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Implications for Management

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Jane K. Turpie, Jeremy R. Goss, and Katherine J. Forsythe

Abstract

Inshore line fish stocks are severely depleted in South Africa. Although management efforts have addressed pressures from the commercial and subsistence sectors, management of the recreational sector still needs to be addressed. Evidence suggests that spatial management measures would be more successful than traditional size and bag limits. In order to inform a spatial approach, this study investigated the determinants of temporal and spatial variability in angler distribution around the coast. Roving-creel data, which included GPS locations of all anglers encountered, were collected in six coastal areas totalling 456.2 km, with each section divided into a number of beats. Beats were divided into sub-beats for analysis, based on shore type. Anglers were encountered on only 17% of beat monitoring days, which meant that the analysis had to deal with a high frequency of zeros. Data were analysed using both two-part models for continuous data and zero-inflated models for count data, with sub-beat length as an offset variable in the latter models. Contrary to expectation, catch per unit effort (CPUE) was a stronger predictor of angler densities than distance from vehicle access points and source populations. This suggests that anglers are more sensitive than expected to catch rates and would benefit from stock conservation measures. Their distribution also suggests a perceived and/or real impact of -human population on fish stocks, resulting in the need to travel farther to find better fishing sites. However, the data also suggest that excess fishing pressure occurs adjacent to populous areas as a result of the simple economics of leisure in time- and income-constrained households. Temporal variation in angler numbers is high and will require a changed approach to enforcement effort.

Key Words: recreational fisheries, angler behaviour, shore angling

JEL Codes: Q22, Q26

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1. Introduction

Inshore line fish stocks around the South African coast have been severely depleted, to the extent that the government declared a State of Emergency for these resources in 2005. Most of the targeted species are slow-growing, and their vulnerability to overexploitation is compounded by the open access or quasi-open access nature of some of the inshore fisheries.

While commercial fishing has historically received most of the blame for declines in fish stocks globally, it has recently been recognised that recreational fisheries potentially also contribute to these declines (Cooke and Cowx 2006). While some effort has been made to reduce effort in the commercial and subsistence fisheries in South Africa, with some apparent success in terms of stock recovery, there has been little change in the management of the recreational fisheries, whose stocks show no sign of recovery. Some of these species, such as galjoen, white steenbras, bronze bream and white musselcracker, are caught almost exclusively in the shore angling fishery. In general, recreational fisheries are not being managed sustainably, and should be treated with the same degree of urgency as commercial fisheries (Cooke and Cowx 2006; Johnston et al. 2010). Indeed, Stoeven (2011) presented a model describing the effects of variation in angler motivations on fish stocks, suggesting that anglers not motivated by catch rates could fish stocks to extinction.

Management of recreational fisheries is particularly challenging, however, because of the open access nature of the fishery and lack of information about the participants. There has been very little research and monitoring on recreational anglers in South Africa, resulting in uncertainty about the numbers of participants, their distribution and habits, and their catch rates

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and impacts on fish stocks. Management measures that have been put in place, such as annual fishing licenses and size and bag limits, have been ineffective (Bennett et al. 1994). This is largely due to the prohibitive cost of effectively policing the entire coastline, especially given the variability in angler numbers in time and space. However, spatial management measures, particularly marine protected areas that are closed to angling, appear to be one approach that has more merit than any of the others (Bennett and Atwood 1991). This suggests that more emphasis should be placed on understanding spatial variation in the pressure on recreational angling fish stocks in order to develop spatial strategies to ensure the recovery and sustainability of these fisheries.

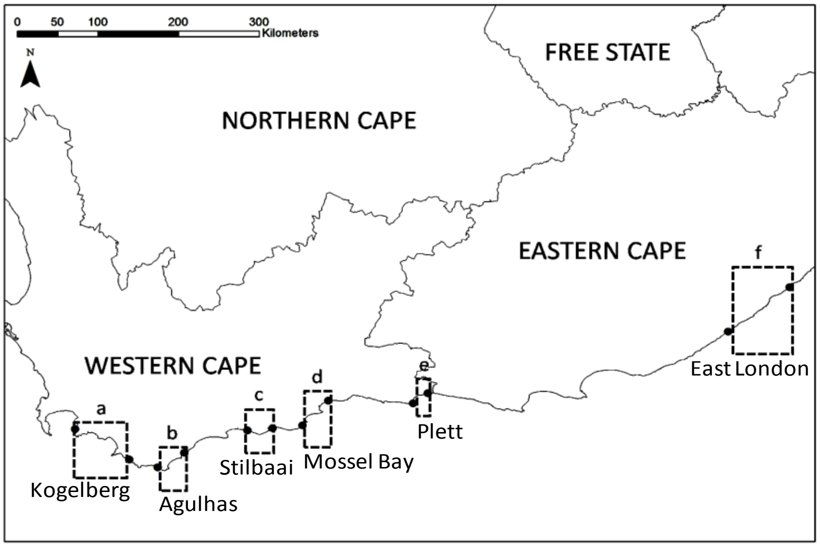
The aim of this study was to develop an understanding of the drivers of spatial distribution of shore-angling pressure around the coast, so as to inform strategies for the recovery and sustainable management of threatened fishery resources.

2. Methods

2.1 Study Area

The study took place at six locations along the south coast of South Africa, within the Eastern and Western Cape Provinces (Figure 1**Error! Reference source not found.**), from just east of Cape Town to just east of East London. The south Cape coast contains a number of towns, including Cape Town, Mossel Bay, Port Elizabeth and East London, and numerous smaller resort towns, such as Hermanus, Knysna, Plettenberg Bay and Port Alfred. This part of the coast is known for its spectacular scenery, and contains a variety of shore types, ranging from rocky and boulder shores to sandy beaches and mixed shores. The coastline is also punctuated by numerous small, medium and large estuaries. Parts of the coast are protected in marine protected areas, most of which are closed to anglers (Figure 1). Recreational activities including shore angling are popular along this entire area, and there are also numerous launch sites for boat-based angling.

Figure 1. Map Showing the Sampling Locations around the Coast



2.2 Roving Creel Survey

A roving creel survey of recreational shore anglers was carried out at the six sampling locations from 28 January 2010 to 30 August 2011. Each sampling location was broken up into a number of survey beats (Table 1). For this study, each beat was further broken down into sub-beats, based on changes in coastal habitat.

Monitors from each location were assigned specific routes within the designated areas, and deployed at different beats according to a roster generated by a randomising program. Monitors employed roving intercept survey techniques by walking the designated beat, counting anglers and interviewing as many of them as possible to collect catch and effort data. The starting position and direction of travel were randomly allocated for each shift. Monitors were required to walk the assigned beats regardless of weather or day of the week, and environmental data such as weather conditions and wind speed were recorded.

On a sampling day, each beat was walked once, and the location of each angler encountered was recorded using a GPS. For each angler, the time spent fishing up to the time of the interview and the details of the catch were recorded.

Table 1. Sampling Periods and Numbers of Beats and Sub-beats for Each of the Study Locations

Location	Total length (km)	Date start*	Date end	# of beats	# of sub-beats
East London	109.2 km	2010/04/02	2011/08/30	20	124
Kogelberg	140.3 km	2010/02/08	2011/08/31	18	62
Mosselbaai	66.9 km	2010/04/26	2011/08/30	12	55
Plettenberg Bay	45.6 km	2010/03/21	2011/08/29	7	42
Stilbaai	39.8 km	2010/02/11	2011/08/30	7	37
Struisbaai	54.4 km	2011/01/17	2011/08/30	8	44

2.3 Angler Densities

Over the study period, a total of 9525 angler records were collected in the various locations. Due to delays in some of the observers receiving GPS units, and due to some GPS co-ordinates being incorrectly recorded or captured, only 8797 of these records could be definitively placed in a sub-beat with a GPS location. This was done by plotting all recorded angler locations in ArcGIS 9.0, and including only those that fell within a 500 m buffer surrounding each sub-beat.

2.4 Explanatory Variables

Angler densities recorded at any point in time were expected to be a function of temporal, weather and locational variables (Table 2). Temporal variables considered included season, weekends and school holidays. Season was treated as a categorical variable, with summer defined as December to February, autumn as March to May, winter as June to August and spring as September to November. It was expected that school holidays would have an effect on the number of shore anglers; two main holiday periods were defined according to the government school calendar and included the periods from 22 June to 16 July, and 7 December to 11 January. A third categorical variable captured whether each observation took place on a weekday or on the weekend. A total of six observations of sub-beats were removed because of missing dates.

Table 2. Temporal, Weather and Locational Explanatory Variables Used to Try and Explain the Angler Density Along the Coastline

Type of variable	Variable	Levels	Average anglers/ km	Standard Deviation
Temporal	Holiday	Holiday	0.566	1.722
		Term	0.411	1.521
	Season	Autumn	0.525	1.847
		Spring	0.403	1.352
		Summer	0.516	1.558
		Winter	0.320	1.308
	Day type	Weekday	0.275	1.136
		Weekend	0.853	2.271
Weather	Wind Speed	continuous		
	Cloud cover	Clear	0.570	1.822
		Mostly clear	0.350	1.167
		Overcast	0.407	1.678
		Partly cloudy	0.304	1.153
		Scattered clouds	0.421	1.478
Locational	Shore Type	Boulder Beach	0.149	0.650
		Estuary Beach	0.497	1.715
		Mixed	0.637	1.852
		Rocky	0.384	1.529
		Sandy Beach	0.360	1.297
	Access	continuous		
	CPUE	continuous		
	Population 0-10 km	continuous		
	Population 10-100 km	continuous		
	Population 100-250 km	continuous		
	Regional CPUE	continuous		

Locational variables used in the analysis included the six sections of the coast, average catch per unit effort (CPUE) as a proxy for expected catch, the nature of the coastline, distance from the nearest vehicle access point and source populations within different distance bands.

The maximum daily bag limit for fish targeted by recreational pole anglers is no greater than ten per angler per day; in any cases where catch was greater than this, the observations were excluded on the assumption that they were records of anglers fishing with hand lines or nets for subsistence purposes. There were 11 instances of removing a sub-beat record for this reason. In order to maintain a large enough sample size, average CPUE was estimated for each shore-type within a beat, rather than at the individual sub-beat level. This was done by summing the total number of fish caught from each shore-type within a beat, dividing this number by the total time that anglers had spent fishing there, and converting this to number of fish/100 hours. Where there were no data for CPUE for a given shore type in a particular beat (i.e., no anglers were ever encountered in that shore type within that beat), the average CPUE of all the other shore types within the same beat was assigned. Weather data included cloud cover (expressed in eighths) and wind speed, measured in knots, recorded on each sampling day in each beat.

To capture the nature of the coastline, each sub-beat was assigned to one of five shore type categories: boulder shoreline, estuary, mixed shoreline, rocky shoreline or sandy beach. The sub-beat breaks and classification were done primarily through examination of the shoreline with Google Earth; where the shore type was indiscernible, it was determined from a national coastline GIS layer.

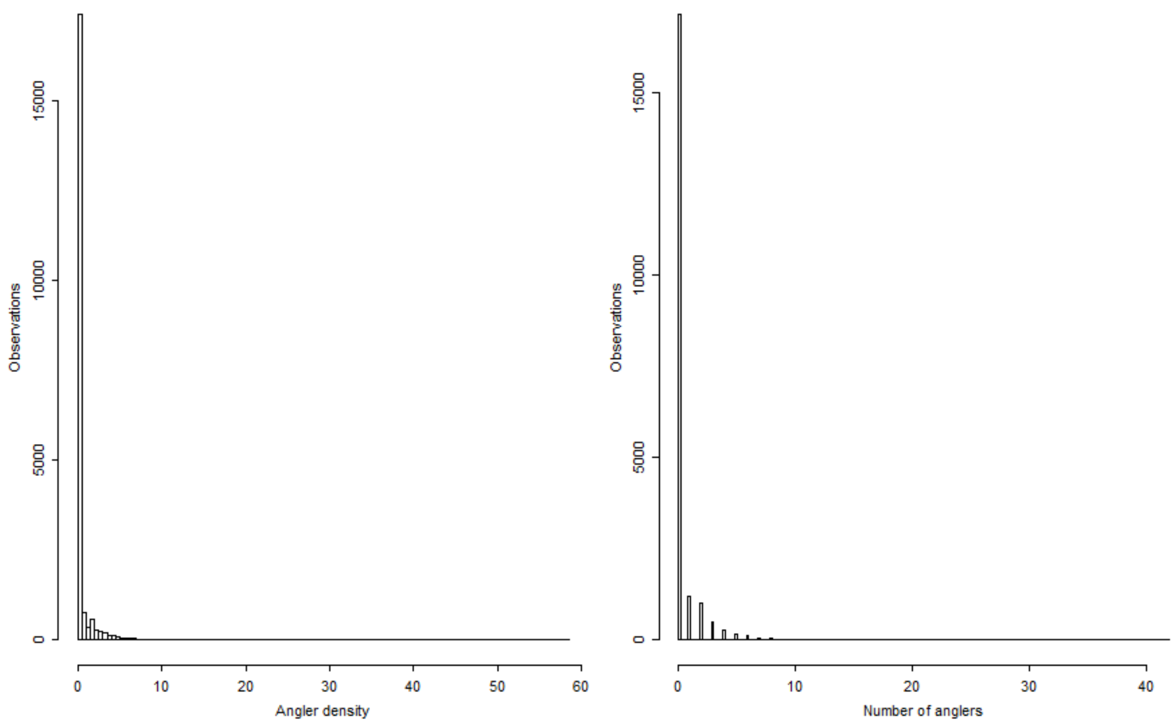
Distance from the centre of the sub-beat to the nearest public vehicle access point was measured in metres, rounded to the nearest 100 metres. Public access points were identified by inspection of Google Earth images and with the help of the observers, and included both gravel and tar roads.

In order to capture the impact of the size of the source population surrounding a stretch of coastline, ArcGIS was used to construct buffers of 1 km, 5 km, 10 km, 30 km, 50 km, 100 km and 250 km around each sub-beat. These were then intersected with a GIS polygon layer of fine-scale census areas ("sub-places") and their populations. Where an entire sub-place fell within a buffer, the whole population was counted in the buffer. Where only a proportion of a sub-place intersected with a particular buffer, the same proportion of the sub-place population was added to the buffer. These buffers were converted into bands (e.g., 0-5 km, 5-10 km, etc.) by subtracting the population within the smaller buffer from that within the larger buffer. Correlations between these bands were assessed and the final input bands (0-10 km, 10-100 km and 100-250 km) were created, in order to limit correlations between bands and also to represent meaningful distances from fishing sites (very near, medium distance and far). Population was measured in thousands of people for all bands.

2.5 Statistical Analysis

Each survey of each sub-beat was treated as an independent observation. Histograms for angler density (anglers per km) and angler count show that there are a large proportion of zeros (83%) in the data, with a right-skewed distribution for the positive values (Figure 2). An understanding of the source of these zeros is important for sensible modelling (Martin et al. 2005). In a small number of cases, the zero arose from observer error, where the observer may have forgotten to bring a GPS and, despite counting the anglers, was unable to record their position, effectively leading to a 'false' zero in the spatial data set. A second and more important contribution to zero observations relates to sampling effort. The observer may have walked the coast at a time when no anglers were present, but anglers may have been present either before or after the survey, leading to another 'false' zero. The 'true zeros' would have occurred when no anglers used the site on a particular monitoring day.

Figure 2. Frequency Distribution of Records of Angler Densities and Numbers at the Sub-beat Scale



The large proportion of zero observations in the data set violates the assumption that a single parametrically-specified probability distribution can adequately describe the population underlying the observed data. Common responses to this problem include transformation of the dependent variable and separation of the data into two groups: those where the outcome is zero and those where the outcome is greater than zero (Karazsia and van Dulmen 2008). There are problems with both of these; transformation of the dependent variable may address non-normality but does not address the abundance of zero observations, and separation of the data ignores meaningful variation (MacCallum et al. 2002). The use of mixture models and conditional models are two common approaches to handling this zero-inflation in datasets.

Conditional models, including Tobit models, two-part models and hurdle models, can be applied in different forms to continuous data (Duan et al. 1983) and discrete data (Welsh et al. 1996). These models consists of a zero mass, the so-called 'hurdle', described with a logit or probit model, and a truncated form of a standard continuous or discrete distribution. In conditional models, the zero mass is thus modelled independently of the non-zero values, and the covariate effects on presence/absence can be interpreted separately from the effects on abundance. Mixed models also have a degenerate distribution with mass at zero, but differ fundamentally from conditional models in that the non-degenerate distribution is not zero-truncated, and zeros can thus arise from both parts of the model. Zero-inflated mixed models were introduced by Lambert (1992) using a Poisson distribution but the term can apply to any distribution to indicate that there are more zeros than would be expected on the basis of the non-zero counts in the data. Specification of a mixed model allows assessment of the likelihood that a zero arose from the degenerate zero mass as opposed to the non-degenerate part of the model, while the conditional models handle the zeros separately from the non-zeros. As the conditional model treats all zeros in the same manner, the mixed models are more useful for analysis of data where a large proportion of sampling or 'false' zeros is expected (Zuur et al. 2009). In this case, we expect sampling zeros and so the mixture models are more appropriate than the conditional models.

Despite the fact that the dependent variable of interest, angler density, is a non-integer better represented by a continuous probability function, we elected to model angler count with the length of the sub-beat included as an offset term. This allowed us to model the integer-value count of anglers for each beat, but to interpret our model coefficients as impacts on angler density.

A number of options exist for modelling count data, including Poisson, negative binomial, zero-inflated Poisson (ZIP; Lambert 1992) and zero-inflated negative binomial models (ZINB; Cameron and Trivedi 1998). The Poisson model is restrictive in its assumption that the mean and variance of the count variable are equal. If this is not the case, then the data are overdispersed and the quasi-Poisson model may be appropriate, as it relaxes the above assumption. The negative binomial model is better designed than the Poisson models to deal with overdispersion, and includes a dispersion parameter. However, there may be situations where overdispersion is a result of a high proportion of zeros in the data, and ignoring this zero inflation may result in biased parameters and standard errors (Minami et al. 2007; Zuur et al. 2009). In such situations, zero-inflated models such as those described above may be appropriate. Zero-inflated Poisson models will reflect data accurately if the overdispersion is caused by the large number of zeros. However, if there is overdispersion beyond what is attributable to the inflated number of zeros, the zero-inflated negative binomial is more appropriate (Long and Freese 2006). Post-hoc statistical tests are available to assess model fit. The negative binomial and

ZINB models are not nested and so can be compared with the Vuong test (Vuong 1989). The ZIP and ZINB models, however, are nested and so can be compared with a likelihood-ratio (LR) test.

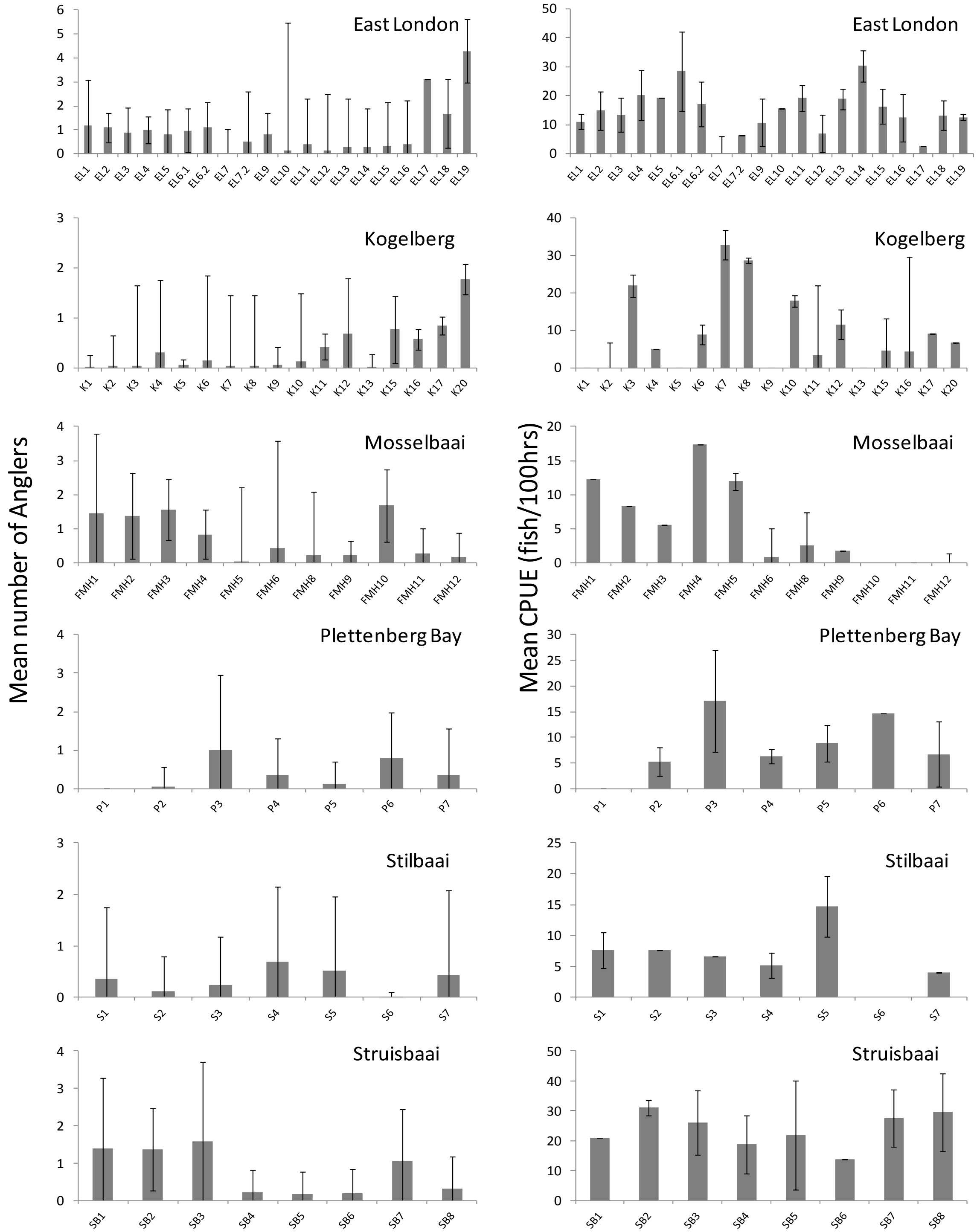
All statistical procedures were completed with R statistical software (R Development Core Team 2011). The ZIP and ZINB models were constructed with the "zeroinfl" function (Zeileis et al. 2008) from the package "pscl" (Jackman 2011). The outcome of the model selection process is presented in the results section.

3. Results

3.1 Angler and CPUE Data

The number of anglers as well as CPUE varied quite considerably both between and within the six sections of coast (Figure 3). The highest numbers of anglers were recorded within the East London sections of the coast, while the lowest were recorded at Stilbaai. CPUE tended to be highest at East London, Struisbaai and along certain sections of the Kogelberg coast.

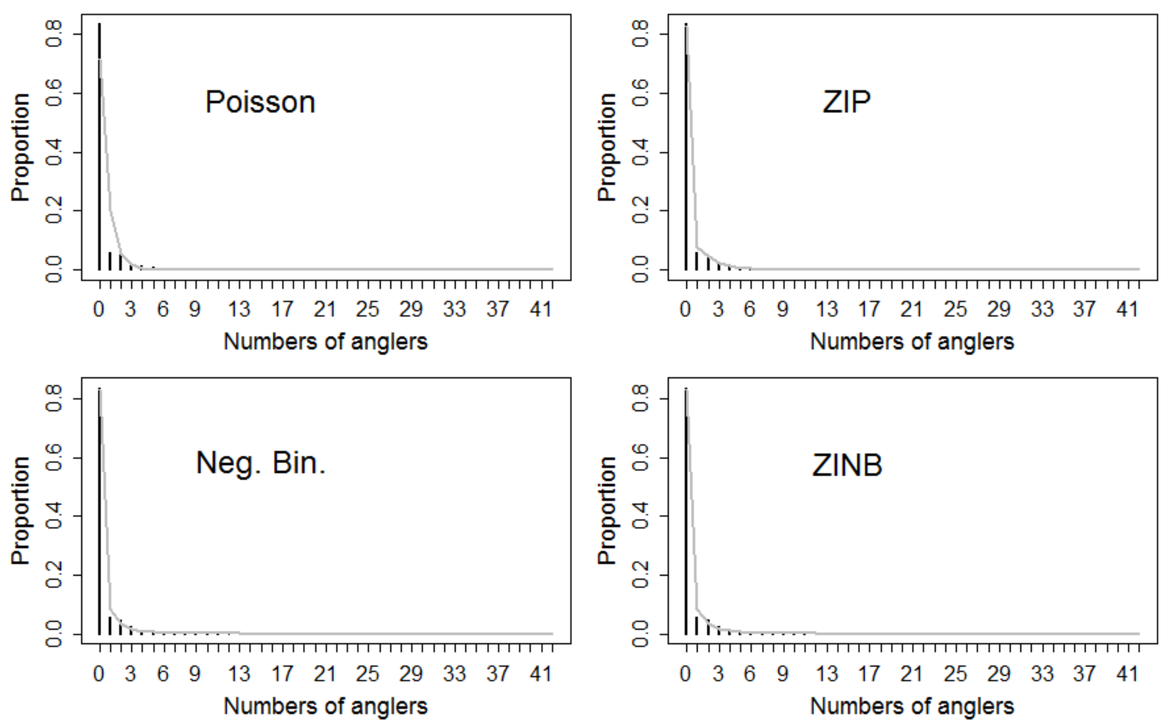
Figure 3. Mean Number of Anglers and CPUE across Different Beats of the Six Different Sections of Coast



3.2 Determining the Appropriate Model

The unconditional mean of the angler count variable was 0.43, which is substantially lower than the unconditional variance of 1.71. The observed variance to mean ratio was 4.02, suggesting that the data were overdispersed. This was confirmed by the dispersion parameter of 3.69 generated for the quasi-Poisson regression. The ZIP, negative binomial and ZINB models all appeared to fit the observed data well (Figure 4).

Figure 4. Poisson, ZIP, Negative binomial and ZINB Models of the Angler Abundance Data



A Vuong test of the negative binomial and ZINB models showed that the ZINB model more accurately represented the data than did the negative binomial (z=-43.75, $p<0.001$). A likelihood-ratio test comparing the ZIP and ZINB models provides overwhelming evidence for the ZINB model ($\chi^2=2448$, $p<0.001$). Variable selection in the ZINB model was done by sequentially dropping variables and testing the model fit with both likelihood-ratio tests and AIC values.

3.3 Model Results

The ZINB model has been shown to be the most appropriate, and the results of the standard negative binomial are presented and interpreted very briefly for comparison. The coefficients for the count components of both regressions were similar, although there were some terms that lost significance in the count component of the ZINB model. The exponential of the coefficient is presented in the table as the risk ratio for the negative binomial components of both models, and as the odds ratio for the logit component of the ZINB models. These values indicate the factor change in odds for every unit increase in the respective independent variable. Coefficients in the continuous outcome part of the ZINB model are interpreted in the same manner as for count models, while, in the dichotomous outcome part of the model, the coefficients reflect the probability of a zero count.

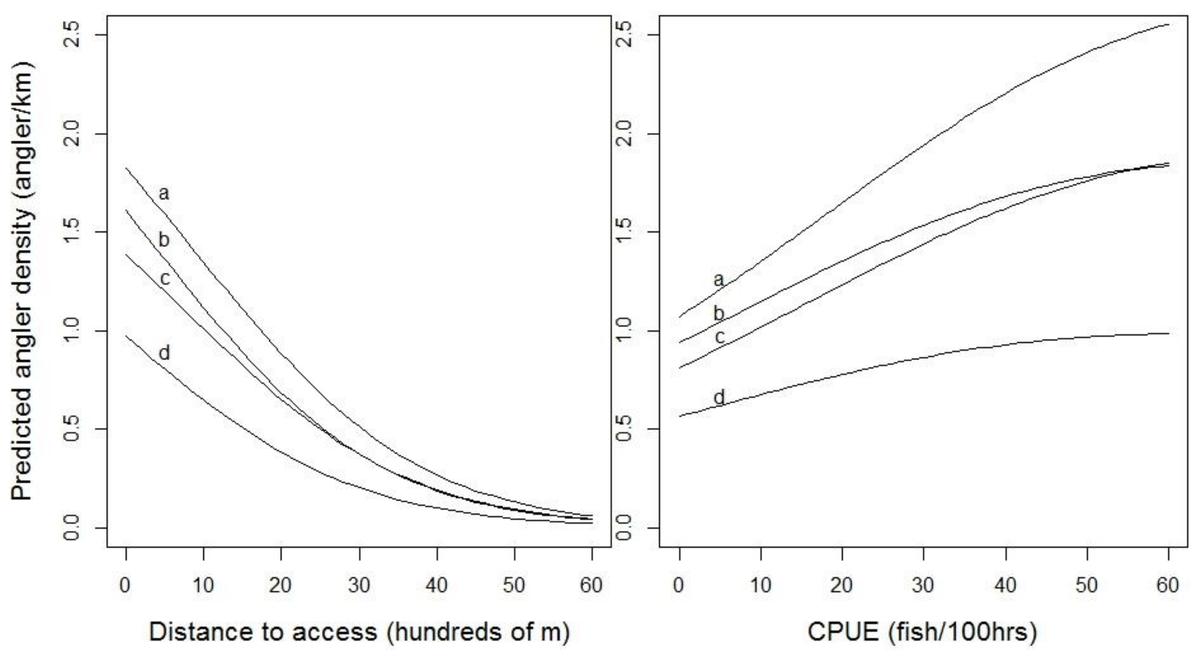
All included terms were significant in the standard negative binomial model, except for the effect of population within 10 km of the angling site. According to the negative binomial model, the highest angler densities were observed in autumn, followed by summer, spring and winter. Angler densities were significantly higher on the weekend and lower during the school term time. An increase in expected CPUE had a significantly positive impact on angler densities. The lowest densities of anglers occurred on boulder beaches, while the highest densities were found on mixed shorelines. An increasing source population between 10 km and 100 km had a significant negative effect, while an increasing source population between 100 km and 250 km had a positive influence. Finally, both increasing wind speed and increasing distance to the nearest public access point had significant negative impacts on angler density.

The signs and coefficient magnitudes were similar for the ZINB, but there were some changes in significance introduced by modelling the excess zeros. For sites where anglers were expected to occur, there was not a significant difference in angler density between autumn and summer, but significantly lower angler densities were expected in spring and winter. Angler density was more than twice as great on the weekends as opposed to weekdays, holding all else constant, and angler density was on average 32% lower during the school term-time than the holidays. Expected CPUE had a significantly positive impact on the density of anglers, increasing the chances of higher angler density by 1.035 for every extra fish/100 hours. Regional CPUE had a negative effect on the density of anglers. The chances of greater angler density at a site decreased by a factor of 0.99 for every 100 m farther away the site was from public access. For every 1000 people within 10 km of the site, or between 10 and 100 km from the site, the chance of greater angler density decreased slightly. For every 1000 people within 100 to 250 km, the chance of greater angler density increased slightly. Wind had a significant negative impact on angler density, and each extra knot of wind decreased angler density by approximately 2%.

The continuous outcome component of the ZINB model can be interpreted in a similar way to the standard negative binomial, and the dichotomous outcome signifies the probability of a site having 'always zero' counts. The odds of not observing anglers at a particular site were expected to decrease significantly for sites surveyed on the weekend, with increasing population within 10 km of an angling site and between 100-250 km, and with increasing regional CPUE. The odds of not observing anglers at a site increased significantly as the source population between 10 km and 100 km increased, as distance to nearest public access and wind increased, and for sites that were surveyed during school term time.

Overall effect graphs combine the effects of the covariates from both parts of the mixed model. In order to present the effects of one variable, the other continuous variables are held constant at their means, and levels need to be chosen for each categorical variable. These suggest that angler density declines rapidly as distance to public access increases, but slows as the predicted angler density drops below 0.5 anglers/km (Figure 5). The predicted angler density increases with expected CPUE, particularly up to about 40 fish/100hrs. The slope of the relationship was much shallower for both access and CPUE for winter than autumn (Figure 5).

Figure 5. Effects of Distance to Access and Expected on Angler Density on Mixed Beaches, During School Term Time, on the Weekend



Notes: All other variables are held at their means. Different graphs are plotted for each season: a) Autumn b) Summer c) Spring and d) Winter.

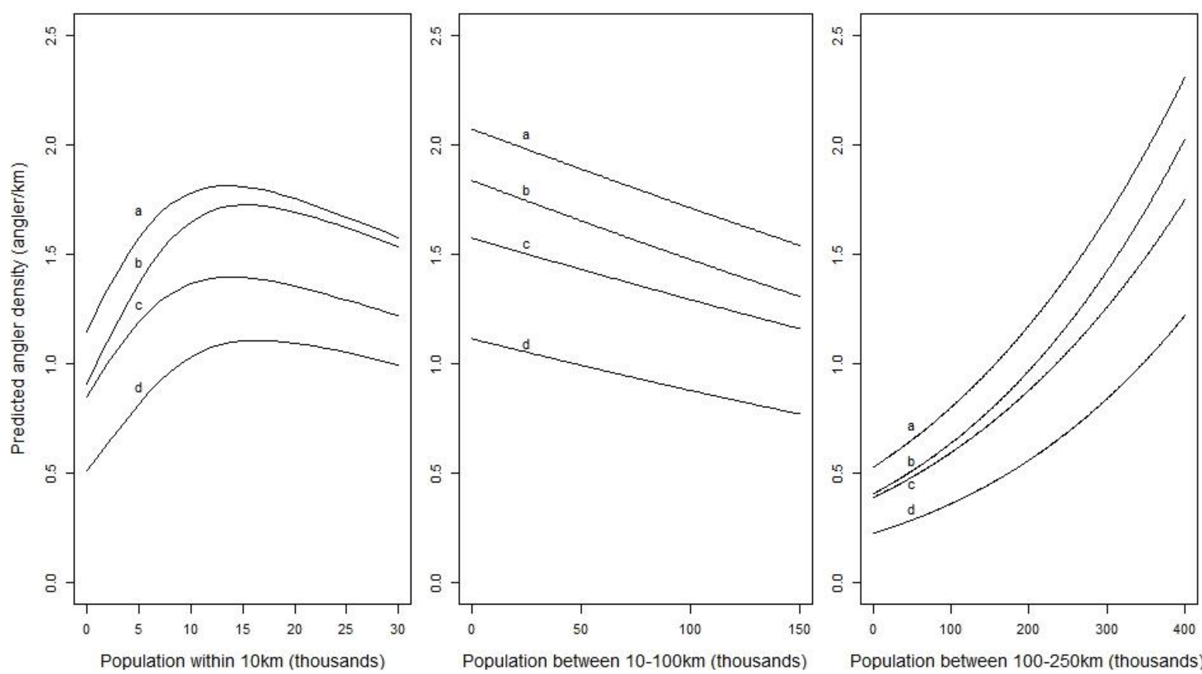
Table 3. Model Outputs for Standard Negative Binomial Model as well as Zero-Inflated Negative Binomial Model

		Standard NB		ZINB	
Variable	**Level**	**Estimate**	**Risk Ratio**	**Estimate**	**Risk Ratio**
Continuous outcome					
Intercept		-1.749 (0.32) ***	0.260	-0.900 (0.40) *	0.406
Season	Autumn (baseline)				
	Spring	-0.282 (0.07) ***	0.755	-0.257 (0.08) ***	0.774
	Summer	-0.206 (0.06) **	0.814	-0.027 (0.08)	0.974
	Winter	-0.634 (0.05) ***	0.531	-0.457 (0.06) ***	0.633
Day	Week (baseline)				
	Weekend	1.164 (0.04) ***	3.202	0.874 (0.05) ***	2.396
School holidays	Holiday (baseline)				
	Term	-0.655 (0.07) ***	0.519	-0.388 (0.08) ***	0.678
Expected CPUE		0.007 (0.00) ***	1.007	0.034 (0.00) ***	1.035
Regional CPUE		-0.043 (0.01) ***	0.958	-0.069 (0.01) ***	0.933
Shore Type	Boulder beach (baseline)				
	Estuary beach	1.521 (0.31) ***	4.576	1.136 (0.38) **	3.113
	Mixed	1.584 (0.30) ***	4.875	1.412 (0.38) ***	4.105
	Rocky	1.078 (0.30) ***	2.939	0.861 (0.37) *	2.367
	Sandy beach	1.264 (0.31) ***	3.541	0.914 (0.37) **	2.493
Distance to access		-0.032 (0.00) ***	0.969	-0.009 (0.00) **	0.991
Population 0-10 km		-0.004 (0.00)	0.996	-0.012 (0.00) ***	0.988
Population 10-100 km		-0.003 (0.00) ***	0.997	-0.001 (0.00) ***	0.999
Population 100-250 km		0.004 (0.00) ***	1.004	0.002 (0.00) ***	1.002
Wind speed		-0.027 (0.00) ***	0.973	-0.019 (0.00) ***	0.981
Theta				-1.002 (0.05) ***	0.367
Dichotomous outcome					**Odds Ratio**
Intercept				0.068 (0.89)	1.070
Season	Autumn (baseline)				
	Spring			0.084 (0.19)	1.087
	Summer			0.380 (0.18) *	1.462
	Winter			0.610 (0.15) ***	1.841
Day	Week (baseline)				
	Weekend			-1.058 (0.13) ***	0.347
School holidays	Holiday (baseline)				
	Term			0.830 (0.19) ***	2.293
Expected CPUE				0.039 (0.01) ***	1.040
Regional CPUE				-0.069 (0.03) **	0.934
Shore Type	Boulder beach (baseline)				
	Estuary beach			-1.002 (0.84)	0.367
	Mixed			-0.544 (0.82)	0.580
	Rocky			-1.750 (0.82) *	0.174
	Sandy beach			-1.856 (0.83) *	0.156
Distance to access				0.071 (0.01) ***	1.074
Population 0-10 km				-0.202 (0.03) ***	0.817
Population 10-100 km				0.004 (0.00) ***	1.004
Population 100-250 km				-0.004 (0.00) ***	0.996
Wind speed				0.026 (0.01) ***	1.026

Notes: The continuous outcome of the zero-inflated model shows the changes in density for increases in given variables. The dichotomous outcome gives the probability of a site having an excess zero count for changes in given variables. Significance * = p<0.05, ** = p<0.01, ***=p<0.001

The overall relationship between source population and angler density depended upon the location of the source population (Figure 6). Angler density increased with increasing population within 10 km of the angling site only up to a population of about 10 000 people, after which angling density declined slightly. Larger populations between 10 and 100 km had a slightly negative influence on predicted angler density, whereas larger populations between 100 and 250 km from the site had a positive effect on the density of anglers.

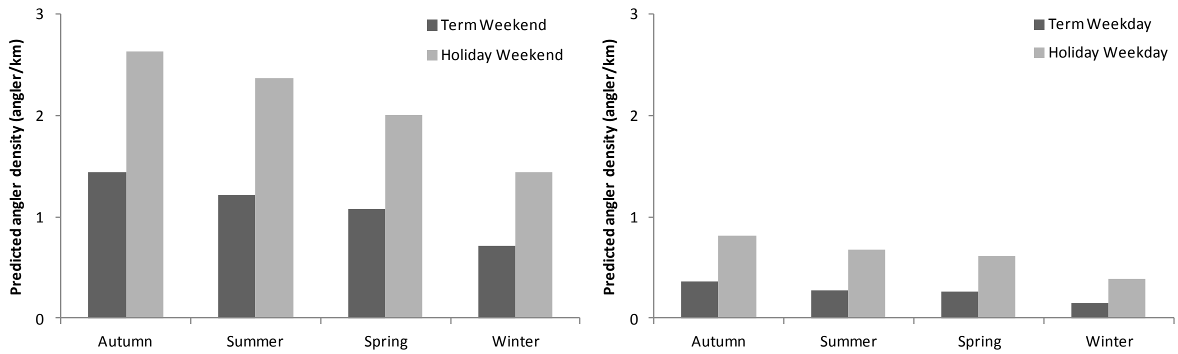
Figure 6. Effects of Distance to Access and Expected CPUE on Angler Density on Mixed Beaches, During School Term Time, on the Weekend



Notes: All other variables are held at their means. Different graphs are plotted for each season: a) Autumn b) Summer c) Spring and d) Winter.

The overall effects, taking into account both parts of the mixed models, predicted angler density to be about 50% lower during term time than holiday time or on the weekends and about 40% lower on weekdays (Figure 7). The predicted angler density was also about two-thirds less on weekdays than during weekends.

Figure 7. Effects of Holiday or Term Time on the Predicted Angler Density across the Four Seasons for Weekends (left) and Weekdays (right)



Note: All other variables are held at their means.

4. Discussion

If anglers were motivated entirely by catch, and assuming a world of perfect information, they would be expected to follow an ideal free distribution (Fretwell and Lucas 1972), or one in which densities of anglers closely corresponded to that of their 'prey', such that the catch rates of fish would be relatively constant among all anglers. This argument could also be extended to the temporal dimension. However, angler choices about when and where to fish are known to be influenced by a range of factors other than the prospect of maximising fish catch. These include the availability of leisure time and disposable income; the expense, time and effort required to reach alternative fishing locations; and co-benefits such as the pleasure of being in an attractive location and enjoying the outdoors or the company. The anticipated enjoyment of fishing is also likely to be influenced by the species and size of fish expected at a location. Indeed, Provencher et al. (2002) found that, among a population of anglers in the USA, different groups could be identified, including those who had high time costs and a high sensitivity to fishing conditions such as temperature and wind and expected catch, as well as those who had low time costs and were not as sensitive to conditions or expected catch. While Provencher et al. (2002) found the expected catch to be of very high importance, Arlinghaus (2006) found that many anglers are relatively insensitive to catch rate, due to the importance of other factors, particularly the overriding enjoyment of the activity of fishing itself. In their study, 80% of the fishing population was classed as having a low catch orientation. Carson et al. (2009) also found anglers to be highly heterogeneous in their behaviour and preferences. Few studies have considered the aggregate effect of these factors on these groups, however.

In this study, angler densities were found to be positively influenced by CPUE, which suggested that anglers actively sought sites where catch rates were expected to be higher. At a local scale, this was reflected in the choice of habitat. Angling effort was found to be highest on mixed shores, followed by estuaries, sandy beaches and rocky shores, while boulder shores had much lower densities of anglers. This pattern probably reflected expected catch more than accessibility. Mixed shores are very productive, as a result of the effects of sand scouring on rocks leading to continual new algal growth, which in turn attracts fish. Estuaries are similarly productive as a result of their retention of nutrient-rich water and the sheltered environment they offer. While not as productive overall, sandy and rocky shores each support different suites of habitat specialists favoured by different anglers. Boulder shores are probably the least productive environments due to their instability. However, at a broader scale, the spatial pattern of angler densities was far from an ideal free distribution, as the slope of the relationship between angler densities and CPUE was closer to 0.5 than to 1. This suggests that the other costs and benefits associated with site choice played a significant role.

It is likely that the costs of getting to a site are the second-most important factor after expected catch. If costs were the primary factor, then angler densities would be strongly correlated with population densities within a local radius. However, whereas the density of anglers at remote sites was strongly influenced by population within a 100-250 km radius, it was negatively influenced by population within 100 km. This could well be a reflection of the perceived and real impacts of human population on fish stocks, resulting in the need to travel farther to find better fishing sites. The fact that this did not hold true within a 10 km radius is likely to be due to opposing forces of the sheer convenience of fishing on one’s doorstep when time or money do not allow trips to ‘better’ locations, and the lack of attractiveness of these sites for those who do have the resources. Because of the former group, these populous localities are the areas in which fishing effort will likely have the greatest risk of driving local stocks to extinction. This is slightly different than the finding of Stoeven (2011), who presented a model suggesting that anglers not motivated by catch rates could fish stocks to extinction. In this case, the excess fishing pressure is likely to be created by the simple economics of leisure in time- and income-constrained households.

While many anglers were clearly prepared to drive long distances in search of better catches, it does appear that they took walking effort into account when choosing a fishing site. This was evident from the lower densities and higher probability of having no anglers in areas that were harder to access. This sensitivity to walking effort carries an important message for conservation strategy, in that effort could be effectively controlled through restricting vehicular access, without having to resort to closing areas completely.

The fact that anglers are catch-sensitive in their choice of angling sites suggests that improving stocks, and therefore expected catch rates, can benefit angler utility. Similarly, Scrogin et al. (2004) also concluded that, while welfare losses might occur as a result of regulations, prudent management of these resources may enhance welfare in the long run by increasing natural resource stocks. Turpie & Goss (2014) also found that anglers would gladly tolerate increased restrictions if this led to improved catches. Nevertheless, adherence to line-fisheries regulation has been found to be extremely poor in South Africa, with levels of compliance being related to levels of enforcement (Brouwer et al. 1997). In their study, fewer than 2% of anglers on the Western and Eastern Cape coasts had been inspected. With limited resources and political will to enforce fisheries regulations, it is unlikely that bag and size limits will be able to curb all illegal fishing. With a targeted approach (focusing on busy times and areas), the current patrolling might be much more effective. This approach requires an understanding of both spatial and temporal variations in fishing effort.

As expected, numbers of anglers were higher during school holidays and weekends. Seasonal variation in angler numbers was comparatively small. The fact that numbers were highest in the autumn is probably due to the very concentrated activity experienced during the Easter holiday period, compared to summer, when holiday activities are spread out over a longer period. These patterns suggest that enforcement efforts should be stepped up considerably during holiday periods, in contrast to current policy, which results in relatively low after-hours enforcement due to the doubled costs of after-hours labour.

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