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Assessing the validity of crowdsourced wildlife observations for conservation using public participatory mapping methods

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ABSTRACT

Public participatory mapping is a method of crowdsourcing where the lay public can contribute spatial information for a range of applications including conservation planning. When used to collect wildlife observation data, participatory mapping becomes a type of "geographic citizen science" that involves collaboration with members of the public. While the potential of crowdsourcing to assist in wildlife conservation appears to be large, the quality and validity of the observational data collected remain a key concern. In this study, we examined the quality and validity of spatial data collected in a public participatory mapping project implemented in northern New South Wales (Australia) in 2018 where the public was asked to identify and map the location and frequency of koala (*Phascolarctos cinereus*) sightings using an internet mapping application. The iconic koala is a nationally-listed threatened species and has wide public recognition, making it an ideal test of our approach to examining the value of citizen science for wildlife. We assessed the validity of koala observation data from two perspectives of *validity-as-accuracy* (positional accuracy and data completeness) and *validity-as-credibility* (characteristics of spatial data contributors). To assess *validity-as-accuracy*, we analysed the distribution of citizen observations of koala sightings compared to an expert-derived probability distribution of koalas (likelihood model). To assess *validity-as-credibility*, we analysed the survey data to determine which participant characteristics increased the credibility of observational data. We found significant spatial association between crowdsourced koala observations and the likelihood model to validate koala locations, but there was under-reporting in more rural, remote areas. Significant variables contributing to accuracy in koala observations included participant knowledge of koalas, age, length of residence, and formal education. We also compared the crowdsourced results to a field-based citizen science koala observation project implemented in the same region and found crowdsourced participatory mapping provided comparable, if not superior results. Crowdsourced koala observations can augment field-based koala research by covering large geographic areas while engaging a broader public in conservation efforts. However, effective geographic citizen science projects require a significant commitment of resources, including the creation of community partnerships, to obtain high quality spatial data.

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1. Introduction

Public participatory mapping and volunteered geographic information (Goodchild, 2007) are methods of crowdsourcing (Howe, 2006) where the lay public can contribute spatial information for a range of environmental applications, including research for conservation planning. Citizen science has been defined as activities in which non-professional scientists participate in data collection, analysis and dissemination of a scientific project (Cohn, 2008). The term "geographic citizen science" refers to a subset of general citizen science where the collection of location information is an integral part of the activity (Haklay, 2013). The potential of crowdsourcing in geographic citizen science to assist in environmental problems, such as species conservation, appears large. However, the quality and validity of the citizen observation data collected remain a key concern (Alabri and Hunter, 2010; Brown et al., 2015). For example, Hunter et al. (2013) describe some of the weaknesses in general citizen science that also apply to geographic citizen science projects including the use of poorly-designed methods of data collection resulting in incomplete or inaccurate data. In participatory mapping, often called public participation GIS (PPGIS), and volunteered geographic information (VGI), a solid framework for assessing the quality of crowdsourced spatial data has yet to be established given these methods are fundamentally different to traditional geospatial assessment. The difference is due to social factors driving public contribution and the variety of types and sources of spatial content (Antoniou and Skopeliti, 2015). Furthermore, comparable authoritative data may not be available for assessing and evaluating citizen contributed data, thus requiring the use of proxy data or modelling estimates of spatial distribution.

Citizen science data can be a valuable source of information on changes in species distributions and biodiversity (Schmeller et al., 2009) but data quality may be limited due to the potential for observational bias, reporting bias, and geographical bias (van Strien et al., 2013). According to Bonney et al. (2009), contributions from citizen scientists now provide a significant quantity of data about species occurrence and distribution around the world, and include well-established projects such as *eBird*, a web-enabled community of bird watchers who collect, manage, and store their observations in a globally accessible unified database (Sullivan et al., 2009). The number of citizen science projects has grown significantly with the *SciStarter* website providing a database of > 2700 searchable citizen science projects and events (https://scistarter.com/about). With the large, rapid increase in citizen science projects, there is an increasing need for research that evaluates the quality and validity of citizen data, examines the best approaches for integration of citizen and professional/specialist science, and the design of citizen science programs for their long-term sustainability and adaptability (Paul et al., 2014).

Our focus here is on identifying and elaborating methods to evaluate the quality of crowdsourced, citizen-contributed geospatial knowledge in the specific context of species location information. Given that crowdsourced spatial data include both the social processes used to collect spatial data, and the actual spatial data generated, an assessment of data quality and validity (fitness for purpose) should include both elements. To evaluate the quality of crowdsourced data, we used the two perspectives described by Spielman (2014): *validity-as-accuracy* and *validity-as-credibility*. The *validity-as-accuracy* perspective assesses the contributed spatial data against authoritative data while the *validity-as-credibility* assesses the characteristics of the data contributors such as reputation, motivation, and place familiarity that may influence spatial data quality. Van Exel et al. (2010) used the term c*rowd quality* to describe these data quality perspectives. As a general concept, *crowd quality* seeks to assess the collective intelligence of crowd-generated data.

The *validity-as-accuracy* perspective examines spatial data quality using criteria applied to expert-derived spatial data such as *positional accuracy*, *attribute accuracy*, *logical consistency*, *completeness*, and *lineage* (see Federal Geographic Data Committee www.fgdc.gov/metadata/csdgm). Additional criteria for evaluating volunteered geographic information (VGI) data against authoritative data include *temporal accuracy* and *usability* (Antoniou and Skopeliti, 2015). The *validity-as-accuracy* perspective has been applied to VGI systems, such as the positional accuracy and completeness of public contributions to OpenStreetMap (OSM) (Haklay, 2010; Girres and Touya, 2010; Zielstra and Zipf, 2010). These studies indicated the positional accuracy of OSM data were comparable to geographical data maintained by national mapping agencies and commercial providers. Within the domain of conservation planning, moderately high levels of accuracy have been found from crowdsourced data in the location of native vegetation in New Zealand (Brown, 2012), in identifying habitat for threatened species conservation (Cox et al., 2014), and for mapped values in areas of high conservation importance (Brown et al., 2015).

The *validity-as-credibility* perspective in participatory mapping or VGI seeks to account for data quality based on the characteristics of citizen contributors. There have been relatively few published studies that evaluate participant-related variables of data quality for geographic citizen science data. Potential reasons for the lack of data quality assessment from a *validity-as-credibility* perspective include absence of participant-related data beyond basic demographic information, a predisposition towards finite citizen mapping projects over longer-term continuous projects that provide greater opportunity for data collection, and project emphasis on spatial information over user-related information. A consistent participant variable found to influence spatial data quality is participant familiarity and experience in the geographic study area. For example, Brown (2012) found that participant familiarity with the study area contributed to spatial accuracy in identifying native vegetation. In general, participatory familiarity with the study area contributes to greater mapping effort which can be a proxy for data quality when mapping subjective spatial attributes, such as place values, experiences, and preferences (Brown, 2017).

1.1. Citizen science and koala observations

There have been several field-based, citizen science projects in Australia with a focus on koalas (*Phascolarctos cinereus*). The koala has an advantage for citizen science projects because it is unique and no other animal looks like a koala. At 5–10 kg in size, it is easy recognizable once spotted and remains in people's memories. Sequeira et al. (2014) produced the first citizen science-generated estimates of koala habitat suitability and population size in South Australia based on a citizen observation program called the "Great Koala Count" which generated 1359 observations from over 1000 data contributors. While the spatial accuracy was high (i.e., *validity-as-accuracy*) because koala locations were logged using GPS technology, the limitations of the citizen-science collected data included a limited sampling window (one day observation) and significant geographic bias—most of koala observations were made within conservation parks, along streets, or in suburban backyards in areas proximate to Adelaide, South Australia. The citizen participants were also not representative of the entire South Australian population (Hollow et al., 2015). A second "Great Koala Count II" was conducted in South Australia in 2016 to address some of the limitations of the first project including an expanded sampling timeframe (see https://www.discoverycircle.org.au/projects/koala/) with results yet to be published.

Similar to the South Australian koala citizen-science projects, a field-based koala observation program was conducted in New South Wales (NSW) in 2013 and 2014 by the National Parks Association of New South Wales (www.npansw.org) and the Atlas of Living Australia (www.ala.org.au). This project was also called the "Great Koala Count" and the project area included the north coast of New South Wales, the geographic focus of the study reported herein. Data from the NSW "Great Koala Count" provide an opportunity to compare the results from two different citizen science methods (field-based "Great Koala

Count" and crowdsourced internet mapping conducted in the current study) against independent koala distribution models.

Predavec et al. (2018) used repeat community (citizen science) surveys in 2006 and 2015 to assess population change in koalas in northwest NSW. The surveys requested participants to identify the locations of koala sightings and eight other common species on hardcopy colour maps and markers in the 2006 survey and a Google Maps application interface using digital markers in the 2015 survey. The two community surveys had 479 and 413 responses respectively, with 813 and 619 reported koala sightings. The study found that koala numbers had declined over time across the study region. A strength of the community survey method was the ability to obtain data over a large geographic region while limitations included response bias in observations towards roads or other public spaces, with observations concentrated around urban centres.

1.2. Purpose and research questions

In this study, we examined the quality and validity of spatial data collected in a participatory mapping project implemented in the north coast region of New South Wales, (Australia) in 2018 where the public was asked to map the location and frequency of sightings of the iconic, but vulnerable koala using an internet mapping application. The independent koala species distribution information for evaluating citizen observations is a koala likelihood mapping model developed by a team of researchers for the NSW government (Predavec et al., 2014, 2015). To evaluate the quality of crowdsourced koala data from a *validity-as-accuracy* perspective, we compared the spatial locations of citizen observations with the koala likelihood map. We asked: Are citizen observations significantly correlated with higher probabilities of koalas being present? We then evaluated the quality of the crowdsourced observation data from a *validity-as-credibility* perspective by examining participant characteristics that may contribute to better predications of koala locations. In other words, what participant characteristics would be desirable to better estimate the geographic distribution of koalas? For comparison, we also evaluated the crowdsourced koala data against observation data collected from the NSW "Great Koala Count" to assess the relative strengths and weaknesses of these two citizen-based observation methods.

2. Methods

2.1. Study area

The study area was located on the far north coast of New South Wales, Australia, and consisted of four Local Government Areas (LGAs)—Ballina Shire, Bryon Shire, City of Lismore, and Tweed Shire. Population estimates (Australian Bureau of Statistics, 2016) for the four LGAs were as follows: Ballina (41,790); Byron (31,556); Lismore (43,135); and Tweed (91,371). The study area was selected because the far north coast of NSW supports nationally significant koala populations and the koala in NSW is listed as vulnerable under both State and Commonwealth laws. Further, the area was the focus of a joint Commonwealth-local government Tweed-Byron Koala Connections project, an ecosystem restoration project that sought to secure the future of wildlife populations by increasing the area, quality and connectivity of habitat.

2.2. Study design and data collection

In 2017, we developed an internet-based participatory mapping survey to assess location-specific community sentiment and willingness to positively engage in koala conservation and recovery programs. The survey used a Google® maps application programming interface (API) where participants were directed to drag and drop digital markers representing koala observations and land use preferences (e.g., residential or tourism development) within the study area. The mapping interface consisted of three "tab" panels with 11 markers related to koala observations located in panel one and eight land use preference markers located in panels two and three. In addition, there were five markers that asked participants to identify koala observations in the categories of *weekly*, *monthly*, *yearly*, and *only once*. There was also a marker to identify the location of *dead or injured* koalas. The survey also included text questions that identified participant characteristics (demographics), such as home location, age, gender, and formal education, as well as questions that asked participants about their knowledge of koalas and places in the study area, their attitudes towards koalas, perceived threats for koala survival, and support for various types of koala conservation efforts.

Study participants were recruited through five primary sources: (1) announcement and promotion of the study through local government (LGA) newsletters and websites, (2) conservation and community organizations such as "Friends of the Koala" and "Bangalow Koalas", (3) Facebook® advertisements, (4) news stories appearing in local media including newspapers and radio, and (5) friend and relative referrals from the above sources. The data collection effort began in December 2017 and extended through March 2018 (approximately 4 months).

2.3. Origin and description of the koala likelihood model

The koala likelihood model (Predavec et al., 2014) shows probable koala occurrence and non-occurrence within 5 km grid cells located in the study area derived from historical observation records of koalas and other mammals in the same grid cell. The historical records come from the Atlas of NSW Wildlife database maintained by the NSW Office of Environment and Heritage. The likelihood model also computes a confidence level in the probability value (high, medium, low) based on the number of wildlife observations. The koala likelihood analysis and map was based on a 20-year data window (1994–2014) of likely koala occurrence and non-occurrence where grid cells with a non-zero probability had at least one koala recorded within the review period. A companion analysis of the likelihood model found broad agreement between likely koala occurrence and locally derived koala habitat mapping (Scotts et al., 2014). The map was subsequently modified and updated based on recommendations from a koala expert workshop held in March 2015 (OEH, 2016) that included a test of the map against an independent koala survey method called the Spot Assessment Technique (SAT) (Phillips and Callaghan, 2011). The SAT survey uses the presence/absence of koala faecal pellets around the base of trees to measure koala activity. A comparison of the likelihood map with four SAT data sites showed a strong positive correlation between the likelihood map and koala activity such that the map provided a good index of koala occurrence (OEH, 2016). The likelihood model has since been updated with koala observation data covering the period from 1997 to 2017. There are, however, several caveats associated with the likelihood model: (1) data in the model come from the Atlas of NSW Wildlife where over 20% of the koala records were derived from a 2006 community survey (Lunney et al., 2009), and (2) the model does not account for local and recent koala population declines (Predavec et al., 2014).

2.4. Analyses

2.4.1. Participant characteristics (geographic and demographic)

We assessed the geographic representativeness of participants by comparing the proportion of participants within each local government area to the expected distribution and by plotting home locations in the study region area to compare with population density mapping based on the 2016 Australian census. We used descriptive statistics to analyse participant characteristics on socio-demographic variables included in the survey. We then compared demographic variable responses (age, gender, education) to population data from 2016 census data for the study area.

2.4.2. Assessing observational accuracy

The spatial data from the survey were prepared for analysis using ArcGIS® v10.4. The koala likelihood grid was clipped to the study area boundary. Full or partial 5 km grid cells within or intersecting the study boundary with likelihood data were retained for analysis resulting in 173 grid cells for analysis. Koala observations were clipped to the study area boundary, with a 3 km tolerance to capture observations in grid cells that partially intersected the study area. The frequency counts of observations for the categories of *weekly*, *monthly*, *yearly*, *once*, and *dead/injured* were tabulated for each grid cell. Observation accuracy was assessed using multiple statistical measures of association between koala observations and the likelihood model as follows:

(1) Spearman's rank correlation coefficients were calculated between the grid cell observation counts and the cell probability value from the likelihood model for each observation category and for the sum of all observation categories. To determine if observation accuracy differed by observation category (e.g., *weekly* vs. *monthly*), we calculated mean cell probability values and used analysis of variance (ANOVA) with Tukey HSD post-hoc tests to identify significant differences.

(2) Presence/absence analysis. Cross-tabulations were generated between the likelihood map and crowdsourced citizen observations where each grid cell was coded based on the presence (1) or absence (0) of one or more koala observations in each cell. This analysis assesses the consistency (spatial concurrence) between citizen observations and historical koala records to indicate whether citizens are likely to over- or under-report the presence of koalas compared to historical records. The phi-coefficient (φ) provides an overall measure of association between presence and absence cells and falls within the range of +1.0 and –1.0 with stronger relationships found at either extreme. Fitz-Gibbon and Morris (1987) suggest the following interpretation: $\varphi < 0.2$—little or no association, $0.2 < \varphi < 0.4$—weak association, $0.4 < \varphi < 0.6$—moderate association, and $\varphi > 0.6$—strong association. For comparison, we also conducted presence/absence analysis with observational data from the NSW "Great Koala Count" (GKC), a field-based citizen science project conducted in 2013 and 2014. GKC participants were requested to register as a citizen scientist and download a smartphone application to record koala sightings within specified time windows. A report on the project was prepared by Cleary (n.d.) and observational data from the GKC are available at https://collections.ala.org.au/public/show/dr799. There were 941 GKC observation records within the study area used in our analysis.

(3) To identify potential measures of spatial association, we calculated bivariate spatial autocorrelation (Bivariate Moran's I) between the summed koala observations and cell probability for each cell using GeoDa® software. The Bivariate Moran's I statistic measures *global* spatial autocorrelation, or the extent to which two different variables cluster (or not) in space based on the *proximity* of high and low grid cell values in the study area. Possible values for Bivariate Moran's I range between −1 and +1 with 0 implying no spatial autocorrelation. Positive values indicate spatial clustering and negative values indicate spatial dispersion. One would expect a positive Moran's I value if participants mapped more koala observations proximate to high koala probability values (high/high) or mapped fewer observations proximate to low probability cells (low/low). Of greater interest is the bivariate *local* indicator of spatial autocorrelation or BiLISA (Bivariate Local Indicator of Spatial Association). Rather than measuring autocorrelation across the whole study region (global), BiLISA looks for significant spatial autocorrelation locally, i.e., for each grid cell. BiLISA maps show which grid cells are statistically significant with high/high and low/low values ("I'm similar to my neighbours") or high/low and low/high values ("I'm different from my neighbours"). Thus, BiLISA maps show local areas within the larger study area where koala probabilities are similar to, or different from, koala observations.

2.4.3. Assessing participant variables contributing to accuracy

To evaluate the *accuracy-as-credibility* perspective, we examined participant variables that may be significantly related to higher cell probability values in the koala likelihood model. The cell probability value was linked to each observation based on its grid cell location. All possible linear regression models were evaluated using the (SPSS® v.25) "Best Subsets" procedure that uses the Akaike Information Criterion (Akaike, 1974) to compare and rank multiple competing models and to estimate which model best approximates the "true" underlying process. The Akaike Information Criterion (AIC) is grounded in information theory and provides an estimate of the relative rank of multiple models based on the trade-off between goodness of fit and the parsimony of the model. The procedure also quantifies model selection uncertainty in cases where no single model stands out as being the best model. By default, the SPSS subsets procedure uses *corrected* AIC which adjusts for small sample sizes.

The regression subsets procedure was run for each observation category (*weekly*, *monthly*, *yearly*, *once*, and *dead/injured*) and for *all observations combined*. The linear regression models included the following participant variables: *age*, *gender*, *education* (1 = less than bachelors, 2 = bachelors/postgraduate), *length of residence in study area*, *familiarity with study area* (1 = poor to 5 = excellent), *knowledge of koalas* (1 = no knowledge to 5 = very high knowledge), *number of observation markers*, and *distance from participant home location to the koala observation*. The model with the lowest AIC was compared to other models using the change in Akaike Information Criterion (ΔAIC) and Akaike weights to assess the uncertainty in selecting the best model. The Akaike weight has a value between 0 and 1 and can be considered the probability that a given model is the best approximating model. Higher weights indicate greater model certainty. Models with ΔAIC values less than two are considered to be as good as the best model (Richards, 2005).

After quantifying the uncertainty associated with the best model for each observation category, we ran the regression model with the predictor variables to generate the goodness of fit statistic (R-squared) and standard beta-coefficients to identify the strongest predictor variables. For each regression model, collinearity diagnostics were run to evaluate multicollinearity or the presence of highly correlated predictor variables. For all regression models evaluated, the variance inflation factors (VIF) were well below four indicating that multicollinearity was not a problem.

3. Results

3.1. Participant characteristics

There were 454 participants who mapped one or more locations in the study area and 397 participants that completed the survey questions. A profile of participants is presented in Table 1. The mean number of koala observations was four per participant, with a total of 1695 koala observations mapped in the study area. Only 2% of participants ($n = 7$) were not residents in the study area. Residents lived in the study area for an average of 20 years.

Participants were 70% female, averaged 53 years of age, and had a high level of formal education, with 65% having a bachelor's degree or higher. Compared to Australia Bureau of Statistics population statistics, study participants were older, contained proportionately more females, and had a significantly higher level of formal education. The sampling bias on age and formal education is consistent with many participatory mapping studies, but inconsistent in that participation is most often skewed towards greater male participation (Brown and Kyttä, 2014).

Participants were asked to self-rate their knowledge of koalas as well as their familiarity with places in the study area. About 58% of participants rated their familiarity with the study area as "excellent" or "good" while only 2% rated their familiarity as "poor". With respect to knowledge of koalas, about 16% rated their knowledge as "very high"

Table 1
Participant profile based on survey responses in the study area. Selected census demographics from the 2016 ABS Census are provided for comparison. Not all percentages total 100% due to rounding.

Mapping behavior	
Number of participants (mapped one or more locations)	454
Number completing post-mapping text survey	397
Number of locations mapped	6362
Range of all markers	1–366
Range of observation-only markers	0–173
Mean (median) all markers mapped	15 (7)
Mean (median) observation only markers mapped	4 (2)
Knowledge of study area	
Excellent	14%
Good	44%
Average	33%
Below average	7%
Poor	2%
Knowledge of koalas	
Very high knowledge	3%
High knowledge	13%
Moderate knowledge	49%
A little knowledge	32%
No knowledge	3%
Resident of study area	
Yes	98%
No	2%
Years lived in study area (mean, median)	20, 18.5
Participant distribution by Local Government Area (percent)	
Ballina (percent of study area population = 20%)	8%
Byron (percent of study area population = 15%)	24%
Lismore (percent of study area population = 21%)	35%
Tweed (percent of study area population = 44%)	33%
Demographics	
Gender (ABS for NSW 2016: Male 49.3%)	
Female (%)	70
Male (%)	30
Age in years (mean/median) (ABS for NSW 2016: mean 48, median 47)[a]	52/53
Education (%) (ABS for NSW 2016: 23.4% Bachelors/postgraduate)	
Less than bachelors	35%
Bachelor's degree/postgraduate	65%

[a] Estimates from 2016 grouped census data for individuals aged 20 or older.

or "high" while about half of participants rated their knowledge as "moderate".

In terms of geographic representation, participants were proportionately over-represented in the Local Government Areas (LGAs) of Byron and Lismore and under-represented in Ballina and Tweed Shires. For example, Lismore has about 21% of the study area population but accounted for 35% of the participants while Ballina has about 20% of the study area population but accounted for only 8% of participants. The geographic distribution of participants based on home location was consistent with population density in the study area (Fig. 1a) with higher concentrations of participants clustered near the population centres of Lismore, Tweeds Head, Pottsville, and Murwillumbah, with other participants widely dispersed in areas of lower population density. The number of unique participants reporting koala observations by grid cell was not systematically related to participant home location (Fig. 1b). For example, grids cells near Lismore and Pottsville had both large numbers of participants and large numbers of unique observers in proximate grid cells. In contrast, Tweeds Heads and Murwillumbah also had relatively large numbers of participants but few unique observers in proximate grid cells.

3.2. Observational accuracy

Crowdsourced koala observations were compared to the koala likelihood model across 173 grid cells in the study region. The grid cells were classified and symbolized into quintiles based on cell probability values (Fig. 2a) and total koala observations in each cell (Fig. 2b). Visually, there was a moderate degree of concordance, but there was also disagreement in some cells. The global Bivariate Moran's I statistic was 0.16 (pseudo p-value = 0.001), indicating weak but significant positive spatial autocorrelation between summed koala observations and neighbouring cell probabilities. Local spatial autocorrelation with high probability and high observations was significant in the south of the study area near Lismore, in the central study area, and on the north coast near Pottsville (Fig. 2c). Local spatial autocorrelation was also significant in the eastern reaches of the study area, and near Ballina where both cell probabilities and koala observation values were low.

The koala observation markers for the categories of *weekly*, *monthly*, *yearly*, *once*, and *dead/injured* were tabulated for each grid cell in the koala likelihood model. Spearman's rank correlations were calculated between cell probabilities and koala observation counts. The correlation coefficients and significance levels were as follows: *weekly* ($r = 0.40$, $p < 0.001$); *monthly* ($r = 0.40$, $p < 0.001$); *dead/injured* ($r = 0.30$, $p < 0.001$); *yearly* ($r = 0.30$, $p < 0.001$); and *once* ($r = 0.20$, $p < 0.01$). The correlation coefficient for *all observations combined* was $r = 0.38$, $p < 0.001$. For comparison, the correlation coefficient for "Great Koala Count" observations with cell probability values was $r = 0.48$, $p < 0.001$.

The mean cell probability values for each observation category were examined using ANOVA with post-hoc comparisons. The greatest accuracy was associated with *monthly* ($\bar{x} = 0.83$, s = 0.17) and *weekly* ($\bar{x} = 0.82$, s = 0.21) observation categories and the least accuracy with *yearly* ($\bar{x} = 0.74$, s = 0.23), *once* ($\bar{x} = 0.73$, s = 0.21), and *dead/injured* ($\bar{x} = 0.76$, s = 0.19) categories. The mean cell probabilities in the *monthly* and *weekly* categories were significantly larger than the cell probabilities in the *yearly*, *once*, and *dead/injured* categories (ANOVA, Tukey HSD, $p < 0.05$). Simply put, koala observations in shorter timeframe categories were more accurate than observations in longer timeframe categories.

The results of the presence/absence analysis are presented quantitatively (Table 2, Fig. 3) and show those grid cells that were inconsistent between the likelihood model and spatial survey (Fig. 3a) and field-based, citizen koala observations from the "Great Koala Count" (Fig. 3b). The presence/absence statistical association between spatial survey observations and historical observations in the likelihood model was weak, but significant (phi coefficient = 0.25, $p < 0.01$). The association between the "Great Koala Count" and the likelihood model was somewhat weaker than the spatial survey (phi coefficient = 0.21, $p < 0.01$). For the spatial survey, the presence/absence analysis indicated 96% consistency (137/142) in observations with the likelihood model where participants had observed koalas. The consistency was 19% (6/31) where participants had not observed koalas, but the model indicated historical presence of koalas. Of the inconsistent cell results, 70% of the cells were classified as low confidence in the likelihood model (Fig. 3c). For the field-based citizen observations, the presence/absence analysis indicated 100% consistency (69/69) in observations with the likelihood model where citizens had observed koalas. This result was expected given that citizen field observations from the Great Koala Count were included in the likelihood model. The consistency was 12% (11/93) where citizens did not observe koalas. Of the inconsistent cells, 51% were classified as low confidence in the likelihood model (Fig. 3d). Thus, both the spatial survey and field-based citizen observation performed well in matching historical records where koalas were observed, but both methods under-reported koala observations in cells where the model indicated koalas were present from historical records. Overall, the spatial survey had 30 inconsistent grid cells compared to 93 cells for the field-based citizen observations.

3.3. Participant predictors of accuracy

Bivariate correlation analysis and multiple linear regression models were run to determine which participant variables contributed to

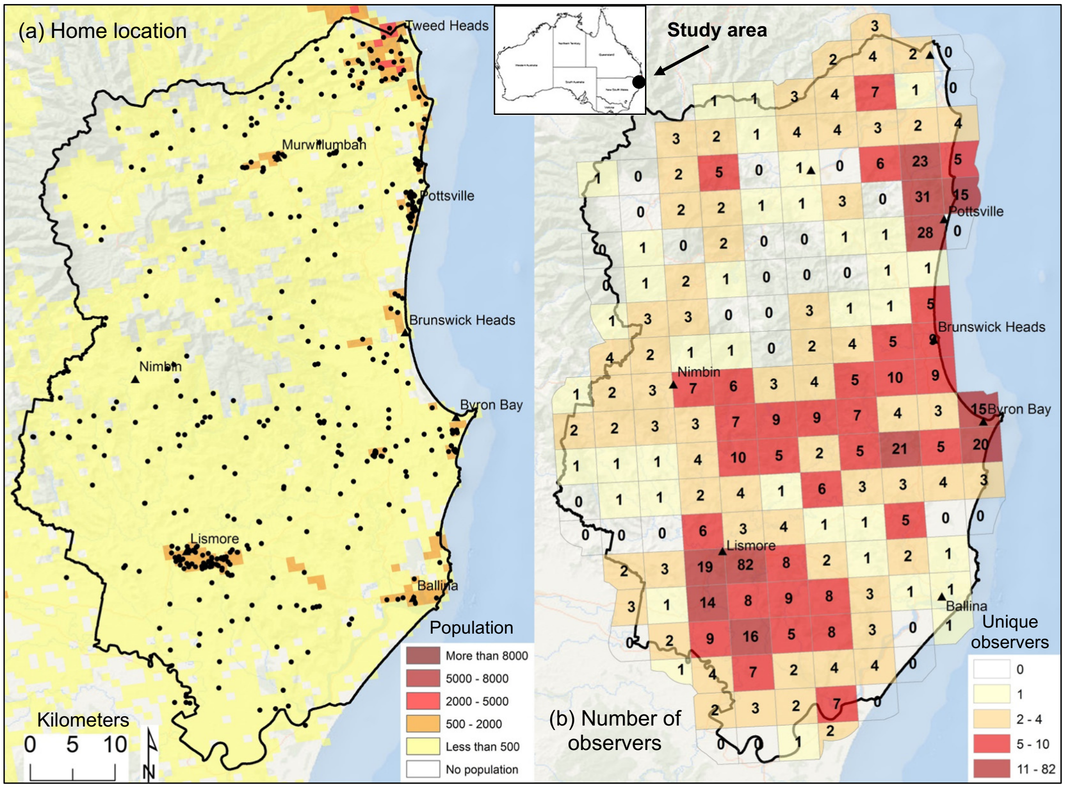

Fig. 1. Distribution of koala observers by (a) home location (points) with population grid in study area, and (b) number of unique koala observers located within 5 km grid cells in the koala likelihood model.

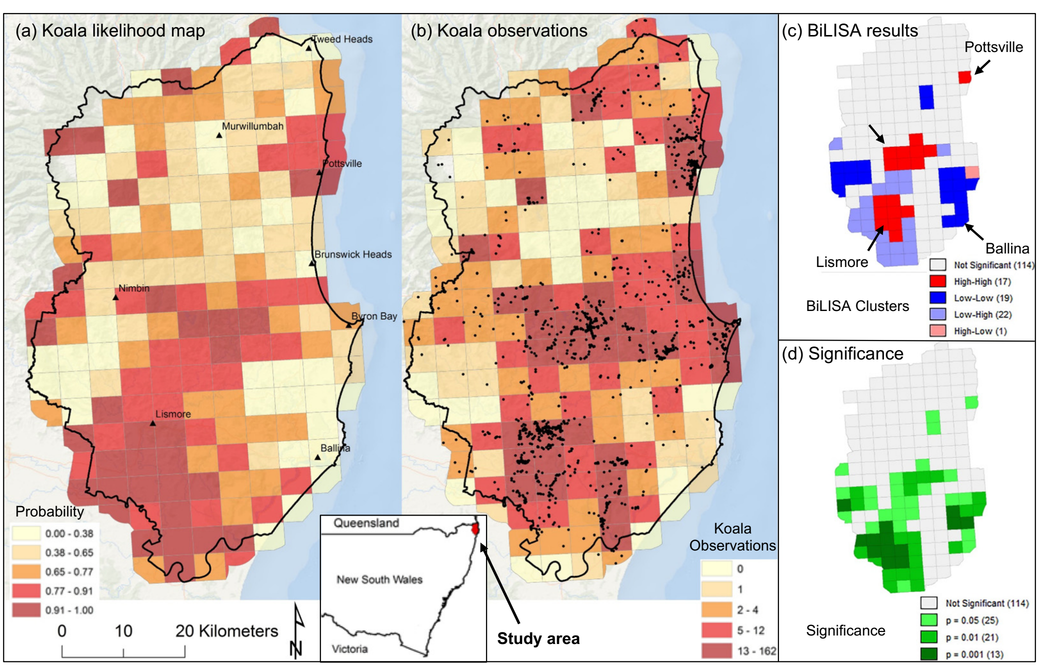

Fig. 2. Maps showing (a) Koala likelihood map with cell probabilities, (b) spatial distribution of koala observations from spatial survey (*weekly*, *monthly*, *yearly*, *once*, *dead/injured*) in the study area, (c) bivariate local indicators of spatial association (BiLISA), and (d) significance levels for BiLISA clusters. Cell probabilities and koala observations are categorized into quintiles for visual comparison.

observation accuracy as represented by koala cell probability values. The largest statistically significant bivariate correlations were found on the participant variables of *age*, *length of residence*, and self-rated *knowledge of koalas* (Table 3). The participant variables of *gender* and *distance from home* to observation were not significantly correlated with observation accuracy. All the regression models were statistically significant with Bonferroni corrections. The strongest predictive model was for *weekly* koala observations ($R = 0.52$, $p < 0.001$) followed by *dead/injured* observations ($R = 0.52$, $p < 0.001$). The weakest model was for *once* observations ($R = 0.31$, $p < 0.001$). The model for all observations combined was $R = 0.38$, $p < 0.001$.

The participant variables that best predicted cell probability values and standardized beta coefficients varied by the observation category model. The *combined* observations model had five significant predictor

Table 2
Presence/absence analysis for (a) spatial survey and (b) "Great Koala Count" with the likelihood model. Presence is one or more koala observations in the grid cell and absence is the lack of any observations.

(a) Great Koala Count[b]

			Absent	Present	
Likelihood Model	Absent	Count	11	0	11
		%	100.0%	0.0%	100.0%
	Present	Count	93	69	162
		%	57.4%	42.6%	100.0%
Total		Count	104	69	173
		%	60.1%	39.9%	100.0%
Model confidence levels for inconsistent cells		High	Medium	Low	Total
		27	18	48	93

(b) Spatial survey[a]

			Absent	Present	
Likelihood model	absent	Count	6	5	11
		%	54.5%	45.5%	100.0%
	present	Count	25	137	162
		%	15.4%	84.6%	100.0%
Total		Count	31	142	173
		%	17.9%	82.1%	100.0%
Model confidence levels for inconsistent cells		High	Medium	Low	Total
		6	3	21	30

[a] Phi coefficient = 0.25, $p < 0.01$.
[b] Phi coefficient = 0.21, $p < 0.01$.

variables and the *once* model had four significant predictor variables. Statistically significant predictor variables found in two or more of the six models were *knowledge of koalas* (5 models), *familiarity with the study area* (4), *age* (3), *length of residence* (3), and *education* (2). The *gender* and *distance from home* variables were not significant in any of the regression models while the *number of observations* was only significant in the *combined* model. Generalizing and interpreting the regression model results for all observations, older, more formally educated, long-term residents who were more knowledgeable about koalas made koala observations in locations with a higher likelihood of koala occurrence.

4. Discussion

This study examined the validity of crowdsourced wildlife (koala) observations from the two perspectives of *validity-as-accuracy* and *validity-as-credibility*. The *validity-as-accuracy* perspective analysed the accuracy of crowdsourced observations against a koala likelihood model using multiple measures of spatial concurrence while the *validity-as-credibility* perspective examined participant variables as potential sources of greater or lesser accuracy. There was significant spatial association between crowdsourced koala observations and the koala likelihood model. Where there were differences in the spatial results, there was lower confidence in the likelihood model due to fewer historical koala observations. Thus, there is the possibility that crowdsourced observations may represent more recent, changed conditions in the distribution or numbers of koalas within the study area. More accurate koala observations were contributed by older citizens with a higher level of self-rated knowledge of koalas, a higher level of formal education, and who had lived in the study area longer.

There are several important implications from this study. The first is that crowdsourced wildlife observations, if sufficient in number and

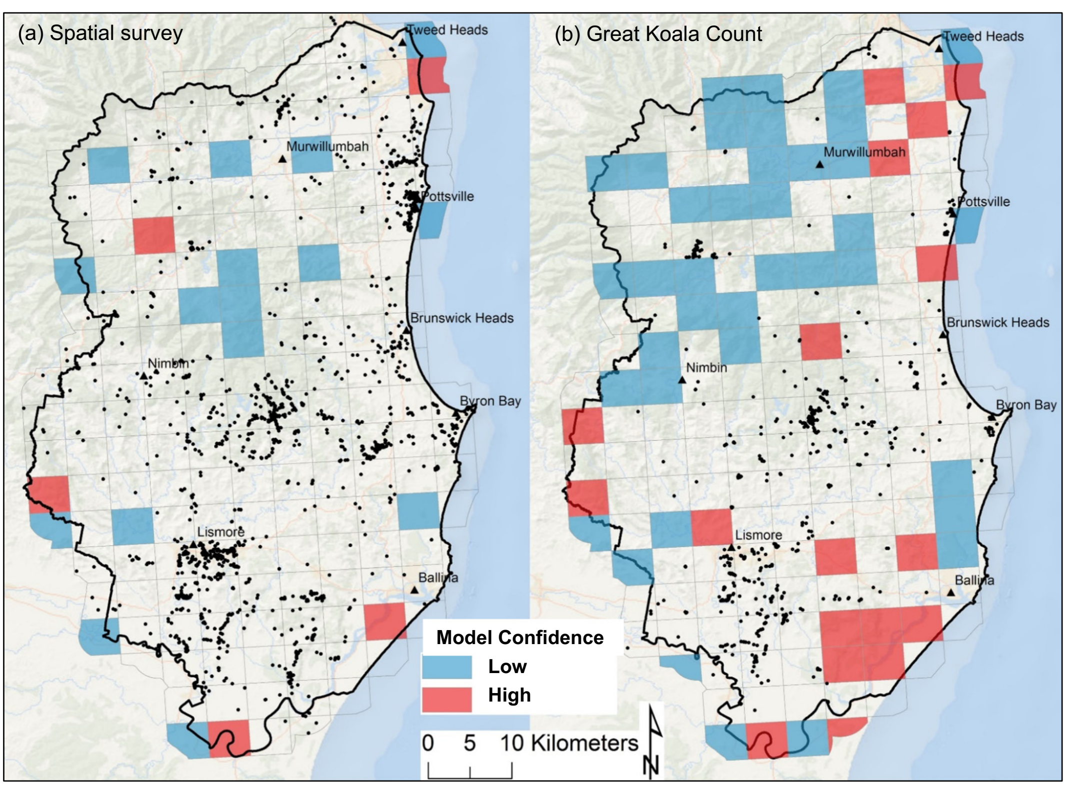

Fig. 3. Presence/absence analysis of koala likelihood model with citizen-based koala observations (black points) collected using two different methods: (a) Spatial survey, and (b) field-based "Great Koala Count". Grid cells with colour (red, blue) indicate koala presence in the likelihood model where there were no citizen observations. Blue cells indicate cells with low confidence in the model and red cells indicate high confidence. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Regression model results using participant variables to predict koala cell probability values. Akaike Information Criterion (AIC) used to select "best" model. Bivariate correlations, model fit, standardized beta coefficients, and significance levels computed for the best model.

	All observations	Weekly	Monthly	Yearly	Once	Dead/injured
Number of cases	1451	238	271	415	388	139
Number of individuals	334	107	135	152	157	78
Mean cell probability (standard deviation)	0.77 (0.21)	0.82 (0.21)	0.83 (0.17)	0.74 (0.23)	0.73 (0.21)	0.76 (0.19)
Bivariate correlations						
Age	0.18***	0.36***	0.20***	0.11*	0.17***	0.16*
Length of residence	0.29***	0.35**	0.33***	0.26***	0.19***	0.45***
Familiarity with study area	−0.03	0.03	0.15***	0.01	−0.02	0.03
Knowledge of koalas	0.32***	0.38***	0.42***	0.21***	0.25***	0.50***
Education	0.13***	0.16**	0.28***	0.09*	0.02	0.24**
Gender[a]	−0.02	−0.09	0.04	−0.02	−0.03	−0.07
Number of observations	0.11***	0.26***	0.09	0.07	0.14**	0.08
Distance from home	−0.04	0.14*	−0.07	−0.07	−0.00	−0.02
Regression subsets analysis using AIC						
Number of potential models as good as the best model[b]	8	3	6	10	6	7
Probability that best model is best approximating model[c]	16%	26%	20%	14%	17%	19%
Best model						
Model fit	R = 0.38 Adj. R^2 = 0.14***	R = 0.52 Adj. R^2 = 0.25***	R = 0.46 Adj. R^2 = 0.20***	R = 0.32 Adj. R^2 = 0.09***	R = 0.31 Adj. R^2 = 0.12***	R = 0.52 Adj. R^2 = 0.25***
Standardized beta coefficients						
Age	0.12***	0.33***	Excluded	Excluded	0.17***	0.12
Length of residence	0.15***	Excluded	0.17*	0.32***	Excluded	Excluded
Familiarity with study area	−0.12***	−0.16**	0.08	−0.11*	−0.18***	−0.09
Knowledge of koalas	0.21***	0.27***	0.22**	0.09	0.35***	0.44***
Education	Excluded[d]	0.08	0.18**	Excluded	−0.17*	0.10
Gender[a]	0.04	Excluded	Excluded	0.09	Excluded	Excluded
Number of observations	0.10**	0.08	Excluded	Excluded	0.10	0.08
Distance from home	−0.04	Excluded	Excluded	−0.07	Excluded	Excluded

[a] Point-biserial correlation where Male = 1, Female = 2.
[b] Based on change in AIC values less than two (Richards, 2005).
[c] Based on Akaike weights.
[d] Variables excluded in best model based on AIC criterion.
* Significance $p < 0.05$.
** Significance $p < 0.01$.
*** Significance $p < 0.001$.

geographic scope, can be used to cross-validate and update wildlife distribution models. Wildlife populations, such as the koala, are dynamic, especially in a study area experiencing significant pressures on the populations from loss of koala habitat, human-induced mortality (e.g., from cars and dogs), and the spread of infectious diseases (Rhodes et al., 2011; Goldingay and Dobner, 2014; McAlpine et al., 2015; Lunney et al., 2016).

There is a temporal lag between observation data and the models constructed to estimate the koala distribution. The crowdsourced observation data could be used to continuously update and refine the koala likelihood model with more current observations of koala locations, similar to the way that annual bird counts can be used to monitor populations of bird species (Butcher et al., 1990; Horns et al., 2018; Niven et al., 2004). In this case, the koala likelihood model could be updated with citizen koala observations to adjust cell probability values and confidence levels. Given the koala is one of Australia's favourite animals (Woods, 2000; Shumway et al., 2015), a more frequent crowdsourced koala observation program (e.g., biennial) could be effective in updating koala distributions in the region.

Another implication is that citizen characteristics influence the quality of spatial data contribution. With crowdsourcing applications, it may not be possible, or even desirable, to directly select participants based on personal characteristics to enhance data quality given the potential social value of engaging a broad and diverse cross-section of the general public in wildlife conservation. However, indirect targeting of participants is possible through advertising and promotion channels that contain a higher proportion of individuals with desirable attributes. An example would be targeting news and information programming in community media whose listener demographics favour older individuals with higher levels of formal education, or Facebook advertisements that target older residents in the region. Wildlife welfare groups such as "Friend of the Koala" would be expected to have individuals with a greater knowledge and awareness of koalas than the general public, although our data did not indicate greater self-rated knowledge of koalas than the rest of the volunteer sample.

The spatial-survey approach to geographic citizen science offers several advantages over the field-based, citizen-science data collection projects, such as the "Great Koala Count" in South Australia. One advantage is the required level of effort to participate in the project. For the spatial survey, the only requirement is that participants have access to the internet to record their observations on a website. In contrast, to participate in field-based observations, participants need to own a Smartphone, download an application to record the specific locations of the koalas, and then upload their data to a website (Sequeira et al., 2014). The additional level of effort to record observations would depend on participant engagement with the activity, ranging from highly active, where participants intentionally travel to specific areas to seek out koalas, to passive engagement where sightings are opportunistic based on the participant's normal lifestyle routine. A second advantage is the ability to obtain much broader geographic coverage of koala observations across a large study area. This is particularly important in a relatively low-density, rural landscape compared with Sequeira et al. (2014) which was largely city-based, and had a greater pool of potential participants to draw from. Both spatial social surveys and field-based observations will contain geographic bias based on participant location, but koala observations from spatial surveys are more likely to cover larger geographic areas, including locations that are more distant from population centres.

There are important limitations of spatial surveys compared to field observations. The most important limitation is the loss of spatial accuracy (resolution) in the recording of koala observations. Field studies use GPS-enabled devices to record locations while spatial surveys record locations using digital markers on a base-map. Field studies can achieve resolution within a few meters while spatial surveys are only likely to be accurate within a few hundred meters. This difference in resolution is not likely to be important when assessing regional geographic distributions (e.g., using 5 km grid cells) if the species in question has a large home range. In the case of the koala, home ranges cover many hectares and koalas regularly travel 100 s of meters per night (Goldingay and Dobner, 2014; Matthews et al., 2016).

A second limitation is that spatial surveys rely on participant memory recall for both the number of observations and locations, resulting in potential temporal and spatial inaccuracy of koala sightings. Lunney et al. (2016) applied the concept of a "forgetting curve" to adjust historical community koala observation data. The "forgetting curve" is a non-linear function in which people remember recent events more than older events (Averell and Heathcote, 2011). In this study, under-reporting of past koala sightings due to limitations in memory recall is likely to have occurred, but the magnitude is unknown. Under the assumption that more recent memories would be more accurate and comprehensive, one could posit that the koala mapping frequency categories of *weekly* or *monthly* may be more accurate than the categories of *yearly* or *once*. Indeed, the *weekly* and *monthly* observation categories were more highly correlated with likelihood model probabilities than the *yearly* or *once* categories, and the mean cell probabilities were significantly larger than the *yearly* and *once* categories. However, without additional information about the observations (e.g., the data/time of the koala observation), it would be difficult to estimate the loss of accuracy and completeness in koala observations associated with memory recall.

A further limitation of spatial surveys is the ambiguity regarding absence data. In this study, participants recorded the location of koala sightings, but not locations where no koalas were seen. Without explicit koala absence mapping by participants, there is ambiguity as to how to interpret the status of areas that do not have mapped locations. Our view is that the absence of mapped koala locations does not indicate the absence of koalas per se because the absence of observations could be explained by incomplete geographic coverage from crowdsourcing. Other researchers have noted the need to collect koala absence data in addition to koala presence data (Flower et al., 2016; Sequeira et al., 2014) to more accurately estimate koala distribution. An approach to absence data has been calculated for koalas by using other, well-known species, as markers for a location of a survey site (Lunney et al., 2009; Predavec et al., 2018).

5. Conclusion

There is strong evidence for the potential of citizen science to contribute to biodiversity research (Predavec et al., 2016; Theobald et al., 2015), which includes crowdsourced geographic citizen science. Yet a relatively small percentage of citizen science data actually reach publication, suggesting the growing citizen science movement is only realizing a small portion of its potential impact (Theobald et al., 2015). To be more effective, participatory mapping for koala conservation, and wildlife conservation in general, would benefit from implementing some of the following recommendations:

1. Broaden recruitment efforts to include household sampling, not just volunteers, to achieve greater geographical representation and study area coverage. This is especially important for rural areas with low population density. Although household survey response rates are typically low and continue to decline (Connelly et al., 2003; Harris and Goldingay, 2003), household recruitment remains an important means to obtain more representative geographic coverage in participatory mapping. The use of internet panels for participant recruitment can increase geographic coverage, but internet panels produce lower quality spatial data compared to other sampling methods (Brown et al., 2012; Brown, 2017).
2. Include absence markers as a component of the spatial survey to be mapped by participants. Absence data are important in estimating wildlife populations and distributions (e.g., Guillera-Arroita et al., 2015; Lunney et al., 2017). Absence mapping does not have to be extensive to be useful. For example, one could ask the participants to place five markers where they expected to see koalas, but did not. With the nearly 400 participants in this study, this minimal effort would have produced 2000 absence locations. However, as a caveat, perceived absence of koalas does not equal real absence.
3. Consider including other fauna sightings as part of the mapping protocol. The lack of absence data in the first NSW state-wide community koala survey in 1986–87 (Reed et al., 1990) presented problems in determining the distribution data. To overcome them, the comparable 2006 NSW survey by Lunney et al. (2009) included a selection of nine other species. The koala likelihood model uses other faunal sightings to generate koala probabilities. However, given that participant mapping effort is finite and increasing the number of spatial attributes to be mapped does not increase the amount of spatial data collected (Brown, 2017), the type and number of markers to be included necessarily involves survey design trade-offs. This study also included the mapping of land use preferences in the region to engage participants. Some of these mapping attributes would need to be eliminated from the mapping interface to collect other faunal data. Geographic citizen science projects involving observations of species other than koalas may confront similar trade-offs. Here, the selection of the other species matters – the animals have to be important (endangered or a pest), unique (koala, platypus), and charismatic (or loathed).
4. Enhance the participatory mapping interface design and user support. The degree of public engagement depends significantly on system usability and the participants' satisfaction with using the system (Meng and Malczewski, 2010). Although mapping in our study was designed to be simple and used a familiar "drag and drop" marker procedure on the most widely used Google Maps interface, a significant number of participants (> 30) quit the application after identifying their home location, the first marker requested to be mapped. This "drop-out" of participants may represent frustration with the mapping interface. This application, and geographic citizen science projects in general, would benefit from a user-centred design approach (Haklay and Tobón, 2003) that includes a systematic useability study before implementation. Further, Newman et al. (2010) provide guidelines to improve citizen science web mapping applications.

Given that the NSW government, in mid-2018, has committed $45 million to koala conservation through its recently-released koala strategy, and the Commonwealth government is committed to preparing a koala recovery plan for the States (ACT, NSW, Queensland) where the koala is listed by the Commonwealth government as vulnerable, it is crucial to provide the best scientific advice possible. However, it is evident that pressure groups, local biases, or shallow committee interpretations can lead to unbalanced decisions for action and the recommendations for the allocation of funds (Shumway et al., 2015). The approach to spatially-explicit, citizen science explored in this study provides a reliable and repeatable means of resolving these problems. However, while citizen science can contribute to identify species presence and may help identify changes in distribution, it should augment, not replace long-term systematic scientific surveys and monitoring.

The koala is a charismatic species, and it can serve a broader conservation and management function than just its own survival (Lunney, 2012). The location we selected for our study – the north coast of NSW-has almost every koala conservation and management problem that exists (McAlpine et al., 2015), except for crippling droughts as experienced in the drier regions west of the Great Divide (Lunney et al., 2012) and overpopulation, but climate change is gradually shrinking coastal koala populations in NSW (Lunney et al., 2014). Given the great geographic spread of the koala from north Queensland to South Australia (Adams-Hosking et al., 2016), detailed, on-ground, labour-intensive surveys are not feasible except in a few locations. Geographic citizen science, as outlined in this study, provides a way forward so that local government, such as the four LGAs in this study, or each State government, or all the range States simultaneously, can gain a reliable grasp of the conservation and management issues facing koalas. An important contribution of our study was to provide evidence that citizen science spatial surveys are a useful investment when considering options for allocating time and money to the raft of conservation and management problems confronting the koala.

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