A report prepared for:

The Central Otago Lakes Branch of the Royal Forest and Bird Society

An analysis of Makarora Mōhua encounter rates

2011–2020

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Summary

Current monitoring of Mōhua (*Mohoua ochrocephala*) in Makarora is effective and meaningful, and likely provides a reasonable representation of how the population may be tracking. A robust analysis of the field data is possible via generalised linear mixed-effect modelling that accommodates zero-inflation.

Analysis of the Makarora Mōhua data indicates that the encounter rates declined dramatically between the period 2011–2012. This phenomenon appears to be attributable to a widespread rat irruption that also caused the collapse of the Mōhua population in the Rees-Dart Valley. In the years since, the encounter rates of Mōhua have recovered to the point that the rates in recent years are returning to the levels seen in 2011. Indeed, the encounter rates in 2018 and 2020 are statistically indistinguishable from the levels recorded in 2011.

The modelling used in the analysis suggests that temperature positively affects the number of Mōhua seen when they are there, and that even slight wind increases the probability of seeing no Mōhua. Consequently, temperature and wind must continue to be recorded, and incorporated into modelling of the encounter rates. Given the complexity of the analysis automation would provide a dramatic cost saving in future, and enable near real-time reporting.

Incorporation of tracking card data from DOC into the analysis has revealed that the encounter rates of Mōhua in Makarora can be predicted from the incidence of rats in the preceding 12 month period. Modelling suggests that once the mean annual incidence of rat tracks in tracking cards exceeds 11% a decline in Mōhua can be expected. Given that rat predation on Mōhua is well documented such declines are almost certainly the result of direct predation. The aerial application of 1080 has been a major factor in reducing rat abundance following large beech masting events and therefore is enabling the ongoing recovery of Mōhua in the Makarora area.

While this analysis infers that landscape-scale rat control through the use of 1080 has likely contributed to the ongoing recovery of the population, it cannot rule out the possibility that localised predator trapping may be contributing to that success. Given the strength of the association between rat and Mōhua abundance the reliability of the predictive rat model, developed through this analysis, should be more deeply investigated in coming years owing to its forecasting potential and ability to guide conservation decision making.

While the Makarora Mōhua population appears to be returning to levels last seen in 2011, this is likely to be a fraction of their historic norm, and should not be mistaken as a benchmark for success.

Purpose

This document reports on an analysis of Mōhua data[1] for the Makarora area over the period 2011–2020. The analysis was requested by the Central Otago Lakes Branch of the Royal Forest and Bird Society (COLBRFBS) due to concerns over the robustness of a previous analysis.

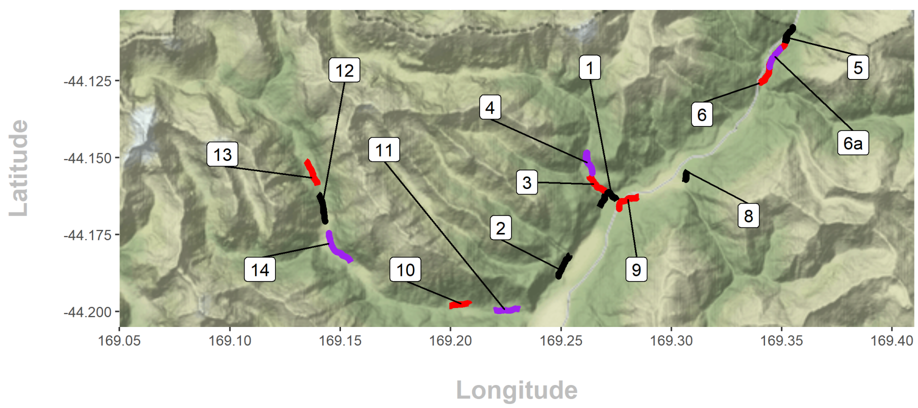

Figure 1: The location of the Mōhua transects in Makarora. Note: there is no transect "7", and for purposes of this analysis transect "6a" was subsumed into transect "6".

Data analysis

All analyses, graphing, and examination of diagnostics occurred in Program R (version 4.0.3) (R Core Team, 2020) with additional functionality provided by the packages 'AICcmodavg' (Mazerolle, 2020), 'Amelia' (Honaker et al., 2011), 'car' (Fox and Weisberg, 2019), 'DHARMa' (Hartig, 2021), 'emmeans' (Lenth, 2021), 'glmmTMB' (Brooks et al., 2017), 'janitor' (Firke, 2021), 'lme' (Bates et al., 2015), 'lubridate' (Grolemund and Wickham, 2011), 'MuMIn' (Barton, 2020), 'readxl' (Wickham and Bryan, 2019), 'stringi' (Gagolewski, 2020), 'tidyverse' (Wickham et al., 2019), and 'vcd' (Meyer et al., 2020). The transects mentioned in this document can be found in Figure 1).

[1] the data used in this analysis was acquired by COLBRFBS via an agreement with the Department of Conservation (DOC), a full description of the field protocols which gave rise to the data are held by DOC and are recorded in a number of reports including Tilson (2017)

Primary analysis

1. Upon detailed checking there were a number of missed values, typographic errors and illogical values in the parent data set. These were either corrected directly in the spreadsheet (where the correct value was obvious and unequivocal), over written only for the analysis in R where the corrected value was assumed, or imputed (created) via the 'Amelia' package in program R if it were missing. A more conservative approach would be to remove any rows of data which contained a mistake or missing value. However, it was clear that the consequence of the latter would likely have more impact than the former, consequently imputation was preferred.

2. A parametric modelling approach[2] was undertaken as decision making in wildlife management rests not only in the predictive power of the algorithm but in understanding the contribution of different explanatory variables to the overall result. Numeric variables were checked for multicolinearity[3] via the 'car' package, however no issues were identified.

3. As raw encounter data can only ever result in whole numbers, the starting point for the analysis would be some kind of a Poisson regression (the Poisson distribution being the type associated with count data).

4. As the transects are of variable length the encounter rate will be determined by a function relating to that length. Consequently, an offset based on length is required[4]. Note: in 2017 the transect at location "6" was lengthened, as a result it was treated as the same transect albeit with a different length (Figure 1).

5. As the monitoring occurs at transects which are repeatedly re-monitored the type of model required will be a generalised linear mixed-effect model (abbreviated to GLMM, formerly known as a 'repeated measures' analyses).

6. Consequently, the starting point for the analysis was a GLMM (using the 'lme4 'package) in which the fixed (main) effects were modified by transect length as an offset, while transect type represented a random effect (essentially a nuisance variable[5]), and

[2]one involving statistical distributions, opposed to a non-parametric approach e.g. machine learning

[3]multicolinearity is a situation where the explanatory variables are revealed to be non-independent (i.e. they can predict each other)

[4]intuitively many people will make the mistake of dividing the count by length, to achieve a rate, however the correct mathematical procedure in Poisson regression is to use a log transformed offset

[5]this refers to a variable which we already know will be different, in a situation where we want to know the overall pattern despite this inherent difference

the link function[6] was consistent with data following a Poisson distribution.

7. Parametric modelling approaches demand that the underlying assumptions of the models are fulfilled. In practice for a GLMM this means ensuring that residuals produced by the model are normally distributed, the data is not over-dispersed (more variable than expected) nor zero-inflated (meaning zero counts are not more common than expected).

8. Diagnostic testing (via the 'DHARMa' package) after the first round of modelling using a GLMM, revealed that the residuals were not normally distributed. Further analysis of a rootogram (via the 'vcd' package) suggested there was zero-inflation and over-dispersion (despite not being picked up the 'DHARMa' package).

9. Consequently, the analysis was shifted to a different type of GLMM which is extended to handle situations of zero-inflation (via the 'glmmTMB' package). The new GLMMs modelled the data as two separate processes which relate to the: (1) prediction of counts (some of which may be zero), and (2) prediction of excess zero counts. Subsequent diagnostic testing revealed that the issues relating to the non-normality of residuals had been overcome.

10. A suite of candidate models representing different hypotheses (i.e. different, yet reasonable combinations of explanatory variables present in the data, including an intercept only uninformative model[7]) were tested in a model selection process using Akaike's Information Criterion (with small sample adjustment) to rank the models in terms of parsimony (*sensu* Burnham and Anderson 2002). Throughout the analysis the variable 'Year' was treated as a factor to allow independence between years.

Supplementary analysis

The acquisition of tracking card data provided by DOC (Figure 4) covering the full monitoring period presented an unexpected opportunity to extend the analysis. Specifically, it allowed the examination of whether changes in the incidence of rat tracks in tracking card data could be used to predict the annual changes in Mōhua encounter rates.

1. The investigation commenced by segmenting the DOC data so that a mean of the tracking card incidence rate was produced for the interval between each monitoring period.

[6] used to transform the data back and forth between different mathematical scales
[7] intercept only models have a formula notation ~ 1

2. Three linear models were then used to establish whether the mean incidence rate of rats (MIR) correlated with annual changes in Mōhua encounter rates (i.e. the model coefficients from the top-rank GLLM model). The three models tested were: (1) MIR having a linear relationship with the coefficients, (2) MIR having a relationship described by a second order polynomial with the coefficients[8], and (3) an intercept only model (~1) which was used as a baseline for uninformative model performance.

3. The top-ranked GLMM model from the primary analysis was then compared via model selection to a new GLMM which utilised rat incidence rather than *Year* as the key explanatory variable. The purpose of this was to determine whether rat incidence could be used to forecast Mōhua encounter rates.

Results

Primary analysis

The analysis revealed the initial top-ranked model to be ~*Year* + *Temp* with the zero-inflation component being ~*Wind* (Table 1). This suggests that temperature and wind speed are critical to interpreting the encounter rates. The coefficients of the top-ranked model (Table 2) demonstrate that more Mōhua were typically encountered at higher temperatures, however, zero counts of Mōhua were more likely to be recorded when conditions were slightly windier (Table 3. *Year* was a universal variable amongst the top 15 models (Table 1), indicating that there were underlying differences between the yearly counts. Pairwise comparisons (Table 4) revealed that a substantial decline occurred between 2011 and 2012 which was maintained until 2018. These comparisons show that in 2018 and 2020 encounter rates had improved to the extent they were statistical indistinguishable from those first recorded in 2011.

Given that no single model had primacy, a model averaging approach was used to examine the trends in the model coefficients associated with *Year*. Model averaging demonstrated that encounter rates (regardless of *Temp* or *Wind*) were beginning to return to the level recorded in 2011 (Figure 2). Currently, model averaged predictions are not available for zero-inflated models created by the 'glmmTMB' package. As a result, model predictions versus observed are graphed using the top-ranked model (Figure 3).

[8]this allows the possibility that both negative and positive relationships exist (e.g. the incidence of rats and encounter rates of Mōhua may increase together initially due positive effects associated with forest productivity until an inflection point is reached at which point rats start preying upon Mōhua resulting in a decline in encounter rates)

Fixed effect model	ZI	K	AIC	Δ AICc	Model weight	LL
~Year + Temp	~Wind	14	1596.33	0.00	0.17	-783.73
~Year + Temp	~1	13	1596.52	0.19	0.15	-784.88
~Year + poly(Temp, 2)	~Wind	15	1597.51	1.19	0.09	-783.26
~Year + poly(Temp, 2)	~1	14	1597.64	1.32	0.09	-784.39
~Year + Temp + Wind	~1	14	1597.76	1.43	0.08	-784.44
~Year	~Wind	13	1598.02	1.69	0.07	-785.63
~Year + Temp	~Temp	14	1598.25	1.93	0.06	-784.69
~Year + Temp + Wind	~Wind	15	1598.31	1.98	0.06	-783.66
~Year	~1	12	1598.38	2.05	0.06	-786.87
~Year	~Temp	13	1599.08	2.75	0.04	-786.16
~Year + poly(Temp, 2)	~Temp	15	1599.44	3.12	0.03	-784.22
~Year + Temp + Wind	~Temp	15	1599.58	3.26	0.03	-784.29
~Year + Cloud + Temp + Wind	~1	15	1599.77	3.44	0.03	-784.38
~Year + Cloud + Temp + Wind	~Wind	16	1600.30	3.97	0.02	-783.58
~Year + Cloud + Temp + Wind	~Temp	16	1601.61	5.29	0.01	-784.24
~Temp	~Wind	5	1653.78	57.45	0.00	-821.83
~Cloud + Temp + Wind	~Wind	7	1654.31	57.98	0.00	-820.04
~1	~Wind	4	1655.06	58.74	0.00	-823.49
~Temp + Wind	~Wind	6	1655.61	59.28	0.00	-821.72
~Temp	~1	4	1655.63	59.31	0.00	-823.78
~Cloud + Temp + Wind	~1	6	1656.22	59.89	0.00	-822.02
~Wind	~Wind	5	1656.53	60.21	0.00	-823.21
~1	~1	3	1657.11	60.78	0.00	-825.53
~Temp	~Temp	5	1657.17	60.84	0.00	-823.52
~Temp + Wind	~1	5	1657.66	61.33	0.00	-823.77
~1	~Temp	4	1657.68	61.35	0.00	-824.80
~Cloud + Temp + Wind	~Temp	7	1657.89	61.57	0.00	-821.83
~Wind	~1	4	1659.11	62.78	0.00	-825.51
~Observer	~1	4	1659.14	62.81	0.00	-825.53
~Temp + Wind	~Temp	6	1659.21	62.89	0.00	-823.52
~Wind	~Temp	5	1659.68	63.35	0.00	-824.78

Table 1: Model selection table: prediction of Mōhua enounter rates by weather conditions at time of monitoring, and year specific effects. Models ranked by AICc (AIC with a small sample correction). Key: ZI = Zero-inflated formula component, K = number of parameters, AICc = AIC with a small sample correction, Δ AIC = difference in AIC value between the model and the top-ranked model, Model weight = model likelihood, LL = log-likelihood (a measure of goodness of fit).

Parameter	Estimate	Standard error	z-value	p-value
(Intercept)	0.473	0.428	1.105	0.269
Year 2012	-0.847	0.231	-3.666	< 0.001
Year 2013	-0.955	0.169	-5.666	< 0.001
Year 2014	-0.957	0.184	-5.196	< 0.001
Year 2015	-0.873	0.170	-5.133	< 0.001
Year 2016	-0.655	0.161	-4.059	< 0.001
Year 2017	-0.608	0.155	-3.937	< 0.001
Year 2018	-0.208	0.141	-1.468	0.142
Year 2019	-0.460	0.147	-3.132	0.002
Year 2020	-0.333	0.147	-2.259	0.024
Temp	0.089	0.046	1.934	0.053

Table 2: Fixed effect coefficients (log transformed) from the top-ranked zero-inflated generalised linear mixed-effect model: ~*Year* + *Temp* with the zero-inflation component being ~*Wind*.

Parameter	Estimate	Standard error	z-value	p-value
(Intercept)	-1.880	0.288	-6.518	0.000
Wind	0.484	0.290	1.665	0.096

Table 3: Zero-inflation coefficients (log transformed) from the top-ranked zero-inflated generalised linear mixed-effect model: ~*Year* + *Temp* with the zero-inflation component being ~*Wind*. A positive value for Wind indicates that a zero count is more likely with increasing wind strength.

Contrast	p-value
2011 - 2012	0.002
2011 - 2013	$<$ 0.001
2011 - 2014	$<$ 0.001
2011 - 2015	$<$ 0.001
2011 - 2016	0.001
2011 - 2017	0.001
2011 - 2018	0.750
2011 - 2019	0.016
2011 - 2020	0.199

Table 4: Pairwise comparisons between encounter rates recorded in 2011 and all other years.Key: Contrast = contrast between years, p-value = probability that the observed difference (or more extreme difference) between the two years could be generated by chance i.e. high p-values suggest that the years have the same encounter rates while p-values approaching zero suggest that they are different.

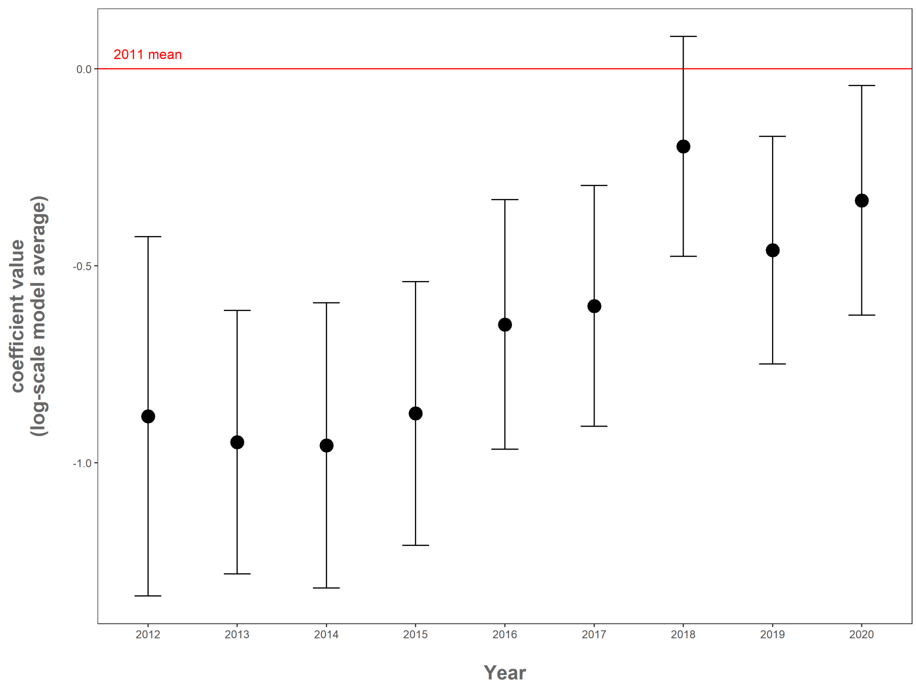

Figure 2: The deviation between 2011 and every other year based on model-averaged coefficients (from 15 models) showing the overall annual trend in the absence of differing weather conditions. Error bars represent $\pm$ 95% confidence intervals.

Supplementary analysis

Model selection revealed the second-order polynomial model described the variability in Mōhua encounter rates between different years well (Table 5). Mean incidence of rats was highly correlated with Mōhua encounter rates ($r^2 = 0.936$) and predicts the inflection point at which point the incidence of rats becomes detrimental to the Mōhua encounter rate (i.e. when the incidence exceeds 11%; Figure 5).

Given the the potential of a predictive relationship, another model selection process was conducted to see whether a GLMM model that had a polynomial relationship with rat incidence but no 'Year' effect (hereafter referred to as the predictive rat model) could out perform the previous top-ranked GLMM. Indeed, this predictive rat model succeeded in being the top-ranked model (Table 6) and was 3.4 $\times$ more likely to be the better model based on evidence ratios. However, the predictive rat model had a slightly poorer goodness of fit that the original model (as demonstrated by having a lower value for log-likelihood; Table 6), but when the two models are compared visually it is very clear

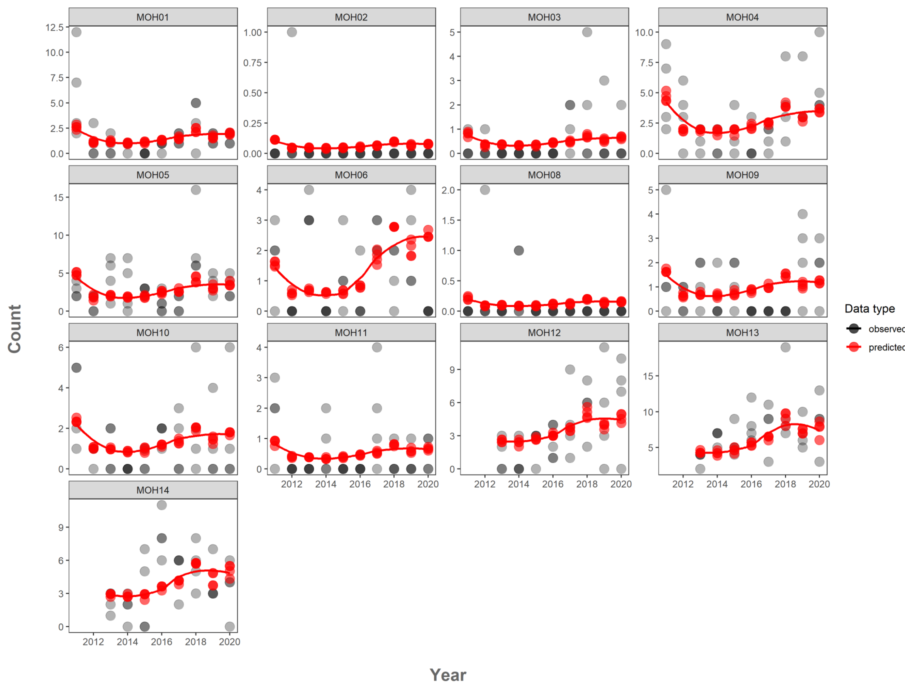

Figure 3: A comparison of the observed counts and predicted for each of the 13 transects based on the top-ranked model: ~*Year* + *Temp* with the zero-inflation component being ~*Wind*. Note: y-axis varies between transects.

that they make almost identical predictions (Figure 6).

Discussion

This analysis reveals a number of interesting patterns and phenomena. The Makarora Mōhua population appears to be still in the process of recovering from a decline that occurred between 2011–2012. This decline coincides with the collapse of the Mōhua population in the Rees-Dart Valley. The Rees-Dart population collapse was attributed to a rat plague which followed a moderate beech masting event. Indeed a rat irruption preceded the 2012 decline in Makarora. The analysis contained in this report suggests that subsequently there has been some kind of recovery, and that in 2018 and 2020 encounter rates appeared to approach to those observed in 2011. Additionally, this outcome demonstrates that the Makarora Mōhua data set was of a sufficient size for a robust analysis.

This report's primary analysis focused on understanding annual trends associated with Mōhua encounter rates. However, the supple-

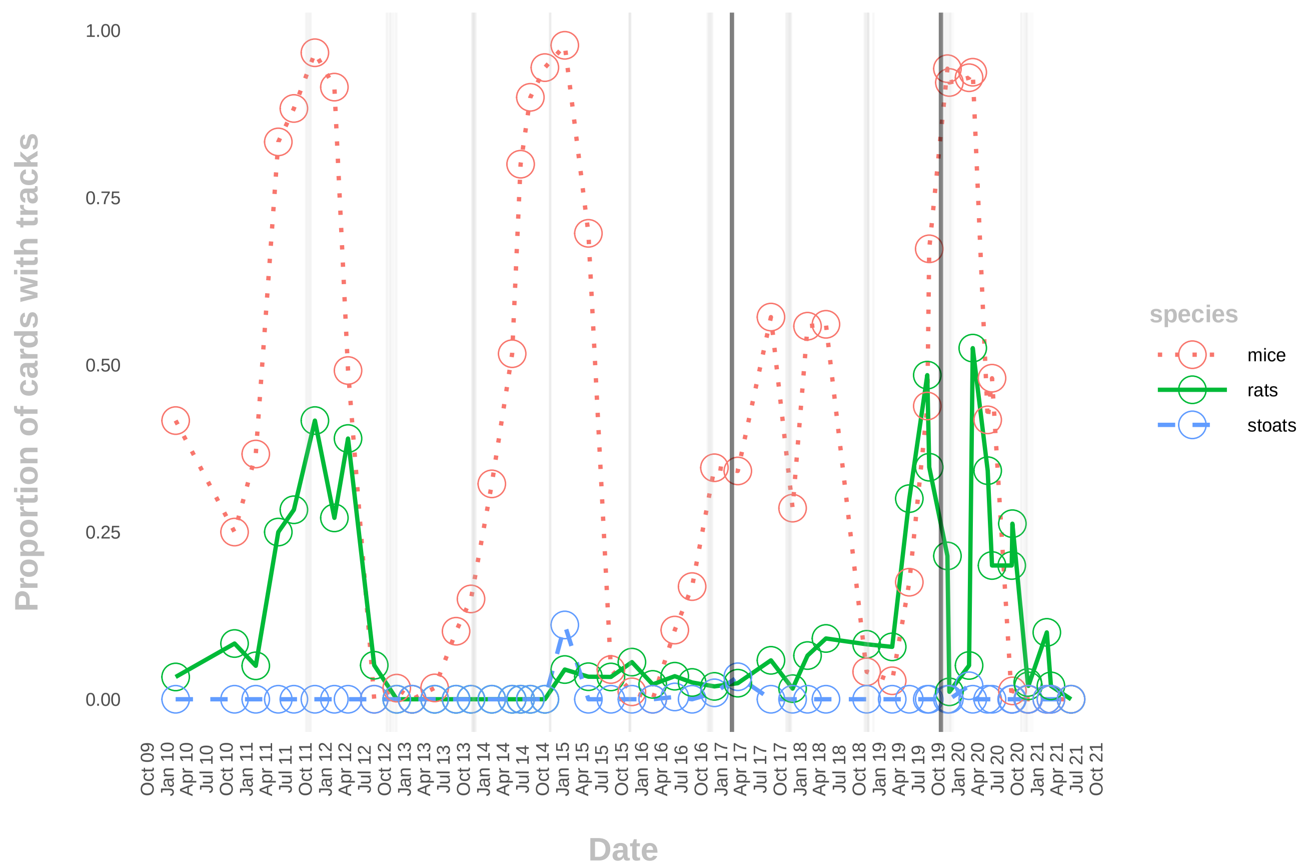

Figure 4: Incidence of rats, mice, and stoats in DOC tracking cards. Key: light grey lines = monitoring sessions, black lines = 1080 operations. Data courtesy of Graeme Elliott (DOC).

Model	K	AICc	Δ AICc	Model weight	LL
~poly (rats, 2)	4	-3.45	0.00	1.00	10.72
~rats	3	11.83	15.28	0.00	-0.51
~1	2	11.90	15.34	0.00	-2.95

Table 5: Model selection table: modelling model coefficients by mean incidence of rats. Models ranked by AICc (AIC with a small sample correction). Key: K = number of parameters, AICc = AIC with a small sample correction, Δ AIC = difference in AIC value between the model and the top-ranked model, Model weight = model likelihood, LL = log-likelihood (a measure of goodness of fit).

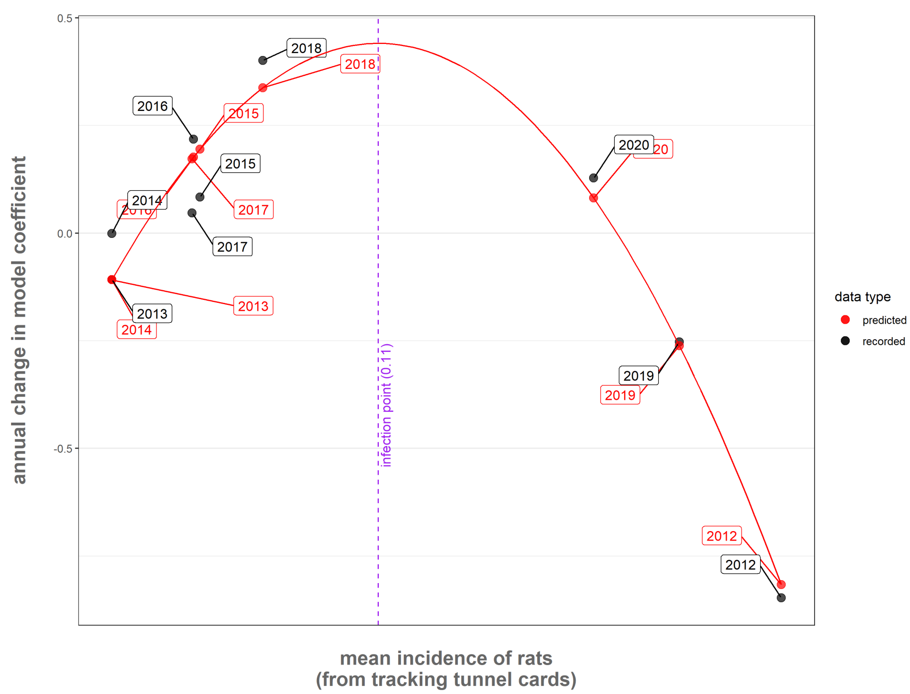

Figure 5: A polynomial relationship between the mean incidence of rats (from DOC tracking cards) and annual change in model coefficients (of the top model) showed a very strong correlation $r^2 = 0.936$. Note: the existence of an inflection point when the mean incidence of rats approaches 0.11 (11%).

Model	K	AICc	Δ AICc	Model weight	LL
~poly (rats, 2) + Temp ~Wind	7	1593.87	0.00	0.774	-789.82
~Year + Temp ~Wind	14	1596.33	2.46	0.226	-783.73

Table 6: Model selection table: a comparison of modelling Mōhua encounter rates by model coefficients by mean incidence of rats versus the previous top-ranked GLMM model based on the *Year* variable . Models ranked by AICc (AIC with a small sample correction). Key: K = number of parameters, AICc = AIC with a small sample correction, Δ AIC = difference in AIC value between the model and the top-ranked model, Model weight = model likelihood, LL = log-likelihood (a measure of goodness of fit)

mentary analysis now shows that the incidence of rats via tracking card data has a lot of predictive power. The major advantage of the predictive rat model over the top-ranked *Year* model is that it allows forward prediction of Mōhua encounter rates as opposed to simply offering a retrospective description. The relationship between rat incidence and Mōhua encounters appears to follow a polynomial function. Such a function is unlikely to be entirely causative, rather it is most likely approximating a situation in which increases in forest productivity initially benefit both rats and Mōhua, but above a certain threshold the abundance of rats becomes highly detrimental to Mōhua (likely through direct predation). The current results suggest such that the critical threshold at which rats become problematic is when the mean tracking card incidence exceeds 11%. Importantly, the relationship described in this analysis is based on only 10 data points (corresponding to the 10 years of data), meaning the inclusion of new data in the coming years has the potential to radically reshape that pattern. Consequently, the relationship described by the predictive rat model needs to be approached with a degree of caution. However, previous studies have indicated that Mōhua populations suffer substantial declines when peak tracking rates of rats exceed 30% (Elliott and Kemp, 2016).

Furthermore, it is specifically the incidence of rats rather than rodents as a group which appears to be driving the declines in Makarora Mōhua. This is demonstrated well in 2014–2015 (Figure 4) when a moderate beech masting event resulted in a large mouse irruption, but only a minor rat irruption, which had no measurable impact on the subsequent Mōhua encounter rate (Figure 2). By contrast in 2019 a very large rat irruption was halted by the aerial application of 1080, however, despite the subsequent collapse of the rat population (Figure 4) the levels of rats had reached a threshold which impacted the Mōhua encounter rate, which dropped from the year before (Figure 2).

Importantly, as encounter rates are an index form of monitoring they do not necessarily emulate real changes in abundance – although this is often assumed. By comparison, estimator methods (such as dis-

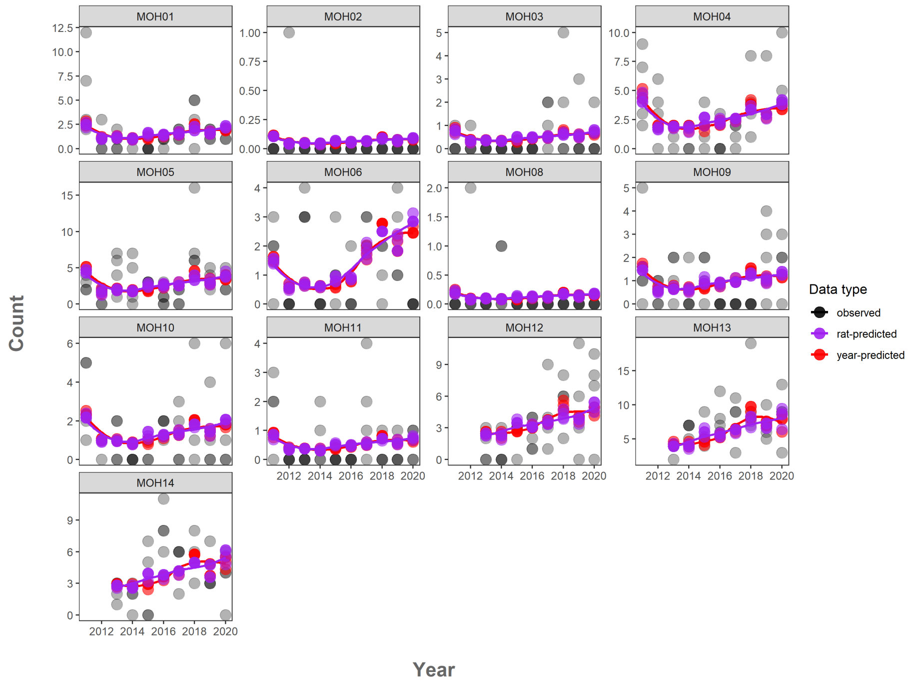

Figure 6: A comparison of the observed counts and those predicted by the top-ranked *Year* model and the predictive rat model for each of the 13 transects based. Note: y-axis varies between transects.

tance sampling e.g. Buckland et al. 2015) can establish absolute abundance. Estimator methods are not necessarily arduous and may be able to be implemented with little additional field cost. Consequently, it is recommended that a feasibility study on the use of such methods is carried out.

It is important to note that the relationships and patterns uncovered in this analysis are, at this stage, only attributable to the Makarora valleys in which the observations were recorded. Until evidence from other sites is collected and analysed the patterns should not be automatically assumed to be applicable to other Mōhua populations located elsewhere. However, the patterns revealed in this analysis are entirely consistent with the broader ecological processes associated with New Zealand beech forest masting events and rodent irruptions (e.g. Elliott and Kemp 2016).

Given that the modelling used in the GLMM analysis suggests that temperature positively affects the number of Mōhua seen when they are there, and that even slight wind increases the probability of seeing no Mōhua both variables must continue to be recorded, and incorporated into modelling the encounter rates in the future.

The current data has a minor problem with some transects being monitored twice in the same day by the same observer (affecting ~15% of transects). This has potential implications for the independence of the observations, as the observations taken on the same day by the same observer will likely be biased. Not only may the observer be unconsciously biased towards recent sighting locations, but the Mōhua themselves are less likely to have dispersed to a new location within a short time frame. Consequently, the occasional practice of resampling the same transect in the same day by the same observer should be avoided.

Conservation implications

As the beech mast-rat dynamic is a widespread landscape-scale process the effective suppression of rodents will require an intervention at a similar scale, such as that provided by the periodic aerial application of 1080. For the same reason, localised ground-based efforts in controlling rats are likely to be impractical and inconsequential.

While this analysis infers that landscape-scale rat control through the use of 1080 since 2012 has likely averted a major Mōhua decline in Makarora, it cannot rule out the possibility that localised predator trapping by COLBRFBS may be contributing to that success. Indeed, hole nesting birds such as Mōhua are known to be particularly susceptible not only to rats but also stoats (Lawrence and Low, 2012). However, the ability to infer the effectiveness of the predator trapping by COLBRFBS is hampered by the absence of 'control' transects (i.e. monitoring transects where predator trapping is not carried out but otherwise subject to the same landscape-scale processes and interventions as the other transect sites).

Given that the Makarora Mōhua population is one of the few recovering mainland populations the current management practices appear to be working and consequentially should be continued. While the Makarora Mōhua population appears to be returning to levels last seen in 2011, this is likely to be a fraction of their historic norm, and should not be mistaken as a benchmark for success.

Conclusions

- Current monitoring of Mōhua in Makarora is effective and meaningful, and likely provides a reasonable representation of how the population may be tracking.
- A robust analysis of the field data is possible via generalised linear mixed-effect modelling that accommodates zero-inflation.

- The Makarora Mōhua population appears to be still in the process of recovering from a decline that occurred between 2011–2012.
- In 2018 and 2020 the Makarora Mōhua encounter rates appeared to approach, if not return, to the rates observed in 2011.
- The encounter rates of the Makarora Mōhua population appear to have a predictive relationship with rats.
- Modelling suggests that once the mean annual incidence of rats in tracking cards exceeds 11% a decline in Mōhua can be expected.
- The aerial application of 1080 has been a major factor in reducing rat abundance following beech masting events and therefore is enabling the ongoing recovery of Mōhua in the Makarora area.

Recommendations

1. The monitoring of the Makarora Mōhua is of high value and should be continued.
2. As the Makarora Mōhua population appears to be recovering, current management interventions should be continued.
3. The occasional practice of resampling the same transect in the same day by the same observer should be avoided, as this is a potential source of bias.
4. Given that modelling revealed that temperature and wind affects encounter rates these variables must continue to be recorded in the field.
5. A feasibility study on the incorporation of an estimator approach into the field methodology should be investigated, as this will allow the production of abundance estimates which are more intuitive and generally less variable than encounter rates.
6. The power of the predictive rat model should be continued to be investigated in coming years owing to its potential for forecasting and guiding decision making.
7. Given the complexity of the data analysis, automation of the analysis could provide a dramatic cost saving in future, and enable near real-time reporting.

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References

Barton, K. (2020). MuMIn: Multi-model inference. R package version 1.43.17.

Bates, D., Mächler, M., Bolker, B., and Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1):1–48.

Brooks, M. E., Kristensen, K., van Benthem, K. J., Magnusson, A., Berg, C. W., Nielsen, A., Skaug, H. J., Maechler, M., and Bolker, B. M. (2017). glmmTMB balances speed and flexibility among packages for zero-inflated generalized linear mixed modeling. *The R Journal*, 9(2):378–400.

Buckland, S. T., Rexstad, E. A., Marques, T. A., and Oedekoven, C. S. (2015). *Distance Sampling: Methods and Applications*, volume 431. Springer.

Burnham, K. P. and Anderson, D. R. (2002). *A practical information-theoretic approach*. Springer New York, second edition.

Elliott, G. and Kemp, J. (2016). Large-scale pest control in new zealand beech forests. *Ecological Management & Restoration*, 17(3):200–209.

Firke, S. (2021). janitor: Simple tools for examining and cleaning dirty data. R package version 2.1.0.

Fox, J. and Weisberg, S. (2019). *An R Companion to Applied Regression*. Sage, Thousand Oaks CA, third edition.

Gagolewski, M. (2020). R package stringi: Character string processing facilities.

Grolemund, G. and Wickham, H. (2011). Dates and times made easy with lubridate. *Journal of Statistical Software*, 40(3):1–25.

Hartig, F. (2021). DHARMa: Residual diagnostics for hierarchical (multi-level / mixed) regression models. R package version 0.4.1.

Honaker, J., King, G., and Blackwell, M. (2011). Amelia II: A program for missing data. *Journal of Statistical Software*, 45(7):1–47.

Lawrence, B. L. and Low, M. (2012). Does hole-roosting behaviour of mohua (mohoua ochrocephala) increase the risk of predation by introduced mammals? *Notornis*, 59:85–87.

Lenth, R. V. (2021). emmeans: Estimated marginal means, aka least-squares means. R package version 1.6.2-1.

Mazerolle, M. J. (2020). AICcmodavg: Model selection and multimodel inference based on (q)aic(c). R package version 2.3-1.

Meyer, D., Zeileis, A., and Hornik, K. (2020). cd: Visualizing categorical data. R package version 1.4.8.

R Core Team (2020). R: A language and environment for statistical computing.

Tilson, J. (2017). Makarora mohua fixed transect survey 2017. Unpublised report.

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., Takahashi, K., Vaughan, D., Wilke, C., Woo, K., and Yutani, H. (2019). Welcome to the tidyverse. *Journal of Open Source Software*, 4(43):1686.

Wickham, H. and Bryan, J. (2019). readxl: Read excel files. R package version 1.3.1.