Final report

Developing environmental indicators to strengthen on-farm reporting

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Abstract

The maintenance of biodiversity is a key component of ecologically sustainable agricultural production, both in the grazing and cropping industries. However, measuring biodiversity, through biodiversity indicators, remains a major challenge. We used a unique set of broad-scale, long-term datasets gathered across inland agricultural Australia to explore the efficacy of biodiversity indicators in threatened Box Gum Grassy Woodlands and compatible plantings on farms. The most important influences of bird biodiversity were Noisy Miners, whether a patch was a planting, and the amount of surrounding woody cover. We developed models that summarise some of the complex relationship between environmental factors and biodiversity. Estimates from these models capture multiple aspects of biodiversity and might be used for improved biodiversity indicators. A web app 'Bird Checker: A Bird Occupancy Estimator' [http://sustainablefarms.org.au/tools/bird-checker], giving easy use of one our models, is publicly available. A similar project in other ecosystems may require bird surveys across at least 230km North-South, and with more than one farm per 2500km^2.

Executive summary

Background

The conservation of biodiversity is now recognized as a key component of initiatives to promote industry sustainability, such as in beef production (the Beef Sustainability Framework [https://www.sustainableaustralianbeef.com.au/]) and sheep production (the Sheep Sustainability Framework [https://www.sheepsustainabilityframework.com.au/]). However, there are many challenges in developing biodiversity indicators for measuring sustainability in agricultural management and production.

The research reported here investigated the efficacy of environmental factors for predicting multiple aspects of biodiversity. The results can be used by farmers and Local Land Service staff to obtain location-specific information on management choices, and existing biodiversity aspects of a farm. Researchers and policy makers can use the results to inform the design of environmental monitoring projects that underpin sustainability frameworks.

Objectives

This project sought to compare and develop new biodiversity indicators. We also compared on-ground measurements, remotely-sensed measurements and climatic factors. The new biodiversity indicators we created were in the form of joint-species bird occupancy estimates.

Methodology

We used long-term biodiversity monitoring data at sites in Box Gum Grassy Woodlands (and compatible plantings) across NSW, and in parts of Victoria and Queensland. We studied the statistical relationships between on-ground environmental measurements, remotely-sensed products, climate, and weather, on more than 60 bird species, on the number of reptile species and on the number of bird species of conservation concern. These relationships were studies using joint-species occupancy-detection distribution models. Comparisons between models allows assessment of the usefulness of environmental predictors. The best models are themselves biodiversity indicators.

Results/key findings

For biodiversity indicators in our study area, we first recommend standardised on-ground surveys. Such surveys give the greatest detail and most comprehensive biodiversity information, and can capture factors not studied in this project. If on-ground surveys are not possible then, due to the complicated relationships between environmental factors and biodiversity, we recommend the use of estimates from the joint-species models developed in this project. These estimates can be considered indicators that summarise plantings (vs remnants), Noisy Miner occupancy, woody canopy, climate and other attributes.

The most important influences of bird biodiversity were Noisy Miners, whether the patch was a planting, woody cover (within 500m and within 3km), and historical climate, particularly annual maximum temperature. However, the impact of these factors differs for different aspects of biodiversity. For example, bird species richness typically decreased with Noisy Miners whilst the vulnerable Superb Parrot was more likely to occur in the presence of Noisy Miners. Woody cover within 500m or 3km appeared to have little association to the number of reptile species detected.

Our sensitivity analysis suggests that developing similar joint-species models in similar ecosystems will require bird surveys across at least 230km North-South, and with more than one farm surveyed per 2500km2.

A key product of this project is the web app 'Bird Checker: A Bird Occupancy Estimator', allowing for scenario comparisons and biodiversity estimates. It is of great interest to Local Land Service staff for use in engagement and potentially reporting.

Benefits to industry

This project provides critical information for populating sustainability frameworks such as the Beef Sustainability Framework and the Sheep Sustainability Framework. For example, the approaches demonstrated in this project will be essential for demonstrating improvements in environmental outcomes as a function of management interventions such as establishing plantings on farms (see for example (Lindenmayer et al., 2012)).

Future research and recommendations

We recommend that stakeholders take advantage of the unique web app 'Bird Checker: a Bird Occupancy Estimator' to gain better understanding of bird biodiversity in their local area. We also recommend research into implementing cost-effective and ecologically effective monitoring that ensures ongoing provision of high-quality monitoring data to populate sustainability frameworks.

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1. Background

The maintenance of biodiversity is a key component of ecologically sustainable agricultural production, both in grazing and cropping industries. How to achieve this remains a major challenge, particularly given the extent of native biodiversity loss that has occurred in agricultural landscapes globally (Maxwell et al., 2016), including in Australia (Williams and Price, 2011). The conservation of biodiversity is now recognized as a key component of initiatives to promote industry sustainability, such as in beef production (the Beef Sustainability Framework [https://www.sustainableaustralianbeef.com.au/]) and sheep production (the Sheep Sustainability Framework [https://www.sheepsustainabilityframework.com.au/]). However, there are many challenges in developing biodiversity indicators for measuring sustainability in agricultural management and production. For example, which metrics are appropriate – given that traditional ones such as species richness can have limitations (e.g. see (Dornelas et al., 2014; Lindenmayer et al., 2015a, 2015b)). In addition, which groups are appropriate for selection as indicators given that different assemblages can respond to management interventions in different ways (e.g. birds versus reptiles (Lindenmayer et al., 2002)) and different species in the same group can respond to the same intervention (e.g. planting) in different ways (Lindenmayer et al., 2014).

In this study, we used a unique set of large-scale, long-term datasets gathered across inland agricultural Australia to explore the efficacy of biodiversity indicators on farms. These indicators will, in turn, have value not only for facilitating the establishment of other kinds of biodiversity monitoring on farms, but also helping embed monitoring within emerging agri-environment schemes such as the Australian Government's Stewardship and Certification programs through which farmers will receive payments for better protecting native biodiversity (see http://www.agsteward.com.au). The datasets we use in the study have been assembled from the past 20 years of detailed biodiversity monitoring on farms from Victoria, NSW and south-eastern Queensland (see (Lindenmayer et al., 2018c, 2018d) (sustainablefarms.org.au). We combined these datasets with information on land cover change and climate conditions during the same sample periods. At the same time, we worked to develop new and highly accessible web-based applications and related e-tools for helping Natural Resource Management personnel to engage with landholders on ways to promote farm-based biodiversity conservation.

2. Objectives

The full list of project objectives, is as follows:

Develop a range of indicators including, but not limited to:

1. total woody vegetation cover
2. amount of planting on a farm
3. amount of natural regeneration on a farm
4. change in the amount of total woody vegetation cover over time
5. number of bird species
6. number of reptile species
7. bird species functional richness
8. richness of bird species of conservation concern
9. biometric score for field sites (a measure of vegetation condition)

10. amount of riparian vegetation as a function of the size and length of creeks/dam/wetlands on a farm

2.1: Ensure all required datasets are in place; all necessary software and skillsets ready within the team to analyse and interpret those datasets; lock in time commitments from team members to ensure timely delivery.

2.2: Conduct exploratory data analysis to flag strengths and weaknesses of available datasets in relation to project goals. Report on proposed project breakdown including conceptual model, study design, statistical methods and required data.

2.3: Run a workshop to agree on proposed project details including conceptual model, statistical modelling and required outcomes. Revise as necessary based on input from lab heads & funding bodies.

3.1: Build time series models combining data from long-term ecological monitoring and LANDSAT; quantify the predictive power of different remotely-sensed variables and their consistency over time; investigate role of lagged responses to environmental change.

3.2: Build models of biodiversity responses to structural complexity from LIDAR; compare predictive power of said model to one based solely on satellite imagery.

3.3: Generate a cost-effectiveness analysis showing the effectiveness of different methods (field studies, LIDAR, satellite imagery) and their combinations as a function of cost.

3.4 Evaluate predictive power of time series models using data from later years & different regions.

4.1: Quantitatively evaluate the potential for expansion of the approach to other ecosystems, elucidating potential benefits, risks, and further research needs.

4.2: Run workshops with landholders on research outcomes

4.3: Run workshops with funders on research outcomes

5.1: Submit paper(s) on analytical approach and modelling results for peer review.

5.2: Launch web portal for interactive visualization of research outcomes

5.3: Submit final report on recommended indicators to funding body

Status of each objective

All objectives except 3.2 and 3.3 are complete. Objectives 3.2 and 3.3 focused on the use of LiDAR data to assist in building models of the occurrence of biodiversity on farms. It was quickly discovered that other information from satellite coverage could provide key data on woody vegetation cover. For example, the woody cover maps we used in this project were created by a model that was developed with the help of airborne LiDAR data (Liao et al., 2020). The additional effort in collating, processing and interpreting LiDAR data was not warranted for the work we have reported here. However, we intend to use LiDAR data in future work, particularly research and monitoring associated with the condition of farm dams.

3. Methodology

3.1 Study area and field sites

Our study encompassed an extensive part of the wheat-sheep belt from the Victoria-NSW border to south-east Queensland. Much of our study region was formerly dominated by temperate woodland (Hobbs and Yates, 2000), but has been cleared of an estimated 85-96% of its original cover to facilitate livestock grazing and cereal cropping. It is one of the most heavily modified agricultural regions worldwide (Fischer et al., 2009) and is characterised by a range of land degradation problems including secondary salinity, soil erosion, weed invasion and extensive biodiversity loss (Lindenmayer et al., 2016b). In an effort to tackle these problems, major restoration programs have been undertaken (Lindenmayer et al., 2016a). There also has been substantial natural regeneration of temperate woodlands in parts of the study region (e.g. (Lindenmayer et al., 2018a)), often as a result of changes in livestock grazing pressure (Fischer et al., 2009).

Our investigation used 462 old growth or regrowth Box Gum Grassy Woodlands field sites and 65 planting sites, on 232 farms. Each site was 2 ha in size and comprised a 200 m long and 100 m wide transect with permanent steel post markers established at the 0, 50, 100, 150 and 200m points along the transect. The size of our sites was broadly matched to the typical size of woodland patches that characterize the heavily modified agricultural areas of south-eastern Australia (Gibbons and Boak, 2002).

Regrowth woodland was existing living trees recovering after disturbance by fire, clearing or both, or regeneration of trees from seeds germinating after being dropped by overstory trees. Areas of regrowth were generally greater than 7 years old, with many 10 – 20 years old. Remnant (old-growth woodland) stands were typically dominated by scattered large trees that were 200 or more years old.

Planted patches were areas of vegetation that had been established either through the use of tubestock or (less frequently) direct seeding (Lindenmayer et al., 2018b). Such areas were typically 3-7 years or older at the time of the commencement of our studies (2002), with sites dominant by local native plants, especially overstorey trees, although some areas also have understorey species that have been planted (Lindenmayer et al., 2018a). Fences initially were constructed to regulate (or totally exclude) domestic livestock grazing in all planted areas. However, over time, the fence lines around some plantings have fallen into disrepair, allowing access to livestock (Lindenmayer et al., 2018b).

3.2 Fauna surveys

3.2.1 Bird surveys

Our standardized protocol entailed 5-minute point interval counts (sensu (Pyke and Recher, 1983)) at the 0 m, 100 m and 200 m points along the 200 m transect at each site. Time of day and approximate indications of windiness, cloudiness, and temperature were recorded before starting each point-interval count. For each point-interval count, an observer recorded all bird species seen or heard within the site and the detection of each individual bird was assigned to one of several distance categories from the centre of a plot; 0–25 m, 25–50 m and > 50 m. We used these data to restrict our analyses to include only those detections made within 50 m of the centre of a field plot point. We did not record birds outside of our 2 ha sites. In each year of our surveys, each site was surveyed twice in spring by two different, highly experienced ornithologists, on different days to account for observer heterogeneity and day effects (Cunningham et al., 1999; Field et al., 2002). We did not treat individual point counts as independent samples, but rather pooled counts across the 0 m, 100 m and 200 m plots within each site to give the presence/absence of each species at that site on any given survey day. We did not undertake surveys during poor weather (rain, high wind, fog or heavy cloud cover). We observed these protocols to reduce the effects of observer heterogeneity and day effects (Lindenmayer et al., 2009).

For this investigation, we removed waterbirds (orders Caprimulgiformes, Accipitriformes, Strigiformes, Podicepiformes, Gruiformes, Pelecaniformes and Anseriformes) and species with large home ranges (order Falconiformes).

3.2.2 Reptile surveys

Reptile survey were completed on all our long-term field sites encompassing plantings, regrowth woodlands, and old growth woodlands. Field surveys included active searches as well as searching around key artificial substrates (roof tiles, wooden sleepers, and corrugated iron) (see (Michael et al., 2012)). The set of search methods (and kinds of substrates) was designed to maximize the detection of different species of reptiles that inhabit temperate woodland ecosystems (Michael and Lindenmayer, 2010).

3.3 Predictors of avian biodiversity

Here we describe the methods used to derive or obtain numerical quantities for a variety of environmental factors that we considered possibly indicative of avian biodiversity. We first describe remotely-sensed quantities. These have a natural spatial scale based on the summary method, which we summarise as patch, landscape or regional scale. We then describe additional patch and regional scale factors; there were no additional landscape-scale factors.

3.3.1 Remotely-sensed quantities

We used the following remote-sensing products:

1. Fcrop: Fraction of land used within the region for cropping (cropping, perennial horticulture, seasonal horitculture; both irrigated and not) from the CLUM national land use mapping.
2. Fmin: Fraction of conservation and natural environments (ALUM class 1 and subclasses)
3. Fnatpos: Fraction of grazing on native pasture (ALUM class 3.3 and subclasses)
4. Fwat: Fraction of land with the region covered with water (ALUM class 6 and subclasses). Can be used to get indication of distance to water.
5. maxBS: annual maximum bi-monthly fraction of bare soil
6. maxPV: annual maximum bi-monthly fraction of photosynthetic vegetation
7. medPV: annual median bi-monthly fraction of photosynthetic vegetation
8. minPV: annual median bi-monthly fraction of photosynthetic vegetation
9. medNPV: annual median bi-monthly fraction of non-photosynthetic vegetation
10. medwater: annual median bi-monthly fraction covered by water (particularly useful for wetlands)
11. WCF: annual woody vegetation cover
12. TWI: topographic wetness index

Many of these products (5 – 11) were obtained from Geoscience Australia's Digital Earth Australia (DEA) [www.ga.gov.au/dea], and were derived from time series of landsat imagery. The Woody

Vegetation Cover (WCF) was by Liao et al (2020) and based on Landsat reflectance data, with the computational parameters selected using airborne LiDAR and other data. An online data explorer is available via http://anuwald.science/tree . The medwater product was obtained from the DEA Water Observations from Space (WOfS) product (Mueller et al., 2016). The bare soil (BS), photosynthetic vegetation (PV) and non-photosynthetic vegetation (NPV) products were from the DEA Fractional Cover (FC) product (Guerschman et al., 2015). The bi-monthly summaries computed were medians over two months of data, of each good pixel. Monthly summaries were avoided due to significant data gaps. The FC and WofS data sets were made internally consistent by allowing for the fractional cover of water (misclassified as BS in the FC product) and ensuring the total of all fractions amounts to 100%.

TWI was obtained from the Australian Soil and Landscape Grid (Gallant and Austin, 2012; O'Brien and Searle, 2020), and the remaining products were from catchment-scale and national-scale land use maps [https://www.agriculture.gov.au/abares/aclump/land-use/land-use-mapping].

For each site post and each product, we computed the average of circled centred on the post, with radii of 100m, 200m, 500m, 1km, 3km, 5km and 10km. The pixel value of the product at the post was considered the 25m radius. The value for the site (all three posts) was the average of the value for each post.

An additional remote-sensing product, weekly gross primary productivity (GPP), was based on MODIS data (Yebra et al., 2015), which has a 500m spatial resolution. GPP is the amount of carbon transferred from the atmosphere into plants for photosynthesis, ignoring the amount of carbon that exits the plants. We used the average of GPP for the pixel containing the centre of each site between January 2000 to December 2019, as well as the difference to this average of the GPP on the days the bird surveys were conducted on.

Values for measures that were generated in circles of radius 200m or smaller (including the 25m radius) were considered to be at the patch scale. Values given by circles for radius larger than 200m and smaller than 5km were considered to be at the landscape scale. Values given by circles of radius 5km or larger were considered regional scale. Due to the spatial resolution of the GPP product, GPP values were considered to be landscape-scale. Given that TWI reflects the location of the site relative to the catchment's topography, TWI was considered to be at the landscape scale.

3.3.2 Additional patch scale quantities

The majority of our additional patch-scale variables contained information on vegetation structure, which we quantified during vegetation surveys at each patch. In remnant patches we measured understorey (<2m in height), midstorey (plants 2-10m high) and overstorey (>10m high) cover by recording the percentage cover in each height class every 5 metres along 100m transect, and taking the average. We used the same approach for quantifying low cover (cryptograms, exotic sub-shrubs, native forbs/herbs/other, native perennial grass, native sub-shrub, organic litter, bare ground, exotic perennial grass and rock), except that we recorded presence of a range of elements every metre, rather than every 5 metres. Another survey methodology was used for assessing vegetation in planted patches.

From these measurements we created three summary quantities. The summed percentage cover of native sub-shrubs, cryptograms, native forbs/herbs/other, organic litter, exotic broadleafs/forbs/other, and coarse woody debris, we termed *low cover*. The summed percentage cover of exotic perennial and annual grasses, exotic sub-shrubs, and exotic broadleafs/forbs/other, which we termed *exotic cover*. The final summary quantity was a biometric structural condition score.

We first defined reference values from the median of sites that expert ecologists described as examples of 'good' condition (11 sites). We then computed a structural condition score according to the 'unweighted structure condition score' used by the NSW Department of Planning, Industry and Environment (DPIE, 2020, p. 96).

We investigated three additional patch-scale factors. 'IsPlanting' was TRUE when the patch was planted, and FALSE otherwise. Planting age, when the patch was a planting. Noisy Miner detection, 'NMdetected' was encoded as TRUE if the Noisy Miner (*Manorina melanocephala*) was detected in any bird survey that season. Noisy Miners are widely known to influence the range of bird species that can exist at a location (Mac Nally et al., 2012), and so we follow (Westgate et al., 2021) in treating Noisy Miner occupancy as a predictor, rather than a response variable as for other bird species.

3.3.3 Additional regional scale quantities

At the regional scale, we also obtained the longitude and latitude of each site centre, and 19 historical bioclimatic variables from worldclim v1.4 (Hijmans et al., 2005), which were averages over the years 1960 – 1990. For each year we also computed similar summaries of the temperatures and rainfall of 12 months from the start of the last spring (i.e. from the start of August the previous year, to the start of August in the current year. Similar summaries for the last 24 months and 36 months were also investigated. These summaries were computed from monthly summaries (Xu et al., 2018) using the dismo software package (Hijmans et al., 2020) for R (R Core Team, 2020).

3.4 Bird occupancy models

3.4.1 Modelling framework

We modelled bird species occurrence using Bayesian joint species distribution models (JSDMs) as described by Tobler et al (2019). Specifically, each model included environmental predictors for each species, latent variables for residual interspecies correlation (Hui et al., 2015; Warton et al., 2015), and accounted for imperfect detection (MacKenzie et al., 2002). We modelled detection probabilities as a logistic regression, and occupancy probabilities using a probit regression. We assumed that species occupancy was independent between years and locations, conditional on environmental predictors. The model exploited commonalities between species by assuming that species-specific loadings of environmental predictors were drawn from a common distribution.

3.4.2 Model selection

Of the field site locations, 10% were reserved as *holdout* locations. Data for these holdout locations were used for assessing model quality and were not used to fit models. The remaining 90% of locations we termed *in sample*. To avoid overfitting our models, we removed species detected less than 100 times.

We began by developing a set of models that included terms from only a single spatial scale. That is, we included one set of models that included variables only from the patch scale; a separate set of models that used variables only from the landscape scale; and a third set that included variables only from the regional scale. Each set contained combinations of variables chosen to represent plausible competing hypotheses about the processes acting at that scale. We avoided collinearity among our regional-scale predictors by progressively removing predictors with highest variance inflation factors until all predictors had a variance inflation factor of 10 or lower (Zuur et al., 2010). In all cases, we fit this first round of models without latent variables or detection predictors, so as to reduce fitting time.

Although we chose each model set to be as small as practical, we then expanded each set of models by using a method of stepwise addition based on Dunn-Smyth occupancy residuals (Warton et al., 2017). Specifically, when we observed systematic variation in Dunn-Smyth residuals in relation to a term already included in the model, we took that as evidence that the effect of that term should be modelled as quadratic or logarithmic term rather than a linear term. Further, if we found a systematic pattern when plotting Dunn-Smyth residuals against a term that was not yet included in the model, we used this as evidence to support including that term in the model. We summarised model quality using the difference in a leave-one-out information criteria (LOOIC) between the model in question, and a 'null' model that contained only intercepts; we named this measure '$LOOIC_{null}$'. The LOOIC was computed by Pareto smoothed importance sampling (Vehtari et al., 2017). It is a more robust version of the Watanabe-Akaike Information Criterion (Vehtari et al., 2017; Watanabe, 2010) and is a natural method for assessing the quality of Bayesian models (Gelman et al., 2014). We stopped adding terms to our models when the $LOOIC_{null}$ was not substantially improved. This process generated a set of fitted models for each group of predictors, where each group contained models with predictors from a single spatial scale.

We constructed our final model by identifying and including terms from each scale that were associated with marked improvements in fit, again as measured using $LOOIC_{null}$. To this final model, we successively added survey year, detection covariates, and latent variables. Throughout the modelling exercise above, models with non-convergent MCMC were excluded from model comparisons. Convergence for the models without latent variables was assessed using multichain Gelman-Rubin statistics (Brooks and Gelman, 1998; Gelman and Rubin, 1992) and effective sample size. The models with latent variables used single-chain MCMC due to an identifiability difficulty with multiple chains (Hui, 2020), and convergence of these models were assessed through Geweke statistics (Geweke, 1991) and effective sample size.

We completed two modelling exercises using the above model selection approach. The first involved only remnant patches and due to time of availability, fewer remote-sensing predictors. The second involved both remnant and planting patches and most remote-sensing predictors, but did not use vegetation structure due to the difference in vegetation structure measurement methods used in plantings. For this second modelling exercise, a forward-stepwise approach was adopted to choose between the remote-sensing products at each scale.

3.5 Bird species richness and functional richness

The expected species richness of birds in occupancy for a site was estimated by summing of estimated occupancy for each posterior draw of the above JSDMs. The standard deviation of species richness for a site was similarly estimated, leading to approximate 95% credible intervals given by two times the standard deviation.

Functional richness, and many other indices of functional diversity, were computed by simulating occupancy and applying the dbFD function from the R package FD (Laliberté and Legendre, 2010). This is the same method as (Ikin et al., 2019) using similar traits.

3.6 Patch dependence model

To make estimates for multiple patches, we assumed that occupancy probability for each species was the maximum of all available patches and ignored dependence between species. These assumptions were consistent with bird species travelling easily between patches, and allowed for computationally efficient estimates of occupancy for multiple patches. However, this model of patch dependence does not account for less dependence in occupancy with greater distance. So, for example, the model cannot be used for making estimates for patches separated by large distances.

3.7 Quantification of predictor power

The predictive power of environmental factors was quantified through the $\mathrm{LOOIC}_{\mathrm{null}}$ of JSDMs using these factors, and through the magnitude of species' loading in final JSDMs.

3.8 Number of reptile species

Poisson, negative-binomial and zero-inflated Poisson/negative-binomial models were fitted to the number of reptile species using the brms package (Bürkner, 2018) in R. Default priors were used. The same sites were used as the remnants and planting bird occupancy model. That is reptile surveys from all plantings and Box Gum Grassy Woodlands were used.

Predictors were the same as the predictors of bird occupancy in the final remnant and planting JSDM. Noisy Miners were considered to be in occupancy if they were detected by the any bird survey in the same calendar year. Noisy Miner occupancy was included as a surrogate for vegetation structure, which was otherwise measured differently across the sites.

MCMC convergence was checked for each of the models. The best model was selected using direct comparison of LOOIC (Vehtari et al., 2017). This best model was further analysed using simulation-based residuals (Hartig, 2021), and improvements to the model were made.

3.9 Bird species of conservation concern

We used the same predictors as in the final remnant and planting JSDM to predict the number of bird species of conservation concern detected by two bird surveys at the same site. Detection difficulty was considered to be equal across all surveys. The brms package (Bürkner, 2018) in R was used to compare Poisson, negative binomial and zero-inflated models.

MCMC convergence was checked for each of the models. The best model was selected using direct comparison of LOOIC. This best model was further analysed using simulation-based residuals (Hartig, 2021).

3.10 Sensitivity analysis (how much data are needed)

The spring bird surveys used to build our model have been conducted since 2002, on farms from Victoria to the NSW-QLD border in some years, and usually at multiple sites within each farm. The surveys were typically repeated two or more times each season. We have experimented with fitting our best remnant-only model, without latent variables, on subsets of the data with fewer years, smaller geographic spread, and lower spatial densities of farms.

We did not quantitatively assess the importance of repeated surveys within a season nor multiple sites within a farm. Repeated surveys within a season are unavoidable, as they are required for removing observational effects such as the time of day of bird surveys. Multiple sites within a farm are also unavoidable as they are essential to estimating and assessing biodiversity across nearby patches.

The quality of the fitted model was assessed using the root-mean-square-error (RMSE) of species richness of the 10% of bird surveys excluded from the model fitting.

3.11 Workshops

In late 2020 a web app presenting estimates from our best model was shown to funders, landholders, and Local Land Service providers. Questions included additions they wanted for the web app, and how they wanted to use it.

4. Results

4.1 Bird Occupancy Models

4.1.1 Remnant Patches Only Models

For this model selection process, we considered the following environmental factors:

- Patch scale: Noisy Miners, low cover, midstorey, overstorey and exotic cover.
- Landscape scale: TWI at the site location, GPP, difference to GPP, WCF within 500m.
- Regional scale: latitude, longitude and five worldclim bioclimatic variable associated with arid limits, cold limits, average climate and seasonal variability: minimum temperature, precipitation in the coldest quarter, maximum temperature, precipitation in the warmest quarter, annual temperature, annual precipitation, annual temperature range and precipitation seasonality. Note that the precipitation seasonality was the coefficient of variation (ratio of standard deviation to mean) of precipitation.

In total, we fitted over 40 different models. Most models passed diagnostic tests using occupancy and detection residuals, and model comparisons were supported by tests on the holdout data.

4.1.1.1 Models using patch scale predictors

We first fitted seven models with one or two patch-scale predictors, along with five models that included interactions interaction between the Noisy Miner and midstorey cover, either alone or in combination with other variables. This larger model had similar $LOOIC_{null}$ to a model that included only the Noisy Miner interacting with midstorey cover, according to the adhoc confidence intervals for $LOOIC_{null}$ (Fig. 1, top). Occupancy residuals of this larger model suggested a need to add additional variables, including cover of native sub-shrubs, exotic short/ground cover, and higher order terms. However, models with these additional terms achieved relatively similar $LOOIC_{null}$ (Fig. 1, top).

4.1.1.2 Models using landscape scale predictors

The $LOOIC_{null}$ of models using landscape scale predictors (Fig. 1, centre) suggested that woody vegetation cover (WCF) within 500m was a much better predictor of bird occupancy than mean GPP, difference from mean GPP, or TWI. Occupancy residuals of the models suggested using the logarithm of woody vegetation cover, rather than the untransformed variable; we then found further (albeit small) improvements in $LOOIC_{null}$ by combining log WCF with TWI, mean GPP and difference from mean GPP.

4.1.1.3 Models using regional scale predictors

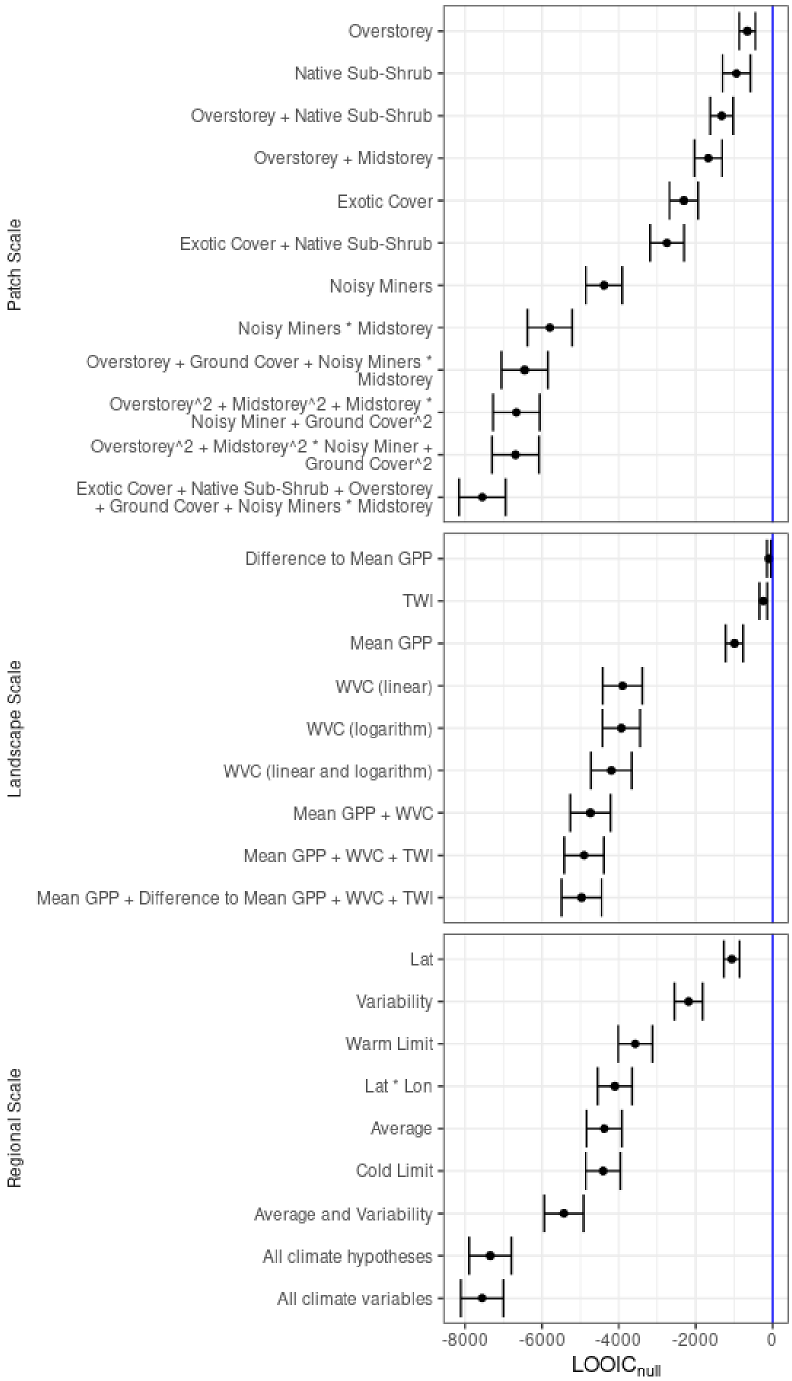
For models using regional-scale predictors, we considered seven hypotheses:

1. occupancy limited by minimum temperature and precipitation in the coldest month (cold limit);
2. occupancy limited by maximum temperature and precipitation in the warmest month (aridity limit);
3. occupancy driven by mean temperature and annual precipitation (average hypothesis);
4. occupancy driven by annual temperature range and precipitation coefficient of variation (stability hypothesis);
5. occupancy linearly related to latitude only; and
6. occupancy linearly related to latitude, longitude and the interaction between latitude and longitude.

We also considered a model that combined all hypotheses. After removal of variables to reduce collinearity, the best fitting model contained the following predictors: annual precipitation, maximum temperature of the warmest month, minimum temperature of the coldest month, precipitation seasonality and latitude. Finally, we also fitted a model that used all climate variables remaining after removal of variables to reduce collinearity.

The poorest quality models were the latitude-only and stability hypothesis model (Fig. 1, bottom). The latitude and longitude model, the average hypothesis model, and the cold limit hypothesis model all performed similarly well. The two best models combined all hypotheses or all climate variables. The confidence intervals for $LOOIC_{null}$ indicated that the quality of these two best models was very similar. Regional-scale models performed similarly well to our models using patch-scale predictors, and performed markedly better than the models that used landscape-scale data only (Fig. 1).

Figure 1: The LOOICnull of models with adhoc 95% confidence intervals (Vehtari et al., 2017). Top: models with patch-scale predictors. Centre: models with landscape-scale predictors. Bottom: models with regional-scale predictors.



4.1.1.4 A model using predictors from all spatial scales

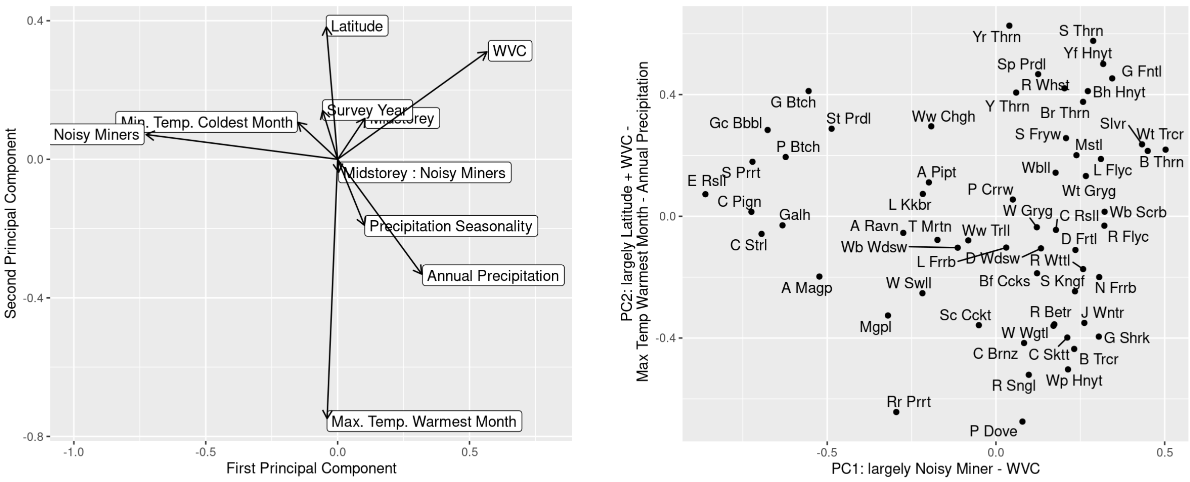
Our final modelling stage was to fit a model that combined the best predictors from each spatial scale. This model included survey year, presence of the Noisy Miner, midstorey cover, and log woody vegetation cover as predictors. It also included five regional-scale variables: annual precipitation, maximum temperature of the warmest month, minimum temperature of the coldest month, precipitation seasonality and latitude. We included survey time and wind speed as predictors of detectability, as our two other detection predictors (temperature and cloud cover) had almost no effect on detectability. We also included two latent variables (LVs), as this was the highest number of LVs that we were able to fit without MCMC chain divergence, while a model with only one LV had poorer fit (as measured by $LOOIC_{null}$). Our final model passed several diagnostic tests, although there was some indication of overfitting.

The only predictor that became redundant in the final model was the interaction between midstorey vegetation cover and presence of the Noisy Miner; the loadings for this predictor were credibly zero (95% HPDI) for all species but the Black-Faced Cuckoo-Shrike. Relative to simpler models, the final model showed fewer species with strong responses to midstorey vegetation cover and minimum temperature of the coldest month, suggesting that there was some redundancy between these two predictors for some species. Similarly, four species (Buff-Rumped Thornbill, Crimson Rosella, Weebill, and White-throated Gerygone) showed marked changes in loadings for woody vegetation cover and the presence of the Noisy Miner, suggesting further redundancy between these variables. Indeed, median loadings for most variables were lower in the final model than in earlier models that contained fewer effects.

Across all 60 species, on average, the predictors with biggest median loadings were for the presence of the Noisy Miner, woody vegetation cover and maximum temperature of the warmest month. The median loadings of these predictors also had the largest range between species. Conversely, on average, the smallest effect sizes were seen for midstorey cover, minimum temperature of the coldest month and survey year, with most species having a credibly zero loading for minimum temperature of the coldest month.

To better visualise patterns among species associations with the full set of predictor variables in our final model, we used principal component analysis (PCA) of their predictor loadings. We found that species were most distinguishable by their response to the presence of the Noisy Miner and the maximum temperature of the warmest month on the vertical axis (Fig. 2, left). Species mapped against the first and second principal components (Fig. 2, right) show a set of species that can persist given presence of the Noisy Miners on the left, while species in the bottom-right are associated with hot summer climates. Species at the top-right of (Fig. 2, right) responded positively to increasing woody vegetation cover (a landscape-scale process) and poorly to both the Noisy Miners (patch-scale process) and high temperatures (regional-scale process). Given known expansion of the Noisy Miner and expected changes in future climate, these species may be at risk of declines under future conditions. They include including the Yellow-faced Honeyeater, Striated Thornbill, Grey Fantail, and Rufous Whistler.

Figure 2: a) The first two principal components from the PCA. b) Ordination of species using the first two principal components from the PCA.



4.1.2 Remnant and Planting Patches Model

The remnant and planting modelling process included the following remotely-sensed variables at all available radii: WCF, maxPV, minPV, medPV, maxBS, medNPV. The remote-sensing product medwater (median fraction covered by water) was used only at the regional scale; at smaller scales medwater was zero for nearly all sites. At the patch scale Noisy Miner detection, planting and planting age, and interactions between planting and Noisy Miner, were also investigated. Vegetation structure was not used as it was not available for both remnant and planting patches. At the regional scale, the same long-term climate variables as the remnant-only modelling were included, along with latitude and longitude. The same climatic summaries for the last 12 months, 24 months, and 36 months were also included.

At the patch scale, with only remote-sensing data, the best model used all remote-sensing data (excluding medNPV at 100m due to collinearity). However, when combined with IsPlanting and NMdetected, models that contained only some of the remotely-sensed quantities and at 25m radius only, performed nearly as well as models with many remotely-sensed quantities. IsPlanting and NMdetected were consistently valuable in these models, but PlantingAge and interactions between IsPlanting, NMdetected did not give substantial $\mathrm{LOOIC}_{\mathrm{null}}$ improvements.

For models using landscape-scale predictors, which were all remotely-sensed, a forward stepwise approach was taken. The best model used (in step order) WCF, maxPV, and maxBS at all landscape-scale radii. No further steps were taken as this model had similar $\mathrm{LOOIC}_{\mathrm{null}}$ to a model that used all the landscape-scale predictors after collinearity reduction by removing predictors with variance inflation factors greater than 10.

For models using regional-scale remote-sensing data, a forward stepwise approach also was taken. Similar to the landscape-scale, the best model used WCF, maxPV and maxBS, and achieved a similar $\mathrm{LOOIC}_{\mathrm{null}}$ to a model that used a set of the region-scale remote-sensing variables obtained by removing predictors with variance inflation factors greater than 10. An indicator of non-zero medwater (median surface water) improved this model, but not significantly according to the $\mathrm{LOOIC}_{\mathrm{null}}$ criterion with approximate error bars.

Similar to the remnants-only model, the combination of climate variables, after removal according to variance-inflation factors, performed much better than smaller models with climate variables. The summaries of the last 12 months of weather improved the model further, but not significantly according to the $\mathrm{LOOIC}_{\mathrm{null}}$ criterion with error bars. Addition of the last 24 and 36 months of weather did improve the climate model significantly, but the gains $\mathrm{LOOIC}_{\mathrm{null}}$ were mild relative to the number of additional predictors.

Models combining all scales started with a combination of the best predictors from each scale: WCF, maxPV, and maxBS for radii 500m and greater, plus the collinearity-reduced long-term climate predictors, NMdetected and IsPlanting. WCF and maxPV at 25m were used for patch-scale remotely-sensed data to be consistent with the other scales. The last 12 months of weather data were included for investigating effects of recent weather on bird occupancy and SurveyYear was incorporated for investigating temporal dependence. This initial model did not converge due to collinearity, particularly between the remotely-sensed predictors. Experiments removing radii and remote-sensing products, guided partly by variance-inflation factors, led to a model with the collinearity-reduced long-term climate predictors, the last 12 months of weather summaries, NMdetected, IsPlanting, and WCF for radii 500m and 3km. All radii for maxPV and maxBS were removed.

This best model combining multiple scales of predictors was then fitted with latent variables. The best number of latent variables was two.

4.2 Bird species richness and functional richness

The final JSDM for both planting and remnants (described above), estimated bird species richness with an average residual standard deviation of approximately 3.75 species. This is equivalent to a standard error of 7.5 species. These species richness estimates can be accessed using the web app at http://sustainablefarms.org.au/tools/bird-checker

We successful in estimating a variety of functional biodiversity indicators using the fitted JSDMs. However, the computational costs are high. As a consequence, function richness was not included in the web app.

4.3 Quantification of Predictive Power

The results of the modelling processes for bird occupancy suggest that the following patch and landscape factors have the strongest predictive power for bird biodiversity:

- Noisy Miners
- whether the patch is a planting
- woody cover (WCF) within 500m
- woody cover (WCF) within 3km
- Exotic cover may also have a strong influence.

We did not directly compare WCF within 500m and WCF within 3km to other radii, so it possible that other radii might work equally as well.

The cost to produce woody cover estimates is negligible for any radii as the woody cover product is freely available online [http://anuwald.science/tree]. Noisy miners are easy for farmers and other citizens to detect with no training. Differentiating a planting from a remnant is also easy for untrained parties (many farmers planted the plantings, plantings can also be detected through diversity of tree size and other features). Compared to the above factors, exotic cover may be very costly to measure, possibly requiring trained ecologists to undertake vegetation surveys.

It is possible to quantify the predictive power of many more environmental factors individually by computing the $\mathrm{LOOIC}_{\mathrm{null}}$ of a modal that includes only the one factor, although such values do not account for climate and weather. A selection of these are in Table 1.

Table 1. A selection of $\mathrm{LOOIC}_{\mathrm{null}}$, expressed as difference in expected log predictive density, which are a factor -2 different from the $\mathrm{LOOIC}_{\mathrm{null}}$. Values are approximate in some cases. Higher values suggest higher predictive power.

Factor	Only Remnant Sites	Planting + Remnant Sites
Overstorey	328	
NMdetected	2192	2000
Native subshrub	470	
Exotic Cover	1155	
TWI	121	
Mean GPP	497	
Diff to Mean GPP	50	
WCF at 500m	1967	
IsPlanting		1000
All WCF at patch-scale		1200
WCF at 25m		700
All WCF at landscape-scale		2100
All WCF at regional-scale		1400
medPV at patch-scales		500
medNPV at patch-scales		200
maxPV at patch-scales		470

4.4 Number of reptile species

According to the LOOIC comparison, the negative binomial model (without zero inflation) performed better than the Poisson model and the zero-inflated negative binomial model. Tests of simulation-based residuals of the negative binomial model suggested that number of outliers, the standard deviation, and the number of zeros were consistent with model assumptions.

However, residuals suggested that season and search methods should be accounted for in the model. There was a low number of summer surveys and these were removed. Rare combinations of search methods were also removed. A new negative binomial model with all the original predictors, search methods, and season was then fitted. Interactions between season and the weather were included. According to LOOIC comparison, this model was better than the previous models.

The predictors with the highest influence on number of reptile species detected, according to this last model, were search methods, season, planting (vs remnant), and weather. Noisy miners and long term average annual temperature maximums were also influential. Woody vegetation cover had relatively little influence.

Tests of simulation-based residuals of the negative binomial model with season and search methods suggested that the observed number of outliers, standard deviation, and number of zeros were consistent with model assumptions. Visual inspection of residuals plotted against predictor values suggests that all predictors in the model were well accounted for, including season and search methods.

4.5 Number of bird species of conservation concern

According to the LOOIC comparison, the best model was the Poisson model. Tests of simulation-based residuals suggested that the observed number of outliers, standard deviation, and number of zeros were consistent with model assumptions. Visual inspection of residuals plotted against predictor values suggests that all predictors in the model were well accounted for.

Noisy Miner occupancy, whether the patch was a planting, woody cover, and aspects of long-term climate were all important to the number of bird species of conservation concern. Remnants, hot summers, wet winters, and woody vegetation cover within 500m were all positively related to the number of species of conservation concern. Woody vegetation within 3 kilometres and Noisy Miners were negatively related to the number of species of conservation concern.

4.6 Sensitivity analysis

Large geographic spread was found to be important for model fitting. Model fitting failed whenever subsets of the data smaller than 1/4 (approximately 230km) of the north-south range were used. Model fitting also succeeded only for subsets with at least one farm per 2500km^2.

The subsets that led to successful model fitting all achieved RMSE values between 3.96 (full training data subset) to 4.94 (subset with 1/4 of original north-south range). Reducing the input data to the four years with the largest geographic spread raised RMSE of species richness from 3.96 to 4.17. Further reduction to only two of these years led to models with a slightly higher average RMSE of 4.41.

4.7 Workshops

The workshops we conducted included the following key stakeholders.

- Five Local Land Services
- Biodiversity Conservation Trust
- Two Catchment Management Authorities
- Landcare groups
- Birdlife Australia
- The Future Drought Fund
- Meat and Livestock Australia

Overall, the feedback was very positive. The web app may become very useful for farmer engagement and for assessing environmental condition. These consultations also identified work that we have since completed: we included planted woody vegetation patches in our model, and have a method for estimating bird occupancy across multiple vegetation patches.

4.8 Web portal

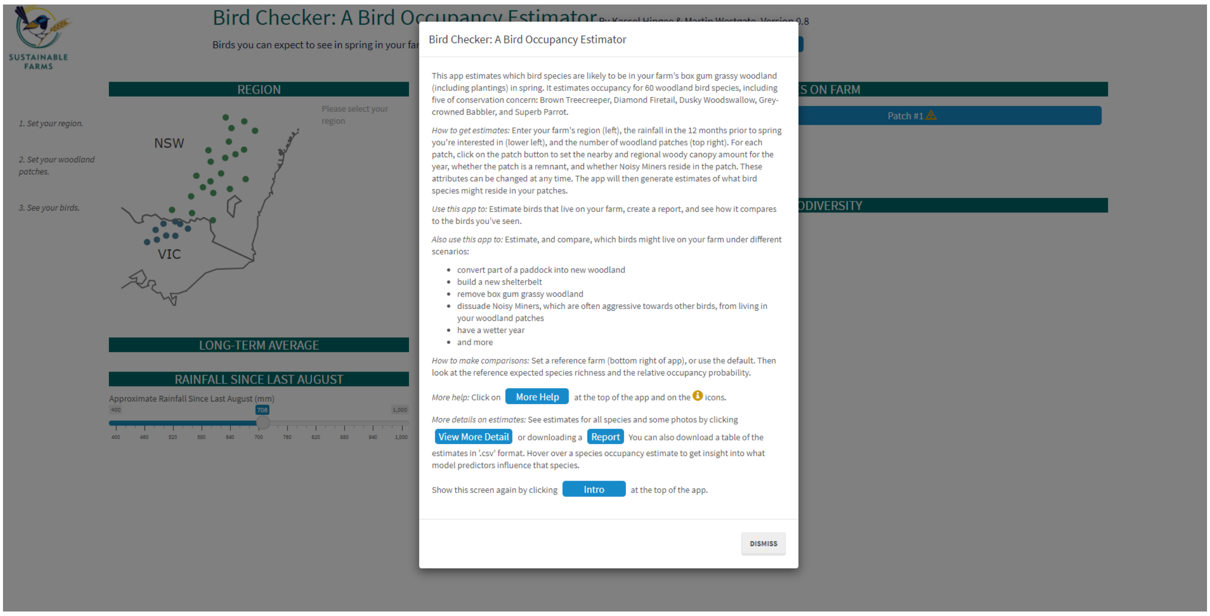
A web app named 'Bird Checker: A Bird Occupancy Estimator' presenting the final remnant and planting occupancy model is available publicly at http://sustainablefarms.org.au/tools/bird-checker . See Fig. 3 for screenshots of the web app.

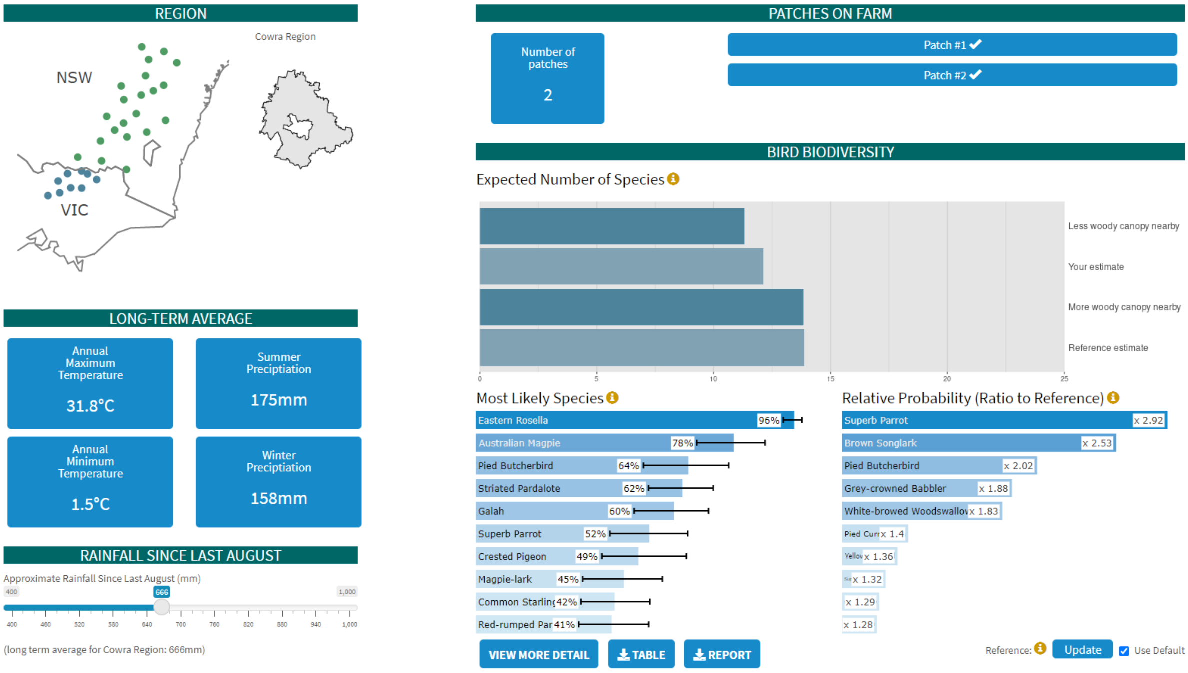
It was very well received at presentations in Wagga Wagga and Orange in late May 2021. The web app can be used to estimate birds that live in a farm's remnant Box Gum Grassy Woodland or plantings, and make comparisons under different scenarios

- convert part of a paddock into new woodland
- establish a new shelterbelt
- remove woodland
- reduce the impact of Noisy Miners, which are often aggressive towards other birds inhabiting woodland patches
- have a wetter year

The results can be downloaded as a pdf report. Images of birds, highlighting birds of conservation concern, are included.

Figure 3: Screenshots of the Bird Checker web app. Top: opening screen. Bottom: after occupancy estimates have been generated.





4.9 Scientific publications

A paper describing the development of the remnant-only JSDM, and corresponding ecological insights will be submitted to a respected scientific journal before June 30, 2021.

5. Conclusion

5.1 Key findings

The most important influences of bird biodiversity at patch and landscape scale were Noisy Miners, whether the patch was a planting and woody cover (within 500m and within 3km). At the regional-scale, climate was very important, particularly annual maximum temperature. However, the impact of these factors differs for different aspects of biodiversity. For example, bird species richness typically decreased with Noisy Miners whilst the vulnerable Superb Parrot was more likely to co-occur with Noisy Miners. Furthermore, woody cover within 500m or 3km appeared to have little association with the number of reptile species.

For biodiversity indicators in our study area, we first recommend standardised on-ground surveys. Such surveys give the greatest detail and most comprehensive biodiversity information, and can capture factors not studied in this project. If on-ground surveys are not possible then, due to the complicated relationships between environmental factors and biodiversity, we recommend the use of estimates from the joint-species models developed in this project. These estimates can be considered indicators that summarise planting (vs remnant), Noisy Miner occupancy, woody canopy, climate and more.

Our sensitivity analysis suggests that developing similar joint-species models in similar ecosystems will require bird surveys across at least 230km north-south, and with more than one farm per 2500km^2.

We have found that the web app ‘Bird Checker: A Bird Occupancy Estimator’ is of great interest to Local Land Service staff for use in engagement and potentially reporting.

5.2 Benefits to industry

This project developed key indicators and models to help better predict the occurrence of native biodiversity in remnant and replanted vegetation of farms. This is critical information for helping populate sustainability frameworks such as the Beef Sustainability Framework and the Sheep Sustainability Framework. Indeed, as the conservation of biodiversity becomes an increasingly important part of market access for agricultural commodities, data, models and insights from the work in this project will be critical. For example, the approaches demonstrated in this project will be essential for demonstrating improvements in environmental outcomes as a function of management interventions such as establishing plantings on farms (see for example (Lindenmayer et al. 2012)).

6. Future research and recommendations

Key areas of future development include:

- Determine how best to implement cost-effective and ecologically effective monitoring that ensures ongoing provision of high-quality monitoring data to populate sustainability frameworks.
- Determine how to expand the scope of the current work to other ecosystems where the red meat industry is an important land user, and where conservation management and the maintenance or improvement of vegetation and other environmental conditions is a key part of sustainability frameworks.
- Continue the expansion in users of the web app, and ongoing improvement of the web app to help communicate biodiversity conservation to members of the red meat industry.

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