Department of Primary Industries
and Regional Development

2025-2026 Annual Waterfowl Quota Report to NSW Department of Primary Industries and Regional Development - Hunting

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July 2025

Published by the NSW Department of Primary Industries

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ISBN:

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www.dpi.nsw.gov.au

Acknowledgments

We thank James Seaman for assistance with the surveys, and Patrick O’Brien for providing comments on a draft of this report.

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Introduction

In New South Wales (NSW), ten native duck species may be legally harvested to minimise damage and promote sustainable agricultural management. The *Game and Feral Animal Control Act 2002* (GFAC Act) requires the Regulatory Authority (DPIRD Hunting) to set annual quotas for native game birds that may be killed under the authority conferred by a native game bird management licence. The annual quotas are "to be set on the basis of the best scientific knowledge available on the estimated regional population of native game birds." (Part 3A Native game bird management licences, 32D (2)(a)).

Sustainable use refers to the utilisation of components of biological diversity in a manner and at a rate that does not lead to the long-term decline of biological diversity, thereby maintaining its potential to meet the needs and aspirations of present and future generations (Convention on Biological Diversity, 1992). Sustainable harvesting is a specific type of use that aims to remove resources from a population or ecosystem while ensuring that the resource is preserved for the foreseeable future. To harvest sustainably, a portion of the population or ecosystem is harvested, and this portion is small enough to allow long-term replacement by birth and growth processes of the population. We aim to minimise the risk of over-harvest with appropriate monitoring and careful consideration of population dynamics. Harvesting strategies that support sustainable practices should include sources of uncertainty in decision-making processes.

To derive annual quotas for waterfowl that can be harvested in NSW, the Vertebrate Pest Research Unit (NSW DPIRD) estimates waterfowl populations on artificial waterbodies within the state of NSW.

The Riverina region's annual quotas are based on the estimated population sizes and the productive capacity of the waterfowl populations to recover from the harvest in the long term.

In this report, we describe the results of population size surveys of waterfowl in the Riverina region of NSW. Surveys were conducted through May-June 2025. Abundance estimates and prescribed quotas for 2025-26 are presented for nine waterfowl species:

Grey Teal *(Anas gracilis)*

Pacific Black Duck *(Anas superciliosa)*

Hardhead *(Aythya australis)*

Pink-eared Duck *(Malacorhynchus membranaceus)*

Australian Wood Duck *(Chenonetta jubata)*

Australian Shelduck *(Tadorna tadornoides)*

Blue-winged Shoveler *(Anas rhynchotis)*

Chestnut Teal *(Anas castanea)*

Plumed Whistling-Duck *(Dendrocygna eytoni)*

Methods

For the 2025-2026 quota, our methods were based on those used in surveys from previous years. Small farm dams and channels were surveyed using a helicopter. Medium, large and extra-large dams and wastewater treatment ponds were surveyed primarily by independent double ground counts or using a drone (UAV). The observed numbers of waterfowl collected from this stratified sub-sample of waterbodies have been extrapolated to the Riverina region to estimate the abundance of each species.

Survey region

In NSW, most waterfowl are harvested from the Riverina region (Figure 1), so estimating abundance within this region is essential for calculating quotas.

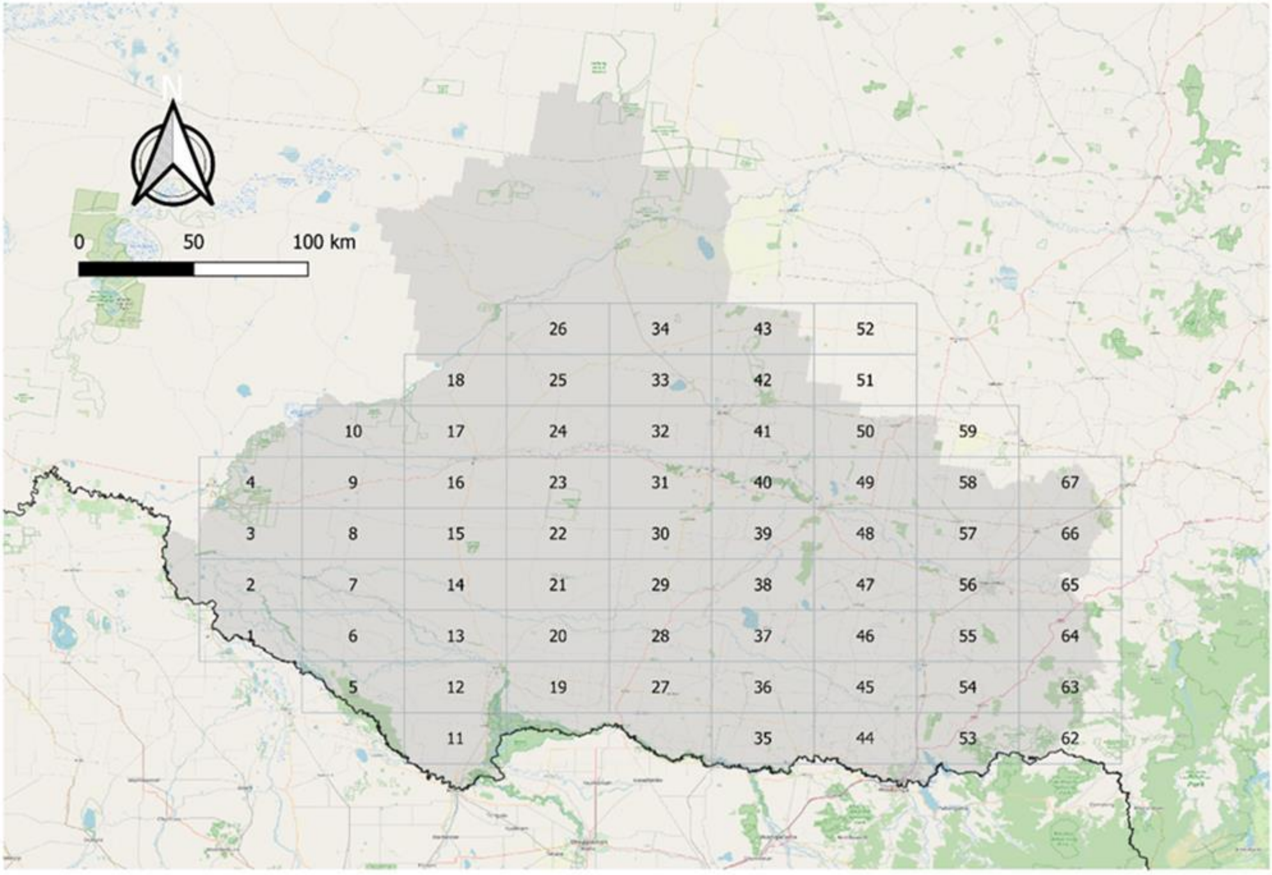

Figure 1: The area defined as the Riverina region as indicated by the Bureau of Meteorology forecast areas (http://www.bom.gov.au/nsw/forecasts/map.shtml).

Sampling Strategy

The sampling strategy for small dams and channels differed from that for larger water bodies. The sampling for small dams and channels followed a two-stage stratified random sampling strategy (without replacement), whereas all other water bodies used a one-stage sampling strategy. The reason for the different methods was based on the total sample size of the survey units, with small dams and channels being two orders of magnitude larger than other waterbody types.

All waterbodies and dams within the Riverina region were mapped and categorised by size (small 0-4.9 ha, medium 5-9.9 ha, large 10-49.9 ha and extra-large ≥ 50 ha) and combined with mapping layers for wastewater treatment ponds, natural lakes and wetlands (Kay, Carter et al. 2012, Bureau of Meteorology 2013).

The process for selecting small dams to be surveyed involved stratifying small dams (<4.9 ha in size) into 0.5° longitude x 0.25° latitude grid blocks across the Riverina region (Figure 1). Within randomly selected blocks, a random sample of dams and irrigation channels was chosen without replacement for surveying, with consideration given to proximity to airports for helicopter refuelling stops. Mapped shapefiles used for previous surveys were revised in 2025 for all dam sizes to confirm that dams were allocated to the correct size class, to remove dams that had been filled in, and to add any newly created dams.

To determine the number of larger irrigation dams to survey, the presence of water within dams (as well as the proportion of dry dams for each size class) was determined using Sentinel WMS imagery within the QGIS program (https://www.sentinel-hub.com/develop/api/ogc/standard-parameters/wms/), taken within the preceding month of the survey. A random sample of large irrigation dams from three size classes (medium, large, and extra-large) was selected from those holding water (Figure 2).

A range of wastewater treatment ponds of different sizes were selected from across the Riverina region (Figure 2). Following the 2017 survey, we found a high correlation (r = 0.89) between the number of ducks present on wastewater treatment ponds and the surface area of the water in these ponds. We excluded wastewater treatment ponds near airports from the drone surveys due to CASA (Civil Aviation Safety Authority) restrictions on flying zones.

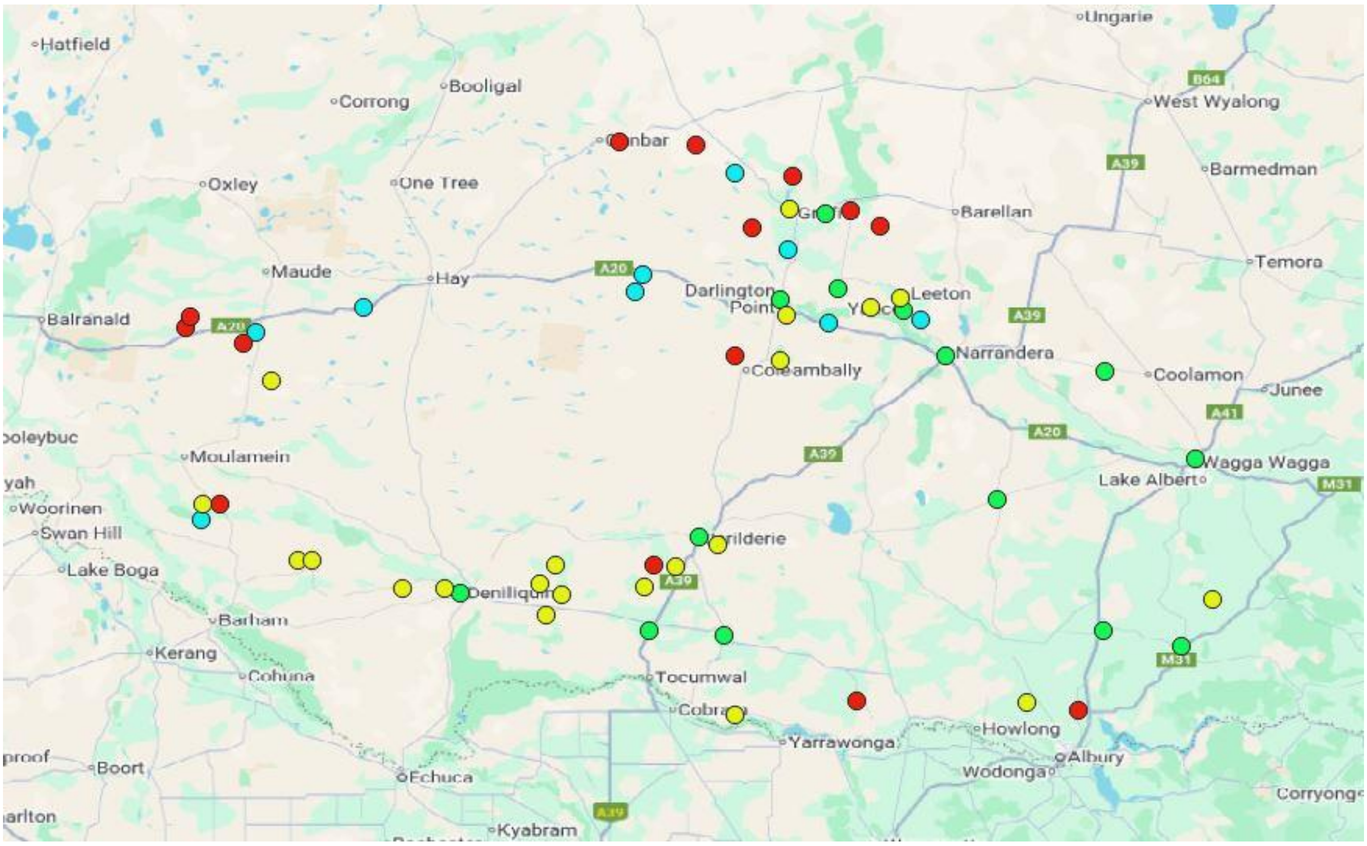

Figure 2: Medium (red), large (yellow), extra-large dams (blue) and wastewater treatment ponds (green) surveyed in 2025 using UAVs/ground counts.

Small Dams

A stratified random sample of dams, ≤ 4.9 ha in size, was selected without replacement. Using a two-stage stratified sampling design, sampling units (dams) were randomly selected without replacement (Lohr 2019). In Stage One, the study site was divided into 67 equal-sized sample blocks (primary sampling units, PSUs), each with dimensions of 0.5° longitude × 0.25° latitude (approximately 46.1 × 27.7 km, totalling 1279 km^2) (Figure 1). These sampling units formed the sampling frame. From the sampling frame, a random sample without replacement of 12 blocks (H) was selected, with each block (h) forming a sample stratum (Figure 3). Within each stratum, a further random sample of dams was selected without replacement (range: 33— 51), resulting in a total sample size (n) of 452 dams from a total of 7896 dams across the sampling frame (Figure 3).

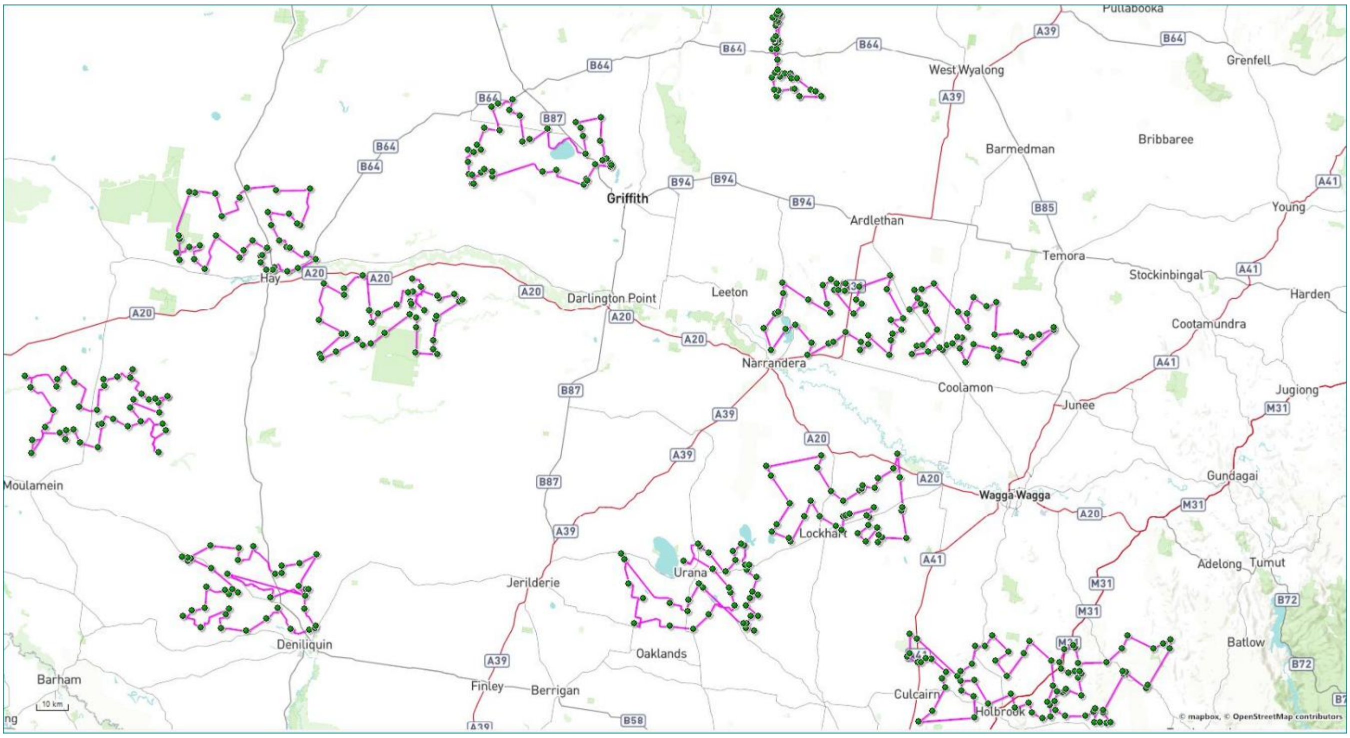

Figure 3: Map of sampled small farm dams for the 2025 surveys. The lines between small dams are the predicted flight path of the helicopter. Where a flight path crossed a channel, the channel was followed for a short time before returning to the flight path to the next small dam.

Channels

Within the same blocks used for the survey of small dams, sections of channel were sampled when the survey path between small dams crossed a channel. A section of channel was then followed, and all ducks observed were counted. Thus, the sampling strategy was similar to that for small dams, where two-stage stratified random samples without replacement were used; however, the number of channel sections followed was not fixed and depended on the number of channel sections crossed by the helicopter flight path. Of the blocks randomly selected for surveying, 11 included channels and one block had no channels. For the blocks that included channels, a total of 348 channel sections were followed, and each section had a mean length of 788 m (range 101 to 9557 m), and a total length of 274 km.

Other waterbodies

For medium, large and extra-large dams, wastewater treatment ponds, a simple random sample without replacement was chosen. Within the Riverina, of the dams that held water: 20% of medium-sized (n = 21) (103 with water and 64 were dry);12% of large (n = 13) (113 with water and 98 were dry); and 56% of extra-large dams (n = 9) (16 with water and 24 were dry) were sampled. In addition, 51% of wastewater treatment ponds were surveyed (n = 20) (39 with water and zero were dry). Access proves to be an issue around surveying natural lakes and larger bodies of water, so only 33% of wetlands were sampled (n = 2) (6 with water and zero were dry). Wet conditions, drought, and access permission limit the number of waterbodies that can be surveyed each year.

Natural waterbodies, including rivers, creeks, swamps, and floodwaters, were not surveyed and therefore did not contribute to the abundance estimates. These waterbodies are likely to have ducks, so the estimated population sizes for each species of waterfowl are conservative.

Helicopter surveys

During the survey, small dams holding no water and those with water but having no waterfowl were noted. For dams with waterfowl, a low and slow circuit was flown around the dam (no lower than 18m for safety purposes), and the observers identified and counted all waterfowl. The helicopter used was a Bell 206 L4, allowing three observers to be seated on the same side of the helicopter. Aerial operations were conducted without the front and rear doors, allowing for better visibility whilst counting.

Data collected during the helicopter surveys represents a multiple observer count (with two observers on the left side of the aircraft, front and back, making simultaneous observations and logging species counts on GPS-enabled tablets using customised software) with a third observer, seated next to the rear observer on the right, recording covariates identified by the front observer that may influence detection probability and occupancy of waterfowl (e.g. presence of trees or crops, vegetation on or around a dam or bare areas, presence of livestock). In addition, at the completion of the observation for each dam, the third observer recorded duck species and whether the dam was greater or less than one hectare, after confirmation by both the front and rear observers.

Channels were surveyed using similar methods.

For this year's surveys, the weather was favourable for surveying, with average temperatures in June ranging from 2.2 to 13.4 degrees Celsius (Bureau of Meteorology, 2025). These conditions were ideal for observations, and most days had fine and clear skies with minimal wind.

Small dam and channel data were analysed using two-stage occupancy-abundance models (Karavarsamis and Huggins 2019, 2020; Fiske and Chandler 2011). Two-stage occupancy-abundance models provide a practical solution for ecological surveys involving unmarked individuals, as they separately estimate detection probability and abundance or occupancy. Theoretically, they build on hierarchical modelling frameworks (e.g., MacKenzie et al., 2002) that account for imperfect detection and then condition abundance or occupancy estimates on detection probability. Practically, this approach reduces model complexity and improves convergence, especially in surveys with large heterogeneity in occupancy and abundance. Two-stage occupancy-abundance models are particularly useful when detection varies across space or time, but abundance is the primary ecological interest, enabling more robust inference without requiring individual identification. All analyses were cone using the statistical programming language R (R Core Team 2025).

Drone and Ground Surveys

Unmanned aerial vehicles are particularly suited for sampling medium to large waterbodies (> 4.9 ha surface area), where helicopters can cause excessive reactive movement of waterfowl, which is particularly an issue when the waterbody has a large number of waterfowl. Seven waterbodies were sampled using the drone, and a further 51 were surveyed by independent double ground counts.

For this year's survey, we used a DJI Matrice 210 UAV with an X5S camera. The UAV features a 20MP camera and can capture high-resolution video footage in 4K at 60fps, providing the required resolution to identify the species. We used the DJI Pilot app to define a survey grid for each surveyed waterbody. For each surveyed wastewater treatment pond, the UAV was flown in a grid pattern to survey all waterfowl present on the pond. For wetlands, an accurate ground count was not possible, so the UAV was used to survey a randomly selected sub-sample of the surface area. Additionally, 9% of Tombullen Storage and 33% of Barren Box Swamp were surveyed.

Depending on the reaction of waterfowl to the drone, the survey height was varied (30m-35m). Flying at a faster speed (20-25kph) also reduced the disturbance to waterfowl sitting along banks or on the water.

We analysed the video using a custom program (duck-counter.bat) written as a simple animal counter app based on the open-source package labelme (https://github.com/wkentaro/labelme). For each video, a single observer manually reviewed all videos, identifying and tagging all waterfowl observed. The flight path of the drone was calculated using maps provided by Airdata (linked to each UAV and displaying individual flights). Using this data, a buffer was created around the flight path, and this mapping information was then used to map the area surveyed on each water body. We then used the area of water present with the area covered by the UAV to calculate the total area covered (%). Survey samples collected using the drone (wastewater treatment ponds and wetlands) were analysed, assuming a detection probability of one for waterfowl.

For waterbodies surveyed by ground counts (n = 51), two observers carried out independent counts using a spotting scope. For most waterbodies, the whole surface of each dam was surveyed. for medium and large dams. For a small number of large (n = 3), extra-large (n = 2) dams and wastewater treatment ponds (n = 3), an unbiased subsample of the surface was counted (ranging between 50-95%).

Statistical Analysis

Statistical Framework for Two-Stage Occupancy-Abundance Analysis

We used a hierarchical two-stage modelling approach to estimate the number of ducks at small dam sites and along sections of channels, taking into account imperfect detection (Dorazio et al. 2006 and Kéry & Royle 2016). This approach addresses one of the primary issues in wildlife surveys where species inhabiting a location go undetected during sampling, resulting in biased abundance estimates if detection probability is not accurately modelled (MacKenzie et al., 2006).

In Stage One, we used single-season occupancy models (MacKenzie et al., 2002) to estimate site-level occurrence probabilities, accounting for imperfect detection probability. The occupancy model consisted of two interconnected sub-models: a biological process model that determined the likelihood of a site being occupied, and an observation process model that estimated the probability of detecting the species if it were present. The occupancy state z_i for site *i* followed a Bernoulli distribution: $z_i \sim Bernoulli(\psi_i)$, with ψ_i denoting the occupancy probability. The observation process is represented as $y_{ij} | z_i \sim Bernoulli(z_i \times p_{ij})$, with y_{ij} denoting the detection/non-detection data for site *i* during survey *j*, and p_{ij} indicating the detection probability. We used logit link functions to model both occupancy and detection probabilities: $logit(\psi_i) = \alpha + \beta X$ and $logit(p_{ij}) = \gamma + \delta W$, where *X* and *W* are site-specific and observation-specific covariates, respectively.

During Stage Two, N-mixture models (Royle, 2004) were used to estimate abundance based on the presence of species at sites where detections were made. The N-mixture model assumes that the actual abundance N_i at site *i* follows a chosen distribution (either Poisson, negative binomial, or zero-inflated Poisson), while the observed counts y_{ij} follow a binomial distribution conditional on abundance: $y_{ij} | N_i \sim Binomial(N_i, p_{ij})$. We compared three mixture distributions to deal with the overdispersion and zero-inflation that are often seen in wildlife count data (Martin et al., 2005; Ver Hoef & Boveng, 2007). We modelled the abundance component as $\log(\lambda_i) = \alpha + \beta X$, where λ_i is the expected abundance at site *i*.

Model selection employed an information-theoretic framework, using Akaike's Information Criterion (AIC), as advocated by Burnham & Anderson (2002). We developed an extensive set of candidate models that included spatial variables (latitude, longitude), habitat features (vegetation composition, water features, habitat diversity), human factors (presence of livestock), and survey-specific variables (observer identity, environmental conditions). We used the formula $w_i = \exp(-0.5 \times \Delta AIC_i) / \sum \exp(-0.5 \times \Delta AIC_j)$ to find the AIC weights (w_i) for each stage. Here, ΔAIC_i was the difference in AIC between model *i* and the best model. For multi-model inference, we retained the models whose weights summed to 95% of the total AIC weight.

Final predictions were obtained by model averaging, weighted by AIC weights, yielding more reliable estimates than a single best-model approach (Burnham & Anderson, 2002; Symonds & Moussalli, 2011). Model-averaged predictions were computed as $\hat{\theta} = \sum (w_i \times \hat{\theta}_i)$, with $\hat{\theta}_i$ denoting the prediction from model *i*. This method accounts for the uncertainty of model selection and provides more accurate confidence intervals by including variation across a set of reasonable models

The parametric bootstrap method was used to include uncertainty across both modelling stages. This method addresses the issues that arise when attempting to refit complex models during traditional bootstrap resampling (Fletcher et al., 2019). We obtained variance-covariance matrices from the fitted models and produced bootstrap samples by incorporating random variation that reflected model uncertainty. We used the relationship $logit(\psi) \sim N(logit(\hat{\psi}),\ 〖SE〗^2\ logit)$, where the logit-transformed value of ψ is approximately normally distributed with a mean $logit(\hat{\psi})$ and variance $〖SE〗^2\ logit$, to do bootstrap sampling on the logit scale for occupancy probabilities. Then, we used the inverse logit function to ensure the probabilities stayed between 0 and 1. For abundance estimates, bootstrap sampling was performed on the log scale using $log(\lambda) \sim N(log(\hat{\lambda}),$ $〖SE〗^2\ log)$, followed by back-transformation through exponentiation to guarantee positive values.

To obtain confidence intervals that were biologically realistic, it was important to use the right transformations. Standard normal approximations on the natural scale can yield implausible values (e.g., negative abundances, occupancy probabilities outside the range [0,1]), especially when sample sizes are small or detection rates are low. The method we used ensured that confidence intervals take biological limits into account while correctly propagating uncertainty through the hierarchical model structure. Site-level confidence intervals integrated uncertainty from both occupancy and abundance components through the delta method approximation, i.e.

$Var(\log(\psi \times \lambda)) \approx Var(logit(\psi)/\psi^2) + Var(\log(\lambda))$.

We used MacKenzie-Bailey goodness-of-fit tests for occupancy models (MacKenzie & Bailey, 2004) and overdispersion diagnostics for abundance models to check how well the models fit. To check for overdispersion, we divided Pearson's chi-squared statistic by the number of residual degrees of freedom. If the result was significantly greater than 1, it could indicate that the model was not sufficiently accurate. When bootstrap convergence was inadequate, we employed fallback procedures utilising model-based standard errors with suitable transformations.

Justification of Change in Analysis Methods

We used a two-stage occupancy-abundance modelling approach, replacing the N-mixture model approach used in previous analyses due to the highly zero-inflated nature of our count data, where over 70% of surveyed patches yielded zero detections. While N-mixture models have been widely applied for abundance estimation from replicated counts (Royle 2004; Fiske & Chandler 2011), they assume a single abundance distribution across all sites, including those where species are truly absent, which can lead to parameter identifiability issues and biologically unrealistic estimates when zeros dominate the dataset (Kéry 2018). Specifically, negative-binomial variants of N-mixture models exhibited identifiability problems in 25% of datasets, despite often being selected by AIC, and models frequently produced ecologically unrealistic parameter estimates when applied to zero-inflated data. The two-stage approach explicitly separates occupancy probability (the probability that a site contains suitable habitat and is occupied) from abundance conditional on occupancy, thereby providing a more realistic representation of the underlying ecological processes (Royle & Nichols 2003). This separation improved model performance by allowing the abundance component to focus exclusively on sites where the species was present, reducing parameter confounding between detection probability, occupancy, and abundance (Ward et al. 2017), and providing more stable parameter estimates with better convergence properties (Joseph et al. 2009). Furthermore, the two-stage framework produced more interpretable parameters with occupancy relating to habitat suitability while conditional abundances reflected local population dynamics at occupied sites (Dibner et al. 2017).

Each species of waterfowl was analysed separately to calculate an independent quota for each species.

Population Estimation Using N-mixture Models

N-mixture models were used for the analysis of ground survey data, as all sites contained waterfowl, and the dataset was not zero-inflated. N-mixture models provide a framework for analysing replicated count data while accounting for imperfect detection and deriving relationships between animal populations and environmental covariates (Royle 2004). Under this approach, each survey site i contains an unknown true abundance N_i of individuals. The state process describing true abundance at site i follows:

$$N\_i \sim Poisson(\lambda\_i)$$

where λ_i represents the expected abundance at site *i*. Each site is surveyed *j* times (for ground surveys, *j* = 2, with counts conducted by two observers working independently), and each individual has a detection probability *p*. The observation process linking observed counts y_{ij} to true abundance is:

$$y\_ij \mid N\_i \sim Binomial(N\_i, p)$$

where y_{ij} represents the count at site *i* during replicate survey *j*. The negative binomial distribution was evaluated as an alternative to the Poisson distribution for the state process, to account for potential overdispersion in the data.

Model Selection and Covariate Effects

Covariates potentially affecting both the state process (the likelihood of waterfowl presence at a site) and the observation process (detection probability given presence) were incorporated into the candidate models when available. Model selection employed multimodel inference (Burnham and Anderson 2002), with well-supported models used to estimate mean abundance per site (λ) and detection probability (*p*).

Model Assumptions

N-mixture models rely on several key assumptions that can affect abundance inference:

1. Distributional assumptions: Poisson and binomial distributions accurately describe state and observation processes, respectively
2. Spatial independence: Abundance at each site is independent of abundance at other sites
3. Population closure: No births, deaths, immigration, or emigration occur between replicate surveys
4. No double-counting: Individual animals are not counted multiple times within a survey
5. Homogeneous detection: All individuals at a site have identical detection probability

Assumption 5 represents the greatest potential source of bias in our study system. Unmodeled heterogeneity in detection probability can lead to under- or overestimation of abundance and population size (Link et al. 2018), but model misspecification is difficult to detect empirically. Future surveys will explore capture-recapture alternatives that can better accommodate individual detection heterogeneity. For the current analysis, we assumed violations of these assumptions were sufficiently minor to not substantially bias abundance estimates.

Wetland survey design and analysis

Duck population data were collected via drone surveys across two wetlands randomly selected from a target population of six wetlands in the study area. The selected wetlands, Tombullen and Barren Box, were partially surveyed with coverage of 8.8% and 32.5% respectively. Drone surveys recorded counts for nine waterfowl species across the surveyed areas, with total area measurements available for both wetlands. The study design followed a two-stage sampling framework where wetlands were randomly selected without replacement (inclusion probability $\pi = 1/3$), and within-wetland sampling employed unequal probability area sampling.

Population estimation was done using a two-stage approach combining Bayesian inference for within-wetland scaling with Horvitz-Thompson estimation for population-level extrapolation. This combination of methods was chosen to address the dual sources of uncertainty inherent in the sampling design: model-based uncertainty resulting from partial area coverage within wetlands and the use of only a single sample, and design-based uncertainty arising from incomplete wetland sampling across the study area.

Stage 1: Bayesian Population Estimation

For each surveyed wetland *i* and species *j*, observed counts Y_{ij} were modelled using a Poisson likelihood conditional on species density λ_{ij} and surveyed area $A_{(sampled,i)}$, such that

$$Y_{ij} \mid \lambda_{ij} \sim Poisson(\lambda_{ij} \times A_{(sampled,i)})$$

Species densities were assigned weakly informative Gamma priors λ_{ij} ~ Gamma(0.5, 0.01) to allow for a wide range of plausible densities while maintaining proper posterior behavior. The conjugate Gamma-Poisson structure enabled efficient Markov Chain Monte Carlo sampling with analytical posterior distributions, i.e.

$$\lambda_{ij} \mid Y_{ij} \sim Gamma(0.5 + Y_{ij}, 0.01 + A_{(sampled,i)})$$

Total species populations within each wetland were estimated by scaling posterior density samples to the full wetland area, $N_{ij} = \lambda_{ij} \times A_{(total,i)}$. MCMC sampling employed 15,000 iterations with 3,000 burn-in, monitoring convergence via Geweke diagnostics and effective sample size criteria.

Stage 2: Horvitz-Thompson Population Extrapolation

Population estimates from Stage 1 were extrapolated to the six-wetland study area using the Horvitz-Thompson estimator. For each species j, the total population estimate across all wetlands was,

$$\hat{N}_{(h,HT)} = (1/\pi) \times \sum_{(i \in s)} \hat{N}_{ij} = 3 \times (\hat{N}_{1j} + \hat{N}_{2j})$$

where *s* denotes the set of surveyed wetlands and $\hat{N}_{ij}$ represents the posterior mean population estimate for species *j* in wetland *i* from Stage 1. This estimator is design-unbiased under the randomisation distribution, ensuring that expected values equal true population totals regardless of which specific wetlands were selected.

Uncertainty Quantification

Full uncertainty propagation was achieved through simulation-based methods applied to MCMC samples from Stage 1. For each posterior sample m, the Horvitz-Thompson transformation was applied to obtain $\hat{N}_{(j, HT)}^{m} = 3 \times (N_{1j}^{m} + N_{2j}^{m})$, creating a sample from the posterior distribution of total species populations. This approach incorporates correlation between wetland estimates and properly accounts for uncertainty from both estimation stages without requiring independence assumptions.

Species-specific credible intervals and summary statistics were computed directly from these transformed MCMC samples. Total duck population estimates were obtained by summing across species, with uncertainty measures calculated from the joint posterior distribution to account for potential correlations in species abundances.

Model Assumptions and Validation

The analysis assumed Poisson count distributions for observed duck numbers, perfect detection within surveyed areas, and representative sampling of wetland habitat by drone coverage. The Bayesian framework assumed that surveyed areas provided unbiased samples of wetland-wide duck densities. The Horvitz-Thompson extrapolation assumed that the random wetland selection protocol and independence of wetland population sizes was followed.

Model validation included assessing MCMC convergence through trace plots and formal diagnostics, evaluating posterior predictive distributions against observed data, and conducting sensitivity analysis with respect to prior specifications. Effective sample sizes exceeded 400 for all parameters, and Geweke diagnostics indicated adequate convergence (|z| < 1.96) for all species with sufficient observations.

Statistical Analysis

The analysis was conducted in R using the MCMCpack (Martin et al. 2011) and coda (Plummer et al. 2006) packages for Bayesian inference and MCMC diagnostics. Species-specific analyses were performed separately to provide detailed population breakdowns while maintaining computational efficiency. Results were compiled to provide both individual species estimates and total duck population estimates across the six-wetland study area, with comprehensive uncertainty quantification suitable for wildlife management decision-making.

Horvitz-Thompson Estimator

Single-Stage Horvitz-Thompson Estimator

A single-stage Horvitz-Thompson Estimator was used for medium, large, and extra-large dams, wastewater treatment ponds, and wetlands.

The Horvitz-Thompson estimator for the population total Y is given by:

$$\hat{Y}_{HT} = \sum_{i \in s} y_i/\pi_i$$

Where y_i is the observation for the i-th unit in the sample, π_i is the first-order inclusion probability (probability that unit i is included in the sample) and s is the sample.

Variance of Single-Stage HT Estimator

The variance of the Horvitz-Thompson estimator is:

$$Var(\hat{Y}_{HT}) = \sum_{i \in s} \sum_{j \in s} (\pi_{ij} - \pi_i \pi_j)/\pi_{ij} \quad y_i/\pi_i \quad y_j/\pi_j$$

where π_{ij} is the second-order inclusion probability (joint probability that both units i and j are included in the sample). When i = j, the term becomes $(1 - \pi_i)/\pi_i \quad (y_i^2)/(\pi_i^2)$, when i ≠ j, the coefficient $(\pi_{ij} - \pi_i \pi_j)/\pi_{ij}$ captures the covariance structure. The variance accounts for the dependency introduced by sampling without replacement.

The formula for the variance takes into account the joint inclusion probabilities of pairs of units in the sample. This accounts for the correlation introduced by sampling without replacement. The more correlated two units are (in terms of their inclusion probabilities), the greater their impact on the variance of the estimator.

Multi-Stage Horvitz-Thompson Estimator

A two-stage sampling design was used for small dams, where in Stage 1, a Primary Sampling Unit (PSU) block was selected without replacement. In Stage 2, small dams within the block (Secondary Sampling Units: SSUs) were randomly selected without replacement.

For a two-stage sampling design, the HT Estimator is

$$\hat{Y}_{HT} = \sum_{i \in s_1} \sum_{j \in s_{2i}} y_{ij}/(\pi_i \times \pi_{(j|i)})$$

where i = index for Primary Sampling Units (PSUs), j = index for Secondary Sampling Units (SSUs) within PSU *i*, π_i = probability of selecting PSU *i* in the first stage, $\pi_{(j|i)}$ = conditional probability of selecting SSU *j* given PSU *i* is selected, $\pi_{ij} = \pi_i \times \pi_{(j|i)}$ = overall inclusion probability for unit *j* in PSU *i*, y_{ij} = observation for unit *j* in PSU *i*, s_1 = sample of PSUs and s_{2i} = sample of SSUs within PSU *i*.

Variance of Two-Stage HT Estimator

The variance has three components:

$$Var(\hat{Y}_{HT}) = V_1 + V_2 + V_{12}$$

Where the between-PSU variance is $V_1 = \sum_{i \in U_1} \sum_{k \in U_1} (\pi_{ik} - \pi_i \pi_k)/\pi_{ik} \quad Y_i/\pi_i \quad Y_k/\pi_k$, within-PSU variance is $V_2 = \sum_{i \in U_1} 1/\pi_i \; Var(\hat{Y}_i \,|i\text{" selected"})$, and the interaction term is $V_{12} = \sum_{i \in U_1} \sum_{k \in U_1, k \neq i} (\pi_{ik} - \pi_i \pi_k)/\pi_{ik} \quad Cov(\hat{Y}_i, \hat{Y}_k)/(\pi_i \pi_k)$

Where $Y_i = \sum_{j \in U_{2i}} y_{ij}$ is the PSU total, $\hat{Y}_i$ is the HT estimator for PSU I, and U_1 = population of PSUs, U_{2i} = population of SSUs in PSU i.

Variance Estimation

For practical implementation, the variance is estimated by substituting sample values, giving

Single-Stage Variance Estimator

$$\widehat{Var}(\hat{Y}_{HT}) = \sum_{i \in s} \sum_{j \in s} \frac{\pi_{ij} - \pi_i \pi_j}{\pi_{ij}} \frac{y_i}{\pi_i} \frac{y_j}{\pi_j}$$

Two-Stage Variance Estimator

$$\widehat{Var}(\hat{Y}_{HT}) = \hat{V}_1 + \hat{V}_2$$

where $\hat{V}_1 = \sum_{i \in s_1} \sum_{k \in s_1} \frac{\pi_{ik} - \pi_i \pi_k}{\pi_{ik}} \frac{\hat{Y}_i}{\pi_i} \frac{\hat{Y}_k}{\pi_k}$

$$\hat{V}_2 = \sum_{i \in s_1} \frac{\widehat{Var}(\hat{Y}_i)}{\pi_i}$$

Results

The helicopter, ground and drone surveys represent a sub-sample of the available waterbodies that waterfowl occupy. To estimate total abundance for all waterfowl species, the observed numbers of waterfowl collected during both the aerial, drone and ground surveys are extrapolated to a known number of dams (separated into waterbody type and size classes) in the Riverina region (minus the estimated proportions of dry dams).

Small (0-4.9 ha) dams - We mapped 44,223 small dams in the Riverina region. During the July survey, we surveyed 461 from the helicopter (Figure 4). A total of 28.0% of small dams were dry at the time of the survey (n = 129 of the dams surveyed).

Medium dams (5-9.9 ha) - We mapped 167 medium dams in the Riverina region. During the survey, we conducted ground counts of 21 (Figure 5). A total of 38% of medium dams were dry at the time of the survey.

Large dams (10-49.9 ha) - We mapped 211 large irrigation dams in the Riverina region. During the survey, we conducted ground counts of 13 (Figure 5). A total of 46% of large dams were dry.

Extra-large dams (50+ ha) - We mapped 40 large irrigation dams in the Riverina region. During the survey, we conducted ground counts of 9 (Figure 5). A total of 60% of extra-large dams were dry.

Wastewater treatment ponds – We mapped 39 wastewater treatment ponds in the Riverina and surveyed 5 of these using a UAV, conducting ground counts on a further 15.

Small Dams

Survey Coverage and Data Summary

A total of 2592 observations were recorded across 461 small dams distributed among 12 survey blocks. After data cleaning and filtering for dry dams, 8668 observations from 332 dams were retained for analysis (Table 1). Of the small dams with water, 154 had no ducks.

Table 1 Summary of survey data by species, including number of detections on dams surveyed, detection rate, and mean counts per detection. (NA = not available).

Species	Dams Surveyed with Detections	Detection Rate	Mean Count	Max Count
Pacific Black Duck	62	0.19	4.12	206
Grey Teal	52	0.16	2.57	129
Australian Wood Duck	107	0.32	6.29	127
Blue-Winged Shoveler	1	0.003	0.0015	1
Chestnut Teal	0	NA	NA	NA
Hardhead	0	NA	NA	NA
Australian Shelduck	14	0.042	0.066	4

Pink-Eared Duck	1	0.003	0.0015	1
Plumed Whistling Duck	0	NA	NA	NA

Two-Stage Occupancy-Abundance Model Results

Model Selection

Model selection was conducted separately for occupancy and abundance components using Akaike's Information Criterion corrected for small sample sizes (AICc). For occupancy models, we fitted 20 candidate models incorporating spatial, habitat, and detection covariates (Table 2). Abundance models included 8 candidates with Poisson, negative binomial, and zero-inflated Poisson distributions (Table 3).

Table 2 Model selection results for occupancy component showing top models and cumulative AICc weight.

Species	Model	ΔAIC	AIC weight	Cumulative weight	Key covariates
Pacific Black Duck	ψ(Livestock)p(.)	0	0.194	0.194	Livestock pressure
Pacific Black Duck	ψ(.)p(.)	1	0.118	0.312	Intercept only
Grey Teal	ψ(Latitude)p(.)	0	0.261	0.261	Intercept only
Grey Teal	ψ(Spatial)p(.)	1.95	0.099	0.359	Spatial (lat/long)
Wood Duck	ψ(Trees)p(.)	0	0.673	0.673	Tree cover
Wood Duck	ψ(Trees+Water)p(.)	2	0.247	0.92	Tree cover
Blue-winged Shoveler	ψ(.)p(.)	0	0.347	0.347	Intercept only
Blue-winged Shoveler	ψ(.)p(Observer)	0.61	0.256	0.603	Observer effect
Chestnut Teal	No detections	NA	NA	NA	No detections
Hardhead	No detections	NA	NA	NA	No detections

Australian Shelduck	ψ(Habitat)p(.)	0	0.782	0.782	Habitat diversity
Australian Shelduck	ψ(.)p(.)	3.67	0.125	0.907	Intercept only
Pink-eared Duck	ψ(.)p(.)	0	0.347	0.347	Intercept only
Pink-eared Duck	ψ(.)p(Observer)	0.61	0.256	0.603	Observer effect
Plumed Whistling Duck	No detections	NA	NA	NA	No detections

Table 3 Model selection results for abundance component (conditional on presence).

Species	Model	ΔAIC	AIC weight	Overdispersion	Mixture type
Pacific Black Duck	lambda(Spatial)p(.)	0	0.818	Moderate	Negative Binomial
Pacific Black Duck	lambda(Global)p(.)	3.19	0.166	Moderate	Negative Binomial
Grey Teal	lambda(.)p(Observer)	0	0.355	Moderate	Negative Binomial
Grey Teal	lambda(Habitat)p(Observer)	1.28	0.187	Moderate	Negative Binomial
Wood Duck	lambda(Spatial)p(.)	0	0.537	Moderate	Negative Binomial
Wood Duck	lambda(Global)p(.)	1.91	0.207	Moderate	Negative Binomial
Blue-winged Shoveler	Observed mean	NA	1	NA	Unknown (not enough data)
Chestnut Teal	No detections	NA	NA	NA	No detections
Hardhead	No detections	NA	NA	NA	No detections

Australian Shelduck	Observed mean	NA	1	NA	Unknown (not enough data)
Pink-eared Duck	Observed mean	NA	1	NA	Unknown (not enough data)
Plumed Whistling Duck	No detections	NA	NA	NA	No detections

Parameter Estimates

Model-averaged parameter estimates revealed significant relationships between waterfowl occupancy/abundance and environmental covariates. Habitat diversity consistently emerged as a positive predictor of occupancy across species, while livestock pressure showed negative associations for most taxa.

Table 4 Model-averaged parameter estimates for key covariates in occupancy models.

Covariate	Species	Estimate	SE	95% CI	Interpretation
Habitat Diversity	Australian Shelduck	1.018	0.668	(-0.291, 2.327)	Strong positive effect of habitat diversity on occupancy
Livestock Pressure	Pacific Black Duck	-0.577	0.347	(-1.256, 0.103)	Moderate negative effect of livestock pressure on occupancy
Spatial (Latitude)	Grey Teal	-0.357	0.162	(-0.674, -0.039)	Weak negative effect of latitude on occupancy

Spatial covariates revealed contrasting abundance patterns between Pacific Black Duck and Wood Duck across the study region (Table 5). Pacific Black Duck showed a significant positive association with latitude ($\beta = 0.645 \pm 0.192$, 95% CI: 0.269-1.021), with abundance increasing substantially (91%) per standardised unit increase in latitude, suggesting higher densities in more northern areas of the study region./. In contrast, Wood Duck exhibited a significant negative relationship with longitude ($\beta = -0.344 \pm 0.114$, 95% CI: -0.567 to -0.121), with abundance declining by 29% per unit increase in longitude, indicating preference for more western locations. The latitude effect for Wood Duck and longitude effect for Pacific Black Duck were not statistically significant, as their confidence intervals included zero. These opposing spatial gradients suggest species-specific habitat preferences or environmental tolerances that vary across the landscape, with Pacific Black Duck favouring northern latitudes while Wood Duck shows stronger affinity for western portions of the study area. The substantial effect sizes for significant relationships (90.6% and 29.1% changes) indicate that spatial location is an important predictor of abundance patterns for these species, likely reflecting underlying environmental gradients or habitat quality variations across the survey region.

Table 5 Model-averaged parameter estimates for key covariates in abundance models.

Covariate	Species	Estimate	SE	95% CI	Multiplicative effect	Interpretation
Spatial (Latitude)	Pacific Black Duck	0.645	0.192	(0.269, 1.021)	1.906	Large increase (90.6%) in abundance per unit increase in latitude
Spatial (Latitude)	Wood Duck	-0.106	0.107	(-0.316, 0.104)	0.9	Moderate decrease (10%) in abundance per unit increase in latitude
Spatial (Longitude)	Wood Duck	-0.344	0.114	(-0.567, -0.121)	0.709	Substantial decrease (29.1%) in abundance per unit increase in longitude
Spatial (Longitude)	Pacific Black Duck	0.179	0.258	(-0.328, 0.685)	1.196	Moderate increase (19.6%) in abundance per unit increase in longitude

Model Diagnostics

Goodness-of-fit assessment using MacKenzie-Bailey tests indicated adequate model fit for Pacific Black Duck, Grey Teal and Australian Wood Duck (all $p > 0.05$) (Table 6). Species requiring sparse data protocols (Blue-winged Shoveler, Australian Shelduck, and Pink-eared Duck) showed acceptable model performance despite limited detections. Overdispersion statistics for abundance models ranged from 274 to 742, with all species showing evidence of overdispersion ($\varphi > 1.5$).

Table 6 Model diagnostic summary.

Species	MacKenzie-Bailey p-value	Overdispersion φ	Bootstrap Success Rate	Model Quality
Pacific Black Duck	0.41	473.15	1	Good
Grey Teal	0.63	742.46	1	Good
Blue-winged Shoveler	0.45	NA	1	Good
Chestnut Teal	NA	NA	NA	No detections
Hardhead	NA	NA	NA	No detections
Australian Shelduck	0.99	NA	1	Good

Pink-eared Duck	0.43	NA	1	Good
Plumed Whistling Duck	NA	NA	NA	No detections
Wood Duck	0.51	274.05	1	Good

Site-Level Predictions

Occupancy Probabilities

Model-averaged occupancy probabilities varied substantially among species and sites (Table 7). Mean occupancy probability was highest for Australian Wood Duck (0.376 ± (0.375, 0.376)) and lowest for Blue-winged Shoveler and Pink-eared Duck (0.03 ± (0.028, 0.032)). Spatial patterns in occupancy reflected habitat associations, with higher probabilities in areas with greater habitat diversity and reduced livestock disturbance.

Expected Abundance

Expected abundance per occupied site (abundance given presence) ranged from 1 individual for Blue-winged Shoveler and Pink-eared Duck to 67 for Australian Wood Duck (Table 7). Site-level expected abundance (occupancy × abundance given presence) was generally low, reflecting the patchy distribution of waterfowl across the survey area. The wide confidence interval for abundance similarly indicates that ducks are patchily distributed, with most dams having no ducks or few individuals and a small number having high numbers.

Table 7 Summary of site-level predictions with uncertainty bounds.

Species	Mean Occupancy	Occupancy 95% CI	Mean Abundance Given Presence	Abundance 95% CI	Sites with Positive Predictions
Pacific Black Duck	0.219	(0.219, 0.22)	39.86	(193.7, 32761.2)	288
Grey Teal	0.185	(0.185, 0.185)	61.48	(47.3, 226961.2)	288
Blue-winged Shoveler	0.03	(0.028, 0.032)	1	(3.1, 335.8)	288
Chestnut Teal	0	(0.001, 0.001)	NA	NA	NA
Hardhead	0	(0.001, 0.001)	NA	NA	NA
Australian Shelduck	0.064	(0.062, 0.065)	2.43	(27, 84.3)	288
Pink-eared Duck	0.03	(0.029, 0.032)	1	(4.8, 198.5)	288

Plumed Whistling Duck	0	(0, 0)	0	(0, 0)	0
Wood Duck	0.376	(0.375, 0.376)	66.57	(33.7, 1539831.5)	288

Population Estimates

Horvitz-Thompson Estimation

Population abundance was estimated using a two-stage Horvitz-Thompson estimator that accounted for the hierarchical sampling design (12 blocks sampled from 67 total blocks, with variable numbers of dams per block) (Table 8). The estimator incorporated model-averaged expected abundance predictions from the occupancy-abundance analysis, with appropriate variance propagation through bootstrap resampling.

Table 8 Horvitz-Thompson population abundance estimates

Species	Population estimate	SE	95% Confidence interval	Design effect
Pacific Black Duck	180168	2472	(175388, 185079)	6.038
Grey Teal	225804	2875.2	(220239, 231510)	5.818
Blue-winged Shoveler	597	7.73	(582, 612)	5.815
Chestnut Teal	0	0	NA	NA
Hardhead	0	0	NA	NA
Australian Shelduck	3401	50.42	(3303, 3501)	6.434
Pink-eared Duck	597	7.73	(582, 612)	5.815
Plumed Whistling Duck	0	0	NA	NA
Wood Duck	531548	7573.2	(516910, 546600)	6.232
Total	**942115**	**8469.5**		**6.025**

Population estimates were highest for Australian Wood Duck (531548 individuals, 95% CI: 516910, 546600), followed by Grey Teal (225804, 95% CI: 220239, 231510). The total waterfowl population using small dams across all eight target species was estimated at 942115 individuals.

Uncertainty Assessment

Bootstrap confidence intervals were successfully calculated for all species using 100 replicates. Log-transformation of confidence intervals prevented biologically unrealistic negative lower bounds while maintaining appropriate coverage probability.

Design effects ranged from 5.8 to 6.4, indicating that the two-stage sampling design generally improved precision relative to simple random sampling, particularly for species with strong spatial clustering. The effective sample size across all blocks was 6.0 dam surveys.

Variance Decomposition

Variance decomposition revealed that between-block variation accounted for an average of 99.9% of the total sampling variance, while within-block variation contributed 0.1% (Table 9). This pattern reflects the spatially heterogeneous distribution of waterfowl populations and justifies the stratified sampling approach employed.

Table 9 Variance decomposition for population estimates.

Species	Total Variance	Between-Block Variance	Within-Block Variance	% Between-Block
Pacific Black Duck	6E+06	6E+06	3969.7	99.9
Grey Teal	8E+06	8E+06	5807.3	99.9
Blue-winged Shoveler	59.72	59.67	0.05	99.9
Australian Shelduck	2542.2	2540.6	1.53	99.9
Pink-eared Duck	59.7	59.65	0.05	99.9
Wood Duck	6E+07	6E+07	38940	99.9

Summary

The integrated two-stage modelling approach successfully provided abundance estimates for six waterfowl species on small dams across the study region. Model selection identified habitat presence and the absence of livestock as primary drivers of occupancy patterns, while abundance given presence was most strongly associated with location and habitat. Population estimates demonstrate considerable variation among species. The analytical framework effectively handled sparse data through model averaging and shrinkage estimation, while log-transformed confidence intervals provided biologically realistic bounds on uncertainty.

Channels

Design and Sampling

Channel surveys were conducted across 67 blocks in the study area using a two-stage probability sampling design. From the total population of blocks, 12 blocks were randomly selected for survey (Stage 1 sampling), representing an 18% sampling fraction. One block contained no channels, so the final Stage 1 sample size was 11 blocks.

Within each selected block, channels were sampled systematically, taking into account accessibility and safety constraints. A total of 348 individual channel sections were surveyed, representing 274 km of channel habitat, out of an estimated 13,000 km of channel available across all blocks. Stage 2 sampling fractions varied by block, depending on the total channel length within the block and the proportion of the channels sampled. One block (block 52) was excluded from the final analysis because it contained no channels, leaving 11 blocks for population estimation.

Detection Probability and Occupancy Modelling

Model Performance and Selection

Two-stage occupancy-abundance models were successfully fitted for all four target species. Model convergence was achieved for all species observed (Pacific Black Duck, Grey Teal, Australian Wood Duck and Australian Shelduck). Blue-winged Shoveler, Pink-eared Duck, Hardhead, Plumed-whistling Duck and Chestnut Teal were not observed on the sampled channels.

Detection probabilities varied substantially among species (Table 10), ranging from 0.67 for Australian Shelduck to 0.87 for Pacific Black Duck. The overall mean detection probability across all species was 0.83 ± 0.038.

Table 10 *Detection probabilities, occupancy parameters, and model selection statistics from two-stage occupancy-abundance models. Detection probability represents the conditional probability of detecting the species during a single survey pass, given presence. SE = standard error.*

Species	N channels with detections	Detection probability	SE
Pacific Black Duck	49	0.87	0.04
Grey Teal	39	0.82	0.05
Australian Wood Duck	83	0.83	0.03
Australian Shelduck	6	0.67	0.18

Species-Specific Detection Results

Pacific Black Duck showed high detection probability (0.874 ± 0.038, indicating good detectability during helicopter surveys. Site occupancy was estimated at 0.161 ± 0.024. Grey Teal had high (0.818 ± 0.052) detection probability, indicating good detectability (0.818 ± 0.052), with occupancy of 0.137 ± 0.021. This species showed similar (0.818 vs. mean of 0.797) detection relative to other species. Australian Wood Duck exhibited high (0.831 ± 0.034) detection probability, indicating good detectability (0.831 ± 0.034), with 0.287 ± 0.043 site occupancy. Australian Shelduck demonstrated moderate to high (0.667 ± 0.181) detection probability, indicating good detectability (0.667 ± 0.181) and occupied 0.026 ± 0.004 of surveyed channel sections.

The variation in detection probabilities among species likely reflects differences in behavioural responses to helicopter surveys, body size, plumage conspicuousness, and habitat use patterns. Detection probabilities ranged from 0.667 to 0.874 (mean = 0.797), reflecting species-specific responses to helicopter disturbance, habitat openness, and behavioural characteristics during surveys.

Population-Level Abundance Estimates

Horvitz-Thompson Population Estimates

Total duck abundance across the study area was estimated at 524861 individuals (95% CI: 305827–743895; CV = 21.3%) using Horvitz-Thompson estimators (Table 11). This represents a density of 40.4 ducks per km of channel habitat (95% CI: 23.5 – 57.2).

Table 11 Population abundance estimates derived using Horvitz-Thompson estimators. Estimates account for the two-stage sampling design and incorporate finite population corrections. CV = coefficient of variation; CI = confidence interval.

Species	Abundance Estimate	SE	CV (%)	Lower 95% CI	Upper 95% CI
Black Duck	152935	53872	35.2	47346	258525
Grey Teal	115811	40795	35.2	35853	195768
Australian Shelduck	3463	1220	35.2	1072	5854
Wood Duck	252652	88998	35.2	78216	427088
Total	**524861**	**111752**	**21.3**	**305827**	**743895**

Species-Specific Population Results

Black Duck was the second most abundant species, with an estimated 152935 individuals (95% CI: 47346-258525), representing 29.1% of the total duck population. The species showed acceptable precision (CV = 35.2%). Grey Teal ranked third most in abundance with 115811 individuals (95% CI: 35853-195768; 22.1% of total). The coefficient of variation was 35.2%, indicating acceptable precision. Wood Duck population was estimated at 252652 individuals (95% CI: 78216-427088; 48.1% of total; CV = 35.2%). Australian Shelduck was the fourth most abundant species with 3463 individuals (95% CI: 1072-5854; 0.007% of total). The estimate had acceptable precision (CV = 35.2%).

Medium, Large, Extra-large and Wastewater Treatment Ponds

Data Summary and Survey Coverage

A total of 54 dams were surveyed using a double-observer protocol, with all sites meeting the criteria for complete observer coverage (two observers present). The final dataset included 486 site-species observations across nine waterfowl species: Pacific Black Duck, Chestnut Teal, Grey Teal, Hardhead, Pink-eared Duck, Australian Shelduck, Plumed-whistling Duck, Australian Wood Duck, and Blue-winged Shoveler.

Survey coverage varied across sites, with percentage surveyed ranging from 50 to 100% (mean = 97% ± 9.6% SD). All nine target species were successfully detected during surveys, though detection frequencies varied considerably among species.

Model Selection and Performance

N-mixture models were fitted to estimate abundance while accounting for imperfect detection using the double-observer data structure. Model selection was conducted using AICc, comparing models with different detection probability structures, including intercept-only, observer effects, coverage effects, and combined observer-coverage models. Poisson, negative binomial and zero-inflated Poisson error distributions were evaluated. Model convergence was achieved for all species, with successful abundance estimation completed for 9/9 species.

Detection Probability Estimates

Detection probabilities varied substantially among species, reflecting differences in behaviour, conspicuousness, and habitat preferences (Table 12). Combined detection probability (accounting for both observers) ranged from 0.355 for Australian Wood Duck to 0.922 for Hardhead (mean = 0.549 ± 0.173 SD).

Table 12 **Detection probability estimates by species and best supported model**

Species	Best Model (mixture)	Combined Detection Probability
Pacific Black Duck	Coverage (NB)	0.506
Grey Teal	Observer (NB)	0.506
Australian Wood Duck	Intercept (NB)	0.355
Blue-winged Shoveler	Intercept (NB)	0.49
Chestnut Teal	Observer (NB)	0.439
Hardhead	Observer (NB)	0.922
Australian Shelduck	Intercept (NB)	0.613
Pink-eared Duck	Observer (NB)	0.417
Plumed-whistling Duck	Intercept (NB)	0.696

Population Abundance Estimates

Horvitz-Thompson Abundance Estimation

Population abundance was estimated using a Horvitz-Thompson approach that corrected raw counts for imperfect detection and incomplete coverage. The abundance estimates represent the total population across all surveyed dam sites (Table 14).

Table 13 Population abundance estimates by species

Species	Sites with Detections	Total Observed (Max)	Detection probability	Raw Population Estimate	Coverage-Adjusted Estimate	Lower 95% CI	Upper 95% CI
Pacific Black Duck	49	3588	0.51	7090	8166	6311	11566
Grey Teal	49	15729	0.51	31110	32974	25482	46706
Australian Wood Duck	37	3405	0.35	9596	10213	7892	14465
Blue-winged Shoveler	11	224	0.49	457	475	367	672
Chestnut Teal	19	246	0.44	560	656	507	930
Hardhead	9	22	0.92	24	32	31	45

Australian Shelduck	15	737	0.61	1201	1242	960	1759
Pink-eared Duck	10	1598	0.42	3837	3849	2974	5452
Plumed-whistling Duck	5	839	0.70	1206	1561	1206	2211

The coverage-adjusted population estimate of 59167 birds represents a 7.4% increase over the raw population estimate of 55080 birds, demonstrating a moderate increase after correcting for both detection probability and incomplete survey coverage.

The 95% confidence intervals for coverage-adjusted population estimates ranged from ± 44.6 % for Hardhead to ± 64.4 % for Pacific Black Duck of the point estimate. The coefficient of variation (CV) averaged 15.8 % across species. Hardhead had the most precise estimate (CV = 11.4 %), while Pacific Black Duck showed the greatest uncertainty (CV = 16.4 %), although the difference was relatively small.

Species-Specific Patterns

Grey Teal was the most abundant species detected, with an estimated 32974 individuals (56% of the total population). Australian Wood Duck and Pacific Black Duck were the following most abundant species, comprising 17% and 13% of the total population, respectively.

Waterbody Type Analysis

Grey Teal were the most common species found on medium to extra-large dams and wastewater treatment ponds. Large waterbodies supported the most ducks (49%), followed by medium-sized dams (30%) and extra-large dams (16%).

Table 14 **Abundance by waterbody type**

Waterbody Type	Number of Sites (total)	Total Abundance	Lower 95% CI	Upper 95% CI	Dominant Species
Medium	20 (103)	90074	54787	148086	Grey Teal
Large	12 (113)	148275	98667	222825	Grey Teal
Extra-Large	6 (16)	47216	23167	96230	Grey Teal, Australian Wood Duck
STP	17 (39)	17834	11902	26723	Grey Teal

Model Validation and Assumptions

The double-observer approach enabled the validation of detection probability estimates through the comparison of observer-specific counts. Agreement between observers was good, with correlation coefficients ranging from 0.281 (Hardhead) to 1, with most correlation coefficients being equal to or greater than 0.95 across species (mean = 0.888)

Model assumptions were evaluated through:

Closure assumption: Surveys were conducted within minutes of each others observations to minimise population changes during sampling

Independence assumption: Double-observer protocol with independent counting minimised observer bias

Detection heterogeneity: Observer and coverage covariates accounted for the main sources of detection variability

Goodness-of-fit testing indicated good model performance for all species, with potential overdispersion addressed through negative binomial models where supported.

Wetlands

Drone surveys were successfully conducted across two randomly selected wetlands from the six-wetland study area. Tombullen Storage (total area 144.3 ha) was surveyed across 12.7 ha (8.8% coverage), while Barren Box Swamp (total area 964.1 ha) was surveyed across 313.1 ha (32.5% coverage). A total of 594 individual ducks were observed across five species (Pacific Black Duck, Grey Teal, Australian Wood Duck, Pink-eared Duck and Chestnut Teal), with 214 ducks recorded at Tombullen and 380 ducks at Barren Box.

Species composition varied between wetlands, with Pacific Black Duck being the most abundant species overall (n = 384), followed by Grey Teal (n = 135) and Australian Wood Duck (n = 39). Five species were observed in sufficient numbers (≥ 14 individuals) for statistical analysis, while four species (Hardhead, Blue-winged Shoveler, Australian Shelduck and Plumed-whistling Duck) were not observed on the wetlands and were excluded from population estimation due to insufficient data for reliable inference.

Stage 1: Bayesian Population Estimation

Bayesian analysis converged successfully for all species with adequate observations. MCMC diagnostics indicated satisfactory convergence, with Geweke statistics |z| < [1.96] for all parameters (maximum |z| = 1.274, and effective sample sizes exceeding 9,000 across all species and wetlands.

Individual Wetland Estimates

Tombullen wetland population was estimated at 2,441 ducks (95% credible interval: 2124–2783, SE: 167). The dominant species in Tombullen was Pacific Black Duck with 1743 individuals (95% CI: 1479–2031), followed by Grey Teal with 651 individuals (95% CI: 491-828).

Barren Box wetland supported an estimated 1171 ducks (95% CI: 1055-1292, SE: 60). Pacific Black Duck was most abundant with 712 individuals (95% CI: 622-808), while Grey Teal comprised 240 individuals (95% CI: 189-297). Barren Box estimates showed higher precision than Tombullen due to its greater sampling coverage.

Stage 2: Horvitz-Thompson Population Extrapolation

Application of the Horvitz-Thompson estimator (inclusion probability $\pi = 1/3$, multiplier = 3.0) to the Bayesian population estimates yielded a total study area population of 10845 ducks (95% CI: 9195-12705, SE: 532.8). This extrapolation indicates that approximately 7230 ducks reside in the four unsurveyed wetlands, based on the abundance patterns observed in the two surveyed sites.

Species-Specific Population Estimates

Pacific Black Duck dominated the wetland area with an estimated 7366 individuals across all six wetlands (95% CI: 6512-8274, SE: 447), comprising 67.9% of the total duck population on wetlands. Grey Teal was the second most abundant species with 2672 individuals (95% CI: 2174-3231, SE: 269.8), representing 24.6% of the total population.

The remaining species showed the following population estimates: Australian Wood Duck 366 individuals (95% CI: 259-494, 3.4% of total); Chestnut Teal 3.7 individuals (95% CI: 177-490, 2.8% of total); and Pink-eared Duck 134 individuals (95% CI: 73-216, 1.2% of total).

Precision Assessment and Uncertainty Analysis

Population estimate precision varied considerably among species, reflecting differences in abundance levels and associated sampling uncertainty. Coefficients of variation ranged from 6.1% for Pacific Black Duck to 27.3% for Pink-eared Duck. Species with higher observed counts generally showed better precision in final population estimates.

Uncertainty decomposition revealed that Stage 1 (within-wetland Bayesian estimation) contributed 26% of the total variance, while Stage 2 (Horvitz-Thompson extrapolation) contributed 74% of the variance in final population estimates. This indicates that between-wetland extrapolation uncertainty was the dominant source of overall estimation uncertainty.

Model Validation

Posterior predictive checks indicated excellent model fit, with 100% of observed species counts falling within 95% posterior predictive intervals. No systematic patterns in residuals were observed, suggesting that model assumptions were reasonably satisfied. Sensitivity analysis with alternative prior specifications ([Gamma(0.1, 0.01)] and [Gamma(1.0, 0.1)]) produced similar results (population estimates within 17.4% of primary analysis), indicating moderate sensitivity to prior choice. The two species that showed the most sensitivity to prior choice were the Australian Wood Duck and the Chestnut Teal. In comparison, Pacific Black Duck and Gery Teal were robust to prior choice.

The final population estimate of 10845 ducks (95% CI: 9195-12705) across the six-wetland study area provides statistically rigorous population estimates for wetland management planning.

Table 15 Estimated abundance of nine species of waterfowl in the NSW Riverina region, May -July 2025. Small dams and channels were surveyed by helicopter, and estimates were made using two-stage occupancy-abundance models. Medium, large, and extra-large dams, as well as wastewater treatment ponds, were surveyed using either a drone or ground counts. An N-mixture model approach was used for ground counts. Surveys of the wetlands were conducted using a drone, and observations were analysed using a Bayesian approach (CI = confidence interval or credible interval for Bayesian analyses, and SE= standard error).

Species	Total	SE	Lower 95% CI	Upper 95% CI
Small dams				
Pacific Black Duck	180168	2471.96	175388	185079
Grey Teal	225804	2875.21	220239	231510
Australian Wood Duck	531548	7573.18	516910	546600
Blue-Winged Shoveler	597	7.73	582	612
Chestnut Teal	0	0	0	0
Hardhead	0	0	0	0
Australian Shelduck	3401	50.42	3303	3501
Pink-Eared Duck	597	7.73	582	612
Plumed Whistling Duck	0	0.0	0	0
Channels				
Pacific Black Duck	152935	53872.2	47346	258525
Grey Teal	115811	40794.9	35853	195768
Australian Wood Duck	252652	88997.9	78216	427088
Blue-Winged Shoveler	0	0.0	0	0
Chestnut Teal	0	0.0	0	0
Hardhead	0	0.0	0	0
Australian Shelduck	3463	1219.9	1072	5854
Pink-Eared Duck	0	0.0	0	0
Plumed Whistling Duck	0	0.0	0	0
Extra-Large Dams				

Species	Total	SE	Lower 95% CI	Upper 95% CI
Pacific Black Duck	5819	3640.9	1707	19837
Grey Teal	17267	6487.7	8267	36061
Australian Wood Duck	14339	4643.7	7600	27051
Blue-Winged Shoveler	203	155.2	45	911
Chestnut Teal	256	202.4	54	1207
Hardhead	0	0	0	0
Australian Shelduck	883	697.8	187	4158
Pink-Eared Duck	8451	6248.6	1983	36000
Plumed Whistling Duck	0	0	0	0
Large Dams				
Pacific Black Duck	26753	8015.6	14871	48129
Grey Teal	84260	28153.2	43774	162192
Australian Wood Duck	16715	7210.9	7176	38934
Blue-Winged Shoveler	3277	1563.6	1286	8350
Chestnut Teal	1620	1285.1	342	7672
Hardhead	188	126.4	50	703
Australian Shelduck	6535	4336.3	1780	23993
Pink-Eared Duck	5528	2983	1919	15919
Plumed Whistling Duck	3399	3213.9	533	21687
Medium Dams				
Pacific Black Duck	10264	2136.6	6825	15435
Grey Teal	69432	21164.2	38203	126190
Australian Wood Duck	8436	3544.4	3702	19221

Species	Total	SE	Lower 95% CI	Upper 95% CI
Blue-Winged Shoveler	180	128.3	44	729
Chestnut Teal	330	118.2	163	666
Hardhead	31	13.6	13	74
Australian Shelduck	989	523.2	350	2790
Pink-Eared Duck	407	355.6	73	2259
Plumed Whistling Duck	5	4.6	0	32
Wastewater Treatment Ponds				
Pacific Black Duck	2631	842	1405	4927
Grey Teal	9507	2022.9	6265	14427
Australian Wood Duck	2014	567.9	1159	3500
Blue-Winged Shoveler	37	24.2	10	135
Chestnut Teal	794	390.8	302	2084
Hardhead	11	5.5	4	30
Australian Shelduck	55	31.2	18	168
Pink-Eared Duck	37	17.7	14	95
Plumed Whistling Duck	2748	2038.6	642	11763
Wetlands				
Pacific Black Duck	7366	447	6512	8274
Grey Teal	2672	269.8	2174	3231
Australian Wood Duck	366	59.5	259	
Blue-Winged Shoveler	0	0.0	0	0

Species	Total	SE	Lower 95% CI	Upper 95% CI
Chestnut Teal	307	79.8	177	490
Hardhead	0	0.0	0	0
Australian Shelduck	0	0.0	0	0
Pink-Eared Duck	134	36.4	73	216
Plumed Whistling Duck	0	0.0	0	0

Table 16 Estimated total abundance for the Riverina region of NSW, May-July 2025. Recommended quotas are based on a maximum allowable harvest of 10% of the population size at the time of the survey.

Species	Total abundance	Quota
Pacific Black Duck	385936	38594
Grey Teal	524753	52475
Australian Wood Duck	826070	82607
Blue-Winged Shoveler	4294	429
Chestnut Teal	3307	331
Hardhead	230	23
Australian Shelduck	15326	1533
Pink-Eared Duck	15154	1515
Plumed Whistling Duck	6152	615

Recommended quotas for waterfowl in NSW

The extensive survey of waterfowl populations in the Riveria region represents the best scientific data currently available to calculate annual quotas. The quotas determine the maximum number of waterfowl that can be sustainably harvested in a year. We recommend setting low-risk, conservative quotas for all duck species hunted in NSW, given the uncertainties in factors influencing duck population dynamics and the effects of harvesting on duck population survival. Quotas may be revised if further information becomes available.

We recommend setting a management quota at 10% of the estimated population size for species whose population dynamics respond predictably to climatic changes and are in high abundance, such as the Pacific Black Duck, Grey Teal, and Australian Wood Duck. We advise that reactive quotas be set for the remaining species (Pink-eared Ducks, Plumed Whistling-Ducks, Chestnut Teal, Hardhead, and Australian Shelduck) because previous modelling has shown that their population dynamics do not respond predictably to changes in climate or occur only in low abundance throughout the Riverina.

Management quotas are established for species where there is a lower risk of exploitation. These ducks have relatively large populations and are widely distributed, and some monitoring data suggest that their populations respond predictably to environmental changes. Reactive quotas are recommended for species with a higher risk of overharvesting due to smaller populations and/or uncertain dynamics. Unless a property is either (1) vulnerable to damage from certain species or (2) able to demonstrate that damage has happened or is highly likely to do so, we advise against allocation of quota from species with reactive quota.

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