Size Matters: The Economic Value of Beach Erosion and Nourishment in Southern California

Keywords
Random Utility Models, Recreational Demand, Beach Valuation, Beach Nourishment

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Abstract

Natural and human forces constantly reshape beaches adding sand to some beaches and taking it from others. Understanding the economic consequences of changes in beach width can be difficult, especially at public beaches where many beach goers don't pay market prices for the pleasure of enjoying wide sandy beaches.

We use data from a panel of beach goers in the Los Angeles area that tracked beach going behavior over twelve months. The beach choice behavior of respondents combined with detailed beach attribute data, including beach width, reveals how changes in beach width affect visitation to beaches in southern California and the non-market economic value enjoyed by these beach goers. We use a random utility approach to show that the value of beach width varies for different types of beach uses: water contact, sand-based activities, and pavement-based activities. We also find that the value of beach width depends on how wide the beach is to begin with.

Beaches are among the most popular outdoor destinations because they offer archetypal tranquility – the repeating white noise of breaking waves, sun-warmed sand and cool breezes, the gentle cry of shorebirds, the sight and sounds of other people enjoying the environment. Yet despite the peaceful appearance of many beaches, they are not static and permanent resources. Just as the footprints along the shore will be wiped clean by the next high tide, the very shape of the beach is subject to dramatic change as currents, wind, and storms constantly move sand and rearrange the coastline.

Humans rely on beaches for a number of services – protection of property from waves and high water during storms, as open spaces for recreation, or a place to spread out and enjoy the sun and sea. Yet people do many things which adversely affect beaches, and some things to protect them. Careless beach development and overuse can level dunes and kill the vegetation which helps preserve the shoreline. Increased surface-water runoff from inland development can cause streams to erode their outlets. Building piers, breakwaters, and jetties can change the way storms and currents hit the shore, causing some spots to erode and other spots to accumulate new sand. Natural events, including sea level rise and severe storms also can reshape beaches – dramatically changing their width and size.

Wide beaches provide venues for various recreational activities, and we show in this paper that many beach users derive benefits from improved beach width and quality. Because beaches attract out-of-area visitors, businesses near the beaches benefit from increased use. Beaches also are in important economic resource for people who live locally, even if these users pay little or nothing for a beach visit. Local day users enjoy a non-market economic benefit from visiting beaches – a value equal to what they would pay to guarantee that these beaches remain available for their use. These non-market values can be substantial and have been estimated to be worth as much as $3 billion/year in California alone (Pendleton and Kildow, 2006, estimate the value at $2 billion, the Southern California Beach Valuation Project estimated that the loss in consumer surplus if all public beaches in Los Angeles and Orange County were closed would be $3 billion, Hanemann, Pendleton, Mohn, et al , 2004).

While the attractiveness of wide sandy beaches seems obvious, relatively little is known about the precise economic value of changes in the size of beaches. Huang and Poor (2004) use stated preference methods to examine the value of protecting against beach loss in the states of Maine and New Hampshire. Although they focus on preserving the status quo rather than changing beaches, they find a general dislike by the public for many of the consequences of beach armoring. Landry, Keeler, and Kreisel (2003) examine a Georgia island community using a hedonic model to quantify benefits to property owners and stated preference techniques to determine the benefits of beach preservation and enhancement strategies. They find that in general people prefer wider beaches, they don't like armoring strategies, and while occasional visitors don't mind retreat strategies, passholders (frequent visitors who are more likely to live nearby) dislike shoreline retreat. Parsons, Massey, and Tomasi (2000) use revealed preference data to look at beaches in New Jersey and Delaware, using models which account for familiarity and favorites, and consider three categories of beach width. They find that, in general, people prefer medium beaches to narrow beaches, with wide beaches being the least favored – however this order does not hold for all models and all categories of beaches. Whitehead, Dumas, Herstine, et al. (2006) use a random effects Poisson model combining revealed preference and stated preference data and find that people prefer increased beach width, although width is only examined using the Stated Preference data.

In this paper, we develop a model that quantifies the economic impact on non-market day use values, of beach width and size for public beaches in Los Angeles and Orange County, California in the United States. While we focus on examining the effects of beach width on visitation to beaches and the non-market value enjoyed by beach goers, our approach and results can be extended easily to estimate potential changes in beach-related spending (by multiplying visitation by estimates of spending per visit). We use beach width measurement data, derived from estimates made in 1999, 2000, and 2008,to augment a revealed preference random utility model (Hanemann, Pendleton, Mohn, et al , 2004) of beach choice originally estimated using panel data on beach use from the year 2000. Unlike previous attempts to value beach width and size, we pay particular attention to how the activity choice of the beach goer affects their preferences for beach width and size.

The Behavioral Data

A panel of more than 2000 individuals was recruited by randomly selecting telephone numbers in the Los Angeles area (from Los Angeles, San Bernardino, Riverside, and Orange Counties). Respondents were asked a series of questions about household composition and past beach recreation activities. Those who reported that they had been to a beach within the past year were asked to record all beach visits and activities for 12 months beginning in December 1999. Those who agreed to join the panel supplied their data in telephone interviews every two months for a year-long total of 6 waves. The panel was augmented halfway through the survey to compensate for attrition. Panelists also answered a variety of questions about education, income, past recreational behavior and other demographic information. Even if a panelist was hesitant to answer a given question, she was kept in the survey since other answers could be useful for some applications of the data.

Every two months, panelists were interviewed to determine daily beach visitation that included which of 43 activities they engaged in at each beach they visited during each two-month interval (called waves) to which they responded. The beach destinations were identified by numeric codes, and were mapped to 51 defined beaches for which we collected detailed information about facilities, access, physical attributes and water quality. Additionally, two site proxies for beaches just north of the study area (Pt. Mugu) and just south of the study area (Oceanside) were included, but detailed information was not collected for these proxies. Some trips could not be matched to a specific beach. These were retained since they still contained useful information about beach activities. If a panelist took a very large number of trips, details were only collected on a subset of the trips, however total trip counts were collected for each month.

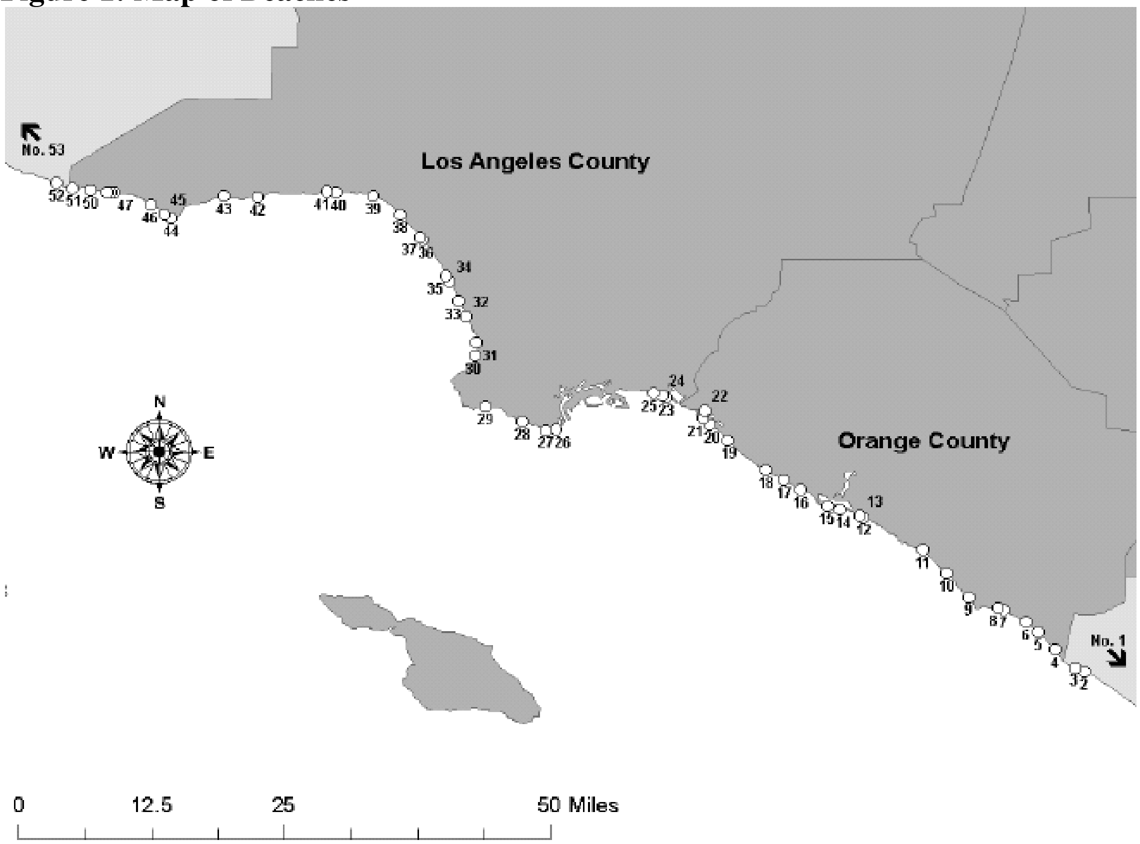
The final panel of beach goers consisted of 1161 individuals, who reported 7676 total trips to the beach. After removing trips which listed multiple destinations and trips which had no identifiable destination, the data contained details on 4545 unique trips (recall that frequent beachgoers reported their total number of trips, but were only required to supply trip details for a subset of these).

Travel costs, from the respondent's home to each possible beach site, were calculated using PCMiler. The distance and travel-time were calculated from the panelist's mailing address to each beach. Costs are based on round-trip time and distance, assuming a distance cost of \$0.145 per mile (in year 2000 dollars) and a time cost of one-half the hourly income.

The Beach Data

The California coastline from Oceanside Beach (at the northern border of San Diego County and Orange County) to Pt. Mugu Beach (at the southern border of Ventura County and Los Angeles County) was divided into 51 beaches (Figure 1) and two additional sites that captured nearby visits to beaches north (Pt. Mugu) and south (Oceanside) of the study area. Beaches in northern San Diego and southern Ventura County were included because they were contiguous with Orange County and Los Angeles County beaches and were separated from other beaches (north and south) by large military bases.

Figure 1: Map of Beaches



1	Southern Proxy	15	Newport	29	Abalone Cove	43	Dan Blocker (Corral)
2	San Onofre South	16	Santa Ana River	30	Torrance	44	Point Dume
3	San Onofre North	17	Huntington State	31	Redondo	45	Free Zuma
4	San Clemente State	18	Huntington City	32	Hermosa	46	Zuma
5	San Clemente City	19	Bolsa Chica	33	Manhattan	47	El Matador
6	Poche	20	Sunset	34	El Segundo	48	La Piedra
7	Capistrano	21	Surfside	35	Dockweiler	49	El Pescador
8	Doheny	22	Seal	36	Mother's	50	Nicholas Canyon
9	Salt Creek	23	Alamitos Bay	37	Venice	51	Leo Carrillo
10	Aliso Creek	24	Belmont Shores	38	Santa Monica	52	County Line
11	Main Beach Laguna	25	Long Beach	39	Will Rogers	53	Northern Proxy
12	Crystal Cove	26	Cabrillo	40	Topanga		
13	Corona Del Mar	27	Point Fermin	41	Las Tunas		
14	Balboa	28	Royal Palms	42	Malibu (Surfrider)		

<u>Beach Attributes: Physical, Management, Visual</u>

The research team collected data on 46 physical, visual, and management attributes of the beaches and a variety of water quality measures (see below). Many beach attribute variables were simple presence/absence measures (1/0). One problem that arises with the large number of 1/0 indicator variables is the fact that indicators of certain types of attributes (and their residuals) may be highly correlated. For instance, the presence of a marina near the beach (1/0) and the indicator for whether the beach is in a harbor are nearly identical (1/0), so including both allows the coefficients to be driven by the residuals on just a few beaches. To handle important, but highly correlated explanatory variables, we created a number of composite variables (e.g. Ugly, Much Development, Harbor/Marina, etc. see Hanemann, Pendleton, Mohn, et al., 2004 for a detailed description of these variables.)

<u>Beach Attributes: Water Quality</u>

Water quality data in Southern California are reported to the public as Beach Grades that are calculated by the not-for-profit Heal the Bay (HTB) and based on fecal indicator bacteria measures made by local health authorities. Water quality data are given in a letter-grade format ranging from F to A+. These grades are available to the public through websites, newspaper updates (similar to weather updates), and through annual beach report cards. HTB beach grade data were available for the beaches for a selection of dates ranging from June 1998 to April 2001, although not all HTB stations reported grades for each date. There are two types of HTB grades – those for “dry” days and those for “wet” days - the distinction involves the presence or absence of precipitation. Because there are not wet grades for each beach for each wave, we use only the dry grades for this analysis. For this analysis, we transform these grades into a numerical scale, then take the average of all HTB grades for a given beach for all dates, even if those measurements were in years other than the survey. This is an attempt to capture a general measure of quality that a user might expect. In other work with these data (see Hanemann, Pendleton, Mohn, et al., 2004), we explored using daily, weekly, monthly, and season summaries of the HTB beach grade. We found that this longer-term summary measure led to better-fitting models than grades which change to reflect the variation over the two-month visitation-data-collection intervals, or than grades averaged only over the 12 months of the study. This likely is due to the fact that people develop perceptions of beach water quality that are driven by their prior experiences and the public attention given to the Annual Beach Report Card that summarizes water quality measures over the last year. Since we are concerned with *ex ante* assessments of quality, multi-year averages are probably better than actual current measures for the majority of panel members who go to the beach only occasionally.

<u>Beach Attributes: Beach Width Data</u>

Finally, the research team collected data to estimate the width of each beach site from the wet sand to the back of the beach, for example, a road, cliff, or other obvious boundary. The data come primarily from the work of a team of geomorphologists led by Anthony Orme from UCLA (including James Zoulas, Carla Chenualt Grady, and Hongkyo Koo). (Zoulas and Orme 2007). Using aerial photographs and digital orthophotography quadrangle images from the USGS, the researchers estimated measurements of width (in meters) at 20 meter transects along the entire length of each site identified in our study. Some variation, and thus measurement error, was introduced into these measures due to the fact that measures for all of the beaches were derived from photographs taken on different dates and different years (see Table 1). The measurements of the UCLA research team included measures for 48 of the 51 beach sites in our study. The remaining 3 sites were Mother's Beach, San Onofre North, and San Onofre South. Sufficiently recent aerial images of these beaches were unavailable. We measured these three sites by hand, at 20 meter transects, using a Bushnell Golf Range Finder.

Table 1

Beach Width Measurement Dates

Code	Beach	Year Beach Width Measured
1	Oceanside	n/a
2	San Onofre South	2007
3	San Onofre North	2007
4	San Clemente State Beach	2001
5	San Clemente City	2001
6	Poche	2001
7	Capitrano Beach	2001
8	Doheny	2001
9	Salt Creek	2001
10	Aliso Creek	2001
11	Laguna	2001
12	Crystal Cove	2001
13	Corona Del Mar	2001
14	Balboa	2001
15	Newport	2001
16	Santa Ana River	2001
17	Huntington State	2001
18	Huntington City	2001
19	Bolsa Chica	2001
20	Sunset Beach	2001
21	Surfside	2001
22	Seal Beach	2001
23	Alamitos Bay	2001
24	Belmont Shores	2001
25	Long Beach	2001
26	Cabrillo	2001
27	Point Fermin	2001
28	Royal Palms	2001
29	Abalone Cove	2001
30	Torrance	2002
31	Redondo	2002
32	Hermosa	2002
33	Manhattan	2002
34	El Segundo	2002
35	Dockweiler	2002
36	Mother’s	2008
37	Venice	2002
38	Santa Monica	2002
39	Will Rogers	2002
40	Topanga	2002
41	Las Tunas	2002
42	Malibu	2002
43	Dan Blocker	2002
44	Point Dume	2001
45	Free Zuma	2001
46	Zuma	2001
47	El Matador	2001
48	La Piedra	2001
49	El Pescador	2001
50	Nicholas Canyon	2001
51	Leo Carillo	2001
52	County Line	2001
53	Point Mugu	n/a

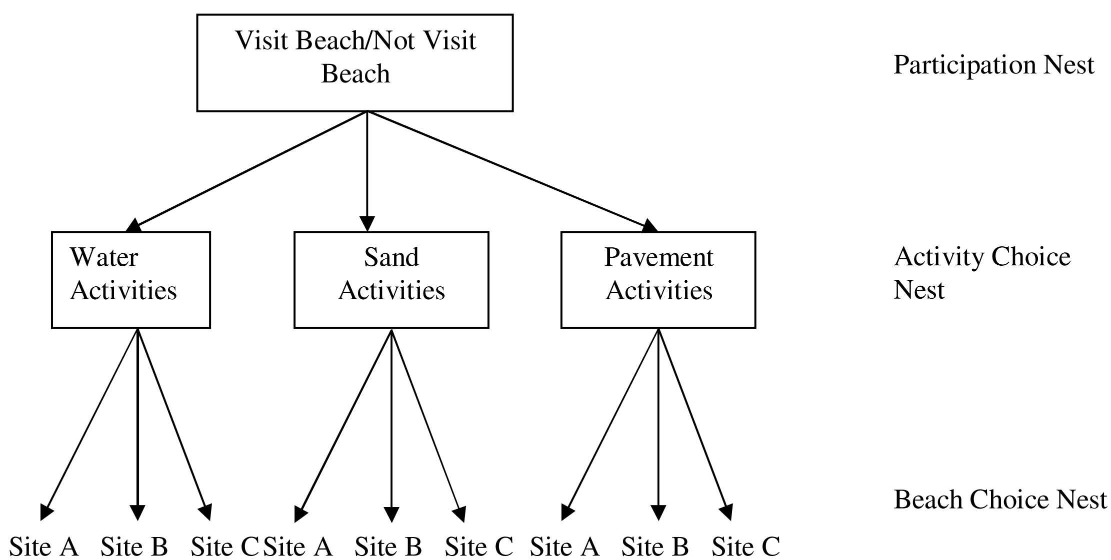
The Model

People planning different activities look for different qualities in a beach and thus may have different preferences for beach attributes. People who plan to wade or swim probably care more about water quality than people who plan to rollerblade along the sidewalk and admire the sunset. People who fish might view a pier or jetty as desirable, but swimmers are likely to have a different opinion. Someone looking for a peaceful place to sit and enjoy a picnic will likely have a different opinion of wide swaths of sand than someone else who wants to haul their surfboards to the water to catch waves.

We incorporate the heterogeneity of preferences for beach attributes by modeling the beach choice decision differently for different classes of activities. We divide the trip data into 3 categories based on the activities that the panelists reported for that trip. We consider activities where the beach goer's primary activity involves: 1) getting in the water (e.g. swimming and wading), 2) actively using the sand or the ground at the beach (e.g. volleyball and kite flying), and 3) activities where the beach goer uses paved trails, sidewalks, or beachfront restaurants. We call beach goers participating in these three activities water recreators, sand recreators, and pavement recreators, respectively. A panelist may engage in different activities on different trips, so we use demographic variables and the expected utilities from the beach choice to model the choice of activity.

The panelist is assumed to choose: whether or not to make a trip to the beach, the activity to undertake at the beach , and the beach to visit based on the option which offers the highest utility. The unobservable utility for each option is assumed to consist of a systematic part which is a function of observable attributes and an estimated parameter vector (preferences for these attributes), and a stochastic term drawn from a generalized extreme value distribution. We use a nested multinomial logit model to analyze the tradeoffs that drive the consumption decision. A description of the model is given in Hanemann, Pendleton, Mohn, et al (2004), we will not repeat the familiar mathematics of the model here, but the basic structure of the model is given in Figure 2.

Figure 2: Model Choice Structure



The Participation Nest models the decision as to whether to take a trip to the beach each day. The Activity Choice Nest models the choice of activity conditional on choosing to visit the beach, and the bottom level models the beach site choice conditional on the chosen activity. The levels of the model are linked by the expected utility derived from the choice below.

Travel cost (including the cost of travel time) enters the beach choice decision for each of the 3 types of activity. To ensure that the marginal utility of money is constant for all options, we restrict the coefficient on travel cost to be the same for all three beach choice sub-models.

<u>A Logarithmic Measure for Site Size</u>

Train (1998) observes that when modeling heterogeneous sites (like beaches), it is necessary to include a variable which is the logarithm of the "size" of the site. This is because each choice option could be thought of, and modeled, as an aggregation of identical subsites of uniform size. For example, the beach goer chooses a site within each beach which is not exactly the same as another site on the same beach. Since we lack detailed information on exactly where the beach goer decided to sit, we lump beach goer choices so that everyone who went somewhere at Beach X, say Huntington State Beach, is treated as making the same choice. If we view each site choice as containing an implicit nest that represents a choice among uniform subsites within that site, the expected utility from this choice is given by the logarithm of the size. The implied nest represents a choice among many micro-sites which differ only in the qualitative attributes. We expect the coefficients on log-size to be between zero and one, as is required of all inclusive values. (Borsch-Supan (1990) relaxed this requirement, but Herriges and Kling (1996) largely closed this loophole). In fact, deviations from our expectation that this value fall between 0 and 1 are expected since we know the assumption of uniformity among subsites is unlikely to hold perfectly. Previous models of beach demand based on this data used the length of the beach as the measure of size. Since we have both length and width data, we use area as the logarithmically transformed size factor recommended by Train when we are considering water- and sand-based activities. We retain the use of beach length, though, as the logarithmically transformed factor for pavement activities since the number of spots to bike or go inline skating at a given beach is more likely to be proportional to length than area. Since the model includes the natural logarithm of beach width, the difference in this specification is primarily done to aid interpretation of the coefficients – because log(area) = log(length) + log(width), the difference in specification merely shifts the value of the parameter capturing the utility of beach width.

Site Specific Constants

Most of the beaches are characterized reasonably well by their attribute levels. However, two beach proxies, north and south of the study area (i.e. the geographic choice set) were also included. These proxies, Oceanside and Point Mugu, were characterized solely by binary indicator variables (Alternative Specific Constants – ASC) and travel costs because we did not have beach attribute data for them. Point Mugu is omitted from water activity and sand-activity choices, since there were no trips to that destination for those activities. This poses an estimation problem for water- and sand-based activities, since there are no observed trips to Mugu for these types of activities. There are few observed trips for pavement-based activities. However, Mugu is not *a priori* eliminated from any choice sets. It is among the most distant of beaches for many panelists, and the lack of observed trips there may be a function of the finite sample size and the relatively high cost to get there. Rather than removing Point Mugu from the choice sets for sand- and water-based trips, we included the Mugu ASC and constrained the coefficient to be the same for all three activity-type sub-models.

Because of the nested structure of the model, we can make use of observations with partially missing data. If a destination among our 53 sites cannot be determined, but we know the activity type, we can still use an observation to estimate activity-choice.

Estimating the Model

We use a simple nested logit structure rather than a mixed-logit (random parameter) model because it gives us more control over the choice structure of the model and allows us to use data for which trip detail may be incomplete. Because the trip count data do not perfectly map to the trip detail data, a mixed-logit model cannot estimate all three aspects of the choice decision. With three activity types, 53 beach options for each, plus the option of no beach trip, there are 160 alternatives in each of 365 days. Considering the large number of alternatives and the large number of beach attributes, the mixed logit model becomes computationally very difficult to estimate.

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Coefficient Estimates

The coefficient estimates for the three-level nested model are given below. All levels and the expected utilities connecting them were estimated sequentially. Table 2 below presents the parameter estimates from the Beach Site Choice nest of the model.

Table 2.a

Site Choice Terms Common to all 3 Activity Types

	Coef.	Std. Err.
Travel Cost	-0.090	0.002
Mogu Dummy	1.977	0.730
Activity Choice Log Likelihood	-12526.746	

Table 2.b

Site Choice Terms For Water Based Activity Choice

	Coef.	Std. Err.
Average Water Quality Grade (HTB)	0.306	0.061
Ln(Length)	0.711	0.064
Width	0.076	0.020
Width >= 60m	-0.065	0.013
$(\text{Width})^2$	4.2 E-4	1.9E-4
$(\text{Width})^3$	-9.5 E-7	4.6 E-7
Ugly	-0.286	0.062
Much Development	-0.186	0.071
Wild	0.246	0.127
Surfing	0.786	0.135
Diving	0.628	0.105
Harbor/Marina	-1.341	0.109
Density of LifeGuard Stations	0.330	0.036
Average Water Quality Grade (February-March)	-0.201	0.137
Oceanside Dummy	3.311	0.378

Table 2.c

Site Choice Terms For Sandy Based Activity Choice

	Coef.	Std. Err.
Ln(Area)	0.373	0.056
Width	0.035	0.020
Width > = 20	-0.067	0.025
Width > = 60	-0.068	0.014
Sandy*(Width)	0.003	0.001
Kids*(Width >= 20)	0.002	0.001
$(\text{Width})^2$	5.8 E-4	2.2 E-4
$(\text{Width})^3$	-1.0 E-6	5.5 E-7
Some Development	0.955	0.092
Wild	1.286	0.143
Harbor/Marina	-0.876	0.087
Restrooms	1.775	0.216
Oceanside Dummy	2.789	0.493

Table 2.d

Site Choice Terms For Pavement Based Activity Choice

	Coef.	Std. Err.
Ln(Length)	0.627	0.074
Width	0.026	0.006
Width >= 60m	-0.019	0.006
Much Development	-0.841	0.085
Wild	0.823	0.171
Parking	-1.772	0.239
Public Facilities Available	-0.563	0.114
Sandy	0.561	0.411
Showers	2.469	0.211
Adjacent On Street Parking	1.549	0.213
Harbor/Marina	0.197	0.081
Nature	0.626	0.214
River at Beach	1.470	0.241
Bikepath	0.434	0.189
Camping	-3.038	0.217
Restrooms	0.968	0.332
Sidewalk	0.647	0.156
Rentals Available	0.039	0.095
Oceanside Dummy	4.674	0.571

The variables affecting beach choice are:

Table 2.e

Site Choice Term Definitions

Variable	Defintion
Tavel Cost	Travel Cost in 2000 US$
Mugo Dummy	Alternative Specific Constant for Mugo
Oceanside Dummy	Alternative Specific Constant for Oceanside
Average Water Quality Grade (HTB)	the average dry grade as reported by Heal the Bay
Ln(Area)	log of the beach area
Ln(Length)	log of the beach length
Width	Beach width
Width >= 20	Indicator of beach width being greater than 20m
Width >= 60	Indicator of beach width being greater than 60m
$(\text{Width})^2$	Beach width squared
$(\text{Width})^3$	Beach width cubed
Sandy*Width	Beach width for sandy beaches
Kids*(Width>=20m)	Indicator of beach width being greater than 20m for households with kids.
Ugly	oil rigs, power plants, etc visible from beach
Wild	beach is wild or remote
Some Development	beach has some development (condos, clubs, vendors, etc)
Much Development	beach has much development
Surfing	beach is good for surfing
Diving	beach is good for diving
Harbor/Marina	beach has a marina or is in a harbor
Restrooms	beach has public restrooms
Density of Firepits	density of firepits
Public Facilites Available	beach has facilities
Sandy	beach is sandy
Parking	beach has parking
Adjacent On Street Parking	beach has adjacent on street parking
Nature	beach adjacent to a natural area
River at Beach	river flows through beach
Bikepath	beach has bikepath
Sidewalk	beach has sidewalks
Camping	beach open for camping
Rentals	beach has equipment rentals
Density of LifeGuard Stations	density of lifeguard stations if trip in june or july
Average Water Quality Grade (February-March)	average dry grade if trip in february or march

For water-based activities, the coefficients on $Width^3$ and (Width>=60) are negative. However, the coefficients on Width and $Width^2$ are positive. This means that wider beaches are better for water recreators, but there are diminishing returns to width, and further increasing a beaches width beyond 60m reduces the economic wellbeing of beach goers. This is intuitive, since while sand has some redeeming value to water recreators, most people would prefer to haul their boats, surfboards or scuba gear across the shortest distance of sand possible. Sand recreators only prefer width in excess of 20m on sandy beaches, and those who have children have a stronger preference for wide beaches. Again this makes sense, since wider beaches provide a bigger buffer between the recreation site and surf which may be dangerous for young children. Pavement recreators also prefer wider beaches. These results suggest that where there is sand, there is always some public benefit obtained from beach nourishment.

The parameter estimates for the activity-choice nest are given below in table 3:

Table 3.a

Activity Choice Nest	Coef.	Std. Err.
Inclusive Vale from Site Choice		
Rho	0.211	0.122
Water Based Activity Choice		
Male	0.562	0.069
Black	-0.892	0.235
Hispanic	-0.137	0.087
(Wave 4)*Kids	0.506	0.141
Wave 2	0.147	0.172
Wave 3	1.560	0.129
Wave 4	1.829	0.224
Wave 5	1.495	0.119
Wave 6	0.921	0.139
Constant	-1.508	0.211
Sand Based Activity Choice		
Wave 2	0.955	0.108
Wave 3	0.535	0.132
Wave 4	1.639	0.121
Wave 5	0.360	0.122
Wave 6	0.370	0.136
Constant	-0.948	0.140

The variables affecting activity choice are:

Table 3.b

Activity Choice Term Defintions	
Variable	**Defintion**
Male	The panelist is male
Black	The panelist is black
Hispanic	The panelist is hispanic
(Wave 4)*Kids	The panelist has kids and the choice was made in June or July
Wave 2	Choice was made is February or March
Wave 3	Choice was made in April or May
Wave 4	Choice was made in June or July
Wave 5	Choice was made in August or September
Wave 6	Choice made in October or November
Rho	Expected Utility from Site Choice

The parameter estimate in the Inclusive Value section is the coefficient on expected utility from the beach choice level of the model for each activity type. The parameters in the Water Based Activity section capture the contribution of the variables to the utility of water-based activities, the parameters in the Sand Based Activity section capture the contribution of the variables to the utility of sand-based activities. The utility of pavement-based activities, being the baseline category, are determined from the expected utility alone. For instance, beach goers are more likely to choose water-based activities from April through September (wave 3, 4, and 5) and Blacks and Hispanics are less likely than others to choose water-based activities.

The parameter estimates for the participation nest are given below in table 4:

Table 4.a

Participation Nest	Coef.	Std. Err.
Inclusive Value from Activity Choice		
Rho2	0.510	0.026
Participation Terms		
Summer	0.019	0.035
Male	0.331	0.026
Black	-0.642	0.067
Hispanic	-0.543	0.033
Kids	-0.359	0.037
Student	-0.178	0.033
Work Part-time	0.176	0.038
Summer*Kids	0.365	0.056
Constant	-4.635	0.059

The variables affecting participation are:

Table 4.b

Participation Nest Term Definitions

Variable	Defintion
Male	The panelist is male
Black	The panelist is black
Hispanic	The panelist is hispanic
Kids	The panelist has kids in their household
Student	The panelist is a student
Work partime	The panelist works part time
Summer*Kids	summer and has kids in household
Rho2	Expected Utility from Activity Choice

The parameter estimate in the Inclusive Value section is the coefficient on the inclusive value from the activity choice level of the model, reflecting the expected utility of choosing a given activity for any beach trip. The fact that it is larger than the coefficient on the beach choice submodel is consistent with a correctly-specified nested logit model capturing utility maximizing behavior. These coefficients combined with the variables give the utility of taking a beach trip relative to not taking a trip (which has utility normalized to zero).

Comparison with an Earlier Model:
The Impact of Adding Beach Width Covariates

This model is based on an exceptionally rich dataset of beach attributes – the raw data has as many attributes as there are beaches, and so clearly the dimensionality had to be reduced by attribute aggregation and selection to define a useful model – including too many variables in a model may yield exaggerated apparent predictive power because of spurious correlations between attributes, while a specification which is too sparse can cause omitted variable bias. When beach width measurements are incorporated into an existing model, there should be relative stability of welfare measure changes for scenarios where beach width is held constant, barring an obvious explanation in terms of the new variable.

We compare three scenarios involving closures and water quality changes, and find that the predicted welfare changes are very close between the two models for cases involving Malibu and Huntington beaches. The case where Zuma's water quality is dramatically changed leads to welfare estimates which differ by a much larger factor – this is because Zuma is a relatively popular beach which offers not only excellent water quality, but it is also much wider than most nearby alternatives, so including beach width in the model greatly tempers the beach-goers' substitution response when water quality is drastically reduced.

Table 5

Scenario	**Welfare Change Model without Width**	**Welfare Change – Controlling for Width**
Malibu Beach Quality Improves from 2.13 to 3.0	\$140,564	\$142,006
Zuma Beach Quality Degrades from 4.24 to 0.0	-\$5,272,578	-\$2,633,015
Huntington State Beach Closes for Summer Months	-\$9,304,186	-\$9,445,647

Estimates of the Economic Cost of Six Scenarios of Beach Width Change

To illustrate the economic consequences of changes in beach width (and thus the value of nourishment or the cost of erosion or sea level rise) we estimate six counterfactual scenarios of beach width (that is, we compare the non-market economic value and number of trips to beaches at current beach widths and at hypothetical beach widths). In choosing the particular counterfactual scenarios we attempted to capture the effects of both extreme and common changes in beach width. We examine potential counterfactuals at 5 different beach sites. From north to south these beaches are, San Clemente City and State Beaches, Huntington City and State Beaches, Topanga, Malibu, and Leo Carrillo Beach

Table 5 below presents the results from each of the six counter factual scenarios we examined. For each scenario the table lists the size of the population affected, predicted change in consumer surplus for the affected population, and the predicted change in trip count, for each of Los Angeles, Orange, Riverside, and Santa Barbara counties. In each column negative dollar values are presented in parentheses.

All of the predicted counterfactual scenarios behave in a matter consistent with beach users gaining positive utility from beach width. In each case that beach width is reduced the change in consumer surplus is negative for all users, meaning that a loss of beach reduces the economic wellbeing of beach goers. In each case that beach width is increased the change in consumer surplus is positive for all users. The largest changes in consumer surplus for a single beach were predicted at Huntington Beach (Columns 2 and 3). This is not surprising as Huntington Beach experienced the largest number of beach trips in our sample.

Residents of counties closest to the affected beach sites uniformly experienced the largest negative consumer surplus changes from beach width loss, however this is not always the case for beach width increases. In the case of increasing beach width in Huntington Beach visitors from Los Angeles County experience a greater positive change in consumer surplus than visitors from Orange County. This may be because Orange County residents already choose Huntington Beach in overwhelming numbers, but very large numbers of residents from Los Angeles also visit Orange County beaches and many might preferentially choose Huntington Beach if it were wider. This effect appears to be unique to Huntington Beach, and may not be generalizable to other beach sites as Huntington Beach draws many more outside visitors than any other beach in our study. To illustrate the preceding point note that while width increases at Malibu's surfrider, as well as reductions at Leo Carrillo and Topanga, greatly affect Los Angeles county residents, the effects are 2 orders of magnitude smaller in all other regions.

Table 5

Counter Factual Scenario Results

	(1)	(2)	(3)	(4)	(5)	(6)
Scenario	50% Increase in Width	50% Decrease in Width	City Beach Size to State Size	100% Increase in Width	100% Decrease in Width	50% Decrease in Width
	San Clemente City and State	Huntington Beach	Huntington Beach	Malibu	Leo Carrillo	Topanga
Total Populatoin	10654480	10654480	10654480	10654480	10654480	10654480
Total Change in CS	$3,154,431.00	($8,516,873.00)	$7,240,547.50	$1,230,381.30	($1,508,063.50)	($1,694,691.00)
Baseline Trips	52709968	52709968	52709968	52709968	52709968	52709968
Change in Trips	29510.199	-80113.172	68396.523	11555.314	-14114.418	-15867.569
Baseline Distance Traveled	3313.643	3313.643	3313.643	3313.643	3313.643	3313.643
Change in Distance Travelec	7.992	-5.466	6.021	1.170	-4.802	-0.124
LA County						
Population	6545710	6545710	6545710	6545710	6545710	6545710
Change in CS	$575,494.69	($3,111,284.30)	$3,128,073.80	$1,187,582.00	($1,441,594.00)	($1,578,302.80)
Baseline Trips	32759234	32759234	32759234	32759234	32759234	32759234
Change in Trips	5386.598	-29301.645	29576.213	11152.124	-13490.063	-14773.818
OR county						
Population	2001550	2001550	2001550	2001550	2001550	2001550
Change in CS	$1,434,066.80	($3,688,999.30)	$2,822,027.30	$8,594.91	($12,566.71)	($34,507.89)
Baseline Trips	12007757	12007757	12007757	12007757	12007757	12007757
Change in Trips	13336.704	-34545.359	26555.416	80.255	-116.918	-321.618
RV county						
Population	1014430	1014430	1014430	1014430	1014430	1014430
Change in CS	$660,701.56	($851,223.69)	$646,526.13	$9,197.69	($14,713.36)	($22,793.98)
Baseline Trips	3861235.8	3861235.8	3861235.8	3861235.8	3861235.8	3861235.8
Change in Trips	6220.648	-8061.761	6141.308	86.779	-138.411	-214.888
SB County						
Population	1092790	1092790	1092790	1092790	1092790	1092790
Change in CS	$484,168.16	($865,365.63)	$643,920.44	$25,006.73	($39,189.50)	($59,086.48)
Baseline Trips	4081740.3	4081740.3	4081740.3	4081740.3	4081740.3	4081740.3
Change in Trips	4566.251	-8204.403	6123.589	236.156	-369.026	-557.245

Negative Currency Values are in Parentheses

Preliminary - Do Not Cite or Quote

Conclusion

This research demonstrates that beach size does matter to the beach users, but the value of increasing beach width is different for different types of users. Beach managers should carefully consider the activities undertaken by beach goers at a particular beach when weighing the potential benefits and costs of beach nourishment or beach erosion. Further, we show that wider beaches are better, but only to a point. Some beaches in southern California are so wide that getting from the car to the water is quite an undertaking. While extremely large beaches are not likely to be targets of beach nourishment, these findings indicate that these beaches could possibly benefit from limited erosion. As natural sources of beach sand become more scarce, sand from extremely large beaches, especially accreting beaches, could be considered as possible source of sediments for the nourishment of eroding beaches.

The model can be used to predict the economic impacts of changes to the width of individual beaches. This can be done relatively simply using the panel assembled for estimation, or it can be done using a representative population drawn from census data for better welfare estimates. Such a model can be used in cost-benefit analyses for specific beach projects to preserve and enhance beaches. This model can also be used to evaluate the impact of beach change due to storms, sea level rise, armoring, or any other factor that causes beach width to change.

References:

Ben-Akiva, Moshe E. and Lerman, Steven R. (1985) *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press, Cambridge, MA.

Bockstaehl, N.E., Hanemann, W.M. and Strand, I.E. (1986) "Measuring the Benefits of Water Quality Improvement in a Recreational Demand Framework". *Water Resources Research* **23**, 951-60

Bookman, C. A., T. J. Culliton, and M. A. Warren. (1999). Trends in U.S. Coastal Regions, 1970 - 1998. National Oceanic and Atmospheric Administration (NOAA). Silver Spring, MD.

Borsch-Supan, Axel. (1990) "On the Compatibility of Nested Logit Models with Utility Maximization." *Journal of Econometrics* **43**, 1990.

Freeman III, A. Myrick; 1993. "Recreational uses of natural resource systems." Chapter 13 in The Measurement of Environmental and Resource Values, Theory and Methods. Resources for the Future, Washington, DC.

Hanemann, W. Michael (1984b) "Multiple Site Demand Models. Part I: Some Preliminary Considerations". Giannini Foundation Working Paper No. 336. Department of Agricultural and Resource Economics, University of California, Berkeley.

Hanemann, W. Michael, Linwood Pendleton, Craig Mohn, James Hilger, Koichi Kurisawa, David Layton, Chris Busch, and Felipe Vasquez (2004) *Using revealed preference models to estimate the effect of coastal water quality on beach choice in Southern California*. Report to U.S. Dept. of Commerce, National Oceanic and Atmospheric Administration (NOAA), U.S. Dept. of the Interior: Minerals Management Service,CA Department of Fish and Game: Office of Spill Prevention and Response (OSPR), CA State Water Resources Control Board, and Santa Monica Bay Restoration Commission

Herriges, Joseph A. and Catherine L. Kling(1996). "Testing the Consistency of Nested Logit Models with Utility Maximization." *Economic Letters* **50** January 1996

Huang, Ju-Chin, P. Joan Poor (2004). "Welfare Measurement with Individual Heterogeneity: Economic Valuation of Beach Erosion Control Programs." Working Paper, Department of Economics, University of New Hampshire.

Landry, Craig E., Andrew G. Keeler and Warren Kreisel (2003) "An Economic Evaluation of Beach Erosion Management Alternatives." *Marine Resource Economics* **18**, 105-127

Parsons, George R., D. Matthew Massey and Ted Tomasi (2000) "Familiar and Favorite Sites in a Random Utility Model of Beach Recreation." *Marine Resource Economics* **14**, 299-315

Pendleton, L. and J. Kildow. "The Non-Market Value of California's Beaches", Shore and Beach (Journal of the American Shore and Beach Preservation Association), v. 74, n. 2, Spring 2006, pp. 34-37. March 2006.

Train, Kenneth (1998). "Recreation Demand Models with Taste Differences Over People." *Land Economics* **74**, 230-39

Train, Kenneth (2003) *Discrete Choice Methods with Simulation.* Cambridge University Press, New York, NY

Whitehead, John C., Christopher F. Dumas, Jim Herstine, Jeffery Hill, Bob Buerger (2006) "Valuing Beach Access and Width with Revealed and Stated Preference Data." Working Paper 06-15. Department of Economics, Appalachian State University, Boone, NC.

Zoulas, J.G. and Orme, A.R. (2007). Multidecadal-scale beach changes in the Zuma Littoral Cell, California. Physical Geography, 28, 4, pp. 277 - 300.