Response models for waterbird species of the south-east of South Australia

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Respect and reconciliation

Aboriginal people are the First Peoples and Nations of South Australia. The Coorong, connected waters and surrounding lands have sustained unique First Nations cultures since time immemorial.

The Goyder Institute for Water Research acknowledges the range of First Nations' rights, interests and obligations for the Coorong and connected waterways and the cultural connections that exist between Ngarrindjeri Nations and First Nations of the South East peoples across the region and seeks to support their equitable engagement.

Aboriginal peoples' spiritual, social, cultural and economic practices come from their lands and waters, and they continue to maintain their cultural heritage, economies, languages and laws which are of ongoing importance.

Warning: Aboriginal readers should be aware that this report may contain names of people and quotes from people who have since passed away.

Preamble

The purpose of this report is to contribute to informing how management of water levels, vegetation and water chemistry in priority wetlands and the broader landscape of the Coorong and South East regions of South Australia is expected to influence the waterbird assemblage.

The report underwent a review process in accordance with the publication protocols of the Goyder Institute for Water Research. This process included a 'fit for purpose' review undertaken by the South Australian Department for Environment and Water (DEW); two external peer reviews; and a review prior to final submission by the Goyder Institute Research Advisory Committee (RAC). Following endorsement for submission by the Goyder Institute RAC, the authors corrected a small coding error which had affected the calculation of proportional water coverage in the broader wetlands network. Relevant content was revised and subsequently approved for submission by the Chair of the Goyder Institute RAC and DEW.

Executive summary

The south-east of South Australia holds most of the state's wetlands, including five Wetlands of International Importance under the Ramsar Convention. Amongst these wetlands, the Coorong, Lower Lakes (Alexandrina and Albert) and Murray Mouth (CLLMM) hosts a diverse and abundant waterbird community, a key factor in the recognition of its international importance as a Ramsar Site. This site is also one of the most important drought refuges for waterbirds in the Murray–Darling Basin. Anthropogenic modification of the natural flow regime to the Coorong during the last few decades, together with other environmental stressors such as drought and filamentous algal blooms, have significantly degraded the condition of this wetland system, particularly in the Coorong South Lagoon, and reduced its quality as waterbird habitat. This long-term condition decline is associated with significant reductions in abundances of many waterbird species, particularly fairy tern and migratory shorebirds. Given waterbirds are highly mobile and move between the Coorong and wetlands in the broader landscape of the south-east of South Australia, appropriate management of the latter could produce additional habitat for waterbirds, increasing the resilience of waterbird populations that use the Coorong.

Appropriate management to sustain a network of wetlands in the broader regional landscape that supports waterbirds requires a good understanding of how waterbird distribution and abundance respond to environmental conditions, such as water level and salinity. However, waterbird responses in this system remain poorly understood. This technical report aims to model waterbird occupancy (i.e. probability of presence) and abundance (when possible, based on available data) given abiotic drivers (e.g. water level and salinity) and vegetation to inform appropriate management of wetlands in the broader regional landscape to support waterbird populations that use the Coorong. To achieve this, we developed quantitative waterbird response models at two different spatial scales:

- **Priority landscape wetlands** identified by the South Australian Government based on their high potential to support 10 key waterbird species (KWS) dependent on the Coorong South Lagoon, including two piscivorous (Australian pelican, fairy tern), two waterfowl (black swan, chestnut teal) and six shorebirds (common greenshank, curlew sandpiper, red-capped plover, red-necked stint, red-necked avocet, sharp-tailed sandpiper). These priority wetlands included Tolderol Game Reserve, Teringie Wetlands, Waltowa Wetlands, and Lake Hawdon North, where we developed response models for some KWS. Notably, however, comprehensive waterbird monitoring has only been undertaken at the Tolderol Game Reserve and response models for the remaining three priority wetlands were based on very limited datasets.
- **Broader landscape wetlands.** Given that the south-east of South Australia holds more than 20,000 wetlands and 119 waterbird species have been recorded in the CLLMM site, we extended the response models to include as many waterbird species and wetlands as permitted by the available data. We also conducted waterbird counts at 31 wetlands in the South East region to assess the availability of shorebird habitat and to make appropriate modelling decisions based on variation in counts and detections (e.g. using presence/absence data as a response instead of abundance).

Waterbird data were collated from multiple historical datasets. Abiotic drivers included on-ground measurements of salinity and turbidity (only available for Tolderol Game Reserve), and estimations from satellite images of the proportion of the wetland covered by water, the area of available habitat within preferred foraging depth, and the proportion of the wetland covered by vegetation.

Priority landscape wetland Key Waterbird Species response models

Tolderol Game Reserve: we used a historical dataset of waterbird counts and water quality measurements from 2009-2020 to model the presence/absence and abundance of seven KWS in response to habitat conditions. In general, the relationships between species occurrence/abundance and environmental predictor variables followed expected patterns; for example, we identified positive relationships between the occurrence and abundance of some shorebird species and the extent of habitat at their preferred foraging depth. KWS diverged in their response to environmental variables, highlighting the importance of specifying clear management goals as it is unlikely that a single management strategy would benefit the entire suite of KWS.

Teringie and Waltowa Wetlands: Historical waterbird survey data were sparse and collected since 2015 at Teringie and 2012 at Waltowa. Only five KWS had sufficient detections to attempt abundance modelling, which explored the influence of proportional water coverage and the area of available habitat within the preferred foraging depth of each species on abundance. Models estimated that the abundance of two shorebirds (sharp-tailed sandpiper and red-capped plover) was highest at low levels of proportional water coverage in these wetlands, while the reverse was true for black swan, and red-necked stint abundance was unrelated to inundation (at least over the range of inundation levels that occurred over the modelled period).

Lake Hawdon North: there were insufficient monitoring data available to develop response models for KWS. Therefore, we used available data from the adjacent Lake Hawdon South (nine waterbird surveys conducted between 2004 and 2020) to develop and compare simple abundance models for six KWS. Models supported a positive relationship between shorebird abundance and the area of available habitat within a 0-10 cm depth range. Consistent with the previous restoration feasibility assessment for Lake Hawdon North, predictions of shorebird abundance were substantially higher under an infrastructure scenario that maintained water levels in Lake Hawdon North throughout spring and summer than for a current no-infrastructure scenario.

Broader landscape waterbird response models

We developed response models for 63 waterbird species using semi-structured citizen science data collated from eBird and Birdata. We used 12,576 checklists collected between 1999 and 2020 within 986 different wetlands to model encounter rates (i.e. presence/absence data) of each species, a proxy of occupancy, as a function of proportional water coverage, vegetation cover, distance to the coast and the availability of surface water across Australia. Satellite imagery revealed that most of the modelled wetlands were dry during the non-breeding season of shorebirds, almost certainly limiting the amount of suitable habitat for migratory shorebirds across the region. Over the range of proportional water coverage that occurred during the modelled period, models estimated a weak relationship between encounter rates of shorebirds and proportional water coverage. In contrast, most waterfowl and piscivorous species were maximised at intermediate proportional water coverage, suggesting that maintaining intermediate water levels throughout summer would benefit these species and produce useful habitat for shorebirds. Our models also provided evidence of higher occurrence of waterfowl, piscivores and rails in wetlands with higher wetland vegetation and saltmarsh coverage, while occurrence of some shorebirds was negatively associated with the coverage of woody, non-woody, mangrove and wetland vegetation. Encounter rates of many waterbird species were generally higher across the region when the Australian continent was drier, supporting the use of the south-east as a drought refuge.

Future recommendations to inform management

Our key findings indicate that:

- maintaining water levels to increase availability of shallow habitat across the region during summer is needed to provide more suitable habitat for migratory shorebirds;
- intermediate proportional water coverage across the region during summer is likely to benefit many waterbird species;
- vegetation control of ‘terrestrialised’ wetlands would likely produce more useful habitat for migratory shorebirds, but works would need to consider fine-scale habitat variation within wetlands and vegetation type;
- clear management goals are needed as it is unlikely the implementation of a single management strategy would benefit all species;
- the paucity of consistent waterbird monitoring severely limits current ability to develop models that provide more conclusive and specific management recommendations.

Managers can use the models developed in this technical report to test the outcome for waterbirds of different water allocation scenarios at a wetland-specific level (for the modelled wetlands) or at a regional level. Further, we provide detailed recommendations for future waterbird monitoring and identify opportunities to better understand waterbird responses to changes in the biophysical characteristics of priority wetlands.

Acknowledgments

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We also thank our Project Advisory Committee for their expert input into this research project. Comments from Goyder Institute and Department for Environment and Water and two external peer reviewers helped to improve this report.

Benthic sampling at Lake Hawdon North was undertaken in September 2021 and November 2021 as part of a broader project led by NGT Consulting, and is described in Appendix A. Refer to Taylor et al. (2022) for full details.

1 Introduction

1.1 Background

The abundance and diversity of migratory and non-migratory waterbirds of the Coorong, Lower Lakes (Alexandrina and Albert) and Murray Mouth (CLLMM) were the key factors in the recognition of the site as a Wetland of International Importance under the Ramsar Convention in 1985 (O'Connor et al. 2012). One hundred and nineteen species of birds reliant on wetland habitat have been recorded in the CLLMM site (Ecological Associates 2010). The Coorong is regarded as one of the most important drought refuges for waterbirds in the Murray–Darling Basin. It hosted 90% of the waterbirds in the basin during the Millennium Drought (Kingsford and Porter 2008), which substantially impacted the Coorong over the period 2001-2010. Anthropogenic modification of the Coorong's natural hydrological regime from basin-wide water allocation, flow-regime modification and additional climate-change effects have led to rapid declines of water levels during spring and summer, along with periods of extreme salinity in the Coorong South Lagoon (> 100 g/L) and/or excessive phytoplankton and filamentous algal growth (Ye et al. 2020, Paton et al. 2020). Poor conditions in the Coorong might diminish its function as a drought refuge and threaten the viability of waterbird populations if alternative suitable habitat is not available.

Waterbirds are highly mobile and their movement patterns vary significantly between species and individuals. For instance, grey teal *Anas gracilis* can move thousands of kilometres over the course of a year in response to local changes in food resources or to access suitable breeding conditions (Roshier et al. 2006). Some migratory shorebird species are coastal specialists that rarely move inland, while others including those found in highest numbers in the Coorong (e.g. red-necked stint *Calidris ruficollis*, sharp-tailed sandpiper *Calidris acuminata*, curlew sandpiper *Calidris ferruginea* and common greenshank *Tringa nebularia*) are more generalist in their habitat use and regularly move between coastal areas and inland wetlands depending on conditions (Higgins and Davies 1996). Recent tracking studies have confirmed that the waterbirds of the Coorong have the ability to move between wetlands (Mott et al. 2022). Hence, it is vital to consider how wetlands in the broader landscape might be managed to provide complementary or alternative habitat for waterbird species that also use the Coorong, particularly while conditions in the Coorong South Lagoon remain poor (Hartvigsen-Power et al. 2019).

Migratory shorebirds are a group of particular concern. Many migratory species of the East Asian–Australasian flyway (EAAF) are affected by rapid population decline, including some species that only occur in Australia over the northern hemisphere winter (Clemens et al. 2019, Studds et al. 2017, Clemens et al. 2016). The CLLMM provides critical habitat for a suite of migratory shorebird species (Clemens et al. 2019), some of which are threatened and formally listed under national and/or state legislation (e.g. curlew sandpiper; O'Connor et al. 2012, Paton et al. 2010). Degradation of foraging habitat in the Coorong has probably contributed to a decline in the local abundance of migratory shorebirds, including the red-necked stint, curlew sandpiper, sharp-tailed sandpiper and common greenshank, whose numbers have remained low compared to their 2000-2015 median (Paton et al. 2020, Prowse 2020). Therefore, management of wetlands in the broader landscape to provide suitable habitat and support the waterbird populations of the Coorong may be particularly important for migratory shorebirds (Brookes et al. 2018).

Previous studies have identified wetlands beyond the Coorong that have the potential to improve support for the waterbird populations of the Coorong through additional evidence-based management. For example, Hartvigsen-Power et al. (2019) detailed the ability of the Tolderol Game Reserve (GR) to provide suitable habitat for some key waterbird species (KWS) affected by deteriorated conditions in the Coorong South Lagoon. The *Lake Hawdon Migratory Shorebird Site Action Plan* suggested that Lake Hawdon North, which receives water from local runoff, groundwater discharge from the regional unconfined aquifer and Drain L catchment, and some overflow from Lake Hawdon South in most years, could better support migratory shorebirds if it did not dry out before the critical pre-migration period in late summer (Ferenczi et al. 2020). Hunt et al. (2019) evaluated 30 wetlands in south-east South Australia and identified four of them as having the highest potential to provide habitat for KWS impacted by deteriorated conditions in the Coorong South Lagoon: Tolderol GR and Teringie South Basin in the Lower Lakes region, and Lake Hawdon North and Lake Frome Conservation Park in the Limestone Coast region. Following this recommendation, feasibility assessments were undertaken for Tolderol GR, Teringie Wetlands, Lake Hawdon North and Waltowa Wetlands (Mason and Hardy 2020a, 2020b, 2020c, Taylor 2020), the latter of which also scored highly in the multi-criteria analysis subject to additional management (Hunt et al. 2019). These assessments considered various additional management actions, including increased ability to control water levels at all four wetlands.

Appropriate management of conditions in wetlands beyond the Coorong to help maintain resilient waterbird populations requires an accurate understanding of how waterbird distribution and abundance respond to environmental conditions, including water levels, salinities and prey abundance. Prior to our study, there were limited studies conducted within wetlands of the broader regional landscape, and comprehensive statistical modelling of the relationships between waterbird abundance and abiotic drivers had not been undertaken.

The Australian and South Australian Governments' *Healthy Coorong, Healthy Basin* (HCHB) Program aims to restore the ecological character of the Coorong by providing evidence-based solutions to current and future threats. The program outlines a range of actions, including on-ground works, management tools, research, trials and investigations, to be undertaken between 2019 and 2024. These actions were informed by the recommendations of an independent expert panel in 2018 (Brookes et al. 2018). Within the HCHB Program, the HCHB Scientific Trials and Investigations Project (T&I) Component 4 Waterbirds aims to maintain viable populations of waterbirds that use the Coorong and to inform management actions to support habitat requirements of waterbirds in the Coorong and the broader regional landscape. In this technical report, we present waterbird response models for priority landscape wetlands (Tolderol GR, Teringie, Waltowa and Lake Hawdon North) and wetlands within the broader regional landscape (986 wetlands within the South East and lower Murray Regions). These models make use of the best available waterbird monitoring data supplied by relevant site-management agencies and citizen science databases (Birdata https://birdata.birdlife.org.au/ and eBird https://ebird.org/home), and environmental covariates derived from satellite imagery.

1.2 Aims

The aim of HCHB T&I Component 4 Waterbirds *Activity 4.3 - Key waterbird species response models for priority landscape wetlands* was to develop response models for ten KWS of the Coorong, chosen because they are representative of the ecology of the Coorong waterbird assemblage, and because many have undergone demonstrable declines in the Coorong South Lagoon since the year 2000 (Prowse 2020). These KWS comprise six shorebirds (common greenshank; curlew sandpiper; red-capped plover *Charadrius ruficapillus*; red-necked stint; red-necked avocet *Recurvirostra novaehollandiae*; sharp-tailed sandpiper), two waterfowl (black swan *Cygnus atratus*; chestnut teal *Anas castanea*), and two piscivorous species (Australian pelican *Pelecanus conspicillatus*; fairy tern *Sterna nereis nereis*).

The work undertaken as part of task 3 of Component 4 Waterbirds aimed to:

- model waterbird occupancy (i.e. probability of presence) and abundance given abiotic drivers (e.g. water level and salinity); and
- use model outputs to inform appropriate management of wetlands in the broader regional landscape to support waterbird populations that use the Coorong.

To achieve the above aims, we developed quantitative waterbird response models at two different spatial scales:

1. **Priority landscape wetlands:** models for the KWS were developed for Tolderol GR, Teringie wetland, Waltowa wetland and Lake Hawdon North. We evaluated the predictive capacity of the models and, in the case of Lake Hawdon North, predicted waterbird abundance under different management scenarios.

2. **Broader landscape wetlands:** models for all possible waterbird species, including as many wetlands as permitted by available data, were developed to better represent the more than 20,000 wetlands present in south-east South Australia and the 119 waterbird species recorded in the Coorong. We also conducted waterbird counts in wetlands of the South East region in January 2022 to assess the availability of shorebird habitat and to make appropriate modelling decisions based on variation in counts and detections.

This project component contributed to informing how management of water levels, vegetation and water chemistry in priority wetlands and the broader landscape is expected to influence the waterbird assemblage. Results help to contextualise management of the Coorong in the broader landscape and inform how wetlands outside the Coorong could be managed to support waterbird species that use the Coorong.

This final technical report presents findings of work completed between January 2021 and April 2022.

2 Methods

We note that in this technical report, salinity is reported in µS/cm (i.e. microsiemens per centimetre), while in other technical reports of Component 4 Waterbirds, salinity is reported in ppt (i.e. parts per thousand). This discrepancy results from salinity being measured in µS/cm in the datasets on wetlands beyond the Coorong provided by data custodians. An approximate conversion from µS/cm to ppt can be obtained by multiplying the measurement in µS/cm by 0.00055. However, since this conversion is imperfect, we reported salinity in the units provided by the data custodians. Refer to 'Measuring Salinity' in the glossary for more details.

2.1 Priority landscape wetlands for Key Waterbird Species of the Coorong

2.1.1 Study area

Tolderol Game Reserve

Tolderol GR is a wetland complex on the north-western shore of Lake Alexandrina and falls within the Coorong and Lakes Alexandrina and Albert wetland Ramsar site (Figure 1). The reserve is Crown land managed by the Department for Environment and Water (DEW) under the guidance of the Tolderol Game Reserve Working Group, a voluntary, community-based working group, convened by the Murraylands and Riverland Landscape Board and National Parks and Wildlife Service South Australia. The reserve consists of a series of 21 artificial basins and interconnecting channels over 202 ha, which are managed via a pump that pumps water into the site from Lake Alexandrina (Hartvigsen-Power et al. 2019). Tolderol GR was not watered between 2006 and 2013 because of reduced water availability during the Millennium Drought. Watering to a subset of the basins re-commenced in late 2014 as part of the water for the environment allocation in the Murray-Darling Basin Plan, and annual volumes of water delivery have since ranged from 361–1,124 megalitres (Hartvigsen-Power et al. 2019). Limitations in water delivery at Tolderol GR have meant that not all basins have received water since the re-commencement of pumping at the site.

Teringie Wetlands

Teringie Wetlands is a wetland complex on the eastern side of Lake Alexandrina, located outside of the Coorong and Lakes Alexandrina and Albert Ramsar Wetland site boundary (Figure 1). The land is owned by the Aboriginal Lands Trust and leased to the Raukkan Community. It consists of isolated saline depressions, ephemeral wetlands and one permanent wetland with an area of 490 ha. Its three key waterbodies include: the North Basin, which is now permanently connected to Lake Alexandrina (since the end of the Millennium Drought in 2010); the South Basin, which is mostly disconnected but receives over-bank splash during times of high water levels and/or pumping of water for the environment; and Teringie East, which is hypersaline and permanently disconnected with some occasional freshwater input from rainfall pooling and groundwater sources (Mason and Hardy 2020b). While the site has been severely degraded from grazing and weed infestation, the Murraylands and Riverland Landscape Board Wetlands and Floodplains Program, Ngopamuldi Corporation and Raukkan Community have worked together for approximately the last 15 years to improve its condition, but without permanent infrastructure to manipulate water levels (Mason and Hardy 2020b).

Waltowa Wetlands

Waltowa Wetlands is a shallow wetland complex on the eastern shore of Lake Albert, located outside of the Coorong and Lakes Alexandrina and Albert Ramsar Wetland site boundary, largely on private freehold land with a small part on Coorong District Council land (Figure 1). It is currently managed by Coorong Tatiara Local Action Planning Committee, Murraylands and Riverland Landscape Board Wetlands and Floodplains Program and landholders. It consists of one large wetland with an area of ~150 ha that was semi-permanent until it became separated from Lake Albert by a causeway, causing elevated salinity which, in conjunction with impacts from ongoing pastoral activity, drought and poor management, has resulted in significant degradation of its condition (Mason and Hardy 2020c). The current agreement with land holders is for spring/summer inundation to a maximum level of +0.3 m Australian Height Datum (AHD; Mason and Hardy 2020c).

Lake Hawdon North

Lake Hawdon North is a seasonally inundated wetland located about 100 km south of the Coorong South Lagoon, outside the Coorong and Lakes Alexandrina and Albert Ramsar Wetland site boundary (Figure 1). It is on unallocated Crown Land with livestock grazing permitted under annual licences, and also includes a 237 ha mining lease for dolomitic limestone (Ferenczi et al. 2020). It has an area of 2,475 ha which, combined with Lake Hawdon South (3,298 ha), makes it one of the largest wetland systems in the region immediately surrounding the Coorong (Taylor 2020). It receives surface water inflows from the Lake Hawdon Connecting Drain (via Lake Hawdon South, an adjacent Conservation Park), Drain L catchment (which currently bisects the wetland east-west), and a network of smaller local drains from adjoining properties as well as seasonal groundwater discharge from the unconfined aquifer (Harding 2018). The wetland typically reaches a maximum depth of 0.5 m when water levels peak in late winter (Taylor 2020).

The bed of Lake Hawdon North is lower than that of Lake Hawdon South which suggests that, before modification of the surface-water regime, Lake Hawdon North would have remained wet for longer into spring and summer (Taylor 2020). Due to the construction of a major drainage line, however, Lake Hawdon North is now the first of the two waterbodies to dry out each summer. As a result, it is likely that the number of waterbirds supported during summers at Lake Hawdon North has declined substantially. This may be especially true for migratory shorebirds, which are recorded in greatest numbers in Australia from October to February, corresponding to their core non-breeding season. To restore a water regime that enables water cover to persist into summer, the construction of a flow regulator at the major bisecting drain (Drain L) on the wetland's western side has been proposed (Taylor 2020). Hydrological modelling under the current baseline scenario and hypothetical ‘target’ water regime achieved through an appropriate regulator has already been conducted and is reported in Taylor (2020).

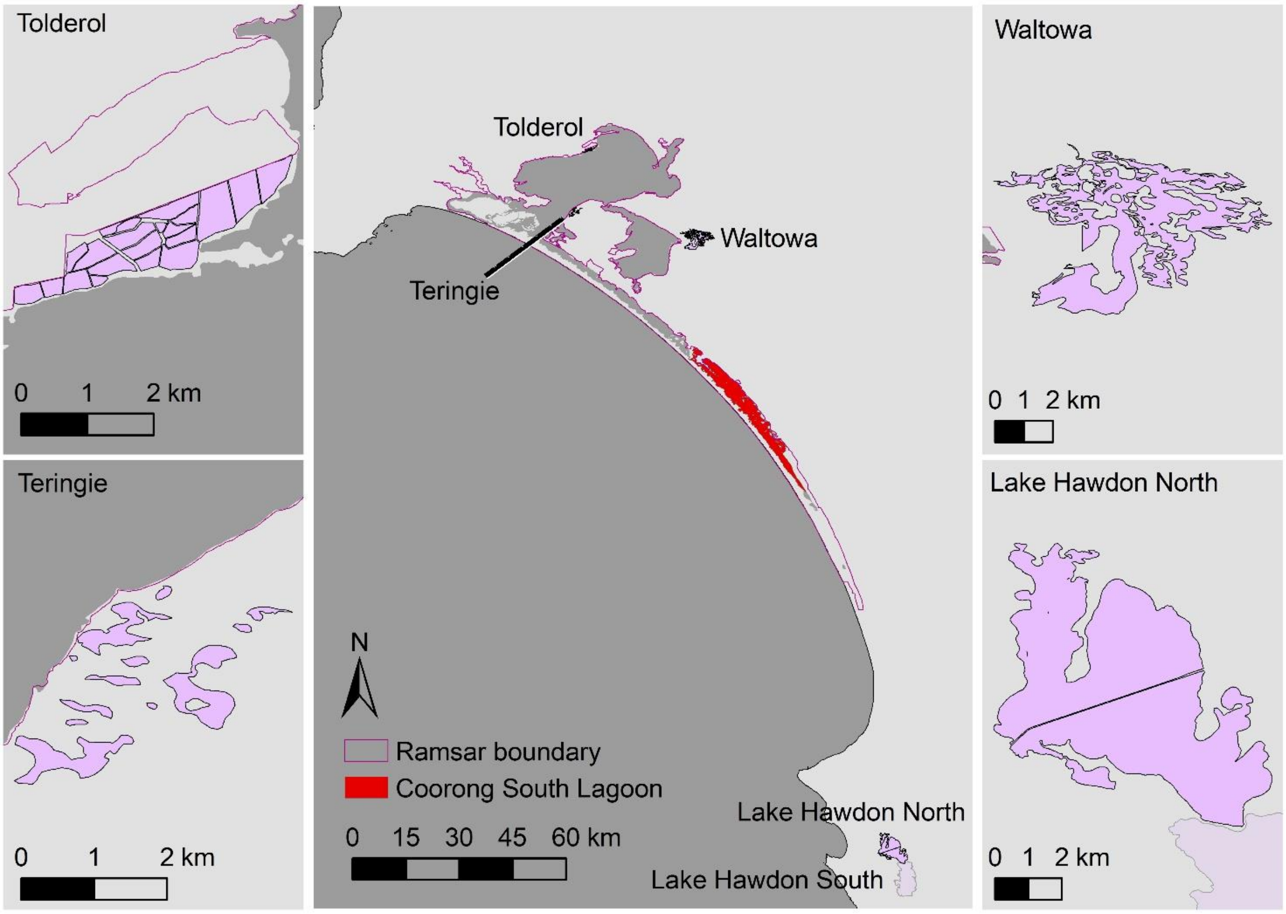

Figure 1. The four priority landscape wetlands for Key Waterbird Species of the Coorong studied in this report (Tolderol Game Reserve, Teringie Wetlands, Waltowa Wetlands and Lake Hawdon North) and Lake Hawdon South, which is shown semi-transparently to facilitate interpretation. For geographic context, the purple line in the middle map represents the boundary of the Coorong, Lakes Alexandrina and Albert Ramsar Wetland site and the red polygon represents the Coorong South Lagoon.

2.1.2 Available monitoring data for Key Waterbird Species

Tolderol Game Reserve

The waterbird dataset from Tolderol GR (supplied by Murraylands and Riverland Landscape Board) included abundance counts of all waterbirds within individual basins. The site was surveyed occasionally (once or twice per year) between 2009 and 2013 when it was not watered, but more frequently once water for the environment recommenced in 2014 (seven to eleven times per year in 2014-2019 and monthly from 2020). Individual basins were surveyed between three and 62 times across these two periods. We modelled the KWS that were recorded regularly (≥ 25 times) at Tolderol GR, namely curlew sandpiper, sharp-tailed sandpiper, red-necked stint, red-capped plover, common greenshank, Australian pelican and black swan. Red-necked avocet, chestnut teal and fairy tern were not modelled because, consistent with Hartvigsen-Power et al. (2019), they were not detected or were detected only infrequently across the time series (< 25 records).

Teringie and Waltowa Wetlands

The Murraylands and Riverland Landscape Board provided waterbird data for Teringie and Waltowa Wetlands collected since 2015 and 2012, respectively. These datasets included abundance counts of all waterbirds within the northern and southern basins of Teringie Wetlands and within the Waltowa Wetlands. There were 21 and 14 waterbird surveys (over 7 unique years) conducted at Teringie South and North respectively, and 21 unique surveys (over 7 unique years) conducted at the Waltowa Wetlands. Across these surveys, six KWS were recorded: sharp-tailed sandpiper, red-necked stint, red-capped plover, black swan, Australian pelican and common greenshank. However, common greenshank was recorded very infrequently, so this species was excluded from subsequent analyses for these wetlands.

Lake Hawdon North

For the Lake Hawdon North priority wetland, very little waterbird monitoring data were available (one waterbird survey conducted in the summer of 2017). However, limited data for Lake Hawdon South were collected in the form of nine waterbird surveys conducted in summer between 2004 and 2020 (by the Friends of Shorebirds, SE Inc. and the Australasian Waders Study Group). Count data are available from these surveys for the six KWS shorebird species (common greenshank, curlew sandpiper, red-capped plover, red-necked stint, red-necked avocet and sharp-tailed sandpiper). Therefore, we used these data from Lake Hawdon South to develop a simple response model for these species, and then used the model to generate abundance predictions under a target water-level management scenario for Lake Hawdon North.

Although this is not ideal, waterbird responses at the two lakes are expected to be similar because of their geographic proximity (Figure 1), physical and biological similarity, similar vegetation (with slightly more *Melaleuca helmaturorum* and open basins in the North); in addition, both are fed directly by drains and groundwater from catchments with similar land use (Taylor et al. 2014). Salinities of 2000–4000 µS/cm have been recorded in Lake Hawdon South while in Lake Hawdon North a salinity range of 2000–8000 µS/cm is more typical (Hammer and Tucker 2011, Hammer et al. 2012, Veale and Whiterod 2019). This difference in salinity between the two wetlands is minor and unlikely to result in different shorebird food availability, noting that both are considerably fresher than the Coorong South Lagoon which is also used by the same shorebird species. The overall ecological similarity between Lake Hawdon South and North is likely to increase under restoration as the hydrological regime of the two wetlands converges. Nonetheless, it is important to note that sheep grazing in Lake Hawdon South stopped in 2009, while sheep grazing in Lake Hawdon North still occurs and is expected to continue. There may be other unknown factors that could result in a different average density of waterbirds in Lake Hawdon South than in Lake Hawdon North, even if the latter is managed to produce optimal vegetation and water levels.

2.1.3 Covariate processing and derivation

Tolderol Game Reserve

We manually digitised the boundaries of each basin based on satellite imagery of Tolderol GR and created a shapefile of these data. Boundaries were positioned according to the maximum possible extent of water (which was typically delineated by the location of levy banks, bund walls or causeways) rather than the water level at the time satellite imagery was collected. These boundaries were then used to calculate pond area.

We downloaded the Global Surface Water Dataset (Pekel et al. 2016), which indicates the presence or absence of water within 25 x 25 m raster cells for each month of the year, and overlaid it with our shape file of each basin at Tolderol. For each month that a waterbird count was conducted, we derived the proportion of each basin that was covered by water in the same month by counting the number of inundated cells within each basin. We only undertook this calculation if at least 80% of the grid squares within a basin had data available (i.e. were not affected by cloud masking) in that month from the Global Surface Water Dataset.

To estimate habitat availability, we then overlaid this new dataset (representing the inundated grid cells in each basin) with a 1 m resolution digital elevation model (DEM; Sharma et al. 2009), representing the height (m) of substrate relative to the AHD, aggregated to a 10 m resolution by averaging all DEM values within each new 10 × 10 m cell. We assumed that if, for example, 70% of the basin contained surface water, that the deepest 70% of the basin would fill first. Using this assumption, we classified each 10 x 10 m cell into three water depth classes: 0-5 cm, > 5-20 cm or > 20 cm. Based on observations that shorebirds at Tolderol GR are mostly observed foraging in muddy substrates with water < 5 cm deep (Hartvigsen-Power et al. 2019), we assumed that the 0-5 cm cells contained suitable habitat for red-necked stint, curlew sandpiper, sharp-tailed sandpiper and red-capped plover. Preferred foraging habitat of Australian pelican and black swan was assumed to be habitat with a water depth greater than 20 cm.

In most cases (58% of counts), a salinity measurement (electrical conductivity in µS/cm) and turbidity measurement (Nephelometric Turbidity Units (NTU)) were available for each basin on the same day as the waterbird count at Tolderol in a dataset of surface water quality (supplied by Murraylands and Riverland Landscape Board).

Note that the manual digitisation of the Tolderol GR's basin boundaries was updated based on a map supplied by Murraylands and Riverland Landscape Board after developing the occurrence models and delivering their results in the HCHB Component 4 Interim report 4.3.1. The updated shapefile was used in the abundance modelling of the Tolderol GR to extract the proportion of each basin covered by water and habitat availability within each month as described above. Figure 2 shows a comparison between the original and updated basin boundaries.

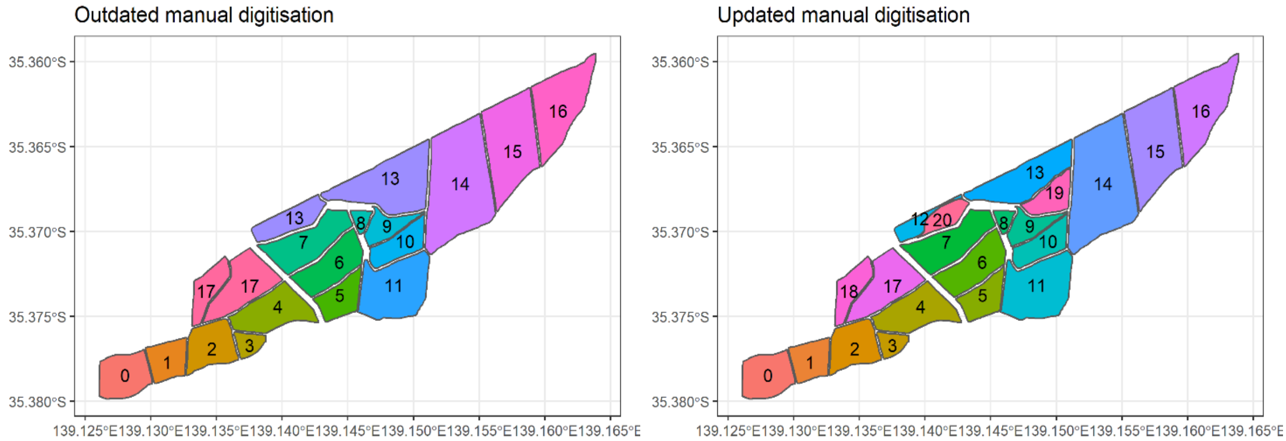

Figure 2. Outdated manual digitisation of the Tolderol Game Reserve ponds and updated version based on a map supplied by Murraylands and Riverland Landscape Board. Numbers indicate the basin number.

Teringie and Waltowa Wetlands

We subset polygons delineating the boundaries of Teringie and Waltowa Wetlands from a shapefile that includes all wetland polygons in south-east South Australia supplied by DEW (Wetlands – Statewide dataset; Department for Environment and Water 2021a). Wetland polygons included waterbodies and adjacent areas that are part of the wetland complex and could hold water. For Teringie Wetlands, we only used the two polygons corresponding to the northern and southern basins where the bird counts were conducted (Figure 3). Water levels are very different in these two basins throughout the year, hence they were kept separate in the dataset. For Waltowa Wetlands, we kept the polygons that had held some water over the past 10 years (Figure 3). We identified these polygons by overlapping the Global Surface Water Dataset (Pekel et al. 2016) with all Waltowa Wetlands' polygons and keeping only polygons that have had at least one inundated 25 x 25 m raster cell over the past 10 years.

We then overlaid the Global Surface Water Dataset with our subset of Teringie and Waltowa polygons. For each month with a waterbird count, we derived the proportion of each basin that was covered by water in the same month by counting the number of inundated cells within each basin. We only undertook this calculation if at least 75% of the grid squares within a basin had data available (i.e. were not affected by cloud masking) in that month from the Global Surface Water Dataset. We lowered this threshold to 75% (compared to 80% for Tolderol GR) as there were some months in spring and summer with *c.* 22% of grid squares within the basin with missing data. To estimate habitat availability, we used the same methodology described for the Tolderol GR data with a 5-metre resolution DEM downloaded from Geoscience Australia (Geoscience Australia 2015).

After matching the month of each waterbird survey to surface-water observations and removing surveys where water observations were not available or insufficient, 12 and 9 unique waterbird surveys (since 2015) were available for Teringie South and North respectively, and 14 unique surveys (since 2014) for the Waltowa Wetlands.

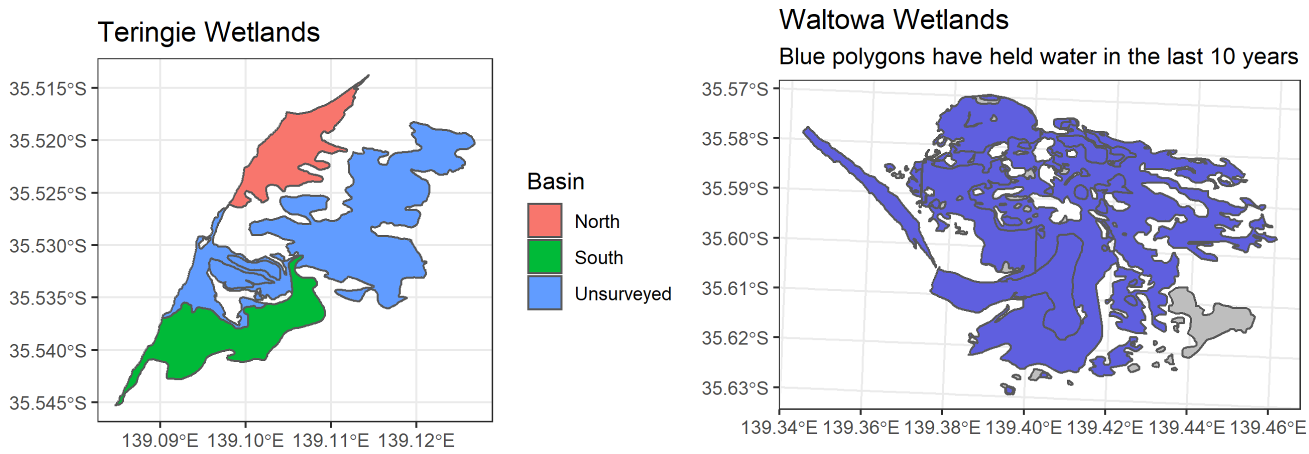

Figure 3. Teringie and Waltowa Wetlands polygons used to derive water extent variables (i.e. proportion of basin covered by water and habitat availability). For Teringie Wetlands, only surveyed basins were included, i.e. north (red) and south (green). For Waltowa Wetlands, only polygons that have held water in the past 10 years (blue) were used.

Lake Hawdon North

We used the data compiled for Lake Hawdon South that were also used in the recent restoration feasibility assessment for Lake Hawdon North (Taylor 2020). Briefly, this report provided a measure of the area of wetland habitat (hectares) within a water depth range of 0-10 cm, which is likely to provide useful foraging habitat for the six shorebird species. The latter area was calculated based upon a satellite-derived polygon of inundation extent near the time of each waterbird survey which, when combined with information from a DEM (Sharma et al. 2009), allowed water depth across Lake Hawdon South to be estimated. A waterbird model developed for Lake Hawdon South was then applied to Lake Hawdon North.

2.1.4 Waterbird response modelling and validation

Tolderol Game Reserve

We modelled the presence/absence of waterbirds in response to habitat conditions at Tolderol GR using data from nine ponds that were actively managed and received regular survey effort. After resolving uncertainties in the dataset regarding species-level counts, we also modelled waterbird abundance in response to habitat conditions at Tolderol GR. For the latter modelling, we used data from ponds where at least 15 monthly counts had been conducted between 2010 and 2021, allowing us to incorporate the nine actively managed ponds and three additional ponds that were not managed. Prior to modelling, the response bird counts was summarised at species level as follows. If there was more than one record of a given species on the same day and within the same pond, the species counts were summed and treated as a single data point. When there was no record of a KWS in a survey and basin, the species was assumed to be absent and a bird count of zero was used.

To model presence/absence data, we used generalised additive models (GAMs) to allow non-linear relationships between the response and the predictors. To fit these models, we used the 'gam' function of *mgcv* package (Wood 2011) in the R statistical environment (R Core Team 2020). A binomial distribution with a logit link function was used for model construction. We built seven model structures based on plausible combinations of environmental predictor variables and applied all seven of the model structures across each of the KWS (see Table 1 for covariates used). Basin number and year were used as random effects to account for unexplained variation in occurrence between basins and years, respectively. Prior to modelling, environmental variables were standardised around their mean value in units of standard deviation to facilitate direct comparison of effect between variables. The seven model structures included an intercept-only model (i.e. without explanatory variables), models that contained only water chemistry variables, models that contained only water extent variables, as well as a model that contained variables for water chemistry and water extent. The complexity of the non-linear relationship between each covariate and the response was controlled by setting the basis dimension (see glossary) for each smooth term to k = 3 in all cases except for the interaction terms (between basin area and proportional coverage) where k = 5. We used thin-plate regression splines (see glossary) for all spline terms, except for the month term for models of resident species (Australian pelican, black swan, and red-capped plover) for which we used cyclic cubic regression splines to ensure continuity in the modelled response between the first and last month of the year.

We used a 9-fold cross-validation process to fit and compare the candidate models. For each species and model structure combination the bird occurrence data were divided into nine data folds (see glossary) based on the ponds that they were recorded in (as mentioned previously, these were the nine ponds that were actively managed and had received regular survey effort in the dataset). An iterative procedure was then carried out in which one data fold (hereafter evaluation dataset) was set aside for evaluating the predictive performance of the GAM constructed with the remaining eight data folds (hereafter training dataset).

The resultant GAMs produced fitted values on a continuous scale from 0 to 1 (i.e. probabilities of presence). To convert these continuous values to binary presence (1) absence (0) values, a threshold that maximised the True Skill Statistic (TSS; Allouche et al. 2006) (see glossary) was selected. The TSS is a metric that ranges from -1 to 1, with values ≤ 0 indicating predictive performance equivalent to or worse than random, whereas a TSS of 1 indicates perfect predictive performance (Allouche et al. 2006). Each GAM constructed with the training dataset was then used to derive presence/absence predictions for the evaluation dataset that had been withheld from model construction. The threshold that maximised the TSS for training dataset was again used to classify the continuous (0-1) predicted values into binary (0, 1) predictions of absence and presence, respectively. The TSS obtained when the model was validated against the evaluation dataset was taken as an indication of predictive performance.

Table 1. Names of the environmental covariates used to model key waterbird species occupancy at Tolderol Game Reserve and a description of their interpretation. The average and range of salinity values are given in the dataset units (µS/cm) and the equivalent approximation in ppt to ease comparison with the Coorong salinity described in other technical reports of Component 4 Waterbirds.

VARIABLE NAME	DESCRIPTION
Basin area	The total area of each individual basin calculated as the maximum area if the basin was completely full.
Proportional coverage	The proportion of the basin area that was covered by water in a given month.
Area of habitat	The area of habitat with water of a depth class preferred for foraging by individual KWS (water depth between 0 and 5 cm for models of common greenshank, curlew sandpiper, red-capped plover, red-necked stint, and sharp-tailed sandpiper; water depth > 20 cm for Australian pelican, and black swan).
Salinity	Water salinity measured via electrical conductivity (µS/cm). Mean = 11,483 µS/cm (*c.* 6.3 ppt); min – max = 133 – 66,700 µS/cm (*c.* 0.2 – 36.7 ppt).
Turbidity	Water turbidity measurement (Nephelometric Turbidity Units (NTU)).
Basin number	A number identifying each individual basin.
Month	Month of the year for non-migratory species (1 = January, 12 = December) or month of the non-breeding period for migratory species (1 = October, 5 = February).
Year	The year in which the data were collected.

Performance based on TSS is usually classified into the following categories: < 0.0 poor; [0.0 to 0.2] slight; (0.2 to 0.4] fair; (0.4 to 0.6] moderate; (0.6 to 0.8] substantial; (0.8 to 1] almost perfect (Landis and Koch, 1977). After each of the nine data folds (one for each pond used in this analysis) had iteratively been used as the evaluation dataset, the mean TSS across all nine model iterations was calculated and the model structure that had the highest mean TSS was considered the best performing model. For each KWS, the selected GAM was then fitted using the best performing model structure and using the complete dataset available (Roberts et al. 2017). This final model for each species was used to produce partial response plots (see glossary) to investigate how environmental variables influence species occupancy of Tolderol GR.

We also used GAMs to model waterbird abundance because data exploration showed non-linear relationships between the candidate predictors and response variables. Counts were overdispersed (i.e. variance greater than the mean) but not zero-inflated (i.e. observed prevalence of zeros was not greater than that expected to arise from a negative binomial distribution with the observed mean and variance). Therefore, we used a negative binomial distribution with overdispersion parameter estimated from the data to model the waterbird counts. Models were fitted using the 'gam' function of *mgcv* package (Wood 2011) in the R statistical environment (R Core Team 2020). Basin number and year were included as random effects to account for unexplained variation in abundance between basins and years, respectively.

We used the environmental predictors in Table 1 to build model structures based on plausible combinations of variables. We checked for collinearity between pairs of environmental predictors using Pearson correlation index, where magnitude > |±0.5| indicate high collinearity (Zuur et al. 2009). Proportional coverage and area of habitat were highly collinear, so these two predictors were not included in the same model. Prior to modelling, environmental variables were standardised around their mean value in units of standard deviation to facilitate direct comparison of effect between variables. We built nine candidate models and applied all nine of the model structures across each of the KWS. The candidate models included an intercept-only model (i.e. without explanatory variables), models that contained only water chemistry variables, models that contained only water extent variables, as well as a model that contained variables for water chemistry and water extent, plus an interaction between basin area and proportional coverage (full model). We specified the splines terms in the same way that for the occurrence models.

We used a 12-fold cross-validation process to fit and compare the candidate models. For each species and model structure combination, the bird count data were divided into 12 data folds (see glossary) based on the ponds that counts were recorded in. An iterative procedure was then carried out in which one data fold (hereafter evaluation dataset) was set aside for evaluating the predictive performance of the model constructed and the remaining 11 data folds (hereafter training dataset) were used to fit the GAM using maximum likelihood (ML) to estimate smoothing parameters.

The predictive performance of each candidate model was assessed based on the average Mean Absolute Error (MAE) across the cross-validation folds. We decided to use absolute error instead of squared errors metrics as MAE is an easy metric to interpret (i.e. average error across all predictions) and is not as sensitive as squared error metrics to outlier prediction errors. For each cross-validation fold and using the evaluation dataset, the MAE was calculated as:

$$MAE = \frac{\sum_{i=1}^{n} |y_i - \widehat{y_i}|}{n}$$

where n is the number of observed counts, y_i is the i^{th} observed count and $\hat{y}_i$ is the i^{th} predicted count. The model candidate with the lowest average MAE across the cross-validation folds is expected to provide the best predictive performance and it was selected as the best model.

Having selected a model based on the lowest cross-validatory MAE, this model was refitted to the full dataset using restricted maximum likelihood (REML) for smoothing parameter estimation. The model was then used to derive partial response plots (see glossary).

Teringie and Waltowa Wetlands

The modelling and cross-validation approach taken for the Teringie and Waltowa wetlands was essentially the same as that used for the abundance modelling for Tolderol GR. However, given the relative paucity of available data at these sites, we considered wetland as a fixed 3-level factor in these analyses (i.e. Teringie South, Teringie North, Waltowa), and only considered the possible influence on waterbird abundance of proportional water coverage or the area of habitat within the 0-5 cm depth range (for the three shorebirds considered) or the area of habitat exceeding 20 cm depth (for the Australian pelican and black swan). Further, we tested models that allowed different covariate responses for each wetland and used a cross-validation procedure that held out individual surveys one-at-a-time for evaluation of predictive performance.

Lake Hawdon North

To model species-level shorebird counts in Lake Hawdon North, we adopted a generalised linear mixed-effects modelling approach suitable for these count data. Preliminary modelling for each species indicated that non-zero counts for many species were substantially overdispersed (i.e. variance greater than the mean). Therefore, we assumed the counts arose from a negative binomial distribution with overdispersion parameter estimated. The models were fitted using function 'glmmTMB' from the R package of the same name (Brooks et al. 2017).

Given the relative paucity of data even for Lake Hawdon South, a candidate set of simple models was developed to model the abundance of all species simultaneously. The models included combinations of the following terms: a random effect of species (to account for systemic differences in abundance between species), a random effect of survey year (to account for unexplained interannual variation in abundance), a trend over time, and the fixed effect of the area of available habitat within the 0-10 cm depth range. Non-linearity in the relationship between shorebird abundance and habitat area was not permitted, because preliminary model testing demonstrated that a linear relationship improved model predictive performance.

To assess the performance of candidate abundance models, we used Akaike's Information Criterion (AIC) which considers model fit but adds a penalty term that increases with increasing model complexity (lower AIC values indicate higher ranked models). As a measure of the structural goodness-of-fit, we also calculated the coefficient of determination (R^2) to quantify the proportion of the variance in the count data that was explained by each candidate model.

To provide a thorough assessment of the predictive capacity of each candidate model, we used 9-fold temporal-block cross-validations. Briefly, we constructed 9 new model-training datasets by removing data for each survey year in turn and evaluated the ability of models to predict these evaluation data when they were excluded from the model-fitting stage. Specifically, we calculated the mean cross-validation deviance (i.e. the average of -2 × the log-likelihood of the evaluation count data assuming the parameters estimated by the model) where lower values indicate models producing better predictions. Further, we calculated the Normalised Root Mean Square Error (NRMSE) for each cross-validation fold as:

$$NRMSE = \frac{\sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}}{\bar{y}}$$

where n is the number of evaluation values, y is the evaluation data vector and $\hat{y}_i$ is the vector of predicted values from the model. The mean NRMSE across the cross-validation folds provides a measure of the expected variance of the predictions as a proportion of the evaluation sample mean. Having selected a model based on the lowest AIC and cross-validatory NMRSE, this model was used to derive response plots and to generate predictions of shorebird abundance for Lake Hawdon North under a baseline and target water-level scenario.

2.2 Broader landscape wetlands

2.2.1 Study area

The south-east of South Australia holds most of the state's wetlands (Bradshaw 2019). Five of the six wetlands in South Australia that are listed as internationally important under the Ramsar Convention are located in the south east of the state (i.e. Banrock Station Wetland Complex, Bool and Hacks Lagoons, Piccaninnie Ponds Karst Wetlands, Riverland, and The Coorong, and Lakes Alexandrina and Albert Wetlands).

For the purposes of this study, we used wetland polygons mapped in the Wetlands – Statewide dataset (Department for Environment and Water 2021a), which is the most updated wetland mapping data for South Australia. Note that the Wetlands – Statewide dataset was last updated in 2009 and wetlands are assigned to 'regions' as per the now outdated Natural Resources Management areas (NRMs). We considered all wetlands within the extent (138.57213, -38.06097) to (141.10000, -33.50380) of the Wetlands – Statewide dataset within the NRMS of the Murray Region (current Murraylands and Riverland Landscape Board) and South East Region (current Limestone Coast Landscape Board) (Figure 4). Because several polygons can be part of the same wetland, for analysis purposes we defined each wetland as all polygons with the unique combination of the fields *REGION, NAME, AUS_WETNR* and *AUS_WETNR_* in the Wetlands – Statewide dataset. We excluded the Coorong, Lake Alexandrina and Lake Albert from the study area extent as our aim was to model the response of waterbirds beyond the CLLMM. In total, 20,989 wetlands with a total area of 334,345 ha were considered.

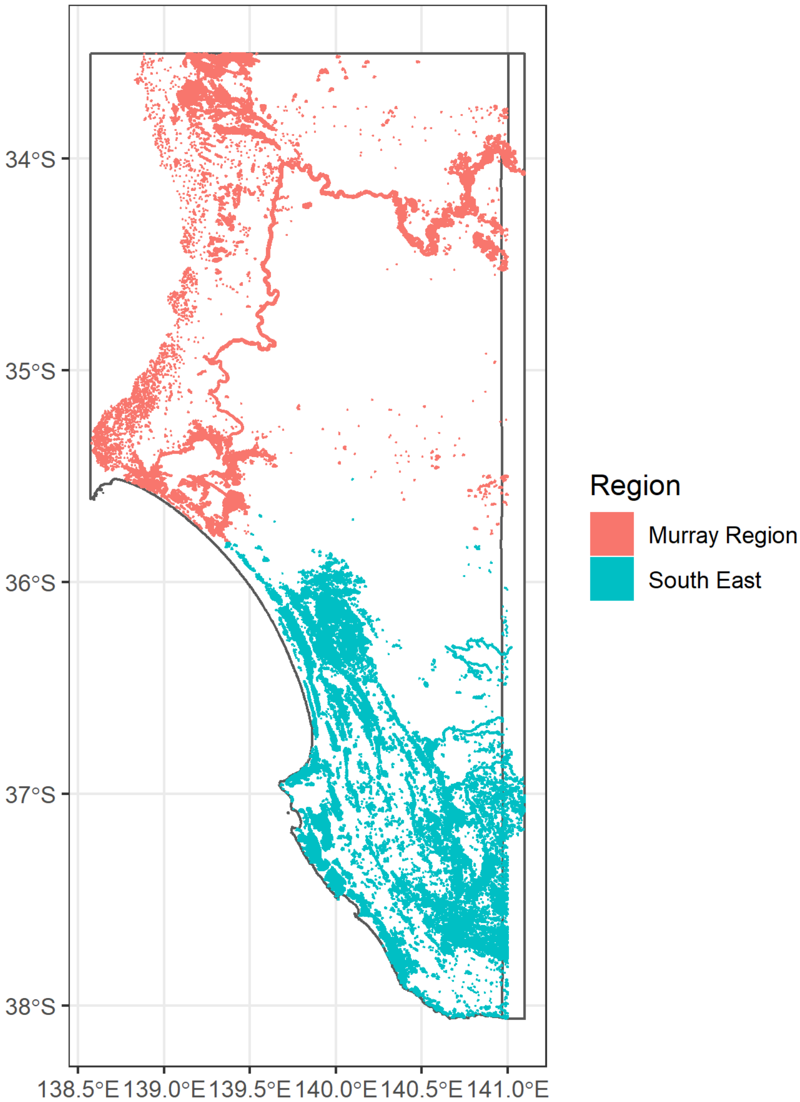

Figure 4. Extent and configuration of the wetlands within the Natural Resources Management areas (NRMs) of the Murray Region (i.e. current Murraylands and Riverland Landscape Board) and South East (i.e. current Limestone Coast Landscape Board) considered in this study. Boundaries are based on the NRMs of the Wetlands – Statewide dataset (Department for Environment and Water 2021a) and might not accurately reflect the current boundaries of the Landscape Board regions.

2.2.2 Waterbird data

We collated waterbird data from five different sources: Biological Databases of South Australia (BDBSA) (Department for Environment and Water 2021b), the Global Biodiversity Information Facility (GBIF), Birdata, eBird (eBird Basic Dataset 2021) and the Australian Waterbird Surveys (AWS) database (Kingsford et al. 2020). We provide a list of all waterbird species recorded at least once in these datasets in Appendix B but we used only the eBird and Birdata datasets for statistical analysis.

Datasets deemed unsuitable for modelling purposes

The BDBSA and GBIF are databases that integrate and provide open access to biodiversity data from different sources. These are large, unstructured datasets of point-location occurrence records. Despite the substantial data available from these sources, the data were not suitable for modelling waterbird responses to abiotic covariates due to the lack of key metadata such as survey method, effort and accurate spatial coordinates. Other reasons for excluding these data were an inability to accurately infer absences and unique sampling events, and duplication of records in other sources such as eBird (e.g. approximately 20% of the bird data available in GBIF is derived from eBird; Sullivan et al. 2017).

The AWS database provides access to the waterbird counts collected from aerial surveys flown across Australia, extending back to 1983 (Kingsford et al. 2020). Amongst these surveys, one of the routes of the Eastern Australian Waterbird Surveys and some locations of the National Waterbird Survey were within our study area. Nonetheless, given shorebirds were not identified at a species level (they were counted as groups of large, medium and small waders), and because the surveys covered just a small part of our study area, we did not use the AWS dataset for modelling purposes.

Datasets used for modelling

The Birdata (https://birdata.birdlife.org.au/) and eBird (https://ebird.org/home; Sullivan et al. 2014) databases provide access to semi-structured community-contributed bird data. Birdata is managed by BirdLife Australia at a national level and eBird is managed by The Cornell Lab of Ornithology, Cornell University, at a global level. Both organisations have data-control filters to screen their records and exclude or flag any potential erroneous observations (e.g. rarities, species documented out-of-season or unusually high counts), which provides some measure of quality control. We downloaded all the bird records available in both databases for our study area. The eBird dataset included 40,450 unique checklists from 1941 until 2021. The Birdata dataset had a total of 47,893 checklists from 1980 to 2020.

Users of Birdata and eBird upload their sightings as checklists that are identified as unique sampling events by an identification (ID) number. Each checklist has a minimum level of metadata associated with it that records the type of survey conducted and whether checklists are complete (where participant reports all birds that they were able to detect and identify) or incomplete (not all birds were recorded, e.g. opportunistic sightings). This checklist structure enables non-detection (i.e. zero counts for the species that were not reported) to be inferred.

We applied the following hierarchical steps and filters to prepare the Birdata and eBird datasets for further analysis:

1. We retained only complete checklists to ensure the accuracy of inferred absences for species not reported (e.g. Horns et al. 2018). We also removed survey protocols that appeared in the dataset and did not represent normal birding activity by the participants, including banding, 5-minute search point and colony surveys. For more information about survey protocol types in eBird and Birdata, check https://support.ebird.org/en/support/solutions/articles/48000950859-guide-to-ebird-protocols and https://birdata.birdlife.org.au/help/survey-techniques, respectively.
2. We intersected the checklist locations with the wetland polygons from the Wetlands – Statewide dataset and retained checklists with locations that fell within a 700 m buffer of a wetland polygon. This buffer was chosen to ensure we accounted for most waterbird sightings in the region. Some eBird and Birdata location sites were not within wetland polygons but checklists contained mostly

waterbird species (e.g. eBird's location Beachport Conservation Park within Lake George is 650m from the wetland boundary), so we assumed these checklists were conducted at the closest wetland within the buffer. Using this approach, we included ~ 80% of all waterbird sightings in the region. We also tested a narrower buffer of 200 m, but > 50% of waterbird sightings were outside this buffer, so this approach was not used. For the Tolderol GR, we used our manual digitisation of pond polygons (described in section 2.1.3 – Tolderol Game Reserve of this report) as, based on satellite images, we considered our boundaries to be more accurate than those in the Wetlands – Statewide dataset.

3. We merged Birdata and eBird datasets and removed duplicates present in both datasets (i.e. some Australian records in eBird are imported into Birdata and it is possible to identify and remove them because Birdata stores the eBird checklist ID in the *Source.Ref* field).
4. We retained checklists that had recorded at least three species, as short checklists often represent low-effort searches or targeted searches for specific species (Szabo et al. 2010).

These steps were performed using R 4.0.1 (R Core Team 2020) software with the packages *dplyr* (Wickham et al. (2021) and *auk* (Strimas-Mackey et al. 2018) for data filtering and *sf* (Pebesma 2018) for spatial intersection. After applying the data filters, sampling effort was extremely low prior to 1999 so we retained checklists recorded between 1999 and 2020, which left 18,470 checklists in 1,261 wetlands remaining for analysis.

Species-level counts were not always available from these datasets and associated metadata did not provide information on whether a whole wetland was surveyed, abundance information when present was difficult to interpret. Therefore, we transformed the data to a presence/absence dataset and aggregated the number of detections and non-detections for each species within each wetland in a given month to model the encounter rate as a response. Encounter rate is defined here as the average rate at which observers encounter and record the species, so it is the product of occurrence and detectability (Johnston et al. 2021). Although not ideal, encounter rate is expected to be proportional to occupancy (i.e. the probability that a species occurs at a wetland).

2.2.3 Covariate processing and derivation

We considered the proportional water coverage of the wetland, vegetation cover of the wetland, Australian "wetness" index and distance to coast as covariates to model waterbird response to abiotic and biotic conditions. Below are details of how each covariate was processed.

Proportional water coverage

We used the Water Observations from Space (WOfS) product of Digital Earth Australia (DEA) (Geoscience Australia 2022) to derive the proportion of each wetland area with surface water over time, hereafter termed proportional water coverage. The WOfS product detects water from 25 m-resolution Landsat satellite images based on a regression tree classification algorithm (Mueller et al. 2016) and provides data for each pass of the satellite (on a 16-day orbital cycle) from 1987 to the present year.

Wetland polygon boundaries from the Wetlands – Statewide dataset were taken as inputs along with the Landsat satellite imaging datacubes available within the DEA platform. In an iterative process, the spatial extent and time period (from 1987 to present year) parameters for each wetland were used to estimate Water Observation (WO) product from the Landsat satellite imaging datacubes as shown in the workflow in Figure 5.

The WO distinguishes the satellite image into different classes with image data stored as a bit field, where each digit of the number is set based on the presence (1) or absence (0) of a particular attribute (water, cloud, terrain etc.). The WO's bit fields were converted into a binary array containing True and False values using the 'make_mask' function in the Python programming language (Python Software Foundation, https://www.python.org/), which allowed us to identify pixels that were wet and dry in each image, by passing the flag *wet = True* and *dry = True* respectively. The wet and dry images were further masked to remove cloud, shadow and other sources of invalid data by setting their pixel values to missing. The masked images with more than 50% missing values were discarded, while the rest were clipped with respect to the boundary of each wetland using the geospatial tool 'GeoPandas' (Jordahl 2014). The clipped images were further analysed by distinguishing the wet *(pixel_value > 0)*, dry *(pixel_value == 0)* and missing value *(pixel_value == Nan)* regions and then their proportional areas were estimated with respect to total area of each wetland polygon with the Python package *rioxarray* (2022). Polygons with a proportional missing value > 0.5 were assigned the proportional wet and dry values of the closest date within 30 days and missing value < 0.5. Remaining polygons with a missing value proportion > 0.5 were discarded from further analysis. We then averaged the proportional wet areas of each wetland over each month/year period in relation to the total wet and dry area of all polygons that formed that wetland to use as covariate in the waterbird response models. In the case of wetlands with more than one polygon, we kept only the proportional coverage of months for which at least 50% of the total area of all polygons had a known wet/dry value.

Vegetation cover

Encroaching vegetation in wetlands has the potential to reduce accessibility to useful habitat for waterbirds, particularly for migratory shorebirds (Hunt et al. 2019). Hence, we were interested in testing the effect of vegetation cover on the encounter rates of waterbirds across wetlands in our study area.

We used the South Australian Land Cover Layers dataset (Willoughby et al. 2018) to derive the vegetation cover information. This dataset consists of a series of 6 spatial layers with 25m resolution from 1987 to 2015. Each spatial layer corresponds to a different epoch, i.e. 1987-1990, 1990-1995, 1995-2000, 2005-2010 and 2010-2015, for which the area of 17 land cover classes across South Australia has been estimated from Landsat satellite images (Table 2) (Willoughby et al. 2018). Since this dataset has not been updated since 2015, we assumed that land cover did not change after 2015 and used the epoch 2010-2015 estimates beyond 2015.

To estimate the land cover within wetlands, polygon boundaries from the Wetlands – Statewide dataset were used to clip the South Australian Land Cover Layers for each epoch. The clipped spatial layers were used to identify and distinguish the 17 landcover classes represented based on pixel values (Table 2). We then estimated the area of each landcover class inside each wetland polygon with the Python package *SciPy* (Virtanen et al. 2020).

We expected increasing vegetation cover to reduce foraging and roosting habitat for shorebirds, whereas for other waterbirds, increasing vegetation cover may provide more roosting and shelter habitat (e.g. reeds for concealment), as well as food resources. We therefore used different vegetation cover estimations to model the responses of shorebirds and all other species differently. For shorebirds, the vegetation cover covariate was calculated as the proportion of the total wetland area (i.e. sum of the areas of all land cover classes) covered by woody native vegetation, mangrove vegetation, non-woody native vegetation and wetland vegetation for each epoch. For all other waterbirds, we calculated the proportion of the total wetland area covered by wetland vegetation and saltmarsh vegetation. We expected the relationship between vegetation cover and encounter rate of shorebirds and the rest of waterbirds to be negative and positive, respectively.

Australian "wetness" index

Because the Coorong (and by extension, south-east South Australia) is understood to be used as a drought refuge by waterbirds (Kingsford and Porter 2008), we wished to test the relationship between waterbird distribution in the broader landscape wetlands and conditions elsewhere in Australia. Therefore, we digitally captured data from a summary figure published by Krause et al. (2021) on the proportional contribution of surface water over time within 295,906 Australian waterbodies ranging in size from 3,125 m^2 to 4,820 km^2. We used the seasonal proportion of surface water across Australia to produce an Australian "wetness" index for testing within the waterbird response models.

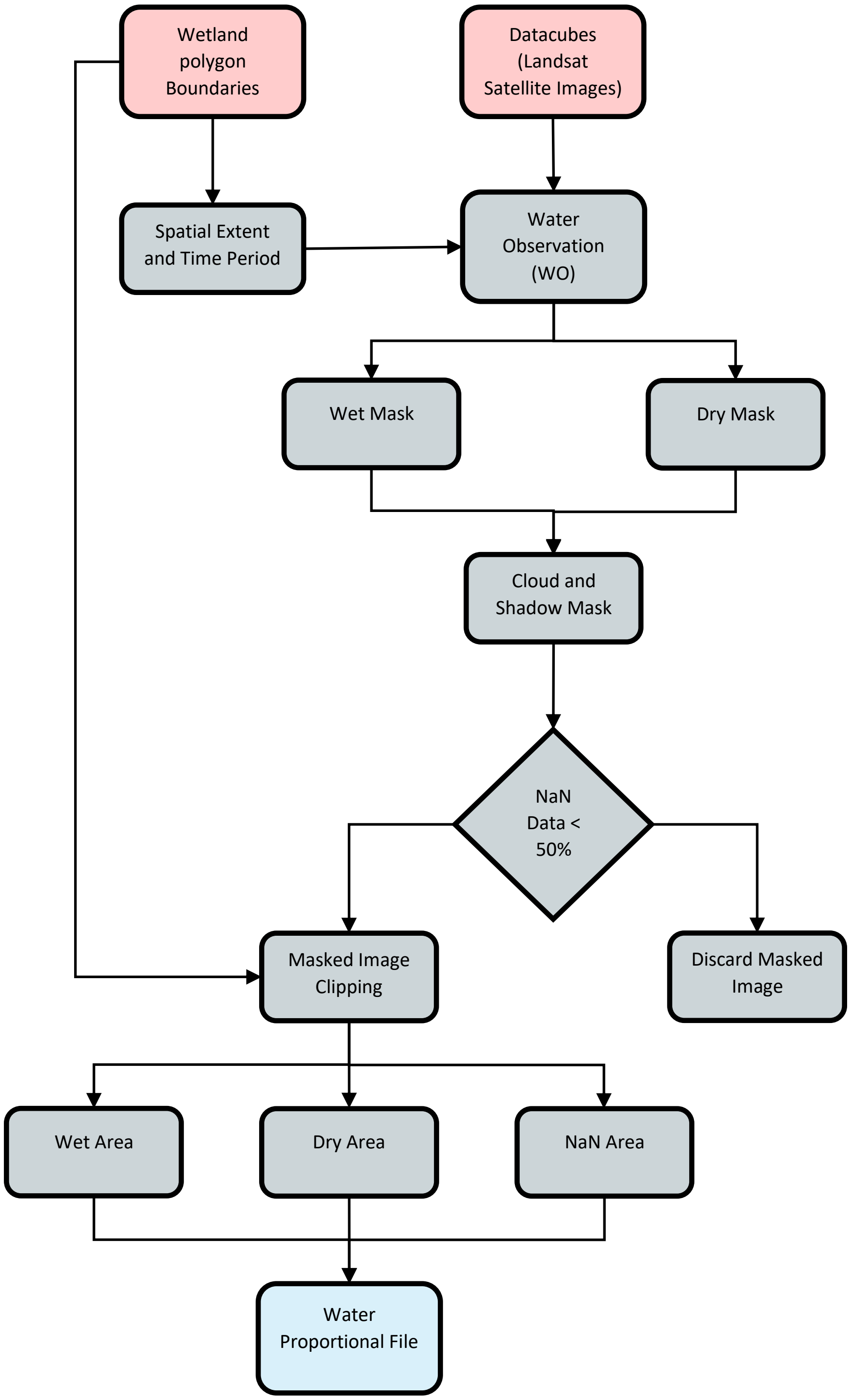

Figure 5. The Water Observations from Space (WOfS) based water estimation workflow applied for wetlands with waterbird data.

Table 2. Description of the land cover classes in the South Australian Land Cover Layers dataset. Adapted from Willoughby et al. (2018).

LAND COVER CLASS	DESCRIPTION
Woody native vegetation	Generally > 1 m tall (e.g. eucalypt forests and woodlands, wattle shrublands, hop-bush shrublands)
Mangrove vegetation	Mangrove dominated forest
Non-woody native vegetation	Generally < 1m tall (e.g. grasslands including herbs and low shrubs)
Saltmarsh vegetation	Low native vegetation in areas with saline soils
Wetland vegetation	Non-woody native vegetation occurring in association with wetlands
Natural low cover	Very sparse native vegetation
Salt Lake / salt pan	Salt lakes and salt pans
Dryland agriculture	Non-native vegetation that is used for dryland cropping and grazing
Exotic vegetation	Any form of vegetation dominated by non-native species and not classified to other non-native vegetation classes
Irrigated non-woody	Irrigated pasture or crops
Orchards / vineyards	Irrigated woody crops
Plantation (softwood)	Pine plantations
Plantation (hardwood)	Plantations other than pine
Urban area	A mix of vegetation and built surfaces
Built-up area	Dominated by built surfaces
Disturbed ground / outcrop	Disturbed ground or outcrop
Water unspecified	Open water bodies

Distance to coast

Since waterbirds are highly mobile and species that use the Coorong have shown regional and larger scale movements (Mott et al. 2022), we wished to test whether encounter rates were sustained across the study region or decreased with increasing distance to the coast.

We obtained the coastline of Australia as a set of linestring geometries (i.e. each linestring is sequence of points connected by straight, non-self intersecting line pieces) with the R package *rnaturalearth* (South 2017). Then, we calculated the shortest distance to coast in kilometres between the coordinates of each checklist and the coastline geometry with the R package *sf* (Pebesma 2018). We used the median distance to coast of the checklists within each wetland and month/year as the covariate for the response modelling.

After merging the waterbird data with the covariates, 84 waterbird species remained for potential modelling, including the ten KWS. However, very few detections (< 100) were recorded for 15 of those species, including the fairy tern (one of the KWS), so these species were excluded from subsequent analyses. We also excluded three beach specialists (ruddy turnstone, pied oystercatcher and sooty oystercatcher) because wetland habitat is less relevant for these species. For migratory species, we only included data for the peak non-breeding months when most individuals are expected to be in Australia (i.e. October – February for summer migratory shorebirds and March – August for the double-banded plover). For non-migratory species, a total of 12,576 checklists (6,350 and 5,088 checklists for summer migratory shorebirds and double-banded plover, respectively) over 986 different wetlands (682 and 628 wetlands for summer migratory shorebirds and double-banded plover, respectively) remained for analysis. Figures 6 and 7 show the distribution of the wetlands and checklists included in the models.

2.2.4 Waterbird response modelling

For the 66 waterbird species retained for analysis, we modelled variation in the encounter rate as a function of proportional water coverage, vegetation cover, the Australian "wetness" index and distance to coast. We adopted a generalised linear mixed-effects modelling approach using wetland and year as random effects and assumed a binomial distribution with a logit link function. To control for differences between regions and among wetlands of different sizes, we also included region (as a 2-level factor: Murray Region and South East) and the area of the wetland (estimated as the sum of the area in ha of all polygons within a wetland) as covariates. Month of the year was also included as a covariate to account for seasonal changes in encounter rates (as shown in Table 1 with respect to the Tolderol GR modelling). Prior to modelling, all continuous covariates (except month and year) were standardised around their mean value in units of standard deviation to facilitate direct comparison of effects between variables.

Data exploration revealed non-linear relationships between encounter rate and two covariates, proportional water coverage and month, so we initially attempted to fit GAMs with the R package *mgcv* (Wood 2011) (i.e. as for Tolderol GR). However, the high number of levels (*c.* 1000) required for the wetland random effect produced long run times for model fitting (*c.* 40-50 minutes per model). Therefore, models were fitted using the function 'glmmTMB' from the R package of the same name (Brooks et al. 2017). To allow non-linear responses, we manually constructed basis functions for the regression splines (see glossary) with the function 'smoothCon' from the package *mgcv* (Wood 2011). Given models were developed for many species, we fitted a single model formulation common to all species:

Encounter rate ~ (1 | wetland) + (1 | year) + Region + Wetland area + s(Proportional water coverage) + Region:s(Proportional water coverage) + s(Month) + Distance to coast + Australian "wetness" index + Vegetation cover,

where *(1 | Wetland)* and *(1 | Year)* denote the random intercepts of wetland and year, respectively, and *s(variable)* indicates a smooth covariate where a thin-plate regression (or a cyclic cubic spline regression in the case of month for resident waterbirds) was fitted. The complexity of the relationship between each smooth covariate and the response was controlled by setting the basis dimension (see glossary) for each smooth term to k = 3. Convergence and/or singularity issues (Brooks et al. 2017) were detected for three species (brolga, black-faced cormorant and double-banded plover); model outputs for these species were therefore deemed unsuitable for ecological interpretation and are not presented in the report.

The model detailed above was used to derive partial response plots (see glossary) illustrating the impact of proportional water coverage on encounter rates.

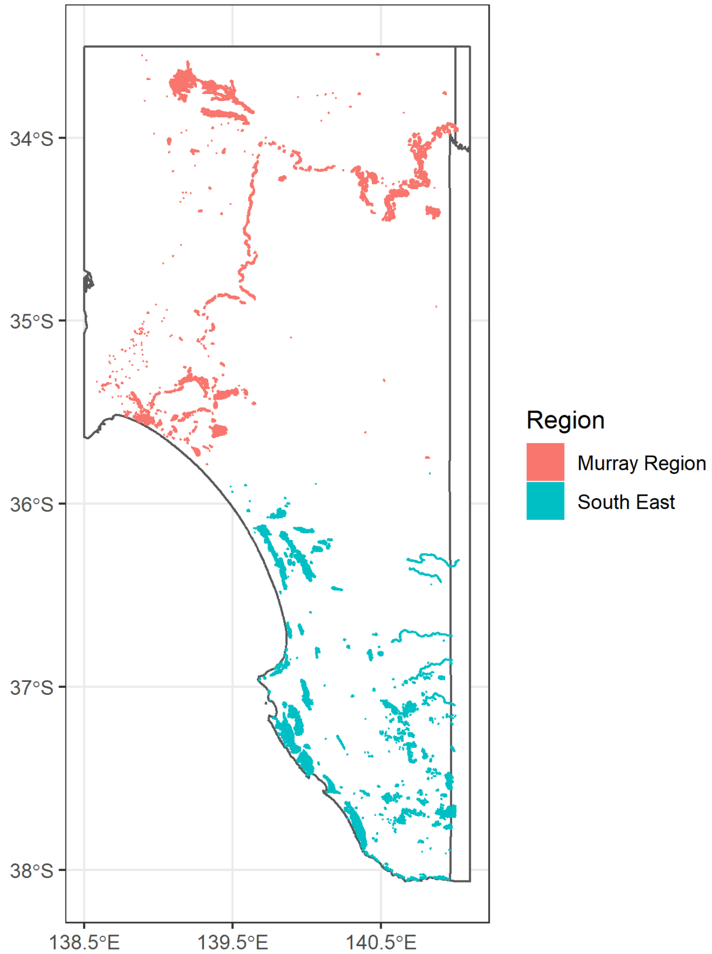

Figure 6. Distribution of the 986 wetlands in the Murray Region (red) and South East (green) included in the waterbird response models for the broader landscape.

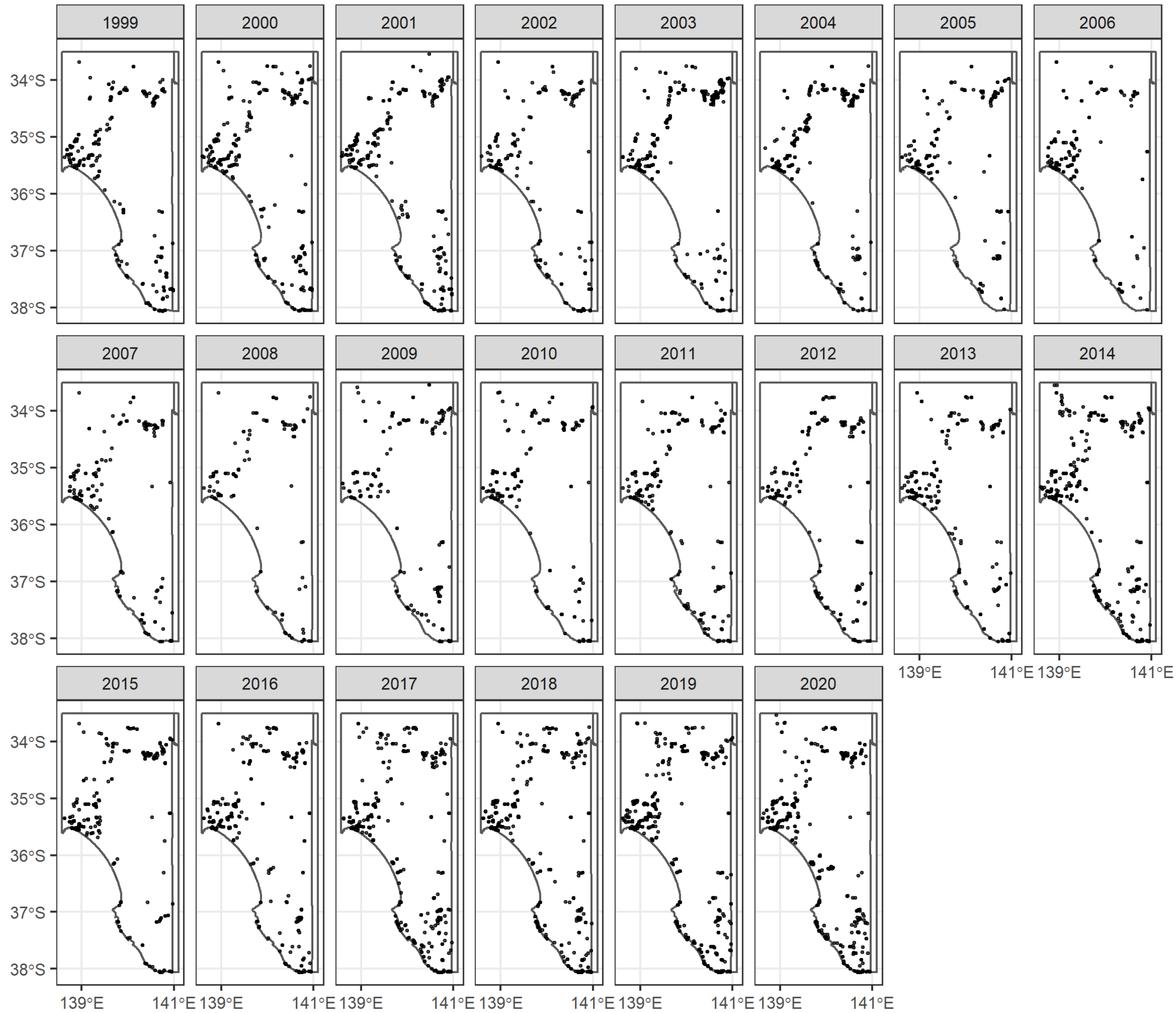

Figure 7. Distribution of the 12,576 checklists included in the waterbird response models for the broader landscape. Each panel represents a different year in the dataset and black points show the location of each checklist in that given year.

2.2.5 On-ground waterbird counts

In January 2022, waterbird surveys were conducted in 31 wetlands within the study area (Figure 8). These wetlands were selected based on the potential of holding some water according to water coverage estimates derived from satellite images (following the methodology described in section 2.2.3) and also information provided by local landholders. The aim of these wetland visits and counts was to assess the availability of shorebird habitat and the diversity of habitat and variation in counts and detections to make appropriate modelling decisions, such as using encounter rates instead of abundance as the response variable. Wetland visits also provided us with the opportunity to consider the accuracy of our satellite-derived estimates of proportional water coverage.

Where possible, we counted all waterbirds across the entire wetland. Two observers for most wetlands (except Fox Lake and Mount Burr Swamp which were counted by one observer) counted and identified all visible waterbirds at species level with the aid of binoculars and one scope from one or more vantage points that covered the entire wetland. Only waterbirds that were on the wetland were counted (e.g. foraging, roosting), we excluded individuals flying over. The only wetland not surveyed in its entirety was Lake George, due to limited access across the northern shore of the largest section. Due to time constraints, counts were performed throughout the day to cover all wetlands in a week, from 24-30 January 2022.

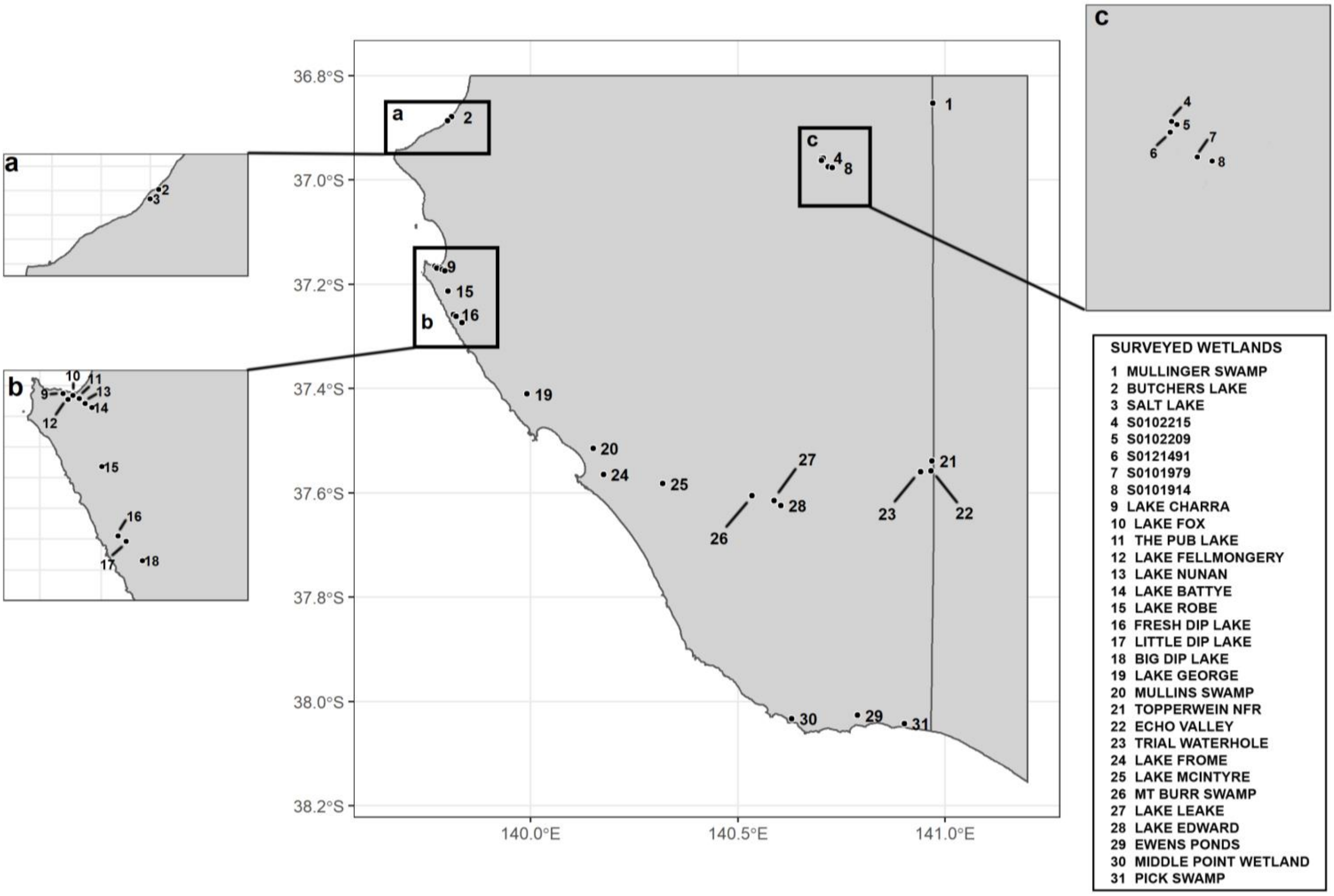

Figure 8. Distribution of the surveyed wetlands in January 2022. Insets a, b, c show the areas of Butchers Lake, Robe area and Naracoorte, respectively. Where the name of the wetland surveyed was not available in the Wetlands – Statewide dataset, the AUS_WETNR label from the same dataset was used (the AUS_WETNR wetland identifiers start with S0, where the three first characters denote the region code, e.g. S01 = South East).

3 Results

3.1 Priority landscape wetlands for Key Waterbird Species of the Coorong

3.1.1 Model comparison and predictive performance

Tolderol Game Reserve – Occurrence models

For Tolderol GR, the best performing occurrence model for each species had only fair to moderate predictive performance (mean TSS for predictions to the evaluation dataset between 0.2 and 0.5), except for black swan which had a lower mean TSS of 0.19 (Table 3; see Table C.1 for full model selection metrics). In some cases, there was very little difference in mean TSS values between the best performing model and competing models (e.g. mean TSS for the top two models for Australian pelican and red-necked stint differed by ≤ 0.03) (Table C.1).

The best performing model for black swan and curlew sandpiper included variables representing salinity and turbidity, whereas the best performing models for Australian pelican, common greenshank, red-capped plover, red-necked stint, and sharp-tailed sandpiper included variables related to the physical characteristics of the pond (Table 3; Figures 9-10). These physical characteristics included basin area, proportion of the basin covered by water, and area of habitat where the water depth was in the preferred range for a given species. Black swans and curlew sandpipers were more likely to occur in ponds with relatively low salinity values (Figures 9b and 10b). Common greenshank and sharp-tailed sandpiper were more likely to occur when a larger proportion of a basin was inundated by water (Figures 10a and 10d), whereas red-necked stint were more likely to occupy basins where the proportion of the basin covered by water was approximately 0.25 (Figure 10c). Conversely, Australian pelicans were more likely to be present when the area of water > 20 cm deep was relatively large (Figure 9a). Red-capped plovers favoured ponds with a larger basin area (Figure 9c). There was also a tendency for occurrence of migratory KWS to peak during February (Figure 10).

The random effect term of basin number was significant in the case of the best performing model for black swan, red-capped plover, red-necked stint, and sharp-tailed sandpiper ($p < 0.05$). The random effect of survey year was significant only for non-migratory KWS (Australian pelican, black swan, and red-capped plover) ($p < 0.05$).

Tolderol Game Reserve – Abundance models

Based on the cross-validatory MAE, the Tolderol GR abundance models with the best predictive performance for Australian pelican, common greenshank and red-necked stint included the environmental variable salinity, whereas for black swan, the best model included both salinity and turbidity (Table 4, Figures 11-12, Appendix D; see Table C.2 for full model selection metrics). The abundance of red-capped plover and sharp-tailed sandpiper were best predicted by habitat availability; that is, the area within a depth range of 0 and 5 cm (Table 4). For curlew sandpiper, the model including only the intercept performed better than any other model (Table 4). Excluding this null model for the curlew sandpiper, the models selected for each species explained between 28.7% (black swan) and 73.4% (Australian pelican) of the variation in the survey data (Table 4).

High abundances of black swan, common greenshank and red-necked stint were associated with relatively low levels of salinity, with predicted abundances being near 0 for these species when salinity exceeded 1000 µS/cm (Figures 11-12). Numbers of black swans were also predicted to decrease in ponds with high turbidity (Figure 11). On the other hand, the relationship between the abundance of Australian pelicans and salinity was positive (Figure 11). Regarding red-capped plovers and sharp-tailed sandpipers, the abundance of both species was modelled to increase with the area of available habitat within a 0-5 cm depth range (Figures 11-12). Abundance of two of the migratory species, red-necked stint and sharp-tailed sandpiper, was predicted to peak during February.

The random effect term of basin number was significant in the case of the best performing model for Australian pelican, black swan, red-capped plover, red-necked stint, and sharp-tailed sandpiper ($p < 0.05$). The random effect of survey year was significant only for Australian pelican ($p < 0.05$).

Table 3. Best occurrence models of the seven key waterbird species at the Tolderol Game Reserve based on the highest mean evaluation True Skill Statistic (TSS). Values shown are mean values ± standard error of the evaluation TSS across each of the nine cross-validation data folds. In the model formula, *s(variable)* denotes spline terms, and *(1|Basin number)* and *(1|Year)* denote a random effect of basin and survey year, respectively. See Table C.1 for complete set of cross-validation metrics of all candidate models considered during model selection.

SPECIES	MODEL FORMULA	EVALUATION TSS
Australian pelican	s(Proportional coverage) + s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	0.25 ± 0.13
Black swan	s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	0.19 ± 0.1
Common greenshank	s(Proportional coverage) + s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	0.4 ± 0.2
Curlew sandpiper	s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	0.4 ± 0.24
Red-capped plover	s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	0.29 ± 0.07
Red-necked stint	s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)	0.3 ± 0.21
Sharp-tailed sandpiper	s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)	0.47 ± 0.14

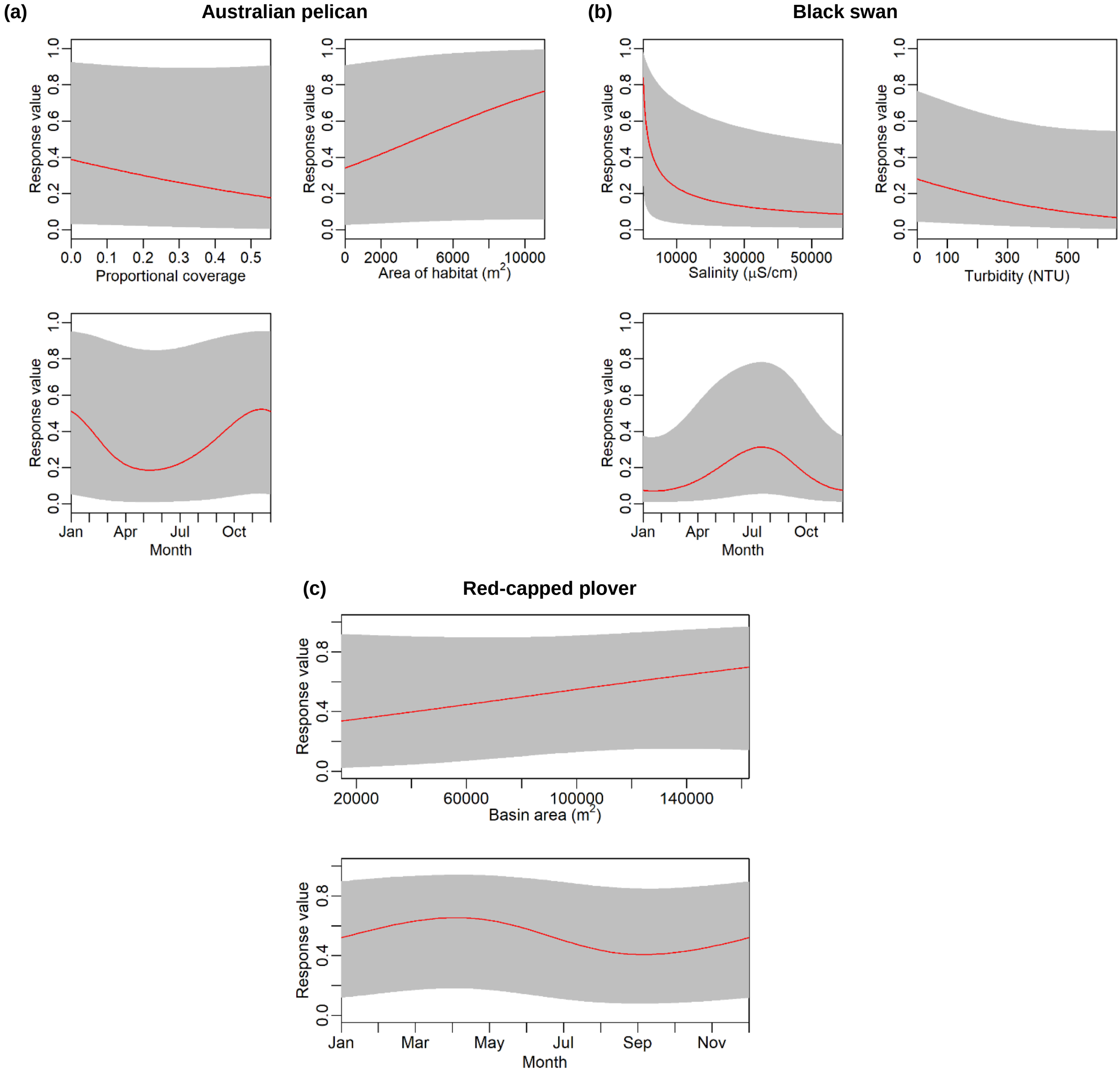

Figure 9. Occurrence partial response plots for the resident key waterbird species (KWS), Australian pelican (a), black swan (b) and red-capped plover (c) showing the influence of each smooth term of the best models on the species occurrence at Tolderol Game Reserve. Area of habitat for the Australian pelican represents the area with a water depth greater than 20 cm. The red line indicates predicted values when other variables are held at their median. Grey shading indicates the 95% confidence interval of that prediction.

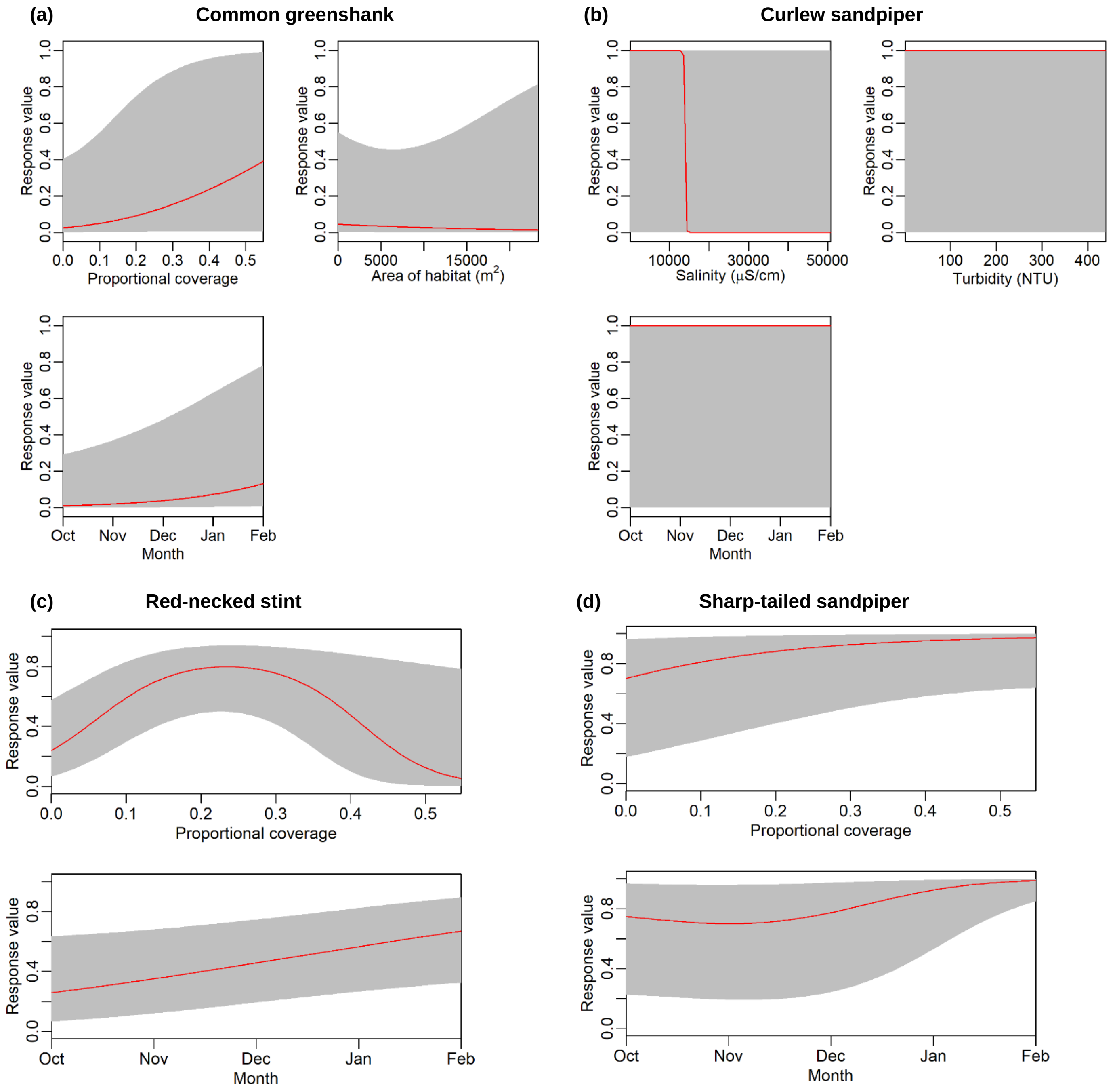

Figure 10. Occurrence partial response plot for migratory key waterbird species (KWS), common greenshank (a), curlew sandpiper (b) red-necked stint (c) and sharp-tailed sandpiper (d) showing the influence of each smooth term of the best models on the species occurrence at Tolderol Game Reserve. Area of habitat represents the area with a water depth between 0 and 5 cm. The red line indicates predicted values when other variables are held at their median. Grey shading indicates the 95% confidence interval of that prediction.

Table 4. Best abundance models of the seven key waterbird species at the Tolderol Game Reserve based on the highest mean evaluation Mean Absolute Error (MAE). Values shown are mean values ± standard error of the evaluation MAE across each of the 12 cross-validation data folds. For each species, the sample size (n), mean raw count ± standard error and minimum and maximum counts of the dataset used to fit the models are also provided, as well as the variance explained by the best model refitted to the full dataset. In the model formula, *s(variable)* denotes spline terms, and *(1|Basin number)* and *(1|Year)* denote a random effect of basin and survey year, respectively. See Table C.2 for complete set of cross-validation metrics of all candidate models considered during model selection.

SPECIES	MODEL FORMULA	EVALUATION MAE
Australian pelican n = 86 mean ± se = 2.08 ± 0.75 min – max = 0 – 52 Variance explained = 73.4%	s(Salinity) + s(Month) + (1|Basin number) + (1|Year)	**2.90 ± 0.53**
Black swan n = 86 mean ± se = 8.24 ± 2.2 min – max = 0 – 114 Variance explained = 28.7%	s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	8.57 ± 2.13
Common greenshank n = 59 mean ± se = 0.15 ± 0.07 min – max = 0 – 3 Variance explained = 42.9%	s(Salinity) + s(Month) + (1|Basin number) + (1|Year)	0.30 ± 0.08
Curlew sandpiper n = 59 mean ± se = 4.76 ± 3.60 min – max = 0 – 200 Variance explained < 1%	**1**	8.67 ± 2.70
Red-capped plover n = 86 mean ± se = 4.71 ± 1.31 min – max = 0 – 65 Variance explained = 72.9%	s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	4.93 ± 1.98
Red-necked stint n = 60 mean ± se = 5.38 ± 2.15 min – max = 0 – 100 Variance explained = 62.8%	s(Salinity) + s(Month) + (1|Basin number) + (1|Year)	5.55 ± 3.02
Sharp-tailed sandpiper n = 60 mean ± se = 114.27 ± 31.23 min – max = 0 – 1000 Variance explained = 31.9%	s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	161.08 ± 39.92

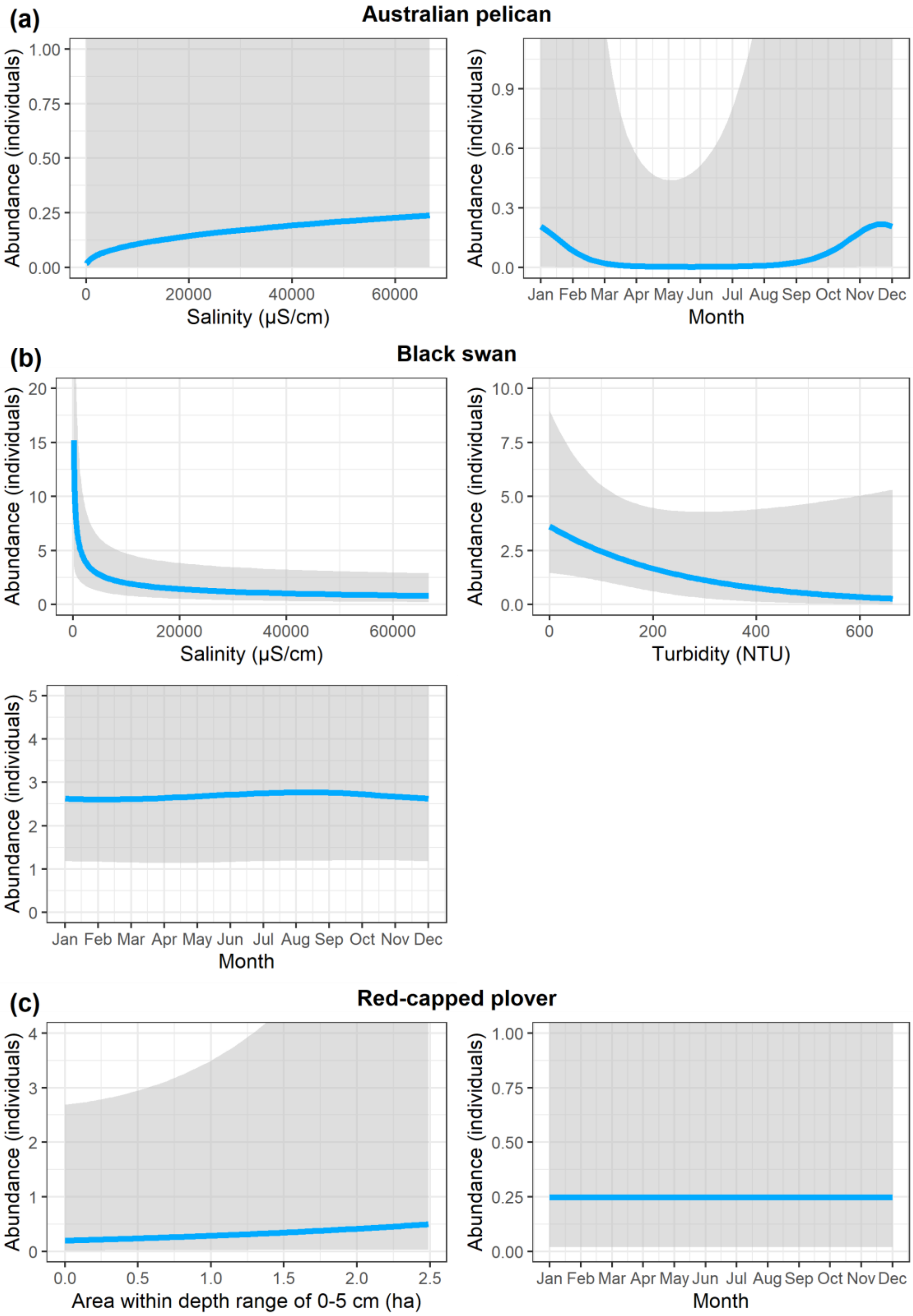

Figure 11. Abundance partial response plots for the resident key waterbird species, Australian pelican (a), black swan (b) and red-capped plover (c), showing the influence of each smooth term of the best models on bird abundance at Tolderol Game Reserve. The blue line indicates predicted abundance when other environmental variables are held at their mean and month at February. Ribbons represent 95% confidence intervals on these responses (and the upper confidence limit has been truncated to improve presentation of predicted abundance).

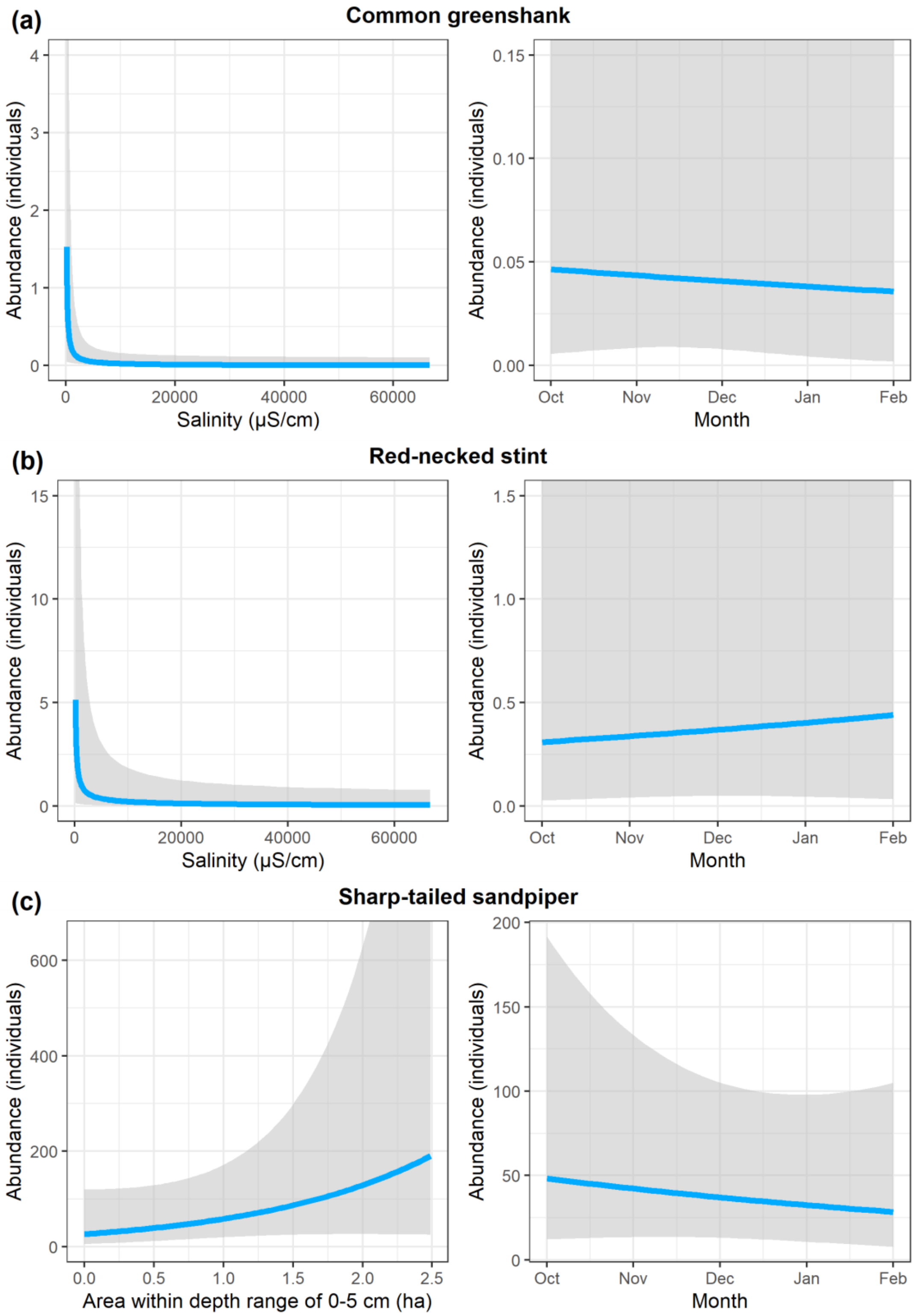

Figure 12. Partial response plots for the migratory key waterbird species, common greenshank (a), red-necked stint (b) and sharp-tailed sandpiper (c), showing the influence of each smooth term of the best models on bird abundance at Tolderol Game Reserve. The blue line indicates predicted abundance when other environmental variables are held at their mean and month at February. Ribbons represent 95% confidence intervals on these responses (and the upper confidence limit has been truncated to improve presentation of predicted abundance).

Teringie and Waltowa Wetlands

Patterns of water coverage (coincident with bird surveys) varied between the Teringie and Waltowa Wetlands. Whereas the proportion of inundated wetland area has generally increased over time at Teringie South, water coverage was relatively stable over time at Teringie North (usually 10-20% coverage) and Waltowa (usually 0-10% coverage) (Figure 13, Appendix E). Best models for each of the five species considered (sharp-tailed sandpiper, red-necked stint, red-capped plover, black swan, and Australian pelican) are shown in Table 5. Full model selection results for the five species considered are shown in Table C.3.

The abundance of two shorebirds (sharp-tailed sandpiper and red-capped plover) was highest at low levels of water coverage in these wetlands (Figure F.1), while the abundance of black swan increased with increasing water coverage in the southern portion of the Teringie wetland (Figure F.1). The abundance of Australian pelican variably increased or decreased with increasing extent of habitat exceeding 20 cm depth depending on the wetland considered (Figure F.2). An intercept-only model was selected for red-necked stint based on AIC rankings, indicating the abundance of this species was unrelated to inundation (at least over the range of inundation levels that occurred over the modelled period).

Lake Hawdon North

Given waterbird monitoring data was very limited for Lake Hawdon North, data from Lake Hawdon South were used to develop the response models. Waterbird responses at the two lakes are expected to be similar and therefore, Lake Hawdon South is used as a proxy for Lake Hawdon North.

For Lake Hawdon South, a simple model incorporating a random effect of species and a fixed effect of shallow habitat area (Count ~ 1|Species + Area) was supported based on both model-fit and cross-validation measures (Table 6). This selected model explained 41% of the variation in the survey data across all species (Table 6) and estimated a positive relationship between shorebird abundance and the area of available habitat within a 0-10 cm depth range (Figure 14). As a result, predictions of shorebird abundance were substantially higher under an infrastructure scenario that maintained water levels in Lake Hawdon North throughout spring and summer than for a current no-infrastructure scenario (Figures 15-16).

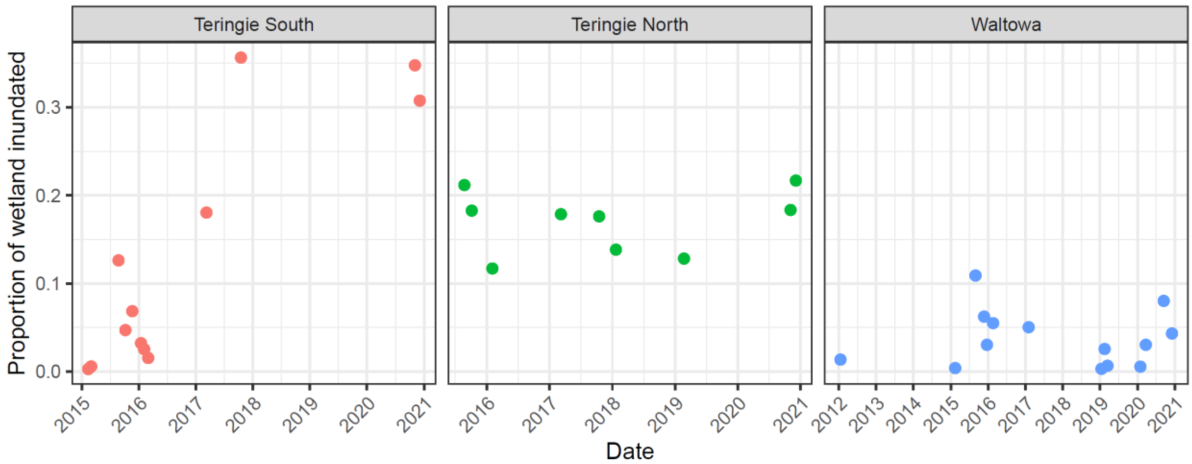

Figure 13. The proportion of inundated area (as derived from satellite imagery) for the Teringie South, Teringie North and Waltowa Wetlands, for the months when waterbird surveys were conducted.

Table 5. Best abundance models for five key waterbird species at the Teringie and Waltowa Wetlands based on Akaike's Information Criterion (AIC). Shown for each model are: AIC; the change in AIC relative to the top AIC-ranked model for each species (ΔAIC); the coefficient of determination (R^2). In the model formula, *Area0to5* denotes the area of wetland within the 0-5 cm depth range, while *AreaGreater20* denotes the area of wetland exceeding 20 cm depth. and *s(variable)* denotes spline terms. Refer to Table C.3 for complete set of cross-validation metrics of all candidate models considered during model selection.

SPECIES	MODEL	AIC	ΔAIC	R^2
Australian pelican	Wetland + s(AreaGreater20,by=Wetland)	110	0	0.76
Black swan	Wetland + s(PropCoverage,by=Wetland)	136	0	0.427
Red-capped plover	Wetland + s(PropCoverage)	74.3	0	0.175
Red-necked stint	1	43.2	0	0
Sharp-tailed sandpiper	Wetland + s(PropCoverage,by=Wetland)	152.4	0	0.296

Table 6. Evaluation of the candidate abundance models for six shorebird species at Lake Hawdon South. The negative binomial models were fitted to bird count data collected over 9 years and assessed with 9-fold (leave-one-year-out) temporal-block cross-validations. Shown for each model are: the number of parameters fitted (k); the log-likelihood of the model (logLik), Akaike's Information Criterion (AIC) for which lower numbers indicate higher ranked models; the change in AIC relative to the top AIC-ranked model for each species (ΔAIC); the coefficient of determination (R^2), the mean predictive deviance obtained by cross-validation (CV Deviance) and its standard error (SE) calculated across the 20 cross-validation folds; and the mean normalised Root Mean Square Error obtained by cross-validation and its standard error (SE). Models are ordered by AIC. In the model formula, *Area* denotes the area of wetland within the 0-10 cm depth range, while *(1|Species)* and *(1|Year)* denote a random effect of species and survey year, respectively.

Model	K	LOGLIK	AIC	ΔAIC	R^2	CV Deviance [SE]	CV NRMSE [SE]
(1|Species) + Area	4	-224.3	456.6	0	0.406	8.22 [1.15]	2.22 [0.78]
(1|Year) + (1|Species) + Area + Trend	6	-224.1	460.2	3.7	0.362	8.23 [1.15]	2.34 [0.85]
(Area|Species)	5	-227.1	464.2	7.6	0.437	8.58 [1.09]	2.6 [0.69]
(1|Species)	3	-233	472	15.5	0.268	8.5 [1.12]	2.73 [0.77]
(1|Species) + Trend	4	-232.3	472.7	16.1	0.340	8.62 [1.17]	2.74 [0.75]
(1|Year)	3	-244.2	494.3	37.8	0.103	10.24 [1.75]	2.4 [1.04]
1	2	-245.7	495.3	38.7	0	9.22 [1.35]	2.69 [0.93]

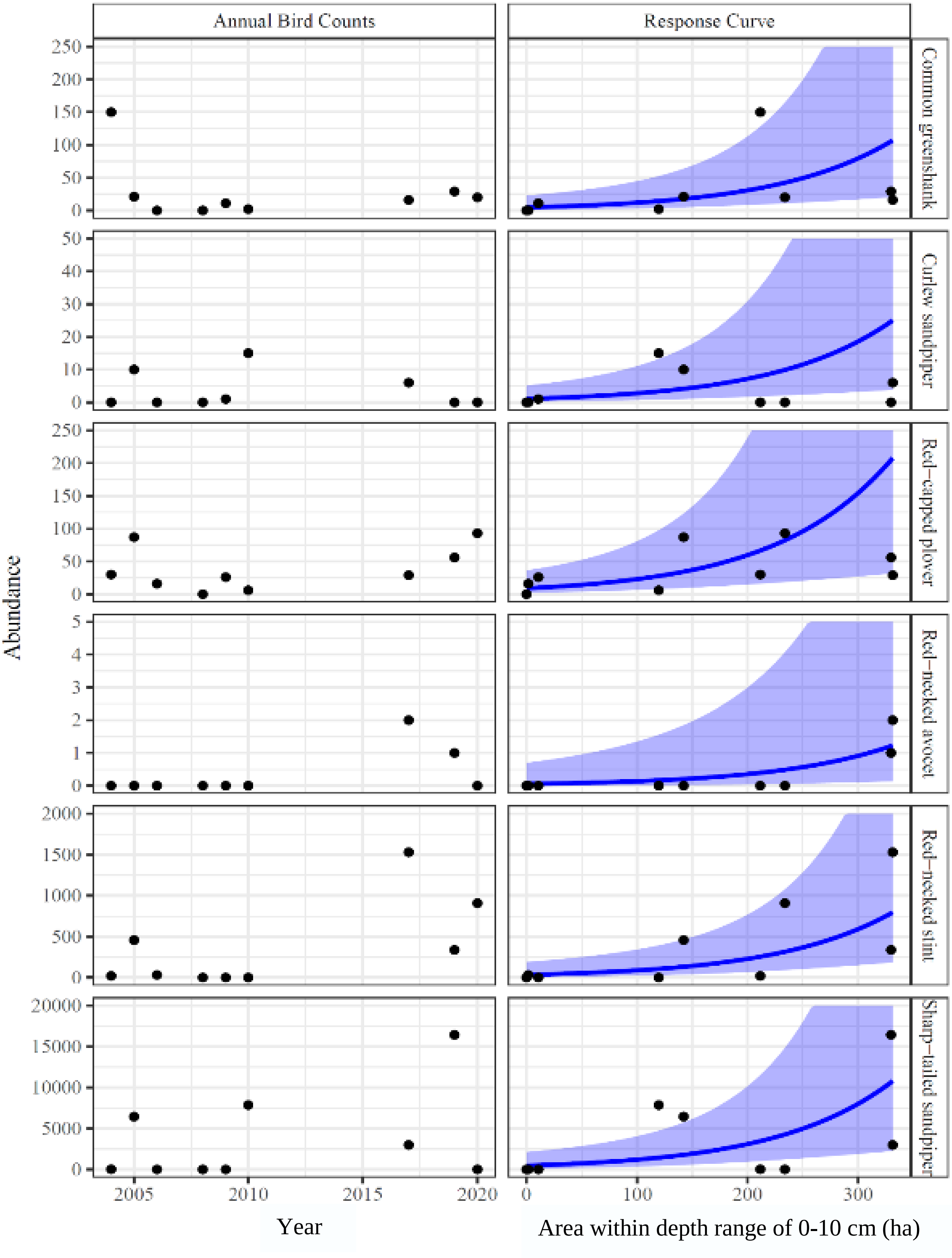

Figure 14. Data and response models for six shorebird species from Lake Hawdon South. The left column shows the count data from nine waterbirds surveys conducted between 2004 and 2020. The right column shows the same data (points) and the modelled relationship (blue lines) between bird abundance and the area of habitat within the 0-10 cm depth range from the selected response model. Ribbons represent 95% confidence intervals on these responses (and the upper confidence limit has been truncated to improve presentation).

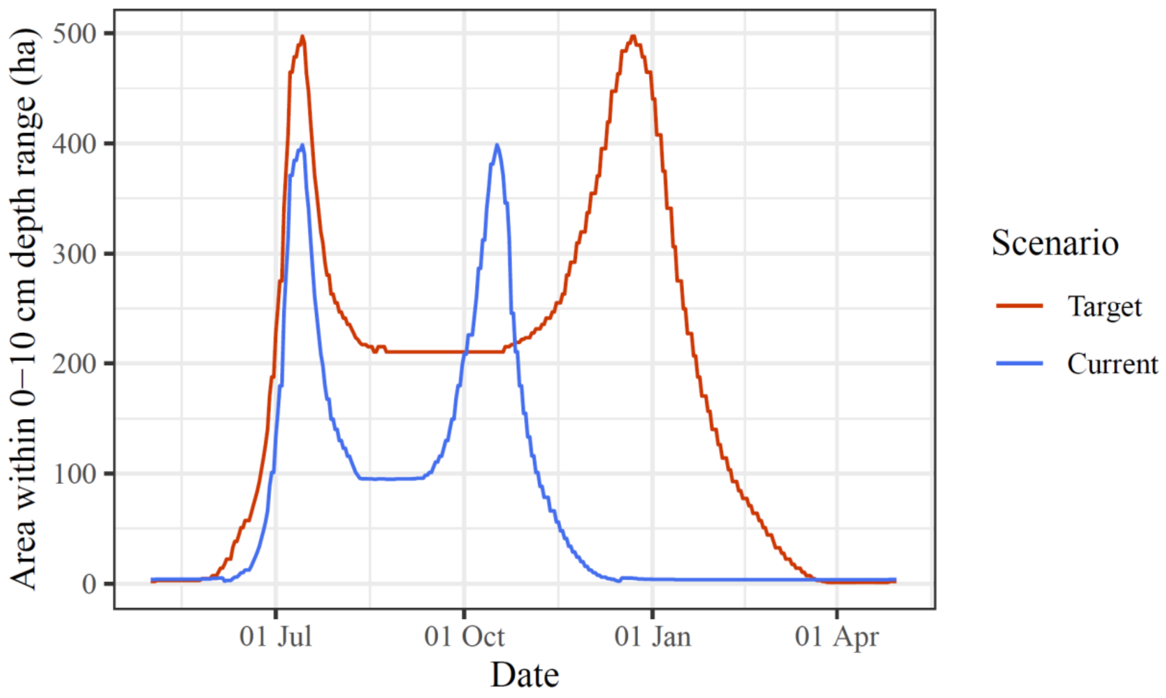

Figure 15. Modelled average area of habitat with the 0-10 cm depth range for Lake Hawdon North, redrawn from Taylor (2020). Lines represent two scenarios: (1, blue) the current scenario in which the area of available shallow habitat declines rapidly in late spring; and (2, red) an aspirational target scenario, in which installation of a regulator downstream of Lake Hawdon North produces a peak area of shallow habitat in early summer.

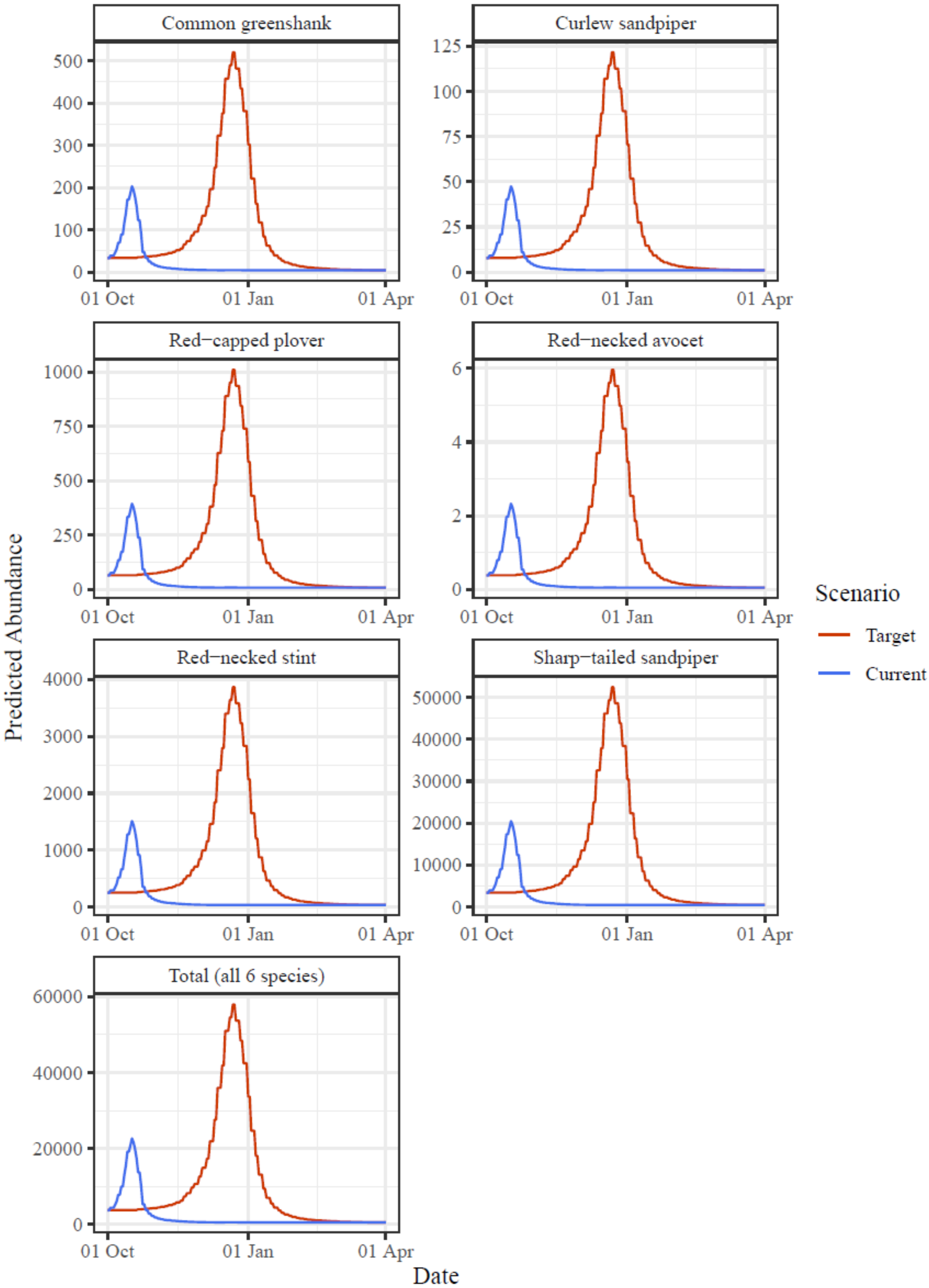

Figure 16. Expected shorebird abundances, and the total abundance across all 6 species, for Lake Hawdon North. These response plots are derived using the selected response model and assuming habitat areas for the current (blue) and the target (red) infrastructure scenarios (as illustrated in Figure 15).

3.2 Broader landscape wetlands

3.2.1 Proportional water coverage

The average monthly proportional water coverage between 1999 and 2020 for the wetlands considered in the models was 0.16 ± 0.27 (mean ± sd) for the Murray Region and 0.08 ± 0.20 for the South East Region. Our proportional water coverage estimation captured a decline in the proportional water coverage across both regions during the Millennium Drought (Figure 17). In the Murray Region, 55% of the wetlands had no water coverage in January and, in July, proportional water coverage at most wetlands was between 0 and 0.25 (Figure 18a and 18b). In January *c.* 80% of the wetlands in the South East region were dry, and in July, most of the wetlands had a proportional water coverage between 0 and 0.25 (Figure 18c and 18d). From October to February, most wetlands considered in the models remained at a proportional water coverage between 0 and 0.1 (Appendix G).

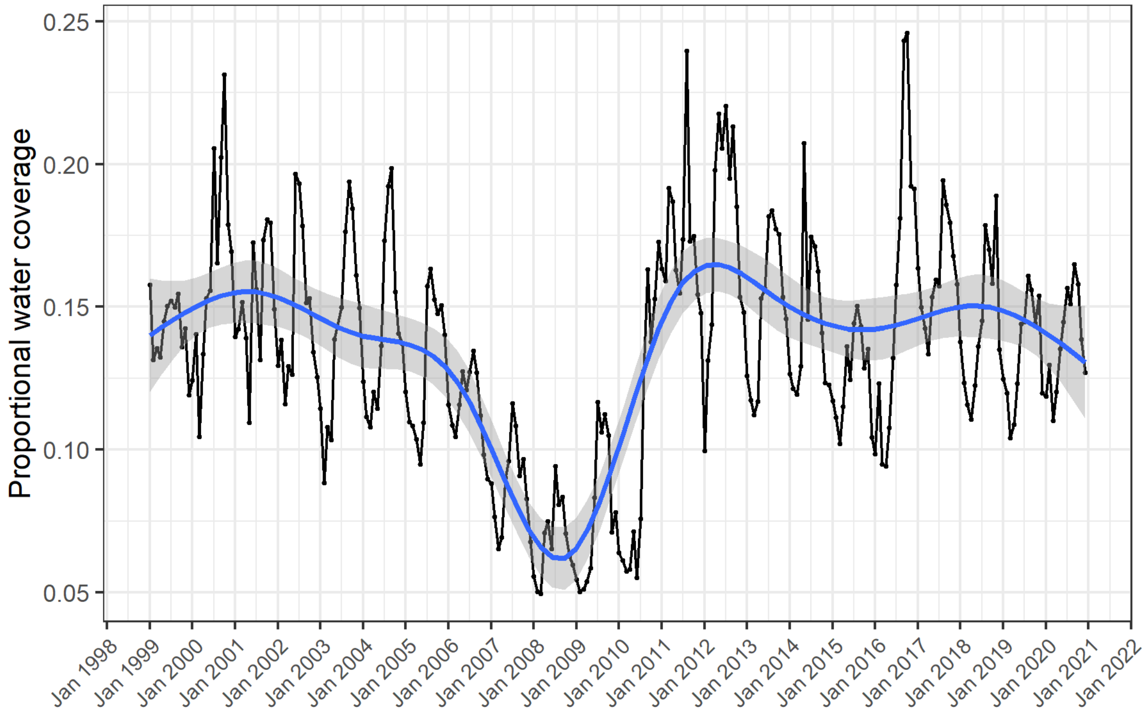

Figure 17. Monthly average of proportional water coverage across the wetlands considered in the waterbird response models for the broader landscape. The blue line is a smooth curve to visualise patterns and the grey ribbon is its 95% confidence interval. An outlier corresponding to June 2003 has been removed as water coverage data was only available for 5 wetlands in this month.

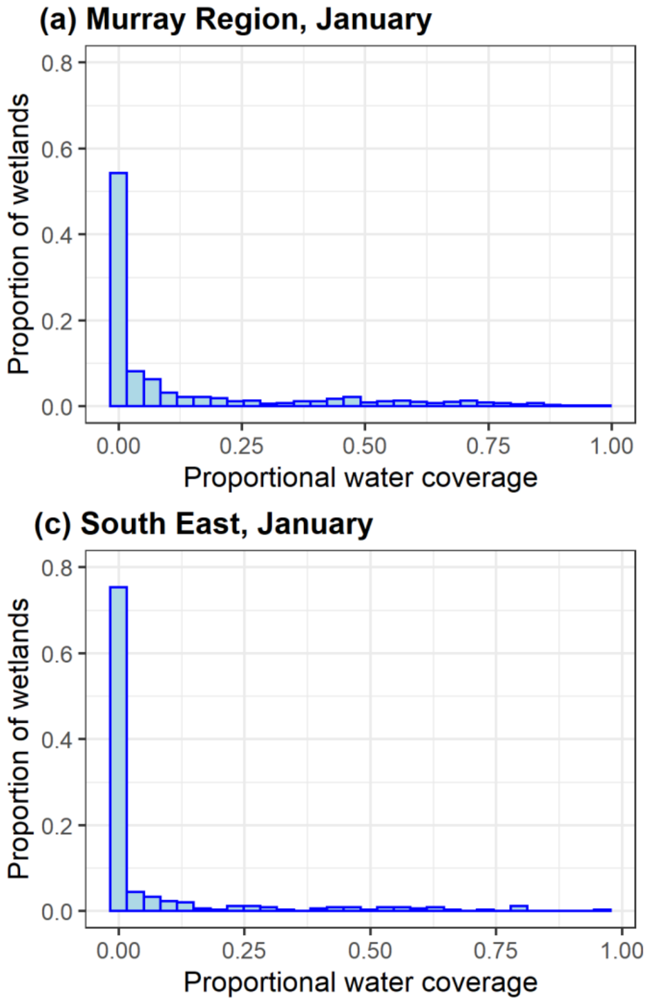

Figure 18. Histograms showing the distribution of the average proportional water coverage in January and July between 1999 and 2020 across the Murray Region wetlands (a, b) and the South East wetlands (c, d) considered in the waterbird response models of the broader landscape.

3.2.2 Vegetation cover

The proportional coverage and total area of five vegetation types (Woody Native Vegetation, Mangrove Vegetation, Non-woody Native Vegetation, Wetland Vegetation and Saltmarsh Vegetation) did not change substantially over time across the wetlands considered for modelling in either region (Figure 19). Although the proportional cover and total area of wetland vegetation has slightly decreased in the South East since 1987, this decrease occurred prior to the timeframe of the modelling (i.e. before 1999-2020) (Figure 19). Non-woody native vegetation was the class with the highest cumulative area across the wetlands in the Murray Region, while in the South East wetland vegetation was the dominant vegetation class (Figure 19b). There was no mangrove vegetation in any of the wetlands and the coverage of saltmarsh vegetation was low compared to the other vegetation classes in both regions (Figure 19).

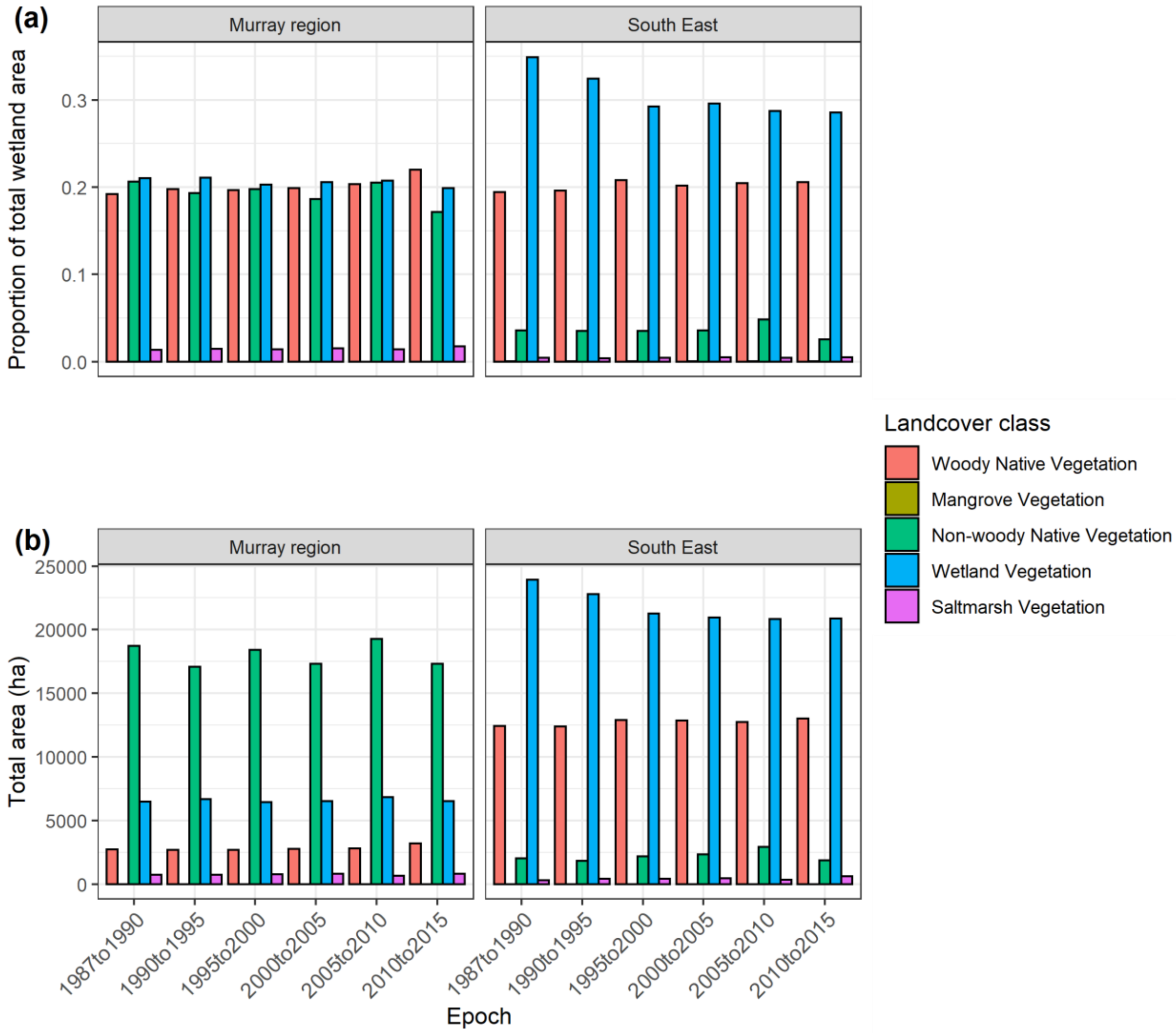

Figure 19. Summary bar plots showing vegetation cover change over time across the Murray Region and South East wetlands considered in the waterbird response models for the broader landscape. (a) Average proportional vegetation cover and (b) total area in ha for the landcover classes Woody Native Vegetation, Mangrove Vegetation Non-woody Native Vegetation, Wetland Vegetation and Saltmarsh Vegetation.

3.2.3 Encounter rate modelling

Overall, the estimated encounter rates for all shorebird and rail species, except the masked lapwing and black-tailed native-hen, were lower than estimates for most of the waterfowl and piscivorous species (Figure 20-23). Shorebirds and rails showed weak responses to water coverage in general (Figures 22-23), whereas waterfowl encounter rates were more strongly related to proportional water coverage than the rest of waterbirds (Figure 20).

Proportional Water Coverage

In the South East region, estimated encounter rates for 12 of 18 waterfowl species peaked when the proportion of the wetland covered by water was *c.* 0.5 (e.g. Australasian shoveler, black swan, Eurasian coot) (Figure 20). For the remaining six waterfowl, encounter rate was either unrelated to proportional water coverage (Australian wood duck, cape barren goose) or predicted to increase with increasing proportional water coverage (chestnut teal, freckled duck, magpie goose and musk duck) (Figure 20). In the Murray Region, the encounter rates of 7 of 18 waterfowl species were predicted to increase with a larger proportion of the wetland being covered by water (e.g. Australian wood duck, black swan, purple swamphen) (Figure 20).

For piscivorous species, the relationship between proportional water coverage and encounter rate varied among species (Figure 21). In general, when there was an impact of proportional water coverage, encounter rates were either predicted to increase with increasing water coverage (e.g. Australian pelican and great egret in the Murray Region) or to peak where the proportion of wetland covered by water was around 0.5 (e.g. Australian white ibis in both the South East and Murray regions, great cormorant, little black cormorant and yellow-billed spoonbill in the Murray Region) (Figure 21).

Responses to proportional water coverage were generally weak among shorebirds. The encounter rate of red-capped plover, red-necked stint and curlew sandpiper decreased slightly with increasing water coverage in the South East region (Figure 22). Encounter rate estimates for black-fronted dotterel, black-winged stilt and masked lapwing were highest at *c.* 0.5 proportional water coverage (Figure 22). Among the migratory species, encounter rates of common greenshank were predicted to increase slightly with increasing proportional water coverage (Figure 22). All rail species were more likely to be encountered where a larger proportion of the wetland was covered by water or at intermediate proportional water coverage (Figure 23).

Vegetation Cover

The estimated effect of vegetation cover, which included coverage of wetland vegetation and saltmarsh, was positive for 16 of 18 waterfowl species (statistically significant effect for 12 of those species, i.e. 95% confidence interval (CI) did not include 0), for 22 of 24 piscivorous species (12 of which had a statistically significant effect), and for four of five rail species (Figure 24). Among waterfowl, these positive effects were strongest for the black swan (estimate = 0.71, 95% CI = 0.52 – 0.90), the grey teal (estimate = 0.68, 95% CI = 0.51 – 0.84) and the hardhead (estimate = 0.82, 95% CI = 0.59 – 1.06) (Figure 24). Encounter rates of the piscivorous glossy ibis were also positively related to vegetation cover (estimate = 1.15, 95% CI = 0.56 - 1.75). Regarding rails, vegetation cover had the highest positive effect on encounter rates of the black-tailed native-hen (estimate = 0.46, 95% CI = 0.27 – 0.65).

For migratory shorebirds, the estimated effect of vegetation cover (which included coverage of woody, non-woody, mangrove and wetland vegetation) on encounter rate was negative for five of the nine migratory species (common sandpiper, curlew sandpiper, pacific golden plover, red-necked stint and wood sandpiper) (Figure 24).

Increased Water Availability Across Australia

The estimated impact of increasing water availability across Australia on encounter rates in our study area was negative for 14 of 18 waterfowl species (statistically significant for eight of these species), for 16 of 24 piscivorous species (seven of which had a statistically significant effect), for 13 of 16 shorebird species (five of which had a statistically significant effect), and for 4 of 5 rail species (statistical significance for the Baillon's crake) (Figure 25). Encounter rates for the Australasian shoveler (estimate = -0.25, 95% CI = -0.35 - -0.14) and the pink-eared duck (estimate = -0.26, 95% CI = -0.40 - -0.12) were strongly negatively associated with water availability across Australia (Figure 25). Among shorebird species, the strongest negative effect of increasing wetness across Australia was observed for the Latham's snipe (estimate = -0.32, 95% CI = -0.59 - -0.05), red-necked avocet (estimate = -0.29, 95% CI = -0.48 - -0.11) and sharp-tailed sandpiper (estimate = -0.26, 95% CI = -0.44 - -0.08) (Figure 25).

Distance to coast

Increasing distance to the coast had an estimated negative effect on the encounter rates of many species (44 of 63), including all shorebird species (e.g. red-necked stint: estimate = -1.97, 95% CI = -2.67 - -1.26; common greenshank: estimate = -1.51, 95% CI = -2.25 - -0.77) except the black-fronted dotterel, the red-kneed dotterel and the red-necked avocet (Figure 26). This negative effect was statistically significant for a total of 21 species: four waterfowl, ten piscivorous and seven shorebird species (Figure 26).

Among species with an estimated positive effect of distance to coast, the Australian wood duck (estimate = 0.81, 95% CI = 0.60 - 1.02), the Australasian darter (estimate = 0.84, 95% CI = 0.62 - 1.06) and the white-necked heron (estimate = 0.74, 95% CI = 0.52 – 0.96) had the strongest effects (Figure 26).

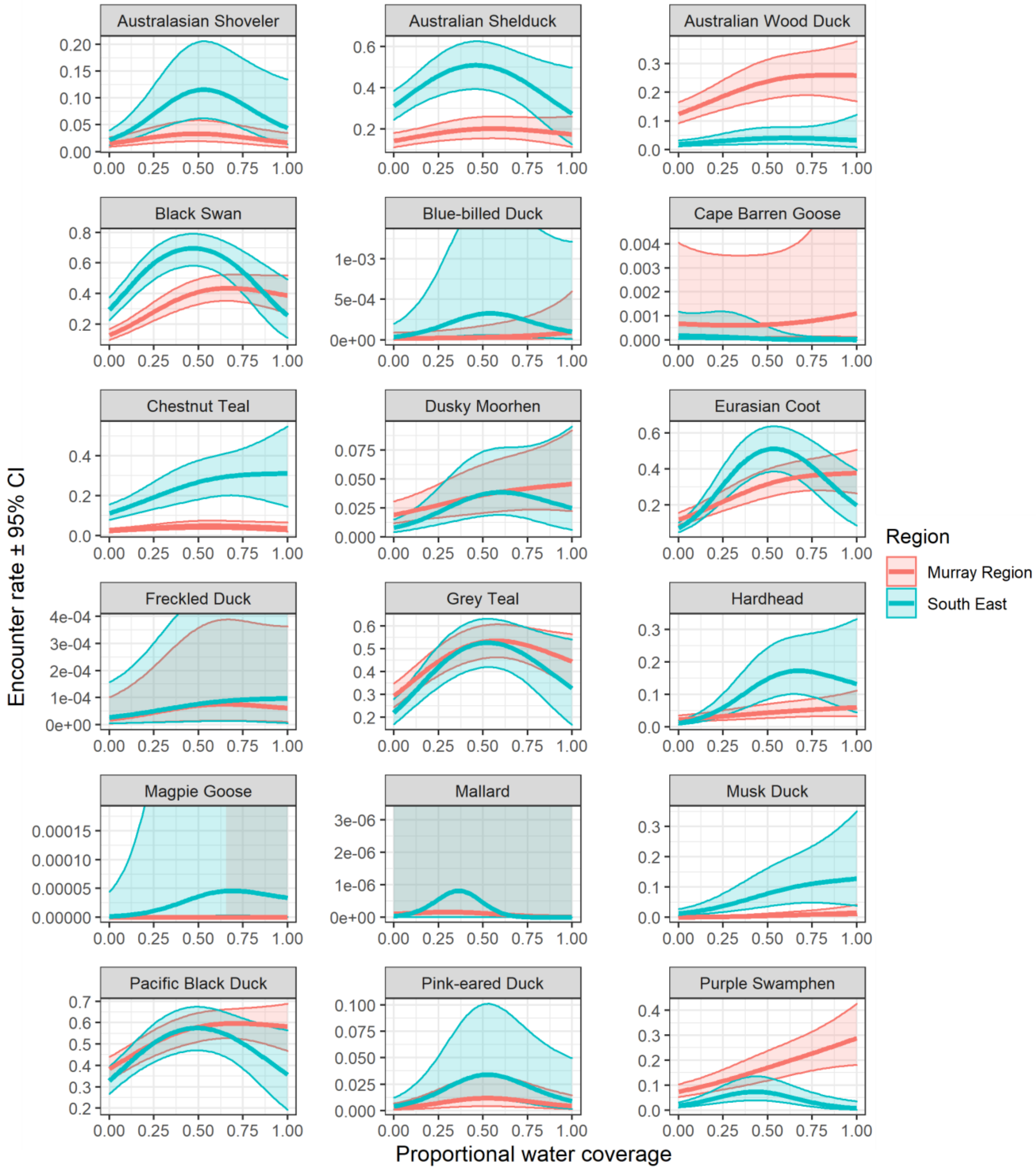

Figure 20. Partial response plots for the waterfowl species modelled showing the non-linear influence of proportional water coverage on encounter rate at the wetlands in the broader landscape of south-east South Australia (Murray Region in red and South East in green). The lines indicate predicted encounter rate when other variables are held at their mean within the region and month is held at February. Ribbons represent 95% confidence intervals on these responses. The upper confidence limit has been truncated to improve presentation of predicted values for species with their highest predicted encounter rate lower than 0.02. Partial response plots with non-truncated confidence intervals are in Appendix H, Figure H.1.

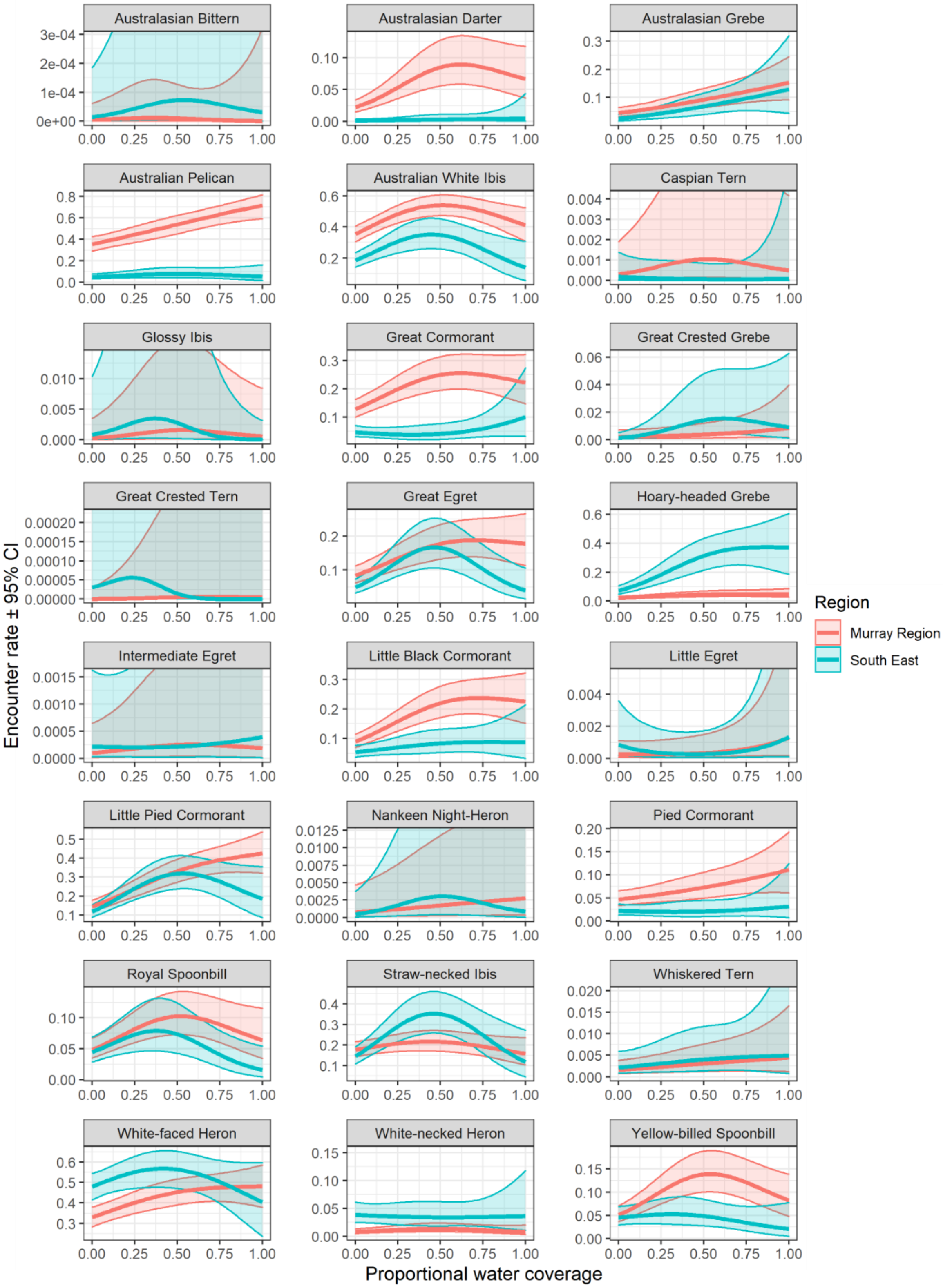

Figure 21. Partial response plots for the piscivorous species modelled showing the non-linear influence of proportional water coverage on encounter rate at the wetlands in the broader landscape of south-east South Australia (Murray Region in red and South East in green). The lines indicate predicted encounter rate when other variables are held at their mean within the region and month is held at February. Ribbons represent 95% confidence intervals on these responses. The upper confidence limit has been truncated to improve presentation of predicted values for species with their highest predicted encounter rate lower than 0.05. Partial response plots with non-truncated confidence intervals are in Appendix H, Figure H.2.

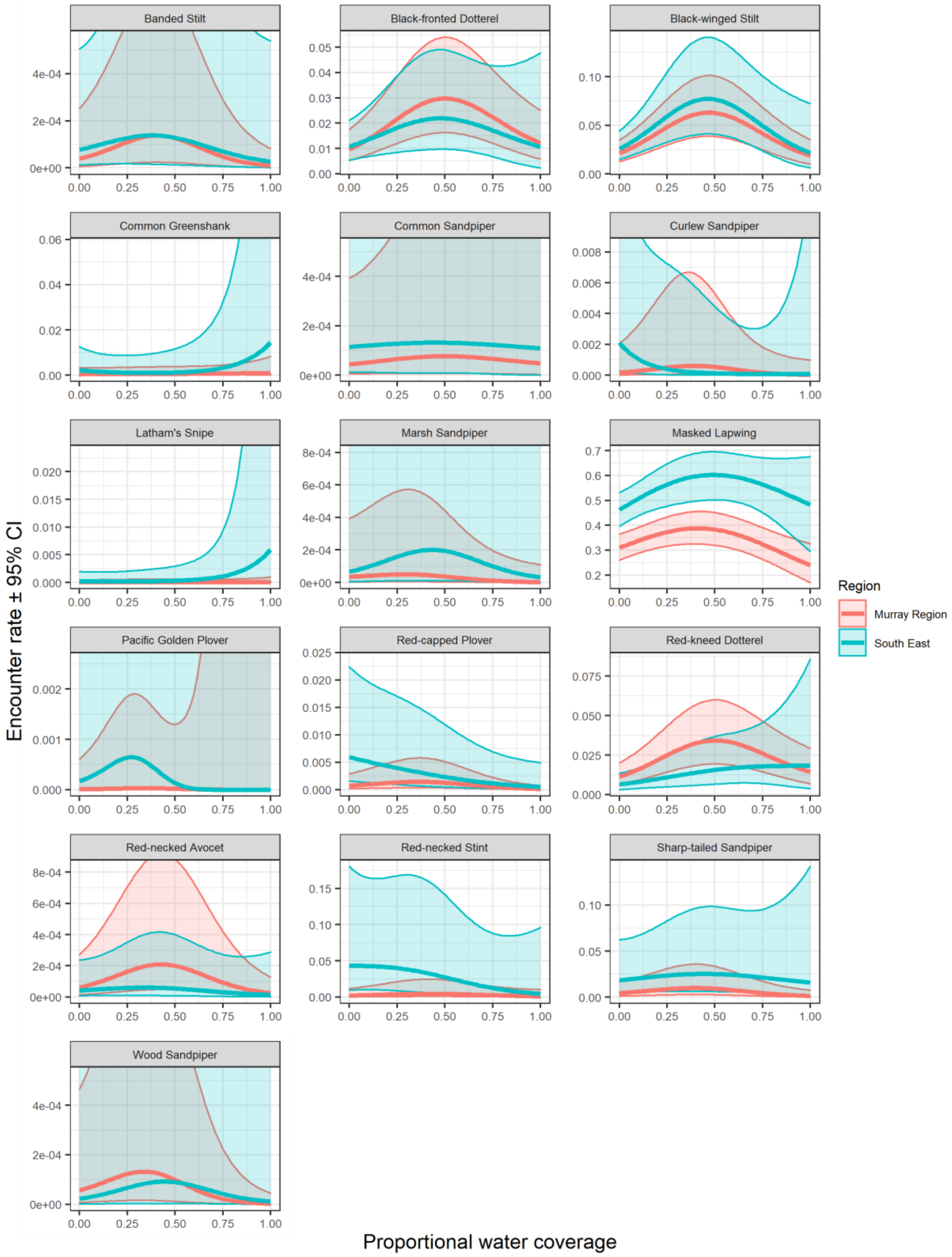

Figure 22. Partial response plots for the shorebird species modelled showing the non-linear influence of proportional water coverage on encounter rate at the wetlands in the broader landscape of south-east South Australia (Murray Region in red and South East in green). Migratory species include: common greenshank, common sandpiper, curlew sandpiper, Latham's snipe, marsh sandpiper, pacific golden plover, red-necked stint, sharp-tailed sandpiper and wood sandpiper. The lines indicate predicted encounter rate when other variables are held at their mean within the region and month is held at February. Ribbons represent 95% confidence intervals on these responses. The upper confidence limit has been truncated to improve presentation of predicted values for species with their highest predicted encounter rate lower than 0.02. Partial response plots with non-truncated confidence intervals are in Appendix H, Figure H.3.

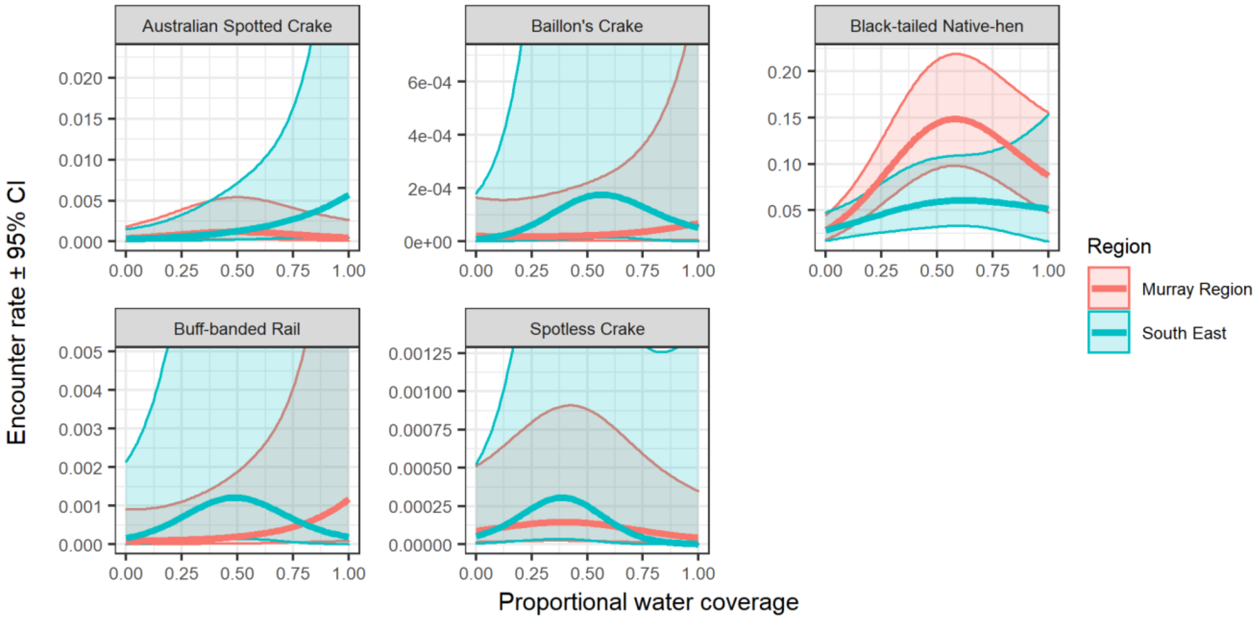

Figure 23. Partial response plots for the rail species modelled showing the non-linear influence of proportional water coverage on encounter rate at the wetlands in the broader landscape of south-east South Australia (Murray Region in red and South East in green). The lines indicate predicted encounter rate when other variables are held at their mean within the region and month is held at February. Ribbons represent 95% confidence intervals on these responses. The upper confidence limit has been truncated to improve presentation of predicted values for species with their highest predicted encounter rate lower than 0.02. Partial response plots with non-truncated confidence intervals are in Appendix H, Figure H.4.

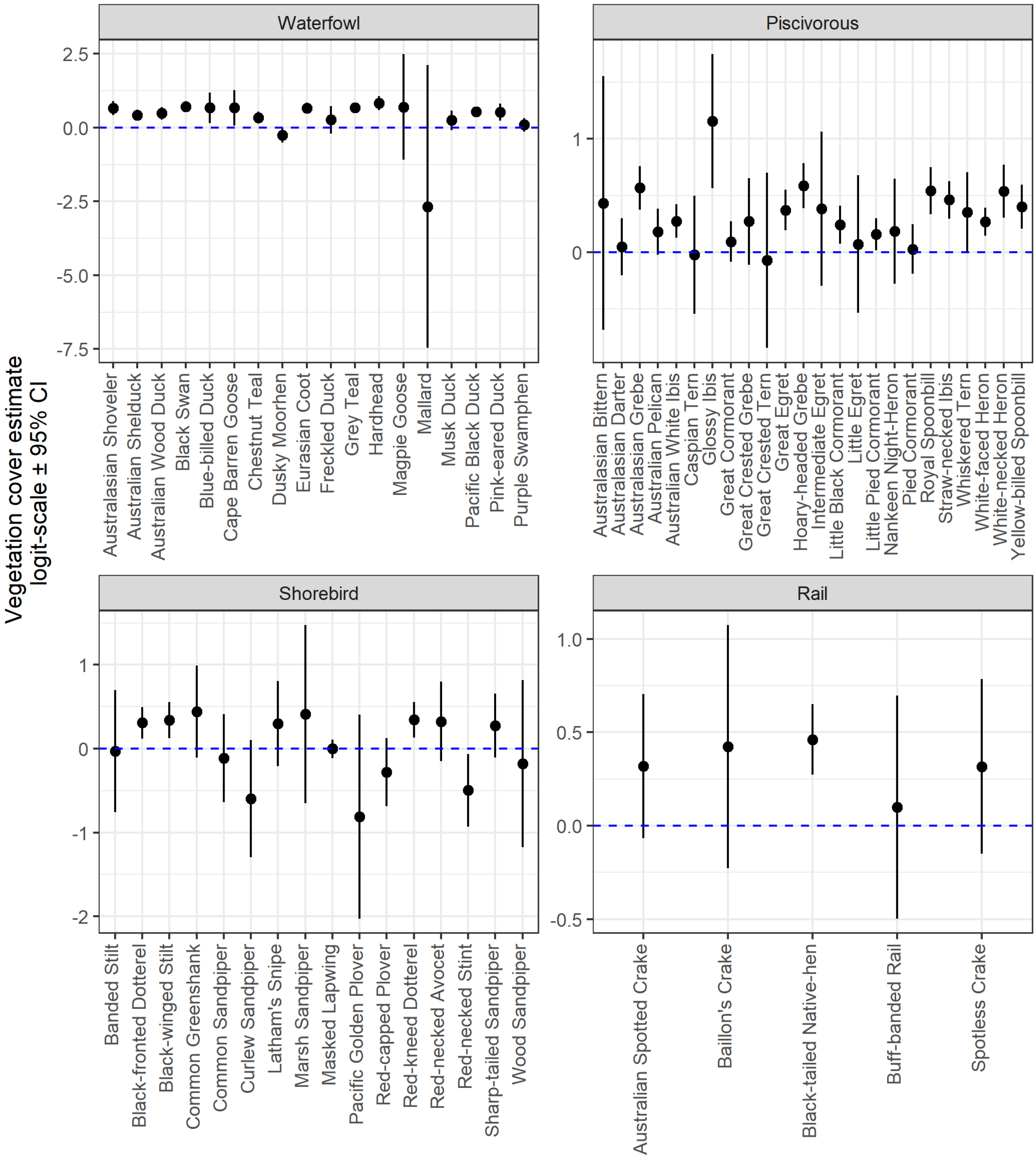

Figure 24. Regression coefficient estimates (points) and 95% confidence intervals (error bars) of the linear covariate vegetation cover for all waterbird species modelled in the broader landscape wetlands. Each panel represents a group of waterbirds (waterfowl, piscivores, shorebirds and rails). For shorebirds, the vegetation cover represents the proportion of the wetland polygon/s covered by wetland woody native vegetation, mangrove vegetation, non-woody vegetation and wetland vegetation. For piscivores, rails and waterfowl, the vegetation cover represents the proportion of the wetland polygon/s covered by wetland vegetation and saltmarsh vegetation. Migratory shorebird species include: common greenshank, common sandpiper, curlew sandpiper, Latham's snipe, marsh sandpiper, pacific golden plover, red-necked stint, sharp-tailed sandpiper and wood sandpiper. The dashed blue line represents a coefficient estimate of 0 to help interpret the sign of the relationship between vegetation cover and the response encounter rate (i.e. negative if estimate < 0 and positive if estimate > 0) and the strength and significance of the effect (i.e. if the confidence interval includes 0, we consider the effect is not statistically significant at significance level of 0.05).

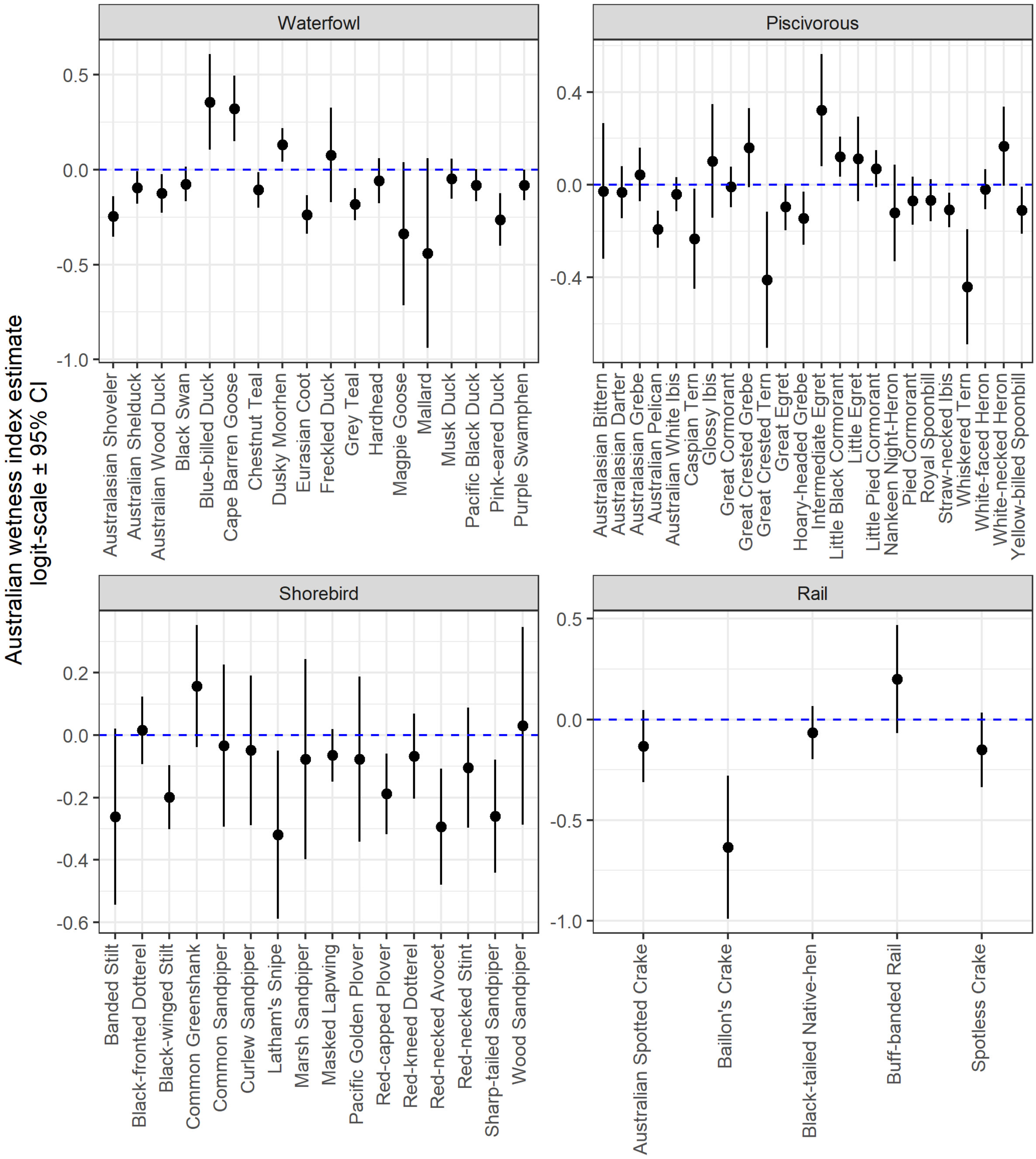

Figure 25. Regression coefficient estimates (points) and 95% confidence intervals (error bars) of the linear covariate Australian "wetness" index for all waterbird species modelled in the broader landscape wetlands. Each panel represents a group of waterbirds (waterfowl, piscivores, shorebirds and rails). Migratory shorebird species include: common greenshank, common sandpiper, curlew sandpiper, Latham's snipe, marsh sandpiper, pacific golden plover, red-necked stint, sharp-tailed sandpiper and wood sandpiper. The dashed blue line represents a coefficient estimate of 0 to help interpret the sign of the relationship between vegetation cover and the response encounter rate (i.e. negative if estimate < 0 and positive if estimate > 0) and the strength and significance of the effect (i.e. if the confidence interval includes 0, we consider the effect is not statistically significant at significance level of 0.05).

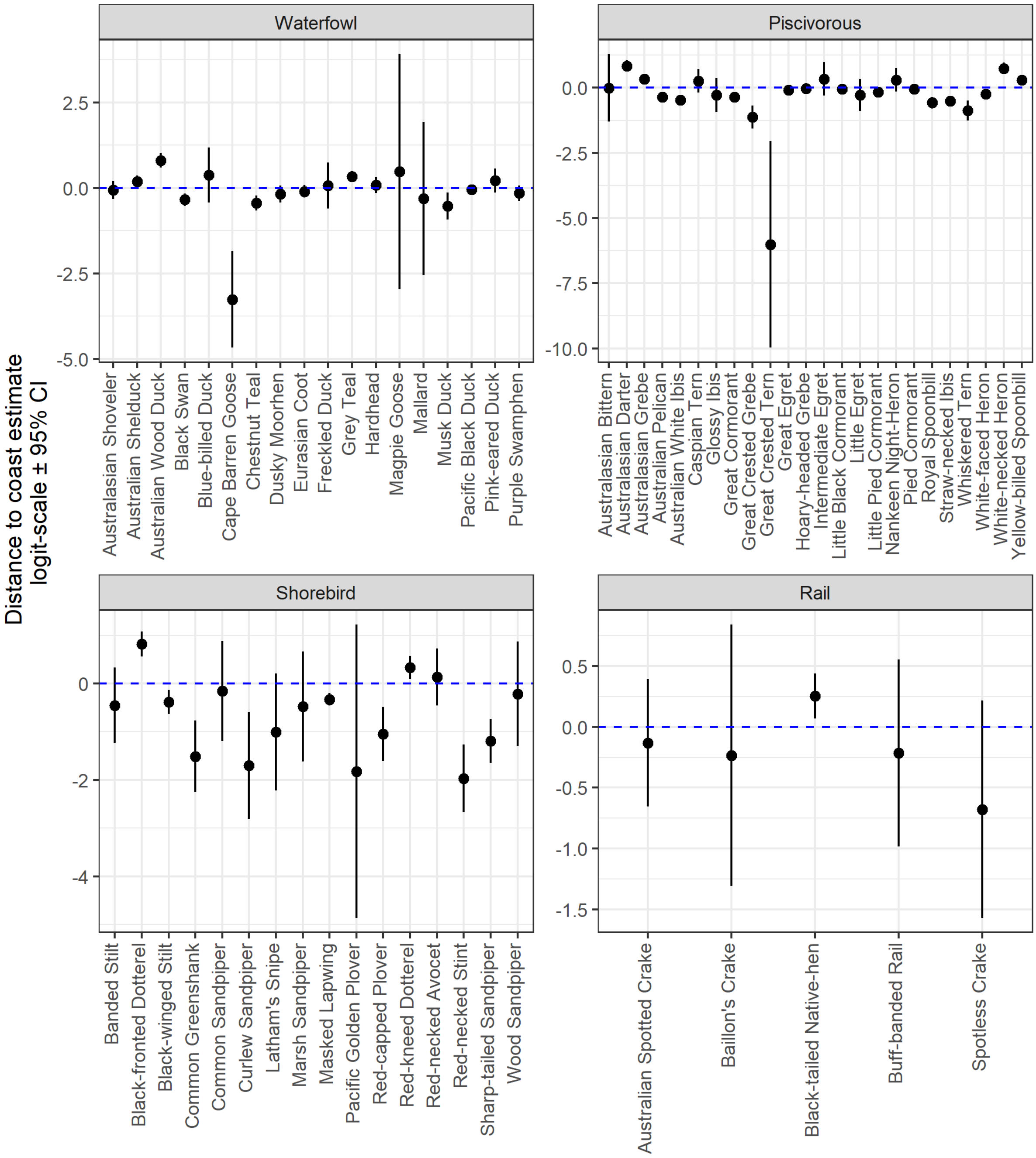

Figure 26. Regression coefficient estimates (points) and 95% confidence intervals (error bars) of the linear covariate distance to coast for all waterbird species modelled in the broader landscape wetlands. Each panel represents a group of waterbirds (waterfowl, piscivores, shorebirds and rails). Migratory shorebird species include: common greenshank, common sandpiper, curlew sandpiper, Latham's snipe, marsh sandpiper, pacific golden plover, red-necked stint, sharp-tailed sandpiper and wood sandpiper. The dashed blue line represents a coefficient estimate of 0 to help interpret the sign of the relationship between vegetation cover and the response encounter rate (i.e. negative if estimate < 0 and positive if estimate > 0) and the strength and significance of the effect (i.e. if the confidence interval includes 0, we consider the effect is not statistically significant at significance level of 0.05).

3.2.4 On-ground waterbird counts

In total, we recorded 42 waterbird species, including five species of migratory shorebird (common sandpiper, curlew sandpiper, red-necked stint, Latham's snipe and sharp-tailed sandpiper). Each migratory shorebird species was recorded in up to 2 of the 31 wetlands we surveyed (Figure 27a). Masked lapwing (17 wetlands), white-faced heron (13 wetlands) and pacific black duck (13 wetlands) were the species recorded in the highest proportion of wetlands (Figure 27a). The two most abundant species were the black swan (5,256 individuals) and Australian shelduck (4,877 individuals) (Figure 27b). The red-necked stint was the most abundant migratory shorebird species (2,545 individuals) (Figure 27b). Overall, the availability of habitat for migratory shorebirds was very limited, with most wetlands being either dry (e.g. Salt Lake, Lake Frome) or full (e.g. Lake Edward, Big Dip Lake). The only shorebirds we recorded in wetlands that were completely dry were the red-capped plover and the masked lapwing. For example, we found red-capped plovers performing distraction displays at the dry southern section of Lake George. All migratory shorebirds, except one Latham's Snipe at Lake McIntyre, were recorded in one of three coastal wetlands including: Lake George where we recorded a flock of > 2,000 red-necked stints; Middle Point Wetland, where we encountered a flock of 250 sharp-tailed sandpipers and 5 curlew sandpipers; and Fox Lake, where we recorded Latham's snipe and common sandpiper.

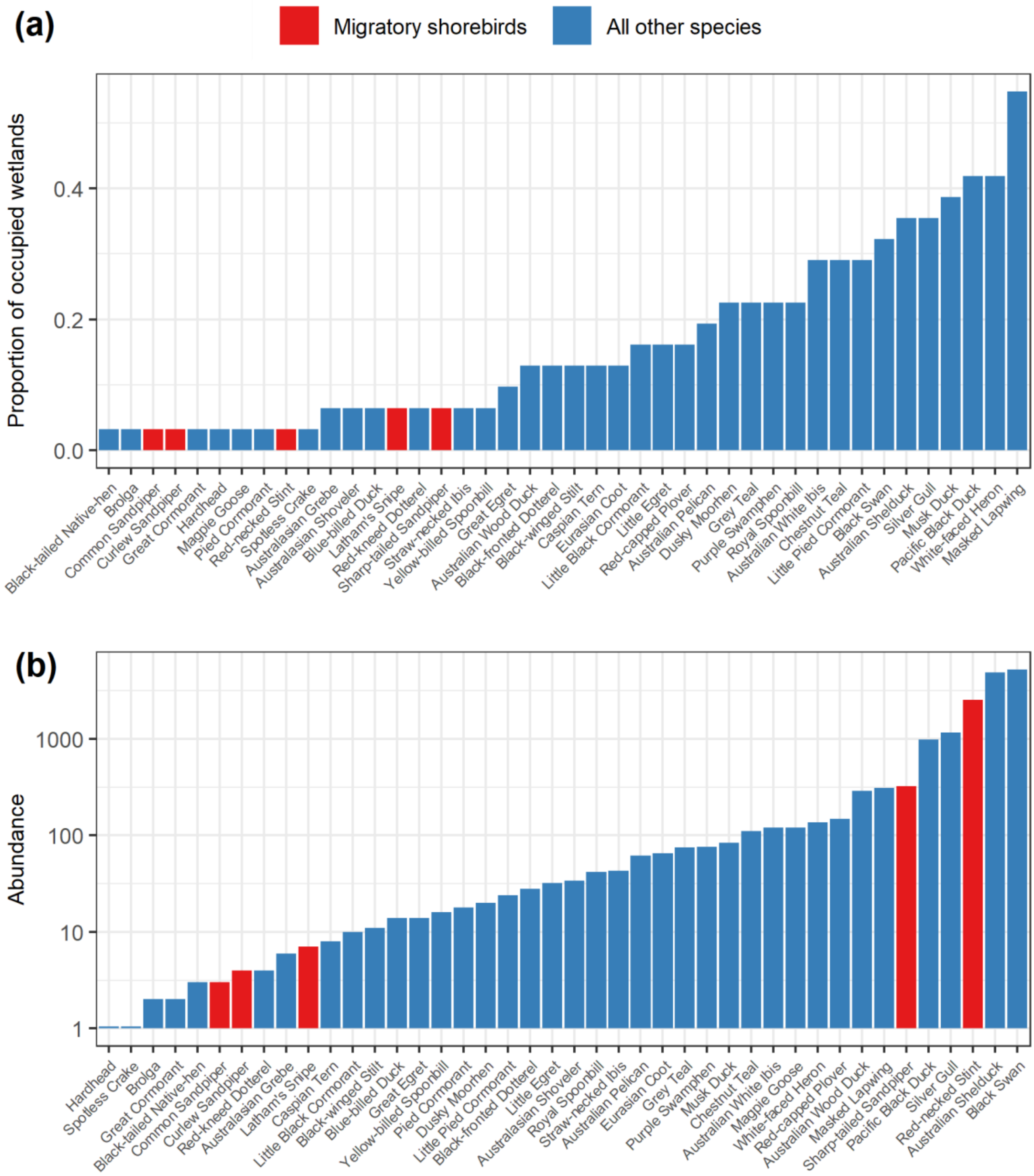

Figure 27. Bar plots showing the proportion of 31 visited wetlands where each species was recorded in January 2022 (a) and total abundance of each species accumulated over the counts at all wetlands (b). The y-axis of plot b is shown on a log scale to improve visualisation. Red bars indicate migratory shorebirds.

4 Discussion

4.1 Abiotic correlates of waterbird occurrence and abundance in priority landscape wetlands

The response of KWS to environmental conditions at the priority wetlands generally followed expected patterns. Response models for Lake Hawdon South, Teringie and Waltowa Wetlands were based on very limited datasets. As a result, there was less opportunity to interpret outcomes in terms of management at those three wetlands, so this discussion focuses mainly on Tolderol GR.

Salinity and turbidity were negatively related to the abundance of black swan at Tolderol GR. This reflects observations that black swans, which feed mainly on aquatic vegetation, are negatively affected by high water turbidity via turbidity-related suppression of aquatic plant growth (Braithwaite 1982, McDougall and Timms 2001). High salinity also has a negative effect on the occurrence and abundance of black swan at the Coorong (Prowse et al. 2022), though a stronger influence of salinity on KWS responses was found for the Coorong (Prowse et al. 2022) than at Tolderol GR in this study. Salinity and turbidity did not have a significant effect on the abundance of other KWS at Tolderol GR. Salinity ranges at the priority wetlands (e.g. Tolderol GR: 133 – 66,700 µS/cm (*c.* 0.2 – 36.7 ppt); Lake Hawdon North: 2000–8000 µS/cm (*c.* 1.1 – 4.4 ppt)) are much lower than salinities at the Coorong, where mean salinity in January is usually > 100 ppt in the South Lagoon (Prowse et al. 2022). Analysis of long-term benthic sampling data from the Coorong (2001-2020) showed that salinity was positively correlated with the density of chironomid larvae (an important prey species for shorebirds in the Coorong; Giatas et al. 2022) across the range of salinities observed (20-130 ppt; Jackson et al. 2022). In contrast, Gopalakrishnan's recent Honours thesis (see Supplementary File) did not find any relationship between chironomid abundance and salinity at the Tolderol GR. Therefore, at the ranges observed at the Tolderol GR, salinity may not be an important abiotic driver of chironomid larvae density and therefore may not strongly influence shorebird abundance. Nonetheless, it is important to continue measuring salinity at this site to monitor potential effects on KWS responses, particularly if salinity ranges change.

Consistent with results from Activity 4.2, which showed that the combined area of exposed mudflat and shallow water was the strongest predictor of site-level shorebird abundance in the Coorong (Jackson et al. 2022), the abundance of red-capped plover and sharp-tailed sandpiper were predicted to increase with the area of habitat within 0 and 5 cm deep at the Tolderol GR. This result also agrees with findings from Gopalakrishnan's thesis (Supplementary File), where relative abundance of short-legged shorebirds (e.g. sharp-tailed sandpipers, red-necked stints) at the Tolderol GR increased during periods with low water levels. At Lake Hawdon South, the area of habitat within a 0-10 cm depth range was also positively associated with shorebird abundance. As a result, and consistent with the previous restoration feasibility assessment for Lake Hawdon North (Taylor 2020), our predictions of shorebird abundance were substantially higher under an infrastructure scenario that maintained water levels in Lake Hawdon North throughout spring and summer than for the current no-infrastructure scenario (where Lake Hawdon North generally dries out in early summer). In contrast, red-capped plover and sharp-tailed sandpiper were associated with low proportional water coverage at the Teringie and Waltowa Wetlands, perhaps because shallow water was maximised at relatively low water coverage in these wetlands. In general, results from this study and results from Activity 4.2 (Jackson et al. 2022) suggest that shorebirds prefer a maximal area of shallow water situated at sufficient distance from the shoreline vegetation. In the context of the priority wetlands discussed here, results suggest that shorebird abundance will be maximised at intermediate water levels.

Our models for Tolderol GR suggest that the KWS responded to different environmental variables when selecting habitat, as evidenced by the different model structures that were selected across the suite of species for both occurrence and abundance. This was also supported by the significance of the random-effect term for individual basins for the majority of models selected. These results suggest that, even within a single small reserve, there are between-basin differences in the habitat quality offered by individual basins. Together, these findings indicate that there is unlikely to be a single best management strategy that can be implemented to benefit the entire suite of KWS considered in this report. Divergent responses and associations with different habitat variables have also been found previously among waterbird assemblages both in the local region (O'Connor and Rogers 2013, Jackson et al. 2022, Prowse et al. 2022) and beyond (Ma et al. 2010). This necessitates that clear management objectives be specified (e.g. identification of which species are the top priority for management, species-specific occurrence and abundance thresholds) because management actions that benefit one species will not necessarily be beneficial for the full assemblage (Ma et al. 2010).

The occurrence and abundance of migratory KWS at Tolderol GR was predicted to peak during February, at the end of the non-breeding period – with the exception of common greenshank, the abundance of which was predicted to be higher at the beginning of the non-breeding period, although the mean abundance of this species (0.15 ± 0.07) was much lower than for the other migratory shorebirds. This corroborates findings from tracking data of sharp-tailed sandpipers that spent the non-breeding period in the Coorong, which provided evidence that sharp-tailed sandpipers make staging visits to other wetlands in south-east South Australia, including Tolderol GR, immediately prior to migration when individuals are maximising energy intake to fuel migration (Mott et al. 2022). There was also a non-significant effect of year in all of the best performing occurrence and abundance models for the migratory KWS in our study at Tolderol GR, suggesting that these species may have high fidelity in their use of wetlands. This is consistent with wider literature showing that migratory shorebirds generally have high between-year site faithfulness to individual feeding and roosting sites used during their non-breeding period (Coleman and Milton 2012, Lourenço et al. 2016, Noel and Chandler 2008) and along their migration routes (Gudmundsson and Lindström 1992). Consequently, it is important that habitat conditions for migratory shorebirds are maintained every year, especially towards the end of their non-breeding period, in order to maximise the survival probability of individuals. In contrast, a random year effect was significant for all three of the non-migratory species. This could indicate that non-migratory shorebirds have more flexibility in their spatial patterns and respond more readily to local- and regional-scale wetland conditions in any given year than their migratory counterparts, impacting on local numbers. Tracking data have shown that many species of non-migratory waterbirds respond rapidly to fluctuations in wetland resource availability at local, regional, and even continental scales (Mott et al. 2022, Pedler et al. 2014, Roshier et al. 2008). Movements such as these may be responsible for the between-year differences in occurrence and abundance for non-migratory KWS in our study.

4.1.1 Modelling limitations

Our waterbird occurrence models for the Tolderol GR had only fair to moderate predictive performance and prediction accuracy of waterbird abundance was also low, with most models underestimating observed abundance for high counts (i.e. > 10 birds, see Figure D.1 for an example). Such limited performance could be due to the small number of waterbird surveys for which count data and coincident environmental data were available. For example, satellite-derived estimates of water coverage were unavailable for the month of June (and most winter months for some years) throughout the study period owing to the effects of cloud masking. Unavailability of satellite-derived covariates due to cloud masking also reduced the datasets of Teringie and Waltowa Wetlands. This meant that bird occurrence and abundance data from June in all years had to be excluded. The limited dataset also resulted in small evaluation datasets that may not provide the most reliable measure of predictive performance. In some cases, the evaluation datasets had few or no positive counts, or the opposite problem was encountered where presences far outnumbered absences (Table C.1). Nevertheless, in the case of the occurrence models, TSS is a metric that is robust to imbalances in the number of presences and absences because it weights a model’s ability to correctly predict absences equally with its ability to correctly predict presences (Allouche et al. 2006). This means it outperforms many other commonly used model evaluation metrics (e.g. Kappa statistic) that are more sensitive to prevalence in the evaluation dataset (Allouche et al. 2006) or threshold selection methods derived from area under the receiver operating characteristic curve (area under the curve or AUC) that may overestimate the occurrence of rare species (Manel et al. 2001).

Another factor that may have contributed to the limited predictive performance of the Tolderol GR models is the generalist habitat requirements of the study species with respect to the modelled habitat variables and the range of variance of those variables at the study site. This is particularly relevant in the case of models based on presence-absence data as opposed to abundance data, especially for taxa that aggregate into large groups (Estrada and Arroyo 2012, Howard et al. 2014). Species with generalist habitat preferences have weak habitat affinities and therefore the ability of a model to discriminate between the conditions that support occurrence and those that lead to absence is constrained (Andrew and Fox 2020, Elith et al. 2006). For example, the red-necked stint is relatively generalist in its habitat requirements, being found anywhere from tidal mudflats, to saltworks, to freshwater swamps (Higgins and Davies 1996). This lack of specificity with respect to habitat preference could mean that at least one individual is often supported by the conditions in a given basin at Tolderol GR. The ability of red-necked stints to occupy habitats across a range of salinity values could have been responsible for models including a salinity term performing worse than random or having only slight predictive performance for this species (Table 3). Similarly, data exploration prior to abundance modelling did not reveal any strong relationship between abundance counts and the available environmental variables, with high and low counts occurring across the range of observed predictor values for all species (see figures in Appendix I), resulting in large confidence intervals of model predictions. Rather than being seen as an inhibitor to implementing management works at Tolderol GR and other priority landscape wetlands, the low predictive performance we report could indicate that any management actions that result in an increase in the number of wetlands in the region may increase the availability of suitable habitat for these species. When coupled with the diversity of variables for the best performing models among KWS, this suggests that any increase in the availability of wetlands will produce suitable habitat for occupancy by at least some of the KWS modelled in this report. The information from the partial response plots we have produced could then be used as part of an adaptive management framework to guide management practices to tailor wetland conditions for occupancy and abundance by species of management priority.

4.1.2 Key management findings – priority wetlands

In general, findings from the priority landscape wetlands support that:

- It is important to continue collecting salinity data at the Tolderol GR, and wherever possible, to be able to monitor salinity ranges and potential responses of KWS.
- Extent of area within preferred foraging depth was positively related with the occurrence and abundance of some shorebirds at the Tolderol GR and Lake Hawdon South. Hence, maintaining water levels that maximise an area between 0 and 5-10 cm depth during summer, and towards the end of thee non-breeding period in February-March, would likely benefit migratory shorebirds.
- Waterbirds respond differently to environmental variables and there will not be a single best management strategy that can benefit the entire suite of KWS. Nonetheless, species with generalist habitat requirements (e.g. red-necked stint, sharp-tailed sandpiper) are likely to benefit from any management actions that result in an increase in the number of wetlands with shallow water that are in the landscape.
- The paucity of waterbird monitoring data limited options to make more conclusive and specific management recommendations, particularly for Terinigie and Waltowa Wetlands. Section *4.3 Recommendations for future monitoring* presents detailed recommendations for waterbird and environmental conditions monitoring.

4.2 Abiotic and biotic correlates of encounter rate in the broader landscape

We identified a decrease in proportional water coverage across the region during the Millennium Drought (2001-2010), suggesting that the effect of this covariate in the models is driven by both temporal change and differences between wetlands. Further, most wetlands were dry by January in most years (according to satellite images from 1999-2020), almost certainly limiting the amount of suitable habitat for migratory shorebirds across the region. The response models suggested that encounter rates for waterfowl and piscivores were maximised at intermediate proportional water coverage, whereas shorebirds showed a weak response to this variable. The lack of temporal change we found in land cover suggests that the variation in encounter rates in response to vegetation cover is mainly driven by differences between wetlands.

On average, during the timeframe of our waterbird dataset (1999-2020), surface water availability in most wetlands in both the Murray Region and the South East was very low throughout the months when migratory shorebirds are expected to be in Australia (October to February; Figure E.1), with *c.* 80% of the South East wetlands being dry by January. Hunt et al. (2019) also found that many wetlands in the South East were dry in summer. This almost certainly limits the amount of suitable habitat for migratory shorebirds across the region, as suggested in our January 2022 surveys, when we only recorded migratory shorebirds at Lake George, Middle Point Wetlands and Fox Lake (and a single Latham's snipe at Lake McIntyre). Benthic sampling at Lake Hawdon North and Lake Hawdon South (Appendix A) further suggests that wetlands which are dry for a fairly long period each year may support a paucity of prey species compared to wetlands that have water for longer, further diminishing the habitat value of wetlands in the south-east of South Australia for shorebirds. In addition, proportional water coverage was the lowest towards the end of non-breeding period for shorebirds (Appendix E). This suggests the broader landscape wetlands do not provide enough suitable foraging habitat for migratory shorebirds at a critical time to maximise energy intake in preparation for the northward migration to their breeding grounds. Hence, where possible, maintaining some water in more wetlands during summer is likely to benefit migratory shorebird species, as our shorebird abundance predictions at Lake Hawdon North also suggested.

Shorebirds forage in shallow water, and results from Activity 4.1 and 4.2 showed that the availability of mudflat and shallow water habitat are primary drivers of shorebird occupancy and abundance in the Coorong (Jackson et al. 2022, Prowse et al. 2022). Assuming that, as proportional water cover drops, a greater area of exposed mudflat (i.e. area not covered by vegetation and more distant from woody vegetation) will be present, we expected encounter rate estimates for shorebirds to increase with decreasing proportional water coverage. However, the only shorebirds that followed this pattern were the resident red-capped plover, and the migrants red-necked stint and curlew sandpiper in the South East Region. This result agrees with our records of red-capped plovers at saltpans during our January 2022 counts, like the dry southern section of Lake George. Prowse et al. (2022) also found that the red-capped plover maximised foraging at extreme salinities in the South Lagoon of the Coorong. The rest of shorebird species showed weak responses to proportional water coverage. This could be due to at least two non-mutually exclusive reasons. The first one is that proportional water coverage might not be a good proxy of mudflat habitat availability for some wetlands, and extent of area of shallow habitat would be a preferred predictor. However, we were not able to use a DEM to estimate habitat availability at preferred foraging depth in the landscape scale analysis (see section *4.2.1 Modelling limitations*). The second reason is that a narrow range in the variable being tested may result in weak modelled response. In other words, there was not a good range of proportional water coverage values to model encounter rates against because water coverage was very low in most wetlands while a few other wetlands were very full. The limited range of proportional water coverage values in the dataset likely masked real responses between occupancy of shorebirds and surface water availability. This may be even more accentuated for species with generalist habitat requirements (Andrew and Fox 2020, Elith et al. 2006), as discussed for the Tolderol GR occurrence models.

Encounter rates for most waterfowl species were either maximised where the proportion of wetland covered by water was *c.* 0.5, or increased with increasing proportional water coverage. Piscivorous species that showed a response to proportional water coverage, such as the Australian white ibis and little black cormorant, had a similar pattern. With the underlying assumption that encounter rates will reflect occupancy rates (Johnston et al. 2021), this result suggests that these species are more likely to occupy wetlands at intermediate and high levels of water coverage. Therefore, maintaining intermediate water levels throughout the year, particularly during summer, would not only benefit shorebirds, but also other waterbird species considered in our study.

The incursion of terrestrial vegetation into wetlands of the South East region has been associated with lower abundance of waterbirds, particularly of migratory shorebirds (Hunt et al. 2019). Across five wetlands (Morella Basin, Butcher Gap CP, Lake Robe, Lake Bonney SE, and Lake George), Hunt et al. (2019) found higher abundances of waterfowl and migratory shorebirds in 1 x 1 km cells with less emergent terrestrial vegetation. For shorebirds, our models considered the vegetation cover of woody native vegetation, mangrove vegetation, non-woody native vegetation and wetland vegetation. Five out of the nine migratory shorebird species modelled were less likely to be encountered at wetlands with higher vegetation cover, supporting the notion that large extents of encroaching vegetation make access to suitable wetland habitat difficult particularly for migratory shorebirds. However, this pattern was not supported for three migratory shorebirds (Latham's snipe, marsh sandpiper and sharp-tailed sandpiper). One possible explanation is that these species (and other shorebirds that showed a positive response to vegetation cover) use wetlands with a relatively high vegetation cover for foraging alone or in small groups. This could particularly be true for generalists like the sharp-tailed sandpiper (Higgins and Davies 1996), and for Latham's snipe, which in Australia and in contrast with most other migratory shorebirds, is known to use a variety of freshwater wetlands generally with low and dense vegetation used as shelter (Frith et al. 1977). In addition, since we considered vegetation cover and presence/absence across entire wetlands, occupancy rates estimated by our models in response to vegetation cover will not necessarily agree with finer-scale abundance counts in particular areas of a wetland, especially in wetlands with a high habitat heterogeneity (e.g. a combination of open shorelines and emergent vegetation). Hence, higher occupancy of some shorebird species is not incompatible with low abundances of these species at wetlands with high vegetation cover.

Our models suggested that occupancy for most waterfowl, piscivorous and rail species considered was positively related to the proportion of wetland cover by wetland vegetation and saltmarsh vegetation. Given saltmarsh vegetation was almost non-existent in both Murray and South East regions, wetland vegetation is likely to drive the positive relationship between vegetation cover and encounter rates of waterfowl, piscivores and rails. Hunt et al. (2019) found a negative association between the extent of terrestrial vegetation in wetlands and abundance of waterfowl and piscivorous waterbirds. Our findings and those of Hunt et al. (2019) suggest that vegetation control that restores wetland vegetation in wetlands that have become 'terrestrialised' would benefit waterfowl, piscivores and rails. We agree with Hunt et al. (2019) in that vegetation control of 'terrestrialised' wetlands would produce more useful habitat for waterbirds, particularly for migratory shorebirds. We further note that such works would need to be planned and conducted based on specific and clear management goals (e.g. providing more foraging habitat for migratory shorebirds, providing an array of habitats for different species) that consider fine-scale habitat variation within wetlands and vegetation type.

For most species (47 out of 63), encounter-rate estimates were higher (and significantly so for 21 species) when surface-water availability was lower across Australia (as indicated by the Australian "wetness" index). This result suggests that species like the sharp-tailed sandpiper, red-necked avocet, chestnut teal and Australian pelican use the wetlands in south-east South Australia as a drought refuge, perhaps due to their proximity to the Coorong. Similar results were found for waterbird response modelling in the Coorong T&I in Activity 4.1 (Prowse et al. 2022). Further, the red-necked avocets that were GPS-tagged during this project left the Coorong in early 2022 and travelled into the wet interior of Australia, further strengthening this argument for this species (Mott et al 2022). Together, these results highlight the value of the broader landscape wetlands in supporting waterbird populations during periods of low water availability.

Waterbirds are highly mobile and some species are generalist in their habitat use and regularly move between coastal areas and inland wetlands depending on conditions (Higgins and Davies 1996). Nonetheless, our models suggest that occurrence of most species (44 of 63) was negatively related to distance to the coast (this effect was statistically significant for 21 species), including all migratory shorebird species, which agrees with our field surveys which only recorded migratory shorebird species in three coastal wetlands in January 2022. Given the ability of some waterbird species of the Coorong to move at regional and larger scales (Mott et al. 2022), the higher encounter rates near the coast for generalists (e.g. red-necked stint and sharp-tailed sandpiper) may be partially due to the lack of water across the region in summer. Maintaining water levels throughout summer in some inland wetlands might provide more suitable shorebird habitat and increased occupancy rates in inland wetlands. However, there is a clear knowledge gap regarding how most waterbird species use and move in the broader landscape (Hunt et al. 2019). Hence, prioritising water levels in coastal wetlands may be a more suitable near-term approach given migratory shorebirds clearly use these wetlands.

4.2.1 Modelling limitations

We were not able to use important covariates like salinity and the availability of habitat within preferred depth ranges in our broader landscape models. Our Tolderol GR models show that salinity is an important driver of abundance and occupancy of black swan, which has also been observed for this species in the Coorong (Prowse et al. 2022). Australian pelican and fairy tern are another two species that show decreasing abundance and occupancy with increasing salinity in the Coroong. Therefore, we expect salinity could be an important abiotic correlate of encounter rate for waterbird species across the entire region, particularly in salt lakes. We attempted to acquire salinity data through Water Data SA but unfortunately the data available were not sufficiently comprehensive for use in the response modelling. Similarly, the availability of habitat within preferred depth ranges was also an important covariate for some KWS in the priority landscapes (see section 4.1 of this report). However, the DEM we used to derive habitat availability at Waltowa and Terinigie wetlands (Geoscience Australia 2015) was affected by too many missing values across the region to be useful for broader modelling. The reliance on satellite images to derive covariates could also be reduced with on-ground data collection of salinity and water depth at key priority wetlands (e.g. see Hunt et al. 2019 for a list of wetlands with high value for waterbirds across the South East and our recommendations for future monitoring in section 4.2).

Overall, some context is needed to aid interpretation of model outputs for the broader landscape wetlands presented here. Although some studies have successfully used this type of citizen science data to model bird species occupancy and identify bird population trends (e.g. Johnston et al. 2021, Horns et al. 2018), others have cautioned against it (Bayraktarov et al. 2019, Kamp et al. 2016). We assumed that encounter rate reflects occupancy rate, but encounter rate also reflects detectability, which we could not estimate from the datasets. Species that are harder to detect (e.g. Australasian bittern and most shorebirds, as suggested by the low raw encounter rates and number of wetlands where these species were detected, see Appendix J) are expected to have lower encounter rates than their actual occupancy rates, and so if this difference was not constant across wetlands, model predictions might be affected for these species. The difference between encounter rate and the true occupancy rate is expected to be lower and more constant across sites in standardised scientific surveys that control for effort than in citizen science data sets. Therefore, the use of data collected following scientific and standardised methods should be prioritised to model the responses of low abundant and difficult to detect species, which are also often threatened species. For species that are easy to detect, such as Australian pelican and black swan, the difference between encounter rate and occupancy rate is expected to be small and so our models will more accurately reflect the probability of the species occupying that habitat.

Our data filtering and modelling approach aimed to address some of this variation in detectability and effort by using only complete checklists with at least three species recorded. Other studies using this type of data apply harsher filters to control further for detection biases (e.g. Horns et al. 2018). However, we did not have enough data to apply other filters or use more variables to control for observer effort. Remaining sources of variation not accounted for in the models may arise from wetland accessibility, with wetlands that are harder to access systematically recording more false negatives. Working with this type of data instead of standardised surveys also meant we needed to invest a significant amount of time preparing, filtering and checking the data before starting any analysis. This highlights the importance of designing and maintaining long-term monitoring programs to address specific questions of interest for management, particularly if the focus of management is threatened bird species with low detectability.

4.2.2 Key management findings – broader landscape

In general, our response models for the broader landscape wetlands support that:

- maintaining intermediate proportional water coverage, particularly during summer, would benefit most waterbird species throughout the year;
- wetland vegetation cover is positively associated with occupancy of most waterfowl, piscivores and rails;
- any vegetation control should consider fine-scale habitat variation within wetlands, including vegetation type (i.e. prioritising wetland vegetation and saltmarsh over woody vegetation);
- the broader landscape wetlands may be used as drought refuge for most of the modelled species; and

- most waterbird species are more likely to occur in wetlands near the coast.

These models may now be used to predict encounter rates across the region under different management scenarios of interest. For the wetlands included in the modelling, managers could use the models to test the outcome from different water allocation scenarios at a wetland-specific level (adding the random intercept for a given wetland to the response) or at a population level (the average response across the region, as shown in the response plots presented in Figures 20-23). For example, managers seeking to increase occupancy of waterbirds across the region and produce useful habitat in more wetlands could deliver a given volume of water to multiple small wetlands rather than to a single large wetland to achieve intermediate water coverage that maximises occupancy in more wetlands. Conversely, managers seeking to optimise conservation outcomes for waterfowl could prioritise water delivery to achieve intermediate water coverage to those wetlands with the highest vegetative cover as opposed to water delivery to wetlands devoid of vegetative cover.

4.3 Recommendations for future monitoring

The main challenge we encountered when compiling this report was the lack of available data across a sufficient time series for modelling. This was particularly true for the broader landscape wetlands, where we could only collate semi-structured citizen science data. Robust monitoring of waterbird abundance and distribution (i.e. monthly counts, or a minimum of one spring and one summer survey, conducted in each relevant section of the wetland), water levels, salinity, vegetation, prey availability and management actions (e.g. ploughing, watering, burning), is desirable before, during, and after additional management is implemented at the priority landscape wetlands. This would provide an opportunity to formally test the predictive power of the models presented in this report, and to better understand environmental factors that we could not explore here (e.g. prey availability and management actions) due to a lack of available data.

Working with the available data from priority landscape wetlands and the broader landscape wetlands to produce this report has led us to develop some recommendations to support the long-term monitoring of these wetlands and to enable managers to model waterbird abundance and occupancy against environmental variables. Our recommendations include:

(1) Monitoring consistency and database management. Data collection should be consistent over time and databases curated according to a documented procedure. All data should be collected within well-defined survey area(s) on each visit, and survey areas should not be modified over time (though additional areas may be added when relevant provided details are also recorded). Survey participants should be briefed on how to record each waterbird and biophysical variable, and should record a complete dataset (i.e. a datum for each variable) on each visit. For long-term knowledge and consistency, a metadata key should be kept alongside the monitoring database to explain how each variable is recorded. GPS coordinates for any site codes used should also be held as critical metadata. Finally, consistent recording of absent waterbird species is critical to interpreting and modelling waterbird abundance data. The full set of ancillary variables less waterbird counts should be included as a record in the database for each survey area in the case where a count was conducted but no birds were present. Ideally, the whole dataset should be zero-filled (i.e. all bird species recorded on every visit, not only species that are present) to avoid ambiguity.

(2) Monitoring frequency. Ideally monitoring should be conducted monthly (as is currently undertaken at Tolderol GR). If logistical constraints prevent this, we recommend a minimum of one spring and one summer survey in each year, plus an additional survey during the core non-breeding season for migratory shorebirds. Specifically, this monitoring design could be configured as a minimum of two surveys between October and February (with these surveys repeated at the same time each year), plus an additional survey around migration departure in March.

(3) Monitoring coverage. For smaller wetlands such as Tolderol, counting waterbirds and environmental variables for the whole wetland divided into discrete survey areas is most ideal. This is particularly feasible in a setting such as Tolderol where basins provide clearly delineated survey areas within the broader site. At larger sites, if the whole wetland cannot feasibly be surveyed, choosing a set of well-defined survey areas based on access, habitat suitability and distance that can be surveyed with a telescope (up to about 500m from a fixed point) is a viable option, but it is important to ensure that the same areas are surveyed each time.

(4) Surface water quality variables. The most relevant surface water variables for waterbirds are likely to be salinity and turbidity, so these should be collected if possible. However, as per above, these variables need to be recorded in a consistent way (including use of consistent units), with clear accompanying metadata, to be useful for subsequent modelling.

(5) Water and vegetation cover. These are important biophysical characteristics that influence waterbird abundance and occupancy. Depending on time and resources, potential approaches to monitoring these variables include:

(a) Direct measurement: observers in the field could implement a simple categorical assessment of % water cover and % vegetation cover for each survey area (for an example, see Jackson et al. 2019). Alternatively, observers could conduct a rapid assessment approach using transects across each survey area, along which water depth and vegetation cover are measured or visually estimated at regular intervals.

(b) Remote sensing: remote sensing datasets can be used to estimate these variables (which was done in this report for water cover), but this approach requires good spatial descriptions of the survey area(s) so that these variables can be appropriately matched to other spatial datasets (e.g. a digital elevation model) and also some skills and software to support GIS analysis.

(6) Management history. Management history is likely to have a substantial effect on waterbird abundance at the wetlands considered here and we strongly advise recording ancillary data on management interventions in the future. This also allows for assessment of the efficacy of management actions, and adaption over time. This could include, for example, maintaining a record of the days since each wetland/pond was watered, ploughed or burnt. It is particularly important if investment in new or altered management is undertaken; records of waterbirds and management action before, during and after the new investment are vital to assessing whether the investment goals are being met.

(7) Prey availability. Instigating monitoring of prey availability at key priority wetlands is also desirable since prey availability is necessarily linked to habitat quality. However, there is little information on the diet of shorebirds at priority wetlands, which may or may not differ substantially from the diet recorded in the Coorong, so diet studies at priority wetlands would also be beneficial. Nonetheless, monitoring the responses of probable prey before and after management interventions at priority wetlands would provide very useful insights into this habitat characteristic.

These recommendations are based on learnings from this study that explored the response of waterbirds to abiotic and biotic factors, and considered these in relation to wetland management. The field study undertaken through Activity 4.2 (Jackson et al. 2022) showed that regularly monitoring local site-level abundance alongside biotic and abiotic parameters (as is suggested above) can inform which parameters are most useful and feasible to consider as habitat quality proxies for different KWS. In the Coorong, the combined area of exposed mud and shallow water were the strongest indicators of local site-level shorebird abundance. Measurements of benthic macroinvertebrate prey were difficult to relate to shorebird abundance, but monitoring of key prey populations was still considered valuable; this relationship may also be more straightforward in priority wetlands if water levels are not as variable as in the Coorong. Measurements of fish and *Ruppia* were considered to be reliable habitat quality proxies for non-shorebird KWS. Some of the parameters that we have suggested for monitoring in priority wetlands including vegetation coverage and management history are generally not applicable in the Coorong, but are likely to be important habitat quality proxies in some broader landscape wetlands, based on literature from other sites. Finally, if the body condition algorithm currently in development (refer to Jackson et al. 2022) is finalised successfully, a useful area for future exploration may be to compare the body condition of KWS in different priority wetlands, if it is feasible to amass a suitable number of images from these wetlands.

4.4 Future directions

If implemented in the near-term, the additional management scenarios presented in the feasibility assessments for the four priority wetlands (Mason and Hardy 2020a, 2020b, 2020c, Taylor 2020) provide an unprecedented opportunity to understand waterbird responses to changes in the biophysical characteristics of these wetlands. Nonetheless, consistent monitoring of waterbirds and environmental variables need to be conducted to achieve this goal (see monitoring recommendations in section 4.3 and Appendix A for an example of macroinvertebrate sampling).

The broader landscape models developed in this report can be used to test management scenarios at the broader landscape level, and further validate model predictions. However, more standardised counts and datasets would be needed to develop more robust models that can inform appropriate and specific management actions. These data could be collected in wetlands ranked highly by Hunt et al. (2019) following our monitoring recommendations in section 4.3.

A final unexplored aspect of our study that warrants further investigation is the additional habitat that drains may provide for some waterbirds. For example, we observed large numbers of black swans and Australian white ibis at different drains during our field surveys in January 2022 but did not count these as they were outside wetland boundaries. Similarly, the response models did not account for encounter rates at drains and hence, the occurrence and counts of species that use drains are likely to be underrepresented by wetland surveys only. Further work is needed to estimate the contribution of the drain network.

5 Summary

This technical report details findings from response models for waterbirds, including KWS that rely on the Coorong South Lagoon, in four priority landscape wetlands, namely Tolderol Game Reserve, the Teringie and Waltowa Wetlands, and Lake Hawdon North, and in 986 wetlands across the broader landscape of the south-east of South Australia. Specifically, we found that:

- the paucity of consistent waterbird monitoring is a key factor limiting the development of response models;
- biochemical variables (i.e. salinity and turbidity) were not selected in the best models of most KWS at the Tolderol GR; however, the continued collection of these parameters is important for monitoring their potential effects on waterbird responses;
- at Tolderol GR and Lake Hawdon South, the extent of shallow habitat was positively related to abundance of some shorebird species;
- maintaining water levels to increase availability of shallow habitat across the region during summer is needed to provide more suitable habitat for migratory shorebirds;
- intermediate proportional water coverage across the region during summer is likely to benefit many waterbird species;
- vegetation control of ‘terrestrialised’ wetlands is likely produce more useful habitat for migratory shorebirds, but works would need to consider fine-scale habitat variation within wetlands and vegetation type;
- wetlands in the south-east of South Australia beyond the Coorong are likely to be used as a drought refuge by many waterbird species;
- clear management goals are needed as it is unlikely the implementation of a single management strategy would benefit all species.

List of shortened forms and glossary

AIC	Akaike's Information Criterion, a metric for comparing different statistical models fitted to the same dataset.
Basis dimension	The complexity of a smoothing spline fitted to a covariate of a generalized additive model which is controlled by the number of basis functions that sum to produce the fitted spline. Larger numbers for the basis dimension allow more complex relationships to be fitted.
CLLMM	Coorong, Lower Lakes (Alexandrina and Albert) and Murray Mouth
Data fold	A unique subset of a dataset. Also known as a data partition. Data folds are used in cross-validation whereby the dataset is split into *n* subsets so that one subset can be used to evaluate the predictive performance of a model trained on the remaining *n*-1 data folds. This process is repeated iteratively until each data fold has been used once as the evaluation dataset.
DEM	Digital Elevation Model
GAM	Generalised Additive Model
Herbivorous waterfowl	The species are exclusively members of the Family Anatidae; they primarily feed on the leaves, flowers, and seeds of aquatic vegetation, and typically have webbed feet and a flattened bill for crushing their plant- or algae-based foods.
Key waterbird species (KWS)	Waterbirds selected as key waterbird species for the purposes of Component 4 of the Healthy Coorong, Healthy Basin Program's Trials and Investigations Project. The ten key waterbird species (sharp-tailed sandpiper, red-necked avocet, chestnut teal, Australian pelican, red-necked stint, curlew sandpiper, common greenshank, red-capped plover, fairy tern, and black swan) were selected because each represents a different ecological group (e.g. foraging guild, migratory strategy, abundance) within the Coorong.
Measuring Salinity	Salinity is the measure of the concentration of dissolved (soluble) salts in water. Different units are often used to describe salinity, such as parts per million (ppm) or milligrams per litre (mg/L), parts per thousand (ppt) or grams per litre (g/L) and microsiemens per centimetre (µS/cm). The latter is a unit of electrical conductivity (EC), which is often used to describe surface water salinity. The following is a conversion factor between µS/cm and ppt, but note that it is an approximation as the conversion depends on the types of salts present: 1 µS/cm = 0.00055 ppt; therefore ppt = µS/cm X 0.00055. See https://www.landscape.sa.gov.au/mr/publications/measuring-salinity for more details.
Millennium Drought	An Australian drought which impacted the Murray-Darling Basin over the period 1996-2010, and substantially impacted the Coorong over the period 2001-2010.
MAE	Mean Absolute Error
NRMSE	Normalised Root Mean Square Error
Partial response plot	A partial response plot shows the relationship between the predicted values of a statistical model and a explanatory variable of interest,

	marginalizing over the values of all other explanatory variables, assigning them a fix value, usually their mean.
Piscivorous waterbirds	These species are solely or primarily fish-eating and have specialised bills and/or talons for catching underwater prey.
Shorebirds	These species forage on intertidal areas and/or the margins of wetlands, and typically they do not swim. Australia is home to **non-migratory** shorebirds which remain in Australia year-round, and also provides habitat for **migratory** shorebirds of the East Asian–Australasian Flyway, which inhabit the northern hemisphere in the austral winter and migrate to the southern hemisphere for the austral summer.
Spline	A smooth curve formed from the linear combination of a set of basis functions. The number of basis functions that contribute to the spline is determined by the basis dimension.
True Skill Statistic (TSS)	The TSS is a metric to assess predictive performance of statistical models based on the matches and mismatches between observations and predictions. It that ranges from -1 to 1, with values ≤ 0 indicating predictive performance equivalent to or worse than random, whereas a TSS of 1 indicates perfect predictive performance.
T&I	Trials and Investigations

References

Allouche O, Tsoa A and Kadmon R (2006). Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *Journal of Applied Ecology* 43: 1223-1232.

Andrew ME and Fox E (2020). Modelling species distributions in dynamic landscapes: The importance of the temporal dimension. *Journal of Biogeography* 47(7): 1510-1529.

Bayraktarov E, Ehmke G, O'Connor J, Burns EL, Nguyen HA, McRae L, Possingham HP and Lindenmayer DB (2019). Do Big Unstructured Biodiversity Data Mean More Knowledge? *Frontiers in Ecology and Evolution* 6. doi:10.3389/fevo.2018.0023

Bradshaw CJA (2019). Opportunities to improve the future of South Australia's terrestrial biodiversity. *Rethinking Ecology* 4:45–77

Braithwaite L (1982). Ecological studies of the black swan IV: the timing and success of breeding on two nearby lakes on the Southern Tablelands of New South Wales. *Wildlife Research* 9(2): 261-275.

Brookes J, Dalby P, Dittmann S, O'Connor J, Paton D, Quin R, Rogers D, Waycott M and Ye Q (2018). Recommended actions for restoring the ecological character of the South Lagoon of the Coorong. Goyder Institute for Water Research Technical Report Series No. 18/04, Adelaide, South Australia. ISSN: 18392725.

Brooks ME, Kristensen K, van Benthem KJ, Magnusson A, Breg CW, Nielsen A, Skaug HJ, Maechler M and Bolker BM (2017). glmmTMB balances speed and flexibility among packages for zero-inflated generalized linear mixed modeling. *The R Journal* 9: 378-400

Clemens R, Driessen J and Ehmke G (2019). Australian Bird Index Phase 2 – Developing Waterbird Indices for National Reporting. Unpublished report for the Department of the Environment. BirdLife Australia, Melbourne.

Clemens R, Rogers DI, Hansen BD, Gosbell K, Minton CDT, Straw P, Bamford M, Woehler EJ, Milton DA, Weston MA, Venables B, Wellet D, Hassell C, Rutherford B, Onton K, Herrod A, Studds CE, Choi C-Y, Dhanjal-Adams KL, Murray NJ, Skilleter GA and Fuller RA (2016). Continental-scale decreases in shorebird populations in Australia. *Emu - Austral Ornithology* 116(2): 119-135. 10.1071/MU15056.

Coleman J and Milton D (2012). Feeding and roost site fidelity of two migratory shorebirds in Moreton Bay, south-eastern Queensland, Australia. *Sunbird* 42: 41-51.

Department for Environment and Water (2022a). https://location.sa.gov.au/LMS/Reports/ReportMetadata.aspx?pu=yandp_no=1222 Accessed on 20-Dec-2021

Department for Environment and Water (2021b). https://www.environment.sa.gov.au/topics/science/information-and-data/biological-databases-of-south-australia Accessed on 20 Nov-2021

Ecological Associates (2010) Literature review of the ecology of birds of The Coorong, Lakes Alexandrina and Albert Ramsar wetlands. Ecological Associates report CC-014-1-D prepared for Department for Environment and Heritage. Department for Environment and Heritage, Adelaide, Australia.

eBird Basic Dataset (2021). Version: EBD_relOct-2021. Cornell Lab of Ornithology, Ithaca, New York. Oct 2021

Elith J, Graham CH, Anderson RP, Dudík M, Ferrier S, Guisan A, Hijmans RJ, Huettmann F, Leathwick JR, Lehmann A, Li J, Lohmann LG, Loiselle BA, Manion G, Moritz C, Nakamura M, Nakazawa Y, Overton JMM, Townsend Peterson A, Phillips SJ, Richardson K, Scachetti-Pereira R, Schapire RE, Soberón J, Williams S, Wisz MS and Zimmermann NE (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography* 29(2): 129-151.

Estrada A and Arroyo B (2012), Occurrence vs abundance models: Differences between species with varying aggregation patterns. *Biological Conservation* 152: 37-45.

Ferenczi M, Formby M, Kidd L, Weller D, Rhodes L and Klose S (2020). Lake Hawdon Migratory Shorebird Site Action Plan. Report from BirdLife Australia to the Limestone Coast Landscape Board Our Coorong Our Coast Project. BirdLife Australia, Carlton, Australia

Frith HJ, Crome FHJ and Brown BK (1977). Aspects of the Biology of the Japanese Snipe *Gallinago hardwickii*. *Australian Journal of Ecology* 2: 341-368.

Geoscience Australia (2015). Digital Elevation Model (DEM) of Australia derived from LiDAR 5 Metre Grid. Geoscience Australia, Canberra.

Geoscience Australia (2022). DEA Water Observations. *https://www.dea.ga.gov.au/products/dea-water-observations*, Accessed on 05-Feb-2022.

Giatas G, Catalano S, Dittmann S, Ye Q, Jackson M, Mott R and Markos K (2022). *Primary food resources for key waterbirds and benthic fish in the Coorong*, Goyder Institute for Water Research Technical Report Series No. 22/02.

Gudmundsson GA and Lindström Å (1992). Spring migration of Sanderlings Calidris alba through SW Iceland: wherefrom and whereto? *ARDEA-WAGENINGEN* 80:315-315.

Hammer M and Tucker M (2011). Baseline study and community monitoring of Australian Mudfish in South East, South Australia. Report to Department for Water, South Australian Government. Aquasave Consultants, Adelaide, South Australia.

Hammer M, Whiterod N, Barnes T and Tucker M (2012). Baseline fish survey and movement study of the Drain L Catchment, South Australia. Report to Department for Water, South Australian Government. Aquasave Consultants, Adelaide, South Australia.

Harding C (2018). Review of the wetland groundwater dependent ecosystem (GDE) monitoring network. DEW Internal Technical note 2018, Government of South Australia, Department for Environment and Water, Adelaide, Australia.

Hartvigsen-Power CA, Furst DJ, Paton DC and Paton FL (2019). Assessment of Tolderol Game Reserve in autumn 2019 to support key species of Coorong waterbirds. Goyder Institute for Water Research Technical Report Series No. 19/19, Goyder Institute for Water Research, Adelaide, Australia.

Higgins PJ and Davies SJJF (1996). Handbook of Australian, New Zealand and Antarctic Birds. Volume 3, Snipe to pigeons, Oxford University Press, Melbourne, Australia.

Horns JJ, Adler FR and Şekercioğlu ÇH (2018). Using opportunistic citizen science data to estimate avian population trends. *Biological Conservation* 221: 151-159. doi:10.1016/j.biocon.2018.02.027

Howard C, Stephens PA, Pearce-Higgins JW, Gregory RD and Willis SG (2014). Improving species distribution models: the value of data on abundance. *Methods in Ecology and Evolution* 5(6): 506-513.

Hunt TJ, Paton FL and Paton DC (2019) An initial assessment of the potential for wetlands in the South East and Lower Lakes regions of South Australia to support key species of Coorong waterbirds. Goyder Institute for Water Research Technical Report Series No. 19/20. Goyder Institute for Water Research, Adelaide, Australia

Jackson MV, Carrasco LR, Choi CY, Li J, Ma Z, Melville DS, Mu T, Peng HB, Woodworth BK, Yang Z, Zhang L. and Fuller RA (2019). Multiple habitat use by declining migratory birds necessitates joined-up conservation. *Ecology and Evolution* 9: 2505–2515.

Jackson M, Mott R, Prowse T, Delean S, Shu Y, Liu L, Brooks J and Cassey P (2022). *Recommended Habitat Quality Measures for Key Waterbird Species in the Coorong*. Goyder Institute for Water Research Technical Report Series No. 21/x.

Johnston A, Hochachka WM, Strimas-Mackey ME, Ruiz Gutierrez V, Robinson OJ, Miller ET and Fourcade Y (2021). Analytical guidelines to increase the value of community science data: An example using eBird data to estimate species distributions. *Diversity and Distribution* 27: 1265– 1277

Jordahl K (2014). GeoPandas: Python tools for geographic data. URL: https://github.com/geopandas/geopandas.

Kamp J, Oppel S, Heldbjerg H, Nyegaard T, Donald PF and Schröder B (2016). Unstructured citizen science data fail to detect long-term population declines of common birds in Denmark. *Diversity and Distributions* 22(10): 1024-1035. doi:10.1111/ddi.12463

Kingsford RT, Porter JL, Brandis KJ and Ryall S (2020). Aerial surveys of waterbirds in Australia. *Scientific data* 7:172. https://doi.org/10.1038/s41597-020-0512-9.

Kingsford RT and Porter JL (2008). Survey of waterbird communities of the Living Murray Icon Sites – November 2007. Final report to the Murray Darling Basin Commission. Murray Darling Basin Commission, Canberra, Australia.

Krause CE, Newey V, Alger MJ and Lymburne (2021). Mapping and Monitoring the Multi-Decadal Dynamics of Australia's Open Waterbodies Using Landsat. *Remote sensing* 13: 1437.

Landis JR and Koch GG (1977). The measurement of observer agreement for categorical data. *Biometrics* 33(1): 159-174.

Lourenço PM, Alves JA, Reneerkens J, Loonstra AJ, Potts PM, Granadeiro JP and Catry T (2016). Influence of age and sex on winter site fidelity of sanderlings *Calidris alba*. *PeerJ* 4: e2517-e2517.

Lüdecke D, Ben-Shachar MS, Patil I, Waggoner P, Makowski D (2021). performance: An R Package for Assessment, Comparison and Testing of Statistical Models. *Journal of Open Source Software* 6(60): 3139. https://doi.org/10.21105/joss.03139

Ma Z, Cai Y, Li B and Chen J (2010). Managing wetland habitats for waterbirds: An international perspective. *Wetlands* 30(1): 15-27.

Manel S, Williams HC and Ormerod SJ (2001). Evaluating presence–absence models in ecology: the need to account for prevalence. *Journal of Applied Ecology* 38(5): 921-931.

Mason K and Hardy S (2020a). Feasibility Assessment Report Tolderol Game Reserve Wetlands. Murraylands and Riverland Landscapes Board, Murray Bridge, Australia

Mason K and Hardy S (2020b). Feasibility Assessment Report Teringie Wetland Complex. Murraylands and Riverland Landscapes Board, Murray Bridge, Australia

Mason K and Hardy S (2020c). Feasibility Assessment Report Waltowa Wetlands. Murraylands and Riverland Landscapes Board, Murray Bridge, Australia

McDougall A and Timms B (2001). The influence of turbid waters on waterbird numbers and diversity: A comparison of Lakes Yumberarra and Karatta, Currawinya National Park, south-west Queensland. *Corella* 25(2): 25-31.

Mott R, Jackson M, Sanchez-Gomez S, Hunt B, Prowse T, Brookes J and Cassey P (2022). *Spatial and temporal habitat use by key waterbird species in the Coorong*. Goyder Institute for Water Research Technical Report Series No. 21/xx.

Mueller N, Lewis A, Roberts D, Ring S, Melrose R, Sixsmith J, Lymburner L, McIntyre A, Tan P, Curnow, S and Ip A (2016). Water Observations from Space: Mapping surface water from 25 years of Landsat imagery across Australia. *Remote Sensing of Environment* 174: 341-352.

Nakagawa S and Schielzeth H (2013). A general and simple method for obtaining R2 from generalized linear mixed-effects models. *Methods in Ecology and Evolution* 4: 133-142. https://doi.org/10.1111/j.2041-210x.2012.00261.x

Noel BL and Chandler CR (2008). Spatial distribution and site fidelity of non-breeding piping plovers on the Georgia coast. *Waterbirds* 31(2): 241-251.

O'Connor JA and Rogers DJ (2013). Response of Waterbirds to Environmental Change in the Lower Lakes, Coorong and Murray Mouth Icon Site. South Australian Department for Environment, Water and Natural Resources, Adelaide, Australia.

O'Connor J, Rogers D and Pisanu P (2012). Monitoring the Ramsar status of the Coorong, Lakes and Murray Mouth: a case study using birds. South Australian Department for Environment and Natural Resources, Adelaide, Australia.

Paton DC, Paton FL and Bailey CP (2020). Condition Monitoring of the Coorong, Lower Lakes and Murray Mouth Icon Site: Waterbirds in the Coorong and Lower Lakes 2019. The University of Adelaide and The Department for Environment and Water, Adelaide.

Paton DC (2010). At the End of the River: The Coorong and Lower Lakes. ATF Press.

Pebesma E (2018). Simple Features for R: Standardized Support for Spatial Vector Data. *The R Journal* 10(1): 439-446. https://doi.org/10.32614/RJ-2018-009

Pedler RD, Ribot RFH, Raoul FH and Bennett ATD (2018). Long-distance flights and high-risk breeding by nomadic waterbirds on desert salt lakes. *Conservation Biology* **32**, 216–228.

Pedler RD, Ribot RFH and Bennett ATD (2014). Extreme nomadism in desert waterbirds: flights of the banded stilt. *Biology Letters* 10: 20140547.

Pekel JF, Cottam A, Gorelick N and Belward AS (2016). High-resolution mapping of global surface water and its long-term changes. *Nature* 540: 418-422.

Prowse T, Delean S, Mott R, Jackson M, Hunt B, Brookes J and Cassey P (2022). *Response models for key waterbird species of the Coorong*. Goyder Institute for Water Research Technical Report Series No. 21/xx.

Prowse TAA (2020). Review of the ecology, status and modelling of waterbird populations of the Coorong South Lagoon. Goyder Institute for Water Research Technical Report Series No. 20/12.

Python Software Foundation. Python Language Reference, version 3.9. Available at http://www.python.orgR Core Team (2020) R: A language and environment for statistical computing. R Foundation for Statistical Computing. https://www.R-project.org/. Vienna, Austria.

rioxarray (2022). Python package. https://pypi.org/project/rioxarray, Accessed on 03-Feb-2022.

Roberts DR, Bahn V, Ciuti S, Boyce MS, Elith J, Guillera-Arroita G, Hauenstein S, Lahoz-Monfort JJ, Schröder, B, Thuiller W, Warton DI, Wintle BA, Hartig F and Dormann CF (2017). Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography* 40(8): 913-929.

Roshier D, Asmus M and Klaassen M (2008). What drives long-distance movements in the nomadic Grey Teal *Anas gracilis* in Australia? *Ibis* 150(3): 474-484.

Roshier D, Klomp N and Asmus M (2006). Movements of a nomadic waterfowl, Grey Teal Anas gracilis, across inland Australia–results from satellite telemetry spanning fifteen months. *Ardea* 94(3): 461-475.Sharma S, Tanner J and Benger S (2009). 'Digital elevation model of the Coorong and surrounds', in *The CLLAMM Dynamic Habitat: Habitat mapping and dynamic modelling of species distributions*. CSIRO: Water for a Healthy Country National Research Flagship and South Australian Research and Development Institute (Aquatic Sciences), Adelaide.

South A (2017). rnaturalearth: World Map Data from Natural Earth. R package version 0.1.0. https://CRAN.R-project.org/package=rnaturalearth

Strimas-Mackey M, Miller E and Hochachka W (2018). auk: eBird Data Extraction and Processing with AWK. R package version 0.3.0. https://cornelllabofornithology.github.io/auk/

Studds C, Kendall B, Murray N, Wilson HB, Rogers DI, Clemens RS, Gosbell K, Hassell CJ, Jessop R, Melville DS, Minton CDT, Possingham HP, Riegen AC, Straw P, Woehler EJ and Fuller RA (2017). Rapid population decline in migratory shorebirds relying on Yellow Sea tidal mudflats as stopover sites. *Nature Commun*ications 8**:** 14895. https://doi.org/10.1038/ncomms14895

Sullivan BL, Aycrigg JL, Barry JH, Bonney RE, Bruns N, Cooper CB, Damoulas T, Dhondt AA, Dietterich T, Farnsworth A and Fink D (2014). The eBird enterprise: an integrated approach to development and application of citizen science. *Biological Conservation* 169: 31–40.

Sullivan BL, Phillips T, Dayer AA, Wood CL, Farnsworth A, Iliff MJ, Davies IJ, Wiggins A, Fink D, Hochachka WM and Rodewald AD (2017). Using open access observational data for conservation action: A case study for birds. *Biological Conservation* 208: 5-14.

Szabo JK, Vesk PA, Baxter PW and Possingham HP (2010). Regional avian species declines estimated from volunteer-collected long-term data using List Length Analysis. *Ecological Applications* 20(8): 2157-2169. doi:10.1890/09-0877.1

Taylor B (2020). Restoration Feasibility Assessment of Lake Hawdon North. Nature Glenelg Trust, Mount Gambier, South Australia.

Taylor B, Gibbs M, Hipsey M, Lewis M, Sharath I, Brookes J, Nicol J, Clarke K, Dalby P, Clark M and Bice C (2014). Investigations to inform diversion rules for the South East Flows Restoration Project in the Drain L Catchment. Government of South Australia, through Department for Environment, Water and Natural Resources, Adelaide.

Veale L and Whiterod N (2019). An update on the status of Australian Mudfish in the South East, South Australia, 2018. Aquasave - Nature Glenelg Trust, Warrnambool, Victoria.

Virtanen P, Gommers R, Oliphant TE, Haberland M, Reddy T, Cournapeau D, Burovski E, Peterson P, Weckesser W, Bright J, van der Walt SJ, Brett M, Wilson J, Millman KJ, Mayorov N, Nelson ARJ, Jones E, Kern R, Larson E, Carey CJ, Polat I, Feng Y, Moore EW, VanderPlas J, Laxalde D, Perktold J, Cimrman R, Henriksen I, Quintero EA, Harris CR, Archibald AM, Ribeiro AH, Pedregosa F, van Mulbregt P, and SciPy 1.0 Contributors. (2020) SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. *Nature Methods* 17(3): 261-272.

Wickham H, François R, Henry L and Müller K (2021). dplyr: A Grammar of Data Manipulation. R package version 1.0.6. https://CRAN.R-project.org/package=dplyr

Willoughby N, Thompson D, Royal M and Miles M (2018). South Australian Land Cover Layers: an Introduction and Summary Statistics, DEW Technical report 2018/01, Government of South Australia, Department for Environment and Water, Adelaide.

Wood SN (2011). Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 73(1): 3-36.

Ye Q, Giatas G, Dittmann S, Baring R, Bucater L, Deane D, Furst D, Brookes J, Rogers D and Goldsworthy S (2020). A synthesis of current knowledge of the food web and food resources for waterbird and fish populations in the Coorong: Goyder Institute for Water Research Technical Report Series; Vol. 20/11. Goyder Institute for Water Research. Adelaide, Australia.

Zuur AF, Ieno EN, Walker N, Saveliev AA and Smith GM (2009). Mixed Effects Models and Extensions in Ecology with R. Springer New York.

Appendix A – Lake Hawdon Benthic Sampling

A.1 Background

This work was undertaken as part of a broader study about the ecology of Lake Hawdon North (Taylor et al. 2022). The purpose of that project was to establish the methodology and obtain the baseline (pre-restoration) ecological data that will enable measurement of ecological outcomes should restoration works at Lake Hawdon North proposed in a recent restoration feasibility assessment (Taylor 2020) proceed.

A.2 Methods

We conducted baseline monitoring of macroinvertebrate abundance and diversity in the wet, muddy sediment (i.e. potential foraging habitat for shorebirds) of Lake Hawdon North (LHN) and Lake Hawdon South (LHS), prior to the drying of LHN and during the migratory shorebird non-breeding season (i.e. September to April). This sampling can be considered the 'before' component of a Before-After Control-Impact statistical design (should additional invertebrate surveys follow the construction of a regulator at LHN) to assess the effectiveness of the action with regard to sediment fauna.

Macroinvertebrate sampling at Lake Hawdon followed a modified version of the protocol used to study shorebird food resources in the Coorong as described in Activity 4.1.2.

Macroinvertebrate surveys were conducted within one sub-region of each lake (hereafter 'survey site'). Surveys were conducted on 22-23 September, 2021; 8-9 November, 2021; and 31 January, 2022. Survey sites were located along the south-western and north-eastern edges of LHN and LHS, respectively (Figure A.1). These sites were easily accessible, had similar substratum and vegetation characteristics, and are expected to provide some inundated shorebird feeding habitat (i.e. wet, muddy sediment) to allow macroinvertebrate sampling on both occasions under current biophysical conditions and management practices.

At each site, five transects were established, approximately 50 m apart running perpendicular to the waterline with three sampling points on each transect, for a total of 15 sampling points per trip, per site. Two sampling points were located at fixed points approximately 150 m apart, one near the shoreline (hereafter "Fixed Point 2"; Figure A.2), and one towards the centre of the lake (hereafter "Fixed Point 1"; Figure A.2). A third sampling point was located wherever the waterline occurred along the transect on the survey date (hereafter "Waterline"; Figure A.2). The water depth at each sampling point was recorded.

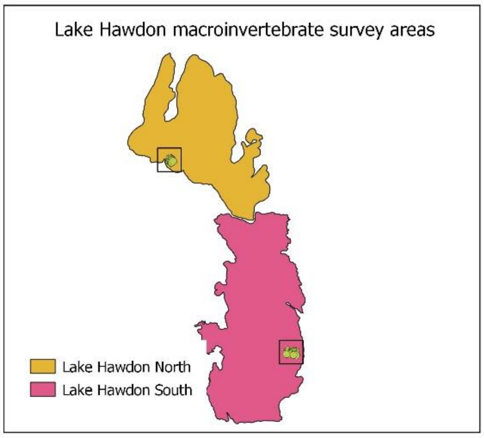

Figure A.1. Lake Hawdon macroinvertebrate survey sites

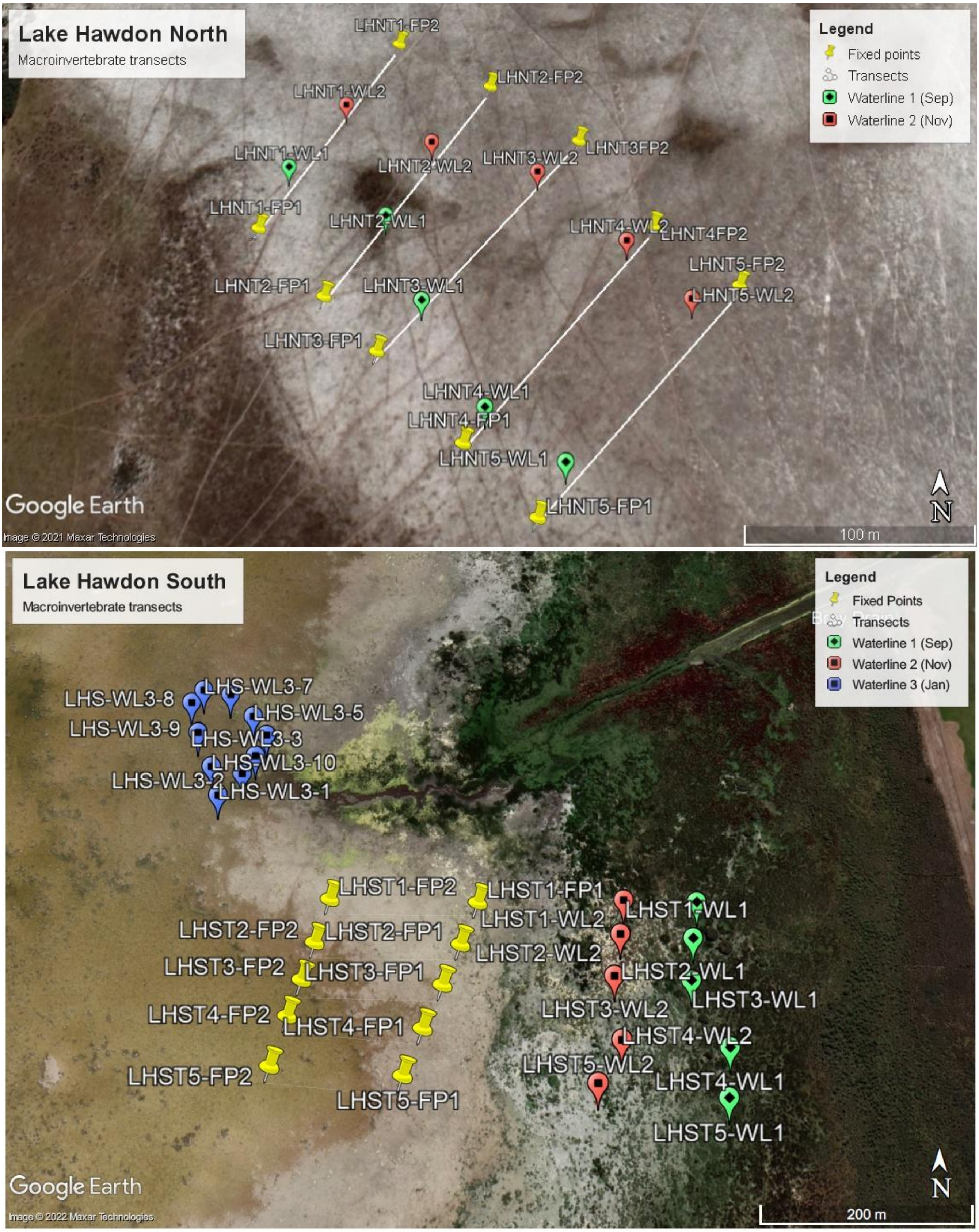

Figure A.1. Lake Hawdon macroinvertebrate sampling transects, showing two fixed points (yellow; "FP1" = Fixed Point 1" and "FP2" = Fixed Point 2) and two waterline points ("WL1" = Waterline 1, points in green and taken in September; ("WL2" = Waterline 2, points in red and taken in November; ("WL3" = Waterline 3, points in blue and taken in January).

A sediment core of 9 cm diameter (0.0064 M^2 surface area) was taken at each of the three locations along each transect. At LHN, the cores reached a depth of 10 cm. At LHS, the deeper substrate of the lakebed prevented the sinking of cores to 10 cm depth in most instances, so a core was taken to the maximum depth possible at each sampling point, and this depth was recorded.

Sediment cores were sieved *in situ* using a 500 µm mesh sieve. All material retained by the sieve was placed in a plastic zipped storage bag. Within 48 hours, samples were transferred to a white invertebrate sorting tray along with some water and all macroinvertebrates were removed using tweezers and stored in ethanol. Later, all macroinvertebrates were sorted under a dissecting microscope into the lowest possible taxonomic group and enumerated.

To visualise the composition of the benthic assemblages of the two lakes, a Non-metric Multi-dimensional Scaling (NMDS) analysis was plotted using the Vegan package (Oksanen et al. 2007) in the R software environment for statistical and graphical computing (R Core Team 2020) version 4.0.2. Analysis was performed using the relative abundance of each organism category (refer to Table A.1) using a Hellinger transformation, which is appropriate for data that have some abundant species and some rare species. Cores in which we did not find any invertebrates were excluded from the NMDS analysis.

A.3 Results

Both LHN and LHS were surveyed in September and November 2021, with 15 samples taken at each site on each trip (five at Fixed Point 1, five at Fixed Point 2 and five at the waterline). In January 2022, the section of LHN around our sampling transects was completely dry and so was not surveyed. Both the Fixed Point 1 and Fixed Point 2 transects at LHS were also dry, and there was only one roughly circular area of shallow water remaining around our sample sites. We therefore took ten samples from LHS in January around the waterline comprising the periphery of the remaining water body (Figure A.2).

A total of 1,656 individual macroinvertebrates were collected across all trips and both sites including 245 at LHN (217 in September and 28 in November; Table A.1) and 1,411 at LHS (767 in September, 351 in November and 293 in January; Table A.1).

At LHN, a total of 107, 50 and 88 organisms were collected from Fixed Point 1, Fixed Point 2 and the Waterline, respectively (Table A.1; Figure A.3). At LHS, a total of 283, 782 and 346 organisms were collected from Fixed Point 1, Fixed Point 2 and the Waterline, respectively (Table A.1; Figure A.3).

At LHN, where core samples were divided into two core depths, a total of 227 organisms were collected at 0-3cm depth (89% of the total) and just 18 organisms were collected at 3-10cm depth. In general, the sediment was compact and difficult to sieve at LHN. Vegetation and vegetation roots were also regularly encountered in the sediment.

Ten invertebrate taxa were identified at LHN and 17 taxa at LHS, as well as two unidentified organisms at LHN (Table A.2; Figure A.4).

At LHN the vast majority of organisms collected (almost 90% of 245 total individuals) were Oligochaetes (Table A.2). These were subdivided according to size, with megadrile Oligochaetes (i.e. Oligochaetes with body thickness > 10mm) most abundant (Table A.2). At LHS the make-up of invertebrates was more diverse with more than 40 individuals of microdrile Oligochaetes (49% of 1,411 total individuals), *Capitella* sp. (19%), *Chironomidae* larvae (13%), *Ostracoda* spp. (8%), *Physidae* sp. (5%) and *Amphipoda* spp. (3%) recorded (Table A.2). Interestingly, megadrile Oligochaetes were absent from LHS sediments.

Since LHN was dry in January and therefore not surveyed, we only included the September and November data in the NMDS analysis to compare the invertebrate community between the lakes. The NMDS plot showed that there was a distinct invertebrate community inhabiting wet muds at the two lakes (A.5).

At LHN, the average water depth across the five transects was 3.9 ± 1.56 cm (September) and < 1cm (November) at Fixed Point 1, and 16.9 ± 1.64 cm (September) and 19.9 ± 14.57 cm (November) at Fixed Point 2. At LHS, the average water depth across the five transects was 48.3 ± 3.23 cm (September) and 31 ± 5.83 cm (November) at Fixed Point 1, and 44.1 ± 2.13 cm (September) and 25.4 ± 3.58 (November) at Fixed Point 2. The average core depth across the five transects at LHS was 7.2 ± 2.78 cm (September) and 6.3 ± 0.45 cm (November) at Fixed Point 1, and 7.9 ± 2.53 cm (September) and 9.2 ± 1.92 cm (November) at Fixed Point 2.

Table A.1. Total invertebrate count from all samples for September and November, 2021 and January, 2022.

LAKE HAWDON NORTH – SEPTEMBER AND NOVEMBER												
	Transect 1		Transect 2		Transect 3		Transect 4		Transect 5		**Total**	
	Sep	*Nov*	*Sep*	*Nov*	*Sep*	*Nov*	*Sep*	*Nov*	*Sep*	*Nov*	***Sep***	***Nov***
Fixed Point 1	1	1	51	17	3	0	11	3	20	0	**86**	**21**
Fixed Point 2	12	0	4	0	1	1	8	4	20	0	**45**	**6**
Waterline	2	0	33	0	0	1	43	0	8	1	**86**	**6**
Total	**15**	**1**	**88**	**17**	**4**	**2**	**62**	**7**	**48**	**1**	**217**	**28**
LAKE HAWDON SOUTH – SEPTEMBER AND NOVEMBER												
	Transect 1		Transect 2		Transect 3		Transect 4		Transect 5		**Total**	
	Sep	*Nov*	*Sep*	*Nov*	*Sep*	*Nov*	*Sep*	*Nov*	*Sep*	*Nov*	***Sep***	***Nov***
Fixed Point 1	38	10	55	11	49	45	15	35	6	19	**163**	**120**
Fixed Point 2	69	10	66	27	116	33	123	67	199	72	**573**	**209**
Waterline	14	9	5	2	2	4	7	3	3	4	**31**	**22**
Total	**121**	**29**	**126**	**40**	**167**	**82**	**145**	**105**	**208**	**95**	**767**	**351**
LAKE HAWDON SOUTH – JANUARY												
Waterline	16	13	29	35	69	39	12	28	29	23	**293**	

Table A.2. Types of macroinvertebrates collected at Lake Hawdon.

ORGANISM	LAKE HAWDON NORTH	LAKE HAWDON SOUTH
Oligochaeta sp. - megadrile	207 (84.5%)	0
Oligochaeta sp. - microdrile	12 (4.9%)	689 (48.8%)
Polychaeta – Capitella sp.	2 (0.8%)	266 (18.9%)
Diptera larvae - Chironomidae	1 (0.4%)	180 (12.8%)
Diptera larvae - Ceratopogonidae	0	2 (0.1%)
Diptera larvae - Stratiomyidae	0	14 (1.0%)
Diptera larve - Dolichopodae	0	2 (0.1%)
Diptera adult spp.	2 (0.8%)	1 (0.1)
Hydrophilidae larvae - Berosus sp.	1 (0.4%)	2 (0.1%)
Hydrophilidae adult - Berosus sp.	0	4 (0.3%)
Dytiscidae larvae - Necterosoma sp.	0	2 (0.1%)
Corixidae nymph - Micronecta sp.	0	8 (0.6%)
Amphipoda spp.	15 (6.1%)	49 (3.4%)
Ostracoda spp.	0	108 (7.7%)
Gastropoda Physidae sp.	1 (0.4%)	64 (4.5%)
Gastropod Coxiella sp.	0	16 (1.1%)
Trichoptera sp.	0	1 (0.1%)
Elyaidae Eylais sp.	2 (0.8%)	3 (0.2%)
Unknown	2 (0.8%)	0
TOTAL	**245**	**1,411**

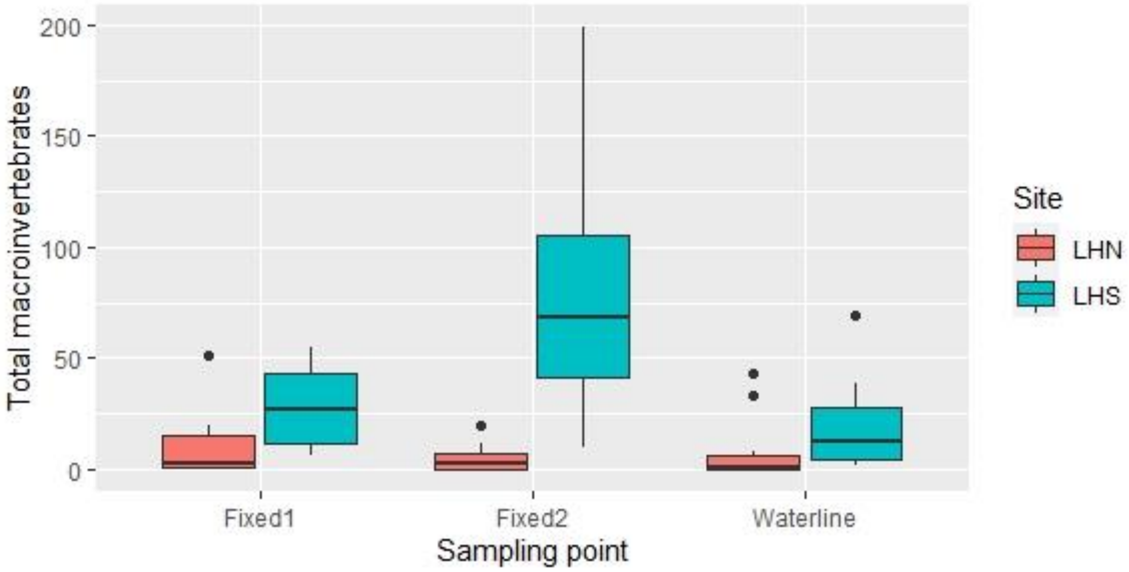

Figure A.2. Number of macroinvertebrates collected at each site at Fixed Point 1, Fixed Point 2 and the Waterline.

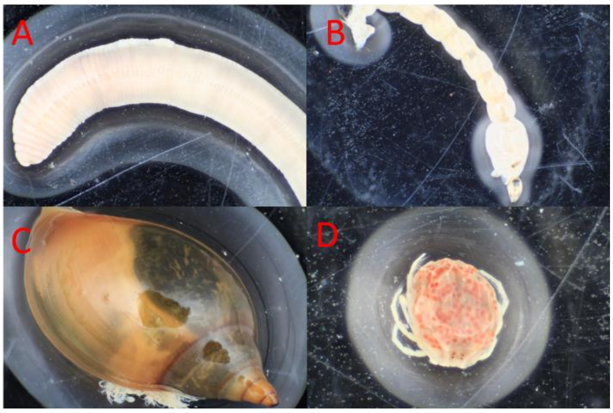

Figure A.3. Examples of invertebrates found at Lake Hawdon North and Lake Hawdon South. A. Megadrile oligochaete; B. Chironomid larvae; C. *Physidae* sp. D. *Eylais* sp.

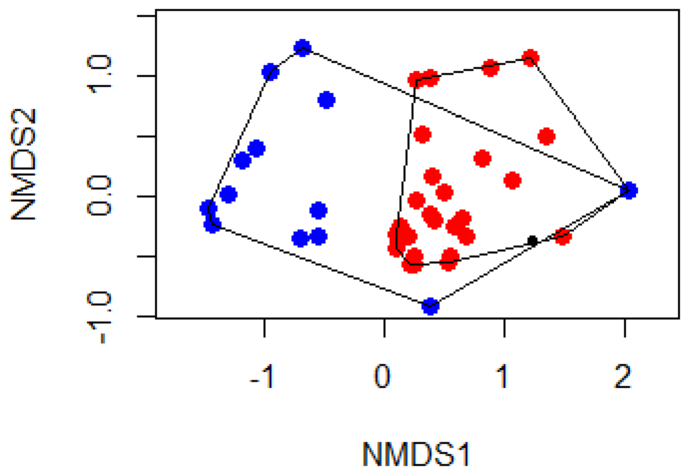

Figure A.4. Non-metric Multi-dimensional Scaling plot (NMDS) of macroinvertebrates at Lake Hawdon North (blue) and Lake Hawdon South (red) in September and November 2021.

A.4 Discussion

More than 85% of the total macroinvertebrates collected came from LHS (1,411 of 1,656) and macroinvertebrates were more diverse at LHS than LHN (Table A.2). This result is unsurprising because the sediment was much more compact and difficult to sieve (and therefore presumably more difficult for invertebrates to colonise) at LHN. This was further reflected in the lack of organisms in the deeper parts of the LHN cores and the dominance of megadrile Oligochaetes in the samples. Freshwater invertebrates have adapted a variety of life history strategies for surviving desiccation in wetlands subject to wetting and drying, however altered water regimes may alter the phenology of desiccation responses, and cause increased local extinctions (Strachan et al. 2015). It may be that the highly altered water regime at LHN prevents most aquatic invertebrates from persisting there under present conditions.

Far fewer organisms were found in November than in September (85% less in LHN and 59% less in LHS). This is unsurprising at LHN where the waterline and water depths had receded significantly between the two periods (Figure A.2), causing the sediment to harden further. It is more surprising at LHS, where conditions seemed broadly similar (though the waterline had receded somewhat (Figure A.2) and water depth was somewhat shallower). A contributing influence could be that recession rate is significantly greater than the invertebrate colonisation rate.

At LHS, fewer organisms were found at the waterline than at either of the fixed points during September and November, but there was no clear pattern at LHN (Table A.1). This result from LHS is unsurprising because the waterline was very high during these two trips, almost to the tall fringing vegetation (Figure A.2). Given its proximity to fringe vegetation and its longer time spent dry, it seems likely that this section would be difficult for invertebrates to colonise. Consistent with this result, the fixed point closer to the centre of the lake, which had deeper water and is likely to remain wet longer into the summer, held more invertebrates than the fixed point further from the centre of the lake during September and November (when the fixed points were underwater; Figure A.3). Further, invertebrates were much more abundant at the waterline in January, when it was much further out towards the centre of the lake, than they were at the waterline in September or November (Table A.1).

At both sites, some invertebrates detected in low numbers in our samples were more frequently observed by the team swimming in the water column, including *Eylais* mites and *Berosus* beetles. These invertebrates have a mostly epi-benthic lifestyle, so additional sampling using a different technique (e.g. seine netting) would be needed to quantify the abundance and diversity of these invertebrates that are more free-moving.

Based on the results of this study, it seems unlikely that either site surveyed provided significant food resources for short-billed shorebirds (e.g. red-necked stint, red-capped plover) in the sediment in September or November. At LHN, megadrile Oligochaetes dominated the benthic fauna, and we did not observe any individuals on the surface. Moreover, the sediment was quite hard and included short grassy vegetation, which is likely to make potential invertebrate prey in the sediment largely inaccessible. Short-billed shorebirds may however find additional food resources from flying insects landing on the ground or benthic organisms swimming in the water column, and we did observe 42 Red-capped Plovers (of which 38 were observed foraging) and 14 Red-necked Stint (of which 12 were observed foraging) during a 20 minute count at LHN in November. At LHS, water levels were mostly too high in September and November (Figure A.2) for short-statured shorebirds to forage, though we observed 170 Black-winged Stilts (of which six were observed foraging) during a 20 minute count in November. In contrast, LHS had dried out so significantly in January that only a small pool of water remained near our transect area (Figure A.2). We observed 15 red-capped plover and 1 sharp-tailed sandpiper during a 20 minute count in January, but no other shorebirds.

In general, these results suggest that water levels at both LHN and LHS fluctuated too much in 2021-2022 to provide consistent foraging habitat (i.e. muddy areas with shallow water) for shorebirds through the summer. Based on the methods outlined above (see Section 2.2.3 – Proportional water coverage), we explored how much of LHN and LHS (as defined by the boundaries shown in Figure A.1) comprised dry areas between September 2021 and February 2022 based on satellite imagery where at least 95% of the wetland could be assessed as wet or dry (i.e. < 5% was obscured due to cloud cover). About 66% of LHN and 70% of LHS were dry on 1 September 2021. This increased to 85% and 77% in LHN and LHS, respectively, by 30 November 2021 and to 92% and 96%, respectively, by 16 January 2022. Historical images from January 2000-2022 show that LHN was dry by January except in rare cases, while water levels in LHS were more variable (Figure A.6). Across both wetlands, this time series suggests that conditions were often too dry at Lake Hawdon to support shorebirds throughout the summer.

A cautionary note about interpretation of our invertebrate sampling results is that the survey areas covered in this study (Figure A.1) were chosen because they seemed to represent the best available shorebird habitat in each lake at present, however they are unlikely to represent the full spatial variation between LHN and LHS, or within each lake. Additional surveys distributed throughout the lakes would be needed to fully document the invertebrate fauna in each lake. Nonetheless, we feel that this initial comparison between a region of LHN and a region LHS that each seem suitable as potential shorebird habitat is instructive and indicates some important considerations for future management interventions.

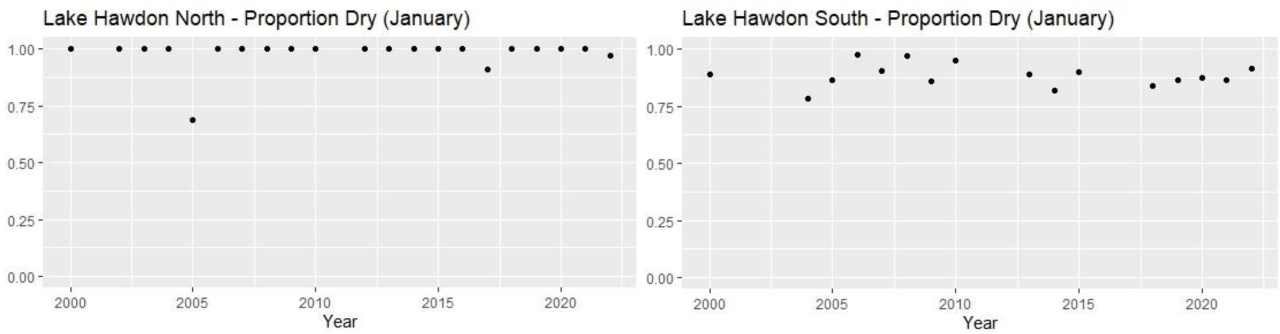

Figure A.6. Proportion of Lake Hawdon North and Lake Hawdon South that were dry in January between 2000-2022 when at least one satellite image from January allowed for > 95% of the wetland to be assessed as wet or dry.

Appendix A References

Oksanen J, Kindt R, Legendre P, O'Hara B, Stevens MHH, Oksanen MJ and Suggests M (2007). The vegan package. *Community ecology package* 10: 719.

R Core Team (2020). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Strachan S, Chester E and Robson B (2015). Freshwater Invertebrate Life History Strategies for Surviving Desiccation. *Springer Science Reviews* 3: 57–75.

Taylor B (2020). *Restoration Feasibility Assessment of Lake Hawdon North*. Report prepared for South Australian Government Department for Environment and Water. Nature Glenelg Trust, Mount Gambier.

Taylor B, Zukowski S, Jackson M, Whiterod N, Haywood B, Tuck J, Farrington L, McEvoy P and Prowse T (2022). *Baseline Ecological Monitoring of Lake Hawdon North, 2021*. Report to the South Australian Government Department for Environment and Water. Nature Glenelg Trust, Mount Gambier, South Australia.

Appendix B – List of waterbird species

Table B.1. List of all waterbird species recorded in south-east South Australia in the datasets assessed for the response models of the wetlands in the broader landscape. Species are ordered alphabetically by their common name and grouped as shorebirds and rails, waterfowl and piscivorous. *Species modelled. **Species deemed unsuitable for modelling due to very low number of detection or non-relevant for wetlands. ***Species deemed unsuitable to interpret model outputs due to convergence and singularity issues. Species without asterisks were recorded at least once within the study area but outside the 700m wetland buffer.

	SCIENTIFIC NAME	COMMON NAME
Shorebirds and rails	***Rostratula australis***	Australian Painted Snipe
	Haematopus longirostris	**Australian Pied Oystercatcher
	Stiltia Isabella	Australian Pratincole
	Porzana fluminea	*Australian Spotted Crake
	Zapornia pusilla	*Baillon's Crake
	Calidris bairdii	Baird's Sandpiper
	Cladorhynchus leucocephalus	*Banded Stilt
	Limosa lapponica	**Bar-tailed Godwit
	Esacus magnirostris	Beach Stone-curlew
	Elseyornis melanops	*Black-fronted Dotterel
	Limosa limosa	**Black-tailed Godwit
	Tribonyx ventralis	*Black-tailed Native-hen
	Himantopus leucocephalus	*Black-winged Stilt
	Calidris falcinellus	Broad-billed Sandpiper
	Gallirallus philippensis	*Buff-banded Rail
	Calidris subruficollis	Buff-breasted Sandpiper
	Tringa nebularia	*Common Greenshank
	Tringa tetanus	Common Redshank
	Actitis hypoleucos	*Common Sandpiper
		Cox's Sandpiper
	Calidris ferruginea	*Curlew Sandpiper
	Charadrius bicinctus	***Double-banded Plover
	Numenius madagascariensis	**Eastern Curlew
	Numenius arquata	**Eurasian Curlew
	Calidris tenuirostris	**Great Knot

Shorebirds and rails (cont.)	***Charadrius leschenaultii***	Greater Sand Plover
	Pluvialis squatarola	Grey Plover
	Tringa brevipes	Grey-tailed Tattler
	Thinornis cucullatus	**Hooded Plover
	Limosa haemastica	Hudsonian Godwit
	Gallinago hardwickii	*Latham's Snipe
	Charadrius mongolus	Lesser Sand Plover
	Tringa flavipes	Lesser Yellowlegs
	Lewinia pectoralis	**Lewin's Rail
	Numenius minutus	Little Curlew
	Charadrius dubius	Little Ringed Plover
	Calidris minuta	Little Stint
	Calidris subminuta	**Long-toed Stint
	Tringa stagnatilis	*Marsh Sandpiper
	Vanellus miles	*Masked Lapwing
	Glareola maldivarum	Oriental Pratincole
	Pluvialis fulva	*Pacific Golden Plover
	Calidris melanotos	**Pectoral Sandpiper
	Gallinago stenura	Pintail Snipe
	Calidris canutus	**Red Knot
	Charadrius ruficapillus	*Red-capped Plover
	Erythrogonys cinctus	*Red-kneed Dotterel
	Recurvirostra novaehollandiae	*Red-necked Avocet
	Phalaropus lobatus	Red-necked Phalarope
	Calidris ruficollis	*Red-necked Stint
	Charadrius hiaticula	Ringed Plover
	Arenaria interpres	**Ruddy Turnstone
	Calidris pugnax	**Ruff
	Calidris alba	**Sanderling
	Charadrius semipalmatus	Semipalmated Plover
	Calidris acuminata	*Sharp-tailed Sandpiper
	Limnodromus griseus	Short-billed Dowitcher

		Snipe spp
Shorebirds and rails (cont.)	***Haematopus fuliginosus***	**Sooty Oystercatcher
	Zapornia tabuensis	*Spotless Crake
		Tattler spp
	Xenus cinereus	Terek Sandpiper
	Numenius phaeopus	Whimbrel
	Tringa glareola	*Wood Sandpiper
Waterfowl	***Spatula rhynchotis***	*Australasian Shoveler
	Tadorna tadornoides	*Australian Shelduck
	Chenonetta jubata	*Australian Wood Duck
		Black Duck-Mallard hybrid
	Cygnus atratus	*Black Swan
	Oxyura australis	*Blue-billed Duck
	Cereopsis novaehollandiae	*Cape Barren Goose
	Anas castanea	*Chestnut Teal
		Domestic Duck
		Domestic Goose
	Gallinula tenebrosa	*Dusky Moorhen
	Alopochen aegyptiaca	Egyptian Goose
	Fulica atra	*Eurasian Coot
	Stictonetta naevosa	*Freckled Duck
	Nettapus pulchellus	Green Pygmy-goose
	Anas gracilis	*Grey Teal
	Aythya australis	*Hardhead
	Anseranas semipalmata	*Magpie Goose
	Anas platyrhynchos	*Mallard
	Biziura lobata	*Musk Duck
	Spatula clypeata	Northern Shoveler
	Anas superciliosa	*Pacific Black Duck
	Malacorhynchus membranaceus	*Pink-eared Duck
Waterfowl (cont.)	***Dendrocygna eytoni***	Plumed Whistling-Duck
	Porphyrio melanotus	*Purple Swamphen

	Radjah radjah	Radjah Shelduck
		Teal spp
		Grebe sp
Piscivorous	***Botaurus poiciloptilus***	*Australasian Bittern
	Anhinga novaehollandiae	*Australasian Darter
	Tachybaptus novaehollandiae	*Australasian Grebe
	Ixobrychus dubius	Australian Little Bittern
	Sternula nereis	**Fairy Tern
	Pelecanus conspicillatus	*Australian Pelican
	Threskiornis molucca	*Australian White Ibis
	Phalacrocorax fuscescens	***Black-faced Cormorant
	Ephippiorhynchus asiaticus	Black-necked Stork
	Antigone rubicunda	***Brolga
	Hydroprogne caspia	*Caspian Tern
	Irediparra gallinacea	Comb-crested Jacana
	Egretta sacra	Eastern Reef Egret
	Plegadis falcinellus	*Glossy Ibis
	Phalacrocorax carbo	*Great Cormorant
	Podiceps cristatus	*Great Crested Grebe
	Ardea alba	*Great Egret
	Ardea sumatrana	Great-billed Heron
	Thalasseus bergii	*Great Crested Tern
	Ardea cinerea	Grey Heron
	Gelochelidon nilotica	**Gull-billed Tern
	Poliocephalus poliocephalus	*Hoary-headed Grebe
	Ardea intermedia	*Intermediate Egret
	Phalacrocorax sulcirostris	*Little Black Cormorant
	Egretta garzetta	*Little Egret
	Microcarbo melanoleucos	*Little Pied Cormorant
	Gorsachius melanolophus	Malayan Night-heron
	Nycticorax caledonicus	*Nankeen Night-Heron
	Phalacrocorax varius	*Pied Cormorant

	Platalea regia	*Royal Spoonbill
	Threskiornis spinicollis	*Straw-necked Ibis
	Butorides striata	Striated Heron
	Chlidonias hybrida	*Whiskered Tern
	Egretta novaehollandiae	*White-faced Heron
	Ardea pacifica	*White-necked Heron
	Chlidonias leucopterus	**White-winged Tern
	Platalea flavipes	*Yellow-billed Spoonbill

Appendix C – Cross-validation summary tables for models of priority landscape wetlands

Table C.1. Model performance of the seven candidate models constructed to predict occurrence of the seven Key Waterbird Species at the Tolderol Game Reserve. We used thin-plate regression splines (see glossary) for all spline terms denoted by s(*variable*) below, except for the month term for models of resident species (Australian pelican, black swan, and red-capped plover) for which we used cyclic cubic regression splines to ensure continuity in the modelled response between the first and last month of the year. The complexity of the relationship between each covariate and its contribution to the response was controlled by setting the basis dimension (see glossary) for each spline term to k = 3 in all cases except for the interaction terms (denoted by *ti()*) where k = 5. Values shown are mean values ± standard error across each of the nine cross-validation data folds (one basin was iteratively left out of model construction to evaluate the predictive performance of that model). Models for each species are presented in order of their mean evaluation True Skill Statistic (TSS) values with models that performed best listed first and in bold. In the model formula *(1|Basin number)* and *(1|Year)* denote a random effect of basin and survey year, respectively.

SPECIES	MODEL FORMULA	# TRAINING PRESENCES	# TRAINING ABSENCES	# EVALUATION PRESENCES	# EVALUATION ABSENCES	TRAINING TSS	EVALUATION TSS
Australian pelican	**s(Proportional coverage) + s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)**	**33.78 ± 1.22**	**84.44 ± 1.06**	**4.22 ± 1.22**	**10.56 ± 1.06**	**0.68 ± 0.02**	**0.25 ± 0.13**
	s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)	33.78 ± 1.22	84.44 ± 1.06	4.22 ± 1.22	10.56 ± 1.06	0.7 ± 0.02	0.22 ± 0.14
	s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	24.89 ± 0.89	102.22 ± 1.31	3.11 ± 0.89	12.78 ± 1.31	0.62 ± 0.02	0.21 ± 0.12
	s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	53.33 ± 1.54	159.11 ± 1.79	6.67 ± 1.54	19.89 ± 1.79	0.48 ± 0.01	0.11 ± 0.08
	s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	33.78 ± 1.22	84.44 ± 1.06	4.22 ± 1.22	10.56 ± 1.06	0.69 ± 0.02	0.1 ± 0.15
	ti(Proportional coverage) + s(Area of habitat) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	13.33 ± 0.69	48.89 ± 0.45	1.67 ± 0.69	6.11 ± 0.45	0.99 ± 0.01	0.06 ± 0.09
	1	53.33 ± 1.54	159.11 ± 1.79	6.67 ± 1.54	19.89 ± 1.79	0 ± 0	0 ± 0

Black swan	**s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)**	**63.11 ± 2.18**	**68.44 ± 1.51**	**7.89 ± 2.18**	**8.56 ± 1.51**	**0.67 ± 0.01**	**0.19 ± 0.1**
	s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	55.11 ± 1.75	70.22 ± 0.97	6.89 ± 1.75	8.78 ± 0.97	0.57 ± 0.01	0.09 ± 0.05
	s(Proportional coverage) + s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	55.11 ± 1.75	70.22 ± 0.97	6.89 ± 1.75	8.78 ± 0.97	0.53 ± 0.02	0.02 ± 0.07
	1	102.22 ± 3.21	116.44 ± 1.99	12.78 ± 3.21	14.56 ± 1.99	0 ± 0	0 ± 0
	s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	102.22 ± 3.21	116.44 ± 1.99	12.78 ± 3.21	14.56 ± 1.99	0.43 ± 0.01	-0.01 ± 0.02
	ti(Proportional coverage) + s(Area of habitat) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	28.44 ± 0.85	40 ± 0.71	3.56 ± 0.85	5 ± 0.71	0.91 ± 0.03	-0.09 ± 0.12
	s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)	55.11 ± 1.75	70.22 ± 0.97	6.89 ± 1.75	8.78 ± 0.97	0.45 ± 0.01	-0.11 ± 0.07
Common greenshan k	**s(Proportional coverage) + s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)**	**8.89 ± 0.39**	**88 ± 1.13**	**1.11 ± 0.39**	**11 ± 1.13**	**0.7 ± 0.03**	**0.4 ± 0.2**
	s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	8.89 ± 0.39	88 ± 1.13	1.11 ± 0.39	11 ± 1.13	0.67 ± 0.02	0.34 ± 0.16
	s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)	8.89 ± 0.39	88 ± 1.13	1.11 ± 0.39	11 ± 1.13	0.67 ± 0.03	0.34 ± 0.16
	s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	11.56 ± 0.5	117.33 ± 1.24	1.44 ± 0.5	14.67 ± 1.24	0.69 ± 0.03	0.22 ± 0.14
	s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	6.22 ± 0.32	62.22 ± 0.62	0.78 ± 0.32	7.78 ± 0.62	0.86 ± 0.03	0.16 ± 0.19
	1	11.56 ± 0.5	117.33 ± 1.24	1.44 ± 0.5	14.67 ± 1.24	0 ± 0	0 ± 0

	ti(Proportional coverage) + s(Area of habitat) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	3.56 ± 0.18	45.33 ± 0.44	0.44 ± 0.18	5.67 ± 0.44	1 ± 0	-0.21 ± 0.12
Curlew sandpiper	**s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)**	**7.11 ± 0.35**	**61.33 ± 0.69**	**0.89 ± 0.35**	**7.67 ± 0.69**	**0.97 ± 0.03**	**0.4 ± 0.24**
	s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	8.89 ± 0.26	88 ± 1.26	1.11 ± 0.26	11 ± 1.26	0.44 ± 0.02	0.21 ± 0.15
	s(Proportional coverage) + s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	8.89 ± 0.26	88 ± 1.26	1.11 ± 0.26	11 ± 1.26	0.47 ± 0.02	0.19 ± 0.14
	s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)	8.89 ± 0.26	88 ± 1.26	1.11 ± 0.26	11 ± 1.26	0.46 ± 0.01	0.1 ± 0.13
	s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	14.22 ± 0.46	114.67 ± 1.31	1.78 ± 0.46	14.33 ± 1.31	0.33 ± 0.02	0.03 ± 0.07
	1	14.22 ± 0.46	114.67 ± 1.31	1.78 ± 0.46	14.33 ± 1.31	0 ± 0	0 ± 0
	ti(Proportional coverage) + s(Area of habitat) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	4.44 ± 0.24	44.44 ± 0.65	0.56 ± 0.24	5.56 ± 0.65	0.99 ± 0.01	-0.12 ± 0.07
Red-capped plover	**s(Basin area) + s(Month) + (1|Basin number) + (1|Year)**	**68.44 ± 2.9**	**158.22 ± 2.97**	**8.56 ± 2.9**	**19.78 ± 2.97**	**0.65 ± 0.01**	**0.29 ± 0.07**
	s(Proportional coverage) + s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	35.56 ± 1.55	89.78 ± 2.47	4.44 ± 1.55	11.22 ± 2.47	0.77 ± 0.02	0.23 ± 0.12
	s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	35.56 ± 1.55	89.78 ± 2.47	4.44 ± 1.55	11.22 ± 2.47	0.75 ± 0.02	0.16 ± 0.08

	s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	42.67 ± 2.06	94.22 ± 1.68	5.33 ± 2.06	11.78 ± 1.68	0.71 ± 0.01	0.09 ± 0.11
	s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)	35.56 ± 1.55	89.78 ± 2.47	4.44 ± 1.55	11.22 ± 2.47	0.75 ± 0.02	0.09 ± 0.05
	ti(Proportional coverage) + s(Area of habitat) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	23.11 ± 1.21	44.44 ± 1.27	2.89 ± 1.21	5.56 ± 1.27	1 ± 0	0.01 ± 0.18
	1	68.44 ± 2.9	158.22 ± 2.97	8.56 ± 2.9	19.78 ± 2.97	0 ± 0	0 ± 0
Red-necked stint	**s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)**	**20.44 ± 0.69**	**76.44 ± 1.37**	**2.56 ± 0.69**	**9.56 ± 1.37**	**0.57 ± 0.02**	**0.3 ± 0.21**
	s(Proportional coverage) + s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	20.44 ± 0.69	76.44 ± 1.37	2.56 ± 0.69	9.56 ± 1.37	0.56 ± 0.02	0.28 ± 0.21
	s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	17.78 ± 0.85	50.67 ± 0.88	2.22 ± 0.85	6.33 ± 0.88	0.76 ± 0.03	0.17 ± 0.17
	s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	20.44 ± 0.69	76.44 ± 1.37	2.56 ± 0.69	9.56 ± 1.37	0.54 ± 0.02	0.15 ± 0.15
	s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	32.89 ± 1.2	96 ± 1.71	4.11 ± 1.2	12 ± 1.71	0.54 ± 0.01	0.12 ± 0.06
	1	32.89 ± 1.2	96 ± 1.71	4.11 ± 1.2	12 ± 1.71	0 ± 0	0 ± 0
	ti(Proportional coverage) + s(Area of habitat) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	9.78 ± 0.52	39.11 ± 0.72	1.22 ± 0.52	4.89 ± 0.72	1 ± 0	-0.02 ± 0.12
Sharp-tailed sandpiper	**s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)**	**55.11 ± 0.65**	**41.78 ± 1.36**	**6.89 ± 0.65**	**5.22 ± 1.36**	**0.69 ± 0.02**	**0.47 ± 0.14**

s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	55.11 ± 0.65	41.78 ± 1.36	6.89 ± 0.65	5.22 ± 1.36	0.7 ± 0.01	0.4 ± 0.09
s(Proportional coverage) + s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	55.11 ± 0.65	41.78 ± 1.36	6.89 ± 0.65	5.22 ± 1.36	0.7 ± 0.02	0.4 ± 0.1
s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	74.67 ± 0.99	53.33 ± 1.62	9.33 ± 0.99	6.67 ± 1.62	0.62 ± 0.02	0.36 ± 0.06
ti(Proportional coverage) + s(Area of habitat) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	32 ± 0.53	16.89 ± 0.68	4 ± 0.53	2.11 ± 0.68	0.99 ± 0.01	0.26 ± 0.23
s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	43.56 ± 0.6	24.89 ± 0.61	5.44 ± 0.6	3.11 ± 0.61	0.76 ± 0.02	0.23 ± 0.16
1	74.67 ± 0.99	53.33 ± 1.62	9.33 ± 0.99	6.67 ± 1.62	0 ± 0	0 ± 0

Table C.2. Model performance of the nine candidate negative binomial generalised additive models (GAM) constructed to predict abundance of the seven Key Waterbird Species, at the Tolderol Game Reserve. We used a thin-plate regression splines (see glossary) for all spline terms denoted by *s(variable)* below, except for the month term for models of resident species (Australian pelican, black swan, and red-capped plover) for which we used cyclic cubic regression splines to ensure continuity in the modelled response between the first and last month of the year. The complexity of the relationship between each covariate and its contribution to the response was controlled by setting the basis dimension (see glossary) for each spline term to k = 3 in all cases except for the interaction terms (denoted by *ti()*) where k = 5. Values shown are mean values ± standard error across each of the 12 cross-validation data folds (one basin was iteratively left out of model construction to evaluate the predictive performance of that model). Models for each species are presented in order of their mean evaluation Mean Absolute Error (MAE) values, with models that performed best listed first and in bold. For each species, the sample size (n), mean counts ± standard error and minimum and maximum counts of the dataset used to fit the models are also provided, as well as the variance explained by the best model refitted to the full dataset. In the model formula *(1|Basin number)* and *(1|Year)* denote a random effect of basin and survey year, respectively.

SPECIES	MODEL FORMULA	EVALUATION MAE
Australian pelican n = 86 mean ± se = 2.08 ± 0.75 min – max = 0 – 52 Variance explained = 73.4%	**s(Salinity) + s(Month) + (1|Basin number) + (1|Year)**	**2.90 ± 0.53**
	s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)	2.95 ± 0.57
	s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	3.05 ± 0.53
	1	3.08 ± 0.49
	s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	3.84 ± 1.40
	ti(Proportional coverage) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	139.90 ± 132.79
	s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	801.62 ± 799.28
	ti(Proportional coverage) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Month) + (1|Basin number) + (1|Year)	1192.39 ± 1187.47
	s(Proportional coverage) + s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	1907.59 ± 1905.10
Black swan n = 86 mean ± se = 8.24 ± 2.2 min – max = 0 – 114 Variance explained = 28.7%	**s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)**	8.57 ± 2.13
	ti(Proportional coverage) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	9.37 ± 2.37
	s(Salinity) + (1|Basin number) + (1|Year)	9.37 ± 1.98
	s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	9.78 ± 2.65

	s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)	10.49 ± 2.25
	1	11.32 ± 1.85
	s(Proportional coverage) + s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	12.92 ± 4.15
	s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	13.77 ± 6.09
	ti(Proportional coverage) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Salinity) + (1|Basin number) + (1|Year)	1175.20 ± 1160.50
Common greenshank n = 59 mean ± se = 0.15 ± 0.07 min – max = 0 – 3 Variance explained = 42.9%	**s(Salinity) + s(Month) + (1|Basin number) + (1|Year)**	0.30 ± 0.08
	s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	0.31 ± 0.08
	s(Proportional coverage) + s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	0.31 ± 0.08
	1	0.31 ± 0.07
	s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)	0.32 ± 0.08
	s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	0.32 ± 0.08
	ti(Proportional coverage) + ti(Basin area) + ti(Proportional coverage, Basin area) + (1|Basin number) + (1|Year)	0.32 ± 0.08
	s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	0.33 ± 0.08
	ti(Proportional coverage) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	0.45 ± 0.13
Curlew sandpiper n = 59 mean ± se = 4.76 ± 3.60 min – max = 0 – 200 Variance explained < 1%	**1**	8.67 ± 2.70
	s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	32.89 ± 22.34
	s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	115.12 ± 92.28
	s(Salinity) + s(Month) + (1|Basin number) + (1|Year)	153.67 ± 80.13
	s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	412.83 ± 408.60
	ti(Proportional coverage) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	4258.82 ± 3380.39
	ti(Proportional coverage) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Month) + (1|Basin number) + (1|Year)	7312.66 ± 5002.87

	s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)	112436.50 ± 111951.34
	s(Proportional coverage) + s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	1079607.34 ± 1079463.46
Red-capped plover n = 86 mean ± se = 4.71 ± 1.31 min – max = 0 – 65 Variance explained = 72.9%	**s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)**	4.93 ± 1.98
	s(Salinity) + s(Month) + (1|Basin number) + (1|Year)	4.95 ± 1.99
	s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	4.95 ± 1.99
	s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)	4.97 ± 1.99
	s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)	5.35 ± 1.98
	ti(Proportional coverage) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	5.97 ± 2.00
	ti(Proportional coverage) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Month) + (1|Basin number) + (1|Year)	6.68 ± 2.40
	s(Proportional coverage) + s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	7.13 ± 2.69
	1	7.40 ± 1.29
Red-necked stint n = 60 mean ± se = 5.38 ± 2.15 min – max = 0 – 100 Variance explained = 62.8%	**s(Salinity) + s(Month) + (1|Basin number) + (1|Year)**	5.55 ± 3.02
	s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)	5.59 ± 2.70
	s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	5.63 ± 2.94
	ti(Proportional coverage) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Month) + (1|Basin number) + (1|Year)	6.81 ± 2.74
	s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)	7.41 ± 3.63
	s(Proportional coverage) + s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	8.48 ± 3.06
	1	8.89 ± 2.28
	ti(Proportional coverage) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	8.92 ± 3.67
	s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	57.96 ± 50.84

Sharp-tailed sandpiper n = 60 mean ± se = 114.27 ± 31.23 min – max = 0 – 1000 Variance explained = 31.9%	**s(Area of habitat) + s(Month) + (1|Basin number) + (1|Year)**	161.08 ± 39.92
	s(Salinity) + s(Month) + (1|Basin number) + (1|Year)	165.31 ± 37.13
	s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	173.19 ± 44.94
	s(Proportional coverage) + s(Month) + (1|Basin number) + (1|Year)	180.42 ± 45.67
	1	181.87 ± 31.70
	ti(Proportional coverage) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Month) + (1|Basin number) + (1|Year)	184.58 ± 52.02
	s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	214.58 ± 38.85
	s(Proportional coverage) + s(Basin area) + s(Month) + (1|Basin number) + (1|Year)	280.30 ± 94.92
	ti(Proportional coverage) + ti(Basin area) + ti(Proportional coverage, Basin area) + s(Salinity) + s(Turbidity) + s(Month) + (1|Basin number) + (1|Year)	382.81 ± 121.92

Table C.3. Evaluation of the candidate abundance models for five waterbird species at the Teringie and Waltowa Wetlands. Shown for each model are: the number of parameters fitted (k); the log-likelihood of the model (logLik), Akaike's Information Criterion (AIC) for which lower numbers indicate higher ranked models; the change in AIC relative to the top AIC-ranked model for each species (ΔAIC); the coefficient of determination (R^2), the mean predictive deviance obtained by cross-validation (CV Deviance) and its standard error calculated across the 20 cross-validation folds; and the Mean Absolute Error (MAE) obtained by cross-validation and its standard error. Models are ordered by AIC and the top-ranked model for each species is in bold. In the model formula, *Area0to5* denotes the area of wetland within the 0-5 cm depth range, while *AreaGreater20* denotes the area of wetland exceeding 20 cm depth.

SPECIES	MODEL	k	logLik	AIC	ΔAIC	R^2	CV Deviance [SE]	MAE [SE]
Australian pelican	**Wetland + s(AreaGreater20,by=Wetland)**	**7**	**-48**	**110**	**0**	**0.76**	**17.43 [12.41]**	**> 10000**
	Wetland + s(PropCoverage,by=Wetland)	7	-49	111.9	1.9	0.753	17.72 [12.41]	> 10000
	Wetland + s(AreaGreater20)	5.995	-51.7	115.4	5.4	-1.309	15.48 [12.17]	199.9 [194.56]
	Wetland + s(PropCoverage)	5.991	-51.8	115.6	5.6	0.222	15.06 [12.12]	11.44 [4.21]
	Wetland	4	-60.5	129	19.0	0.207	15.63 [11.85]	12.02 [3.71]
	1	2	-64.8	133.7	23.7	0	3.83 [0.86]	13.04 [3.75]
Black swan	**Wetland + s(PropCoverage,by=Wetland)**	**7.792**	**-60.2**	**136**	**0**	**0.427**	**13.8 [6.14]**	**16.85 [6.9]**
	Wetland + s(PropCoverage)	5	-63.6	137.3	1.3	0.149	11.18 [5.59]	19.91 [9.06]
	Wetland	4	-64.8	137.6	1.6	0.112	10.9 [5.36]	20.79 [5.86]
	Wetland + s(AreaGreater20)	5	-64.1	138.2	2.2	0.407	12.84 [5.8]	224.25 [201.96]
	Wetland + s(AreaGreater20,by=Wetland)	7.905	-61.7	139.3	3.3	0.46	10.72 [4.82]	20.38 [7.31]
	1	2	-68.9	141.9	5.9	0	4.03 [0.97]	23.07 [5.53]
Red-capped plover	**Wetland + s(PropCoverage)**	**5.957**	**-31.2**	**74.3**	**0**	**0.175**	**2.43 [0.81]**	**1.65 [0.36]**
	Wetland	4	-33.5	75.1	0.8	0.075	2.05 [0.59]	1.61 [0.32]
	1	2	-36	76	1.7	0	2.14 [0.6]	1.65 [0.31]
	Wetland + s(Area0to5)	5	-33.7	77.4	3.1	0.075	3.88 [2.06]	1.7 [0.33]
	Wetland + s(PropCoverage,by=Wetland)	7.763	-32.2	80	5.7	0.145	2.46 [0.8]	1.71 [0.36]
	Wetland + s(Area0to5,by=Wetland)	7	-34	81.9	7.6	0.072	2.67 [0.9]	1.94 [0.38]

Red-necked stint	**1**	**2**	**-19.6**	**43.2**	**0**	**0**	**1.49 [0.83]**	**1.61 [0.71]**
	Wetland	4	-18.3	44.6	1.4	0.047	4.97 [3.98]	1.59 [0.73]
	Wetland + s(Area0to5)	5.481	-18.2	47.4	4.1	0.031	4.94 [3.95]	6.19 [4.61]
	Wetland + s(PropCoverage)	5.576	-18.5	48.1	4.9	0.079	18.71 [14.67]	1.57 [0.74]
	Wetland + s(Area0to5,by=Wetland)	7.999	-17.5	51	7.8	-1.149	> 10000	8.9 [6.37]
	Wetland + s(PropCoverage,by=Wetland)	7	-19.3	52.5	9.3	-1.015	> 10000	4.73 [2.09]
Sharp-tailed sandpiper	**Wetland + s(PropCoverage,by=Wetland)**	**7.669**	**-68.5**	**152.4**	**0**	**0.296**	**104.15 [79.57]**	**> 10000**
	Wetland	4	-73.6	155.1	2.7	0.252	87.53 [77.88]	49.16 [17.02]
	Wetland + s(PropCoverage)	5.001	-73	156	3.6	0.285	185.23 [123.25]	44.41 [18.01]
	Wetland + s(Area0to5)	5	-73.7	157.4	5.0	0.212	87.57 [77.63]	826.39 [766.1]
	Wetland + s(Area0to5,by=Wetland)	7.38	-71.7	158.2	5.8	0.254	87.21 [77.22]	> 10000
	1	2	-78.6	161.3	8.9	0	4.58 [1.19]	70.6 [16.82]

Appendix D – Black swan abundance partial response plots with raw counts

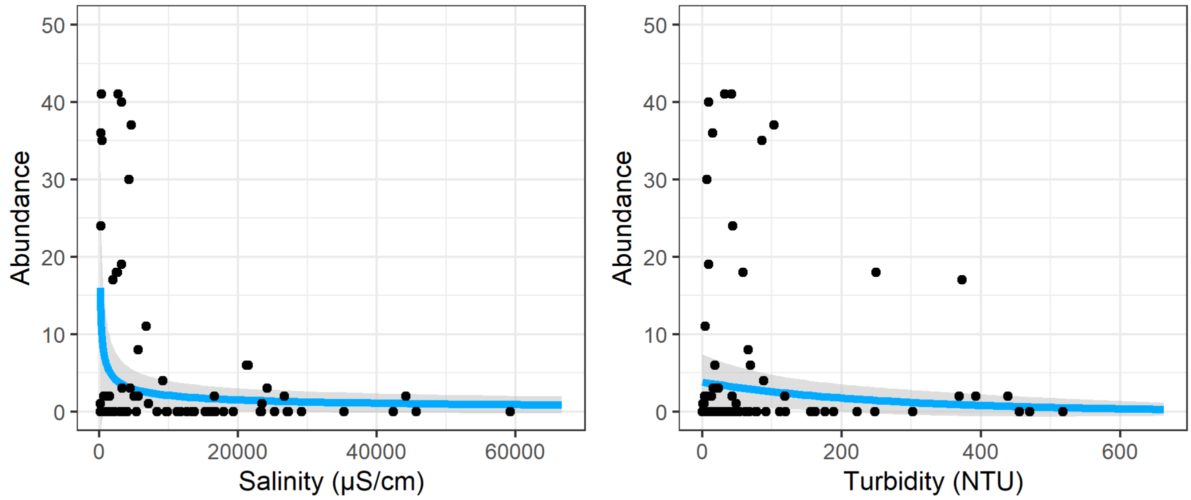

Figure D.1. Partial response plot of the top-ranked abundance model for black swan at Tolderol Game Reserve. Blue line indicates the modelled relationship between abundance and salinity (left plot) and turbidity (right plot) when other variables are held at their mean. Ribbons represent 95% confidence intervals on this response. Points are the observed black swan counts. Note how most counts higher than 10 birds are underestimated by the model (i.e. point is above the blue line and ribbon).

Appendix E – Raw counts at Teringie and Waltowa Wetlands

Figure E.1. Raw survey counts at Teringie and Waltowa Wetlands for six KWS against the proportion of each wetland covered by water in the month of each survey.

Appendix F – Partial response plots of best abundance models for Teringie and Waltowa Wetlands

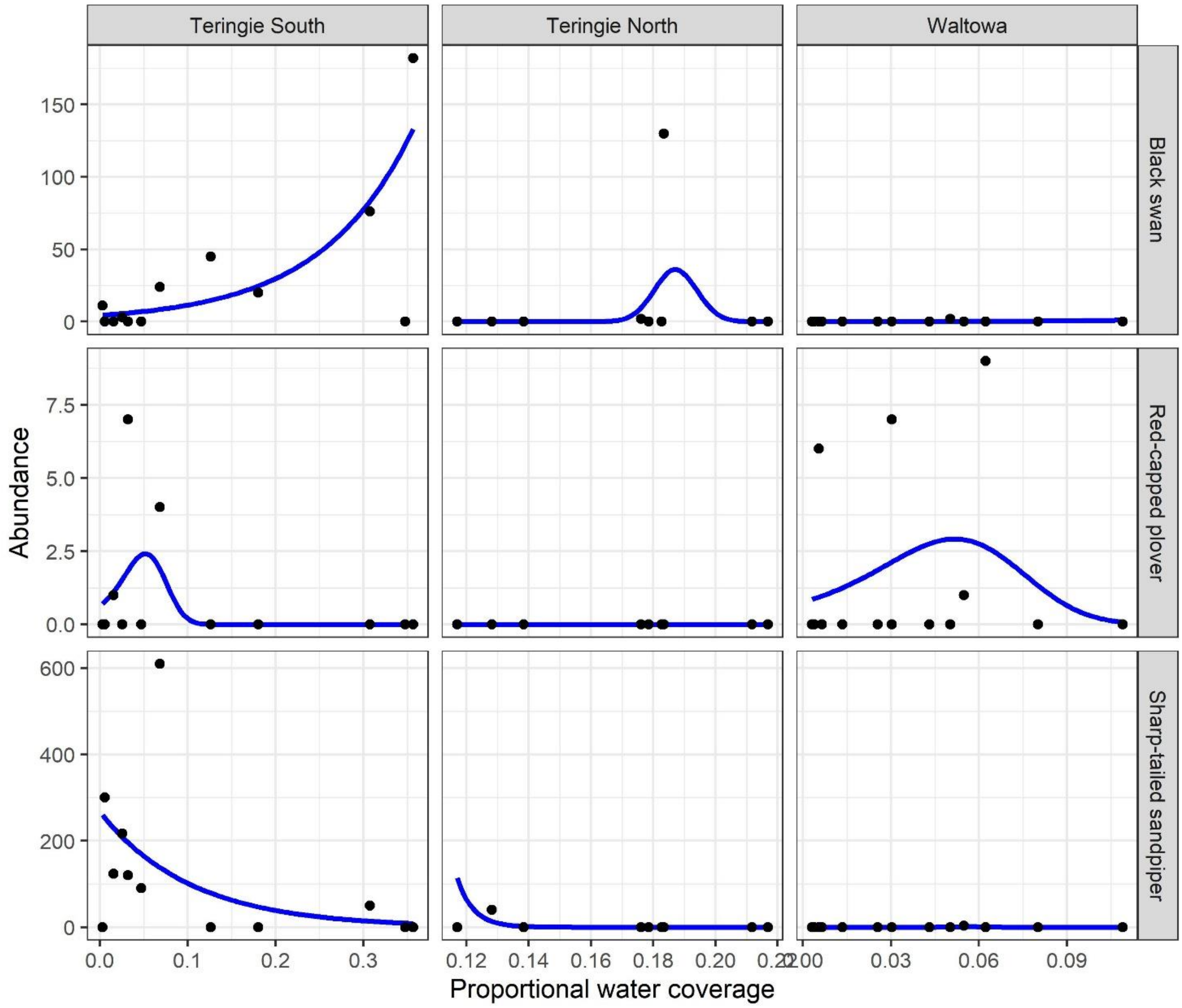

Figure F.1. Partial response plots for the best models of black swan, red-capped plover and sharp-tailed sandpiper, showing the influence of proportional water coverage on bird abundance at Teringie and Waltowa Wetlands. Blue line indicates predicted abundance when other variables are held at their mean and black dots are the raw abundance counts.

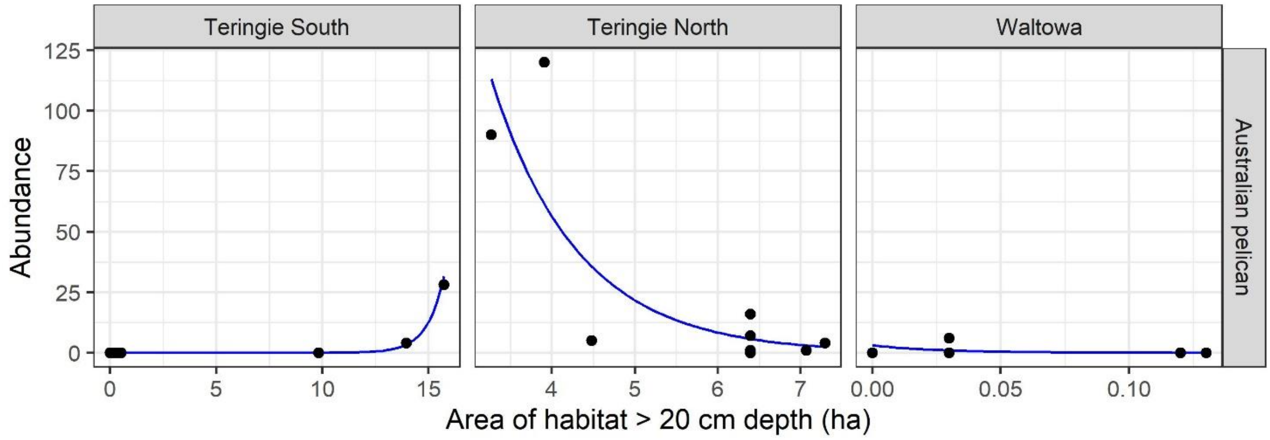

Figure F.2 Partial response plots of the best model for Australian pelican black swan showing the influence of area of habitat deeper than 20 cm on bird abundance at Teringie and Waltowa Wetlands. Blue line indicates predicted abundance when other variables are held at their mean and black dots are the raw abundance counts.

Appendix G – Proportional water coverage histograms

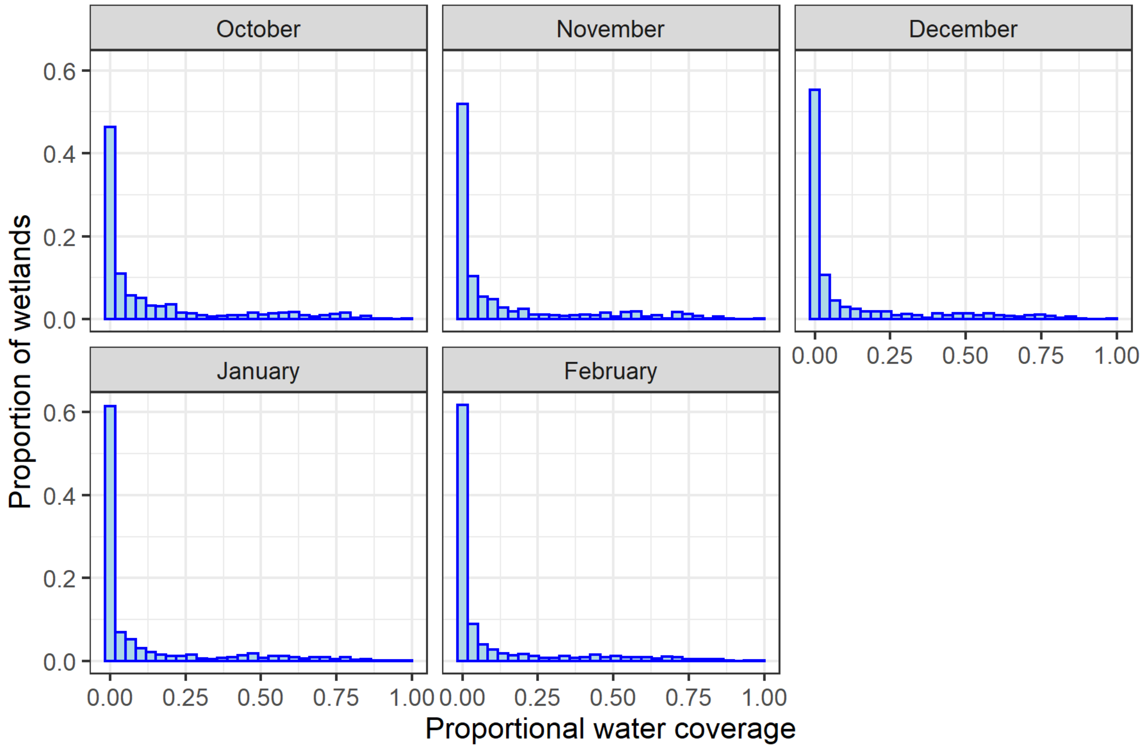

Figure G.1. Histograms showing the distribution of the average proportional water coverage across the wetlands considered in the waterbird response models of the broader landscape of south-east South Australia during the months when migratory shorebirds are expected to be in Australia (i.e. October to February) between 1999 and 2020.

Appendix H – Partial response to proportional water coverage in the broader landscape

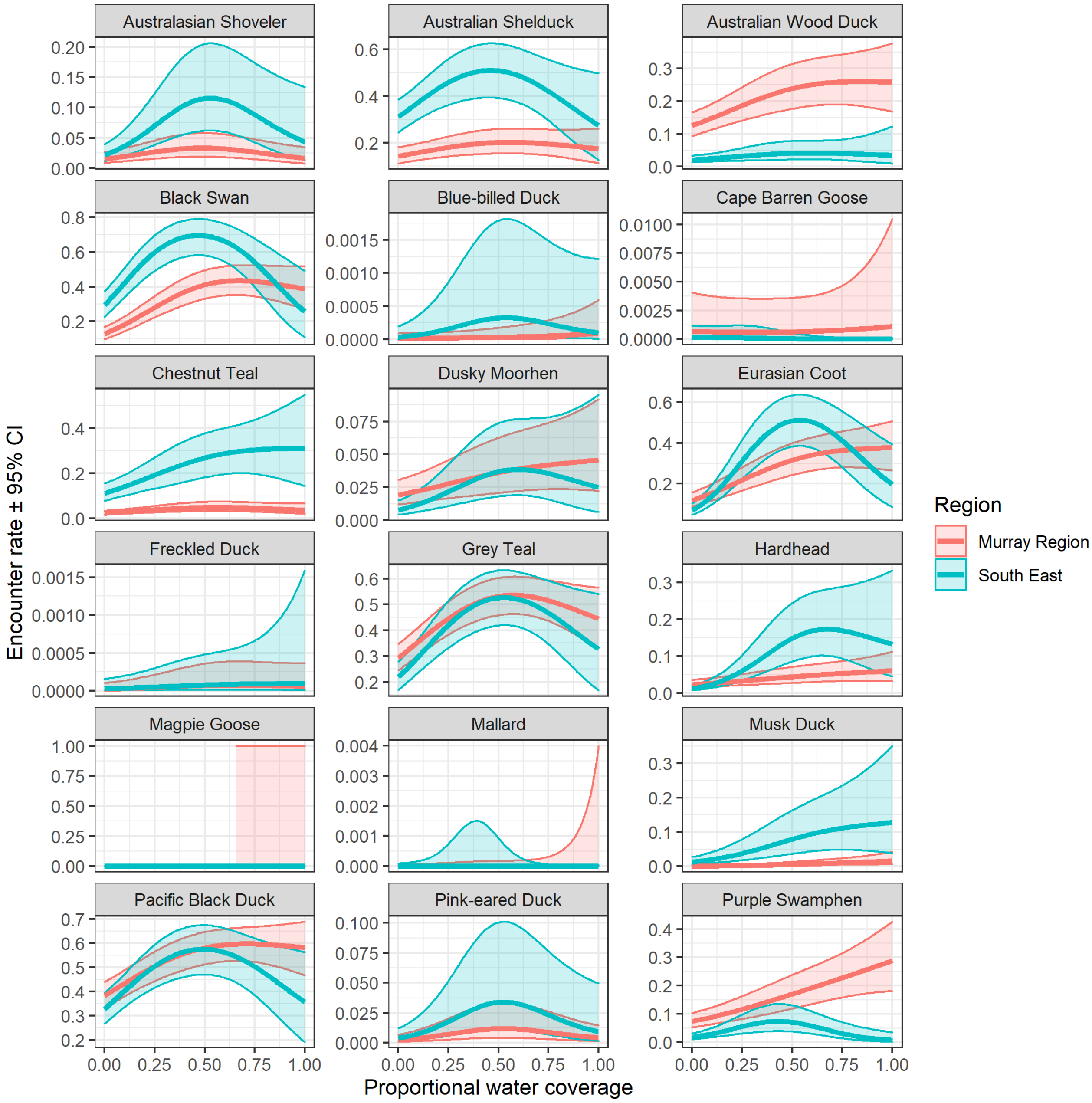

Figure H.1. Partial response plots for the waterfowl species modelled showing the non-linear influence of proportional water coverage on encounter rate at the wetlands in the broader landscape of south-east South Australia (Murray Region in red and South East in green). The lines indicate predicted encounter rate when other variables are held at their mean within the region and month is held at February. Ribbons represent 95% confidence intervals on these responses.

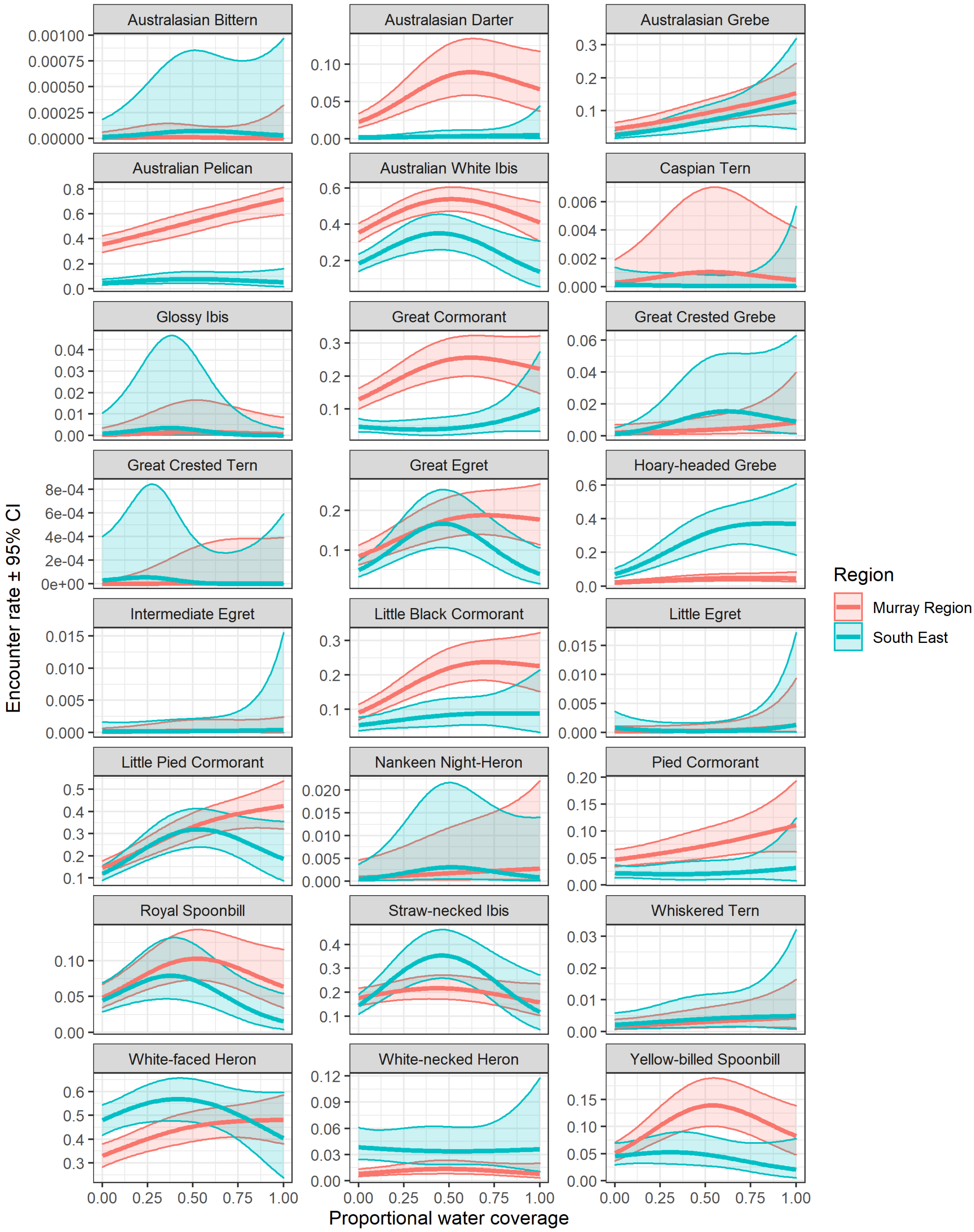

Figure H.2. Partial response plots for the piscivorous species modelled showing the non-linear influence of proportional water coverage on encounter rate at the wetlands in the broader landscape of south-east South Australia (Murray Region in red and South East in green). The lines indicate predicted encounter rate when other variables are held at their mean within the region and month is held at February. Ribbons represent 95% confidence intervals on these responses.

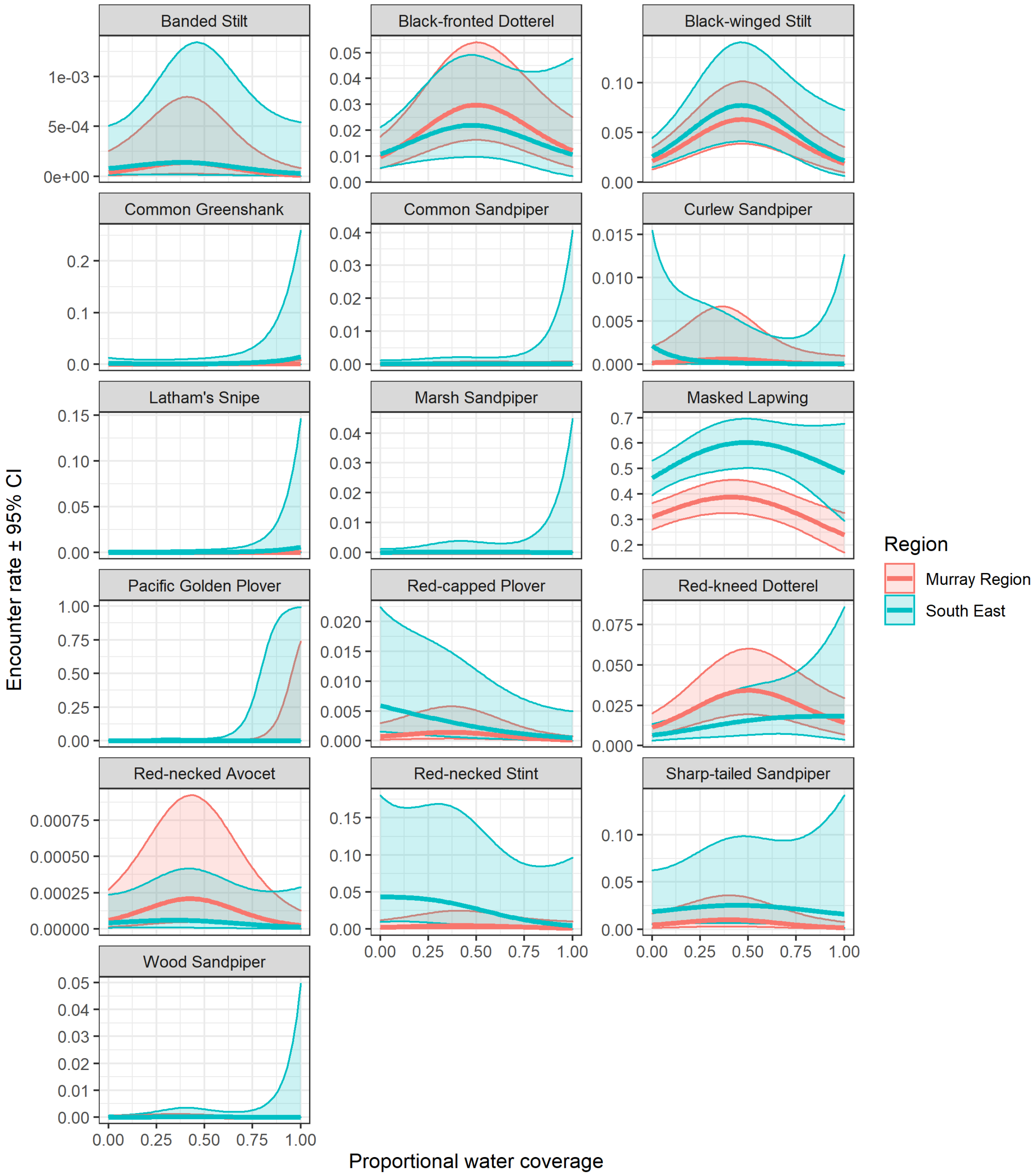

Figure H.3. Partial response plots for the shorebird species modelled showing the non-linear influence of proportional water coverage on encounter rate at the wetlands in the broader landscape of south-east South Australia (Murray Region in red and South East in green). The lines indicate predicted encounter rate when other variables are held at their mean within the region and month is held at February. Ribbons represent 95% confidence intervals on these responses.

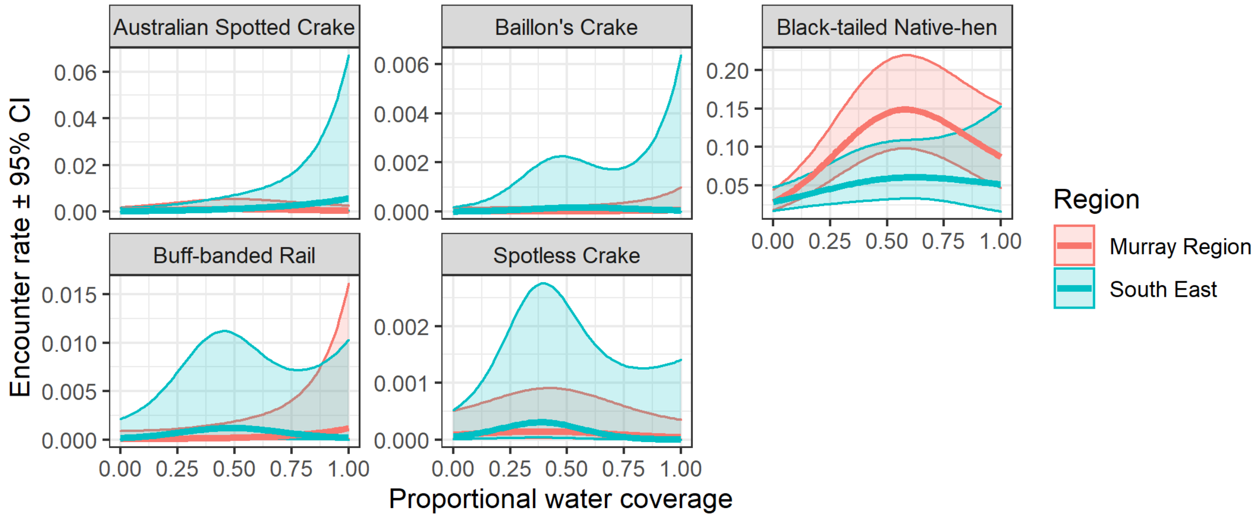

Figure H.4. Partial response plots for the rail species modelled showing the non-linear influence of proportional water coverage on encounter rate at the wetlands in the broader landscape of south-east South Australia (Murray Region in red and South East in green). The lines indicate predicted encounter rate when other variables are held at their mean within the region and month is held at February.

Appendix I – Raw Tolderol Game Reserve counts plotted against predictors

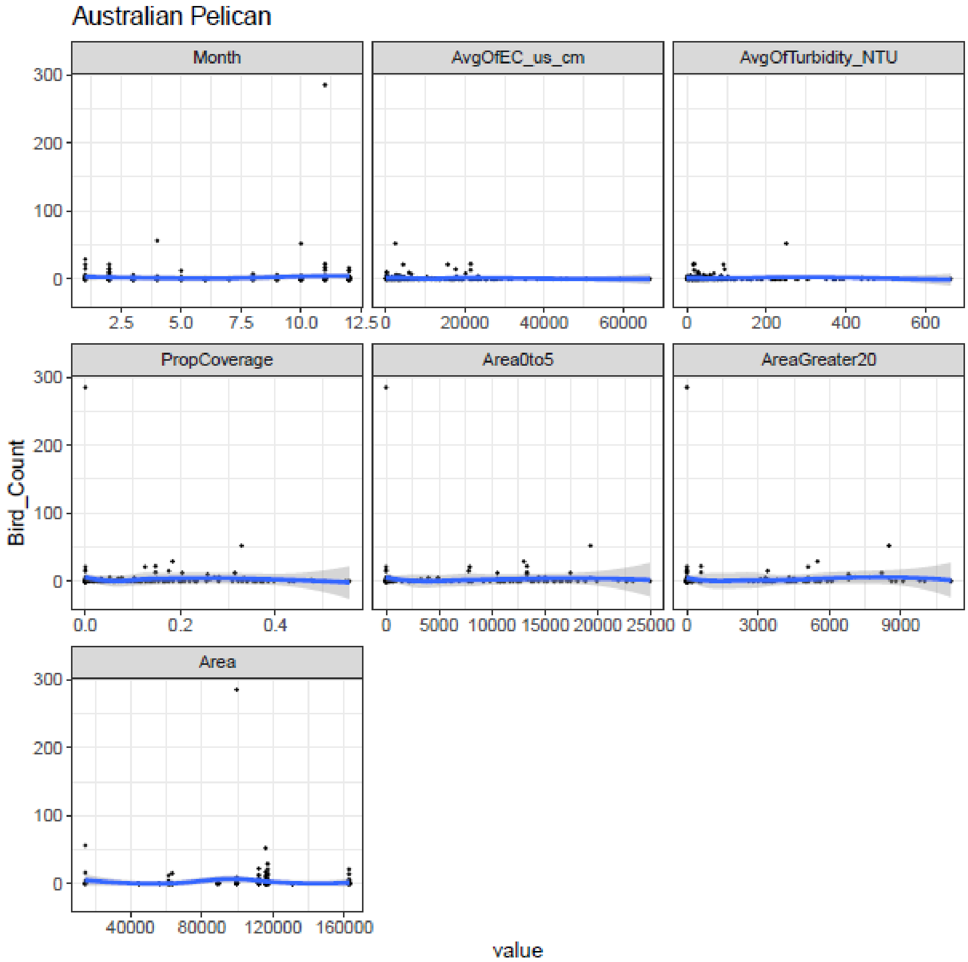

Figure I.1. Australian raw pelican counts (black dots) from the Tolderol Game Reserve surveys plotted against the potential predictors used to model abundance. The blue line is a loess smooth curve to visualise patterns and the grey ribbon is its 95% confidence interval.

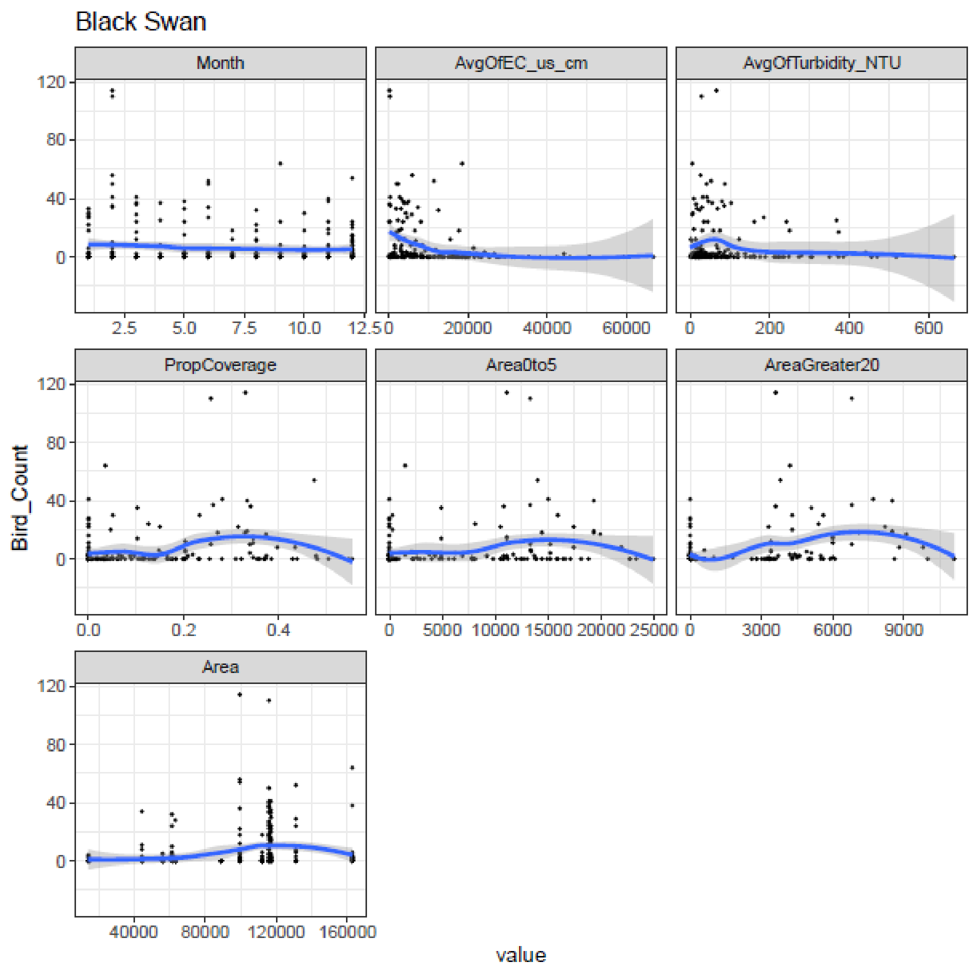

Figure I.2. Black swan counts (black dots) from the Tolderol Game Reserve surveys plotted against the potential predictors used to model abundance. The blue line is a loess smooth curve to visualise patterns and the grey ribbon is its 95% confidence interval.

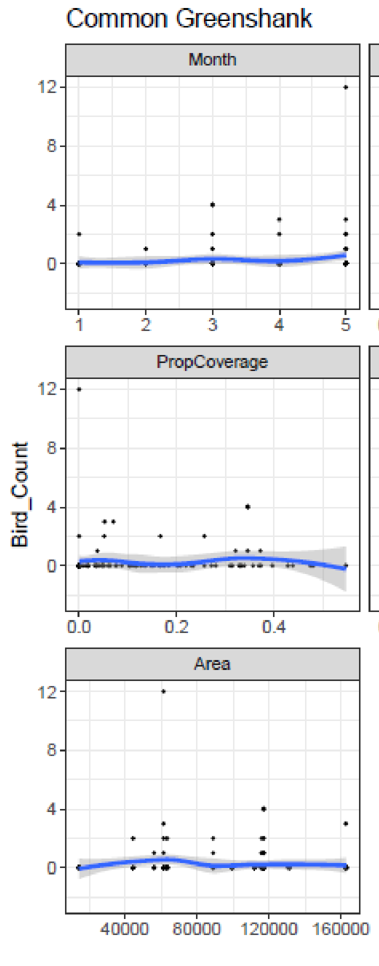

Figure I.3. Common greenshank counts (black dots) from the Tolderol Game Reserve surveys plotted against the potential predictors used to model abundance. The blue line is a loess smooth curve to visualise patterns and the grey ribbon is its 95% confidence interval.

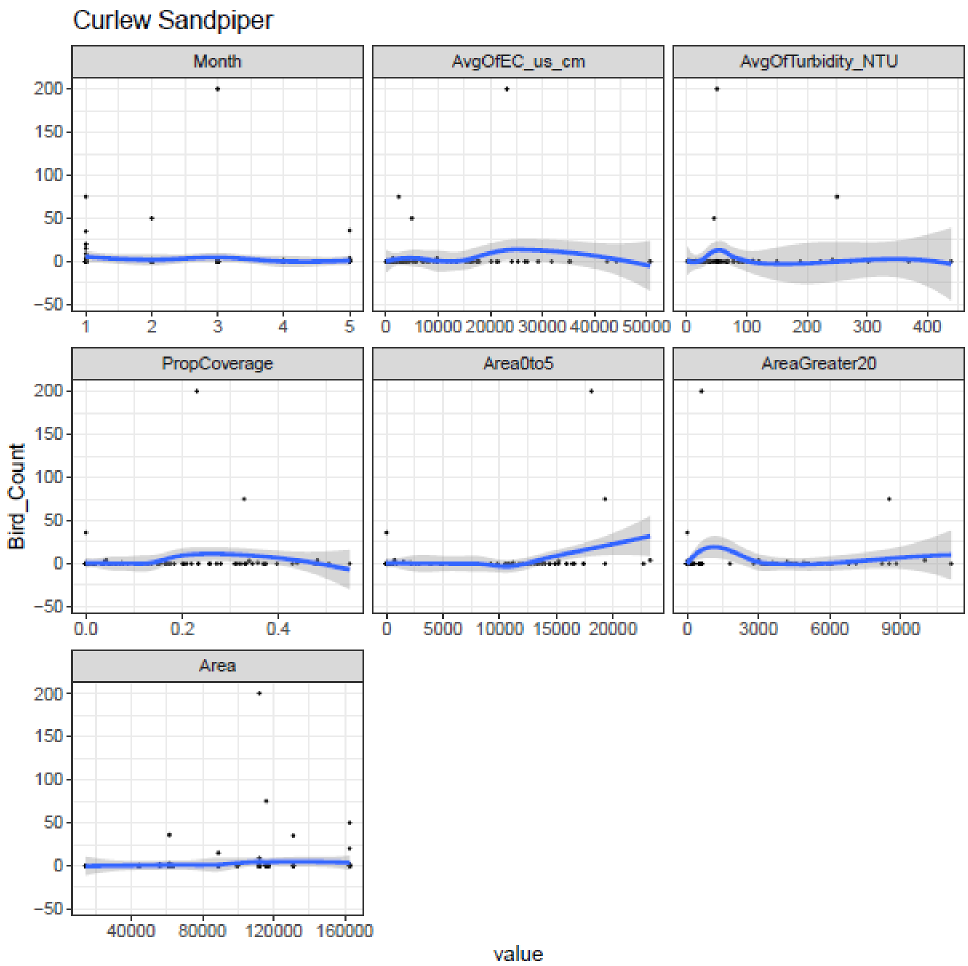

Figure I.4. Curlew sandpiper counts (black dots) from the Tolderol Game Reserve surveys plotted against the potential predictors used to model abundance. The blue line is a loess smooth curve to visualise patterns and the grey ribbon is its 95% confidence interval.

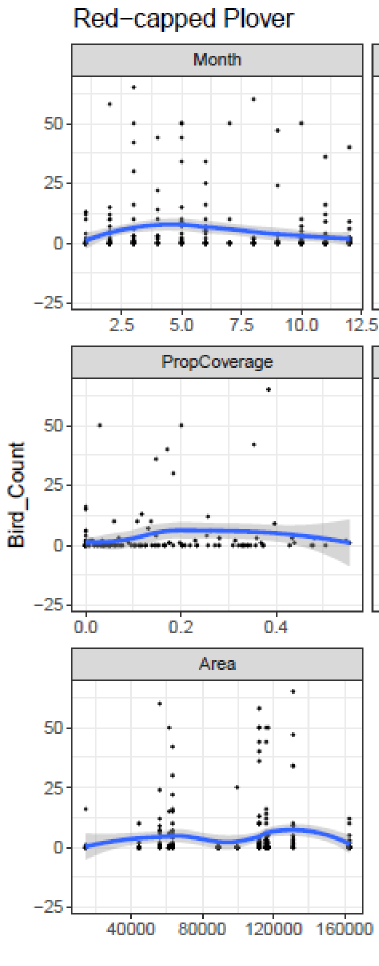

Figure I.5. Red-capped plover (black dots) from the Tolderol Game Reserve surveys plotted against the potential predictors used to model abundance. The blue line is a loess smooth curve to visualise patterns and the grey ribbon is its 95% confidence interval.

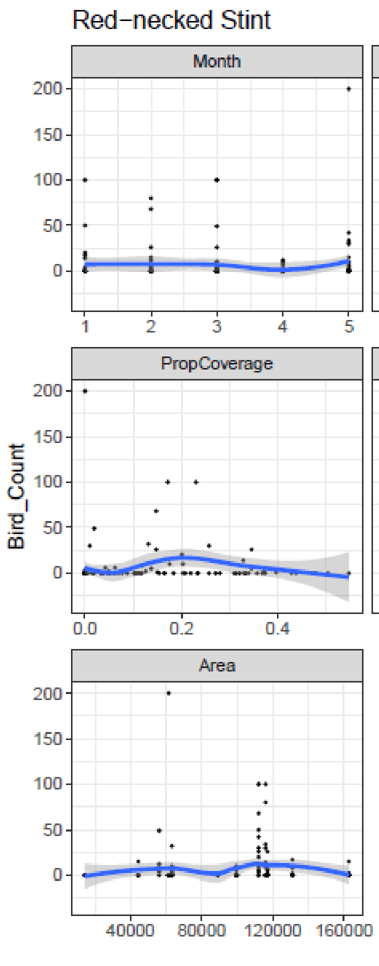

Figure I.6. Red-necked stint counts (black dots) from the Tolderol Game Reserve surveys plotted against the potential predictors used to model abundance. The blue line is a loess smooth curve to visualise patterns and the grey ribbon is its 95% confidence interval.

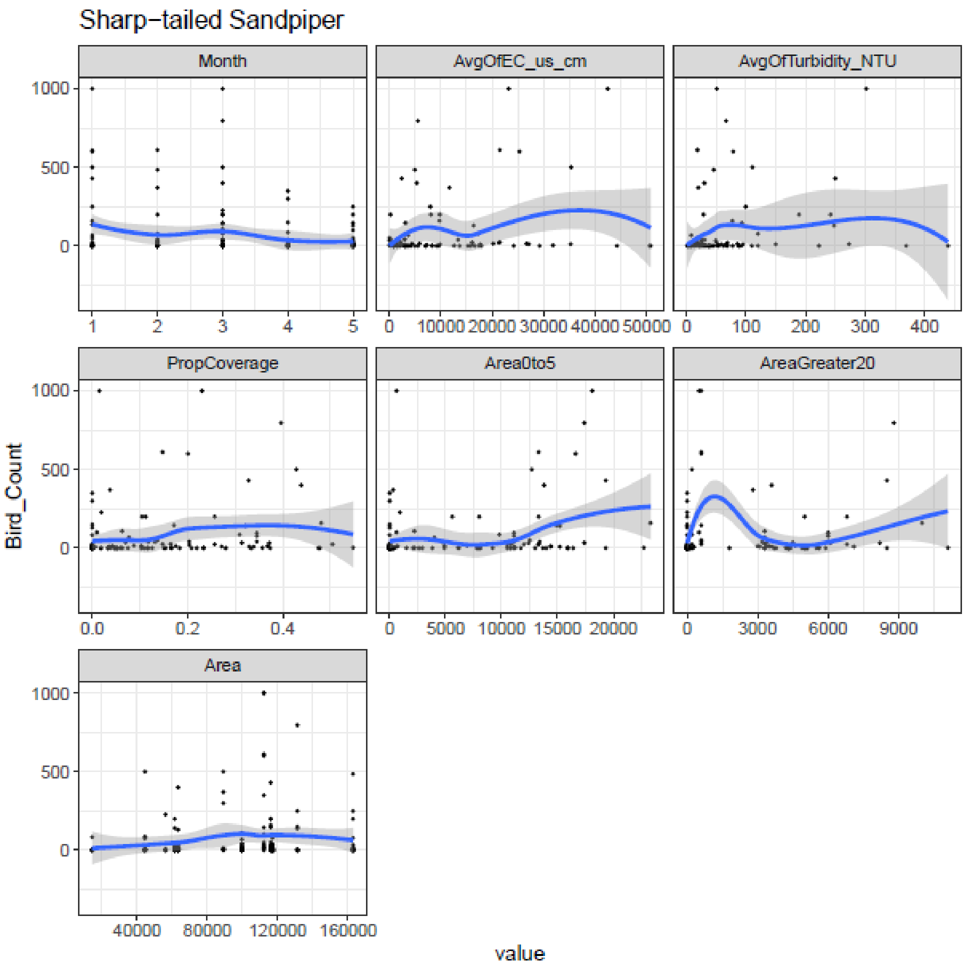

Figure I.7. Sharp-tailed sandpiper counts (black dots) from the Tolderol Game Reserve surveys plotted against the potential predictors used to model abundance. The blue line is a loess smooth curve to visualise patterns and the grey ribbon is its 95% confidence interval.

Appendix J – Number of wetlands with waterbird detections

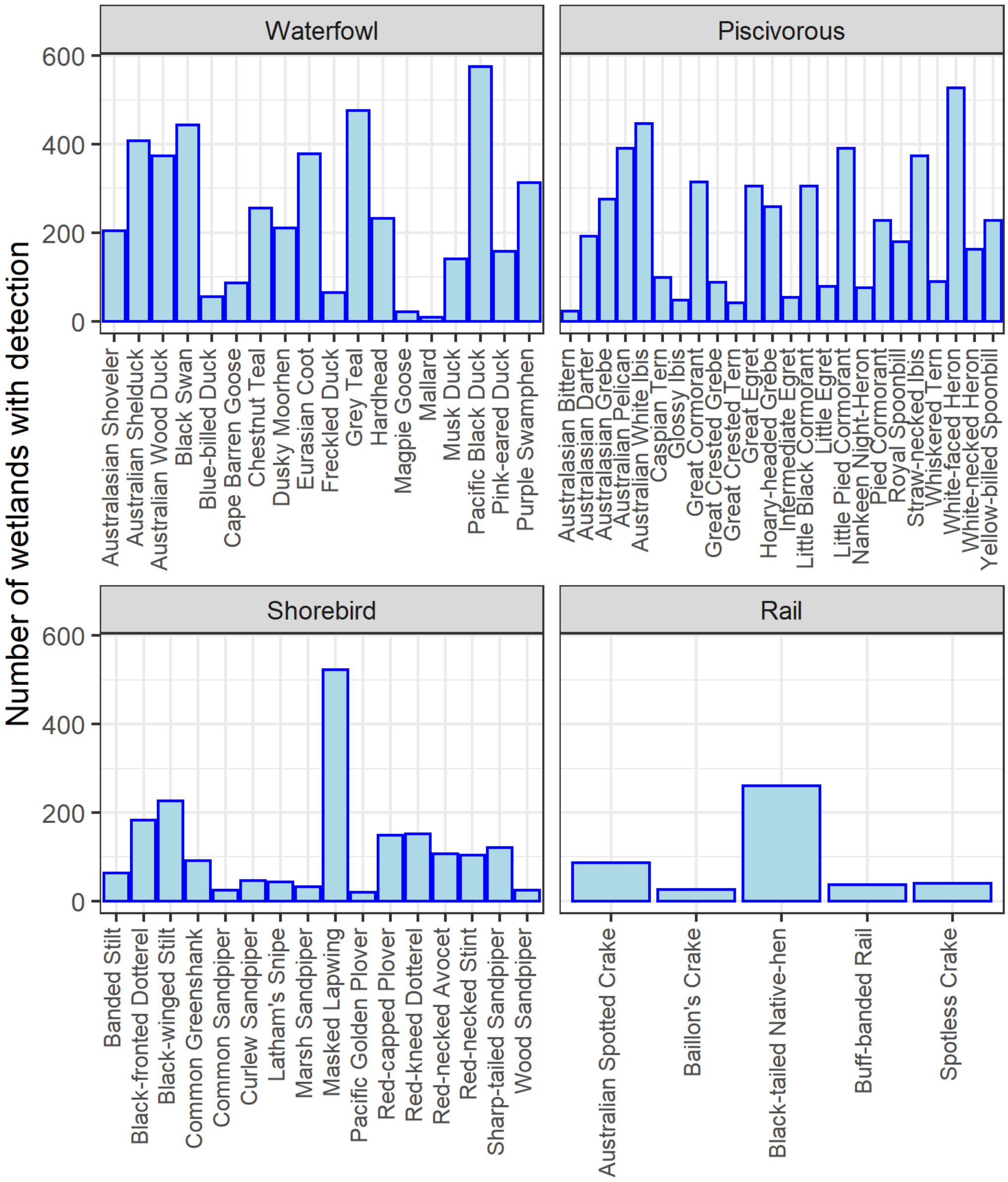

Figure J.1. Number of wetlands in the broader landscape where each species has been detected at least once in the waterbird dataset used to develop the response models.

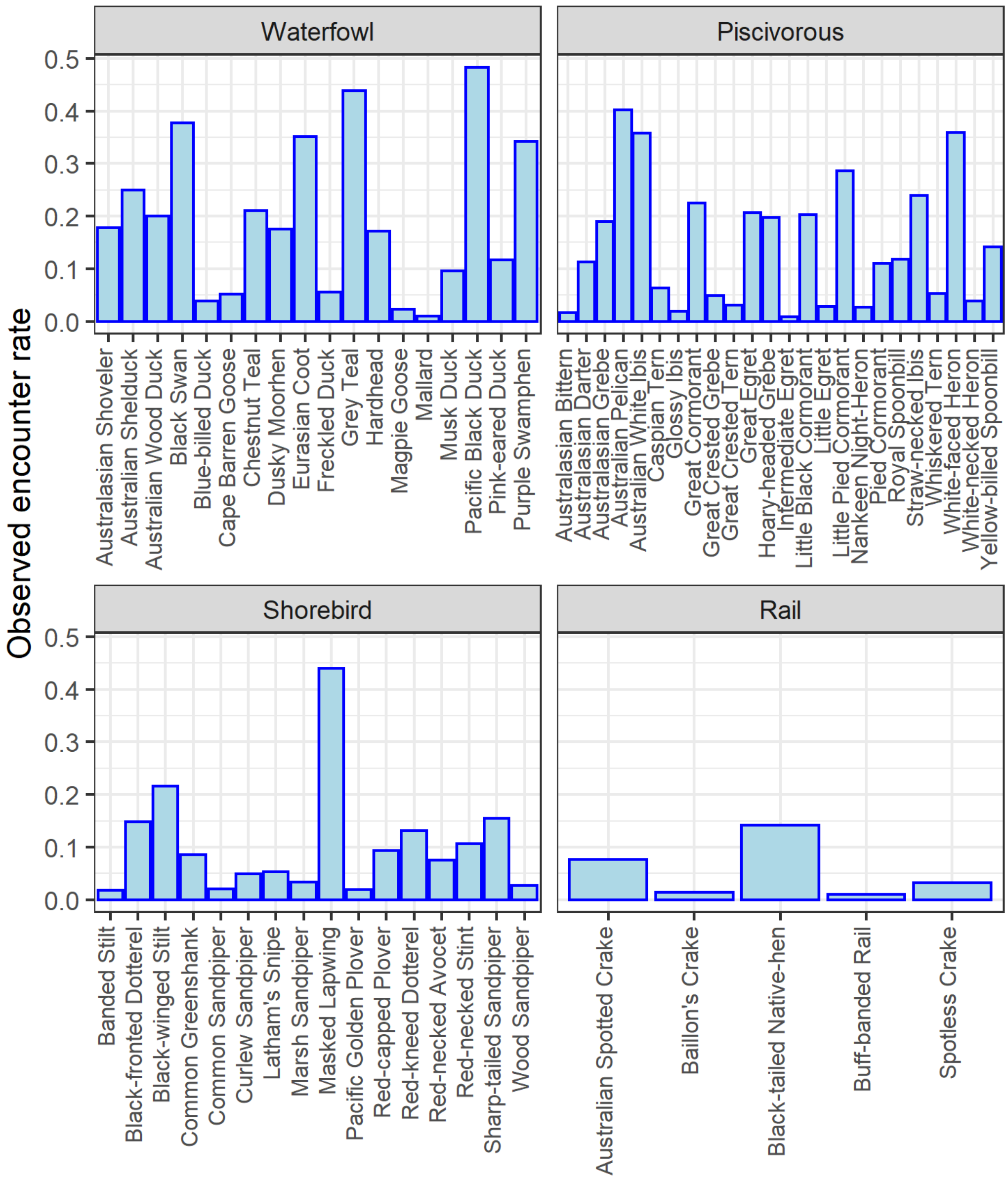

Figure J.2. Raw encounter rates of each species recorded in the waterbird dataset used to develop the response models for wetlands in the broader landscape of south-east South Australia.

The Goyder Institute for Water Research is a research alliance between the South Australian Government through the Department for Environment and Water, CSIRO, Flinders University, the University of Adelaide and the University of South Australia.