

1-1-2009

## Predicting avian distributions to evaluate spatiotemporal overlap with locust control operations in eastern Australia

Judit K. Szabo  
*University of Wollongong, judit@uow.edu.au*

Pamela J. Davy  
*University of Wollongong, pjd@uow.edu.au*

Michael Hooper  
*Texas Tech University*

Lee Astheimer  
*University of Wollongong, lee@uow.edu.au*

Follow this and additional works at: <https://ro.uow.edu.au/scipapers>



Part of the [Life Sciences Commons](#), [Physical Sciences and Mathematics Commons](#), and the [Social and Behavioral Sciences Commons](#)

---

### Recommended Citation

Szabo, Judit K.; Davy, Pamela J.; Hooper, Michael; and Astheimer, Lee: Predicting avian distributions to evaluate spatiotemporal overlap with locust control operations in eastern Australia 2009, 2026-2037. <https://ro.uow.edu.au/scipapers/3747>

---

# Predicting avian distributions to evaluate spatiotemporal overlap with locust control operations in eastern Australia

## Abstract

Locusts and grasshoppers cause considerable economic damage to agriculture worldwide. The Australian Plague Locust Commission uses multiple pesticides to control locusts in eastern Australia. Avian exposure to agricultural pesticides is of conservation concern, especially in the case of rare and threatened species. The aim of this study was to evaluate the probability of pesticide exposure of native avian species during operational locust control based on knowledge of species occurrence in areas and times of application. Using presence-absence data provided by the Birds Australia Atlas for 1998 to 2002, we developed a series of generalized linear models to predict avian occurrences on a monthly basis in 0.5 degrees grid cells for 280 species over 2 million km<sup>2</sup> in eastern Australia. We constructed species-specific models relating occupancy patterns to survey date and location, rainfall, and derived habitat preference. Model complexity depended on the number of observations available. Model output was the probability of occurrence for each species at times and locations of past locust control operations within the 5-year study period. Given the high spatiotemporal variability of locust control events, the variability in predicted bird species presence was high, with 108 of the total 280 species being included at least once in the top 20 predicted species for individual space-time events. The models were evaluated using field surveys collected between 2000 and 2005, at sites with and without locust outbreaks. Model strength varied among species. Some species were under- or over-predicted as times and locations of interest typically did not correspond to those in the prediction data set and certain species were likely attracted to locusts as a food source. Field surveys demonstrated the utility of the spatially explicit species lists derived from the models but also identified the presence of a number of previously unanticipated species. These results also emphasize the need for special consideration of rare and threatened species that are poorly predicted by presence-absence models. This modeling exercise was a useful a priori approach in species risk assessments to identify species present at times and locations of locust control applications, and to discover gaps in our knowledge and need for further focused data collection  
Copyright 2009 by the Ecological Society of America.

## Keywords

Predicting, avian, distributions, evaluate, spatiotemporal, overlap, locust, control, operations, eastern, Australia

## Disciplines

Life Sciences | Physical Sciences and Mathematics | Social and Behavioral Sciences

## Publication Details

Szabo, J. K., Davy, P. J., Hooper, M. J. & Astheimer, L. B. (2009). Predicting avian distributions to evaluate spatiotemporal overlap with locust control operations in eastern Australia. *Ecological Applications*, 19 (8), 2026-2037. Copyright by the Ecological Society of America.

## Predicting avian distributions to evaluate spatiotemporal overlap with locust control operations in eastern Australia

JUDIT K. SZABO,<sup>1,2,4</sup> PAMELA J. DAVY,<sup>3</sup> MICHAEL J. HOOPER,<sup>1</sup> AND LEE B. ASTHEIMER<sup>2,5</sup>

<sup>1</sup>*Institute of Environmental and Human Health, Texas Tech University, Lubbock, Texas 79416 USA*

<sup>2</sup>*Institute for Conservation Biology and Law, University of Wollongong, Wollongong, NSW 2522 Australia*

<sup>3</sup>*School of Mathematics and Applied Statistics, University of Wollongong, Wollongong, NSW 2522 Australia*

**Abstract.** Locusts and grasshoppers cause considerable economic damage to agriculture worldwide. The Australian Plague Locust Commission uses multiple pesticides to control locusts in eastern Australia. Avian exposure to agricultural pesticides is of conservation concern, especially in the case of rare and threatened species. The aim of this study was to evaluate the probability of pesticide exposure of native avian species during operational locust control based on knowledge of species occurrence in areas and times of application. Using presence–absence data provided by the Birds Australia Atlas for 1998 to 2002, we developed a series of generalized linear models to predict avian occurrences on a monthly basis in 0.5° grid cells for 280 species over 2 million km<sup>2</sup> in eastern Australia. We constructed species-specific models relating occupancy patterns to survey date and location, rainfall, and derived habitat preference. Model complexity depended on the number of observations available. Model output was the probability of occurrence for each species at times and locations of past locust control operations within the 5-year study period. Given the high spatiotemporal variability of locust control events, the variability in predicted bird species presence was high, with 108 of the total 280 species being included at least once in the top 20 predicted species for individual space–time events. The models were evaluated using field surveys collected between 2000 and 2005, at sites with and without locust outbreaks. Model strength varied among species. Some species were under- or over-predicted as times and locations of interest typically did not correspond to those in the prediction data set and certain species were likely attracted to locusts as a food source. Field surveys demonstrated the utility of the spatially explicit species lists derived from the models but also identified the presence of a number of previously unanticipated species. These results also emphasize the need for special consideration of rare and threatened species that are poorly predicted by presence–absence models. This modeling exercise was a useful a priori approach in species risk assessments to identify species present at times and locations of locust control applications, and to discover gaps in our knowledge and need for further focused data collection.

**Key words:** Australia; Australian plague locust; avian species occurrence; *Chortoicetes terminifera*; ecotoxicology; fipronil; generalized linear models; locust control pesticides; locust outbreaks; organophosphates; predictive models; risk of exposure to pesticides.

### INTRODUCTION

Agricultural pesticide effects on birds are a concern worldwide (Mineau and Whiteside 2006). Locust control operations represent one of the greatest uses of pesticides in Australia due to the potential impact of these insects on extensive agricultural areas. The most destructive orthopteran pest in eastern Australia is the Australian plague locust (*Chortoicetes terminifera* Walker), with outbreaks typically requiring

control in one of every two years (see Plate 1). The Australian Plague Locust Commission (APLC) is responsible for controlling locust populations that pose an interstate threat in eastern Australia (Symons 1984). Since its operation began in 1977, the APLC has used aerially applied broad-spectrum chemical insecticides in this task. Whenever possible, the control strategy has been preventive, spraying flightless hopper bands, aiming to prevent swarm formation and invasion of agricultural areas (Casimir 1965, Hunter 2004). Over the last 50 years various broad-spectrum chemical insecticides have been applied aerially over eastern Australia, with the prevalence of the organophosphate fenitrothion in the last two decades (Hunter 2004). In an attempt to reduce the rate of application and potential effects on vertebrates (Story et al. 2005), fipronil, a novel

Manuscript received 6 February 2008; revised 23 January 2009; accepted 26 January 2009; final revision received 9 March 2009. Corresponding Editor: J. A. Powell.

<sup>4</sup> Present address: The Ecology Centre, School of Integrative Biology, University of Queensland, St. Lucia, QLD 4072, Australia. E-mail: j.szabo@uq.edu.au

<sup>5</sup> Present address: Deakin University, Geelong VIC 3217 Australia.

phenyl-pyrazol insecticide (Cole et al. 1993), was introduced in 1999 as an alternative to organophosphate use. Although an effective insecticide at very low application rates (Balança and de Visscher 1997), fipronil has longer environmental persistence than organophosphates (Ying and Kookana 2002). Locust outbreaks provide an important ephemeral food source for birds and are often accompanied by wide and diverse bird assemblages (Szabo et al. 2003). Thus, use of the moderately persistent fipronil has the potential to prolong pesticide exposure to birds and other animals consuming locusts. Also, indirect effects of fipronil have been shown to be substantial: in Madagascar the numbers of termite-feeding mammals and reptiles have decreased because of long-term decline in their termite prey (Peveling et al. 2003). Australian birds native to semiarid regions are of particular concern in that they are highly mobile and are attracted to the same areas of recent rainfall and increased productivity that stimulate locust outbreaks (Davies 1984, Maclean 1996). Many avian species preferentially consume locusts when available (Loyn et al. 2001) and such food abundance provides excellent conditions for breeding (Immelman 1963). These conditions compound risks of both pesticide exposure and effect, as evident in similar conditions of ephemeral insect abundance, where the use of insecticides has led to substantial mortality in predators inadvertently exposed to pesticide control agents (Hooper et al. 2003).

The APLC has increased its level of environmental responsibility; for example, pesticides of lower toxicity are used at reduced application rates as barrier treatments and *Metarhizium anisopliae* var. *acridum* FI-985, an entomopathogenic fungus, is used in environmentally sensitive areas (Story et al. 2005). Nonetheless, exposure of nontarget animals remains a problem (Fildes et al. 2006, Story et al. 2007). More than one-third of Australia's threatened bird species occur in the arid and semiarid zones (Reid and Fleming 1992), where locust outbreaks also occur. Therefore, it is a conservation and management priority to identify areas where birds and locust control coincide spatially and temporally to anticipate potential for avian exposure to, and potential effects of, locust control pesticides.

The aim of this study was to evaluate the potential for avian exposure to operationally applied locust control pesticides in eastern Australia based on knowledge of species occurrence in areas and at times of application. We link bird survey data with environmental and other spatiotemporal variables to predict the probability of occurrence of a species in areas and times of interest. We test the strength of these models in predicting species occurrence and their resulting utility for informing environmental managers of possible risks prior to insecticide applications.

## METHODS

### *Data set*

Data were obtained from the Birds Australia Atlas project database for continental eastern Australia, between 136.00° and 152.00° E longitudes, and 17.00° and 37.00° S latitudes for the period 1998 to 2002. Based on their geographical distribution, 280 species present in the general area of locust control operations were identified for inclusion in the analysis. Our database extract contained 2 344 589 bird observations recorded in 141 876 surveys. Each observation included a record form number, location name and coordinates, start and finish date, and survey method. The common name and the Royal Australasian Ornithologists Union (RAOU) code of the species observed at each location were also recorded. From these data, a presence-absence matrix was generated for the 280 species for each survey.

Sightings for each species were converted into point coverage in ArcView GIS version 3.2a (ESRI 1992–2000). This point layer was overlaid with a 0.5° grid, rainfall, and vegetation polygon layers to consolidate these attributes of the survey event and deduce spatial and temporal information concerning the distribution and habitat preference of each species. We used this relatively coarse grid size based on the available bird data; clearly in situations in which data density is greater, it would be desirable to reduce the grid size.

Daily rainfall data for Australia for 1998–2004 were obtained in a raster format from the Australian Bureau of Meteorology. These data were converted into polygon format, and monthly total rainfall values for the 0.5° grid cells were generated by summing individual daily interpolations in ArcInfo version 7.0.3 (ESRI 1995–2000). To simplify calculations, the obtained monthly total rainfall values were treated as the real value for each point of an individual 0.5° grid cell. The habitat layer was based on the Vegetation-Post-European Settlement (1988) database of Geoscience Australia (1990), reclassified into 18 categories. For a detailed description of the methods and the resulting habitat categories, see Szabo et al. (2007).

The Birds Australia Atlas data were collected by volunteers in an ad hoc manner, using various area-search methods and incidental observations. Analyses of the data demonstrated potential limitations for their use, specifically, that surveys were spatially and temporally biased (Szabo et al. 2007). In an effort to develop predictive capabilities and based on the characteristics of the data, such as presence-absence records and non-normal distributions, generalized linear models (GLM) were identified as a suitable method to predict probabilities of bird species occurrence (McCullagh and Nelder 1983). Generalized linear models are a widely used tool to predict species distributions on the basis of environmental variables and have been used to model avian distributions, such as patterns of distribution in Australian woodland birds (MacNally 1990) and bird

species distributions based on bird atlas results (Osborne and Tigar 1992). In the case of bird survey data, GLM consider all surveys simultaneously, thus avoiding the necessity for using data for an isolated spatial point or temporal instant. GLM can also handle different binomial, ordinal and continuous, and temporal variables (Harrison and Navarro 1994).

#### Model building

Given the binomial nature of the dependent variable (i.e., yes–no data on bird species presence), the logit-link function and binomial error function were used to identify which variables explained a significant proportion of the presence of a particular bird species. The general equation of the logistic regression model was:  $P(y) = (e^{LP}) / (1 + e^{LP})$  or  $\ln[p / (1 - p)] = LP$ , where LP was the linear predictor fitted by logistic regression. To obtain probability values, an inverse-link transformation was used (Guisan and Zimmermann 2000).

In the model, presence–absence data were used as the dependent variable. Based on our knowledge of the biology of the species in question, 23 environmental variables were derived from a GIS as the explanatory variables, including climatic (rainfall), geographic (coordinates), temporal (month), and habitat variables (see Appendix A). To obtain the general equation, some variables were transformed. All response functions were modeled as linear, quadratic, or trigonometric. Several ecologically sound models were tested for each species, and the best-fit model was selected based on the Akaike information criterion (Akaike 1973). The geographic variables used were:  $x$  (latitude),  $y$  (longitude),  $x^2$ ,  $y^2$ ,  $xy$ . The time variable “month” was 1 for January, 2 for February, and so on. The functions  $cm6 = \cos(\text{month} \times \pi/6)$ ,  $sm6 = \sin(\text{month} \times \pi/6)$ ,  $cm3 = \cos(\text{month} \times \pi/3)$  and  $sm3 = \sin(\text{month} \times \pi/3)$  were taken into account as new time variables to capture the periodic nature of modeled phenomena. The variable “rain” was the rainfall in the considered month in the grid cell of the observation, whereas “lagrain” was the rainfall of the previous month in the same grid. To minimize the influence of high rainfall events that could influence the results out of proportion, the square root of the rainfall values was used in the models. Habitat preference was calculated independently for each species. To incorporate habitat preference as a variable (“habpref”) into the model, habitats with more than 10% of a species’ observed occurrences were included in “like,” while those with less than 2% were included in “dislike.” Although habitat-specific reporting rates were continuous variables, habitat preference by a given species was entered in the model as categorical variables “like” and “dislike.” The variable “method” had four categories, three formal survey types, “2-ha area search” for 20 minutes, “area search within a 500 m radius” for at least 20 minutes, and “area search within a 5 km radius” for at least 20 minutes; plus an additional provision for

“incidental” sightings, in which no formal survey was made (Barrett et al. 2003).

The models were run using R version 2.0.1 (R Development Core Team 2004). Each species was modeled in a separate run using a possibly different combination of predictors. Given the different habitat preference and the highly variable reporting rates of different species, the general model was tailored to data available for a given species. This species-specific subset of predictors proved more predictive at the model calibration step than one general model for all species.

Our original goal was to generate similar models for all bird species. However, because the number of observations for each species limited the complexity of the model, the models were adapted to this limitation. Because of this, the individual species models consisted of a general term (LP1) accounting for the species-specific habitat preference, and a specific term (LP2) that encompassed the “observability” of the species. Due to the large number of terms, it is convenient to adopt a “coefficient-free” form of model specification, as is common in statistical packages. For example,  $x + y$  specifies a linear predictor of the form  $\beta_0 + \beta_1x + \beta_2y$ , while  $(x + y) \times z$  is interpreted as  $\beta_0 + \beta_1x + \beta_2y + \beta_3z + \beta_4xz + \beta_5yz$ . In other words, multiplication signs ( $\times$ ) indicate interactions between the terms in the parentheses.

Because some species were never sighted in some habitats, it was not feasible to include a nominal predictor variable with 18 habitat types due to collinearity. In order to get around this issue without losing information by imposing coarser classification of habitat, the following procedure was adopted. For combination of species and habitat type, a habitat preference ratio “habpref” was calculated as  $N_{si}/N_{su}$ , where  $N_{si}$  = number of sightings,  $N_{su}$  = number of surveys in the same habitat. For each species, the linear predictor LP1 included the individual indicator variable of all “liked” habitats with “habpref”  $> 0.10$  and  $N_{si} > 3$ , together with a species-specific indicator variable “dislike,” lumping together all habitats with “habpref”  $< 0.02$ . When all habitats were either liked or disliked, the “dislike” term was omitted to avoid collinearity. The second part of the model (LP2) was based on spatial coordinates ( $x$ ,  $y$ ), cyclic trigonometric functions of month of the year ( $cm6$ ,  $sm6$ ,  $cm3$ ,  $sm3$ ), rainfall (in mm) at the location of the survey in the given and previous months (rain, lagrain), and survey method (method). In the case of rare species, it is only feasible to fit a GLM with a small number of terms. For abundant species, a relatively complex model including interactions among time, space, and rainfall is needed in order to capture interesting features such as migratory behavior. Therefore a set of four models of increasing complexity were adopted according to the number of sightings of a particular species. The simplest model ignores time and has only three terms. As the number of sightings increases,



additional terms can be added without introducing problems of collinearity or overfitting:

No. sightings	Model for LP2
$N_{si} < 100$	$x + y + \sqrt{\text{rain}}$
$100 \leq N_{si} \leq 500$	$x + y + x^2 + y^2 + \text{cm6} + \text{sm6}$ $+ \text{cm3} + \text{sm3}$ $+ \sqrt{\text{rain}} + \sqrt{\text{lagrain}}$
$500 \leq N_{si} \leq 5000$	$(x + y + x^2 + y^2)$ $\times (\text{cm6} + \text{sm6} + \text{cm3} + \text{sm3})$ $+ (x + y) \times (\sqrt{\text{rain}} + \sqrt{\text{lagrain}}) + xy$
$N_{si} > 5000$	$(x + y + x^2 + y^2)$ $\times (\text{cm6} + \text{sm6} + \text{cm3} + \text{sm3})$ $+ (x + y) \times (\sqrt{\text{rain}} + \sqrt{\text{lagrain}})$ $+ xy + \text{method}$ .

Convergence problems were identified by the number of Fisher iterations: when this number was higher than 12, the fitting was repeated with a model simplified by one step (McCullagh and Nelder 1983). This was usually the case for species with few observations (reporting rate  $< 0.0005$ ). Model performance was evaluated based on the  $r^2$  of the model fit and the area under curve (AUC) values (Pearce and Ferrier 2000).

The probabilities of occurrence of each species in each month and each grid cell were calculated in R and the results were imported to ArcView for visual display. In general, the results of GLM can be visualized easily in a GIS, with the calculation of the inverse of their link function (Guisan and Zimmermann 2000).

The probability of co-occurrence of a given bird species with APLC locust-spraying events was calculated in R by running the models at the time and location of locust control events (data obtained as a GIS layer from APLC). Between 1998 and 2005, 2277 spraying events occurred in the study area. The 50 events that occurred in January 1998 were excluded because the variable "lagrain" was not available from the previous month. The models were run to obtain probabilities for grid cells instead of discrete points to allow for the variation in the area of land sprayed and the mobility of birds. For this, rainfall data were recalculated for grid cells, percentages of all vegetation categories in the particular grid cell were used, and the coordinates used were those of the center of the grid cell. For the very common species, in which "method" was one of the predictors, the category "2-ha area search" was used for the predictions. For each species, the probability of co-occurrence with one locust control event was calculated separately by summing the probabilities of being present in each spraying grid-month. Grid-month is a unit defined both spatially and temporally, including events that occurred in a particular grid cell within the same calendar month. For instance, spraying events on 31 January and 1 February at the same exact location were considered two separate grid-month events, whereas one on 1 March

and another on 31 March at the same location were counted as one. Two events on the same day at a relatively close location but in different grid cells were counted as two grid-months events.

Probabilities of occurrence in the grid-month of locust-spraying events were calculated for all bird species. The probabilities of occurrence were compared among species and the 20 species with the highest probabilities of being present at each locust control grid-month were identified.

#### Model evaluation

To evaluate the model we used two independent data sets, the so-called "training" and "evaluation" data sets, sensu Guisan et al. (1999). The Birds Australia Atlas data were used as the training data set, while the evaluation data set was obtained during field trips, which occurred before the model was developed to avoid bias in the data collection. Nine field trips, of 5–22 days in duration, were conducted by one of the authors (J. K. Szabo) between 2001 and 2005 in areas of known or potential locust infestations and insecticide treatment in New South Wales (NSW) and Queensland (Qld) (Fig. 1). Most observations were made in highly modified agricultural habitat, predominantly grazing land. The Riverina region of NSW was visited three times: in 2001, 2004, and 2005. In the first year, there was minimal locust activity, whereas during the other two trips, large locust swarms of medium to high density were seen. Another trip was conducted in northern NSW in 2001, covering an area of 55 000 km<sup>2</sup> over a variety of habitats. Surveys were spatially scattered and no locust bands or swarms were observed; however, birds were seen feeding on locusts and other insects. The Armidale field trip included three study sites, one with a creek system, previously sprayed with fenitrothion. All survey locations had drying green vegetation, mostly tussock grasses and thistles. Locust hoppers were present in higher densities and were sprayed with Metarhizium and fipronil by the APLC. All other field trips were conducted in Queensland. The Quilpie sites, visited in 2003 and 2004, had "Arid grass" vegetation with sparse *Acacia* cover, cleared for grazing (for vegetation category descriptions, see Szabo et al. 2007). Locust activity only occurred in 2004 and the locust bands were sprayed with fipronil and fenitrothion. Additionally, Astrebla National Park was surveyed in 2003 and Windorah in 2004. Two trips were made to central Queensland near Tambo in 2003 and 2005 to areas covered mostly in open "Astrebla" pastures and cleared "Eucalypt woodland" habitat. Overall, field trips varied in the number of survey points, with the fewest (24) in Quilpie 2004, and the most (61) in Riverina 2004. At each survey location, 20-minute area searches were conducted as described by Loyn (1986), and geographical location ( $x, y$  coordinates), day, month, year, time of the day, species, maximum numbers of birds seen, and their activity (e.g., feeding on locusts) were recorded.

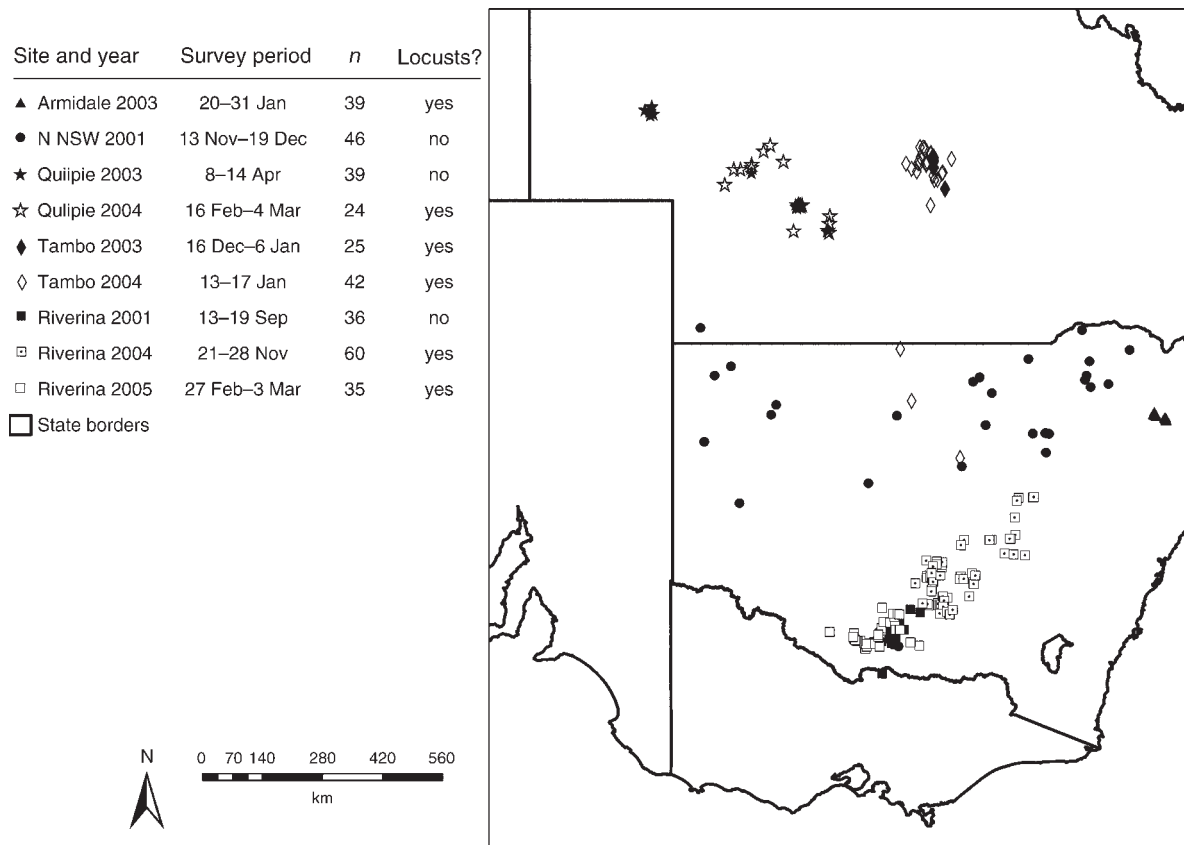


FIG. 1. Survey locations used in GLM evaluation. Field trip descriptions include the time of the survey, the number of survey points (*n*), and presence or absence of Australian plague locusts. All sites with locusts were controlled.

Models for each species on the training data set were evaluated at particular locations and times corresponding to those of the field trips that provided the evaluation data set. The individual probabilities of being present at locations in a field trip were summed to obtain a cumulative predicted occurrence for each species. This value was compared with the total number of sightings of the same species at that particular field trip. From the expected cumulative occurrence vs. the observed numbers regression, residuals were calculated for each species for each field trip. Because under- and over-predicted probabilities of particular species indicate ineffectiveness in the model's predictability for the given site, species with high absolute residual values ( $<-5$  or  $>5$ , arbitrarily chosen) were selected in each field trip data set for further interpretation. References to species refer to their common names as recorded in the Birds Australia Atlas; scientific nomenclature follows Sibley and Ahlquist (1985). Scientific names and families of the species mentioned in the figures and tables are shown in Appendix B.

## RESULTS

Species-specific significant coefficients were selected from the individual model runs for each species. For

most species, geographic location was important in linear, as well as quadratic and interaction, terms. Time as a predictor was significant in approximately half of the species. As noted in *Methods*, a different set of habitats was included in the model for each species, and from these, not all were significant as a single term. The number of species for which particular parameters were significant is shown in Appendix C. The predictive value of the models was highly variable depending on the species (Fig. 2).

The 2227 point locations of locust control spraying events from 1998 through 2005 corresponded to 326 grid-month control events. When bird species were ranked according to the probability of occurrence, the order of species was different in each spraying grid-month. Given the spatial and temporal variability of the locust control events, a high number of species (108) were among the top 20 in at least one grid cell with locust control (Table 1).

A total of 346 point locations from nine field-derived evaluation data sets were used to evaluate the species models (Fig. 2). Observed and cumulative predicted species occurrences were compared for each field trip (see two examples in Fig. 3). Even though these data sets were spatially and temporally different, their results were

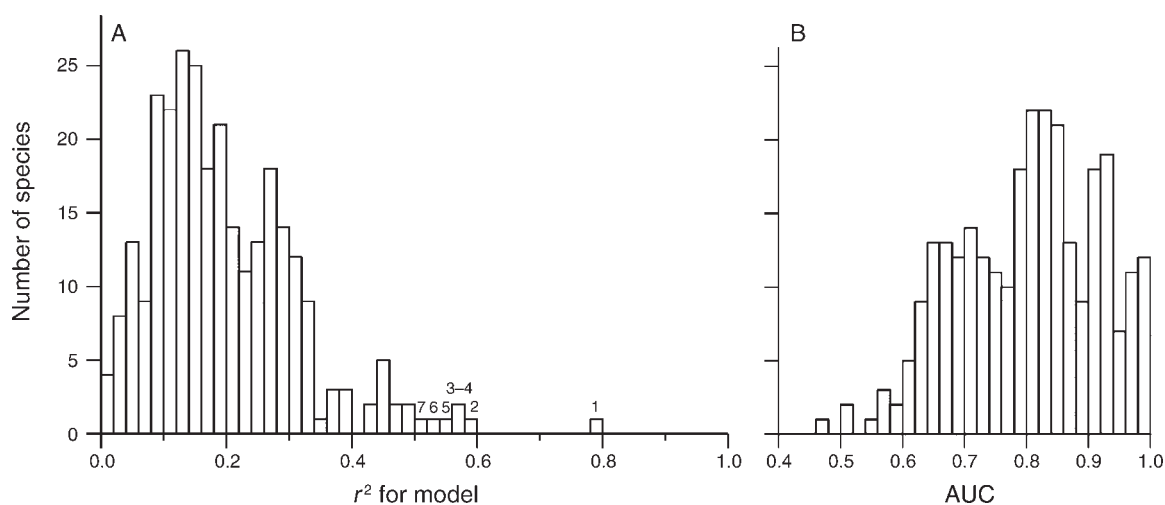


FIG. 2. Comparison of correlation coefficient ( $r^2$ ) and area under curve (AUC), two accuracy techniques for the predictive models for 280 bird species. (A) Distribution of  $r^2$  values. Species for which  $r^2 > 0.5$  are identified by numerals above histogram bars: 1, Chestnut-banded Whiteface ( $N = 63$  individuals); 2, Yellow-plumed Honeyeater ( $N = 6261$ ); 3, Torresian Crow ( $N = 7206$ ); 4, Banded Whiteface ( $N = 246$ ); 5, Eyrean Grasswren ( $N = 126$ ); 6, Thick-billed Grasswren ( $N = 55$ ); 7, Spinifex Pigeon ( $N = 424$ ); mean = 0.198, SD = 0.119. The panel is based on Szabo et al. (2007), with permission. (B) Distribution of area under curve values: mean = 0.802, SD = 0.113.

quite similar. For most species, the prediction was reliable; that is, under- and over-predicted species did not represent a high proportion of all species. Interestingly, under-predictions were biased toward sites with locusts present: 29 species were under-predicted only at sites with locust presence, 11 species were under-predicted on both locust and non-locust sites, and three species were under-predicted at sites without locusts (Table 2). Compared to the number of under-predicted species, fewer species (19) were over-predicted at sites with locust presence only, six species were over-predicted on both locust and non-locust sites, and no species were over-predicted at sites without locust only (Table 3). In both under- and over-predicted species, the more species observed at a site, the greater the accuracy of the prediction ( $r^2 = 0.2252$  between the number of species seen and the percentage of low residuals, IB (in balance) values in Table 4, for all sites). Locust presence improved this relationship ( $r^2 = 0.4856$  for sites with locusts). The number of species seen at a site was inversely related to the proportion of under-predicted species and the strength of this relationship also improved with locust presence ( $r^2 = 0.3598$  and  $r^2 = 0.8118$  for all sites and for sites with locusts, respectively). The number of over-predicted species similarly declined with the increase in the number of observed species, although  $r^2$  values were very low ( $<0.05$ ; Table 4).

## DISCUSSION

### Model predictions

We used two different measures to evaluate model performance,  $r^2$  and AUC. The reasons for many very high AUC values are twofold. Even without using any data at all, a prediction that a species will never be

present would turn out to be correct a large proportion of the time and the ROC curves on which the AUC is based only depend on the relative order of the predicted probabilities, rather than the actual values of these probabilities. Thus it is possible for the predicted probabilities to be quite inaccurate and still obtain a good AUC. AUC measures thus gave an overly optimistic assessment of prediction performance, whereas  $r^2$  measures give an overly pessimistic assessment.

TABLE 1. Bird species predicted most frequently to be present at each locust control event and the probability of their occurrence in the eastern Australia study areas.

Species	Percentage
Willie Wagtail	100
Galah	99.69
White-plumed Honeyeater	99.39
Australian Magpie	97.85
Crested Pigeon	97.24
Magpie-lark	96.01
Australian Raven	79.75
Weebill	76.07
Striated Pardalote	72.70
Grey Shrike-thrush	59.51
Spiny-cheeked Honeyeater	55.83
Yellow-throated Miner	53.37
Rufous Whistler	52.45
Brown Treecreeper	46.93
Black-faced Cuckoo-shrike	46.63
Singing Honeyeater	43.56
Red-rumped Parrot	42.33
Australian Ringneck	40.80
Pied Butcherbird	36.20
Noisy Miner	32.21

Notes: Percentage indicates the proportion of times the species occurred among the top 20 in each of the 326 grid-month units. For scientific names see Appendix B.



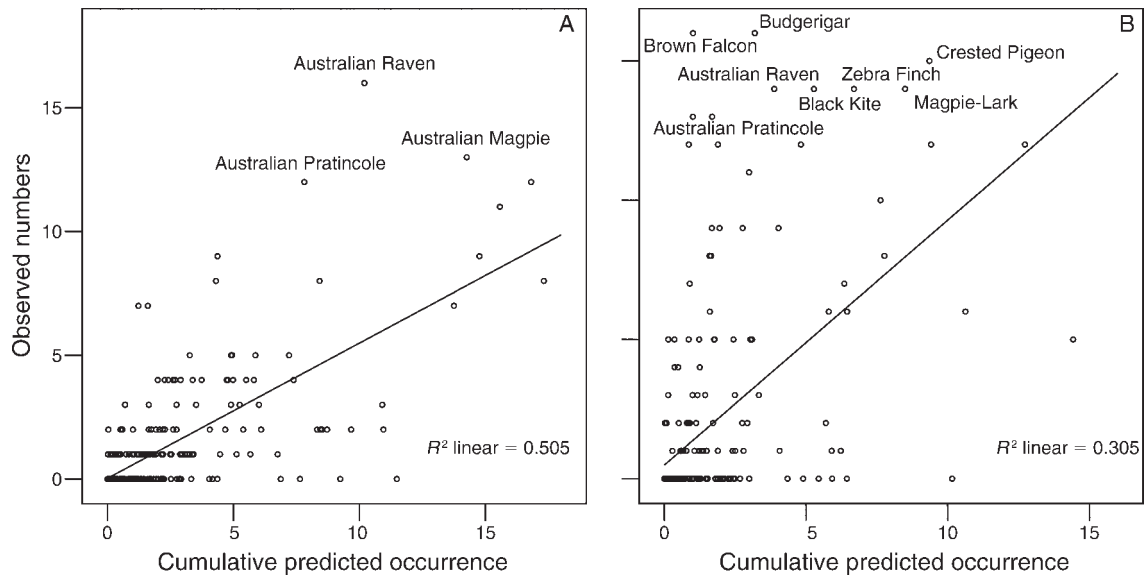


FIG. 3. Cumulative predicted occurrence and field observations of bird species at field trip locations: (A) Northern NSW (without locusts present) and (B) Quilpie/Windorah 2004 (with locusts present). The most under-predicted species are labeled by species name.

The GLM predicted that high numbers of avian species are likely to coincide spatially and temporally with locust control events in eastern Australia. Widely distributed, common species were predicted to be present at more than 95% of the locust control events, with maximum predicted probabilities of presence in locust-spraying grid-month units ranging from 0.391 (Magpie-lark *Grallina cyanoleuca*) to 0.703 (White-plumed Honeyeater *Lichenostomus penicillatus*). Rare, habitat-specialist species were predicted to be present at fewer locust control sites with lower probabilities. For instance, the highest predicted probabilities of presence for habitat specialists Gibberbird (*Ashbyia lovensis*) and Plains-wanderer (*Pedionomus torquatus*) in a locust

control grid-month were only 0.062 and 0.037, respectively. However, these species had low predicted probabilities of occurrence not only in locust control grid-month units, but also at other times and locations. Rare species with a restricted range could be present with high probabilities at locust control events that occur in their preferred habitat. In fact, we know from previous studies on the Plains-wanderer (Story et al. 2007) that this particular species has a high risk of exposure; thus we assume that the probabilities predicted by the models for similar rare species are under-predictions due to a lack of sufficient data. For the Plains-wanderer and other similar species, more data are required for reliable predictions. A study focusing on a

TABLE 2. The number of times a bird species was under-predicted by GLM with residuals  $>5$  at sites with and without locusts.

Species	No. under-predictions	
	Locusts present	No locusts
<b>Australian Magpie</b>	5	2
<b>Australian Raven</b>	5	1
<b>Nankeen Kestrel</b>	4	3
<b>Brown Falcon</b>	4	2
<b>Richard's Pipit</b>	4	1
<b>White-browed Woodswallow</b>	4	0
<b>Masked Woodswallow; Budgerigar; Brown Songlark</b>	3	0
<b>Black Kite; Zebra Finch; Singing Bushlark</b>	2	1
<b>Galah; Masked Lapwing; Crested Pigeon; White-faced Heron; Straw-necked Ibis; White-necked Heron; Wedge-tailed Eagle; White-breasted Woodswallow; White-winged Triller</b>	2	0
<b>Australian Pratincole</b>	1	2
<b>Banded Lapwing; White-winged Chough</b>	1	1
<b>Apostlebird; Blue Bonnet; Noisy Miner; Grey-crowned Babbler; European Starling; Australian Wood Duck; Yellow-rumped Thornbill; Grey Teal; Little Pied Cormorant; Chirruping Wedgebill; Diamond Dove; Whistling Kite; Magpie-lark; Black-faced Woodswallow</b>	1	0
<b>Australian Bustard; Emu; Black-shouldered Kite; White-winged Fairy-wren</b>	0	1

Notes: Boldface font indicates that the species was observed feeding on locusts. For scientific names see Appendix B.

TABLE 3. The number of times a bird species was over-predicted by GLM with residuals less than  $-5$  at sites without locusts and at sites with locust occurrences.

Species	No. over-predictions	
	Locusts present	No locusts
White-plumed Honeyeater	3	2
Striated Pardalote	2	1
Rufous Whistler	2	0
Grey Shrike-thrush; Weebill; Yellow-throated Miner; Pied Butcherbird	1	1
Superb Parrot; Noisy Friarbird; Yellow-rumped Thornbill; Rufous Songlark; Superb Fairy-wren; Brown Treecreeper; Sulfur-crested Cockatoo; Sacred Kingfisher; Noisy Miner; Grey Butcherbird; Black-faced Cuckoo-shrike; Grey Fantail; White-throated Gerygone; Spotted Bowerbird; Australian Ringneck; Peaceful Dove; <b>Apostlebird</b> ; Rainbow Bee-eater	1	0

Notes: Boldface font indicates that the species was observed feeding on locusts. For scientific names see Appendix B.

single species with a high conservation interest in a high-risk area (the Plains-wanderer in the Riverina region of NSW), is currently underway (J. K. Szabo, *unpublished data*).

Using the models developed here, the occurrence of rare species cannot be predicted with confidence, due to the limitations of the Birds Australia Atlas data set. For some species, additional variables should be included in the model to reliably predict their distribution. The scarcity of available data restricted the complexity of the predictive models (Szabo et al. 2007). However, the models worked better for other, more common species. Although classification techniques such as support vector machines and tree-based methods are very effective for a variety of situations, they are also prone to overfitting, especially when the domain of the test data differs from that of the training data. One of the many challenges in this study was that the times and locations of particular interest (i.e., locust outbreaks and sprayings) did not correspond very closely to typical times and locations within the database. Another challenge was the high degree of inherent variability: whether or not a particular species was sighted on a particular occasion was largely a matter of chance rather than a reproducible phenomenon. We believe that, in

this situation, simpler models such as logistic regression can outperform more sophisticated techniques.

The Birds Australia Atlas data provide a novel and hitherto unavailable source of data on Australian birds. Unlike grid-based national atlases, the Birds Australia Atlas is point based, which is one of its most important features, allowing for georeferencing (Barrett et al. 2003). Its data collection was limited as it depended upon a relatively small number of dedicated volunteers in a vast and mostly unpopulated country. Nevertheless, it does represent the only large-scale attempt to evaluate species presence in remote and poorly populated areas. Because the abundance of certain avian species is likely to increase in locust infested areas (as observed in the case of some species), the use of presence-absence data alone will result in a conservative evaluation of pesticide risk to avian populations. Of course, predictions would be more accurate were the data actual counts of individuals, as opposed to presence-absence.

In some instances, when low predicted probabilities at locust control locations were reliable, this may have been a result of habitat preference of these species, particularly avoidance of agricultural and pastoral areas where locust control activities typically occur. However, locust control sometimes occurs on nonagricultural and non-pastoral lands, and it is these events that will have

TABLE 4. Summary of the comparison of the model predictions and the evaluation data sets per field trip.

Study site, year, and locust presence-absence	No. species recorded	Correlation (predicted/observed)	No. species		Proportion		
			UP	OP	UP	OP	IB
Locusts present							
Riverina 2005	99	0.607	5	2	0.05	0.02	0.93
Riverina 2004	90	0.620	14	13	0.16	0.14	0.70
Quilpe 2004	81	0.553	10	15	0.12	0.19	0.69
Tambo 2005	81	0.492	8	0	0.10	0.00	0.90
Tambo 2003	72	0.479	14	3	0.19	0.04	0.76
Armidale 2003	56	0.461	17	6	0.30	0.11	0.59
Locusts absent							
N.NSW 2001	114	0.461	7	2	0.06	0.02	0.92
Riverina 2001	65	0.670	7	2	0.11	0.03	0.86
Quilpe 2003	49	0.519	6	3	0.12	0.06	0.82

Notes: Pearson correlation values between predicted and observed numbers were all at  $P < 0.01$ . For under-predicted (UP) species, residuals  $< -5$ ; for over-predicted (OP) species, residuals  $> 5$ ; in-balance (IB) species have residuals between  $-5$  and  $5$ .

the greatest potential to lead to exposure of birds that avoid disturbed habitats.

The validity of the predictions in a model depends on the quality of the input data and the statistical components. Model choice took into account the goals that it was set to achieve and represented a compromise between reliability and complexity. A very simple model rarely explains the phenomenon studied, whereas a complicated model can be impossible to develop completely (Burnham and Anderson 2002). When included, rainfall seemed to be a strong temporal force, especially as it was the only factor reflecting between-year difference in the same month of different years (year not being included as a factor). Because the models were developed to predict probabilities at locust control events, ideally locust presence should have been among the predictors. Unfortunately, data available describing locust presence (as opposed to locust control events) is not reliable enough for this purpose, and predicting the probability of occurrence of locust species presents the same problems as those predictions for birds, i.e., lack of data and dependence on unpredictable variables, such as rainfall.

The inclusion of additional predictors would further complicate bird models and, for some species, the complexity of the model was already restricted by data availability (i.e., the number of observations available in the Birds Australia data set). For these and potentially additional species with insufficient data, further complicating the models would not be a useful exercise. Compared to species with robust data sets, models for rarely observed species were simpler, with lower quality fit; as a consequence, their distribution was not well explained by their models. The solution for these species would be additional field surveys, preferably at sites with locust presence or control. These data could be incorporated into the training data set to improve predictions.

Because the input to the species models was bird sightings, the models do not predict occurrence, but rather the “observability” of species, i.e., the probability of seeing the species if we searched in that particular location at a particular time. Therefore, the model will necessarily under-predict hard-to-see, rare, or cryptic species.

The GLM approach that we used requires a minimal data set; the smaller or more diffuse the data, the less reliable the assessments will be for rare species. GLM makes a number of assumptions about the data that require testing before application. Typically, these assumptions imply the following conditions: (1) there exists a probability (dependent variable) for any possible linear combination of the independent variables; (2) the variability of the dependent variable is linearly explained by the independent variables as a linear predictor; and (3) the distribution of the dependent variable (the inverse of which is the link function) is known (in this case, it was assumed that GLM with a logit-link

function would fit well); (4) the values of errors were independent of each other across observations, as well as independent of the independent variables in the model; (5) the covariance of dependent variables was constant across cells; and (6) there was no multicollinearity (i.e., linear independence) among the independent variables (McCullagh and Nelder 1983, Venables and Ripley 1994). There were limitations in our ability to meet all of these assumptions, which were a result of working with field data. Coarse data resolution and data bias probabilities are unavoidable when working on field data collated centrally from various sources without a consistent sampling strategy.

Even though the amounts of data available seem vast compared to other countries with locust outbreaks, there was a lack of bird survey data for both areas and times of locust control, given the spatiotemporal bias in the Atlas surveys (Szabo et al. 2007). As our main interest was to predict avian presence-absence at these exact locations and times, it was necessary to use more complicated models for data extrapolation. The predictions of the model were less reliable in locations with fewer visits because the model interpolates data from more frequently visited locations, causing spatial uncertainties. This problem was especially relevant in the case of rarely recorded bird species that were often such a small component of the data set that they cannot be reliably used to build predictive models. Intensive sampling would be necessary to develop predictive models for rare species and quantify their habitat preference.

Different bird species “behaved” differently in the sense that different factors, such as sampling intensity and method, affected them to a varying degree, which required customized models when predicting their distributions. Also, avian species differed in their distribution, rarity, habitat preference, and temporal variations in the number of times they were recorded. For most species, the abundance data showed a highly skewed distribution, with zeros (species not found) occurring most frequently. Results of the habitat preference calculations were in accordance with the literature for those species with sufficient input data, but are contradictory for rare species, for which a few odd sightings can distort the results.

The Australian Atlas data set was composed of four different survey methods (Barrett et al. 2003); however, for the model predictions for field trip and spraying locations, only one method, the 2-ha area search, was used. Because the spraying predictions refer to grid cells instead of a point location, it might have been better to use an average of all methods according to their proportions in the database, or to choose a method that maximizes the probability for that particular species. The method with the maximum reporting rate is species specific, but it would only be an issue for very common species ( $n \geq 5000$ ), as “method” was not chosen as one of the predictors for all other species in



PLATE 1. Australian plague locust (*Chortoicetes terminifera* Walker) swarm photographed during the 2004 Riverina outbreak. Inset: a mature individual. Photo credit: J. K. Szabo.

order to reduce model complexity. For very common species, the method with the highest proportion of sightings was usually the 5-km area search. The 2-ha area search method was chosen as a predictor because this was the method used on the field trips.

In summary, because of the high number of uncontrolled variables inherently present in a non-manipulative design, models based on such data may have high uncertainties associated with them (Oreskes et al. 1994).

#### *Model evaluations*

In general, it is possible to reject a model when its results are not credible, but it is not possible to validate a model by comparing its results to limited sampling data (Rykiel 1996). Predictions reported in this study are probabilities of occurrence of a bird species at a given location at a given time, with values between 0 (absence) and 1 (presence). A high probability value does not infer the presence of a species at one visit to the area (Nicholls 1989); rather, probabilities can be interpreted as the proportion of times the species is expected to be seen out of a large number of visits (e.g., a probability of 0.01 means that the species would be expected to be present at the given location around 30 times if the area is visited 3000 times). As relatively few locations were visited during the individual field trips, the predictions of the models were tested on a small data set and a perfect fit

could not be expected. Still, the field surveys of avian species occurrence and behavior during locust outbreaks demonstrated the strength of the derived species list, identified under-predicted and unanticipated species and emphasized the need for special considerations for rare and threatened species. For the majority of the species, the models were in agreement with the field-collected evaluation data set. In general, the more species seen at a site, the greater the accuracy of the predictions and the lower the proportion of under-predicted species. Locust presence further improved this relationship. In field trips in which there was a high level of locust activity, a higher number of species was under-predicted than over-predicted, suggesting that aspects of the site (i.e., abundance of an irruptive food source) positively attracted the birds to it. For these species, the absolute value of the residuals was higher at field trips with locust activities than at field trips without significant locust activities. This suggests that locust presence contributed to the higher occurrences of some avian species, such as the Australian Raven (*Corvus coronoides*), Richard's Pipit (*Anthus novaeseelandiae*), White-browed Woodswallow (*Artamus superciliosus*), Masked Woodswallow (*A. personatus*), and Brown Songlark (*Cincloramphus cruralis*). All of these species have been observed feeding on locusts in the field (J. K. Szabo, unpublished data). Other, non-insectivorous bird species were also under-



predicted at some field trips, some of which, notably the Zebra Finch (*Taeniopygia guttata*) and the Budgerigar (*Melopsittacus undulatus*), are nomadic, and were probably attracted to the sites by the abundance of grass seeds (Wyndham 1983, Zann 1996). Over-predicted species, such as the White-plumed Honeyeater, Rufous Whistler (*Pachycephala rufiventris*), Sacred Kingfisher (*Todiramphus sanctus*), and Grey Shrike-thrush (*Colluricincla harmonica*) are species primarily associated with riparian habitats and woodlands (Morcombe 2000). The underrepresentation of these species can be explained by the bias in the location of the field trips. Field trip surveys were mostly conducted in "locust habitats," typically open grasslands and agricultural areas. Therefore, there was a bias in the field trip survey locations compared to the Birds Australia survey locations (which may have focused on sites with greatest avian abundance for the interest of the volunteer observer). It is not surprising that avian species that feed on grasses and seeds (i.e., the same irruptive food source on which locusts are feeding), other temporarily abundant insects, or on the locusts themselves, will select the same habitats as locusts. Such species were overrepresented in the field trip evaluation data sets and under-predicted by the models, which were based on the general, coarse habitat characterization of the location. Species preferring more dense habitats were over-predicted by the model and underrepresented in the evaluation data set.

This study was the first attempt to predict avian species occurrences in areas of locust control in eastern Australia. For the users of a model, the usefulness of its predictions is more important than its complete reliability (Rykiel 1996). With these species-specific models, we hoped to achieve usefulness.

High numbers of species were predicted to be present at times and locations of locust control and therefore would be likely to be exposed to locust control pesticides. This method could be used as an a priori approach in species risk assessments to identify species that would be present at times and location of locust control applications, as well as to help identify gaps in our knowledge and need for further data requirements.

#### ACKNOWLEDGMENTS

The APLC provided logistic assistance during field trips. We especially thank Ted Deveson for his help in the locust and pesticide GIS models, as well as Graham Hamilton, Laurie McCulloch, and Paul Story. Eugenio Fedriani Martel (Universidad Pablo Olavide, Spain) provided statistical advice. Thanks to Birds Australia for providing us with the Atlas data and to the volunteers who conducted the surveys. Thanks to Terry O'Dwyer, David Bain, and Karen Fildes for their assistance in the field. Thanks also go to the Institute of Environmental and Human Health, Texas Tech University, USA, and the Institute of Conservation Biology and Law, University of Wollongong, Wollongong, Australia. Maria Beger and Simon Blomberg from the University of Queensland and three anonymous reviewers provided valuable comments on earlier drafts of this paper.

#### LITERATURE CITED

- Akaike, H. 1973. Information theory and an extension of the maximum likelihood principle. Pages 267–281 in B. N. Petran and F. Csaki, editors. International Symposium on Information Theory. Akademiai Kiado, Budapest, Hungary.
- Balança, G., and M.-N. de Visscher. 1997. Effects of very low doses of fipronil on grasshoppers and non-target insects following field trials for grasshopper control. *Crop Protection* 16:553–564.
- Barrett, G., A. Silcocks, S. Barry, R. Cunningham, and R. Poulter. 2003. The new atlas of Australian Birds. Royal Australian Ornithologists Union, Hawthorn East, Victoria, Australia.
- Burnham, K. P., and D. R. Anderson. 2002. Model selection and multimodel inference: a practical information-theoretic approach. Second edition. Springer, New York, New York, USA.
- Casimir, M. 1965. The locust problem: its history and development in New South Wales. *Journal of the Australian Institute of Agricultural Science* December:267–274.
- Cole, L. M., R. A. Nicholson, and J. E. Casida. 1993. Action of phenylpyrazole insecticides at the GABA-gated chloride channel. *Pesticide Biochemistry and Physiology* 46:47–54.
- Davies, S. J. J. S. 1984. Nomadism as a response to desert conditions in Australia. *Journal of Arid Environments* 7:183–195.
- ESRI. 1992–2000. ArcView GIS. Version 3.2a. ESRI, Redlands, California, USA.
- ESRI. 1995–2000. ArcInfo. Version 7.0.3. ESRI, Redlands, California, USA.
- Fildes, K., L. B. Astheimer, P. G. Story, W. A. Buttemer, and M. J. Hooper. 2006. Cholinesterase response in native birds exposed to fenitrothion during locust control operations in eastern Australia. *Environmental Toxicology and Chemistry* 25:2964–2970.
- Geoscience Australia. 1990. Vegetation: Post-European Settlement c. 1988. Electronic database. (<http://www.ga.gov.au/meta/ANZCW0703005426.html>)
- Guisan, A., S. B. Weiss, and A. D. Weiss. 1999. GLM versus CCA spatial modeling of plant species distribution. *Plant Ecology* 143:107–122.
- Guisan, A., and N. E. Zimmermann. 2000. Predictive habitat distribution models in ecology. *Ecological Modelling* 135: 147–186.
- Harrison, J. A., and R. A. Navarro. 1994. Modelled reporting rates as indices of changes in relative abundance with altitude and season. Pages 607–618 in E. J. M. Hagemeyer and T. J. Verstrael, editors. Bird numbers 1992. Distribution, monitoring and ecological aspects. Proceedings of the 12th International Conference of the IBCC [International Bird Census Committee] and the EOAC [European Ornithological Atlas Committee], Noordwijkerhout, The Netherlands. Statistics Netherlands, Voorburg/Heerlen and SOVON, Beek-Ubbergen, The Netherlands.
- Hooper, M. J., P. Mineau, M. E. Zaccagnini, and B. Woodbridge. 2003. Pesticides and international migratory bird conservation. Pages 737–754 in D. J. Hoffman, B. A. Rattner, G. A. Burton, Jr., and J. Cairns, Jr., editors. Handbook of ecotoxicology. CRC Press, Boca Raton, Florida, USA.
- Hunter, D. M. 2004. Advances in the control of locusts (Orthoptera: Acrididae) in eastern Australia: from crop protection to preventative control. *Australian Journal of Entomology* 43:293–303.
- Immelman, K. 1963. Drought adaptations in Australian desert birds. Proceedings of the International Ornithological Congress 13:649–657.
- Loyn, R. H. 1986. The 20 minute search: a simple method for counting forest birds. *Corella* 10:58–60.



- Loyn, R. H., G. Cheers, P. Neville, J. Wainer, D. Ward, A. Yen, S. Kennedy, and E. McNabb. 2001. Effects of locust control on non-target animals in western Victoria, October–December 2000: results of biodiversity monitoring and associated studies. Arthur Rylah Institute, Department of Natural Resources and Environment, Melbourne, Victoria, Australia.
- Maclean, G. L. 1996. *Ecophysiology of desert birds*. Springer, Berlin, Germany.
- MacNally, R. 1990. Modelling distributional patterns of woodland birds along a continental gradient. *Ecology* 71: 360–374.
- McCullagh, P., and J. A. Nelder. 1983. *Generalized linear models*. Chapman and Hall, London, UK.
- Mineau, P., and M. Whiteside. 2006. Lethal risk to birds from insecticide use in the United States: a spatial and temporal analysis. *Environmental Toxicology and Chemistry* 25:1214–1223.
- Morcombe, M. 2000. *Field guide to Australian birds*. Steve Parish Publishing, Archerfield, Queensland, Australia.
- Nicholls, A. O. 1989. How to make biological surveys go further with generalised linear models. *Biological Conservation* 50:51–75.
- Oreskes, N., K. Shrader-Frechette, and K. Belitz. 1994. Verification, validation, and confirmation of numerical models in the earth sciences. *Science* 263:641–646.
- Osborne, P. E., and B. J. Tigar. 1992. Interpreting bird atlas data using logistic models: an example from Lesotho, southern Africa. *Journal of Applied Ecology* 29:55–62.
- Pearce, J., and S. Ferrier. 2000. Evaluating the predictive performance of habitat models developed using logistic regression. *Ecological Modelling* 133:225–245.
- Peveling, R., A. N. McWilliam, P. Nagel, H. Rasolomanana, L. Raholijaona Rakotomianina, A. Ravoninjatovo, C. F. Dewhurst, G. Gibson, S. Rafanomezana, and C. C. D. Tingle. 2003. Impact of locust control on harvester termites and endemic vertebrate predators in Madagascar. *Journal of Applied Ecology* 40:729–741.
- R Development Core Team. 2004. *R: A language and environment for statistical computing*. Version 2.0.1. R Foundation for Statistical Computing, Vienna, Austria. (<http://www.R-project.org/>)
- Reid, J., and M. Fleming. 1992. The conservation status of birds in arid Australia. *Rangeland Journal* 14:65–91.
- Rykiel, E. J. 1996. Testing ecological models: the meaning of validation. *Ecological Modelling* 90:229–244.
- Sibley, C. G., and J. E. Ahlquist. 1985. The phylogeny and classification of the Australo-Papuan passerine birds. *Emu* 85:1–14.
- Story, P., D. Oliver, T. Deveson, L. McCulloch, G. Hamilton, and D. Baker-Gabb. 2007. Estimating and reducing the amount of Plains-wanderer (*Pedionomus torquatus* Gould) habitat sprayed with pesticides for locust control in the New South Wales Riverina. *Emu* 107:308–314.
- Story, P., P. W. Walker, H. McRae, and J. G. Hamilton. 2005. A case study of the Australian Plague Locust Commission and environmental due diligence: Why mere legislative compliance is no longer sufficient for environmentally responsible locust control in Australia. *Integrated Environmental Assessment and Management* 1:1–7.
- Symmons, P. M. 1984. Control of the Australian plague locust, *Chortoicetes terminifera* (Walker). *Crop Protection* 3:479–490.
- Szabo, J. K., L. B. Astheimer, P. G. Story, and W. A. Buttemer. 2003. An ephemeral feast: birds, locusts and pesticides. *Wingspan* 13:10–15.
- Szabo, J. K., P. J. Davy, M. J. Hooper, and L. B. Astheimer. 2007. Predicting spatio-temporal distribution for eastern Australian birds using Birds Australia's Atlas data: survey method, habitat and seasonal effects. *Emu* 107:89–99.
- Venables, W. N., and B. D. Ripley. 1994. *Modern applied statistics with S-Plus*. Springer Verlag, New York, New York, USA.
- Wyndham, E. 1983. Movements and breeding seasons of the budgerigar. *Emu* 82:276–282.
- Ying, G. G., and R. Kookana. 2002. Laboratory and field studies on the degradation of fipronil in a soil. *Australian Journal of Soil Research* 40:1095–1102.
- Zann, R. A. 1996. *The Zebra Finch: a synthesis of field and laboratory studies*. Oxford University Press, Oxford, UK.

#### APPENDIX A

Details of environmental variables available for inclusion in models developed to predict the probability of occurrence of 285 avian species in eastern Australia (*Ecological Archives* A019-084-A1).

#### APPENDIX B

Scientific names mentioned in the tables following Sibley and Ahlquist (1985) (*Ecological Archives* A019-084-A2).

#### APPENDIX C

Model fit summary and significance of logistic regression coefficients for 280 species (*Ecological Archives* A019-084-A3).