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Promising the moon? Evaluation of indigenous and lunar fishing calendars using semiparametric generalized mixed models of recreational catch data

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Abstract Previous studies that have investigated relationships between the lunar cycle and recreational fishing success have all suffered from various problems – most notably, the failure to account for potential confounders in a statistically rigorous manner. We propose methods to account for season, fisher identity, fishing effort, day, and variation in biomass, all of which have previously either been omitted or handled in an *ad hoc* way. These are applied to two sets of data on recreational fishing of the snapper *Pagrus auratus* in New Zealand. In addition to estimating effects due to lunar phase, we also implement these methods to analyse the performance of a lunar-based indigenous Māori fishing calendar. Recreational fishers in New Zealand often make use of such calendars in order to predict fishing success on specific days, however little is known about the performance of such predictions or whether they hold any practical use to the everyday angler. A relationship between lunar phase and fishing success is identified, as well as support for some aspects of the Māori fishing calendar predictions. The magnitudes of these effects are small, however, casting doubt on the practical relevance of lunar based fishing predictions. In addition to the known seasonal trend associated with annual migration, an unexpected second trend is detected, and postulated to be associated with intense local fishing pressure over the summer vacation period.

Keywords Recreational fishing · Seasonal effects · Snapper *Pagras auratus* · Nonlinear regression

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1 Introduction

A substantial body of research has shown various relationships between migratory, spawning and feeding behaviors of marine species and the lunar cycle (e.g., Farbridge and Leatherland, 1987; Haraldstad, Vollestad, and Jonsson, 1985; Horning and Trillmich, 1999; Rahman, Takemura, and Takano, 2000). Theories behind such findings include differing light intensities (Takemura, Susilo, Rahman, and Morita, 2004), tidal patterns (Vance and Staples, 1992) and behaviour of other organisms (Vingare, França, and Cabral, 2006) across the phases of the moon. With observed changes in marine behaviour at different points of the lunar cycle, it would be reasonable to hypothesize that fishing success may also vary in a similar way. Indeed, relationships between catch-per-unit-effort (CPUE) and lunar phase have been presented for a number of commercially targeted species and their associated fishing methods. Examples include the prawn *Penaeus plebejus* (Courtney, Die, and McGilvray, 1996; Griffiths, 1999), the lake whitefish *Coregonus clupeaformis* (Collins, 1979), the silver eel *Anguilla anguilla* (Cullen and McCarthy, 2003) and the South African anchovy *Engraulis capensis* (Agenbag et al, 2003).

Although he mechanisms behind any such effects are not yet well understood, many recreational fishers are firm believers in the moon playing a pivotal role in the success of an individual fishing trip (e.g., Johannes, 1981; Ring, 2002). It is not clear, however, how far results from commercial fisheries can be translated across to a recreational fishery; different fishing methods are generally employed in each, and lunar effects may be specific to species and to the gear used.

The existing literature raises the question of whether or not it is indeed possible to use the lunar cycle to reliably predict specific days which will yield a higher CPUE for a recreational fisher. In New Zealand, fishing calendars are published which aim to carry out this exact function. These are usually based on Māori lore, and contain a strong lunar component. In general, such calendars allocate each individual day to a particular rank, corresponding to the supposed success to be enjoyed by a fishing trip undertaken on that day. The most popular fishing calendar, produced by New Zealand fishing guru Bill Hohepa, allocates a rank of either 'Bad', 'Fair' or 'Good' to each day. There has been great debate within recreational fishing circles as to whether or not these lunar-based indigenous fishing calendars hold any practical predictive power (G. Dixon, Editor of NZ Fishing News, personal communication, 10 August 2011), yet the only research published in the literature (Millar, McKenzie, Bell, and Tierney, 1997) with the aim of answering this question yielded inconclusive results.

Millar et al (1997) found weak evidence of relationships between recreational CPUE of the snapper *Pagrus auratus* and both the rankings of a Māori fishing calendar and the lunar phase. Investigation was based on data collected during a yearlong diary survey in 1993–1994. The fishing calendar employed was an older version published by Bill Hohepa, which consisted of a five-point scale, rather than the aforementioned three-point scale. The analyses were restricted by the methods, software and computer power available at the time, resulting in the inability to appropriately incorporate random effects, and the use of nonparametric tests as an alternative to their more powerful counterparts. In addition, the analysis of the effect of lunar phase on CPUE involved the subdivision of observations into four lunar quarters, which were then compared. This categorization of an otherwise continuous variable is somewhat arbitrary and leads to a further loss of statistical power (deBruyn and Meeuwig, 2001). Various transformations applied to the data also rendered the estimated size of lunar and fishing calendar effects impossible to quantify in an interpretable way.

Our literature review revealed only two further studies which investigated the effect of the moon on recreational fishing success. Lowry, Williams, and Metti (2007) reported significant effects of lunar phase on CPUE for black marlin *Makaira indica*, blue shark *Prionace glauca*, shortfin mako shark *Isurus oxyrinchus*, dolphin fish *Coryphaena hippurus* and yellowfin tuna *Thunnus albacares* in an Australian gamefish-tournament fishery. Although, as recommended by deBruyn and Meeuwig (2001), the authors did implement periodic regression (Batschelet, 1981) to analyze the lunar effect, the data eventually analysed were an aggregation of individual trips into thirty observations, each of which corresponded to a particular lunar day. Information in the data related to fisher identity, the time of year and the day remained unused, which potentially could have accounted for a proportion of the variability in the observed catch rates. Simultaneous estimation of these effects may have resulted in an estimate of the lunar effect that is less likely to be subject to the influence of these potentially confounding variables.

An initial analysis (Ponce-Diaz, Ortega-Garcia, and Hernandez-Vazquez, 2003) of data on striped marlin *Tetrapturus audax* catches in Mexican sport fisheries also failed to account for potentially confounding variables, but a subsequent reanalysis (Ortega-Garcia, Ponce-Diaz, O'Hara, and Merila, 2008) of the same dataset did. There, a significant but small effect of lunar phase was identified through use of generalized additive mixed models (GAMMs). These also accounted for the effects of the boat and crew, the El Niño-Southern Oscillation, the sea surface temperature and the date. One weakness of this study, arising from lack of available data, is that CPUE was defined as marlin caught per fishing trip, regardless of the excursion's duration or number of participants. Any correlation of trip length or number of fishers with the lunar cycle could therefore be the cause of the significant lunar effect observed. On the other hand, differences in fishing quality could be obfuscated by compensatory changes in fishing effort. For example, on a day of poor fishing quality it may still be possible to achieve a good catch by fishing for a longer time and with more lures in the water. A second weakness of this study is that an additive effect of time, the date covariate in this case, does not make biological sense. The dominant vehicle through which this affects CPUE is almost certainly biomass, and, as such, should have a multiplicative relationship with CPUE. Note that the preponderance of zero CPUE trips prevented use of log(CPUE) as the response variable.

An additional serious flaw in the previous studies is the failure to account for effects of individual days; trips undertaken by different boats, but on the same day, are unlikely to be independent. A number of factors, such as underwater abiotic conditions (e.g., water visibility) and sea state, potentially affect day-to-day fishing success. Failing to include day effects will, in effect, artificially inflate the degrees of freedom available to detect a lunar effect, and hence could drastically increase the Type I error.

Two separate analyses are presented here. The first is a reanalysis of the data used by Millar et al (1997), but now using Bayesian generalized nonlinear mixed effects models to allow for the simultaneous fitting of seasonal, fisher, day, fishing calendar and lunar effects. The second involves the analysis of a new set of data, based on various boatramp surveys conducted throughout the years 1990–2008. Similar, but frequentist, models are implemented, and include a semiparametric estimation of the seasonal trend. The choice of paradigm under which the models for the two datasets are fitted simply reflects what is most suitable for the given situation rather than any prior ideological disposition.

The conclusions drawn from the analyses are of great practical importance; fishing is an extremely popular leisure activity in New Zealand, with the prevalence of recreational fishers in the population estimated to be as high as 39% (Kearney, 2002). In addition, the rankings of the fishing calendar analysed here, that produced by Bill Hohepa, are published in the New Zealand Herald, by far the most widely read daily newspaper in the country (Nielsen Media Research, 2009). The calendar is also available online.

This article therefore aims to make multiple contributions. The analyses we present appear to be some of the first parametric models that account for possible confounders in a study investigating the role of the moon on CPUE. We also draw attention to a number of components of our models that, until now, have not been implemented in this area. In addition, we endeavor to determine the usefulness of Māori fishing calendar predictions by providing quantifiable and interpretable estimates of the effects involved. Finally, we look to add insight into the relationship between the moon and recreational fishing success. Sections 2.1 and 2.2 include data description and methods used for analysis of the diary and boatramp datasets respectively, before results are provided in Section 3 and a discussion in Section 4.

2 Data and methods

Given species-specific behavioral and CPUE relationships with the lunar phase, it is sensible to restrict analysis to one particular species. A similar argument can be made regarding the fishing method employed; relationships between the lunar cycle and catch rates may vary depending on the gear used. Therefore, both the diary and the boatramp data were restricted to trips targeting snapper using rods or handlines deployed from boats.

The choice of snapper was obvious; it is the most popular species targeted by amateur fishermen in New Zealand, with an estimated recreational catch of over 2 600 tonnes in 2005 (New Zealand Ministry of Fisheries, 2010). Given the popularity of the species, any fishing calendar published in New Zealand that claims to be able to accurately predict recreational fishing success should apply primarily to snapper.

2.1 Diary data

2.1.1 Data description

The diary data were collected as part of New Zealand's Ministry of Fisheries research initiative. A sample of recreational fishers was obtained through a random phone survey of houses in the upper North Island. In total, 15 015 houses were called, of which

3 363 contained fishers who were eligible for the survey. Eligibility rules required an individual to be over 15 years of age and not a commercial fisher. Of those eligible, 2 728 agreed to the survey and were given a fishing diary to document each fishing trip taken between 1 December 1993 and 30 November 1994.

Respondents recorded a variety of information including date, hours fished, species targeted, fishing method used and the number of fish caught of each species. Fishers were instructed only to record and comment on information relevant to their own fishing and not of their fishing companions. In addition, fishing calendar predictions based on Hohepa's five-point scale (used in the analysis of Millar et al (1997)) and the newer three-point scale were obtained. Although both sets of predictions were investigated, only analyses pertaining to the calendar currently published are presented, as these results have greater practical importance. The phase of the moon during each trip was determined using lunar calendars provided by the Royal Astronomical Society of New Zealand.

2.1.2 Methods

In order to model the success of the fishing trips across the phases of the moon and fishing calendar rankings, a number of other variables must be considered. Firstly, the observed daily CPUE data show a strong seasonal component (Figure 1). Inshore migration occurs during the warmer months and results in greater numbers of snapper being available to the recreational fishery. Most snapper move back offshore to deeper waters for the winter (Crossland, 1976; Paul, 1992), although some appear to take up long-term residency on reefs (Willis, Parsons, and Babcock, 2001). This pattern looks as though it could be well approximated by a sinusoidal function, and so a sine curve was used to estimate the seasonal effect.

Secondly, it is likely there is between-fisher variability in snapper CPUE due to differences in skill, experience, gear, choice of fishing spot and other such factors from one individual to another. This can be modeled by fitting random fisher effects. Lastly, in a similar way, weather, abiotic conditions, and a variety of other factors will vary from day to day, causing some individual days to be more successful than others, and thus random day effects were also included.

Models were fitted separately to analyze the fishing calendar and lunar effects on fishing success. The ranking from the fishing calendar partitions trips into three groups and can be modeled using indicator variables, and thus adds the term

$$\gamma_i = \alpha_{r(i)} \tag{1}$$

to the predictor. Here, $r(i) \in \{1,2,3\}$ is the fishing calendar ranking given to the day on which the i^{th} trip was fished, and therefore $\alpha_{r(i)}$, where $\boldsymbol{\alpha} = (0, \alpha_F, \alpha_G)$, is the difference in effect between a 'Bad' fishing calendar ranking and the ranking of the day on which the i^{th} trip was fished.

Lunar effects were modeled using periodic regression, following the parameterization of deBruyn and Meeuwig (2001). This uses the term

$$\gamma_i = \beta_{LS} \sin\theta_i + \beta_{LC} \cos\theta_i \tag{2}$$

in place of Equation (1), where β_{LS} and β_{LC} are parameters to be estimated, and θ_i is determined from the position of the i^{th} trip within the lunar cycle measured in radians. That is, θ_i is close to 0 or 2π for trips occurring near the full moon, and therefore close to π for trips occurring near the new moon.

Let Y_i and h_i be the number of snapper caught and the hours fished on the i^{th} trip respectively, and let μ_i be the expected number of snapper caught. Using CPUE as a measure of catch rate is equivalent to assuming that, holding all else constant, μ_i is directly proportional to h_i. Thus, taking Y_i to be the response variable, the number of hours fished by a trip can be included in our models as an offset. Using a log link function, as is common when dealing with count data, allows the effects to act multiplicatively. The specification of μ_i then becomes

$$\log(\mu_i) = \eta_i + \gamma_i + \log(h_i), \tag{3}$$

where η_i incorporates the aforementioned seasonal, fisher and day components of the model, and can be written

$$\eta_i = \beta_0 + \beta_A \sin\left(\frac{2\pi\beta_P \times t_i}{365} - \beta_X\right) + u_{f(i)} + v_{d(i)}.$$

The parameters β_A, β_P and β_X control the amplitude, period and horizontal shifts of the sine wave fitted to the seasonal trend respectively. Note that the period of the seasonal trend is not assumed to be 365 days, but rather is being estimated by virtue of parameter β_P. This is because the timing of the inshore migration is dependent on increasing water temperature, and the timing of this is known to vary considerably from year to year. The seasonal trend is a function of the day of the year, given by t_i, which takes a numeric value for the day on which the i^{th} fishing trip took place. A value of 1 refers to 1 December 1993 and a value of 365 refers to 30 November 1994. The terms $f(i) \in \{1, \cdots, 449\}$ and $d(i) \in \{1, \cdots, 365\}$ denote the fisher and day on which the i^{th} trip was undertaken respectively, and so $u_{f(i)}$ and $v_{d(i)}$ represent the random fisher and day effects to which the success of the i^{th} trip is subject to. These fisher and day effects are assumed to be independent realizations from normal distributions with variance parameters σ_f^2 and σ_d^2 respectively. Posterior predictive checks (Gelman, Carlin, Stern, and Rubin, 2003) were used to check this assumption.

After fitting exploratory models, there were indications that the data suffer from both overdispersion and zero-inflation. The snapper counts were therefore instead modeled with a zero-inflated negative binomial distribution, $ZINB(p, \mu_i, \tau)$, with density function

$$f(y_i; p, \mu_i, \tau) = \begin{cases} p + (1-p)\frac{1}{\tau^{\mu_i/(\tau-1)}}, & y_i = 0, \\ (1-p)\frac{\Gamma(y_i+\mu_i/(\tau-1))(\tau-1)^{y_i}}{y_i!\,\Gamma(\mu_i/(\tau-1))\tau^{\mu_i/(\tau-1)+y_i}}, & y_i = 1, 2, 3, \cdots. \end{cases} \tag{4}$$

Under this parameterization, the snapper count from the i^{th} trip is assumed to either be 0 (with probability p) or a realization from a $NB(\mu_i, \tau)$ distribution, where μ_i is the mean and $\tau \in (1, \infty)$ is the ratio of the variance to expected value, that is,

$$\text{Var}(Y_i) = \tau\mu_i. \tag{5}$$

In this case, $\mathrm{Var}(Y_i)$ is a linear function of μ_i. This parameterization was found to give a better fit, in terms of homoscedasticity of standardized residuals, than the more widely used one in which $\mathrm{Var}(Y_i)$ is a quadratic function of μ_i,

$$\mathrm{Var}(Y_i) = \mu_i \left(1 + \frac{\mu_i}{m}\right). \tag{6}$$

In the above models, fisher and day are included as crossed random effects, with 449 and 365 levels respectively. Consequently, maximizing the model likelihood was not computationally viable, and hence these models were fitted under the Bayesian paradigm. The zero-inflation parameter, p, was given a $Beta(0.5, 0.5)$ prior. All other parameters were given a flat (improper) prior. In particular, the prior on τ had a lower bound at 1, and the standard deviations of the random effects, σ_f and σ_d, were given flat priors on the positive reals (Gelman, 2006).

These models were implemented in OpenBUGS (Lunn, Spiegelhalter, Thomas, and Best, 2009) through Markov chain Monte Carlo (MCMC) with a burn-in period of 5 000 iterations, and a follow up period of 100 000 iterations, of which every 10$^{\text{th}}$ was stored.

2.2 Boatramp data

2.2.1 Data description

The boatramp data were collected from a series of surveys conducted intermittently over the years 1990–2008 and consisted of interviewing fishers upon their return to the boatramp. Not all surveys were carried out for a full year, and as a result there were more data available for the months January through April than for the remainder of the calendar year. In total, interviews from 82 092 fishing trips were obtained on 1 331 unique days. Due to computational complications that would arise in attempting to model each trip as a sampling unit (which would then require the fitting of 1 331 random day effects), we instead decided to take day as the sampling unit and to analyze daily aggregated data. Again, data were restricted to trips targeting snapper using methods involving the deployment of a rod or line from a boat for reasons similar to those mentioned in Section 2.1.1.

The aggregated daily information most of interest here include the date, the number of legal snapper caught and hours fished. Data pertaining to the fishing and lunar calendars were collected from the same sources as for the diary survey analysis.

2.2.2 Methods

Since fisher identities were not recorded and day is the sampling unit, fisher and day effects are no longer required. However, models must still incorporate the seasonal trend and fishing effort, and the lunar or fishing calendar effects.

Although a sinusoidal function was again considered to estimate seasonal variation in catch rates, investigation suggested that this was not suitable; snapper CPUE drops sharply in December before recovering through February and peaking once more in late March (Figure 2). This seems inconsistent with the known migratory patterns of the snapper, as one would expect consistently higher catch rates over the warmest period of the year (December – February). We provide possible reasons for this discrepancy in Section 4. Given the complicated relationship between the time of year and CPUE, a flexible method for estimating the seasonal trend is required. The choice of a cyclic cubic spline (Figure 2) allows for this flexibility whilst still imposing the required restriction of the same seasonal trend every year.

These data span a sampling duration of approximately 19 years, and hence it would be appropriate to consider the possibility of any long-term factors that could influence catch rate. The most obvious would be change in the abundance of snapper. It is a standard assumption in fisheries modeling to assume that catch rate is proportional to biomass, in which case, if biomass b_i was known, it could be fitted as an offset in the model

$$\log(\mu_i) = s(t_i) + \gamma_i + \log(h_i) + \log(b_i), \tag{7}$$

where μ_i and h_i are defined in the same way as in Section 2.1, but with index i now denoting days rather than trips. Similarly, γ_i incorporates either the fishing calendar or lunar effects (see Equations (1) and (2)). The term t_i is also analogous to its previous form; this variable takes a value of 1 for 1 January and 365 for 31 December, regardless of the year. The term $s(t_i)$ is the value of the cyclic spline function fitted to the seasonal trend for the day of the year the i^{th} day falls on.

Although they are known to have considerable uncertainty, estimates of biomass in the Hauraki Gulf and Bay of Plenty snapper stock (in which most fishing trips interviewed took place) indicate a more or less linear increase in the time period covered by the surveys (New Zealand Ministry of Fisheries, 2010). We therefore assume biomass is a linear function of time,

$$b_i = \beta_{b0} + \beta_{b1} d_i, \tag{8}$$

where β_{b0} and β_{b1} are parameters to be estimated, and d_i is a numeric value corresponding to the i^{th} day, where 1 refers to 1 November 1990, 2 to 2 November 1990, and so on, up to 6388, representing the last day surveyed. Substituting Equation (8) into Equation (7) gives

$$\log(\mu_i) = s(t_i) + \gamma_i + \log(h_i) + \log(\beta_{b0} + \beta_{b1} d_i),$$

and, following some some rearrangement,

$$\log(\mu_i) = s(t_i) + \gamma_i + \log(h_i) + \log(\beta_{b0}) + \log\left(1 + \frac{\beta_{b1}}{\beta_{b0}} d_i\right).$$

This model is overparameterized as the seasonal spline contains an intercept term and is hence confounded with the $\log(\beta_{b0})$ term. The latter term can therefore be dropped, and only $\beta_B = \frac{\beta_{b1}}{\beta_{b0}}$ is required to be estimated, giving

$$\log(\mu_i) = s(t_i) + \gamma_i + \log(h_i) + \log(1 + \beta_B d_i). \tag{9}$$

As with the diary survey data, these data were also found to be overdispersed. However, being aggregated over days, there were few zero catches, and a zero inflation model was not required. The negative binomial was fitted under both the linear and quadratic variance-mean relationships, but plots of standardized residuals showed heterogeneous variability under both of these formulations. Further exploration showed that overdispersion increased with fitted value, $\hat{\mu}_i$, and suggested a relationship of the form

$$\log(\tau_i - 1) = \beta_{\tau 0} + \beta_{\tau 1}\log(\mu_i), \tag{10}$$

where $\beta_{\tau 0}$ and $\beta_{\tau 1}$ are parameters to be estimated.

Therefore, the snapper counts were modeled with a negative binomial distribution, $NB(\mu_i, \tau_i)$, with density function equivalent to the negative binomial part of Equation (4),

$$f(y_i; \mu_i, \tau_i) = \frac{\Gamma\left(y_i + \mu_i/(\tau_i - 1)\right)(\tau_i - 1)^{y_i}}{y_i!\,\Gamma\left(\mu_i/(\tau_i - 1)\right)\tau_i^{\mu_i/(\tau_i-1)+y_i}}. \tag{11}$$

The parameter τ is no longer common to all observations, and varies subject to Equation (10) above.

Again, the lunar and fishing calendar models were fitted separately, but since the model for $\log(\mu_i)$ (Equation (9)) does not contain random effects, it was more convenient to use a frequentist framework. The parameters were estimated by maximum likelihood using the freely available AD Model Builder software (Fournier et al, 2012).

3 Results

The diary survey models introduced in Section 2.1 were compared to a model with neither fishing calendar nor lunar effects fitted (henceforth referred to as the null model) using the Deviance Information Criterion (DIC). The model with the lowest DIC can be viewed as the most suitable, and, as a rule of thumb, a model with a DIC at least 3 higher than this has considerably less support (Spiegelhalter, Best, Carlin, and van der Linde, 2002). Differences in the DIC of the fishing calendar and lunar models from that of the null model were both greater than this threshold (Table 1) suggesting that the lunar and fishing calendar effects considerably improved the suitability of the model. There was no indication to suggest that the assumption of normality of the fisher and day effects was violated in any of the diary survey models.

For the boatramp data, likelihood-ratio tests for the null hypotheses of no fishing calendar effect ($H_0 : \boldsymbol{\alpha} = \mathbf{0}$) and no lunar effect ($H_0 : (\beta_{LS}, \beta_{LC}) = \mathbf{0}$) returned p-values of 0.125 and 0.052 respectively, the latter approaching statistical significance at the 5% level. Determining the presence of lunar and fishing calendar effects is the central focus of our analyses, and so the above hypothesis tests are the most appropriate form of assessment. Nevertheless, it is interesting to note that the Akaike Information Criterion (AIC) favours the fishing calendar and lunar models over the null model (Table 1).

It is worth comparing the estimated effects from the boatramp analyses with their respective Bayes estimates from the diary analyses in order to ascertain the level of agreement between the two independent sets of models. Although the estimated lunar effect size was considerably larger for the diary data analysis (Table 2, Figure 3), the peak times to fish in the lunar cycle were estimated to be very similar (Figure 3). In a ca. 29.5 day cycle, the estimated lunar effect from the diary data peaked just 717 minutes (11 hours 57 minutes) later than that of the boatramp data. This close agreement indicates that both models are indeed estimating the same true lunar effect rather than solely being a result of sampling error; the probability of observing a difference less than or equal to that observed simply due to chance is approximately 0.035. This p-value cannot formally provide evidence against H_0 (that no lunar effects exist) as the test was not specified *a priori*. It does, however, emphasize that the boatramp survey analysis further strengthens the support obtained from the diary data for the presence of a lunar effect.

Estimated fishing calendar effects from the two datasets also show a degree of similarity; both sets of estimates follow the same ordering, with days ranked as ‘Fair’ outperforming those ranked as ‘Good’, and ‘Bad’ days showing the lowest estimated fishing success (Table 2). Again, estimated effect sizes for the diary data analysis are larger than that of the boatramp data analysis. Although the similarities between the two models are less clear-cut here than they were when investigating the lunar effects, it is likely the boatramp analysis simply lacked statistical power. The diary data models show a clear preference for inclusion of fishing calendar effects over the null model.

Although we have identified relationships between snapper CPUE and both the lunar cycle and the Māori fishing calendar, the magnitudes of the estimated effects themselves are small. For example, the diary lunar model estimates that, holding all other covariates constant, a fishing trip undertaken at the most successful point in the cycle will have an expected catch 13.7% greater than a corresponding trip at the opposite point of the cycle (Table 3). This is equivalent to one extra snapper about every 6.4 hours if fishing in March, or every 15 hours if fishing in August (Table 3). Corresponding estimates for the boatramp lunar model are even more pessimistic.

Similar findings are evident when investigating the performance of the fishing calendar; the two analyses estimate that trips on ‘Fair’ days (estimated to be the most successful ranking) catch just 9.6% and 5.4% more snapper than those that occur on ‘Bad’ days (Table 3).

4 Discussion

It is interesting to note that the estimated lunar effects here are similar to many of those identified by Lowry et al (2007), where CPUE for the blue shark, shortfin mako shark, dolphin fish and the yellowfin tuna also exhibited peaks between the new and first quarter moons (Figure 3). Lowry et al (2007) hypothesized that the patterns in CPUE were caused by the targeted species responding to vertical migratory movements of prey to deeper waters, which, in turn, react to illumination from the full moon. However, given that the species mentioned above are capable of reaching greater depths than the snapper, this possibility does not apply so strongly here.

Instead, the illumination of the moon could have a direct effect on the snapper themselves. Feeding at night during the full moon is plausibly much easier than it is during the new moon, especially at shallow depths as the extra light available would make it easier to spot potential prey. If this is indeed the case, it is likely that snapper are hungrier during the day following a darker night, therefore biting with higher intensity, resulting in larger catches for recreational fishers.

A further noteworthy result is that the estimated effects of 'Fair' calendar rankings are larger than that of 'Good' rankings. Although the differences could plausibly be due to sampling variation, we have certainly found no support whatsoever to indicate that fishing on a 'Good' day will return the largest catches. Days ranked as 'Bad', however, do seem to have lower catch rates.

It is possible the differences in catch rates between calendar rankings are simply due to their relationship with the lunar phase; more than half of days ranked as 'Fair' occur during the first lunar quarter, while more 'Bad' days fall in the full moon quarter than any other. In any case, estimated effect sizes are larger with the lunar models, suggesting that a fisherman deciding upon the date of their next fishing trip would be better off selecting a day based directly on the lunar phase rather than consulting the fishing calendar analysed here.

Despite this, all analyses returned estimated effect sizes that were small in magnitude. Even the most optimistic estimate for fishing during the most successful time of the year suggests that, on average, one additional fish will be caught about every 6.4 hours if a trip occurs during the most profitable point of the lunar cycle in comparison to a similar trip undertaken during the opposite phase (Table 3). Further estimates from different models and for trips carried out at different times of the year are even more pessimistic, suggesting that a trip is required to have a duration of up to 42 hours in order to expect to catch one additional fish. It is unlikely that these differences are large enough to convince a fisher to postpone a trip by two weeks in order to capitalize on a marginally higher catch rate. Indeed, factors such as the weather and sea conditions have an influence on the overall enjoyment of a fishing trip, and therefore a fisher is far more likely to benefit by choosing a date based on these than they are from consulting a lunar calendar. Granted, the uncertainties associated with the diary survey percentage difference estimates are large enough so that the upper bounds of their 95% credible intervals exceed 20% in both cases (Table 3). Some may argue that this is a substantial enough increase to justify paying close attention to fishing calendars or the phase of the moon. However, considered alongside the intervals obtained from the boatramp data, true parameter values of this magnitude no longer seem plausible; even so, these differences still only relate to a maximum increase in catch rate of less than 0.3 snapper per hour. Our results therefore suggest that lunar-based fishing predictions seem to hold little practical significance to recreational fishers.

A further interesting result uncovered is the discovery of a seasonal trend that incorporates a sudden dip in CPUE during the warmer months. It would have been reasonable to presume the opposite, as the migratory patterns of the snapper suggest that their density within the recreational fishing grounds should be the highest during this period. We present a number possible reasons for this apparent inconsistency.

The time period in question surrounds Christmas, New Year, and the associated public holidays. This is when the weather in New Zealand is generally favourable, and a large proportion of the population have free time in which to fish, both of which lead to an increase in the number of recreational fishing trips undertaken. This suggests three plausible mechanisms that could be responsible for the sudden substantial drop in CPUE.

First, the sheer numbers of fishers no doubt leads to an increased total daily catch of snapper. This increased fishing pressure could temporarily diminish local snapper stocks, resulting in a lower localized density of fish, and therefore lower CPUE, before recovering in February and March. This is consistent with the findings of Willis and Millar (2005), who reported dramatic local depletion of legal sized snapper between spring and autumn in fishing grounds adjacent to no-take marine reserves.

Second, during this time, a different demographic of fishers is probably active in comparison to the rest of the year. It is likely that many anglers only participate in fishing trips during the summer. These individuals are likely to be, on average, less experienced and less skilled than anglers who fish all year round and are prepared to brave the comparatively harsher conditions of winter. This type of fisher, through inexperience and lack of skill, quite likely spends a longer time fishing for each snapper caught. The sudden drop in catch rates could have nothing to do with the fish or fishing conditions, but is possibly caused by the greater proportion of inexperienced fishers on the water. Therefore, the lower observed CPUE does not necessarily imply that a particular fisher will catch less in December or January than they will in November or February.

A third plausible explanation concerns the behavior of the fish. Spawning of the snapper peaks around November and December and probably takes place between the sea bottom and the midwater (Paul, 1992). This coincides with the initial decline in snapper CPUE over the summer and spawning behavior therefore possibly contributes to this observed effect; it could be that snapper are more interested in spawning than feeding during this period.

An analysis of the diary data was conducted to distinguish between the first two explanations for the unexpected summer decline in CPUE, and provided no evidence to suggest that year-round fishers were more successful during the summer months than those who only fished during this period. However, the difference in fishing skill and experience between the two groups is bound to be smaller here than it is for the boatramp data; individuals were only recruited to keep a diary if they readily indentified themselves as a fisher in their initial phone interview, while those approached as part of the boatramp survey were unable to avoid the sampling process, even if they very rarely fish. A similar analysis of the boatramp data was not possible as fisher identity was not recorded.

From a statistical perspective, the methods used here emphasize the importance of being flexible in the modeling process. While Occam's razor dictates that we should ensure our models are not fraught with overcomplexity, it remains necessary to improve upon simplistic approaches that are unable to include salient features of the data. This is evidenced here in: i) the choice of statistical framework, ii) the choice of distribution with which to model the fishing counts, and iii) the specification of the mean.

We stress a pragmatic approach to the modeling of the multi-level CPUE data used herein. Our frequentist analysis of the diary data reached a computational obstacle, as the likelihood cannot be specified in a separable way due to the crossed fisher and day random effects. Thus, it contains an integral of dimension $449+345=794$ (as 449 diarists fished on 345 unique days), rendering numerical maximisation of the function infeasible, and a Bayesian approach was adopted instead. On the other hand, in the absense of random effects, maximum likelihood estimation of the boatramp models was possible. AD Model Builder proved to be an ideal tool, as it allowed the flexibility our models require, and provided efficient, stable maximisation of the likelihood.

For the diary data, the use of the zero-inflated negative binomial arose following the rejection of a number of more popularly used candidates, namely the Poisson, zero-inflated Poisson and negative binomial distributions. The parameterization of the negative binomial part in Equation (4), coined by Nelder and Lee (1992) as the NBα distribution, is not the standard generalized linear model (GLM) formulation, and indeed does not belong to the exponential family. Using the GLM version of the negative binomial appeared to misspecify the variance of the count data. Therefore, our eventual choice was a mixture distribution, of which one component was given in its non-standard form. Despite its complexity, this appears to be the simplest candidate that satisfactorily explains the data at hand.

Similar issues were encountered with the boatramp data, however the same approach was deemed unsuitable and further complexity was required. This resulted in the variance to expected value ratio parameter, τ, being modeled with expected catch, μ (Equation (10)). Solving Equation (10) (ignoring the subscript i) for τ gives

$$\tau = \exp(\beta_{\tau 0} + \beta_{\tau 1}\mu) + 1. \tag{12}$$

Substitution of this into the NBα density function (Equation (11)) provides the probability density function of a new distribution. This distribution has parameters μ, $\beta_{\tau 0}$, and $\beta_{\tau 1}$, and is equivalent to the NBα distribution in the special case $\beta_{\tau 1}=0$. The variance to mean relationship can be obtained following substitution of Equation (12) into Equation (5), giving

$$\mathrm{Var}(Y) = \mu\left(\exp(\beta_{\tau 0})\mu^{\beta_{\tau 1}} + 1\right).$$

Modeling a response variable with this distribution is conceptually equivalent to using the NBα distribution with a τ parameter that increases with μ, as was the case for our boatramp survey analyses. We therefore present a more flexible alternative to the negative binomial distribution, ideal in cases where overdispersion appears to depend on the mean.

Finally, our analyses are novel in this area of research as they account for a number of covariates associated with catch rates, in addition to the effects due to lunar phase and a fishing calendar. A multiplicative biomass effect using time as a proxy variable, and an offset to account for fishing effort were used in the specification of the mean, both of which have not been considered in previous models. In particular, we emphasize our use of random effects to model differences in fishing success between different individuals and on different days. These are all too often ignored, which can result in the reporting of spuriously high evidence of effects.

To date, we provide the most comprehensive, holistic approach to modeling the effect of the moon on catch rates in any fishery, and provide quantifiable and interpretable results. In addition, our methods are far more rigorous than those of Millar et al (1997), and we therefore present the most thorough and extensive analysis of the predictive performance of a recreational fishing calendar.

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Table 1 DIC values for the diary data models and AIC values for the boatramp data models. The fishing calendar and lunar models are favoured over the null in both cases.

Dataset	Model	Criterion value
Diary	Null	19282.10
	Fishing calendar	19277.47
	Lunar	19278.68
Boatramp	Null	13905.56
	Fishing calendar	13905.40
	Lunar	13903.64

Table 2 Model parameter estimates from the diary and boatramp data. Estimates for the diary data are Bayes estimates (the means of the posterior distributions) while for the boatramp data they are maximum likelihood estimates. The SD column represents the standard deviations of the posterior distributions for the diary models and the standard errors of the estimates for the boatramp models. Fishing calendar effects have also been adjusted so that they give the percentage change from the same baseline trip as the lunar effects shown in Figure 3.

Dataset	Model	Parameter	Estimate	SD	% Change
Diary	Calendar	α_B	0	–	−4.66
		α_F	0.0918	0.0473	+4.51
		α_G	0.0565	0.0410	+0.88
		β_0	−0.2218	0.0522	–
		β_A	−0.4146	0.0342	–
		β_P	1.1780	0.0335	–
		β_X	3.8418	0.1044	–
		σ_d	0.1235	0.0213	–
		σ_f	0.6000	0.0295	–
		p	0.0609	0.0079	–
		τ	3.0232	0.1032	–
Diary	Lunar	β_{LS}	−0.0375	0.0247	–
		β_{LC}	−0.0520	0.0241	–
		β_0	−0.1592	0.0433	–
		β_A	−0.4140	0.0354	–
		β_P	1.1828	0.0333	–
		β_X	3.8408	0.1041	–
		σ_d	0.1219	0.0276	–
		σ_f	0.5992	0.0291	–
		p	0.0609	0.0081	–
		τ	3.0221	0.1029	–
Boatramp	Calendar	α_B	0	–	−3.00
		α_F	0.0527	0.0319	+2.26
		α_G	0.0495	0.0279	+1.93
		β_B	0.0193	0.0035	–
		$\beta_{\tau 0}$	1.4865	0.1105	–
		$\beta_{\tau 1}$	0.4320	0.0220	–
Boatramp	Lunar	β_{LS}	−0.0207	0.0174	–
		β_{LC}	−0.0363	0.0171	–
		β_B	0.0186	0.0035	–
		$\beta_{\tau 0}$	1.4820	0.1106	–
		$\beta_{\tau 1}$	0.4328	0.0220	–

Table 3 Differences in fishing success between the best and the worst points of the lunar cycle and the best and the worst estimated calendar rankings. The fishing calendar rows therefore compare a 'Bad' ranking to a 'Fair' ranking. These are provided as a percentage difference (with 95% credible (diary) and likelihood profile confidence (boatramp) intervals), the difference in estimated number of snapper caught per hour (Fish/Hr) and the difference in hours taken to catch a single fish (Hrs/Fish). The latter two are provided for the best (March) and worst (August) times to fish in the year. Values presented for the diary analyses apply to the average fisher on the average day, and those presented for the boatramp analyses apply to the final calendar year in which surveys were conducted.

Dataset	Model	% Diff	95% CI	March		August	
				Fish/Hr	Hrs/Fish	Fish/Hr	Hrs/Fish
Diary	Calendar	9.61	$(-0.03, 20.21)$	0.110	9.1	0.048	20.7
Diary	Lunar	13.68	$(5.34, 25.36)$	0.155	6.4	0.068	14.7
Boatramp	Calendar	5.41	$(-1.01, 12.20)$	0.043	23.5	0.024	42.4
Boatramp	Lunar	8.71	$(1.64, 16.26)$	0.068	14.6	0.038	26.1

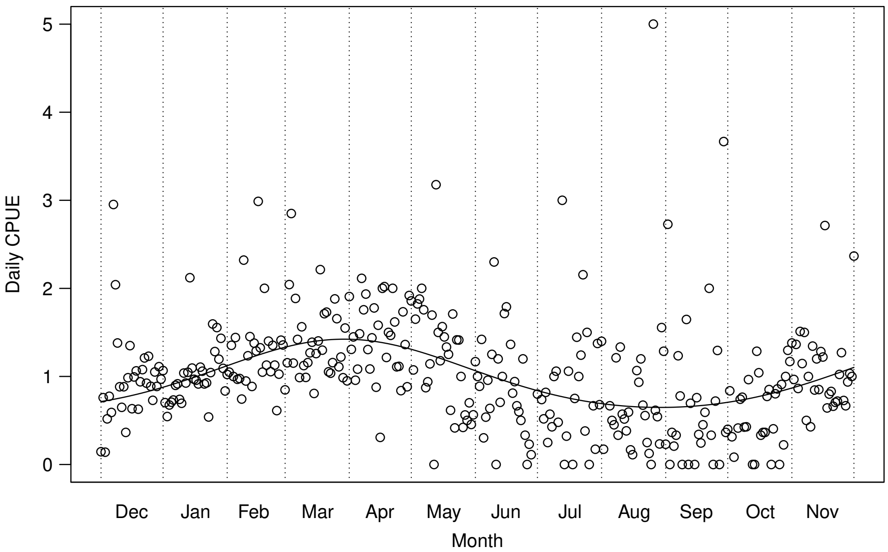

Fig. 1 Scatterplot showing daily CPUE (catch per hour) from the diary survey. The solid line is the fitted sine wave, and shows a strong seasonal trend in fishing success.

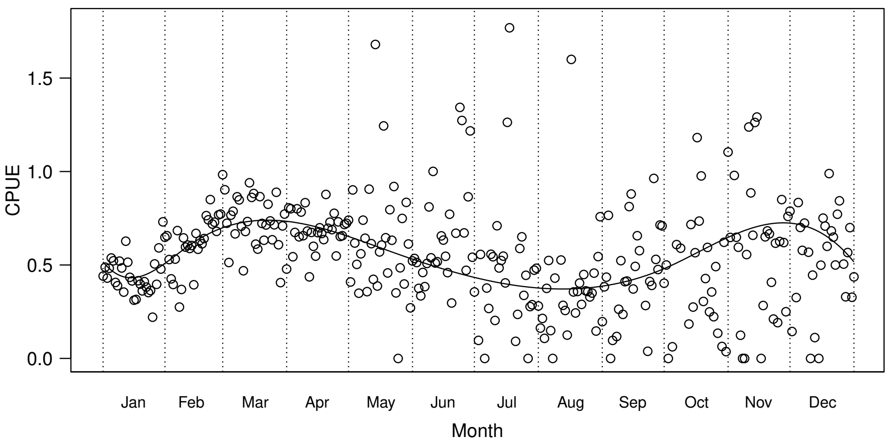

Fig. 2 Estimated seasonal trend from the boatramp data collected from 1990 to 2008. For each calendar day of the year, all CPUE values available for that day (over multiple years) are shown, in order to display the seasonal trend over a single calendar year. The fitted periodic spline is overlaid. Note that CPUE for days earlier in the year correspond to comparatively more person hours fished than those later in the year, and are thus subject to less sampling variation. For this reason, these points follow the observed trend more closely.

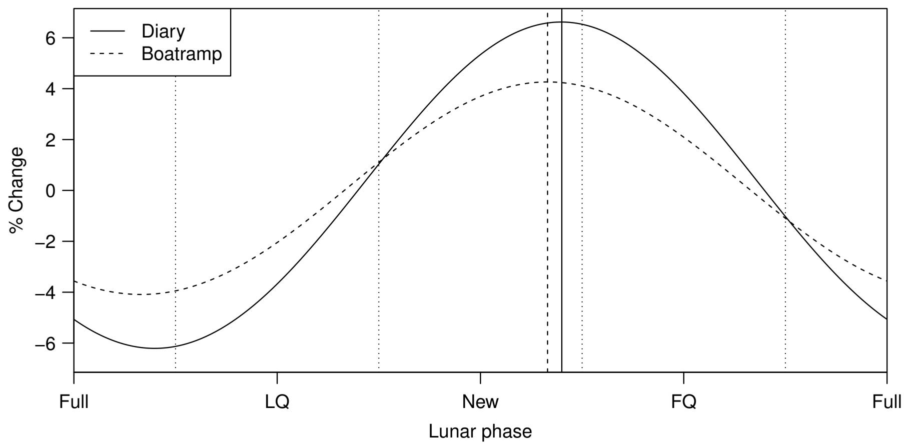

Fig. 3 Estimated effects of the lunar phase on catch rates from analyses of the diary and boatramp survey data, given by the estimates of β_{LS} and β_{LC} in Table 2. Vertical lines are shown at the estimated peak fishing times for each, and to divide the cycle into its four quarters. Effects are given in terms of a percentage change from a hypothetical baseline trip where the lunar effect is 0.