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Monitoring of North Island fantail (*Rhipidura fuliginosa placabilis* Bangs, 1921, Rhipiduridae) distribution on Tiritiri Matangi Island using several spatial methods for processing volunteer data

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Abstract

The Aotearoa / New Zealand pīwakawaka / fantail, *Rhipidura fuliginosa* (Sparrman, 1787), Rhipiduridae, is an iconic species and conspicuous in a range of habitats. However, island populations of the species are said to fluctuate dramatically. This project set out to investigate the population dynamics of Te Ika a Māui / North Island subspecies *Rhipidura fuliginosa placabilis* Bangs, 1921 on Tiritiri Matangi Island using a volunteer-based monitoring scheme. To achieve this goal, we developed a pilot sampling grid and determined spatial-distribution characteristics using several approaches, including geostatistical tools in ArcMap, species distribution modelling (SDM) and occupancy modelling. Fantail presence data was recorded twice a year by volunteers assigned to specific grids at different seasons for two years on Tiritiri Matangi Island. Recorded count data shows distinctive differences between the sampling periods and different areas of the island. Significant hotspots, as well as clustering of abundance, show different patterns, with significantly higher abundance and widespread distribution during May compared to November. Spatial analysis identified vegetation, particularly replanted areas, as influencing the fantail counts. Results of SDM show areas of the island suitable for the species, and occupancy models further describe the seasonal spatial characteristics of fantail. The effort also highlights the importance of volunteers in providing bird-count data to generate the knowledge base required for the management of an island sanctuary.

Keywords

Volunteer data, Aotearoa / New Zealand fantail, *Rhipidura fuliginosa placabilis*, spatial distribution, Tiritiri Matangi Island

Introduction

The use of GIS with a combination of tools used for processing data gathered by volunteers is recognised as an efficient and economical method to monitor and characterise bird populations, given the area covered, the seasonality of the observations and the nature of bird-count reporting itself (Hadidan et al. 1997; Turner 2003; Miller et al. 2016). Bird surveys have a long history of involving volunteers in data gathering, with such efforts proven to be useful for describing aspects of bird migration (Baillie et al. 2006). The increasing availability of online resources such as apps and websites for citizen-science bird-data reporting, and the importance of data-collection methods being based on scientific approaches is recognised (Scofield et al. 2012).

The Aotearoa / New Zealand pīwakawaka / fantail

The Aotearoa / New Zealand pīwakawaka / fantail, *Rhipidura fuliginosa* (Sparrman, 1787), is the only resident representative of the family Rhipiduridae in the Aotearoa / New Zealand archipelago (Powlesland 2013). It is widely distributed throughout Aotearoa / New Zealand, with four subspecies recognised: North Island fantail, *R. fuliginosa placabilis* Bangs, 1921; South Island fantail, *R. fuliginosa fuliginosa* (Sparrman, 1787); Chatham Island fantail, *R. fuliginosa penita* Bangs, 1911, and the extinct Lord Howe Island fantail, *R. fuliginosa cervina* Ramsay, 1879. The fantail utilises a wide variety of habitats including old growth or native and plantation forests, scrub, farmland, gardens, orchards, parks and grassland. In small islands, local populations of fantail can reduce or disappear during the rainy and cold seasons (Powlesland 2013), indicating a need for close monitoring and regular observation. This is particularly important in designated reserves or parks, where the promotion of biodiversity conservation to visitors, supporters and the public requires the visible presence and significant abundance of the species.

This study was focused on Tiritiri Matangi Island, an island sanctuary located 3.5 km distant from Whangaparāoa Peninsula, Tīkapa Moana / Hauraki Gulf, Te Ika a Māui / North Island, Aotearoa / New Zealand (Figure 1). Operating since 1984, and designated as an open sanctuary where tourism is promoted to the public, Tiritiri Matangi meets the need for the conservation of endemic and iconic species while providing a venue to enhance public awareness (Galbraith & Cooper 2013; Fergus et al. 2013). The presence of the facility has translated to motivated volunteers providing the much-needed data requirements for studies, including bird counts and species surveys. Through the Supporters of Tiritiri Matangi (SoTM), the involvement of volunteers in the scientific monitoring of bird species of the island is well recognised and acknowledged as a unique endeavour supporting science-based conservation management (Galbraith 2013). This unique island public / scientific sanctuary setup allows the provision of long-term monitoring data on a continuous basis for many endangered species (Thorogood et al. 2013). Studies conducted on Tiritiri Matangi have resulted in increased knowledge of the effects of rat eradication on bird populations (Veitch 2002), translocations of endangered species (van Winkel et al. 2010; Graham et al. 2013), monitoring of bird populations (Parker 2008), species translocations (Parker & Laurence 2008) and ecological restoration (Galbraith & Cooper 2013).

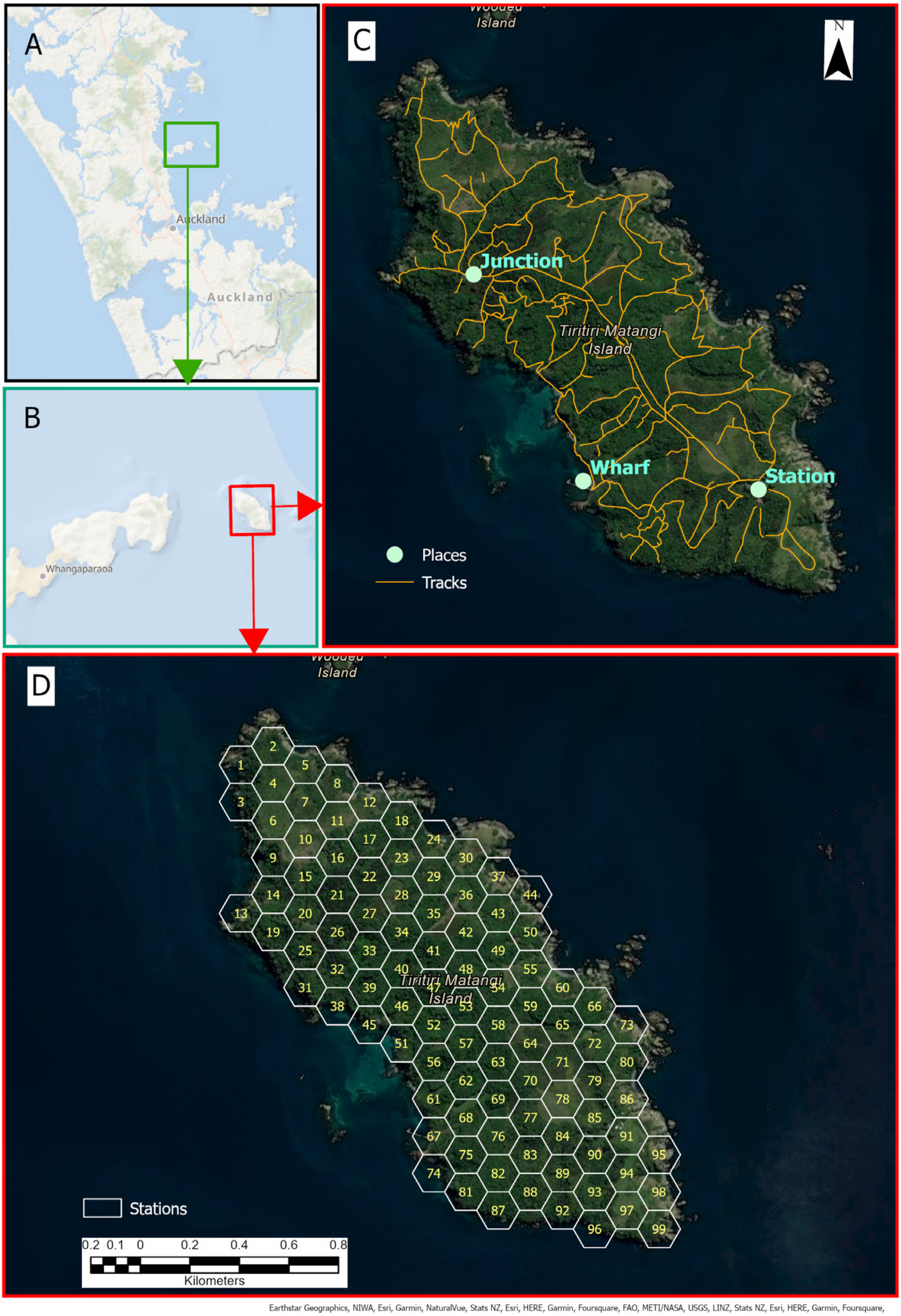


Figure 1. Sampling grid for fantail monitoring at Tiritiri Matangi Island.

To provide further support for the conservation management of the sanctuary, an effort to institute a spatial modelling system for monitoring changes in species present on the island started in 2014. The pilot to this study was the North Island fantail (*Rhipidura fuliginosa placabilis*) – hereafter referred to as 'fantail'. At the onset of the study, volunteers conducted bird counts, then a geodatabase for data gathering was established, and modelling approaches for describing the relationships and interaction amongst the species and the island's environment were investigated.

Geospatial species monitoring

The variety of available tools and software in spatial modelling provides choice, flexibility and the ability to address the multitude of questions related to species biogeography, and reflects the attempt to provide answers, even if incomplete, to those questions in view of the prerequisites of conservation management (Araújo & Peterson 2012; Costanza & Voinov 2004). The available tools and approaches, however, require significant investment in modelling and tool-performance evaluation to determine which are the most relevant and effective for the given problem and the study's objectives. Some tools with default values may not be applicable when applied to a different data set, or in different environmental conditions. Misleading results may also occur when species data and environmental variables are not adequately considered, and applied without addressing inherent biases (Villero et al. 2017; Banerjee et al. 2014). This results in sometimes complex and misleading models, which in turn leads to limited use of modelling in conservation planning (Jiménez-Valverde 2012). A combined approach using the most appropriate and widely used tools is recommended as one of the best ways to address weaknesses inherent not only in individual tools but also in the wider category of spatial modelling and statistical systems, to provide acceptable results at various stages of analysis and modelling (Aguilar et al. 2015; Mazzolli et al. 2016). We used a combination of spatial analytical tools available in the ArcMap v10.5 GIS software, SDM using the Maxent algorithm and occupancy modelling, for characterising fantail distribution on an island sanctuary.

To implement a systematic collection of data, a hexagonal grid-based system allocating specific areas for volunteers to cover was implemented to address location-based bias in recorded counts (Wiest et al. 2016; Berkunsky et al. 2016). With the entire island covered, the hexagonal grid provides efficiency in data collection over time, convenience in assigning volunteers to record data, and maintaining the geodatabase while allowing for consistency in using the many different tools involved. The grid-based system also addresses spatial autocorrelation biases associated with non-grid data. In addition, the grid setup provides consistency for a long-term monitoring system not only of the fantails, but of other birds and important species on the island, while providing relevant data on environmental variables that may affect species distribution characteristics.

SDM has become widely used to predict the suitability of a geographical area for a certain species, with many different algorithms developed, tested and compared (Fourcade et al. 2014; Elith & Graham 2009). Notable contributions of SDM include the identification of areas for further surveys of populations and species (Pearson et al. 2007; Araújo & Guisan 2006), description of invasive species ranges and potential for invasion (Ficetola et al. 2007; Roura-Pascual et al. 2008; McDowell et al. 2014), and effects of climate change on species distribution (Milanovich et al. 2010) and endangered species (Matyukhina et al. 2014).

Occupancy modelling has found popular use in developing models estimating occupancy and detection of a species over single or multiple seasons (MacKenzie et al. 2003; Zeller et al. 2011). While SDM produces the probability of a geographical location to be suitable for a species, occupancy modelling estimates the probability of an area to be occupied by and/or detected with a target species. Multiple season models could be produced, with estimates of colonisation and extinction also made available (MacKenzie et al. 2003). Occupancy modelling has been used to describe monitoring data of birds in Switzerland (Kéry et al. 2010), grassland birds (Sliwinski et al. 2016), aquatic snakes in North America (Durso et al. 2011), macaws (Psittacidae) in Bolivia (Berkunsky et al. 2016), jaguars (*Panthera onca* (Linnaeus, 1758)) in Mexico (Petracca et al. 2014) and mammals in Africa (Rich et al. 2016). Hexagonal grids and occupancy modelling were used in identifying population trends in threatened parrots (Berkunsky et al. 2016). Efforts to compare and evaluate SDM and occupancy modelling approaches report varying performance and applicability based on species detectability characteristics, with occupancy models showing better performance for species with low detectability and SDM performing better with highly detectable species (Comte & Grenouillet 2013). We implemented these modelling approaches to accommodate the consistent influx of data for fantails and other species monitored at the island. Using multiple approaches also considers the finding that the mean differences in performance between consensus SDM and occupancy modelling was found to be relative minor (Comte & Grenouillet, 2013).

In this paper we set out to implement a grid-based monitoring system with data collection involving volunteers, to determine the spatial characteristics of an iconic species, determine the relationship between species occurrence and selected environmental variables, and provide a framework for a long-term monitoring system of the island's important species.

Methods

Tiritiri Matangi Island is located 3.5 km east of the Whangaparāoa Peninsula, Te Ika a Māui / North Island, Aotearoa / New Zealand. The island has a slightly elongated shape, with an area of 220 hectares orientated northwest to southeast, measuring 3.5 km along its length and 1 km wide. Taking into consideration the capability of project participants to detect fantail presence, the island was subdivided into 99 hexagonal grids, each with a radius of 50 m (Figure 1). Fantail counts were carried out in November and May from 2014 to 2016, which were the months when differences in abundance and sightings had been noted over the years. Volunteers were assigned to monitor 3–4 grids each during sampling days and record detected presence of fantails for each grid. Each count consisted of three 5-minute counts (Hartley 2012) replicated over two days. Bird counts were entered into a geodatabase in ArcMap 10.5, and maps depicting average abundance for each sampling month were produced to show distribution characteristics.

Environmental parameters used for modelling included elevation, slope, aspect, vegetation and tracks. The 1-metre resolution Auckland LIDAR data was downloaded (https://data.linz.govt.nz/layer/3405-auckland-lidar-1m-dem-2013/) and used as the basis for generating elevation, slope and aspect raster datasets using the tools available in ArcMap. The vegetation type derived from the Landcover Database (LCDB4.1: https://lris.scinfo.org.nz/layer/48423-lcdb-v41-land-cover-database-version-41-mainland-new-zealand/) for each of the grid cells was identified and used as an environmental variable. The numerous tracks on the island were included as an environmental variable, with buffered distances providing values for the raster layer.

Using the average count overall, the global Moran's I statistic (Mitchell 2005) was used to examine underlying spatial autocorrelation patterns to identify whether the data itself was clustered (positively significant), randomly distributed, or dispersed (negatively significant). While the global Moran's I statistic indicated clustering, it did not identify where that occurred. Such specific location of hotspots was determined by the Getis-Ord Gi* statistic (Getis & Ord 1992), with the distance band results from the Moran's I statistic. The Getis-Ord Gi* statistic identified the group of neighbouring hexagonal grids where bird-count values hotspots or coldspots were clustered (using the Z scores and p-values of 95% confidence levels [CI] +1.96 and −1.96 standard deviations). Hotspots depicted locations where there were higher concentrations of fantails as compared to surrounding areas, whereas coldspots indicated the opposite (Ord & Getis 1995; 2001). The Gi* statistic is widely used in ecology and species distributions (Rozylowicz et al. 2013; Rissler & Smith 2010; Shaker et al. 2010), diseases (Kao et al. 2010), historical analysis (Zhang et al. 2011), avian influenza (Bevins et al. 2014), roadkill (Seo et al. 2015) and stray-cat (*Felis catus* Linnaeus, 1758) distribution (Aguilar & Farnworth 2013).

Another geostatistical tool used to characterise clusters and statistically significant spatial outliers is Anselin's Local Moran's Index (I-value) (Anselin 1995). This statistic determines similarities or dissimilarities of a cell with the surrounding cells. Using inverse weighted distance squared and the Euclidean distance measurement in the analysis, groupings of positive I-values with significant z-scores provide evidence of clustering, while groupings of negative I-values provide an argument for a lack of clustering. The hexagonal shape allows six significant positive indices in proximity as evidence of clustering, similar to the work of Schuurman et al. (2009). In this study, to further characterise results of Anselin's Local Moran's I, areas with statistically significant indices (p-value <0.05) were classified using local and global mean averages (local mean was the average fantail count density based on the area's neighborhood). Results were presented as cluster/outlier types (COType) that included the types HH, LL, HL and LH. The classification of statistically significant HH indicates clusters of high value while LL are statistically significant clusters of low value. For statistically significant outliers, HL is a high value surrounded by low values and LH is a low value surrounded by high values (Mitchell 2005).

The ordinary least squares (OLS) tool was used to determine the relationship between fantail abundance and the explanatory variables, including vegetation, tracks or roads, aspect, slope and elevation. OLS as implemented in ArcMap produces statistical measures used to evaluate the results of the analysis (Năpăruș & Kuntner 2012; Mitchell 2005). To compare the robustness of the OLS model results and provide an alternative spatially related analysis, geographically weighted regression (GWR) was utilised to take advantage of its capability of providing local r2, local standard errors, and measures of significance that provide an indication of spatial influences between variables (Legendre 1993; Brunsdon et al. 2002). The Akaike information criterion (AIC) was then used to compare the performance of OLS and GWR, with lesser values of 3 or greater indicating better performance (Zhang et al. 2011; Fotheringham et al. 1997).

To determine the suitability of the island for the fantail based on several environmental variables, SDM using the tool Maxent was conducted (Phillips et al. 2006; Phillips & Dudík 2008). In other studies, Maxent has been used to assess the spatial distribution of the lesser prairie chicken (Jarnevich et al. 2016), the distribution of beach-nesting birds (Maslo et al. 2016) and the fatality risk of bats near wind farms (Santos et al. 2013). In this study, the occurrence input for Maxent consisted of presence or absence based on the mean of counts and located at the centroid of each hexagon. The same environmental variables used in geostatistical analysis and occupancy modelling were also used, consistent with the observation that selected variables with observed species-specific responses improve model outputs (Molloy et al. 2016). Prediction maps for each of the sampling periods and the overall counts were generated using standardised regularisation and cross-validation for generating the goodness-of-fit measures. Different values of regularisation were tested to determine the best-performing model, as determined by the area under the curve (AUC) (Merow et al. 2013). Cross validation with five replicates was used for model evaluation, to measure the range of the model's predictive ability.

Occupancy modelling detects the probability of occupancy (psi), defined as the probability that a sampling unit is occupied by a species, and detectability (p), which is the probability that at least one individual of a species will be detected. Since first described in MacKenzie et al. (2002), it has been extended and used for a wide variety of applications and species. One of these extensions is the ability to model multi-year data and estimate, aside from occupancy (psi) and detectability (p), the component of changes in species distribution, including colonisation (gamma), extinction (epsilon) and rate of occupancy, sometimes called growth rates (lambda) (MacKenzie 2006; Royle & Kéry 2007). We used the software Presence v11.7 (Hines 2006), based on the work of Royle and Kéry (2007). Data consisted of all sampling records (four days in November 2014; six days each in May 2015, November 2015 and May 2016). Site covariates were the same variables used in Maxent modelling, with vegetation also used as both site and sample covariates. The values of the covariates were standardised, using the approach of MacKenzie et al. (2006) to reduce the effect of the magnitude of the values of the variables. Multi-season models were generated and compared according to the AIC, with the best-performing model used to provide estimates of occupancy and detectability (Peterman et al. 2013).

Applications of both SDM and occupancy modelling have been reported for guiding survey efforts on salamanders (Peterman et al. 2013), a freshwater fish (Albanese et al. 2014), African mammals (Rich et al. 2016), anuran populations (Villena at al. 2016) and citizen-science-produced data on birds (Higa et al. 2015).

Results

Fantail observations differed significantly between May and November, using the average count for two years (paired t-test; p-value <0.0000). The month of May showed much greater sightings, with only 13.13% of grids showing no counts, while November had 74.74% showing zero counts. For the overall sightings, the highest count was recorded at Grid 20, which is near the old-growth forest and covers the junction of the main access-road and an old track (Figure 2). The next highest was at Grid 67, which is near the wharf, followed by Grid 60, on the east coast, just below the centre of the island.

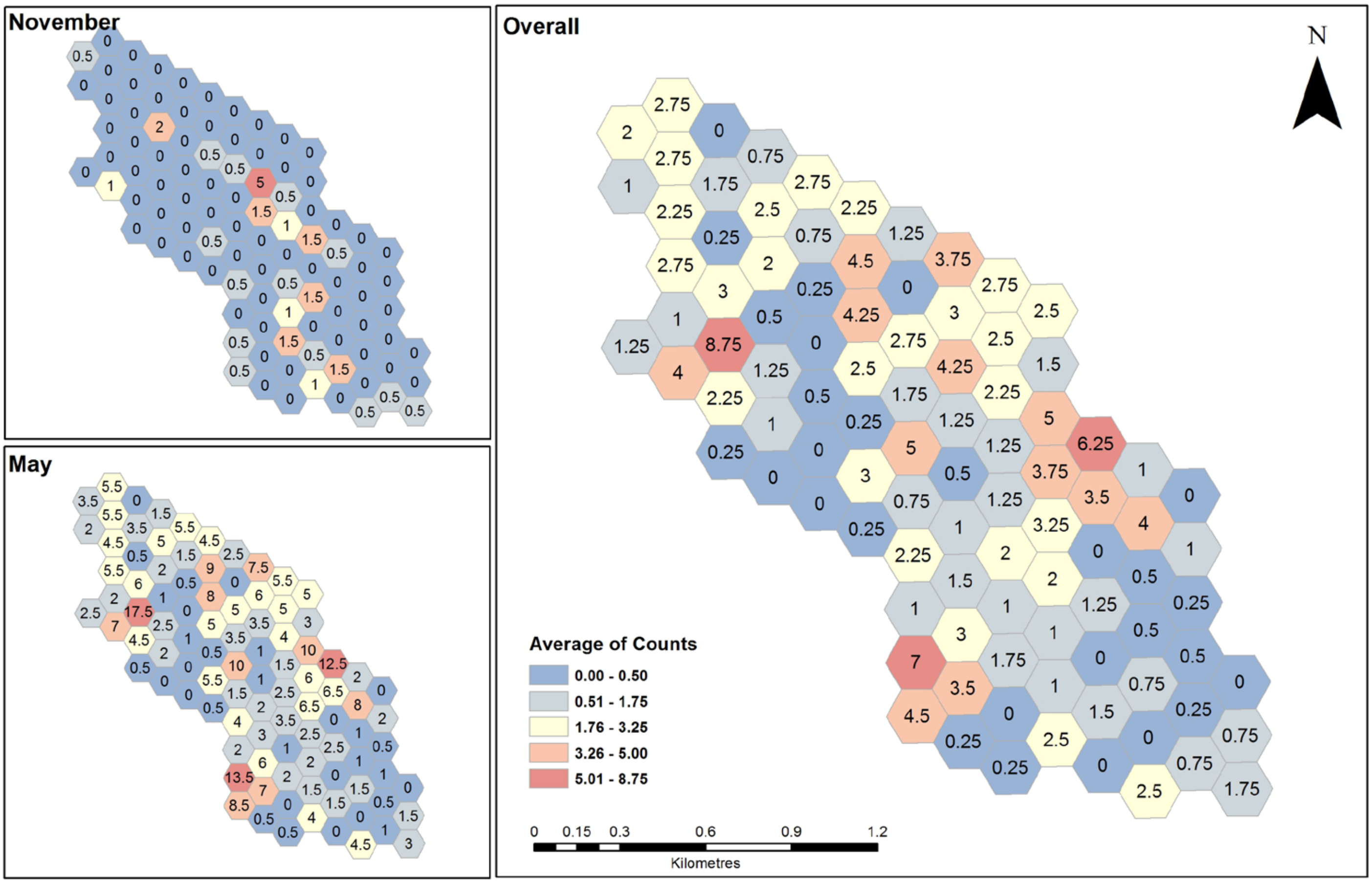


Figure 2. Average Aotearoa New / Zealand fantail count for November, May and overall during the survey period.

GIS modelling

Global Moran's I showed that the data was significantly clustered, with hotspots present in the overall count data (I = 0.162; z = 2.78; p-value = 0.004). When the Getis-Ord Gi* statistic was run for May, November and overall count data, hotspots with significant values were found at different areas of the island. One hotspot for November was located on the central eastern side of the island, while three hotspots were found for May. Two May hotspots were found on the west coast and another on the east coast of the island, slightly south of the May hotspot. The November northwest hotspot is consistent with the area where the highest fantail counts were obtained for the month. Significant coldspots were found in the May count, one to the south of the northern hotspot and another at the open area near the southern ridge area of the island and near the lighthouse. The overall hotspot and coldspot pattern is remarkably similar to the May hotspot, with the disappearance of significant hotspots in the central east side, which was a hotspot in November (Figure 3).

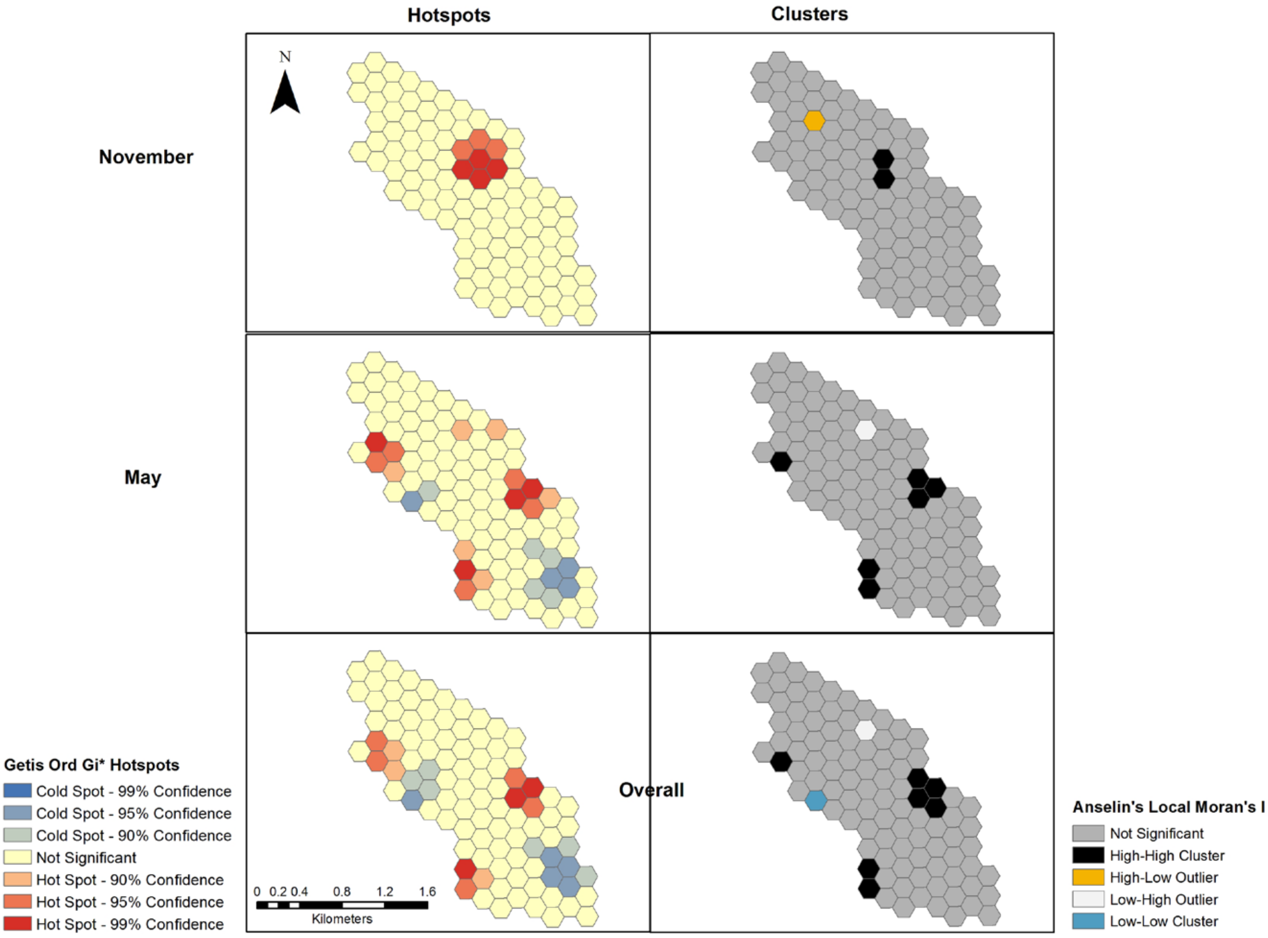


Figure 3. Hotspot analysis, and cluster and outlier analysis output maps.

In terms of cluster and outlier analysis (CLOA), the November count showed significant HH clusters where the hotspots are located and one grid with a significant HL cluster in the upper northern part. For May, HH clusters were found in the same areas with significant hotspots, while an LH cluster was found at one grid in the upper northeast. The overall CLOA shows similar patterns as the May map, with the difference of an LL cluster found at the central western part of the island.

Results of both hotspot and CLOA analysis show distinct patterns between the different months, implying a change in the spatial and temporal distribution of the fantail. Areas of the island that show hotspots also show consistent clustering patterns, providing information on areas where the species concentrates at certain times of the year.

Geostatistical results using the OLS tool in ArcMap, with elevation, distance from tracks, slope, aspect and vegetation used as exploratory variables and the average count as a dependent variable, showed no significant relationships. When GWR was run, the AIC values for GWR (393.392) were only very slightly better than OLS (393.389), showing no considerable advantage between using OLS and GWR as analytical tools.

Processing LIDAR raster data resulted in the elevation, slope and aspect maps shown in Figure 4. The island is hilly, with a main ridge running at the central section and the highest elevations at 81 m. Cliffs surround the island, with a few beaches at small coves around the island's perimeter. Gullies run from the main central ridge and dissect the island regularly at the eastern and western sides. The island is raised from the sea, with an average elevation of 41.2 m. Except for coastal cliffs, slopes are modest, with a mean slope of 19.7%, while flat sections are rare. Vegetation was recorded in situ for each of the sampling cells, and consisted of old-growth forest (14.1%), dense coastal forest (26.3%), replanted forest (27.3%), dense shrub (21.2%), flax shrub (5.1%) and grassland (6.1%). Other areas outside of the grid consisted of beach or rocky areas, and are included in this variable. In terms of aspect, 37% of the island faces south, southwest, and west, while 31% faces north, northeast and east.

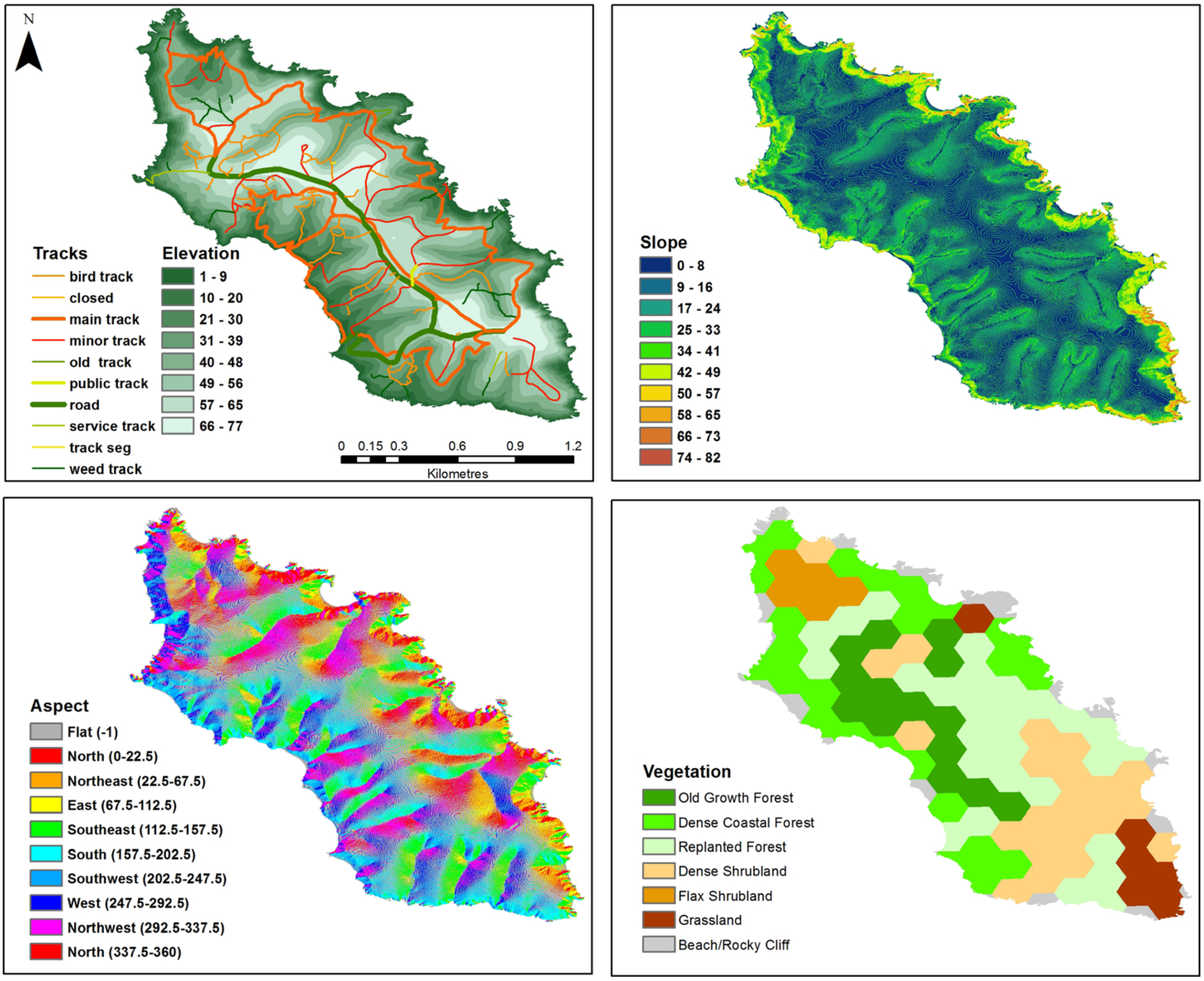


Figure 4. Parameters used for OLS, GWR analysis and species distribution modelling.

Species distribution modelling

The variable contributions were different between May and November. In May, tracks had the highest percentage contribution, followed by slope and land cover, but when permutation importance was considered, slope was highest, followed by tracks and land cover (Table 1). In November, aspect had the highest percentage contribution and highest permutation importance, followed by land cover.

Table 1. Contributions of the variables reported by Maxent.

Variable	May		November	
	Percent contribution	Permutation importance	Percent contribution	Permutation importance
Vegetation	15.4	4.7	51.1	55.9
Aspect	21.0	17.7	30.7	26.8
Slope	20.3	22.8	8.0	10.3
Tracks	35.2	36.2	7.1	2.7
Elevation	8.1	18.6	3.1	4.3

The model's responses for each variable show similarities between the May and November sampling periods (Figure 5). In terms of the vegetation categorical variable, there is a difference in the importance of grassland, replanted forest and dense shrubland, where the May sampling showed much higher response for grassland compared to November.

Replanted forest and dense shrubland, on the other hand, showed greater influence in November than grassland. The variables with the highest responses provided a hint on what variable to focus on when running the occupancy model.

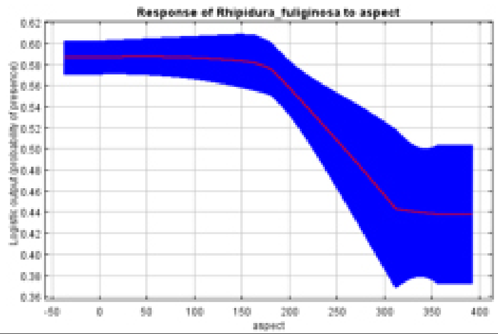
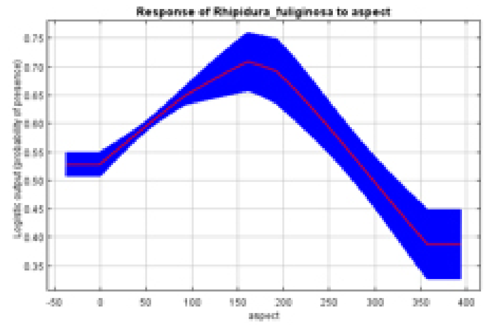
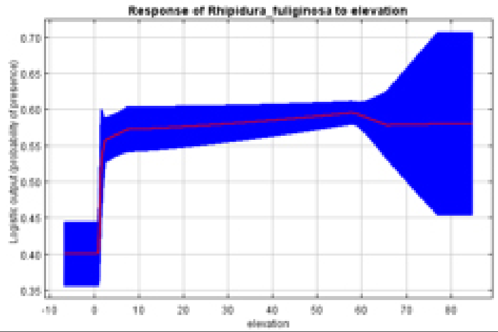
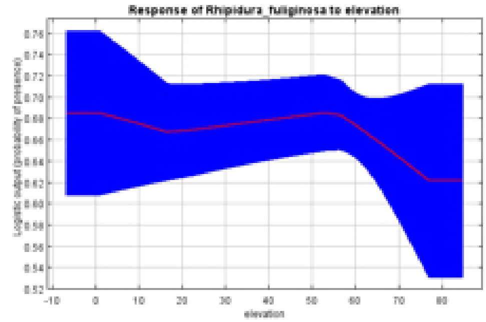
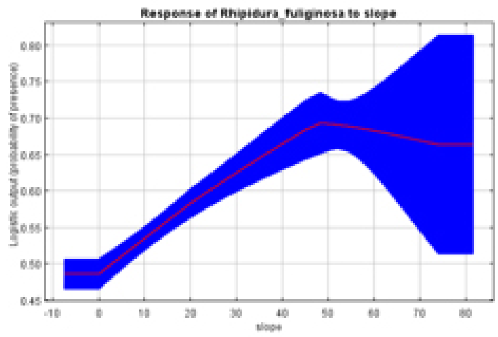
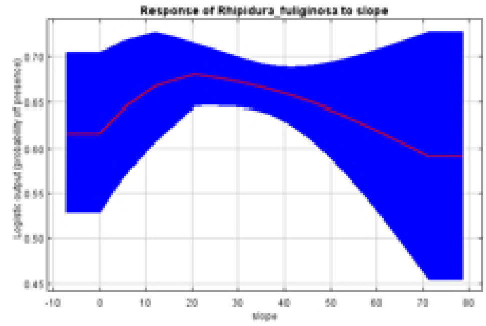
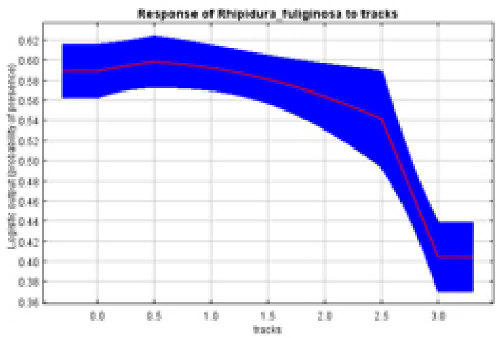
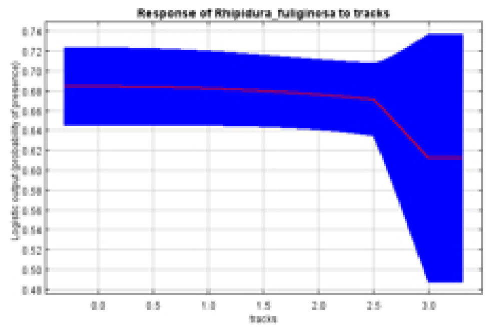
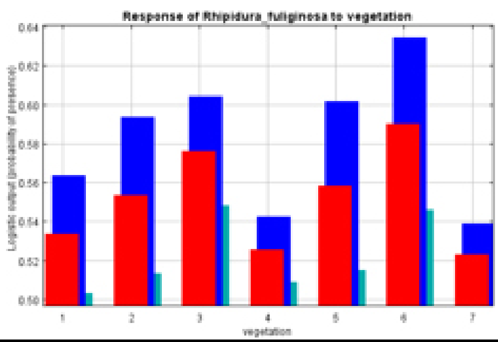
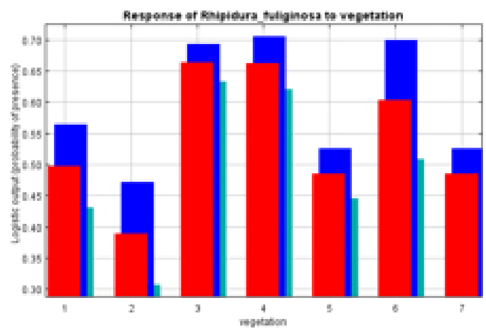
Variable	May	November
Aspect		
Elevation		
Slope		
Tracks		
Vegetation		

Figure 5. Response curves for May and November in Maxent (vegetation types: 1 – old-growth forest; 2 – dense coastal forest; 3 – replanted forest; 4 – dense shrub; 5 – flax shrub; 6 – grassland; 7 – beach areas).

The resulting prediction map of suitability shows differences between the two sampling periods (Figure 6). For May, the highly suitable areas coincide with the tracks and higher slopes at the northeast side of the island, which has more sunlight during these cooling months, while for November, the higher suitability sites coincide with vegetation and aspect, with the replanted forest vegetation type showing more suitable sites.

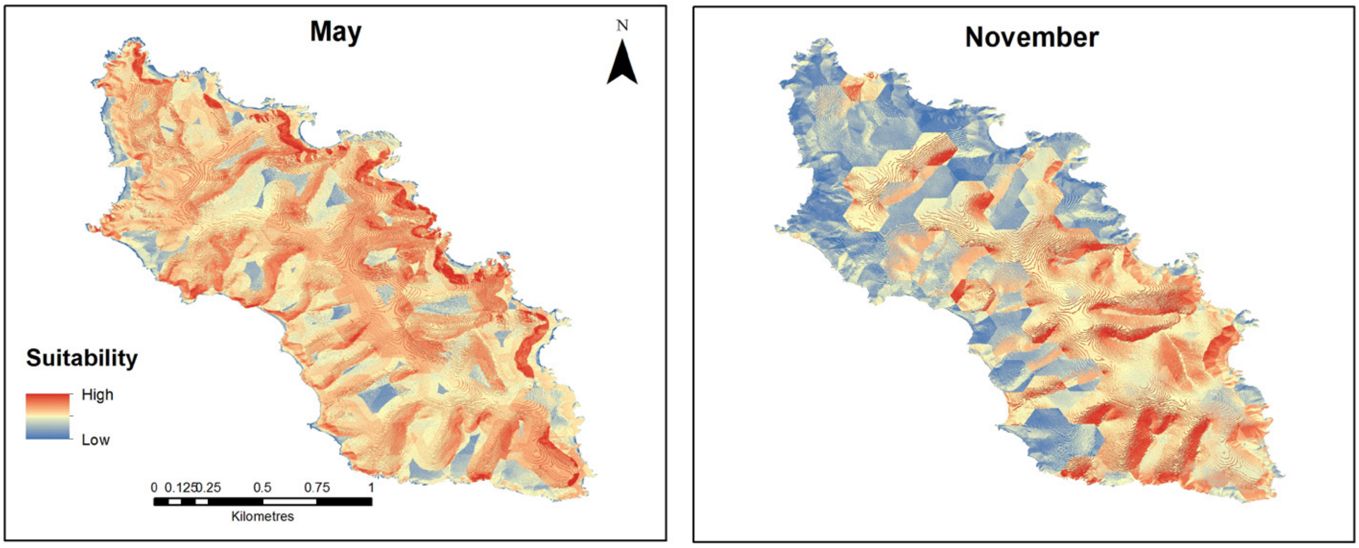


Figure 6. Suitability map produced by Maxent.

Occupancy modelling

Naïve occupancy, or the proportion of cells where fantails were detected, was 0.63. Using the distinct categories of vegetation cover as covariates in the occupancy model showed that the model with a variable combination of replanted forest, flax shrubland and grassland had the highest predictive value, as indicated by the AIC, followed by the combination of grassland and flax shrubland (Table 2). Models with the sole variables of replanted forest areas, followed by grassland, provided the highest predictive results, as shown by the values of delta AIC (the difference between the model and the lowest AIC). The models with the variables of aspect, elevation, tracks and slope showed much lower AIC compared to the categories in the vegetation cover. Of the vegetation categories, old-growth forest showed the lowest AIC.

Values for occupancy are higher in May than in November for both seasons, and the same is true of detectability (Figure 7). The rate of occupancy (lambda) also reflects the characteristic change in occupancy between the sampling months. Values of gamma and epsilon, representing colonisation and extinction, show the differences between May and November.

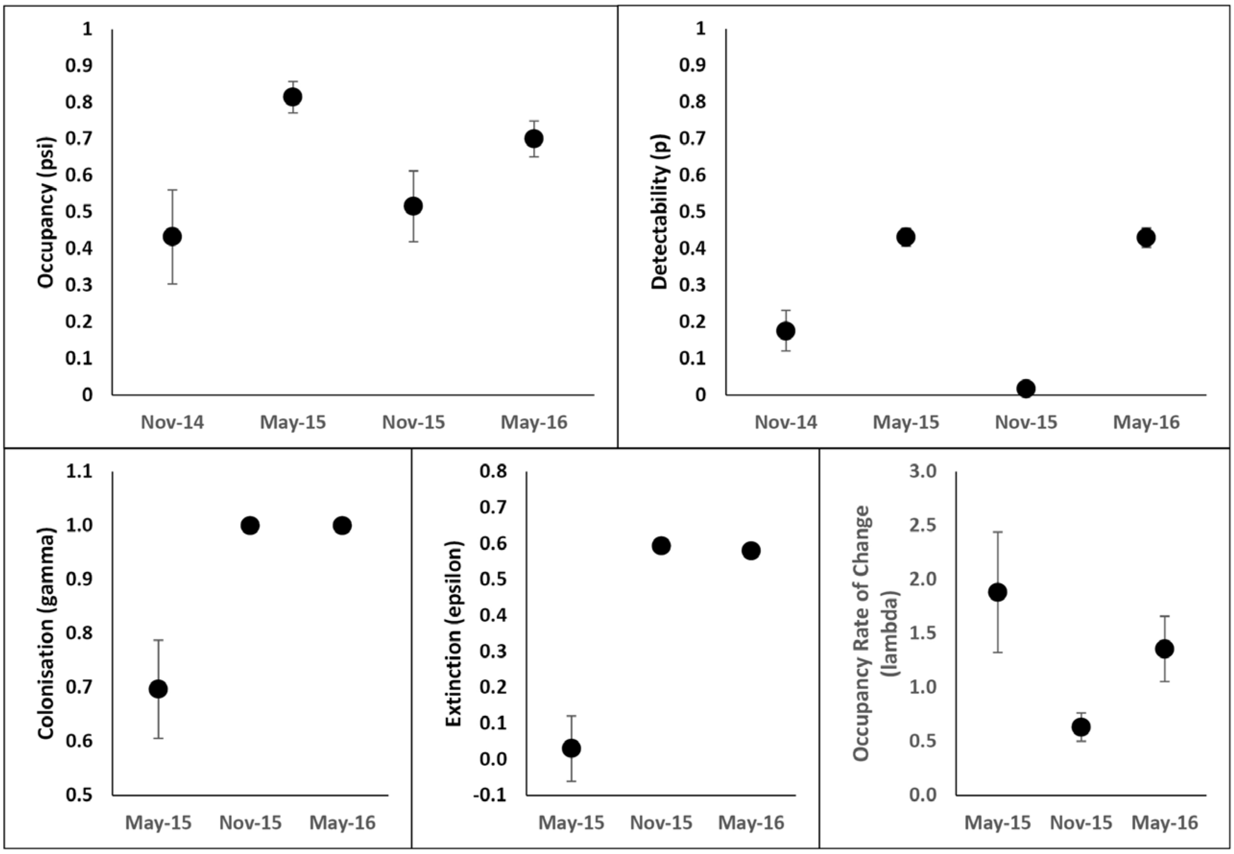


Figure 7. Occupancy (psi), detectability (p), occupancy rate of change (lambda), colonisation (gamma) and extinction (epsilon) for the sampling periods November 2014 (1), May 2015 (2), November 2015 (3) and May 2016 (4).

Discussion

The results of geostatistical analysis, including the Getis Ord Gi* and Local Anselin's statistics, provide significantly defined distribution characteristics represented as graduated colours of the hexagonal grids. Differences between May and November are highlighted by the coldspots/hotspots and the COType maps. Grids where these two statistics are significant are also consistently in the same neighbourhood for each of the seasons, indicating a consistent measure of abundance for the area for each season.

Results of SDM help guide future related studies on the relationship of species occurrence and selected environmental variables. The resulting suitability maps depict conditions that are different between seasons, with tracks and slope showing a greater influence in May, while vegetation type and aspect are more significant in November. These maps can help guide future surveys in locating where the birds may be located and help focus monitoring efforts. The results on variable influence may also help guide occupancy modelling in determining which variables to use as covariates.

Occupancy modelling provided a convenient measure of the importance of a categorical variable's elements on model results. In this case, the importance of the replanted forest, flax shrubland and grassland as combined covariates was determined from the AIC results (delta AIC <2). This result is also consistent with the Maxent results showing the response curve for vegetation where these categories contribute the highest for both May and November. The values of occupancy for the sampling seasons May and November were found to be consistent with the results of geostatistical tools in ArcMap and the predictive maps produced by Maxent. The higher values of occupancy and detectability in May compared to November are consistent for the three approaches. Colonisation and local extinction rates also reflect the changes from the second season to the last sampling period. A major advantage of occupancy modelling for continued long-term monitoring is that observation efforts over the years increase the probability of species detection (Kéry et al. 2010).

The combination of these approaches provides options in exploring aspects of a volunteer-based monitoring system, with the GIS model supplying an abundance map of the species, SDM providing a map of area suitability, and occupancy modelling determining the probability of occupancy and detectability for each sampling season. The vegetation types of replanted forest, flax shrubland and grassland combined show the highest AIC compared to the other models. When only one variable is used in the model, the replanted forest influencing detectability shows the best AIC. This result hints at this vegetation type as having higher influence on the species detectability compared to other types. Future count data is expected to further enhance the understanding of the spatial characteristics of this iconic bird. This approach is expected to be applied to other species on the island, to include an investigation of inter-specific influences on the occupancy modelling aspect.

Volunteer-based monitoring of a species that provides a steady stream of count data allowed trying different approaches for characterising the distribution characteristics of the Aotearoa / New Zealand fantail. The resulting maps, depicting the distribution, results of geostatistical analysis and species distribution, provide not only material for technical publications but also intuitive feedback to the volunteers in the form of maps, giving proof of relevant results that provide motivation for continued engagement in the effort. Such outputs form part of volunteer project-evaluation tools that are proven to contribute to sustainable long-term monitoring in citizen science projects (Chandler et al. 2017).

The natural extension of this effort is to explore the approach with other species of importance on the island. Continuous input of data from the biannual bird counts is expected to further improve the quality of the models developed and provide much clearer descriptions of the spatial distribution of the Aotearoa / New Zealand fantail and other bird species of importance. Use of other capability extensions of occupancy modelling on the fantail and other species is certainly warranted.

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Author Contributions

Glenn Aguilar: Conceptualisation; data curation; formal analysis; methodology; project administration; resources; software; validation; visualisation; writing – original draft, review and editing.
Mel Galbraith: Conceptualisation; funding acquisition; supervision; methodology; data collection; writing – review and editing.
Hester Cooper: Logistics; data collection; writing – review.

Declaration of Competing Interest

The authors declare that they have no known competing interests or personal relationships that could have appeared to influence the work reported in this paper.

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