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A Typology of Australian Terrestrial Bird Communities

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ABSTRACT

Aim: Holistic measurement of the response of fauna communities to interventions requires suitable community condition metrics. However, the development of such metrics is hindered by the absence of broad-scale typologies at suitable spatial and ecological resolutions. We aimed to derive a preliminary typology of terrestrial bird communities for Australia, based on bird co-occurrence data, and describe and map the likely distribution of each community type across the continent.

Location: Mainland Australia, continental islands.

Time Period: 1973–2022.

Major Taxa Studied: Aves.

Methods: We used fine-scale co-occurrence data from standard 2-ha surveys in BirdLife Australia's citizen-science database. After filtering to reduce bias, we used hierarchical clustering followed by iterative consultation with experts to identify reliably distinct and recognisable terrestrial bird communities across Australia. We used Maxent to model the likely distributions of each community and developed community descriptions based on each community's composition and distribution.

Results: The resultant typology included 29 reliably distinct and recognisable bird communities with major clusters corresponding with seven broad geographical regions. The distributions of bird communities did not correspond tightly to the boundaries of major vegetation groups, with most communities occurring across multiple vegetation types.

Main Conclusions: Our preliminary typology of bird communities provides a standard classification at a continental scale. It newly defines distinct bird communities as entities for which condition benchmarks can be established to allow assessment of their conservation status and monitoring of change over time. Refinement will enable cryptic communities in areas with sparse data to be identified. The method could be translated to other regions where adequate coverage of data in the form of standardised surveys of fauna is available. Vast biodiversity datasets delivered through citizen science programs provide the opportunity to develop such typologies for fauna communities, as a precursor to developing targeted and informative community condition metrics.

For affiliations refer to page 19.

1 | Introduction

The new Global Biodiversity Framework has shifted conservation focus from slowing the rate of biodiversity decline toward actively improving the health of biodiversity holistically over time (Xu et al. 2021; GBF 2022). Tracking such ecosystem-level change requires a set of measures that provide meaningful information about the state of all taxa and the ecological communities of which they are a part (Hughes and Grumbine 2023). However, we currently monitor only a small fraction of even the most threatened species (Verdon et al. 2024), and terrestrial ecosystem condition monitoring is limited; where it occurs, it focuses primarily on plant communities and vegetation structure (Lindenmayer et al. 2020) or relies on remotely-sensed indices (e.g., forest integrity index: Grantham et al. 2020).

Because vegetation condition may not accurately reflect faunal community condition, methods to measure the overall condition, and monitor trends in condition of terrestrial fauna communities remain a critical gap (Redford 1992; Wilkie et al. 2011). A more complete set of indicators of biodiversity health that includes fauna community condition is urgently needed. Such indicators allow us to understand where ecological communities are in good condition and where they are degraded; to inform the need for conservation interventions; and to assess the performance of those interventions in halting declines in and restoring faunal community condition (Nicholson et al. 2021).

Defaunation can be cryptic (Dirzo et al. 2014). For example, the Asian songbird crisis severely depleted bird populations even within extensive remnant forest areas due to intensive trapping (Harris et al. 2017; Lees and Yuda 2022). Hunting and snaring have depleted mammal communities across vast areas of forest in west Africa (Brashares et al. 2004). Most terrestrial ecosystems in Australia have lost a suite of small to medium-sized mammals due to novel predation pressure exerted by introduced cats and foxes (among other pressures) (McKenzie et al. 2007; Woinarski et al. 2011). Furthermore, factors such as the extent and connectivity of available habitat, at landscape, bioregional or indeed continental scales, can override local habitat condition, such that ostensibly good habitat is no longer occupied by certain species (Radford et al. 2005).

An understanding of fauna community condition is required in many situations, such as impact assessments, fauna community threat assessments, or evaluating effectiveness of conservation management. Sites at which the vegetation is moderately degraded or disturbed can nevertheless support fauna assemblages in very good condition (Ives et al. 2016; Selwood et al. 2018); conversely, structurally and compositionally intact vegetation communities can be fauna depauperate (Redford 1992; Wilkie et al. 2011). In these cases, the standard approach of focusing on vegetation extent and condition serves as a blunt tool. For these reasons, measures more reliably linked to the condition of fauna communities are needed.

Community condition is fundamentally a subjective concept, but generally measured relative to some sort of ‘reference’ state deemed appropriate to that community (Gibbons and Freudenberger 2006). Hence, before estimating the condition of a community, one first needs to know what community type it is, to know what its reference state should look like. Therefore, a barrier to the development of metrics that directly indicate fauna community condition is the lack of broad-scale typologies of fauna communities at appropriate spatial and ecological resolution. In the terrestrial realm, information used to distinguish ecosystem types tends to focus on soils, terrain, and vegetation (Sattler and Williams 1999; Parkes et al. 2003; Eyre et al. 2015; Keith et al. 2022). At broad scales, vegetation-based ecosystem classifications can be informative proxies for fauna community patterns (Thomson et al. 2009; McAlpine et al. 2016). However, at finer resolutions, the spatial distributions of faunal communities do not necessarily align with those of vegetation communities; in particular, similar faunal communities may occur in multiple vegetation types (Kikkawa 1968) and quite different faunal species compositions can occupy similar vegetation formations either side of biogeographic barriers (Godinho and Da Silva 2018).

While broad biogeographic divisions have long been developed for fauna (Kikkawa and Pearse 1969; Spencer and Horn 1994; Ebach 2012; Hermogenes De Mendonça and Ebach 2020), their resolution is of limited use for understanding expected occurrence of a particular assemblage of species at a given site. Such bioregionalisations are based on patterns of species co-occurrence across wide regions, but applications that involve measuring site-level fauna condition require classifications of communities that can be directly translated to the site scale. For example, estimating the relative intactness of a site requires knowledge of what species would be expected to co-occur at that site in the absence of human-induced disturbance and species extirpations, not the full pool of species that occurs in the wider area. However, research identifying distinct faunal community types at an appropriate resolution, based on site-level co-occurrence of species, generally has a narrow scope, focussing on particular landscapes or regions (e.g., Burbidge 1960; Pavey and Nano 2009). Because different studies use different methods and criteria for differentiating community types, this means that the criteria that distinguish one community from another are not consistent among studies, limiting their ability to underpin a nationally consistent typology.

Here, we document the first step required to underpin continental-scale faunal community condition metrics: the development of a data-driven, fauna-based typology of communities. We explore the potential to generate a recognisable classification, or typology, of bird communities using citizen-science collected data, and demonstrate this novel approach for Australia's terrestrial bird communities. We aim to derive this classification from the site-level co-occurrence patterns of bird species, independently of existing bioregionalisations or other environmental classifications and typologies, to reveal the major communities of birds directly, without relying on proxies such as vegetation types. In doing so, we provide a typology that lays the foundation for enabling monitoring and assessment of bird communities as ecological entities.

The ideal foundation for a community typology is a dataset covering the entire area of interest and comprising lists of all species detected at a site at a given point in time. Such data enable the development of a typology independent of vegetation or bioregional classifications, driven solely by co-occurrence patterns of the fauna. Thanks largely to citizen science initiatives, site-level bird survey data are among the most widely available and comprehensive faunal data both in Australia and globally (Troudet et al. 2017; La Sorte and Somveille 2020). We used fine-scale co-occurrence data from BirdLife Australia's Birdata database (BirdLife Australia 2022) to develop an empirically-derived bird community typology for Australia. The database contains more than 410,000 surveys conducted using a standardised method: the 2-ha, 20-min count (Loyn 1986).

We explored the questions: can we generate a typology consisting of distinct categories of bird communities, recognisable by experts, from citizen-science data; and, to what extent do the emergent communities correspond with existing classifications of major vegetation types? Using hierarchical clustering to a large sample of these surveys, followed by iterative consultation with experts, we identified 29 distinct and recognisable terrestrial bird communities across Australia. We used MaxEnt to model the likely distributions of each community and developed community descriptions based on species that typify the community and summaries of the vegetation groups in which each community is commonly detected. This yielded a preliminary set of distinct, recognisable terrestrial bird communities based on consistent criteria for community classification, which were not strongly related to patterns of vegetation types. Emergence of faunal typologies such as this is a first step in developing metrics to measure and track their condition directly, rather than relying on vegetation as a proxy.

2 | Methods

2.1 | Bird Co-Occurrence Data

In developing our typology, we aimed to define bird communities based on distinct patterns of species co-occurrence, rather than imposing boundaries based on vegetation types or geographic regions. We used site-scale data, collected using a standard 2-ha 20-min survey method, from BirdLife Australia's Birdata database with surveys from 1973 to 2022, with the vast majority recorded since 1998. Birdata follows the Working List of Australian Birds taxonomy, version 2 (BirdLife Australia 2022). It contains hundreds of thousands of bird surveys contributed by thousands of citizen scientists, conducted in all seasons of the year and across all parts of Australia.

This typology was developed for terrestrial bird communities only. Bird communities occurring in aquatic ecosystems (e.g., wetlands, marine areas), shorelines and intertidal zones were deliberately excluded because birds that typify such environments are much more likely to be surveyed using a range of methods that vary in effort and area surveyed. Terrestrial communities had the advantage (for our analysis) of a commonly-used, standard sampling unit—the 2-ha 20-min survey (Loyn 1986). In this way, we ensured that variation in site-level sampling method or effort was unlikely to be an important driver of the clustering results, which we might have expected had we also included surveys using other methods. Although conceptually, community typology development can be extended to non-terrestrial communities, the approach taken will need to differ.

Any standard survey method detects only a sample of the bird community, and is necessarily biased, performing better in some habitat types than others, and being more likely to detect some bird species than others (D. M. Watson 2017). However, the objective was to develop a typology based not on perfect information about bird presence at a site, but rather based on the suite of species typically detected in standard survey units. This was because our primary motivation was to develop a typology that could be used in conjunction with those standard surveys, and that was intuitive to observers. As such, species that might be less likely to be detected using such methods, such as nocturnal species or raptors, were less likely to contribute substantially to the distinction among communities.

2.2 | Data Filtering Process

We applied a set of filters to the full dataset (Figure 1):

1. We excluded surveys conducted outside of mainland Australia and its continental islands.
2. We excluded surveys that used methods other than the standardised 2-ha 20-min survey method to reduce the chance that the typology reflected different survey methods (D. M. Watson 2003) rather than different underlying

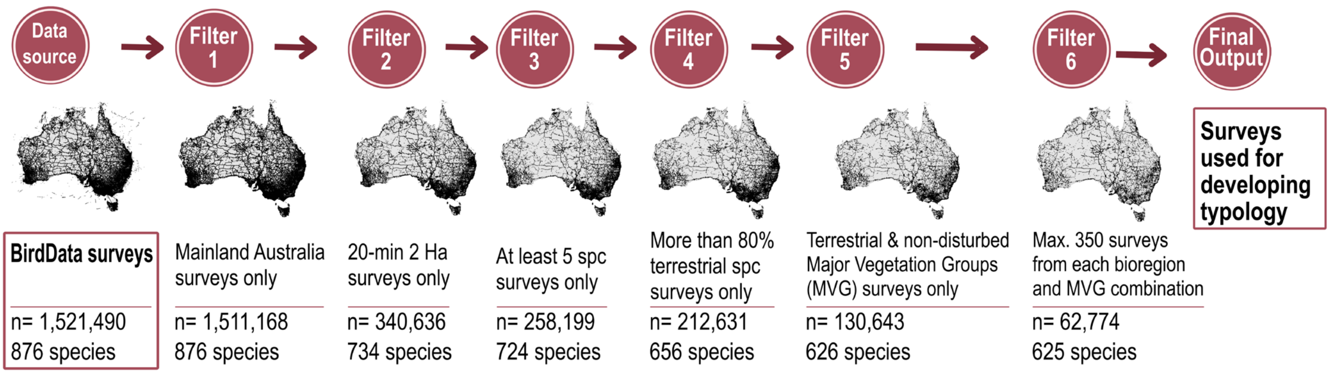

FIGURE 1 | Filtering phases of the Birdata survey data (BirdLife Australia 2022) used to develop bird community typology. Shown are the number of individual bird surveys and number of species included in them after each filtering step, yielding the final sample of 62,774 surveys used for clustering analysis.

patterns of co-occurrence of birds. The 2-ha 20-min survey approach is the most commonly used approach for terrestrial bird surveys in Birdata.

3. We excluded surveys with < 5 species recorded to improve the chance that surveys we retained contained adequate information about the community from which they were derived.
4. We excluded surveys that included > 20% non-terrestrial species (see Supporting Information S1 for a classification of terrestrial species).
5. We excluded surveys that were done in locations classified as aquatic (sea and estuaries), highly disturbed (cleared, non-native vegetation, buildings), or have unclassified or unknown data according to Australia's National Vegetation Information System (NVIS Technical Working Group 2017). This is because we sought to derive a typology that reflected naturally-occurring terrestrial community types, rather than characterising the communities that occur in highly modified landscapes, or reflected wetland communities (which require separate treatment).
6. Last, we reduced spatial bias in sample location by stratifying sites included according to bioregion and vegetation. Certain areas, particularly close to population centres, have much higher survey density (Tulloch and Szabo 2012; Backstrom et al. 2024); on the other hand, the south east and coastal areas of Australia not only have the highest density of surveys, but also have a relatively higher diversity of vegetation types and landforms, so they might be expected a priori to require a greater sampling effort to generate equivalent coverage of their different bird communities compared with more environmentally uniform parts of the continent. To attempt to balance these competing challenges, we overlaid the Interim Biogeographic Regionalisation for Australia (IBRA) system (DCCEEW 2024) with the Major Vegetation Groups (MVGs, hereafter 'vegetation groups'), following the approach of Carwardine et al. (2008). This resulted in 1124 distinct combination groups, and we randomly sampled a maximum of 350 surveys for each combination. This resulted in the final sample of 62,774 surveys used for the initial clustering analysis (Figure 1).

2.3 | Clustering Analysis and Expert Consultation

As this was an exploratory analysis, we used a non-supervised clustering approach. This allows the data to fall into clusters based on the bird composition of survey lists alone without preset categories; in our case, we wanted the categories to emerge from the data (Bishop 2006; Miyamoto 2022). The unit of analysis was the individual 2-ha 20-min survey, comprising the list of species detected. We used presence-only data to reduce the influence of very common or abundant species, which tend to contribute little to distinctions among communities (Hirzel et al. 2002; Wilson 2012).

We applied hierarchical agglomerative clustering (HAC) on a Euclidean distance matrix using the ward.D2 method in R to group surveys based on similarities in species composition. Euclidean distance was chosen as our aim was to explore potential clusters with no prior assumption of existing patterns and no need to specify the number of clusters (Everitt et al. 2011; Murtagh and Legendre 2014). The ward.D2 algorithm was chosen as it is less sensitive to outliers (Legendre and Legendre 2012; Murtagh and Legendre 2014). The clustering was visualised in a dendrogram depicting major groupings through to minor clusters, with different heights/similarity levels in the dendrogram corresponding to different resolutions of a candidate community typology.

Interpreting unsupervised learning outputs (such as our hierarchical cluster outputs) can be challenging as it requires strong qualitative understanding of the data. We therefore iteratively explored and refined our results with ornithological experts. The consultation assisted in identifying the level of similarity at which recognisable and distinct bird communities emerged, and also in identifying clusters that were likely to represent non-naturally occurring bird communities (i.e., disturbed or degraded communities).

To do this, we consulted with ornithologists and experts (including co-authors on this paper) iteratively. Experts were primarily current or retired professional ornithologists, ecologists, or active citizen-scientists who were familiar with bird communities, and who had field experience. The initial consultation (in May 2022) presented 28 experts with summary data about terminal clusters resulting from truncations of the dendrogram at different heights, ranging from 5 to 50 clusters. The summary data included the reporting rates of species in the cluster, and the geographical distribution and vegetation associations of the surveys included in the cluster. The extent to which these 'candidate communities' reflected bird communities that were both recognisably distinct to experts and adequate in capturing expert-judged variation in bird communities across the continent drove the decision to truncate the dendrogram at a height which yielded 39 clusters as candidate communities (i.e., below this height, experts were often unable to distinguish the candidate communities from one another). Of these, experts considered the extent to which the candidate communities reflected 'naturally-occurring' bird communities and identified, by consensus, 'degraded communities' on the basis of high reporting rates of introduced species or generalists associated with transformed landscapes, such as urban areas or agricultural fields. This process resulted in agreement that 11 were likely representative of degraded communities, leaving 28 main communities in the candidate typology.

We next sought to refine and corroborate the communities through further consultation with experts, ensuring that the expert group included at least one expert familiar with each of the 28 communities we identified in the previous step. For this consultation, we prepared more detailed information describing each of the 28 communities, excluding the 11 degraded communities which were not considered to represent best-on-offer. First, we prepared maps of the locations of all surveys classified into each candidate community. Second, we summarised the reporting rate for the 50 most commonly-occurring species in each community (the proportion of surveys classified into that community in which a species occurred). Third, we summarised for each community the proportion of surveys located within each

Major Vegetation Group. Finally, we calculated 'importance scores' indicating the contribution of each species to the distinctiveness of a community within each region by developing a predictive model using random forest, a powerful predictive model algorithm increasingly used for species distribution modelling (Valavi et al. 2021).

We calculated importance scores for species present within each of the seven regions, such that a species' importance score indicated its contribution to distinctions among communities within the region (not among all communities in the typology). Not all species contribute to distinctions among communities; some are ubiquitous, others are equivalently rare among communities. To identify the species that were most important in differentiating communities within each region, we first removed uninformative species using the feature (or variable) selection approach using the Boruta function from the Boruta package in R (Kursa and Rudnicki 2009). Following the removal of these species, we extracted species importance values using the varImp function using the caret and randomForest packages in R (Breiman et al. 2002). Species with high importance scores were either substantially more likely or substantially less likely to occur in that community than in the other communities in the region.

Species could contribute to community distinctions through either being more or less likely to occur in a given community, and importance values derived from random forest models did not provide this information. Therefore, we additionally used partial dependence plots (using the edarf package (Jones and Linder 2016) in R) to determine whether a species' presence or absence was important. Larger positive values indicated that a species' presence is important for distinguishing the community from others in the region, larger negative values indicated that its absence from a community was distinctive, and values closer to zero indicated the species contributed little to differentiating communities. We retained the raw importance values for our analysis and for the community descriptions in the Supporting Information S2 (see Supporting Information: S2.1–S2.8 for importance scores and descriptions by region); however, we rescaled the importance values (ranging from −1 to 1) when we consulted with experts to aid interpretation.

This set of information about the 28 candidate communities was presented to a larger group of experts at a workshop in December 2022 with 32 participants, as well as in individual follow-up sessions with experts who could not attend. We sought feedback on whether major communities appeared to be missing or merged into single candidate communities, as well as whether the candidate communities were recognisably distinct from one another. Our aim was to identify a 'Goldilocks' degree of similarity such that clusters identified based on a lower similarity cutoff were considered by experts as too generic and encompassing multiple distinct community types, but those that emerged based on a higher similarity level (i.e., further splitting the clusters) were too similar for experts to clearly identify as distinct from one another. This round of expert consultation concluded that one of the 28 candidate communities also represented a degraded state, but that three of them should be further split at a marginally lower height on the dendrogram, each into two sub-groups, resulting in a set of 30 tentative communities representing the Australian Bird Community Typology at this step.

2.4 | Refining and Characterising Communities

Despite the summary information about each of the 30 tentative communities representing recognisably distinct assemblages, it was evident that many individual surveys comprised primarily widespread species that were common to many communities. Such generic surveys often have a similar probability of being classified into multiple communities. This can introduce noise into the community descriptions, which aim to present typical and diagnostic aspects of the community. Generic surveys also result in implausible spatial outliers when examining the distribution of a community. We sought to further refine the community descriptions and distributions by excluding these as outliers. We did this by feeding all surveys back into our random forest model and extracting information on the probability of each survey being classified into the community to which it was allocated in the original hierarchical clustering. We excluded all surveys that were classified with lower than 60% probability for the main clusters (that were not split further into two), and 50% for the six sub-group communities (see Figure 2 for example). This resulted in 17,521 surveys retained across the 30 previously-identified clusters. This step to retain only surveys that were classified with high confidence reduced considerably the incidence of spatial outliers. Post-outlier removal, we re-calculated species reporting rate, species importance scores, and proportion of surveys classified into each Major Vegetation Group.

Following the exclusion of outliers, some of our identified communities retained <100 high-confidence surveys. We retained these sparse communities only where they occurred in areas with sparse survey effort and experts judged them to be clearly recognisable as distinct communities. For example, Arid Woodland occurred mainly in the Great Victoria Desert, a relatively sparsely-surveyed area, and was retained despite only 68 surveys being classified with high confidence. We removed one cluster at this stage because it only had 19 high-confidence surveys and we considered this insufficient information to define a community. The typology resulting from this stage was again shared with relevant experts, finalising the typology consisting of 29 communities formed from 17,502 surveys. Finally, we ran the random forest model again to analyse the change in our typology's distinctness. The accuracy of predictive model classification increased from 82% before outlier removal to 98% post-outlier removal.

2.5 | Predicting Community Distribution

We used MaxEnt (Phillips et al. 2024) to model, separately, the distribution of each of the resultant 29 bird communities as a function of a set of environmental predictors (see Supporting Information S3 for details). MaxEnt compares the probability densities of a set of spatial environmental variables at 'presence' locations (in this case, the locations of all surveys classified into a given community after outliers were excluded) against a random background sample, following the principle of maximum

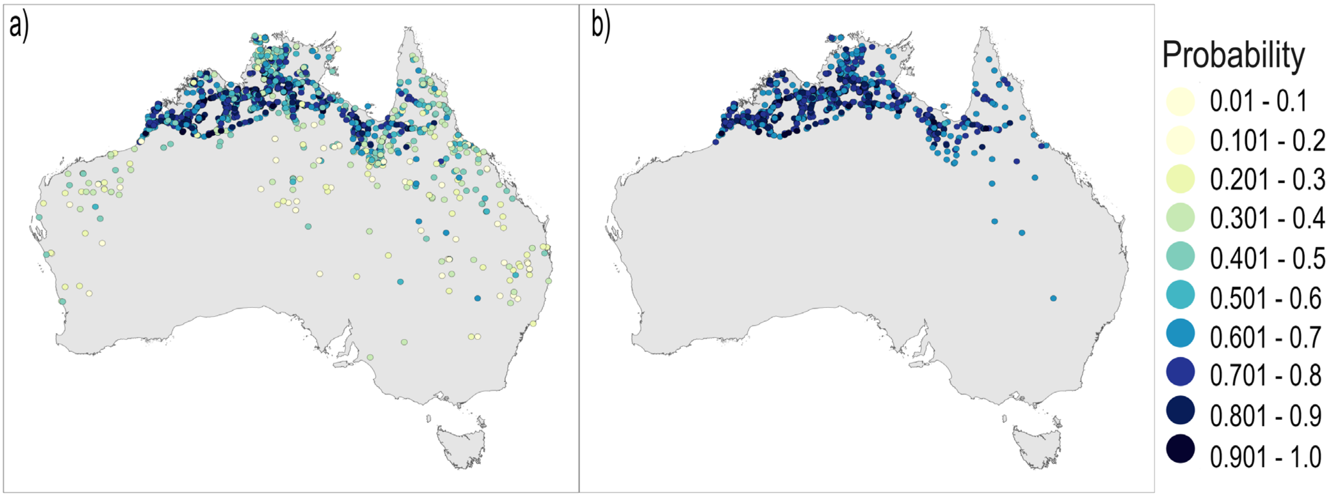

FIGURE 2 | Example of community refinement through outlier exclusion. Panel (a) shows the distribution of all surveys classified into a particular community and panel (b) shows the distribution of only those surveys classified into that community with Pr > 0.6.

entropy to make the fewest assumptions, to generate probability distributions of locations suited for the community (Elith et al. 2011). MaxEnt is commonly employed to predict species distributions (e.g., Reside et al. 2010) and, albeit less commonly, to predict community distributions (e.g., Raney and Leopold 2018).

The presence data for the models were the locations of the BirdLife Australia surveys used to define the typology. Despite attempts to reduce spatial bias for the hierarchical clustering, some spatial bias remained evident in the surveys—e.g., following roadways in the arid interior. This violates Maxent's default assumption of unbiased occurrences (Elith et al. 2011), so for each community, we created a kernel density layer from all presence (survey) points in ArcMap 10.8.2 that we used to weight Maxent's background selection. This ‘target-group sampling’ approach has been shown to significantly improve model performance by reducing sample selection bias (Phillips and Dudík 2008).

Environmental variables were sourced from WorldClim, TERN, and Geoscience Australia. From WorldClim we used four variables on precipitation (Annual and seasonal precipitation, along with precipitation on the driest and wettest quarter) and four on temperature (minimum temperature, maximum temperature, temperature seasonality, and mean annual temperature). From TERN we used information on total vegetation cover. From Geoscience Australia, we used a digital elevation model. We also created a distance to water layer by calculating the Euclidean distance from the Digital Earth Australia Waterbodies v2 layer from Geoscience Australia. We did not include variables that described human influence, as our objective was not to model the current distribution of the communities, considering human modification, but rather to model their potential, or underlying, distribution in the absence of such disturbance, similar to ‘pre-clearing’ modelled vegetation mapping products. This was because we wanted to be able to use the modelled distribution to identify which community would be the expected naturally occurring community at a given location, to enable the relevant condition benchmarks to be applied. Further details on the environmental variables used, including selection methods, can be found in Supporting Information S3.

3 | Results

3.1 | Major Clusters

At its coarsest level, the clustering algorithm revealed major splits between terrestrial bird communities of south eastern Australia and those occurring across the rest of the continent; within this second large group, the major split was between communities of the tropical north and those of the arid inland and south-west. These broad splits corresponded broadly to the Bassian, Torresian and Eyrean biogeographic regions (Burbidge 1960; Spencer and Horn 1994), with one group of clusters within the latter comprising mainly degraded communities (Figure 3).

With the input of experts, we identified a level of dissimilarity that split the dataset into 39 clusters, which yielded reliably recognisable bird communities. These 39 clusters fell into seven major groups, which we refer to as ‘regions’ as they reflected broad geographic patterns: Tasmania; eastern wet forests and coastal heath; south-eastern woodland; northern Australia; arid zone; inland eastern woodland; and south-western Australia, mallee and mulga (Figure 3; Table 1; Supporting Information S4).

3.2 | Exclusion of ‘Degraded’ and Sparse Clusters

Of the 39 clusters, 12 were considered by experts to represent groups of very generic survey lists, or strongly anthropogenically altered or degraded examples of bird communities. These clusters were excluded from the typology, but summaries of the seven with adequate survey points are included in Supporting Information S4. Excluded clusters predominantly comprised very widespread and abundant species, or those often associated with highly modified landscapes, such as introduced species or native generalists such as Australian Magpie *Cracticus tibicen* (reporting rate across all surveys [RR] 0.52), Galah *Eolophus roseicapilla* (RR 0.39), and Magpie-lark *Grallina cyanoleuca* (RR 0.31), but no or very few distinctive species. In three cases, clusters that were deemed ‘degraded’ were dominated by *Manorina* species—either yellow-throated (*M. flavigula*) or noisy miners

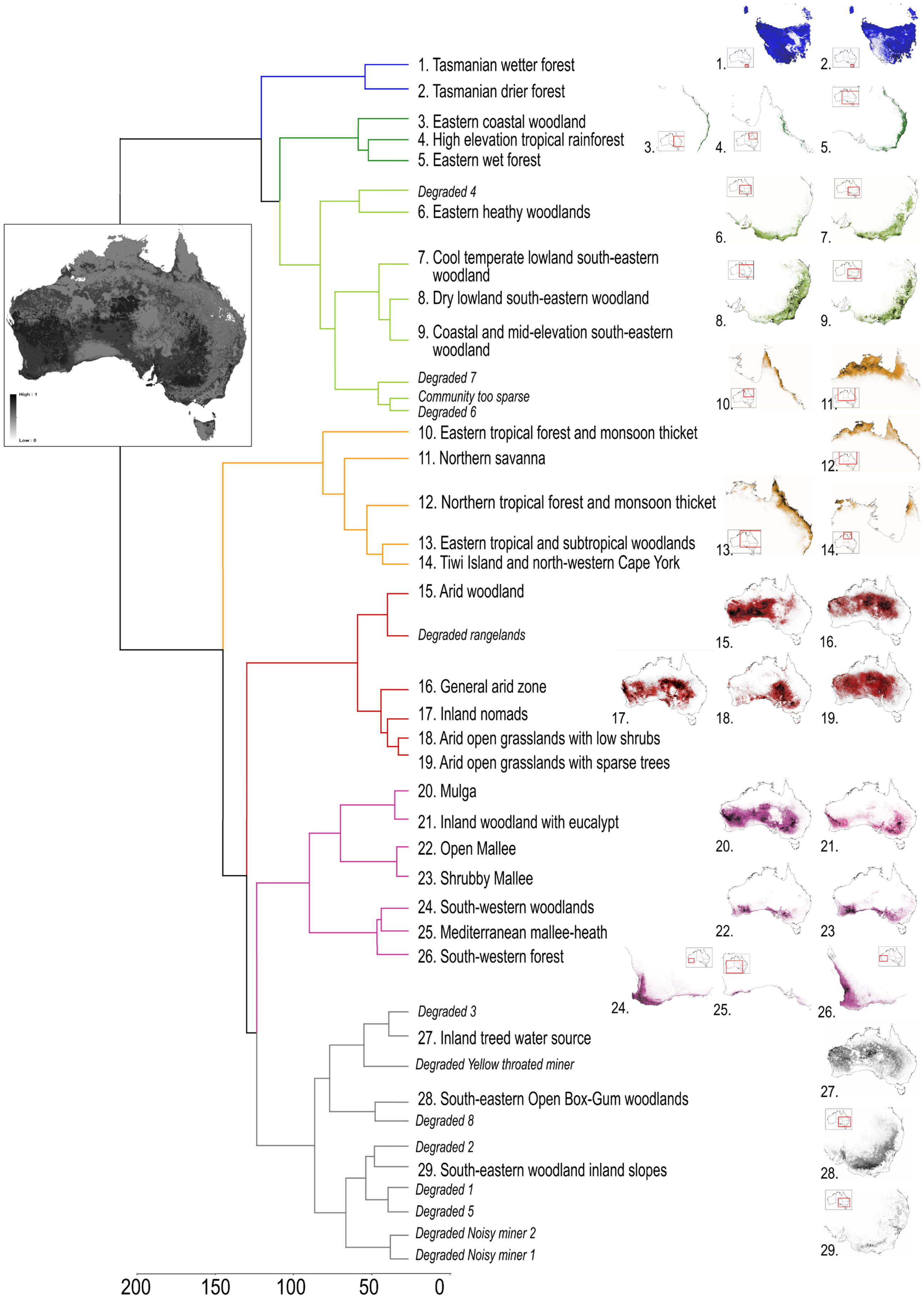

FIGURE 3 | Legend on next page.

FIGURE 3 | The dendrogram representing the relationships among the community types identified based on clustering. The inset map of Australia shows the stacked distribution of all communities retained in the typology, with darker areas indicating where more communities potentially occur. Colours distinguish higher level groupings representing seven regions. Degraded communities are listed in the dendrogram but are not included in the final typology.

(*M. melanocephala*), both of which are known to exclude many smaller passerines (Maron et al. 2013). Overabundance of Noisy Miners is also a listed Key Threatening Process under Australia's EPBC Act (DCCEEW 2022a, 2022b). Surveys classified into these 11 clusters ($n = 12{,}403$) could arise due either to the site supporting a highly simplified or degraded bird community, or simply through the particular timing and/or location of the survey failing to detect species that would, at other times, be present.

The next step of refinement of the typology involved the exclusion of surveys that were not classified into any community with high confidence (> 60%). This step removed 32,850 surveys, resulting in 17,521 surveys. This smaller and more refined subset of surveys provided a stronger basis for the description of distinct communities, without dilution due to the inclusion of surveys that may not represent that community. At this stage, one cluster was represented by too few high-confidence surveys to retain, resulting in a total of 29 clusters that we judged were distinct, not highly disturbed, and able to be characterised with high confidence. This set of 29 clusters, described using 17,502 surveys, became the basis of the communities in the preliminary typology, and was used for subsequent descriptive analysis and MaxEnt modelling of communities.

Differences among community types in the number of surveys classified with high confidence reflected both the distinctiveness of the communities, as well as variation in the initial number of surveys in each. For example, communities of the south-eastern Australian woodland were well surveyed, but there were several closely related communities in this region, and as a result, they only ended up with a modest number of surveys classified with high confidence. Conversely, although *High Elevation Tropical Rainforest* was a small-extent community with relatively few surveys, 78% (216) of the surveys originally classified into that community were classified with high confidence. Greater uncertainty exists about the composition and distinctiveness of communities that were informed by a smaller number of high confidence bird surveys.

3.3 | Community Distribution and Naming

The modelled distribution of the 29 communities identified extended across all bioregions of Australia, with most bioregions including more than one community type (Figure 3). Supporting Information S3 provides details of the Maxent modelling performance and outputs. Supporting Information S4 provides a summary of each region's community types, including their modelled distributions, reporting rates of the most common species, the proportion of surveys that occurred in different vegetation groups, and ordinations showing the multivariate relationships among communities within each region.

The locations of surveys associated with a particular community type corresponded to some extent with particular vegetation groups. In some cases, such as *High Elevation Tropical Rainforest*, this was a very close correspondence, with almost all surveys being located within areas mapped as rainforests and vine thickets (Supporting Information S4). However, in most cases, a particular community occurred across multiple dominant vegetation groups, and some vegetation groups supported multiple bird communities. For example, surveys classified as belonging to the *Eastern Wet Forest* bird community were located within vegetation groups representing a range of wetter forest types including rainforests and vine thickets, Eucalypt tall open forests, and Eucalypt open forests. Eucalypt woodlands, a widespread vegetation group, included surveys that were classified into at least 11 different bird community types.

Despite the lack of close alignment between vegetation group boundaries and most community types, fine-scale vegetation type and other habitat features typically inhabited by each community were generally evident to experts based on distributions and species composition. As such, most of the working names we assigned to communities reflected a combination of vegetation type, specific habitat features, and/or geographic region. A notable exception was the *Inland Nomad* bird community, a small but very widespread community identified within the arid zone of Australia. This community was dominated by a large number of highly nomadic species and was considered likely to reflect a temporary influx of species which could occur almost anywhere in the arid zone following suitable seasonal conditions.

4 | Discussion

Our analysis yielded a comprehensive typology of terrestrial bird communities, representing patterns of local co-occurrence of species, at a continental scale. The 29 bird communities we identified describe reliably distinct and recognisable groupings of birds that co-occur, mostly spanning large geographic areas and a range of vegetation types. Modelled distributions of the communities suggest expected distributions of at least one community type across all parts of mainland Australia. Our data-driven approach was an advance on the fully expert-driven approach used by Fraser et al. (2018) to develop a typology of woodland bird communities in several regions of Australia. Our approach enabled us to build in valuable expert guidance, ensuring the resultant typology was intuitive and useable, while deriving the basis of the typology entirely from comparably collected data across the continent, hence tempering subjectivity and the influence of biases inherent to expert judgement (O'Hagan 2019). Our typology represents a first step toward developing fauna-focussed metrics of community condition, to enable evaluation and tracking of condition over time at scales from individual properties to regions to entire continents. We propose that this method can be applied to a

TABLE 1 | Summary of major terrestrial bird communities and their main characteristics, including the IBRA bioregions and vegetation groups (MVGs) in which each community typically occurred.

Regions	Community name	No. surveys (high confidence)	No. species with RR > 0.1	Mean richness per survey	Bioregions with ≥ 15% of surveys	MVGs with ≥ 15% of surveys	Five species with highest reporting rate	Five most important contributors to distinctiveness from other communities in the region (by their presence)[a]
A1	Tasmanian Wetter Forest	1094	23	9	King Tasmanian South East Tasmanian Southern Ranges	Eucalypt Tall Open Forests	Tasmanian Thornbill Tasmanian Scrubwren Grey Fantail Crescent Honeyeater Yellow-throated Honeyeater	Tasmanian Thornbill Tasmanian Scrubwren Crescent Honeyeater Pink Robin Black Currawong
A1	Tasmanian Drier Forest	1562	30	11	Tasmanian South East Tasmanian Northern Slopes Tasmanian Northern Midlands	Eucalypt Open Forests Eucalypt Woodlands Eucalypt Tall Open Forests	Grey Fantail Brown Thornbill Superb Fairy-wren Forest Raven Yellow-throated Honeyeater	Brown Thornbill Forest Raven Superb Fairy-wren Striated Pardalote Common Blackbird
A2	Eastern Coastal Woodland	232	45	17	South-Eastern Queensland NSW North Coast	Casuarina Forests and Woodlands Melaleuca Forests and Woodlands	Lewin's Honeyeater White-cheeked Honeyeater Little Wattlebird Bar-shouldered Dove Torresian Crow	White-cheeked Honeyeater Little Wattlebird Brown Honeyeater Bar-shouldered Dove Welcome Swallow
A2	High Elevation Tropical Rainforest	216	46	18	Wet Tropics	Rainforests and Vine Thickets	Grey-headed Robin Lewin's Honeyeater Spotted Catbird Bridled Honeyeater White-throated Treecreeper	Grey-headed Robin Spotted Catbird Bridled Honeyeater Chowchilla Macleay's Honeyeater

(Continues)

TABLE 1 | (Continued)

Regions	Community name	No. surveys (high confidence)	No. species with RR > 0.1	Mean richness per survey	Bioregions with ≥ 15% of surveys	MVGs with ≥ 15% of surveys	Five species with highest reporting rate	Five most important contributors to distinctiveness from other communities in the region (by their presence)[a]
A2	Eastern Wet Forest	1528	38	14	South Eastern Queensland NSW North Coast	Eucalypt Tall Open Forests Rainforests and Vine Thickets Eucalypt Open Forests	Lewin's Honeyeater Eastern Whipbird Eastern Yellow Robin Grey Fantail Golden Whistler	Australian Brush-turkey Eastern Yellow Robin Eastern Whipbird Wonga Pigeon Golden Whistler
A3	Eastern Heathy Woodland	848	29	13	South East Coastal Plain	Other Shrublands Eucalypt Woodlands	Superb Fairy-wren Brown Thornbill New Holland Honeyeater Red Wattlebird Grey Fantail	New Holland Honeyeater Superb Fairy-wren Brown Thornbill Red Wattlebird Common blackbird
A3	Coastal and Mid-elevation South-eastern Woodland	161	17	8	Sydney Basin	Eucalypt Woodlands Heathlands Eucalypt Open Forests	Eastern Spinebill Yellow-faced Honeyeater White-throated Treecreeper Brown Thornbill New Holland Honeyeater	Eastern Spinebill White-throated Treecreeper Yellow-faced Honeyeater New Holland Honeyeater Red Wattlebird
A3	Cool Temperate Lowland South-eastern woodland	426	28	13	South Eastern Highlands Kanmantoo Flinders Lofty Block Southern Volcanic Plain	Eucalypt Open Forests Eucalypt Woodlands	White-throated Treecreeper Crimson Rosella Grey Fantail Superb Fairy-wren White-browed Scrubwren	Crimson Rosella White-throated Treecreeper Grey Fantail Superb Fairy-wren White-browed Scrubwren

(Continues)

TABLE 1 | (Continued)

Regions	Community name	No. surveys (high confidence)	No. species with RR > 0.1	Mean richness per survey	Bioregions with ≥ 15% of surveys	MVGs with ≥ 15% of surveys	Five species with highest reporting rate	Five most important contributors to distinctiveness from other communities in the region (by their presence)[a]
A3	Dry Lowland South-eastern Woodland	210	29	11	NSW North Coast	Eucalypt Open Forests Eucalypt Woodlands	Yellow-faced Honeyeater Rufous Whistler Grey Fantail White-throated Treecreeper Superb Fairy-wren	Rufous Whistler Yellow-faced Honeyeater Grey Fantail White-throated Treecreeper Scarlet Honeyeater
B	Eastern Tropical Forest and Monsoon Thicket	878	35	13	Cape York Peninsula Wet Tropics	Rainforests and Vine Thickets Eucalypt Woodlands Melaleuca Forests and Woodlands Eucalypt Open Forests	Yellow-spotted Honeyeater Mistletoebird Varied Triller Little Shrike-thrush Yellow Oriole	Yellow-spotted Honeyeater Graceful Honeyeater Little Shrike-thrush Olive-backed Sunbird Helmeted Friarbird
B	Northern Savanna	1895	41	15	Dampierland Victoria Bonaparte	Eucalypt Woodlands Tropical Eucalypt Woodlands/ Grasslands	Peaceful Dove Willie Wagtail Magpie-lark Brown Honeyeater Rufous Whistler	Yellow-tinted Honeyeater Willie Wagtail Peaceful Dove Restless Flycatcher Little Friarbird
B	Northern Tropical Forest and Monsoon Thicket	977	34	12	Darwin Coastal Brigalow Belt North	Tropical Eucalypt Woodlands/ Grasslands Eucalypt Woodlands	Bar-shouldered Dove Peaceful Dove White-gaped Honeyeater Brown Honeyeater Rainbow Bee-eater	White-gaped Honeyeater Olive-backed Sunbird Little Shrike-thrush Peaceful Dove Lemon-bellied Flycatcher

(Continues)

TABLE 1 | (Continued)

Regions	Community name	No. surveys (high confidence)	No. species with RR > 0.1	Mean richness per survey	Bioregions with ≥ 15% of surveys	MVGs with ≥ 15% of surveys	Five species with highest reporting rate	Five most important contributors to distinctiveness from other communities in the region (by their presence)[a]
B	Eastern Tropical and Subtropical Woodland	367	33	12	Einasleigh Uplands South Eastern Queensland Cape York Peninsula Brigalow Belt North	Eucalypt Woodlands Melaleuca Forests and Woodlands	Rainbow Lorikeet Torresian Crow Blue-faced Honeyeater Striated Pardalote Noisy Friarbird	Rainbow Lorikeet Australian Magpie Noisy Friarbird Pale-headed Rosella Blue-faced Honeyeater
B	Tiwi Island and North-western Cape York	116	34	15	Cape York Peninsula Tiwi Cobourg	Eucalypt Open Forests	White-throated Honeyeater Rufous Whistler White-bellied Cuckoo-shrike Leaden Flycatcher Little Friarbird	Rufous Whistler Little Friarbird Lemon-bellied Flycatcher Leaden Flycatcher White-throated Honeyeater
C	Arid Woodland	68	14	8	Great Victoria Desert	Acacia Shrublands Hummock Grasslands	Crested Bellbird Spiny-cheeked Honeyeater Singing Honeyeater White-fronted Honeyeater Rufous Whistler	Crested Bellbird Spiny-cheeked Honeyeater White-fronted Honeyeater Rufous Whistler Singing Honeyeater
C	General Arid Zone	639	25	10	None ≥ 15%	Hummock Grasslands Eucalypt Open Woodlands Acacia Shrublands	Zebra Finch Diamond Dove Budgerigar Willie Wagtail White-plumed Honeyeater	Diamond Dove Zebra Finch White-plumed Honeyeater Budgerigar Brown Honeyeater

(Continues)

TABLE 1 | (Continued)

Regions	Community name	No. surveys (high confidence)	No. species with RR > 0.1	Mean richness per survey	Bioregions with $\geq 15\%$ of surveys	MVGs with $\geq 15\%$ of surveys	Five species with highest reporting rate	Five most important contributors to distinctiveness from other communities in the region (by their presence)[a]
C	Inland Nomad	34	19	9	Simpson Strzelecki Dunefields Burt Plain Mulga Lands Geraldton Sandplains	Acacia Shrublands Heathlands Hummock Grasslands	Masked Woodswallow Pied Honeyeater White-winged Triller Crimson Chat Budgerigar	Masked Woodswallow Pied Honeyeater Crimson Chat White-winged Triller White-browed Woodswallow
C	Arid Open Grassland with Low Shrubs	245	21	7	Channel Country Simpson Strzelecki Dunefields	Chenopod Shrublands, Samphire Shrublands and Forblands Hummock Grasslands Tussock Grasslands	White-winged Fairy-wren Australasian Pipit Brown Songlark Zebra Finch Orange Chat	White-winged Fairy-wren Orange Chat Horsfield's Bushlark Banded Whiteface Brown Songlark
C	Arid Open Grassland with Sparse Trees	311	14	8	Simpson Strzelecki Dunefields	Hummock Grasslands Acacia Shrublands	Black-faced Woodswallow Singing Honeyeater Crimson Chat Zebra Finch Budgerigar	Black-faced Woodswallow Crimson Chat Budgerigar Zebra Finch Willie Wagtail
D	South-eastern Woodland Inland Slopes	64	27	11	NSW South Western Slopes Sydney Basin Victorian Midlands Nandewar	Eucalypt Open Forests Eucalypt Tall Open Forests Eucalypt Woodlands	Fuscous Honeyeater Yellow-tufted Honeyeater Brown Treecreeper Grey Shrike-thrush Dusky Woodswallow	Fuscous Honeyeater Yellow-tufted Honeyeater Black-chinned honeyeater Little Lorikeet Noisy Friarbird

(Continues)

TABLE 1 | (Continued)

Regions	Community name	No. surveys (high confidence)	No. species with RR > 0.1	Mean richness per survey	Bioregions with ≥ 15% of surveys	MVGs with ≥ 15% of surveys	Five species with highest reporting rate	Five most important contributors to distinctiveness from other communities in the region (by their presence)[a]
D	South-eastern Open Box-Gum Woodland	782	32	13	Riverina Flinders Lofty Block	Eucalypt Open Forests Eucalypt Woodlands	White-plumed Honeyeater Brown Treecreeper Galah Red-rumped Parrot Willie Wagtail	Red-rumped Parrot Brown Treecreeper White-plumed Honeyeater Sulphur-crested Cockatoo Dusky Woodswallow
D	Inland Treed Water Source	208	18	9	Burt Plain MacDonnell Ranges	Eucalypt Open Woodlands Acacia Shrublands	White-plumed Honeyeater Magpie-lark Yellow-throated Miner Willie Wagtail Crested Pigeon	Magpie-lark Yellow-throated Miner White-plumed Honeyeater Grey-crowned Babbler Pied Butcherbird
E	South-western Forest	712	28	11	Warren Jarrah Forest	Eucalypt Open Forests Eucalypt Tall Open Forests	Grey Fantail Golden Whistler Red-winged Fairy-wren Australian Ringneck Silvereye	Red-winged Fairy-wren Golden Whistler Grey Fantail Inland Thornbill Western Spinebill
E	South-western Woodland	758	35	13	Swan Coastal Plain Jarrah Forest	Eucalypt Woodlands Other Forests and Woodlands	Brown Honeyeater Australian Ringneck Western Gerygone Australian Raven Grey Fantail	Brown Honeyeater Western Gerygone Splendid Fairy-wren Australian Ringneck Australian Raven

(Continues)

TABLE 1 | (Continued)

Regions	Community name	No. surveys (high confidence)	No. species with RR > 0.1	Mean richness per survey	Bioregions with ≥ 15% of surveys	MVGs with ≥ 15% of surveys	Five species with highest reporting rate	Five most important contributors to distinctiveness from other communities in the region (by their presence)[a]
E	Mediterranean Mallee-heath	120	20	9	Esperance Plains	Mallee Woodlands Heathlands	New Holland Honeyeater Southern Scrub-robin Weebill Western Whipbird Tawny-crowned Honeyeater	New Holland Honeyeater Western Whipbird Southern Scrub-robin Tawny-crowned Honeyeater Blue-breasted Fairy-wren
E	Open Mallee	894	23	9	Coolgardie Murray Darling Depression	Mallee Woodlands Eucalypt Woodlands	Yellow-plumed Honeyeater Striated Pardalote Grey Shrike-thrush Weebill Red Wattlebird	Yellow-plumed Honeyeater Rufous Treecreeper Jacky Winter Purple-crowned Lorikeet Grey Shrike-thrush
E	Shrubby Mallee	667	20	8	Coolgardie Mallee	Mallee Woodlands Eucalypt Woodlands	Weebill White-eared Honeyeater Red Wattlebird Striated Pardalote Inland Thornbill	White-eared Honeyeater Weebill Red Wattlebird White-fronted Honeyeater Inland Thornbill
E	Inland Woodland with Eucalypt	259	28	11	Cobar Peneplain	Acacia Shrublands Eucalypt Woodlands	Red-capped Robin Weebill Chestnut-rumped Thornbill Rufous Whistler Spiny-cheeked Honeyeater	Weebill Red-capped Robin Chestnut-rumped Thornbill Rufous Whistler Yellow Thornbill

(Continues)

TABLE 1 | (Continued)

Regions	Community name	No. surveys (high confidence)	No. species with RR > 0.1	Mean richness per survey	Bioregions with ≥ 15% of surveys	MVGs with ≥ 15% of surveys	Five species with highest reporting rate	Five most important contributors to distinctiveness from other communities in the region (by their presence)[a]
E	Mulga	472	19	9	Murchison	Acacia Shrublands Acacia Forests and Woodlands	Chestnut-rumped Thornbill Red-capped Robin Spiny-cheeked Honeyeater Splendid Fairy-wren Singing Honeyeater	Chestnut-rumped Thornbill Red-capped Robin Splendid Fairy-wren Southern Whiteface Singing Honeyeater

Note: [a]: Within the Arid Open Grasslands with Low Shrubs community only four species were important contributors to distinctiveness. Arid Open Grassland with Low Shrubs is the only community where there are only 4 species presented in the “Five species with highest reporting rate” column. we want readers to know that's not a mistake. We also want to refer people to the full descriptions of the community. The communities are described in greater detail in Supporting Information S4.

Abbreviations: MVG, major vegetation group; RR, reporting rate.

range of terrestrial faunal groups to generate community typologies, complementary to those that exist for plant communities (e.g., Sattler and Williams 1999).

4.1 | Relationships With Vegetation Communities

It has long been recognised that the boundaries of plant community types often do not align with those of distinct bird communities (Kikkawa 1968; Recher et al. 1991). Australia's national vegetation typology (NVIS' Major Vegetation Groups: MVGs) did not always map neatly to the distributions of bird communities we identified. For example, the *Eastern Heathy Woodland* bird community occurred across 21 different vegetation groups with a maximum of 22% of surveys included in a single vegetation group (‘other shrublands’). Part of this mismatch may relate to the resolution and accuracy of the national-scale vegetation data, which can have a high error rate when downscaled to individual sites (Tierney 2023). Nevertheless, in a few cases, a particular community fell largely within a single MVG; for example, 86% of surveys classified as belonging to the *High Elevation Tropical Rainforest* bird community were within the rainforests and vine thickets vegetation group. However, other communities also occurred in this MVG. Many birds are more sensitive to vegetation structure than floristic composition, and sub-strata are particularly important in driving their patterns of local occurrence (Tassicker et al. 2006; Munro et al. 2011). This means that from the perspective of birds, variation within a Major Vegetation Group can be more influential on their local occurrence than variation among them.

At a fine resolution, the boundaries of bird communities may correspond with those of vegetation communities. To identify this alignment, however, we would need to consider the vegetation community types at a much finer scale, but while such fine-scale typologies exist, they differ among jurisdictions across Australia. For example, the state of Queensland uses a system of Regional Ecosystems, of which there are 1435 nested within 98 Broad Vegetation Groups (Neldner et al. 2022). Most bird communities are therefore likely to occur across multiple Regional Ecosystems and, indeed, Broad Vegetation Groups, as our analysis identified 21 distinct major bird communities occurring within Queensland. This demonstrates the value of a distinct fauna typology, as assuming a one-to-one relationship between even Queensland's Broad Vegetation Groups (for example) and bird communities would result in an unnecessarily complex typology. Nevertheless, further work to match finer-resolution vegetation types identified under each of the State vegetation mapping exercises to bird communities (in most cases, a many-to-one relationship) could enable at least an initial indication of likely bird community distributions at a fine scale. Such matching may also enable alignment of bird community types with function-based ecosystem classifications, such as the IUCN Global Ecosystem Typology (Keith et al. 2022).

The classification of ecological communities requires that continuous gradients and temporally dynamic systems reflective of natural systems are reduced to discrete, fixed classes. As such, the resultant typology will necessarily be a highly simplified and subjective representation of nature, imposed by humans to align with human perceptions. This is perhaps most problematic for irruptive bird communities such as those from the arid zone (Pascoe et al. 2021) and northern Australia (Reside et al. 2010). Such typologies also imperfectly reflect ecotones or successional processes through which one community may shift to another over time, following disturbance or lack thereof (Baker et al. 2002; Serong and Lill 2012). Indeed, at least one community emerged which represented a group of species likely to co-occur only under particular post-rainfall conditions during periods of ephemeral resource availability (e.g., Inland Nomads, see Supporting Information S4), meaning that a given location could support different communities at different times. Despite this complexity, the simplification of nature into categorical and measurable units is necessary for myriad applications (De Cáceres et al. 2015; Luxton et al. 2021).

4.2 | Comprehensiveness of the Typology

While we are confident that the communities identified represent genuine and distinct community types, more work is required to develop a fully comprehensive typology. Some bird communities are less well surveyed due either to access constraints or smaller extent, and lack the quantity of data that would allow our model to distinguish them. Although the citizen science data we used in our analysis is extensive, the majority of the Australian land mass is sparsely populated and access is challenging, meaning that some areas are poorly represented. So, although some quite localised communities (e.g., *Tiwi Islands and Cape York*) were detected, others will certainly have been missed. Potential examples include small but biogeographically distinct areas such as the Iron and McIlwraith Ranges of far northern Cape York (Johnson and Hooper 1973), the *Banksia* woodlands of coastal south-west Western Australia (Crisp et al. 2001), and the eastern coastal heaths. Further, community types that are naturally less speciose, such as grasslands, may not have been detected due to our decision to exclude lists of fewer than five species when compiling the typology. However, now that we have identified a level of multivariate dissimilarity that consistently yields recognisably distinct bird communities, a targeted approach can be used to evaluate the distinctiveness of additional communities that may have been missed in the original typology due to relevant surveys having been excluded or too sparse. This can be assisted by encouragement of citizen-science efforts to contribute further surveys in areas noted as likely to support such cryptic communities.

We excluded clusters that were deemed not to represent 'naturally-occurring' community types. This is because our objective was specifically to distinguish communities that may exist in the absence of recent human-induced extirpations (Ward et al. 2022) and intensive pressures recently introduced to the landscape, such as industrial agriculture, urbanisation, and introduced species (Ford et al. 2001). Essentially, our next steps are to identify the 'reference condition' for each naturally occurring bird community, enabling deviation from those reference conditions to be measured using a set of condition indices (Fraser et al. 2018). As such, some clusters were excluded from the typology as they comprised surveys that were too generic to represent a distinct and recognisable bird community. The 2-ha 20-min surveys we used represent small snapshots of the bird community occupying a particular place at a particular time, and so surveys from one location can vary considerably from hour to hour, let alone from year to year, even in the absence of any local environmental change (Field et al. 2002). Such snapshots can be dominated by a small number of widespread generalist species, even in sites that at other times would yield a richer and more distinct set of species. On the other hand, some sites are persistently dominated by generalists, species commensal with humans, or introduced species. Such assemblages, although they may be accurate representations of the bird community of a site (e.g., in urban areas and artificial habitats), were considered not representative of a naturally-occurring community type, and the 12 clusters apparently representing these were excluded from the typology, given our focus on naturally-occurring bird communities. These judgements are, by necessity, subjective and follow a concept of 'best on offer', in that we recognise we do not and cannot know the state of communities historically (McNellie et al. 2020).

The focus on 'naturally-occurring' communities does not imply that such communities existed in the absence of human intervention. All of Australia's ecosystems have been shaped by Indigenous human practices for millennia. It is therefore important to recognise that what we consider 'naturally-occurring' is based on the impressions of contemporary experts familiar with examples of bird communities occurring in what were considered ecosystems less-disturbed by modern industrial practices and recent disruptions. In reality, of course, all of Australia's ecosystems have been altered substantially in the 250 years since European colonisation and associated replacement of Indigenous land management practices (Woinarski and Legge 2013; Fletcher et al. 2021). The extent of these ecosystem-level disruptions is still poorly recognised and understood, hence our focus on a contemporary 'best on offer' conceptualisation of bird community types as a proxy for naturally-occurring communities.

We see our typology as the necessary first step to enable the development of benchmarks of community condition. This, in turn, will enable the assessment of conservation status, tracking of trends, evaluation of management interventions, and reporting of environmental change at multiple scales—from sites and properties, to regions and nationally. For example, changes over time in reporting rate or population for individual species or groups of species, such as threatened species, are already used to illustrate overall trends (Gregory et al. 2008; Bayraktarov et al. 2021). Our work sets the groundwork to be able to do this for entire communities holistically, reflecting the health or condition of communities under different conditions, in different locations, or over time. The test of a useful typology is therefore not whether it is 'correct', but whether it is fit for purpose, yielding categories distinguished on a consistent basis, which users of the typology can recognise reliably. Over the coming years, our proposed typology will doubtless be refined as it is tested through application.

4.3 | Limitations of the Typology

Despite efforts to minimise it, data bias unavoidably influenced our typology. There is a strong spatial bias in the locations most likely to be surveyed across Australia (Barry and Elith 2006), and this will have contributed to variation in sampling adequacy among communities. Indeed, the number of bird surveys that informed each community varied substantially, despite our attempts to improve the spatial evenness of survey effort. For example, there were very few bird surveys available for the *Inland Nomad* community, relative to the nearby *Northern Savanna* community. As we did not know a priori the spatial distributions of the different communities, we attempted to control for the regional bias in the number of bird surveys by ensuring that no combination of bioregion and vegetation group (MVG) was represented by more than 350 surveys, retaining every survey in combinations with fewer than this number. However, some combinations remained poorly sampled, and so communities local to those areas may have been missed, such as those outlined above.

The dataset we used also contains relevant temporal bias. Northern Australia has fewer surveys during the wet season, as does the arid zone during the hotter summer months. Although Australia's terrestrial bird fauna is not as dominated by long-distance migrations as northern hemisphere avifaunas (Dingle 2008), such biases are likely to result in reduced detection of summer migrants. While this is unlikely to have led to entire communities being missed, their description and specification are likely to be affected, so future work to examine temporal variation in community composition, particularly in the arid zone and tropical north, will be valuable. For most communities the temporal distribution of surveys was similar, with the majority of surveys between 1998 and 2022, but two were somewhat temporally biased: most Tasmanian Wetter Forests surveys were more recent, and the very localised Tiwi Islands and North-western Cape York surveys occurred earlier on in the period, when focussed survey effort was applied in those quite remote areas (Supporting Information S4).

The sampling units that formed the basis of this analysis were individual 2-ha 20-min survey results. Even multiple such snapshots are unlikely to fully capture all the birds that may occupy a given location at some point over time (Maron et al. 2005; Reid et al. 2024), and differences in detectability among sites also limit the extent to which the snapshots reflect the reality of sites. One way to address this could have been to use sites rather than surveys as the unit of analysis, with only sites that had multiple repeat surveys included. This approach could enable correction for detectability as well. However, the number and geographical coverage of repeatedly-surveyed sites was not adequately comprehensive. Further, as the aim was to use the resultant typology as the basis for a sample-based condition scoring approach, a typology based on what observers are likely to detect is useful. Further, the expert input steps were used to ensure that no communities emerged that appeared simply to reflect artefacts of the data or issues such as intraspecific or among-site variation in detectability. Only one community type was judged likely to reflect not a distinct community but a particular state of it at one point in time: the Inland Nomads community.

4.4 | Extension to Other Taxa and Regions

To our knowledge, this is the first continent-wide study exploring fauna-based communities based on co-occurrence, rather than distribution, data. It provides an approach that can be applied in other regions and to other taxa beyond birds. However, our specific method for deriving the typology relied upon extensive citizen science data that used a sampling approach standardised for effort and area, and which is likely to capture a substantial proportion of species within the taxonomic group of interest that are present at the time of the sample. A similar approach could be used in other instances where there are adequate data available; for example, other structured citizen science programs, potentially including acoustic monitoring of birds, bats or frogs, or collecting eDNA data for aquatic species.

For taxa such as mammals and reptiles, no single survey method is likely to capture a large proportion of species present at a site, and so moderately comprehensive site-level inventories are less likely to be available across the spatial extents required to develop broadscale typologies. For such taxa, approaches will likely rely more heavily on modelled distributions and habitat associations as well as expert elicitation, similar to the approach of Fraser et al. (2018), rather than focusing on co-occurrence. Our method also benefited from the relatively small size of the individual sampling units (2 ha), which meant that it was less likely that the sampled area contained multiple different bird community types, as might be the case if we had used, for example, data from 5-km area searches (another survey method available in Birdata). As such, citizen science programs that use larger units for the aggregation of data [e.g., Southern Africa's Bird Atlas Program uses 5×5 min ‘pentads’ (Brooks et al. 2022)] will require a different approach to the identification of community types.

4.5 | Applications of a Faunal Typology

We hope that this typology will be used in a range of ways. We provide full descriptions of each community in the Supporting Information S4, including the most common and the most distinctive species associated with each, in the hope that future users will be able to qualitatively identify the community to which their site belongs. However, we are currently developing an algorithm to automatically assign a survey to the community it is most likely to represent, based on both the species detected and its location.

The development of this typology was motivated by the need to develop metrics that provide information about the condition of faunal communities, beyond a species-by-species focus and without relying on vegetation condition as a surrogate. These metrics will provide important context to accompany ongoing work that targets threatened species. The need for a suite of direct indicators of condition for a given ecosystem is particularly evident when the health of a given fauna community is not well predicted from metrics based on vegetation structure and composition. This occurs especially where the threats that impact fauna community condition are related to direct human disturbance, hunting, and conflict; disease, introduced predators and competitors; or where faunal community responses (e.g., to climate change) substantially lag or lead those of the vegetation community (Redford 1992; Shoo et al. 2005; Wilkie et al. 2011; Woinarski et al. 2015; Scheele et al. 2019).

What constitutes 'good' or 'healthy' condition will differ from one community type to the next, as will the metrics that best indicate condition. For this reason, a necessary precursor to developing metrics of condition is an understanding of those different community types. The typology we have developed enables recognition of fauna community types at the site level, based largely on the combination of species observed.

From here, we aim to develop a set of metrics that indicate the relative condition of each community type, in a manner similar to Fraser et al. (2018). This process involves identifying the attributes of examples of each community that represent 'good' versus 'poor' condition examples. Such metrics are usually standardised relative to their reference condition, representing what is considered 'intact' or 'best-on-offer' (Thorpe and Stanley 2011; McNellie et al. 2020). As this is, ultimately, a subjectively judged property of a community, structured expert elicitation will be employed to derive estimates of condition based on data from surveys done in each community type. If experts converge in their judgements of which surveys represent 'good' versus 'poor' condition, we can develop models to estimate condition from survey lists (Fraser et al. 2018), and develop sampling protocols that ensure those estimates are robust to spatial and temporal variation. The ultimate aim is to develop a series of condition metrics able to be calculated from standard samples, in much the same manner as plant community condition metrics. These metrics will then enable comparable, standardised tracking and reporting on bird community condition through time, exploring broad correlates of community condition, identifying community types that may satisfy criteria for listing as threatened, and augmenting environmental accounts from the level of individual properties to the national level.

4.6 | Conclusions

Our empirically-derived typology of the avifaunal communities of an entire continent demonstrates the value of coordinated, high-quality citizen science efforts. The typology itself is subject to refinement, but presents an immediate basis for developing metrics of bird community condition for the majority of the terrestrial bird communities of Australia. Our typology represents one of the first instances globally of continental-scale classification of faunal communities based on co-occurrence data. Therefore, we hope our approach can initiate similar efforts for other regions and taxa. This work represents a first step to support the development of comprehensive and comparable monitoring of the state and trajectory of faunal communities alongside vegetation, to build a more comprehensive understanding of ecosystem health.

Author Contributions

All authors contributed to investigation, writing, and editing the manuscript. Additionally: M. M. contributed to conceptualization, funding acquisition, methodology, project administration, resources, and supervision. K. I. contributed to data curation, formal analysis, methodology, validation, and visualization. H. F. contributed to methodology, project administration, supervision, and validation. C. B. M. contributed to methodology, and visualization. H. P., J. R., A. E. R., H. M. all contributed to methodology and supervision. J. M. A. contributed to visualization.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Summary data for all communities including importance score analysis and reporting rates are provided as Supporting Information S1.

Raw data used for analysis are available under licence from BirdLife Australia; a version from which species for which their location data are sensitive (e.g., species of conservation significance which are at particular risk of disturbance if site locations are revealed) are removed, along with code used for analyses, is available at https://osf.io/p4wdn/?view_only=6157448eb72e44aaa8da8d4f6fc01fa3.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Supporting Information S1:** Terrestrial vs. non-terrestrial birds. **Supporting Information S2:** Summary data for communities, divided by region. **Supporting Information S3:** Maxent methods and results. **Supporting Information S4:** Community descriptions by region.