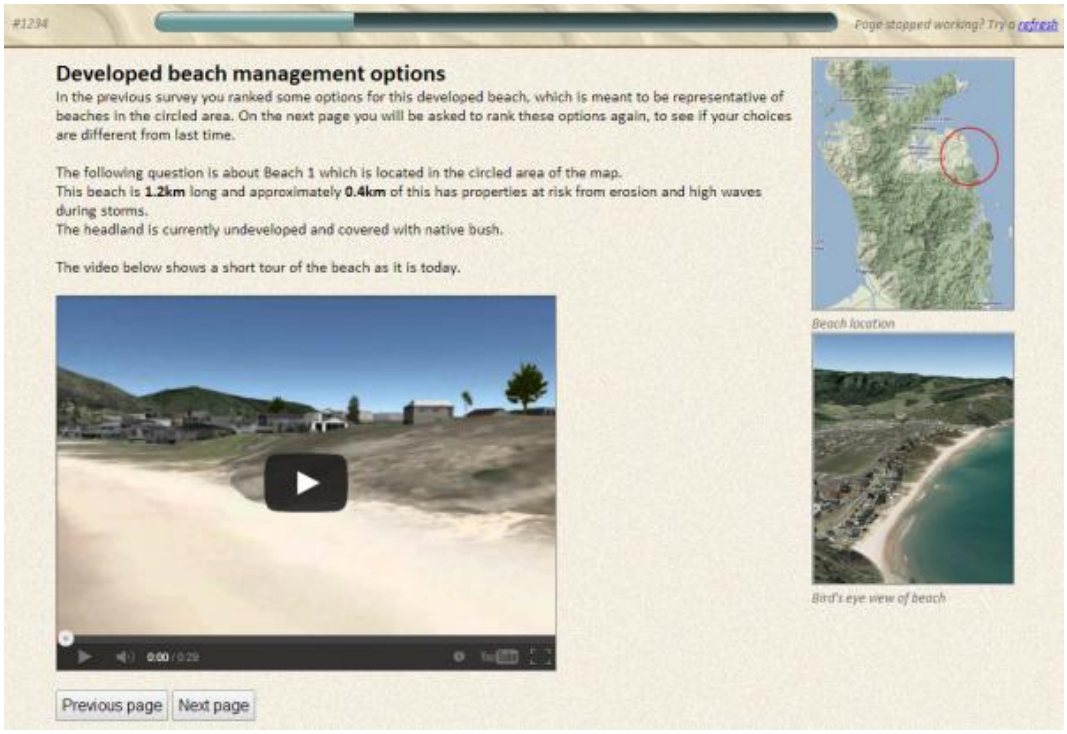


Figure 7-6 - Developed beach choice experiment introduction

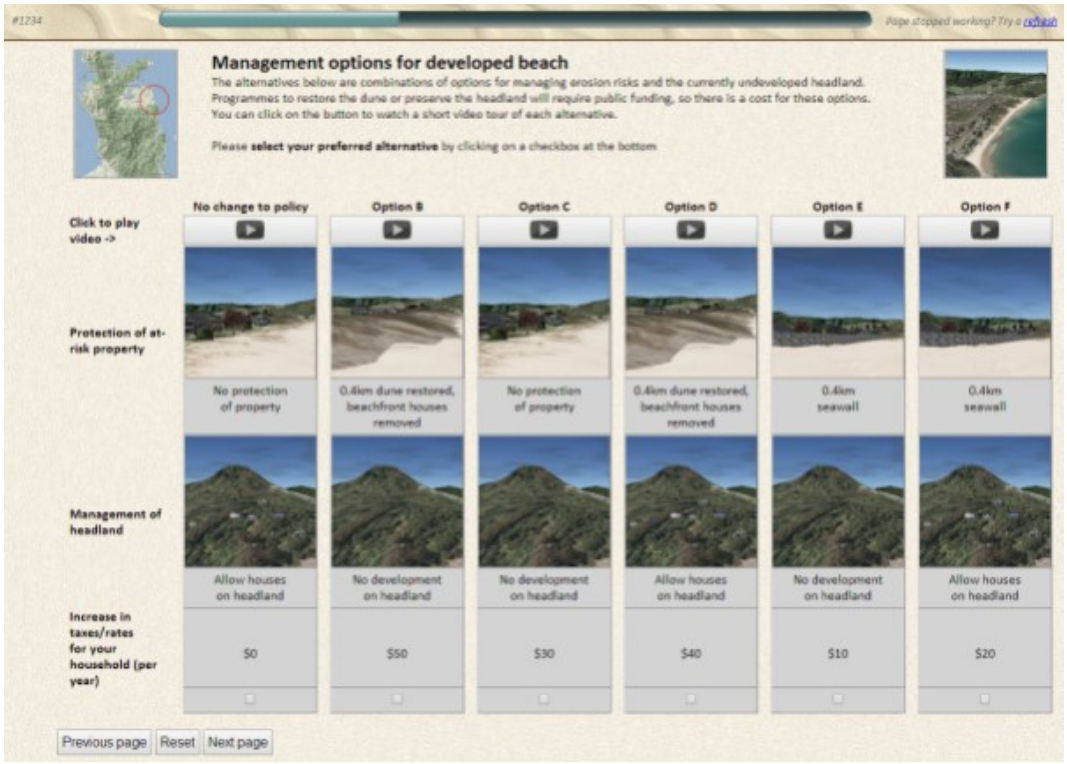


Figure 7-7 - Developed beach choice card

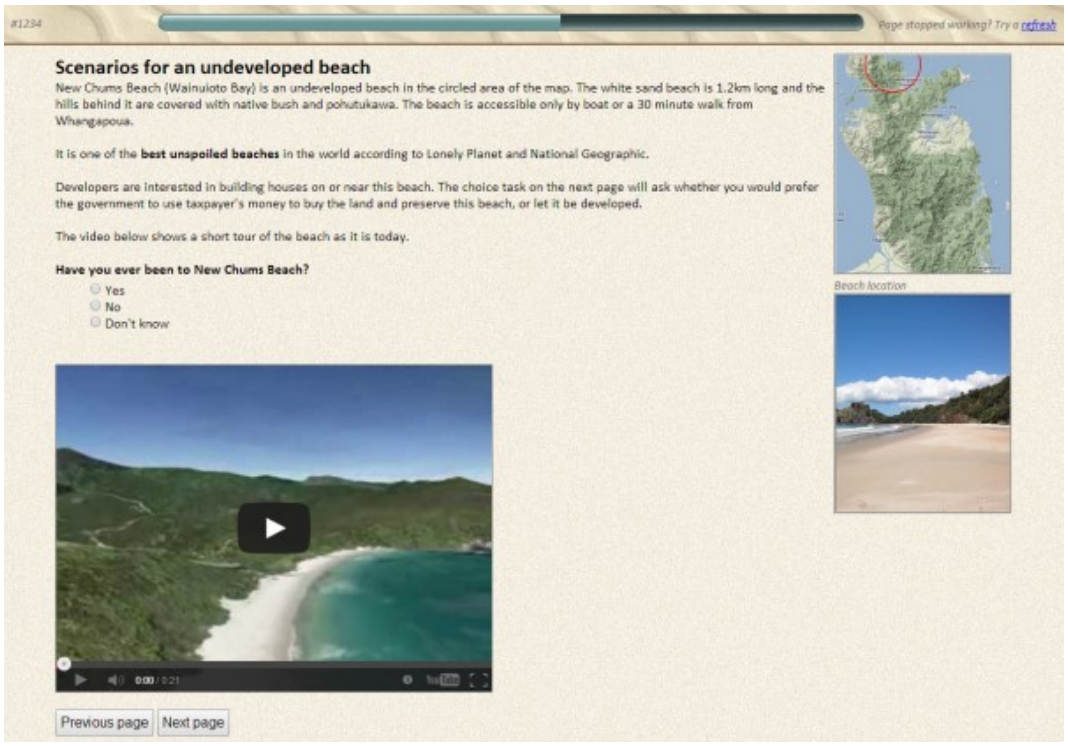


Figure 7-8 - Undeveloped beach choice experiment introduction (wave 3 only)

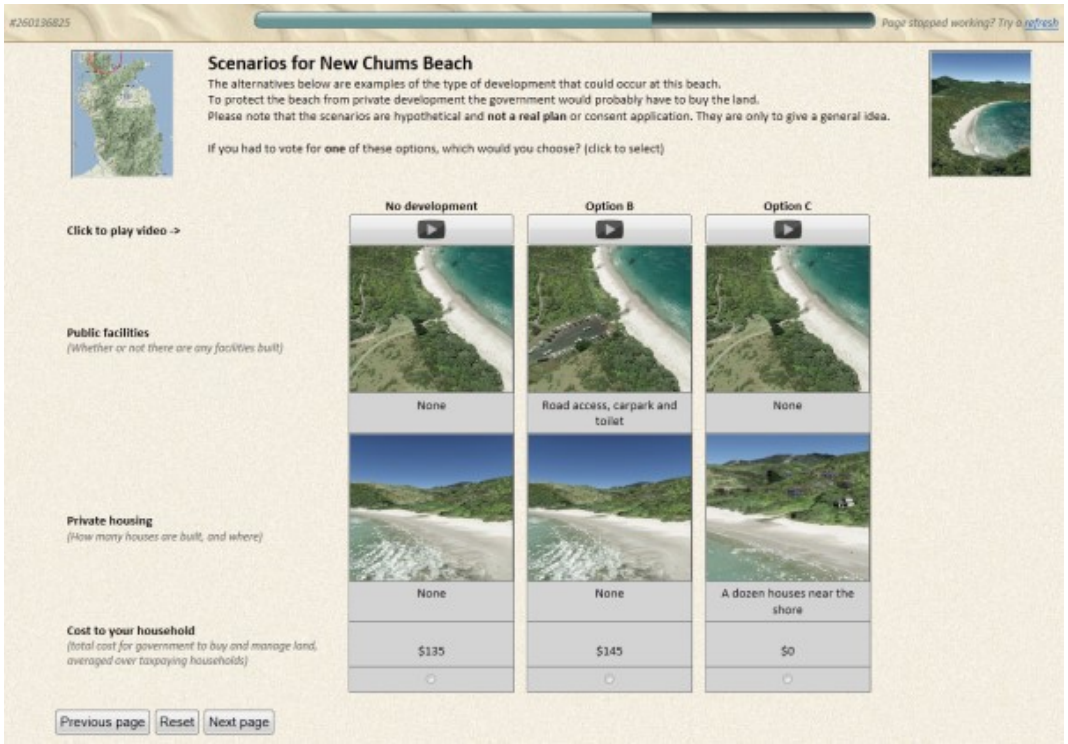


Figure 7-9 - Undeveloped beach choice card (wave 3 only)

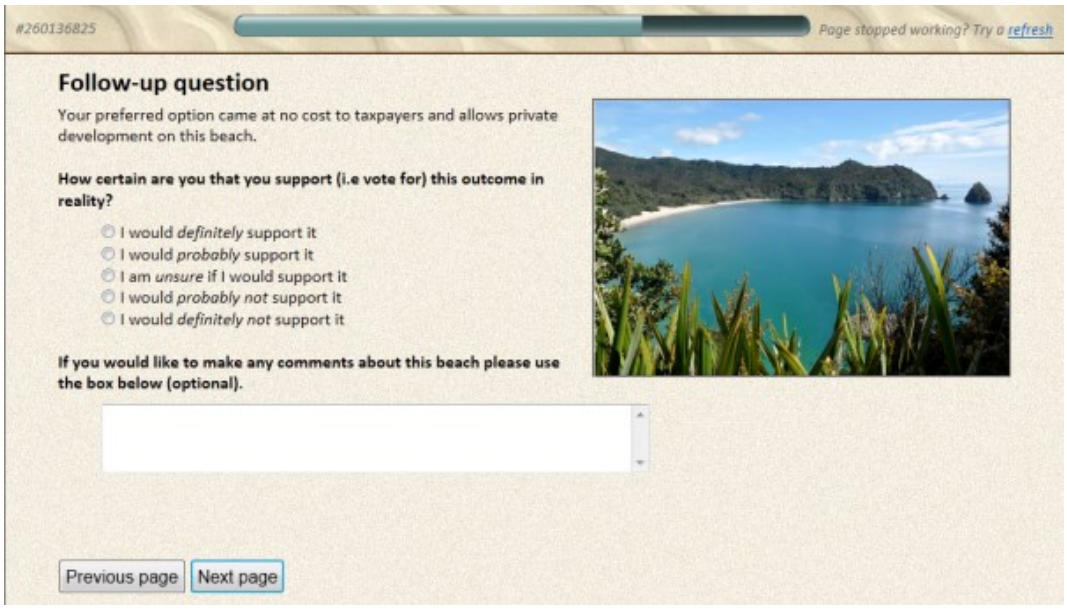


Figure 7-10 - Choice experiment follow-up question

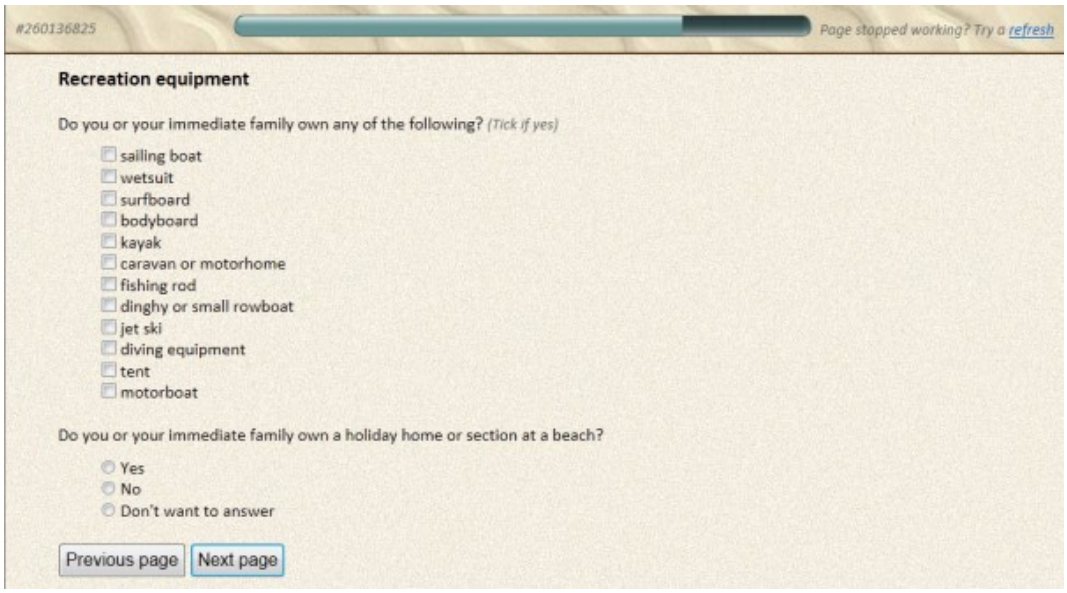


Figure 7-11 - Recreation equipment

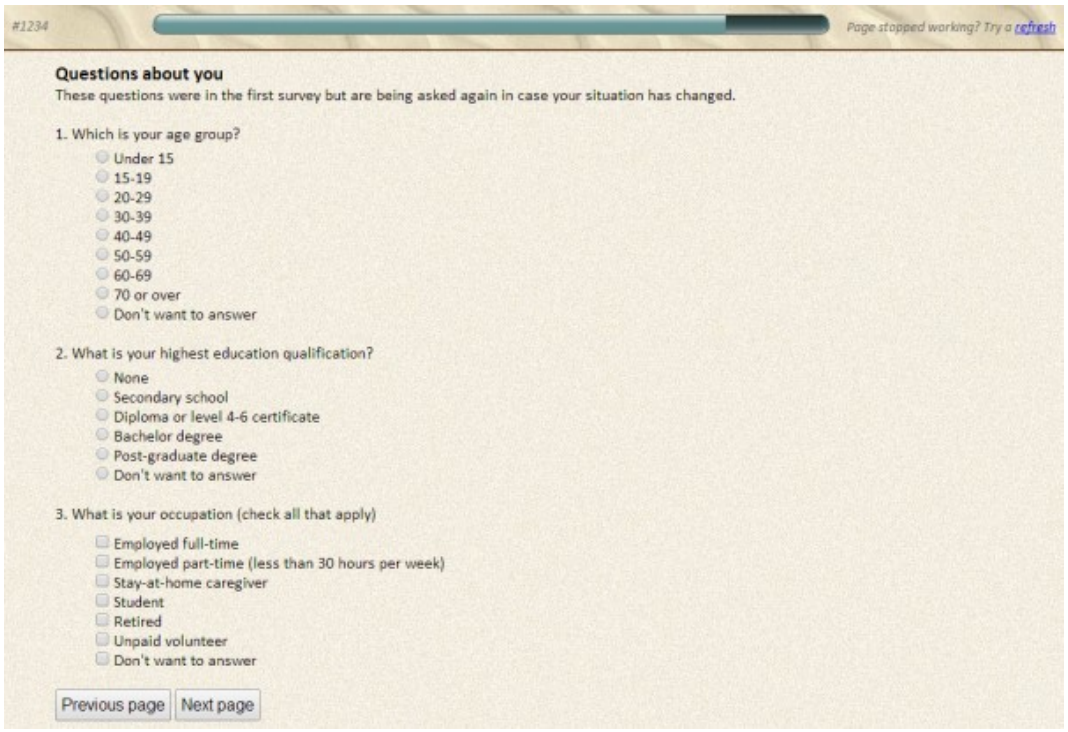


Figure 7-12 – Individual and household questions

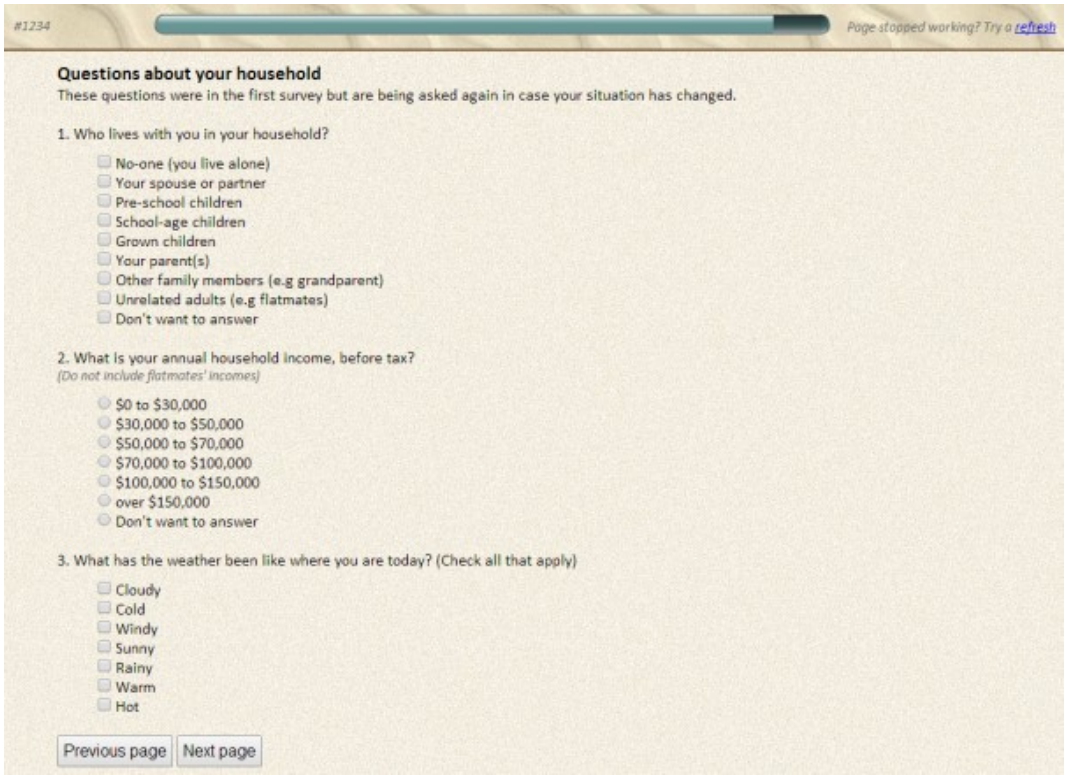


Figure 7-13 – Individual and household questions (cont.)

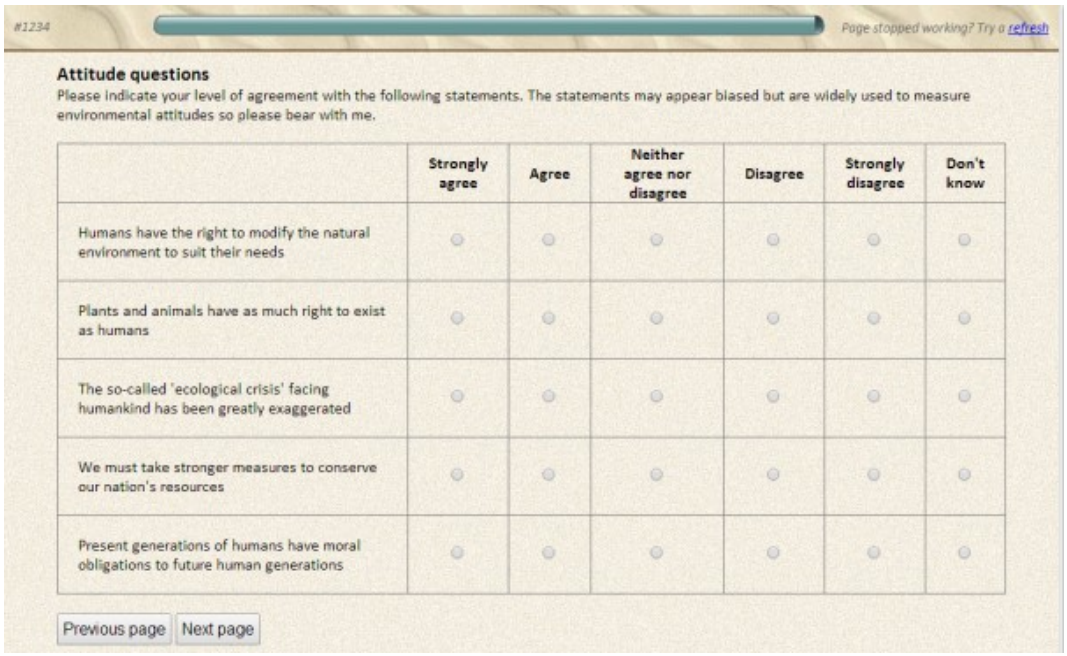


Figure 7-14 – Attitudinal questions

8. APPENDIX B: SURVEY RESULTS

8.1 RECRUITMENT RESULTS

The recruitment campaigns were run in parallel during October 2013. Table 8-2 shows the number of impressions (number of times the advertisements appeared on a screen), number of clicks on the survey link, number of people who started the survey, number who passed the screening question, and the number who completed the survey. For the online panel the number of email invitations sent is reported instead of page impressions

Table 8-1 - Impressions, clicks and completed surveys by recruitment type

	Impressions / emails	Clicks	Started	Passed screen	Completed
Adwords - prize draw no odds	865852	786	673	430	151
Adwords - prize draw 1/500	729472	735	595	423	127
Adwords - prize draw 1/200	614190	672	605	425	136
Adwords - $5 voucher	542722	546	511	352	88
Adwords total	**2752238**	**2739**	**2384**	**1630**	**502**
Facebook	419054	2147	1041	625	244
Online panel	20978	2493	2441	1164	784
Grand Total		**7379**	**5866**	**3419**	**1530**

There were 2.75 million page impressions for the Adwords advertisements and only 2,739 clicks by unique individuals. Table 8-2 shows this corresponds with a click-through rate (CTR) of 0.1 per cent. Such a low CTR is not an unusual result. Similar to survey response rates, click-through rates have declined over time (Zorn, Olaru, Veheim, Zhao, & Murphy, 2012). Zorn et al. report a worldwide average of 0.09 percent. CTR is largely driven by advertisement relevance and advertising that is highly targeted to users' searches can achieve CTRs of 10 per cent of more (Haans, Raassens, & van Hout, 2013). Few people browse the internet looking for surveys to fill in so it would be unrealistic to expect a high click rate for this study.

The Facebook advertisements achieved a CTR more than five times as high, perhaps because people browsing Facebook were less task-focussed and more open to diversion. The CTR of 0.51% is similar to the 0.48% reported by Samuels & Zucco (2012) for survey promotion on Facebook. Samuels also reports trialling an Adwords campaign but found it was not cost effective enough to continue.

The click rate for email invitations sent to the panel was a lot higher at almost 12%, probably because receiving an email is more difficult to ignore than an ad on a web page.

The vast majority of respondents who clicked on the survey link started the survey (by answering the screening question). The exception is the Facebook sample with a start rate of only 48%. They had an unavoidable intermediate step because the reported "click" only took them to the sponsored post. They had to click a second time to get to the survey web page. The start rate for the $5 voucher ad (94 per cent) was significantly higher than for the prize draw with 1/500 odds (81 per cent)

The proportion of people who passed the screening question (they had to have visited the Coromandel Peninsula in the past 12 months) was around 60-70 per cent for the online advertisements. The pass rate was significantly lower (48 per cent) for the online panel, reflecting the fact that they were not told the topic of the survey in the invitation email.

The online panel had a much higher completion rate (67 per cent) than the self-selected samples. The Facebook sample had the next highest completion rate at 39 per cent. Completion rates for the Adwords samples varied from 25 per cent for the voucher advertisement to 35 per cent for the no-odds prize draw. An ANOVA F-test statistic is not significant for the four Adwords samples so the differences are not statistically significant. The difference between the Adwords and Facebook sample completion rates is significant at 5 per cent ($p = 0.037$).

Table 8-2 – Click, start, pass and complete rates by recruitment type

	Click rate	Start rate	Pass rate	Complete rate
Adwords - prize draw no odds	0.09%	86%	64%	35%
Adwords - prize draw 1/500	0.10%	81%	71%	30%
Adwords - prize draw 1/200	0.11%	90%	70%	32%
Adwords - $5 voucher	0.10%	94%	69%	25%
Adwords total	0.10%	87%	68%	31%
Facebook	0.51%	48%	60%	39%
Online panel	11.88%	98%	48%	67%
Grand Total	N/A	79%	58%	45%

Table 8-3 presents the demographic composition of each sub-sample. The Adwords sub-samples had fewer Waikato residents, fewer women, more full-time employees, more school-age children and the oldest average age (42 years). The Facebook sample had very few Bay of Plenty residents, more women, less post-school education, fewer full-time employees, no volunteer workers, more preschool children and a much younger average age of 28 years. The online panel had fewer people from other regions because samples were selected from a database of Auckland, Waikato and Bay of Plenty residents.

The online panel had fewer people whose family own a bach or holiday home on the Coromandel Peninsula. The self-selected samples appear to be biased in favour of people with a vested interest (property) in the Peninsula. There are approximately 15,000 intermittently occupied dwellings in Thames-Coromandel district[44] and visitor nights at these dwellings could make up between 20-40 per cent of all visitor nights on the Peninsula.

[44] Based on the difference between the number of rateable residential properties and number of dwellings occupied on Census night March 5, 2013

Table 8-3 - Descriptive statistics by recruitment type

	Adwords prize no odds	Adwords prize 1/500	Adwords prize 1/200	Adwords $5 voucher	Adwords Total	Face book	Panel
Waikato region	25%	24%	19%	21%	23%	43%	36%
Auckland region	46%	48%	49%	51%	48%	39%	38%
Bay of Plenty	15%	12%	17%	18%	15%	2%	22%
Other region	14%	16%	15%	10%	14%	16%	3%
Female	45%	48%	46%	37%	44%	76%	65%
Post-school	65%	57%	65%	65%	63%	54%	63%
Employed full time	75%	66%	67%	82%	73%	30%	46%
Volunteer	5%	4%	3%	4%	4%	0%	4%
School children	40%	30%	35%	43%	37%	24%	22%
Preschool children	5%	11%	8%	7%	8%	24%	18%
Holiday home	30%	25%	33%	34%	30%	31%	19%
Age	48	43	37	38	42	28	38
Count	151	127	88	136	502	244	784

The following table presents the proportion of non-qualifying individuals, average free-text characters provided and the proportion who indicated they were uncertain about their choices. The Adwords sample had relatively fewer non-qualifiers and provided longer answers on average. The Facebook sample had lower uncertainty.

Table 8-4 - Data quality measures by recruitment type

Sample source	Non-qualifiers	Free text	Stated Uncertainty
Adwords prize no odds	0.280	137	0.150
Adwords prize 1/500	0.333	164	0.190
Adwords prize 1/200	0.222	142	0.167
Adwords $5 Voucher	0.286	144	0.179
Adwords Total	0.285	146	0.171
Facebook	0.364	128	0.152
Panel	0.341	96	0.238
Grand Total	0.332	106	0.223

8.2 DESCRIPTIVE STATISTICS

Table 8-5 shows basic demographic statistics for the sample in each wave. Survey respondents were skewed towards female (59 per cent) but since the unit of analysis is the household rather than the individual this is not an issue. Respondents tend to be more highly educated, more likely to have children and less likely to have low incomes than the general population of Auckland, Waikato and Bay of Plenty regions. However, visitors to Coromandel beaches do not necessarily have the same demographics as the general population so we cannot draw any conclusions about representativeness.

Table 8-5 - Sample descriptive statistics

	Wave 1	Wave 2	Wave 3	Population[45]
Count of respondents	1059	551	429	2,113,110
Average of measure:				
Age (in years)	43	44	44	45[46]
Post-school education	0.46	0.49	0.51	0.40
Female	0.59	0.63	0.63	0.51
Preschool children in household	0.17	0.16	0.17	N/A
Any children in household	0.39	0.40	0.39	0.36
Annual household income < $50k	0.30	0.32	0.31	0.37
Annual household income > $100k	0.30	0.29	0.27	0.31
Number of trips prev year	2.36	2.57	2.29	N/A
TCDC Resident	0.06	0.04	0.02	0.01
Waikato Resident	0.38	0.37	0.37	0.19
Auckland Resident	0.38	0.40	0.41	0.67

8.3 DEFINITION OF SITES

A "beach" site is defined as a named bay, harbour or a stretch of coast associated with a settlement. Some larger beaches such as Whangamata are divided into north, south and ocean or estuary/harbour sites. There are 127 sites in total. Islands are excluded due to the difficulty in estimating travel cost and relatively small number of visitors. Figure 8-1 shows the location and geographic extent of beach sites used in this study. There are too many to label but larger maps in the results section have labels. The different colours are simply to show the demarcation of distinct sites and have no other meaning.

[45] 2013 Census figures for Waikato, Auckland and Bay of Plenty Regions.

[46] Excludes children under 15 because they were not eligible to do the survey

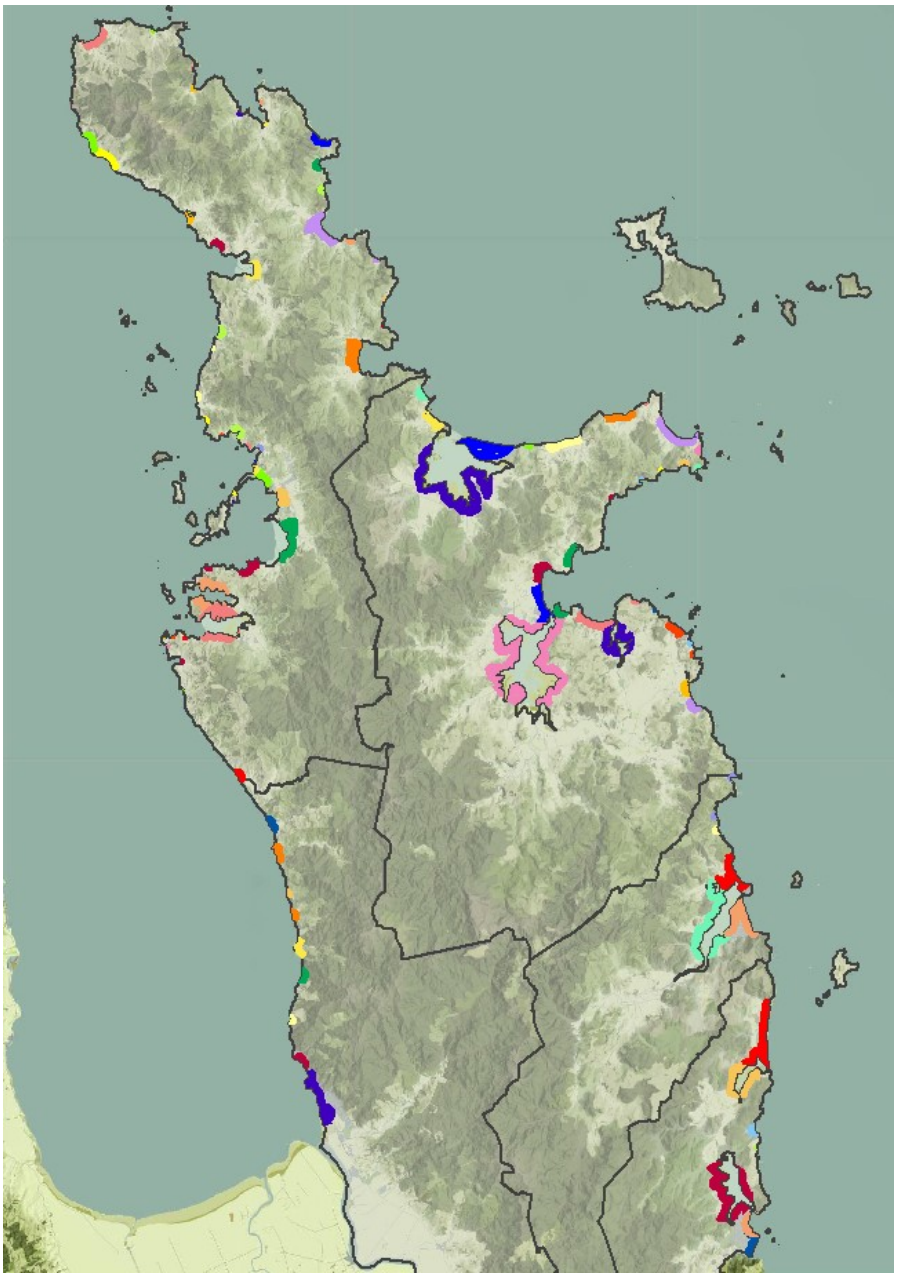


Figure 8-1 – Map of beach sites

8.4 BEACH VISITS

Survey respondents reported a total of 3972 beach visits to the Coromandel Peninsula over the survey period. Figure 8-2 is a heat map which shows the spatial distribution of beach visits by survey participants. Each data point in the same area changes the colour one shade towards red, so tThe red areas indicate hot spots where visits were most highly concentrated. It shows that beach visits are distributed right around the Peninsula, even on the remote northern coast

where some areas are accessible only by boat. However, the largest hot spots are around the urban areas of Whangamata, Tairua and Mercury Bay.

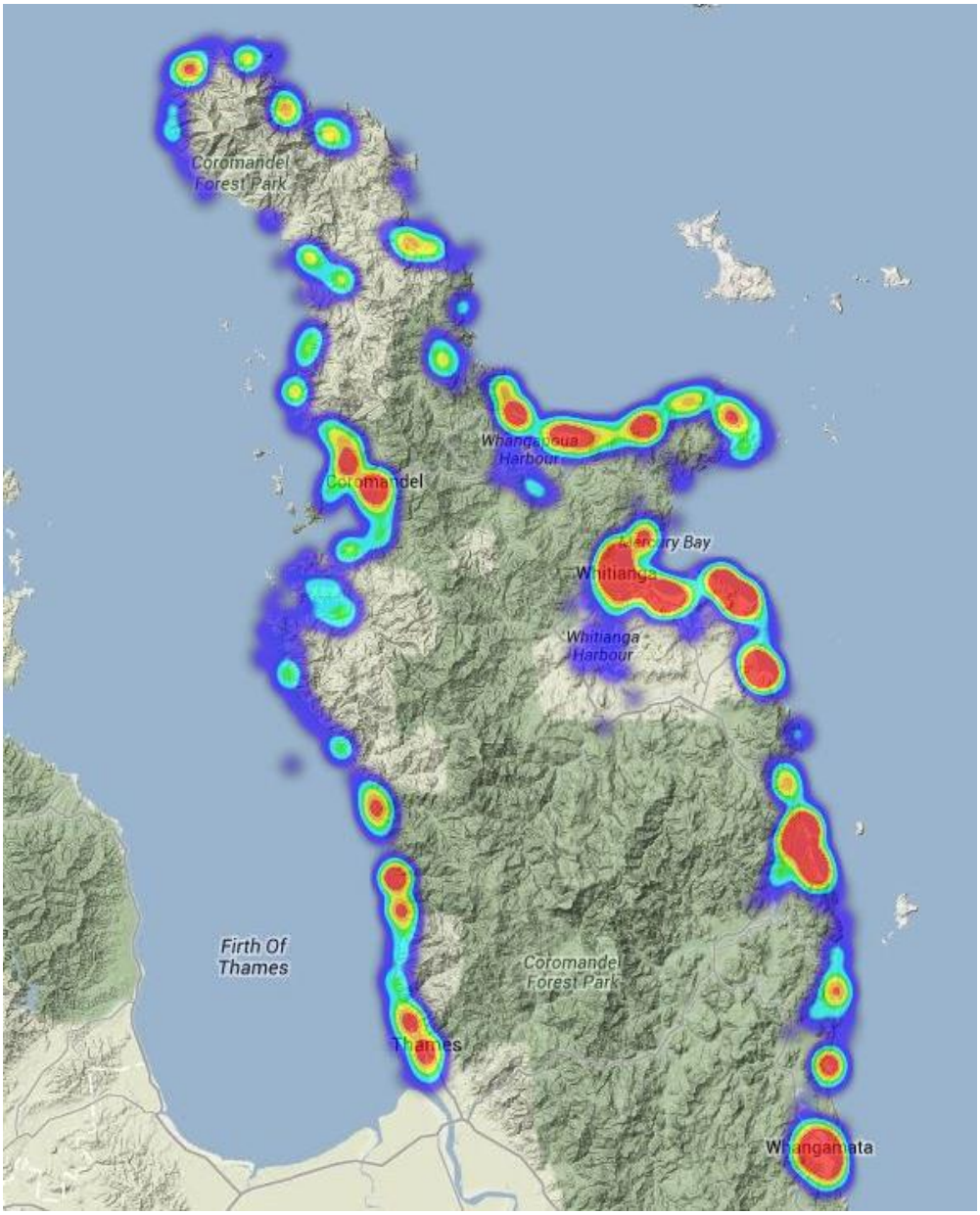


Figure 8-2 – Heat map of visited beaches

Figure 8-3 shows the fifteen most popular beaches, which together account for two-thirds of all visits. Whitianga/Buffalo beach is the most popular with almost 400 visits.

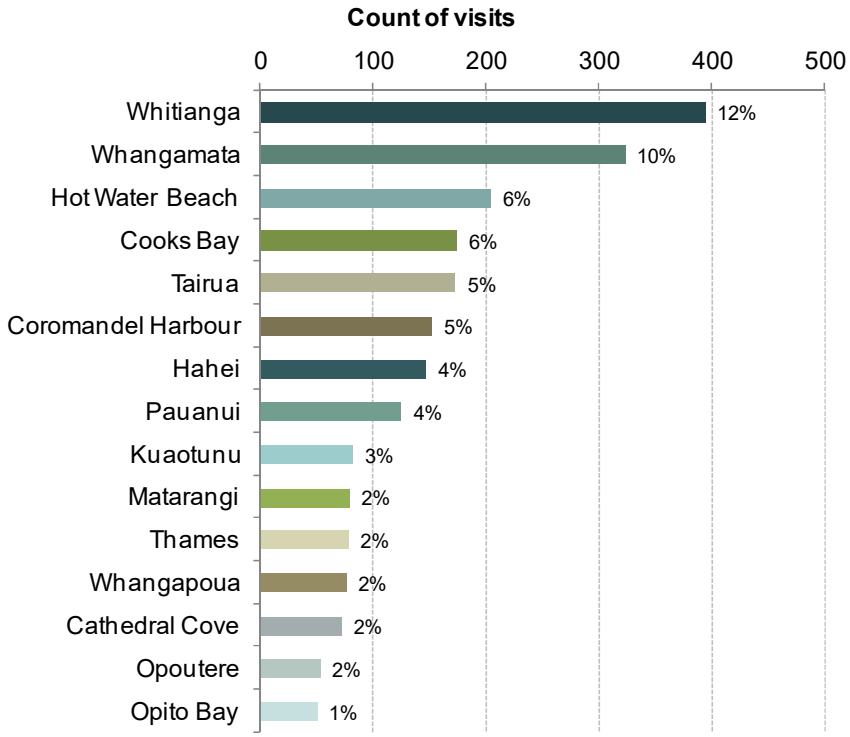


Figure 8-3 - Count of unique visitor groups to the 15 most popular beaches

Figure 8-4 shows the proportion of beach visits in each community board area. Mercury Bay is the most popular area with 47 per cent of all reported beach visits.

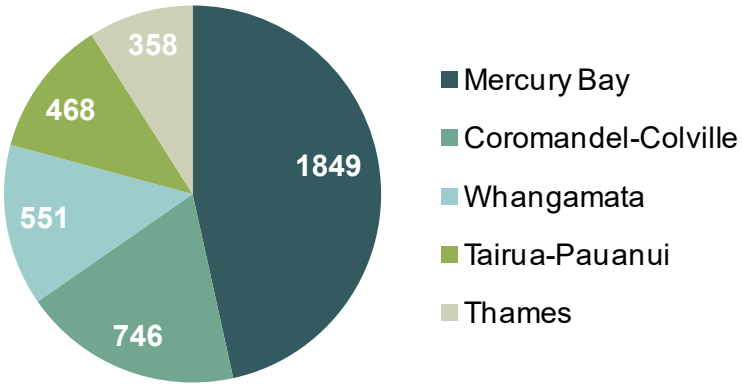


Figure 8-4 - Proportion of beach visits by Community Board area

8.4.1 MULTI-BEACH TRIPS

There are many popular beaches within close proximity to each other on the Coromandel Peninsula and many people visit more than one beach during a trip. The following figure shows the number of beaches visited on each trip. The average was 1.54 beaches per trips but two thirds of trips included only one beach. Longer trips were more likely to include more than one beach. Multiplying 1.8 million beach recreation trips by 1.54 beaches per trip yields a total of 2.8 million Coromandel beach visits per year.

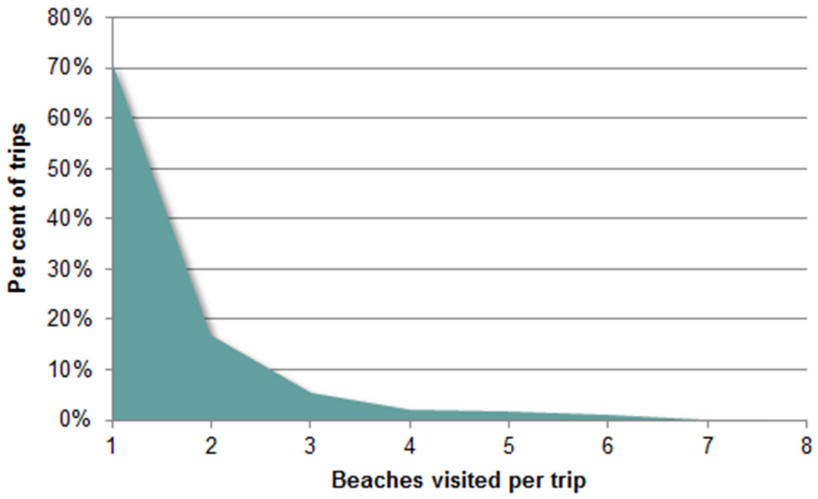


Figure 8-5 - Number of beaches visited per trip

8.4.2 LENGTH OF STAY

The median duration of a recreational trip to the Coromandel Peninsula was three nights, which is consistent with results from the DTS travel survey[47]. Trips can include multiple beaches and the average beach visit duration is 1.8 days. Half of all beach visits were day trips. Figure 8-6 shows the number of visits of various lengths for the 15 most popular beaches. Some beaches are mostly used for short stops on the way to somewhere else, while the larger population centres Whitianga and Whangamata are more popular for multiple-night stays. The beach where people stayed the longest was Te Puru with an average of 4

[47] http://www.mbie.govt.nz/info-services/sectors-industries/tourism/tourism-research-data/domestic-travel-survey

nights. The beach with the shortest visits was Stingray Bay near Cathedral Cove with an average duration of less than 2 hours.

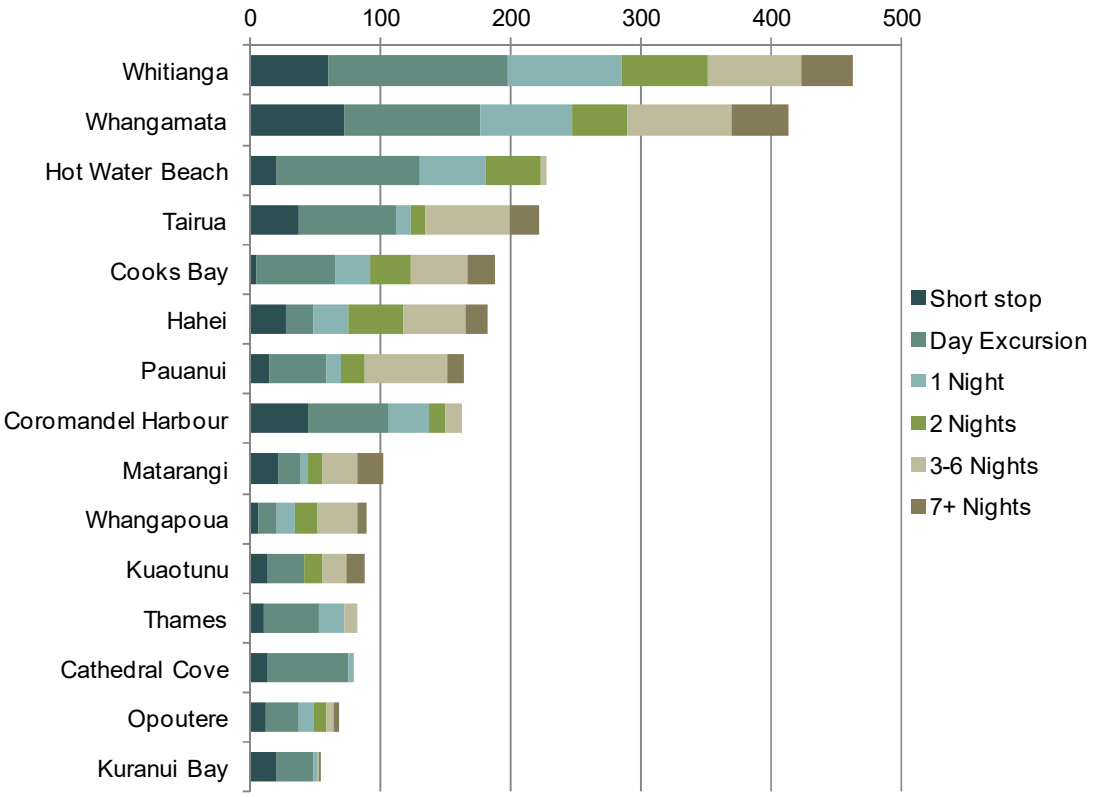


Figure 8-6 - Length of stay for the 15 most visited beaches[48]

8.5 TRAVEL COST

People who live near Coromandel beaches tend to visit more often. The average cost of a trip which includes one or more beach visits is $136 but the median is lower at $124. Figure 8-7 shows the distribution of travel costs per trip and per beach. After apportioning the cost of multi-beach trips the median cost per beach is only $67 and a fifth of all visits cost less than $25.

[48] These are visit counts while the previous figure showed unique visitor counts so the beach order is different

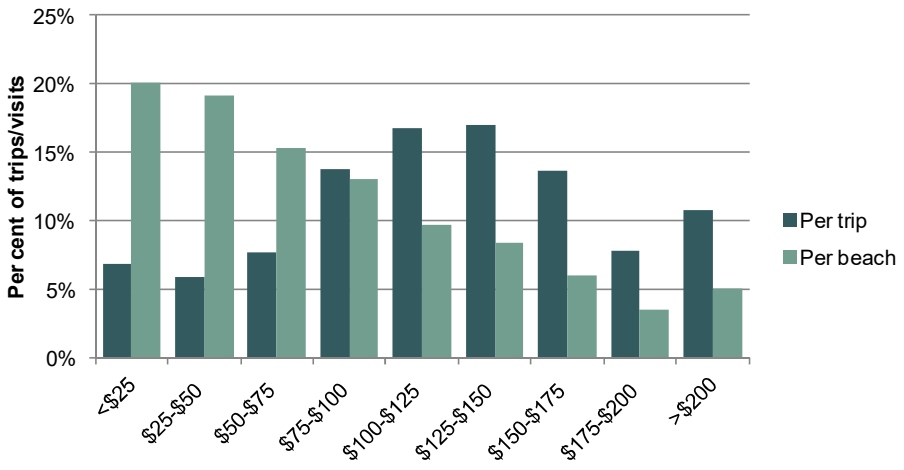


Figure 8-7 - Distribution of beach visit costs

Figure 8-8 shows the estimated total travel cost per year to each of the five community board areas based on 2.79 million domestic visits per year. The total for the Peninsula is $240 million dollars and Mercury Bay beaches visits account for nearly half of this. Beaches in the Coromandel-Colville area are more remote and have higher travel costs but tend to be visited less often so the overall cost is lower.

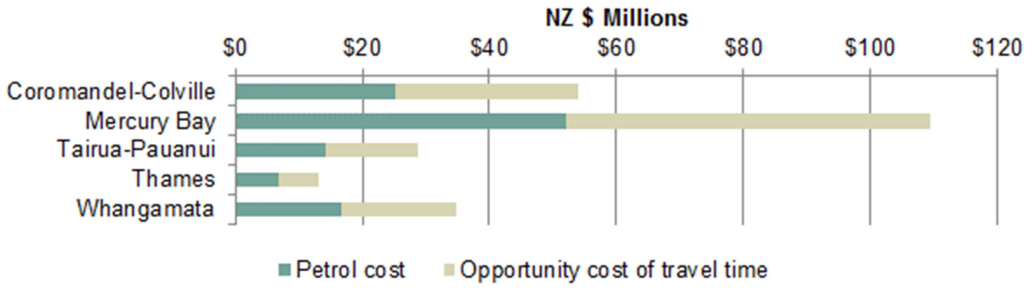


Figure 8-8 – Total travel cost per year for all domestic visitors

8.5.1 TOTAL OPPORTUNITY COST BY SITE

The following maps show the total opportunity cost of beach recreation attributed to each site, per year. This total is based on average travel cost for the site and proportion of visits multiplied by the 2.79 million total beach visits per year (from MBIE tourism statistics) for the whole peninsula. Some sites are unlabelled because they are part of a larger area or do not have a distinct name.

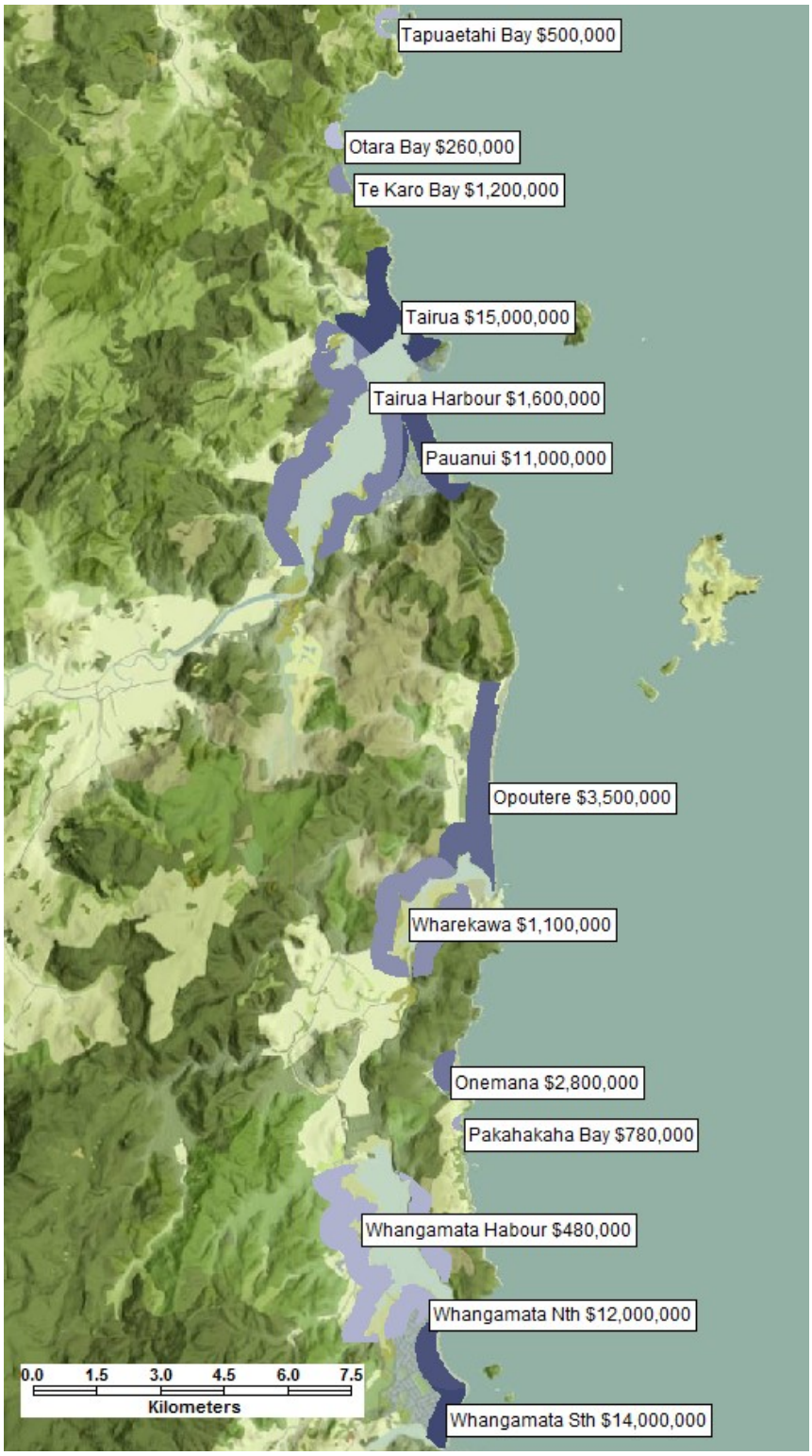


Figure 8-9 – The opportunity cost of beach recreation in Tairua and Whangamata areas

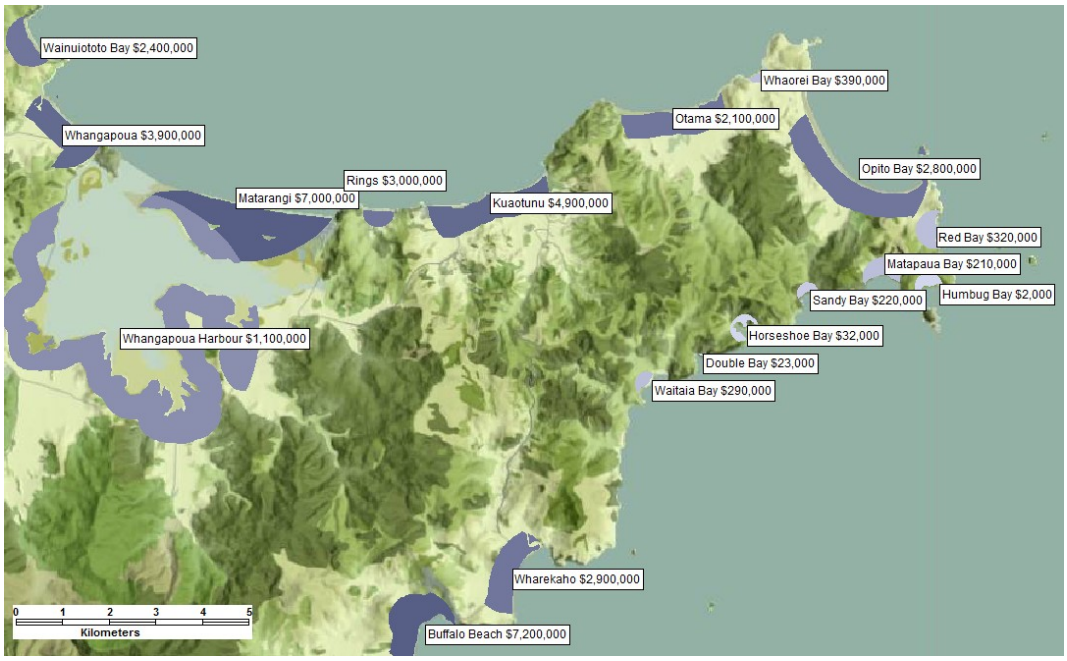


Figure 8-10 - The opportunity cost of beach recreation in northern Mercury Bay area

Figure 8-11 - The opportunity cost of beach recreation in southern Mercury area

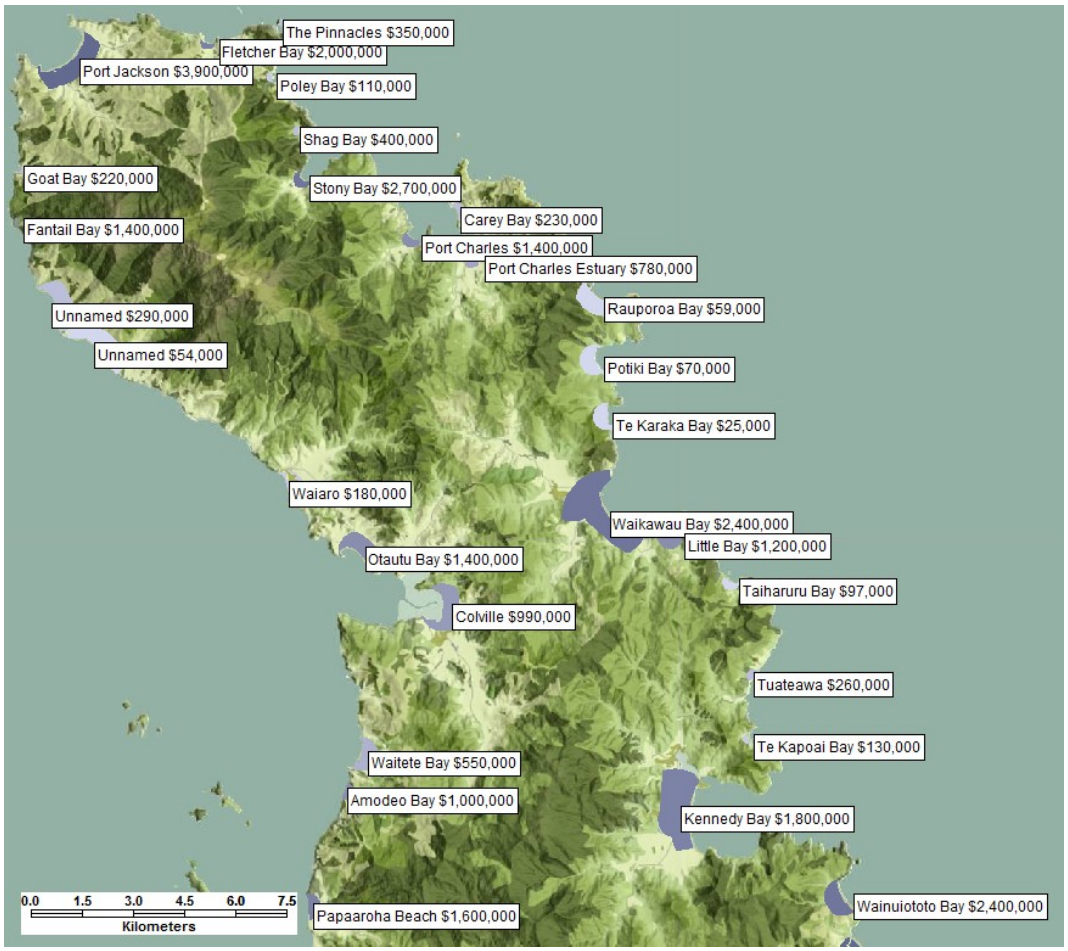


Figure 8-12 - The opportunity cost of beach recreation in Colville area

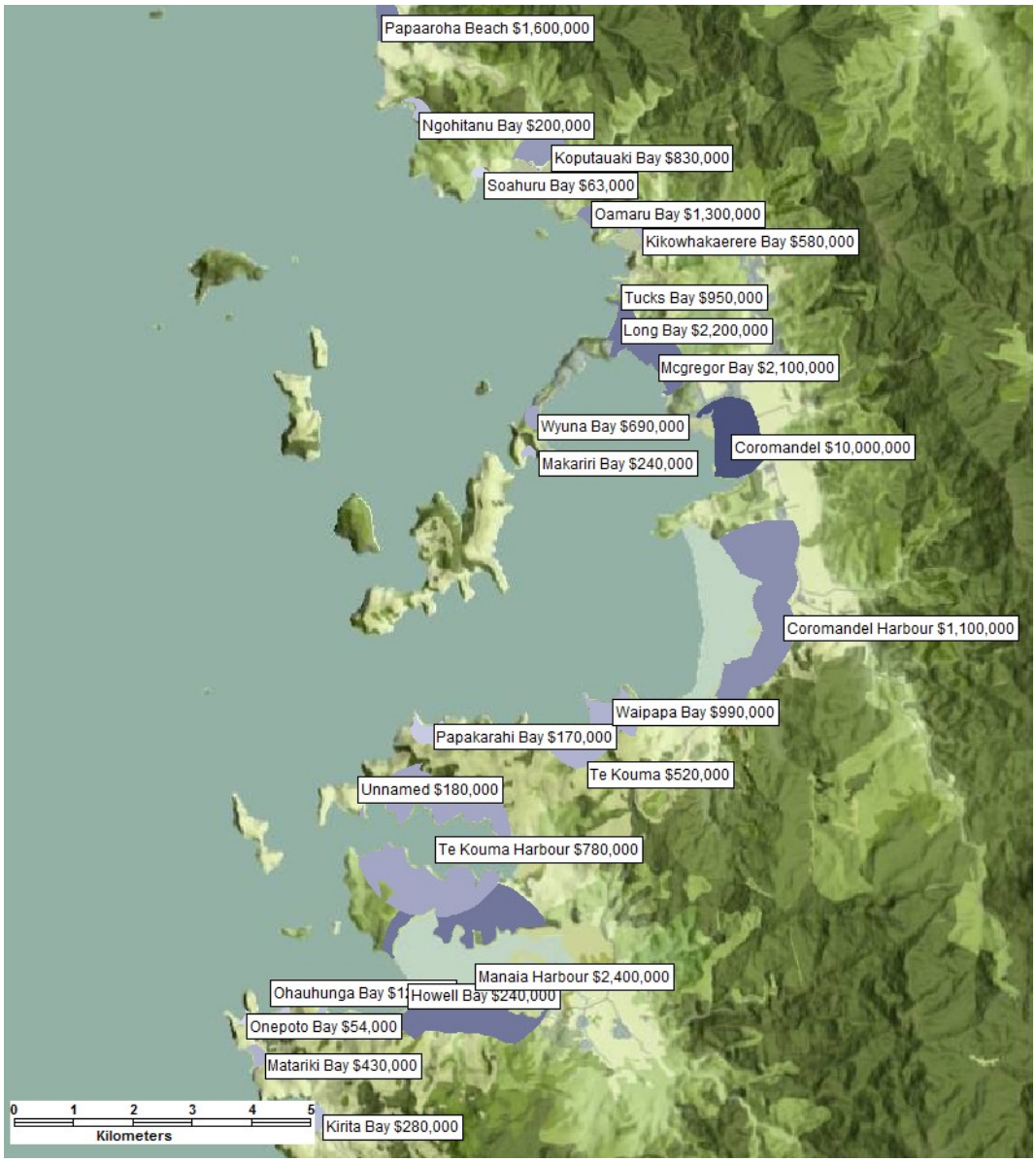


Figure 8-13 - The opportunity cost of beach recreation in Coromandel area

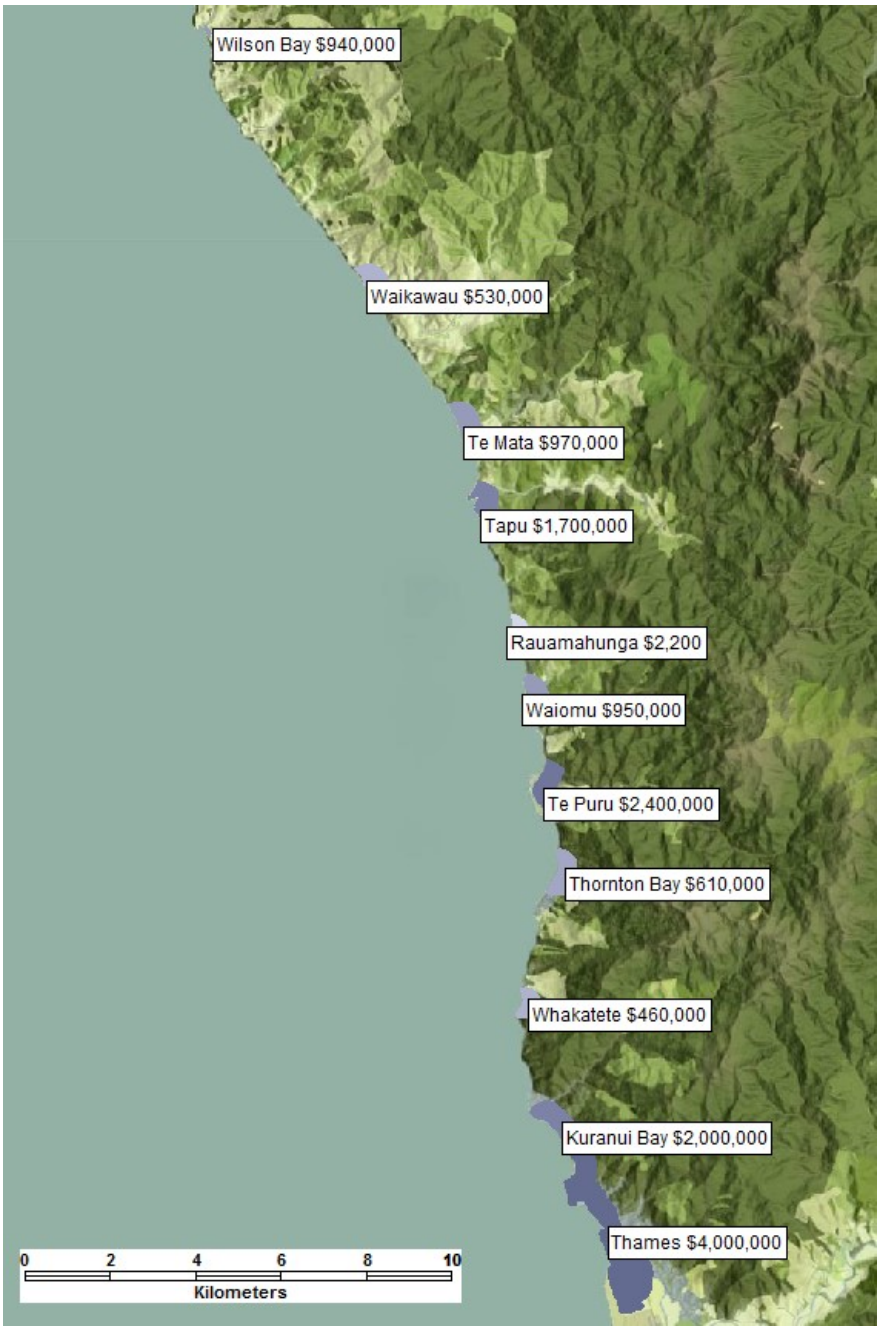


Figure 8-14 - The opportunity cost of beach recreation in Thames area

8.6 ACTIVITIES BY BEACH

Beach visitors engage in a variety of recreation activities on the shore and in the water. The most common activity is walking, occurring at 73 per cent of all beach visits. The popularity of water-based activities varies between different beaches. Figure 8-15 shows the proportion of visitors who do in-water activities (swimming or surfing), on-water activities (boating or watersports), fishing and

seafood gathering for the fifteen most visited beaches. Opoutere is the beach with the highest rate of in-water activity (90 percent of visitors) and Coromandl Harbour has the lowest rate (30 per cent). Opito Bay had the highest rate for in-water recreation (40 per cent), while the lowest rate was at Cathedral Cove (3 per cent). Half of all Matarangi visitors fished but only 2 percent of visitors to Hot Water Beach fished. Opito Bay also had the highest rate of seafood (kai moana) gathering (40 per cent) while there was none at Cathedral Cove and Kuaotunu.

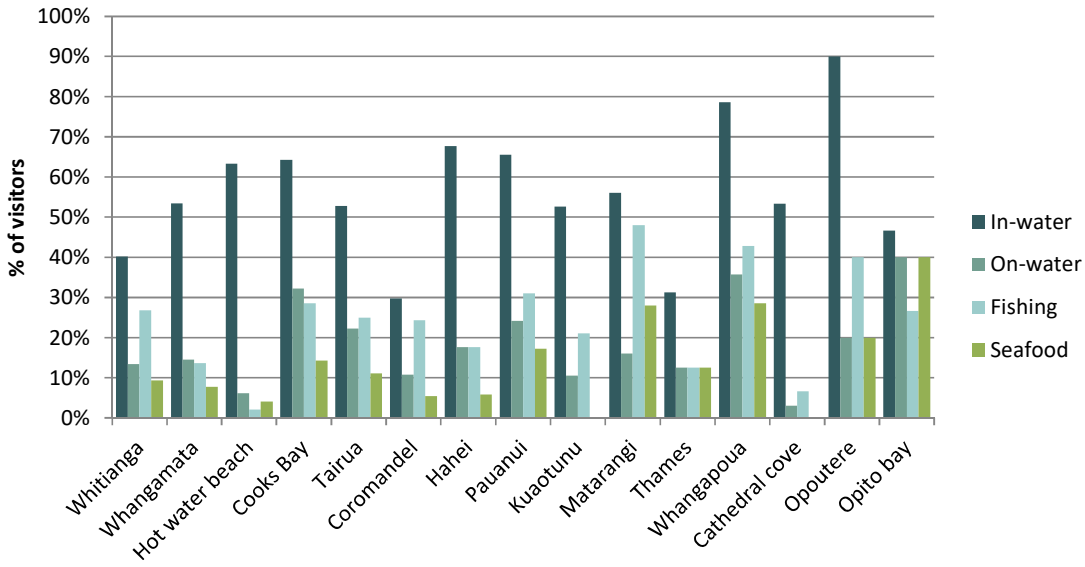


Figure 8-15 – Visitor water-based activities for top 15 beaches

8.7 REASONS FOR CHOOSING A BEACH

Respondents were asked what is important to them when choosing which beach to visit. The answer was free-form so people were more likely to say only what most influenced them rather than every possible factor. The answers were coded into 22 common categories which include economic (cost and time), state-dependence (the influence of previous decisions), environmental quality and services relating to recreation. Figure 8-16 shows the proportion of respondents who mentioned each factor.

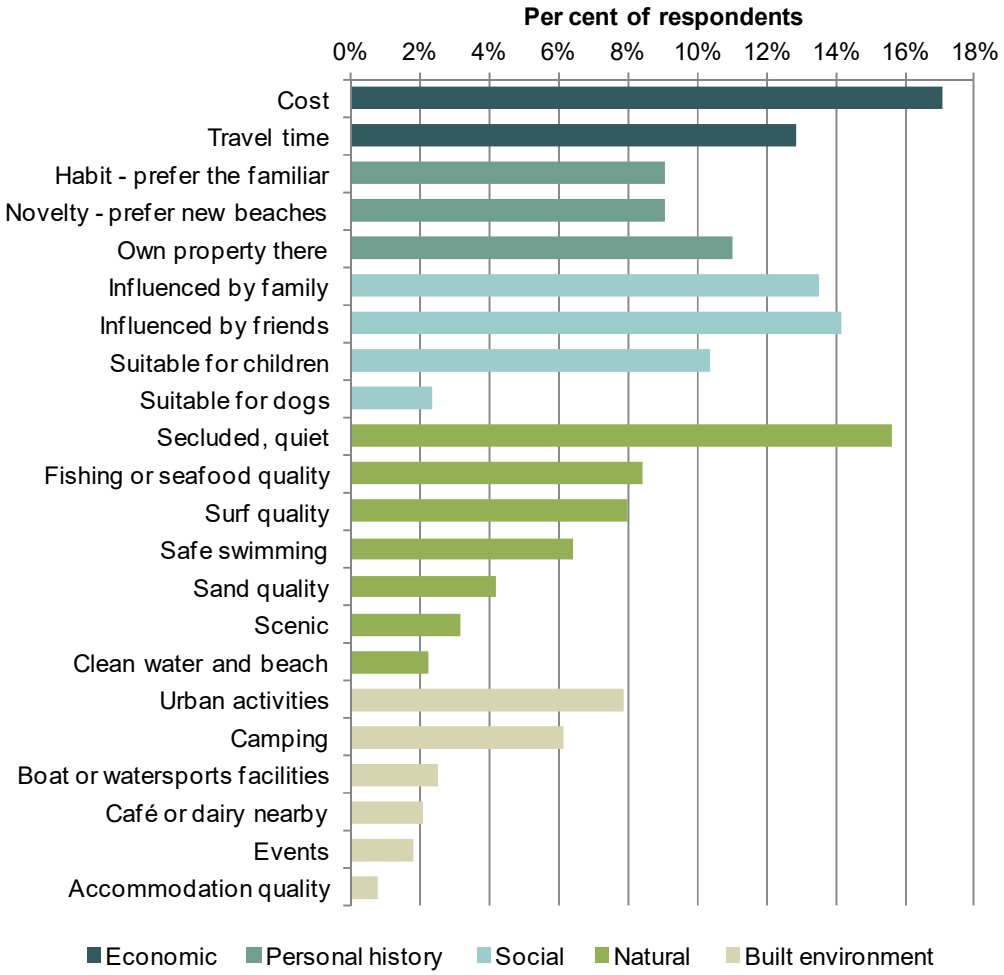


Figure 8-16 - Reasons given for visiting a particular beach

Cost was the most commonly mentioned factor, with seclusion not far behind. People who did not mention cost or distance presumably still have some budget constraints but that may not be the most important factor when choosing a beach. Historical decisions and the desire for familiar versus novel is important too. Some people said they just visit the same beach they always visited while a similar number of people said they prefer new locations. Eleven per cent of people said they visit a beach because they have family property (or a caravan) there.

A common answer was something like “close to town but quiet and safe for the kids” which highlights the somewhat conflicting desire to experience nature without giving up the comforts of civilisation. Some people place relatively more

importance on nature and want secluded beaches (15 per cent). Other people prefer to be in or near a town (8 per cent). There is also a strong social aspect to beach visits. Almost a fifth of respondents said visiting friends or family or recommendations from friends or family is a primary reason for choosing the beach. Suitability for children or dogs is important for households that include children or dogs.

The various reasons that people gave for choosing a beach highlights the difficulty of predicting these decisions using only physical information about the beaches. At an individual level predictive power is likely to be low.

8.8 VISITOR DEMOGRAPHICS BY BEACH

The demographics of beach visitors vary around the Peninsula. Figure 8-17 and 8-18show which beaches tend to be favoured by Waikato versus Auckland residents. Waikato residents are more likely than Aucklanders to visit west coast beaches, Tairua and Whangamata. Auckland residents are more likely to visit the Mercury Bay area, Coromandel, Pauanui, Opoutere, and some remote northern beaches that are only accessible by boat.

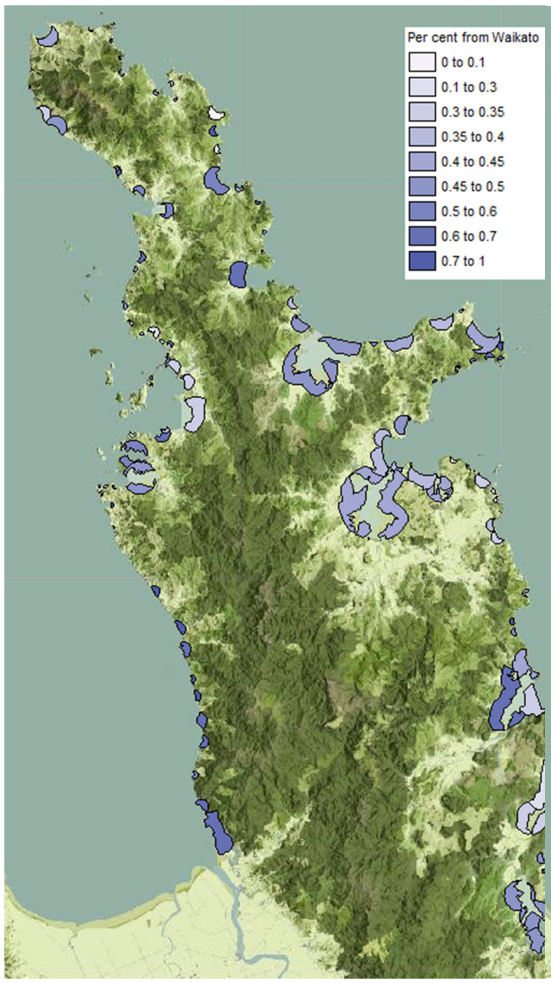


Figure 8-17 - Visitors from the Waikato region

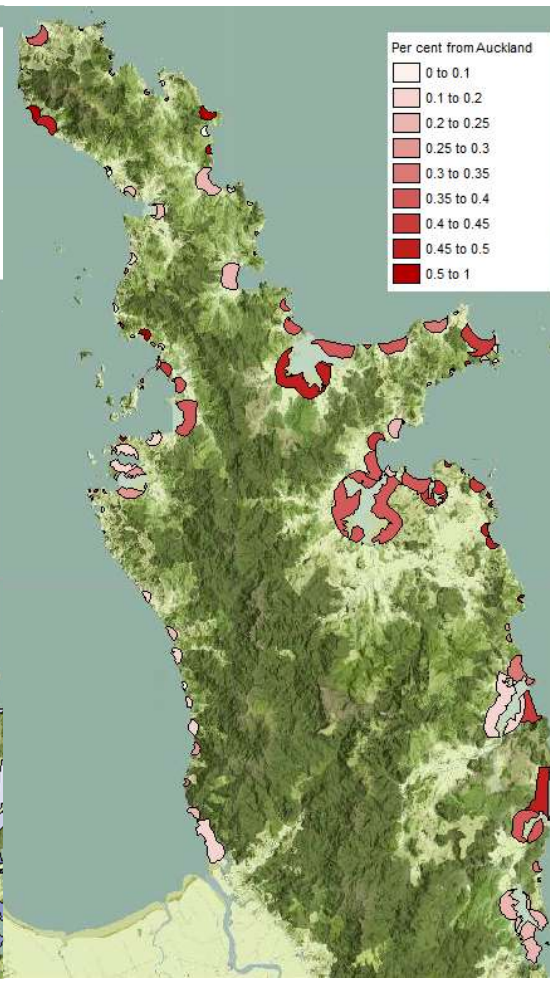


Figure 8-18 - Visitors from Auckland region

There are also differences in the average age of visitors. Figure 8-19 shows that people with children (under 13 years) are more likely to visit Cooks Beach, Kuaotunu, Whangapoua, Kennedy Bay and Waikawau. Conversely, Figure 8-20 shows that people over 60 years old are more likely to visit beaches with marinas or boat ramps such as Whangamata, Tairua, Whitianga and various west coast beaches along the main road.

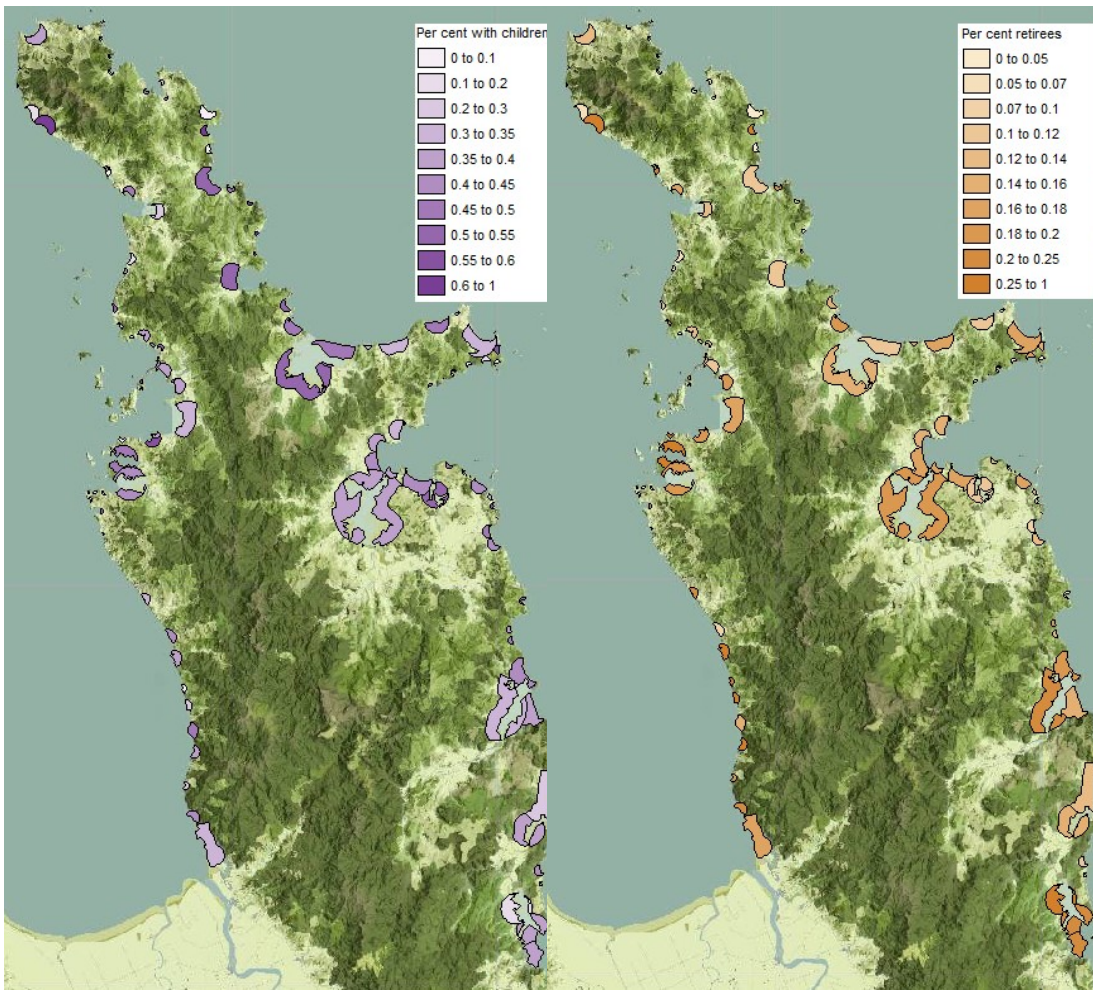


Figure 8-19 – Visitors with children **Figure 8-20 – Visitors over 60 years**

Beaches visitors also have varying levels of household income. Figure 8-21 shows that beaches along the top of Mercury Bay area such as Wainuototo, Whangapoua, Matarangi, Kuaotunu and Opito Bay have visitors with higher mean incomes. Whangamata, Coromandel harbour and small west coast beaches had lower income visitors on average.

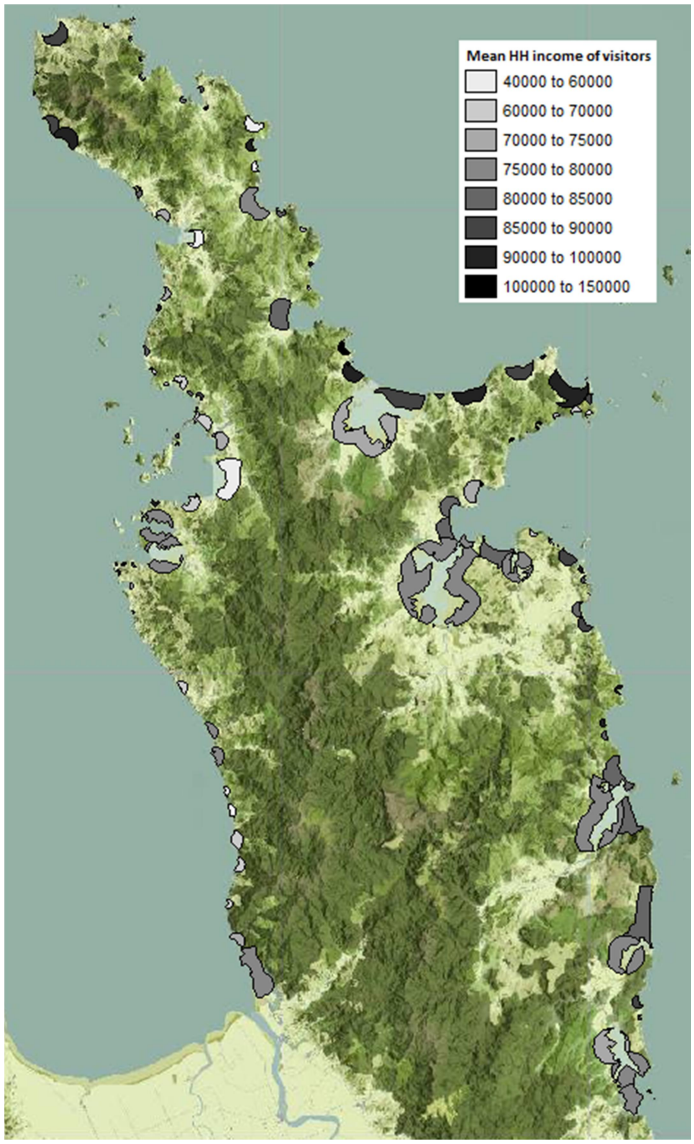


Figure 8-21 - Mean annual household income of visitors

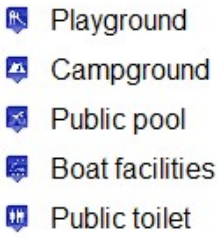
8.9 DETAILED MAPS FOR MOST-VISITED BEACHES

8.9.1 LEGEND FOR MAPS

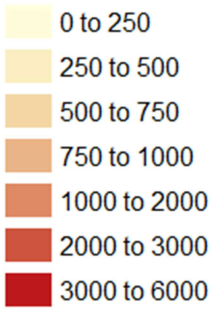
Each of the following maps depicts relative residential land values, the locations of public facilities and like/dislike markers placed by survey respondents.

Features liked or disliked by visitors

Facilities



Residential land value per square metre



8.9.2 WHANGAMATA

Many Whangamata visitors like the surf, easy beach access and proximity to cafes and facilities. The undeveloped headland and small islands are appreciated for scenic value. Some visitors dislike the dangerous surf, crowds and concentrated development.

Figure 8-22 - Detailed map of Whangamata

8.9.3 WHITIANGA/BUFFALO BEACH

Beach users at Whitianga enjoy the scenery, fishing, ease of access and proximity to cafes and accommodation. At the northern end of Buffalo Beach people dislike the lack of high-tide access, crowding and erosion.

Figure 8-23 - Detailed map of Whitianga beach

8.9.4 HOT WATER BEACH

Visitors to Hot Water Beach appreciate the surf, shallow stream, wide sandy beach and hot water (categorized as “other”). Negative aspects include crowds, poor stream water quality, dangerous surf and lack of road access and facilities at the northern end.

Figure 8-24 - Detailed map of Hot Water Beach

8.9.5 Cooks Beach

Many people like the safe swimming, sandy beach and forested headland at Cooks Beach. The main dislike is development and erosion at the east end where houses are right on the foreshore.

Figure 8-25 - Detailed map of Cooks Beach

8.9.6 TAIRUA

Visitors like the cafes and safe paddling provided on the estuary side of Tairua. They also enjoy the easy access, surf, sandy beach and dunes at the ocean beach. The main dislike is crowding.

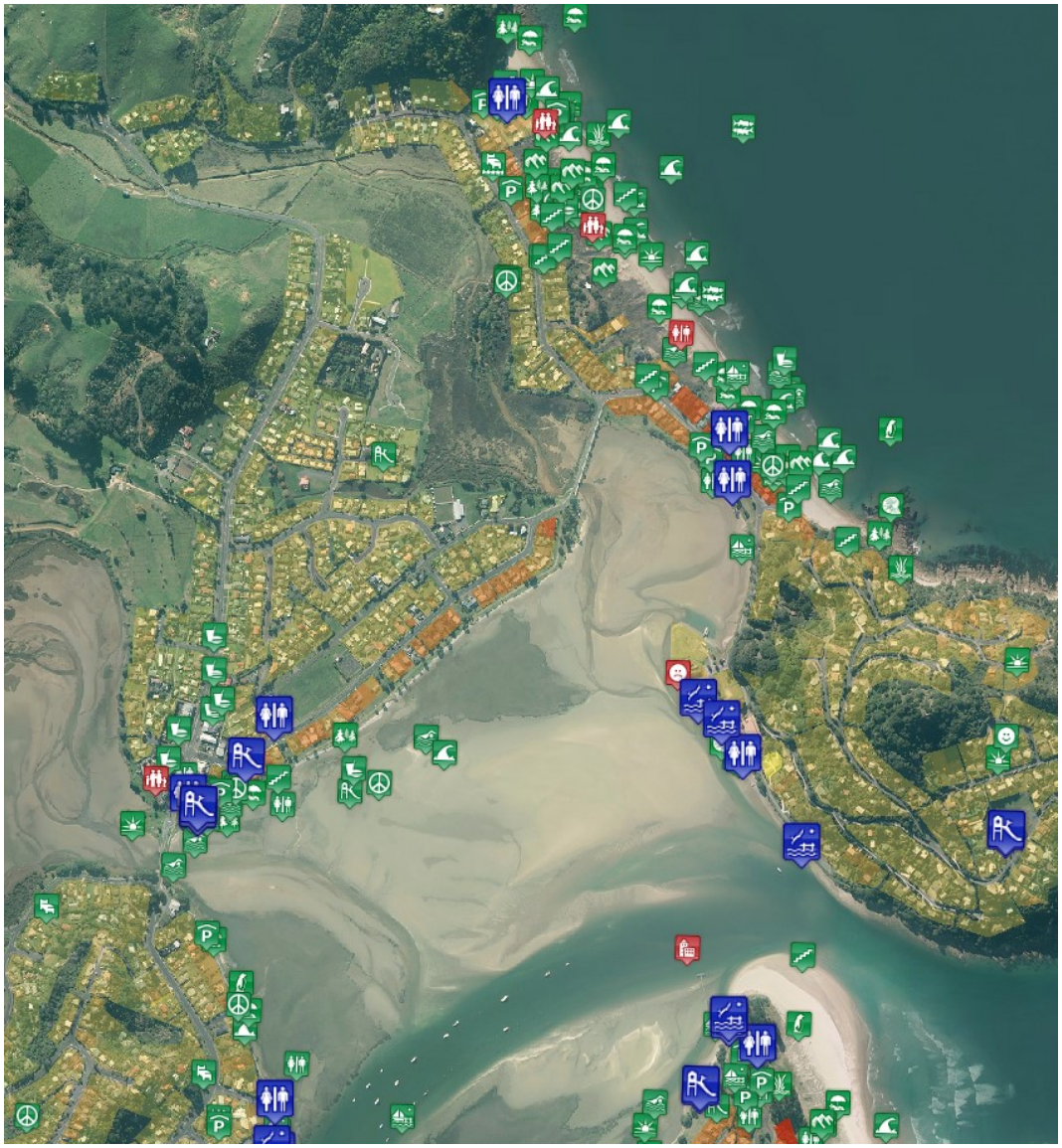


Figure 8-26 - Detailed map of Tairua beach

8.9.7 COROMANDEL HARBOUR

Visitors to Coromandel harbour predominantly enjoy the peace and quiet, shellfish and boating facilities. Dislikes include crowded boating areas and lack of public toilets in some areas.

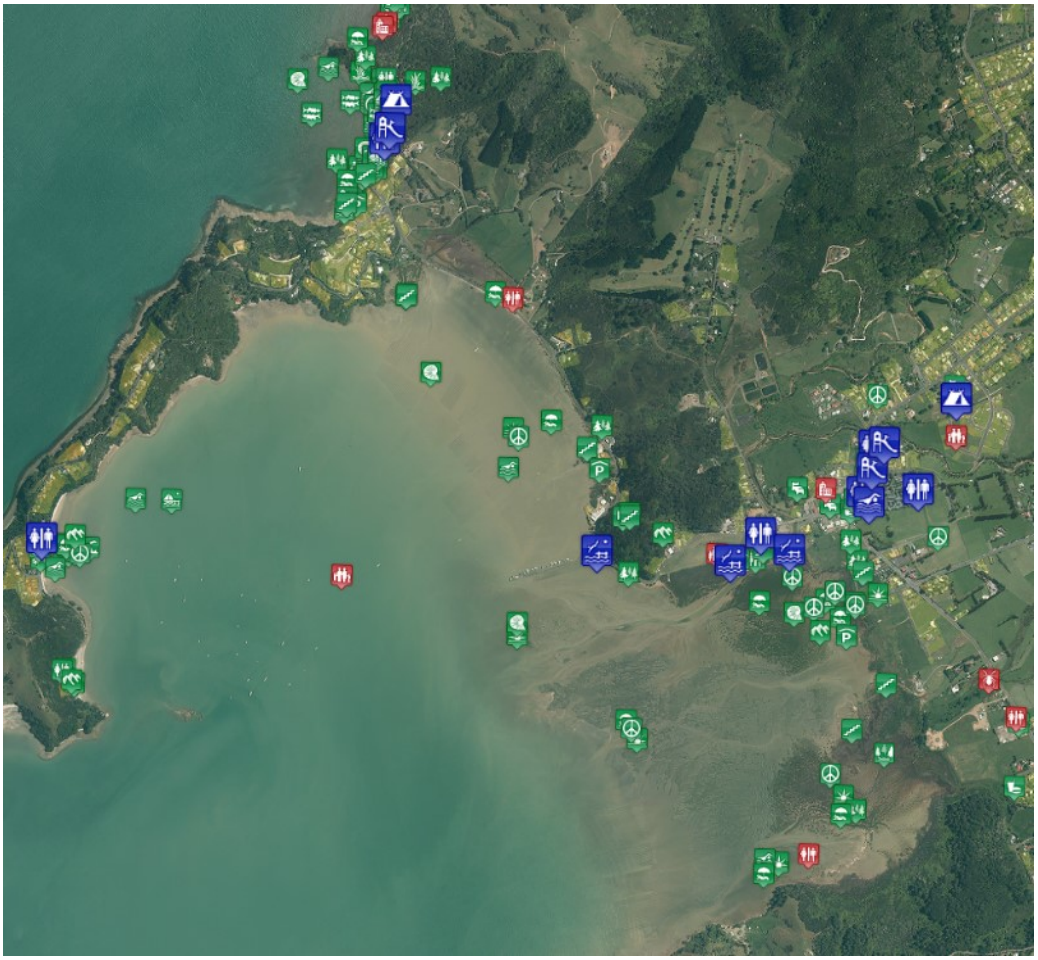


Figure 8-27 - Detailed map of Coromandel Harbour

8.9.8 HAHEI

Hahei beach users like the safe swimming, sandy dunes, trees at the north end and stream to the south east. The shopping area with cafes is also appreciated. Dislikes include crowding and development closest to the beach.

Figure 8-28 - Detailed map of Hahei beach

8.9.9 PAUANUI

Pauanui visitors like the sandy beaches, safe swimming, surf, trees and plentiful options for food and accommodation. The only dislike was some dune erosion, although some Tairua visitors thought that Pauanui development spoiled the view from across the harbour.

Figure 8-29 - Detailed map of Pauanui

8.9.10 KUAOTUNU

Visitors to Kuaotunu liked fishing, swimming, surfing and the food available from the local store and café. The only dislike was unsafe swimming near the rocks.

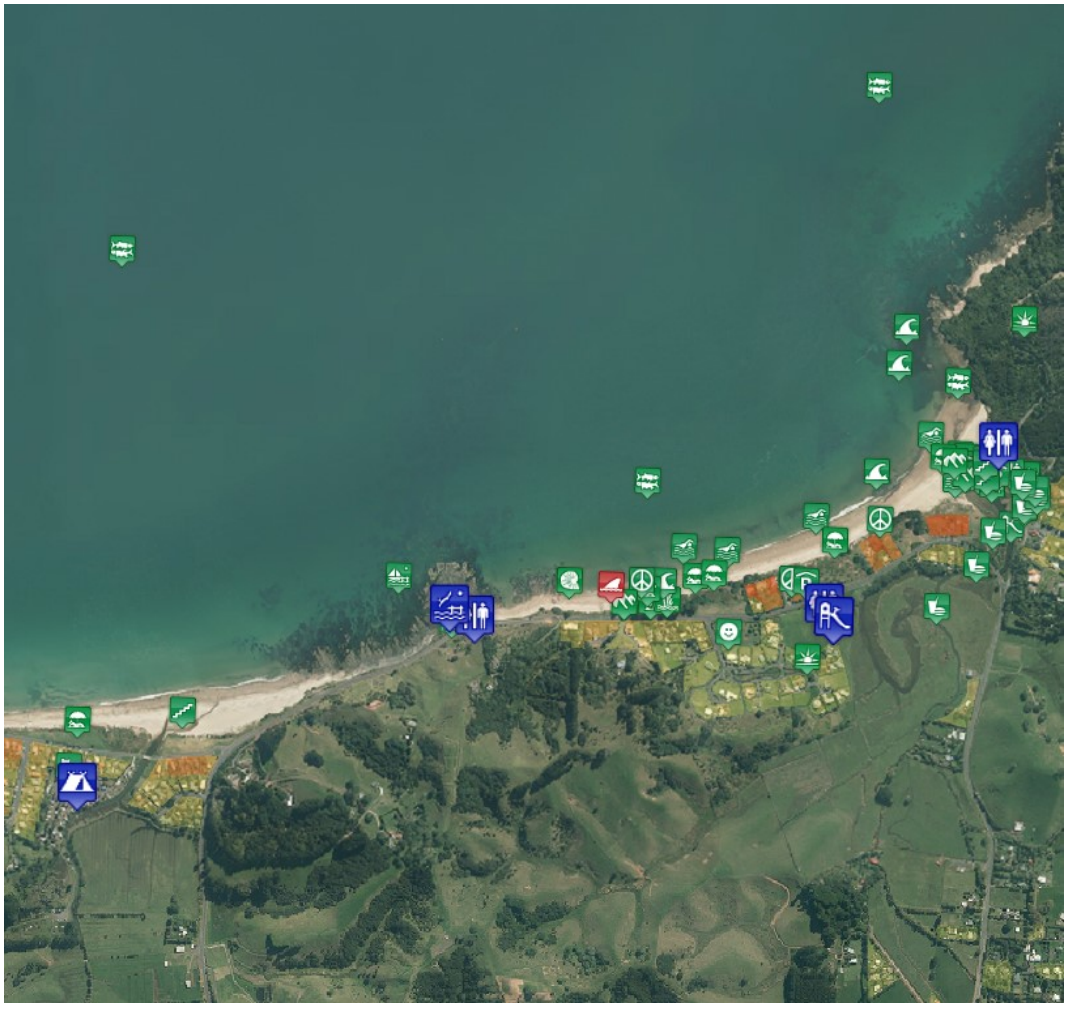


Figure 8-30 - Detailed map of Kuaotunu

8.9.11 MATARANGI

Matarangi visitors enjoy the fishing (particularly from the rocks), sandy dunes, swimming, surfing and peacefulness of the beach. They dislike the lack of toilets and food vendors close to the beach.

Figure 8-31 - Detailed map of Matarangi

8.9.12 THAMES

Thames is a popular area for short stops. Visitors don't tend to swim but do appreciate the few sandy areas, easy access and convenient facilities. People dislike the crowds in the central shopping area and the unsuitability for swimming.

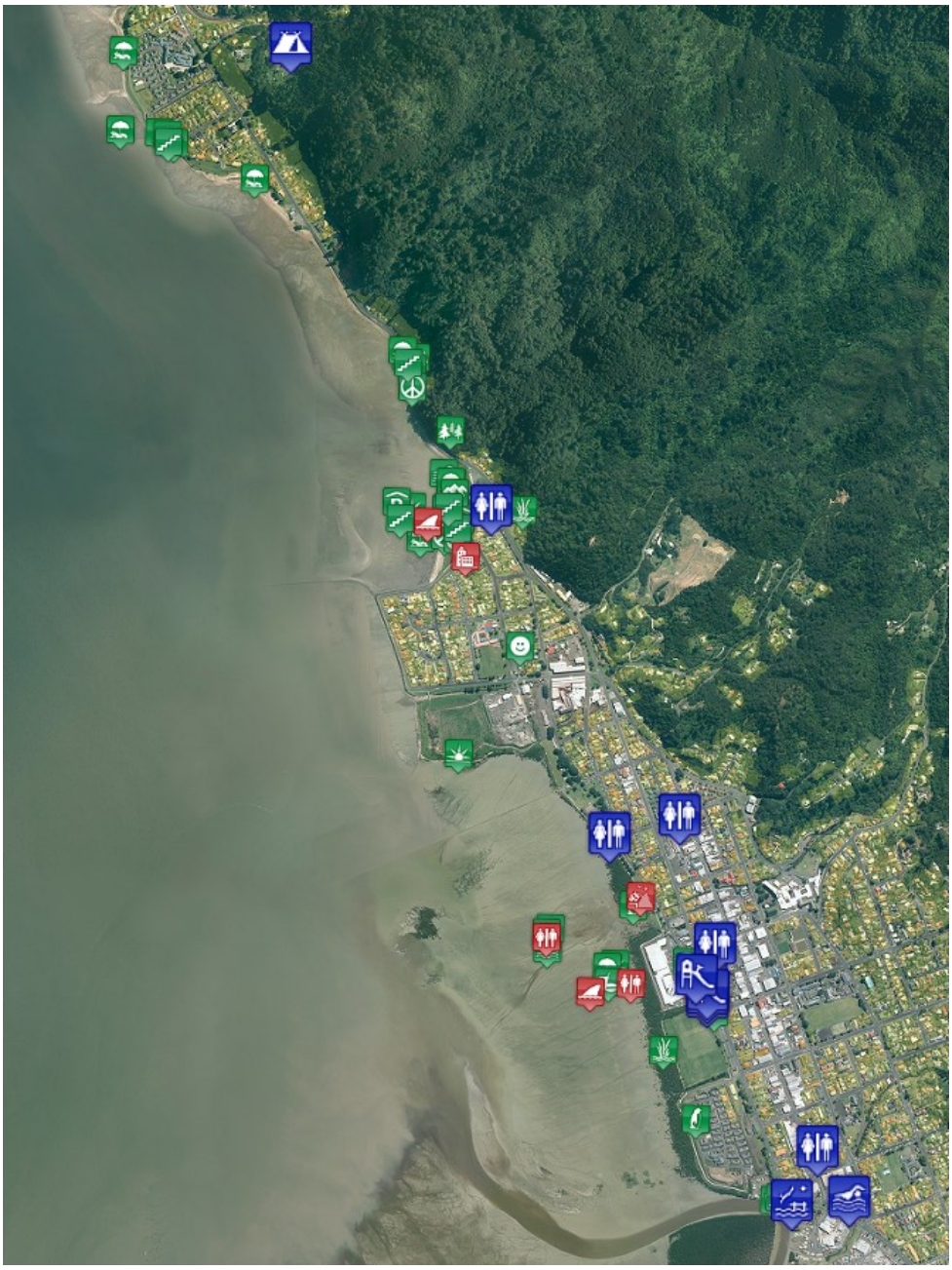


Figure 8-32 - Detailed map of Thames beach

8.9.13 WHANGAPOUA

Whangapoua visitors enjoy the surf, wide sandy beach and scenic views of bush-clad headland. Visitors also acclaim the peacefulness and scenic appeal of New Chums Beach; a short walk around the headland from Whangapoua. There were no disliked features.

Figure 8-33 - Detailed map of Whangapoua

8.9.14 Cathedral Cove

Visitors to Cathedral Cove like the iconic scenic cliffs and pohutukawa trees. Some people found it peaceful while others said it was too crowded (probably during peak season). Despite the long walk required no-one complained about the difficult access.

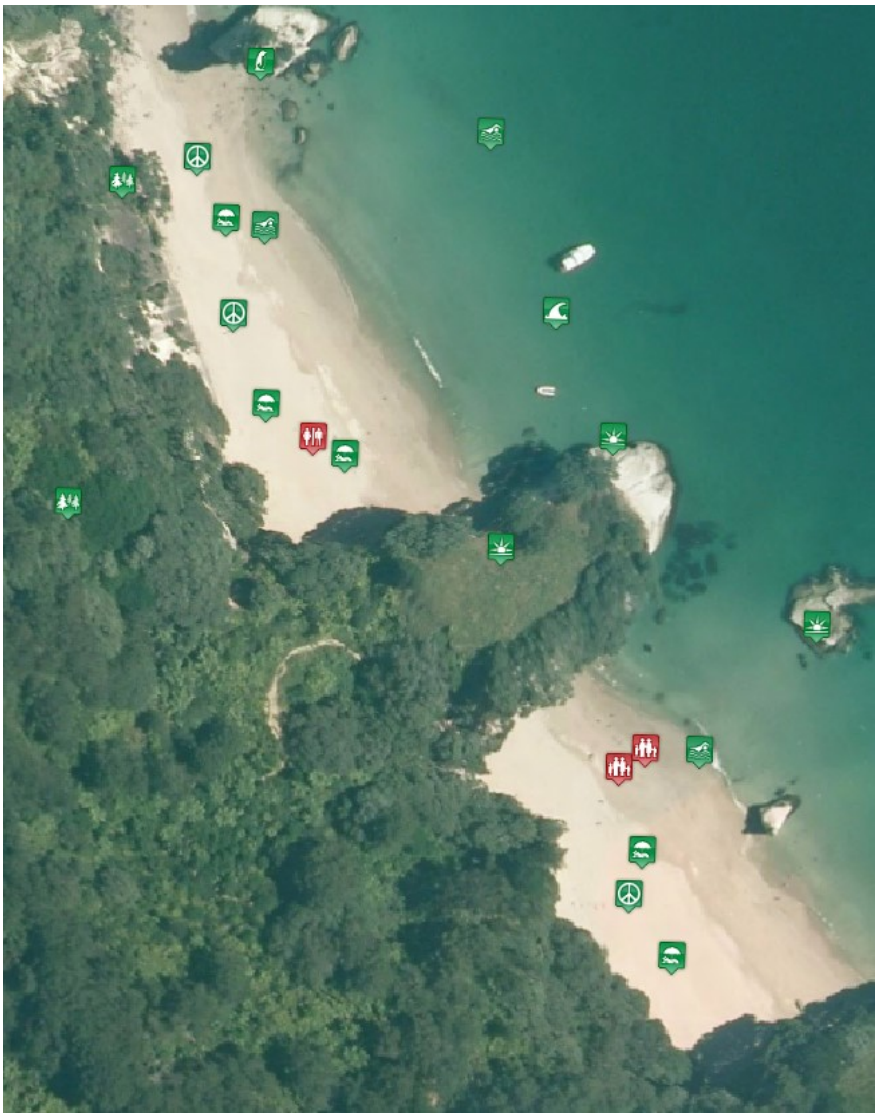


Figure 8-34 - Detailed map of Cathedral Cove

8.9.15 Opoutere

Opoutere is enjoyed for the wide white sand beach, dunes and pine forest. Visitors also liked the wildlife and peacefulness of the area.

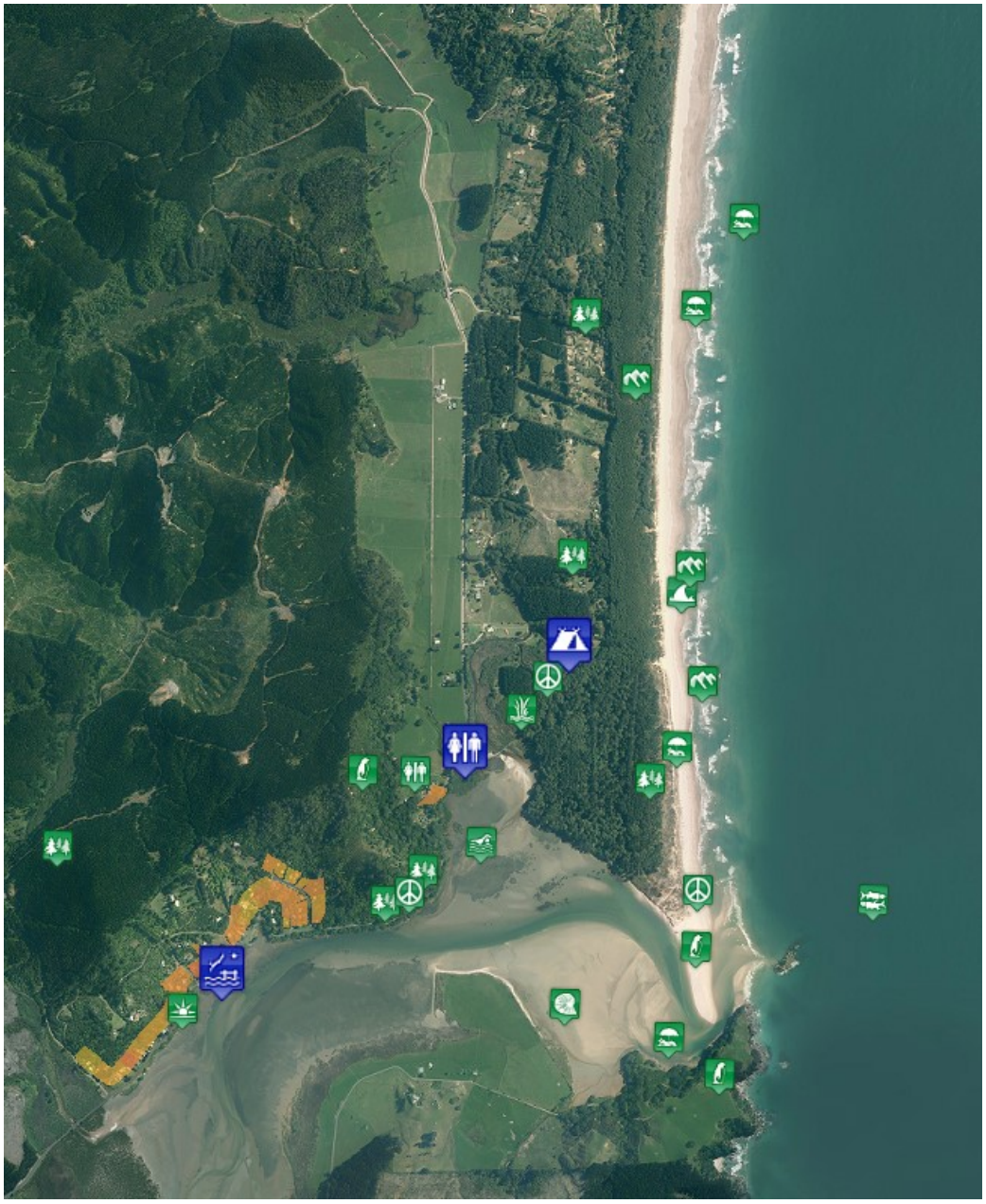


Figure 8-35 - Detailed map of Opoutere

8.9.16 Opito Bay

Opito Bay is relatively remote and not on the main highway. Visitors enjoy the peacefulness, sandy dunes, fishing, safe swimming and forest. There are no dislikes.

Figure 8-36 - Detailed map of Opito Bay

8.9.17 WHAREKAHO

Wharekaho, also known as Simpsons Beach, is just around the corner from Whitianga. People enjoy the easy access, sandy beach, fishing and good value rental accommodation. Dislikes include foreshore development, rubbish, lack of a café or dairy and unsafe swimming for children.

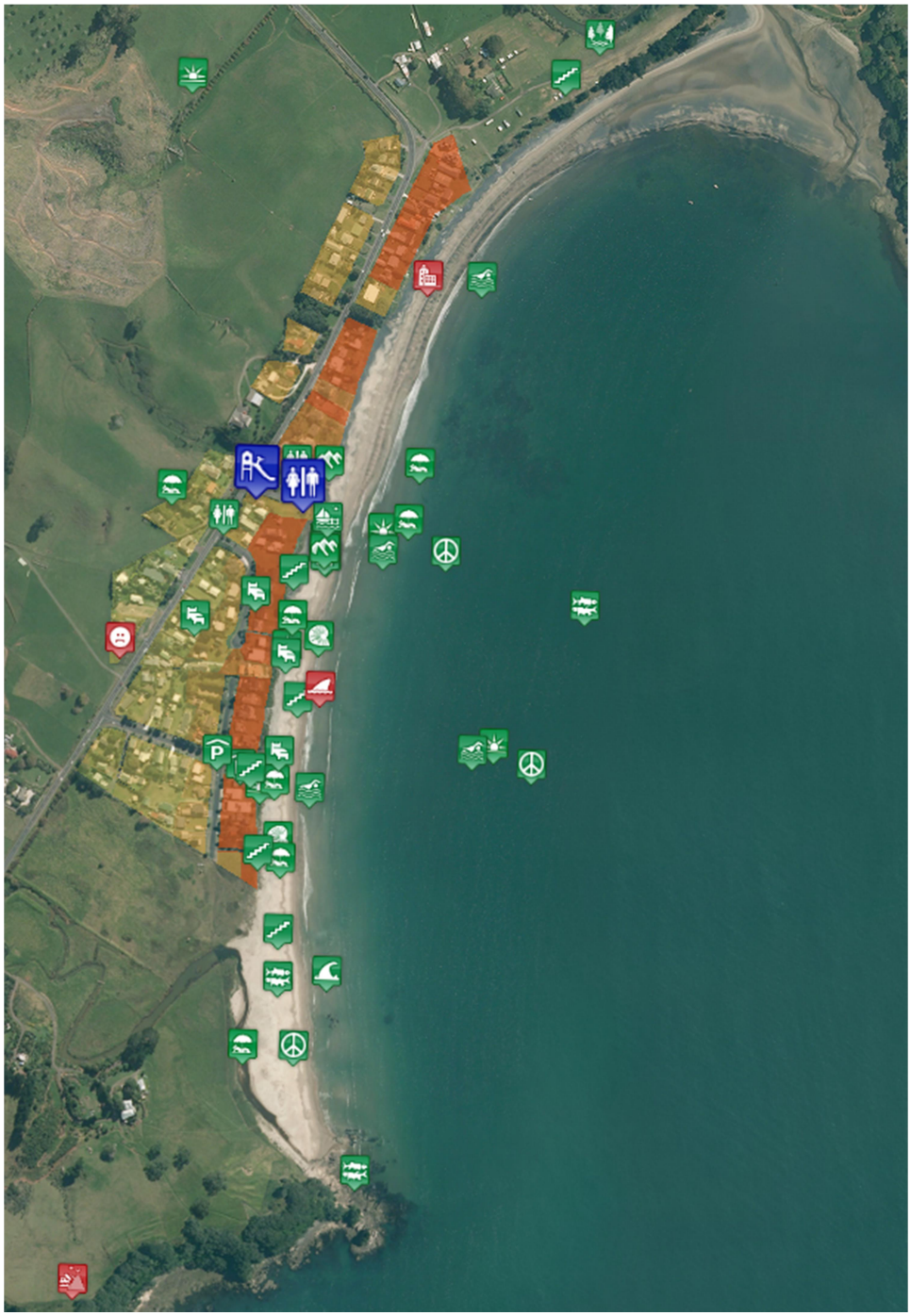


Figure 8-37 - Detailed map of Wharekaho

9. APPENDIX C: CO-AUTHORSHIP FORMS

THE UNIVERSITY OF WAIKATO

Co-Authorship Form

Postgraduate Studies Office
Student and Academic Services Division
Waharoa Ratonga Mataurauranga Akonga
The University of Waikato
Private Bag 3105
Hamilton 3240, New Zealand
Phone +64 7 838 4439
Website: http://www.waikato.ac.nz/sasd/postgraduate/

This form is to accompany the submission of any PhD that contains research reported in published or unpublished co-authored work. **Please include one copy of this form for each co-authored work.** Completed forms should be included in your appendices for all the copies of your thesis submitted for examination and library deposit (including digital deposit).

[redacted]

Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter 2:
"Using virtual environments to improve the realism of choice experiments: A case study about coastal erosion management"
Published in the Journal of Environmental Economics and Management

Nature of contribution by PhD candidate	Data collection, analysis, writing
Extent of contribution by PhD candidate (%)	85

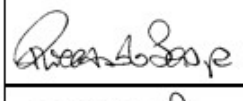
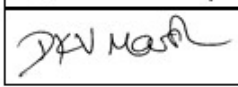
CO-AUTHORS

Name	Nature of Contribution
Ric Scarpa	Funding, modelling assistance, reviewing
Dan Marsh	Funding, reviewing

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
Yvonne Matthews		27 Feb 2017
Ric Scarpa		5th March 2017
Dan Marsh		27 Feb 2017

THE UNIVERSITY OF WAIKATO
Te Whare Wānanga o Waikato

Co-Authorship Form

Postgraduate Studies Office
Student and Academic Services Division
Waharoa Ratonga Matauranga Akonga
The University of Waikato
Private Bag 3105
Hamilton 3240, New Zealand
Phone +64 7 838 4439
Website: http://www.waikato.ac.nz/sasd/postgraduate/

This form is to accompany the submission of any PhD that contains research reported in published or unpublished co-authored work. **Please include one copy of this form for each co-authored work.** Completed forms should be included in your appendices for all the copies of your thesis submitted for examination and library deposit (including digital deposit).

Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter 3:
"Virtual environments for the unexperienced: a choice experiment about coastal conservation"
Submitted to the Journal of Outdoor Recreation and Tourism

Nature of contribution by PhD candidate	Data collection, analysis, writing
Extent of contribution by PhD candidate (%)	85

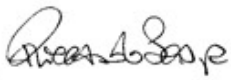
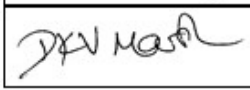
CO-AUTHORS

Name	Nature of Contribution
Ric Scarpa	Funding, reviewing
Dan Marsh	Funding, reviewing

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
Yvonne Matthews		27 Feb 2017
Ric Scarpa		5th March 2017
Dan Marsh		27 Feb 2017

THE UNIVERSITY OF WAIKATO
Te Whare Wānanga o Waikato

Co-Authorship Form

Postgraduate Studies Office
Student and Academic Services Division
Waharoa Ratonga Mataurarua Akonga
The University of Waikato
Private Bag 3105
Hamilton 3240, New Zealand
Phone +64 7 838 4439
Website: http://www.waikato.ac.nz/sasd/postgraduate/

This form is to accompany the submission of any PhD that contains research reported in published or unpublished co-authored work. **Please include one copy of this form for each co-authored work.** Completed forms should be included in your appendices for all the copies of your thesis submitted for examination and library deposit (including digital deposit).

Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter 5:
"Cumulative attraction and spatial dependence in a destination choice model for beach recreation"
Submitted to EARE 2017 conference

Nature of contribution by PhD candidate	Data collection, analysis, writing
Extent of contribution by PhD candidate (%)	85

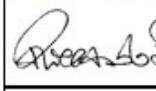
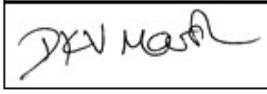
CO-AUTHORS

Name	Nature of Contribution
Ric Scarpa	Funding, modelling assistance, reviewing
Dan Marsh	Funding, reviewing

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
Yvonne Matthews		27 Feb 2017
Ric Scarpa		5th March 2017
Dan Marsh		27 Feb 2017

THE UNIVERSITY OF WAIKATO
Te Whare Wānanga o Waikato

Co-Authorship Form

Postgraduate Studies Office
Student and Academic Services Division
Waharoa Ratonga Matauranga Akonga
The University of Waikato
Private Bag 3105
Hamilton 3240, New Zealand
Phone +64 7 838 4439
Website: http://www.waikato.ac.nz/sasd/postgraduate/

This form is to accompany the submission of any PhD that contains research reported in published or unpublished co-authored work. **Please include one copy of this form for each co-authored work.** Completed forms should be included in your appendices for all the copies of your thesis submitted for examination and library deposit (including digital deposit).

Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter 4:
Stability of willingness-to-pay for coastal management: a choice experiment across three time periods
Under review (2nd stage) at the Journal of Ecological Economics

Nature of contribution by PhD candidate	Data collection, analysis, writing
Extent of contribution by PhD candidate (%)	85

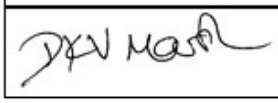
CO-AUTHORS

Name	Nature of Contribution
Ric Scarpa	Funding, modelling assistance, reviewing
Dan Marsh	Funding, reviewing

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
Yvonne Matthews		27 Feb 2017
Ric Scarpa		5th March 2017
Dan Marsh		27 Feb 2017