Recreational and tourism value of healthy rivers
Extension A
Final Report

Water & Environment Research Program Theme 4:
Research Question 12.2 Extension A
Deliverable 12.2.6

Report prepared by

James C.R. Smart[1,2]

Jeremy Harte[1]

[1]Australian Rivers Institute, Griffith University, Brisbane

[2]School of Environment and Science, Griffith University, Brisbane

For:

Murray–Darling Water and Environment Research Program

October 2024

An Australian Government Initiative

Funded through the Murray–Darling Water and Environment Research Program

Version	Issue Date
V1.0	21st October 2024
V1.1	29th October 2024
V1.2	5th November 2024

Approvals

Author signature: .... Date 05/11/2024

Author Name: Associate Professor James C. R. Smart

Author signature: .... Date 05/11/2024

Author Name: Mr Jeremy Harte

Author contact details

☏ 07 3735 5290

✉ j.smart@griffith.edu.au

https://www.griffith.edu.au/australian-rivers-institute

Report citation

Smart, J. C. R. and Harte, J. 2024. Murray-Darling Basin Authority Water & Environment Research Program Theme 4: Research Question 12.2, Deliverable 12.2.6 *Recreational and tourism value of healthy rivers: Extension A – Final Report*. Australian Rivers Institute, Griffith University, Brisbane.

Contents

List of Figures

List of Tables

Abbreviations

ABS	Australian Bureau of Statistics
AIC	Akaike Information Criterion. A metric used to compare the fit of regression models.
BuD	'Birder user Day' derived from geo-located, time-stamped bird species lists from the eBird.org citizen science website.
eBird	A citizen science website on which bird watchers can log bird species checklists. Each checklist is time-stamped and geo-located. (eBird, Cornell Lab of Ornithology, Ithaca, New York: www.ebird.org)
MDB	Murray-Darling Basin (also referred to as 'the Basin')
MDBA	Murray-Darling Basin Authority
MD WERP	Murray-Darling Water and Environment Research Program
NB	Negative binomial distribution and the negative binomial count data regression model which uses a negative binomial distribution for its count data dependent variable.
PuD	'Photo user Day' derived from geo-located, time-stamped photo posts from the Flickr.com photo posting website.
VGI	Volunteered geographic information

Acknowledgements

The authors acknowledge and thank the Murray-Darling Basin Authority's Water and Environment Research Program (WERP) for providing funding for this research.

eBird citizen science data were obtained for research use, with authorization (see Appendix 1), from the Cornell Lab of Ornithology, 159 Sapsucker Woods Road, Ithaca, NY, 14850, USA; eBird@cornell.edu (Sullivan et al., 2014). The authors particularly thank Jenna Curtis (eBird Project Leader) for helpful comments and suggestions.

This research was conducted in accordance with Griffith University Human Research Ethics approval Ref No: 2023/963.

Executive Summary

Expenditures associated with recreational activities such as bushwalking, boating, swimming, fishing and birdwatching provide profit opportunities for recreational businesses and their supply chains across the Basin. Additionally, recreational visitors receive enjoyment and benefits to their mental and physical health and well-being from their recreational activities. Economics posits that the benefit a rational visitor receives from a recreational visit should exceed the cost they incur to make that visit. This individual-level excess of benefit received over cost incurred is termed the *consumer surplus* arising from a visit to the recreation site.

Consumer surplus per visit is an important metric because, when combined with records of visitor numbers, it reports the 'added value' a recreation site delivers to visitors, over and above the costs incurred in visiting. The net value visitors obtain from visiting a recreation site can be used in social cost benefit analysis (Boardman et al., 2001) to explore whether the benefits from increased visitation exceed the costs incurred in modifying site management or enhancing site condition to attract additional visitors.

Direct surveys are conventionally used to estimate site-specific recreational consumer surplus, but the need for adequate sample sizes and representative sampling make this time consuming and costly. This study uses volunteered geographic information (VGI) in the form of eBirder user days (BuDs) from anonymous birdwatchers who post time-stamped, geo-located bird species sighting lists to the eBird citizen science website (www.ebird.org). This information is used to apply the *travel cost method* to estimate the average per person, per day consumer surplus obtained by birdwatchers visiting the Coorong, or the Gunbower National Park together with Kondrook-Perricoota State Forest (hereafter Gunbower, Koondrook, Perricoota (GKP)). An equivalent approach was attempted using photo user days (PuDs) from anonymous photographers who post time-stamped, geo-located photographs to the Flickr photo posting website (www.flickr.com); however, data sizes proved insufficient for robust estimation.

The central objective of the research is to compare consumer surplus estimates obtained using BuD-derived visit data with published consumer surplus results for the same sites produced using conventional on-site or off-site visitor surveys (Cheesman et al., 2021; Dyack et al., 2007; Rolfe and Dyack, 2019, 2011, 2010). VGI-derived data have been used for recreational valuation at sites overseas (e.g., Kolstoe et al., 2022; Kolstoe & Cameron, 2017; Sinclair et al., 2018, 2021, 2022; Jayalath et al., 2023). However, to the best of the authors' knowledge, the research reported here is the first time VGI-derived data have been used to estimate per visitor, per day consumer surplus for recreation sites in Australia.

Results from our BuD-derived count data models that regress the number of eBirder visit days to the Coorong and GKP on cost per visit day, along with proxies for age and household income, demonstrate that BuD-derived visitation data shows some promise as a method to estimate the consumer surplus birdwatchers obtain from visiting a recreation site in the Murray-Darling Basin.

Our BuD-derived consumer surplus estimates aligned relatively well with results from the literature at GKP but considerably less well at the Coorong. At GKP, the 95% confidence intervals around our consumer surplus estimates overlapped those reported in the literature, although our mid-point estimates (between \$158 and \$232, depending on the exact data used) were 50%–60% higher. Conversely, at the Coorong our 95% confidence intervals did not overlap those in the literature, and our mid-point estimates were at least three times higher than the previous studies (after adjusting all valuations to April 2024 AUD\$).

These differences in valuation performance may be partly because the limited set of driving variables included in the current iteration of our BuD-derived datasets was not sufficient to model differences in eBirder visitation behaviour at the two sites. Further, the fit of the regression models, and therefore the robustness of the consumer surplus estimates obtained, differed considerably between the two sites, with the model fit to Coorong data being particularly poor. A high level of data attrition occurs

when travel cost methodologies that have been tailored to the strengths of traditionally collected data are applied to VGI-derived data with minimal modification. This likely contributes to the model fitting difficulties experienced with the Coorong data.

The economist and statistician Harold Hotelling first suggested the travel cost method for estimating the value of national parks in a letter to the Director of the U.S National Parks Service in 1947 (Alvarez and Larkin, 2010; Arrow and Lehmann, 2005). The method has since benefited from almost 80 years of development and refinement. The research findings reported here suggest that travel cost-based valuations with VGI-derived data show considerable promise, but there undoubtedly remains considerable scope for further innovation and improvement to produce the most informative and reliable valuation estimates from this new data source.

Three particular challenges were identified in applying standard travel cost valuation methods to VGI-derived data: high levels of data attrition, which reduces the size of regression datasets and decreases the precision of consumer surplus estimates, the absence of direct information on individual-specific socio-demographics and behaviour of visitors, and the absence of information on the number of visitors on a trip, which may lead to inflated per person estimates of consumer surplus. We suggest how each of these challenges might be addressed by modifying data collation and analysis methodologies to make best use of the advantages of VGI data, compared with data collected by traditional methods.

These suggestions for methodological improvements when applying the travel cost method to VGI-derived data provide several opportunities for further research:

- Use of categorical variables that identify visit context (for example, weekend visit or holiday season visit) to improve the precision of consumer surplus estimates in our Coorong and GKP models.
- Opportunities to increase dataset size by identifying plausible trip origins from ‘on the road’ eBird postings in the days immediately prior to an eBird post at the focal recreation site.
- Opportunities to incorporate group size in randomly re-sampled datasets, by drawing on group size data from the MD WERP RQ12.2 Extension B birdwatching survey with members of Birdlife Australia’s local birdwatching groups.
- Opportunities to implement site choice models across multiple wetlands in the Basin to investigate how environmental watering programs (together with differences in bird species abundance, diversity and rarity) affect the consumer surplus birdwatchers receive from visiting a site. This ability to assemble visitation data and conduct consumer surplus valuation for multiple sites across the Basin is a key advantage of VGI-derived data, suggesting considerable opportunities for further research in this direction.
- Suggestions by Cameron and Kolstoe (2022a) to explore how auxiliary population samples might be used to make eBird-derived valuation results more useful for policy makers.

1. Research Objective

RQ12.2 Extension A: Objective

Murray-Darling Water and Environment Research Program, Theme 4, Research Question 12.2 Extension A sought to:

- Use quasi-home locations derived from anonymous individuals who post digital photographs to the Flickr website (www.flickr.com) or anonymous birdwatchers who post bird species sighting lists to the eBird citizen science website (www.ebird.org) to estimate the net benefit (or 'consumer surplus') obtained by visitors to the Coorong and Gunbower – Koondrook – Perricoota via the travel cost method.
- Compare the net benefit results obtained using Flickr- and eBird-derived visit data with published results for the same sites obtained using conventional sampling methods, drawing on prior literature (Cheesman et al., 2021; Clara et al., 2018; Dyack et al., 2007; Rolfe and Dyack, 2019, 2011, 2010).

This Report describes findings from MD WERP RQ12.2 Extension A research.

Section 2 provides a brief overview of approaches for estimating the economic value of recreation, describes prior estimates of recreation value for sites in the Basin, and briefly describes the approaches used to deliver the intended objectives of RQ12.2 Extension A. Section 3 describes the methodology used for each step in the analysis. Collated data are described in Section 4. Analysis results are presented in Section 5. Section 6 provides a discussion and concludes.

2. Background

2.1. The economic value of site-based recreation

Bushwalking, boating, swimming, fishing, birdwatching and other forms of recreation are undertaken at multiple locations across the Basin. Expenditures associated with recreational activities provide profit opportunities for businesses that supply recreation services (e.g., boat and equipment hire, guided recreational experiences), accommodation, food and beverages to visitors, and further profit opportunities for businesses that supply goods and services to recreational businesses. Additionally, visitors receive enjoyment and benefits to their mental and physical health and well-being from their recreational visits. Neo-classical economics posits that the value of the benefit received by a rational recreational visitor should exceed the cost the visitor incurs in making their recreational visit. This individual-level excess of benefit received over cost incurred is termed the *net benefit*, *consumer surplus* or *access value* arising from the recreational visit at a particular recreation site (Haab and McConnell, 2002). The *average per person, per visit consumer surplus* is the usual statistic produced by a travel cost valuation at a recreation site.

Consumer surplus per visit is an important metric because, when combined with estimates or records of visitor numbers, it reports the 'added value' a recreation site delivers to visitors, over and above the costs incurred in visiting. The net value visitors obtain from visiting a recreation site can be used in social cost benefit analysis (Boardman et al., 2001), to explore whether the benefits from increased visitation exceed the costs incurred in modifying site management or enhancing site condition to attract additional visitors.

2.2. Prior valuations of recreation at Basin sites

The per person, per visit consumer surplus has been estimated for two recreation sites in the Basin (Figure 1): the Coorong (Dyack et al., 2007; Rolfe and Dyack, 2019, 2011, 2010), and Gunbower National Park together with Koondrook-Perricoota State Forest (Cheesman et al., 2021). At the Coorong, Rolfe and Dyack collected visitation data in 2006 and 2013 via 'drop off and collect' on-site visitor surveys. Rolfe and Dyack's on-site visitor surveys asked about the number of visits respondents made to the Coorong over the two-year periods preceding 2006 and 2013, producing 783 and 778 usable observations, respectively. At Gunbower – Koondrook – Perricoota (hereafter GKP) Cheesman et al. collected data in 2021 via online, off-site surveys of 1,300 individuals in NSW and the ACT, 1,100 individuals in Victoria and 560 individuals in South Australia. Cheesman et al's online surveys asked about the number of day visits and overnight stays made by domestic visitors to Gunbower National Park and (separately) Koondrook-Perricoota State Forest between 2010 and 2021, to produce estimates of the number of domestic visitor days and corresponding consumer surpluses per visit to the two sites in 2010 and 2015. The per person, per visit consumer surplus valuations produced from best-fitting travel cost models from the Rolfe and Dyak and Cheesman et al. studies are shown in Table 1.

Figure 1: Location of the Coorong, Gunbower National Park and Koondrook-Perricoota State Forest.

Table 1: Per person, per visit consumer surplus valuations produced for visits to the Coorong (Rolfe and Dyack, 2019) and GKP (Cheesman et al., 2021).

Coorong from Rolfe and Dyack, (2019)		
Coorong	Consumer surplus per visit ($)	
Year	Mid-point	95% confidence interval
2006	$134.91	($119.11 – $154.91)
2013	$211.15	($184.18 – $250.73)
2006 & 2013 combined	$139.87	($131.79 – $149.27)
GKP from Cheesman et al. (2021)		
Gunbower	Consumer surplus per visit ($)	
Year	Mid-point	95% confidence interval
2010	$91.17	($30.39 – $182.34)
2015	$80.20	($26.73 – $160.39)
Kondrook-Perricoota	Consumer surplus per visit ($)	
2010	$94.74	($31.57 – $189.47)
2015	$92.78	($30.93 – $185.57)

Note: Valuations were reported originally in 2013 AUD$ for the Coorong and 2021 AUD$ for GKP. The valuations in Table 1 are reported in April 2024 AUD$, converted via the Consumer Price Index (Australian Bureau of Statistics, 2024).

2.3. Site-based recreation valuation using volunteered geographic data

Figure 2 outlines the research approach for valuing average per visit consumer surplus for visits to the Coorong and GKP using volunteered geographic data, which are then compared to prior estimates in the literature produced using conventional data collection.

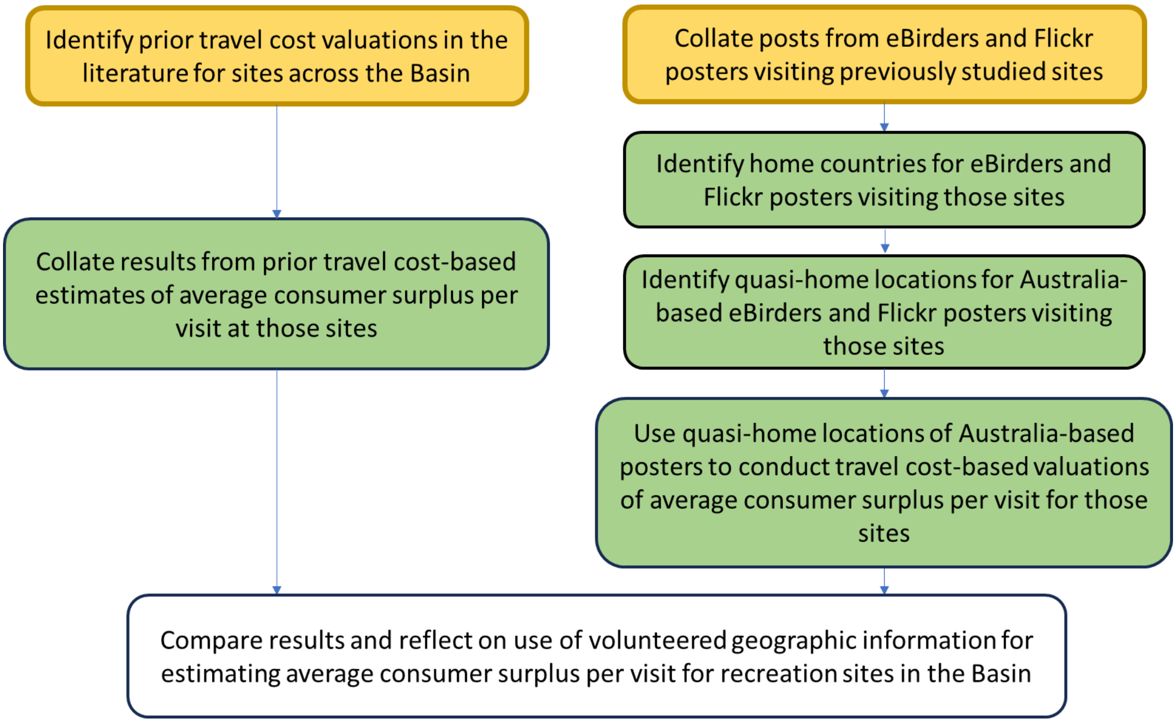

Figure 2: Research approach for comparing estimates of average per visit consumer surplus derived using volunteered geographic data and consumer surplus values in the literature produced from site-based data collection.

Flickr-derived PuDs have been used as the basis for estimating consumer surplus values for recreation sites in several papers in the literature, with works by Sinclair being particularly prominent (Sinclair et al., 2022, 2021, 2020a, 2019, 2018). Sinclair's papers developed methodologies for determining home country, and home location within a country, from PuD-derived data, before applying standard travel cost methodologies to PuD-derived datasets.

Literature contains fewer applications of the travel cost method to eBird-derived data. Kolstoe and Cameron, and Jayalath et al. used random utility models to conduct multi-site travel cost analyses to quantify the visitation value contributed by site-specific attributes such as bird species richness at birdwatching locations in Oregon and Washington states in the USA, and the province of Alberta in Canada, respectively (Jayalath et al., 2023; Kolstoe et al., 2018; Kolstoe and Cameron, 2017). These eBird-derived valuations used eBirders' self-stated home locations as trip origins because self-stated home postcodes were available previously, prior to a revision of privacy protocols for the eBird citizen science website. Cameron and Kolstoe have also investigated use of auxiliary samples to expand the usefulness of eBird-derived site-specific valuations for policy makers (Cameron and Kolstoe, 2022a; Kolstoe et al., 2022).

3. Methods

3.1. Recreational valuation via the travel cost method

The average per person, per visit consumer surplus for a recreation site can be derived using travel cost methods (Haab and McConnell, 2002; Martínez-Espiñeira and Amoako-Tuffour, 2008). Travel cost methods estimate a *demand curve* for visits to a recreation site from data derived from a sample of visitors to the site on how the number of visits to the site reduces as travel distance – and thus also travel cost – to the site increases. The demand curve describes the relationship between the cost of a good and the level of demand for that good: all else being equal, the number of visits to a recreation site will be expected to decrease as the cost incurred in visiting the site increases, or – equivalently – as the 'daily price of recreation' at the site increases for a recreational visitor (Figure 3). An average per person, per visit consumer surplus from a recreational visit to the site can be derived from that estimated demand curve (see Appendix 4 for the mathematical derivation).

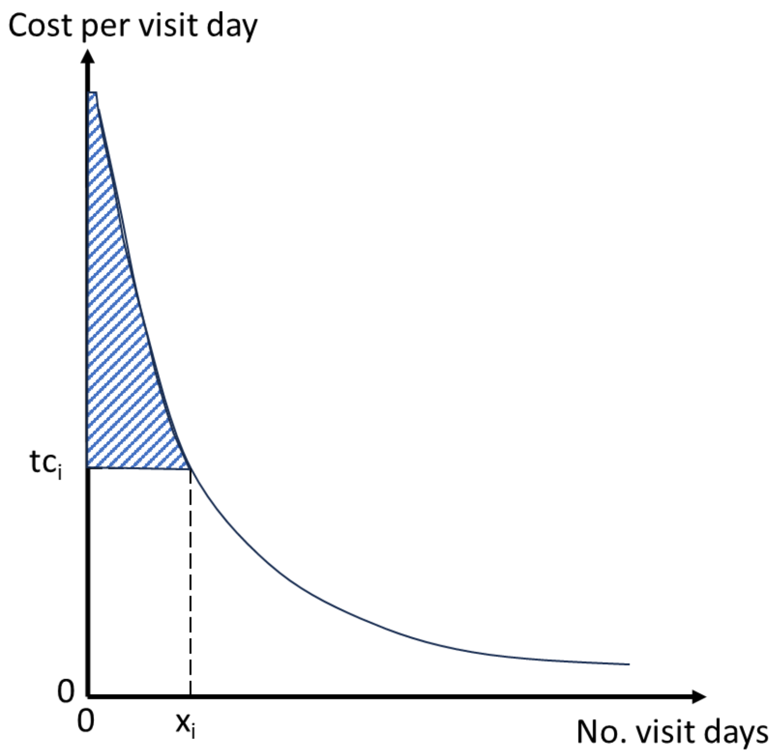

Figure 3: A demand curve for the number of visit days an individual visitor would be expected to make to a recreation site as the cost they incur per visit day varies.
Here visitor i incurs a cost tc_i per visit day and spends x_i visit days at the site. The consumer surplus visitor i derives from visiting the site is shown by the blue shaded area.

A demand curve for the recreation site can be estimated from data on the number of recreational visits individuals make to a site, the cost each individual incurs in making those visits, and – where available – other factors that might affect an individual's preferences for the recreational experience available at the site (e.g., the individual's age, income, family context, preferred recreational activities).

In traditional travel cost analysis, data on travel costs, number of visits made to the site, and relevant individual attributes are collected via surveys with recreational visitors. Data collection can either be conducted on-site (via 'car park surveys') or off-site (via online surveys of the wider population, only some of whom will have visited the recreation site). However, when adequate sample sizes and representative sampling are required, direct survey approaches are time consuming and costly, particularly if data are to be collected at multiple sites. Consequently, data volunteered by members of the public via social media (termed Volunteered Geographic Information

(VGI) (Cameron and Kolstoe, 2022b; Goodchild, 2007)) are being used increasingly as a data source to quantify an overall visitation rate (e.g., (Teles da Mota et al., 2022)), spatial and temporal variation in visitation (Hausmann et al., 2019), visitor activities, experiences and sentiment (Bhatt and Pickering, 2022), and for estimating the demand for and valuation of visitor experiences (Jayalath et al., 2023; Kolstoe and Cameron, 2017; Sinclair et al., 2022, 2020b, 2018).

In this study, VGI in the form of photo user days (PuDs) derived from geo-located and time-stamped photo posts to the photo posting website www.flickr.com (Ghermandi, 2022; Tenkanen et al., 2017; Wilkins et al., 2021), or birder user days (BuDs) derived from geo-located and time-stamped bird species lists posted to the citizen science website eBird (www.ebird.org) (eBird, 2021; Sullivan et al., 2009) provide a substitute for on-site data, helping determine the number and duration of visits an individual Flickr photo poster or eBird species list poster ('eBirder') made to the site over the study period.

The steps shown in the right-hand section of Figure 2 enable a home country and subsequently a quasi-home location to be estimated for Australia-based Flickr photo posters or eBirders. Travel distance, travel time and thus travel cost can then be estimated by assuming the quasi-home location is the origin for trips to the recreation site. An accommodation cost can be added for visits that comprise multiple consecutive days at the site, and thus an estimated cost per visit day at the site can be calculated for a visiting individual Flickr photo poster or eBirder. Broad-brush estimates for individual-specific age and household income can also be derived using census data on median age and household income at the quasi-home location (Sinclair et al., 2022).

Once data has been assembled on the number and duration of trips, together with travel and accommodation cost, the cost incurred per site visit day can be calculated. The number of visit days on-site can then be regressed against cost per visit day, proxy age and proxy household income to estimate a demand curve for visits to the site (Haab and McConnell, 2002; Martínez-Espiñeira and Amoako-Tuffour, 2008; Rolfe and Dyack, 2019). The estimated regression coefficient for cost per visit day determines the instantaneous slope of the fitted demand curve for visit days at the recreation site (Figure 3). Given the mathematical form of the fitted regression line, the average consumer surplus per visit day across the visitor sample can be obtained from the reciprocal of the estimated regression coefficient for visit cost (Haab and McConnell, 2002; Martínez-Espiñeira and Amoako-Tuffour, 2008; Rolfe and Dyack, 2019). See Appendix 4 for the mathematical derivation.

The methodology for conducting a travel cost method using PuDs or BuDs as the data source comprises a combination of data collation, data processing, and regression analysis in the sequence shown in the right-hand column of Figure 2.

3.2. Initial data collation: PuDs and BuDs for the Coorong and GKP

Geo-located, time-stamped photo posts on Flickr have been particularly widely used to produce proxies for visitation rate. Recent reviews by Ghermandi (2022) and Wilkins et al. (2021) generally found acceptable levels of correlation between geo-located Flickr photo-posts and separate assessments of visitation rate from, for example, separately administered site-based surveys. Use of PUDs as a proxy for visitation rate has been found to be reasonably reliable (Ghermandi, 2022; Sinclair et al., 2020c), although reliability can be affected by factors such as the overall popularity of the location, the age profile of visitors to that location and temporal variation in the popularity of the social media site.

Geo-located, time-stamped bird sighting checklists on the eBird citizen science website (https://ebird.org/home) (eBird, 2021; Sullivan et al., 2009) have also been used as a source of VGI in visitation research (Cameron and Kolstoe, 2022a; Guilfoos et al., 2023; Jayalath et al., 2023; Kolstoe and Cameron, 2017). The eBird site operators (Cornell Lab of Ornithology) facilitate and encourage use of eBird data for scientific research and have granted permission for eBird data to be used in this project (see authorisation email in Appendix 1). A recent special issue of the Ecosystem Services journal is dedicated to future opportunities for use of crowd-sourced VGI data in cultural ecosystem service assessments (Langemeyer et al., 2023).

3.3. Determining 'home country' for PuD or BuD posters

Following the analysis steps shown in Figure 2, a home country is estimated for PuD and BuD posters who visited the Coorong and GKP. Home country locations are estimated (separately for PuDs and BuDs) from the locations of all PuD or BuD posts by anonymously ID-numbered Flickr and eBird users in 2-year window(s) preceding their PuD or BuD post(s) from the Coorong or GKP during the case study duration. Flickr-derived PuDs from the Coorong or GKP were collated between January 2000 and January 2022 (22 years), and eBird-derived BuDs were collated between January 2000 and January 2024 (24 years).

Home country is assigned as follows. The number of BuDs or PuDs are counted in each country the visitor posted from during the 2-year window(s) preceding their PuD or BuD post(s) from the Coorong or GKP. A home country is assigned to that visitor if they posted on at least 20 PuDs or BuDs in total in the 2-year window *and* if the number of PuDs or BuDs posted from the country in which they posted most often is at least *three times higher* than the number of PuDs or BuDs posted from the country with their second-highest number of PuD or BuD posts. These are stricter criteria for determining home country than others that have been used in the literature when home country location has not been volunteered directly by the anonymous individual who provided the VGI, or when privacy conditions prevent release of such information (as is the case currently for eBird). For example, Sinclair et al. (2022) assign home country based solely on the country in which a Flickr poster accrued most PuDs across their entire library of public Flickr photographs. By using stricter home country selection criteria, we assign home country with more certainty but must discard visitors for whom home country cannot be determined. This is the first step in a continuing sequence of data attrition.

Visits from international or long-distance visitors are frequently discarded from travel cost analyses in the literature (Beal, 1995; Fleming and Cook, 2008; Martínez-Espiñeira and Amoako-Tuffour, 2008). In our current iteration of the travel cost methodology, visitors with home countries other than Australia are discarded from our analysis as we assume that a visit to the Coorong or GKP was not the underlying motivation for their visit to Australia. (In the Discussion section we describe an alternative approach which does not immediately discard overseas visitors in this initial step.)

3.4. Determining quasi-home location for Australia-based PuD or BuD posters

Having estimated each Flickr or eBird poster's home country, a quasi-home location is identified for Australia-based Flickr and eBird posters who posted BuDs or PuDs from the Coorong and/or GKP during the respective 22-year and 24-year case study periods. Quasi-home locations for Australia-based Flickr and eBird posters are estimated separately for PuDs and BuDs using the locations of all Flickr photo posts or eBird species list posts in Australia by anonymously ID-numbered Flickr and eBird users in 2-year windows preceding their PuD or BuD post(s) from the Coorong or GKP.

Quasi-home locations for Australia-based PuD or BuD posters are assigned as follows, across a 700km^2 hexagon grid – see Figure 4 for a diagrammatic representation for BuDs.

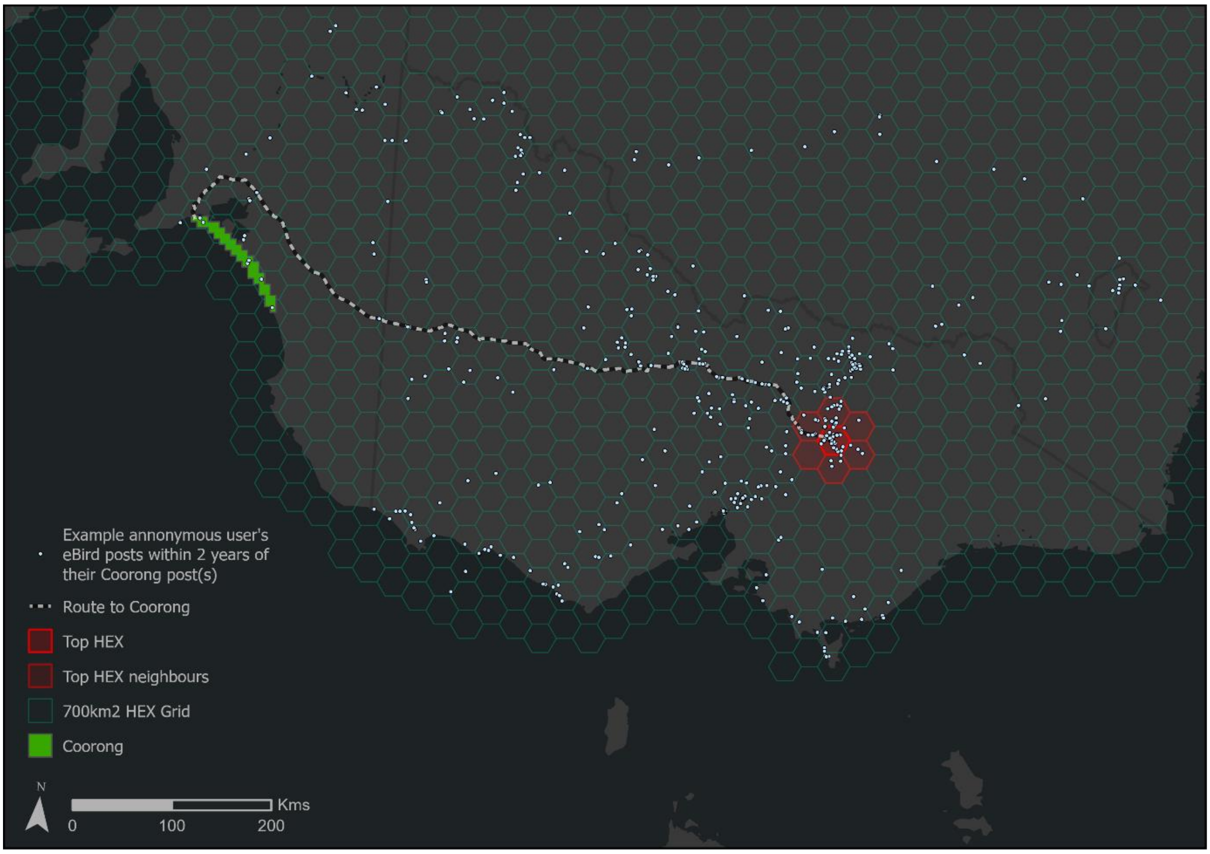

Figure 4: Estimation of quasi-home location via BuD posts per 700km^2 gridcell.

Australian BuDs are collated for individual Australia-based eBird posters within 2-year widows of the date(s) when they posted a BuD(s) from the Coorong or GKP. BuDs per 700km^2 grid cell are counted for the individual eBirder. The hex grid cell containing the highest number of BuDs is identified, and the number of BuD posts in that 'top' hex grid cell are counted together with the number of BuD posts in the six hex grid cells neighbouring the top hex grid cell (Figure 4). This broadly follows the standard approaches for assigning home location from Flickr-derived VGI in the literature (Ghermandi, 2018; Sinclair et al., 2022, 2020a, 2018). However, as was the case for home country, here we adopt stricter criteria for assigning quasi-home location. This is because in our current travel cost iteration home location is assumed to be the origin for trips to the Coorong and GKP. Consequently, through its impact on travel distance and travel cost, quasi-home location is highly influential over the valuation results produced. Furthermore, since some eBirders post bird species listings very regularly, often several times per week, eBird-derived BuDs can potentially provide a very clear indication of likely home location. For these reasons we use three levels of stringency in assigning quasi-home location to explore how valuation results are affected by reducing uncertainty surrounding quasi-home location whilst the size of the dataset for analysis reduces because of increasing data attrition.

Our most stringent criteria for assigning a quasi-home location require that the top hex grid cell and its six bordering grid cells contain 60% of all BuDs posted during the 2-year time window *and* the maximum time gap between posts in that seven-cell neighbourhood is no longer than five days ('most stringent criteria'). Less stringent criteria for assigning quasi-home location are 50% of all BuDs posted and a maximum time gap between posts of seven days ('moderately stringent criteria'), or 40% of all BuDs posted and a maximum time gap between posts of ten days ('least stringent criteria').

Quasi-home locations for PuD and BuD posters who visited the Coorong or GKP are assigned using all three levels of stringency. Data attrition increases as fewer PuD or BuD posters are assigned a quasi-home location at higher levels of stringency.

3.5. Calculating number of visit days at the recreation site

A Flickr photo poster or eBirder posting on consecutive PuDs or BuDs indicates a multi-day visit. An advantage of using PuD- or BuD-derived visitation data (compared with traditional travel cost data collection methods) is that multi-day visits can be identified and their duration recorded. The number of single-day visits and the number and duration of multi-day visits can be counted for each visitor via time-stamped PuD or BuD data. The number of visit days each individual makes to the recreation site, and the corresponding per day visitation cost (see Section 3.7), are two key elements of data in travel cost analysis.

3.6. Calculating travel cost

Travel cost is calculated by finding the travel distance and travel time through the Australian road network from a visitor's quasi-home location to the Coorong or GKP (as relevant). Travel is assumed to be by private car. Travel cost is taken to comprise the cost incurred in operating the vehicle and the opportunity cost of travel time. Following Rolfe and Dyack (2019) and Cheesman et al. (2021), vehicle operating cost is calculated using the FY2024/25 Australian Tax Office mileage rate ($0.88/km) and following standard practice in the travel cost literature (Martínez-Espiñeira and Amoako-Tuffour, 2008; Parsons, 2013; Rolfe and Dyack, 2019), the opportunity cost of travel time is costed at one third of the May 2023 Australian average weekly wage (assuming a 36-hour working week) (Australian Bureau of Statistics, 2023). The resulting opportunity cost of travel time is $13.79/hour.

3.7. Calculating cost per visit day

An accommodation cost of $150 per night (AUD$ 2024) is assumed for multi-day visits as this was the median accommodation cost reported by eBird users in the survey of Birdlife Australia local group members conducted as part of MD-WERP RQ12.2 Extension B. A cost per visit day can then be estimated for single-day visits (comprising solely travel-related costs from the quasi-home location), and for multi-day visits (comprising travel-related costs from the quasi-home location plus accommodation costs incurred over a visit of known duration).

A disadvantage of using PuD- or BuD-derived visitation data is that the number in the travelling group cannot be determined. Lacking this information, we assume that all visitors travel as individuals.

3.8. Multi-purpose trips

A fundamental assumption underlying the travel cost method is that the expenditure a visitor incurs in visiting a recreation site provides a lower-bound estimate of the value they receive from their recreational experience at the site. Trips undertaken for multiple purposes and/or trips in which multiple sites are visited are therefore problematic because the costs incurred are split across multiple outcomes or experiences. Multi-purpose trips are generally screened out from travel cost data that have been collected by traditional methods through including questions about trip purpose and trip destination(s) in the data collection survey (Dyack et al., 2007; Rolfe and Dyack, 2019, 2011).

PuD- and BuD-derived data typically indicate a high proportion of single-day and two-days visits. However, without detailed investigation of anonymous photo poster's and eBirder's posting history, it is difficult to determine which of these single- or two day-visits are likely to be part of a multi-purpose or multi-destination trip. Single- or two-day visits that are incorrectly assumed to be single-destination trips to the focal recreation site are particularly problematic when travel costs are constructed based on quasi-home location as this could lead to infeasibly high travel costs which – after regression analysis – will produce implausibly high consumer surplus estimates.

Here we guard against this possibility by screening single-day and two-day visits via upper limits on travel times. For inclusion in the regression data, we impose a 7-hour maximum round-trip travel time on single-day visits, and a 16-hour maximum round-trip travel time on two-day visits, and remove single-day and two-day visits with longer travel times from the regression data. Similar approaches based on travel distance or travel time are used in the literature (Sinclair et al., 2022). Whilst this alleviates some of the potential for excessive valuation, it further reduces the size of the regression data set (which will already have been reduced through removal of PuD or BuD posters for whom a home country or a quasi-home location could not be assigned conclusively).

3.9. Econometric analysis

The econometric analysis used to quantify the relationships between individual-specific number of visit days at the recreation site and individual-specific cost per visit day, proxy age and proxy household income is explained in detail by Haab and McConnell (2002) and Martínez-Espiñeira and Amoako-Tuffour (2008). Complications arise because the number of visit days is a strictly positive integer: hence, count data regression models are used, with either Poisson or Negative Binomial models selected depending on the amount of overdispersion present in the data. Also, since PuDs and BuDs are a form of on-site sampling, the number of visit days reported for an individual can never be less than one. Consequently, the visit count record is truncated at zero. This necessitates either that a zero-truncated form of count data regression is used, or that a count of one is subtracted from all visit counts and a standard count data regression model is used (Martínez-Espiñeira and Amoako-Tuffour, 2008).

Regression analysis seeks to produce a count data-form model which provides a plausible prediction of the number of visit days that would be expected when a visitor of a given age and with a given household income would incur a particular per-day cost if they visited the site. Mathematical forms of Poisson- and negative binomial-form count data models were presented in the Final Reports for MD WERP RQ12.2 and RQ12.2 Extension B, so are not repeated here. Martínez-Espiñeira and Amoako-Tuffour (2008) present mathematical forms for zero-truncated versions of the Poisson and negative binomial models and explain how these variants accommodate the zero-truncation inherent in visitation data that have been collected on-site.

4. Data

4.1. PuD and BuD data for the Coorong and GKP

Flickr-derived PuDs (between January 2000 and January 2022) and eBird-derived BuDs (between January 2000 and January 2024) in Australian Bureau of Meteorology 5.6km x 5.6km reporting grid squares overlapped by spatial polygons for the Coorong and GKP sites produced PuD-derived and BuD-derived records of individual-specific visitation to each site over 22-year and 24-year periods, respectively (Figure 5 to Figure 8).

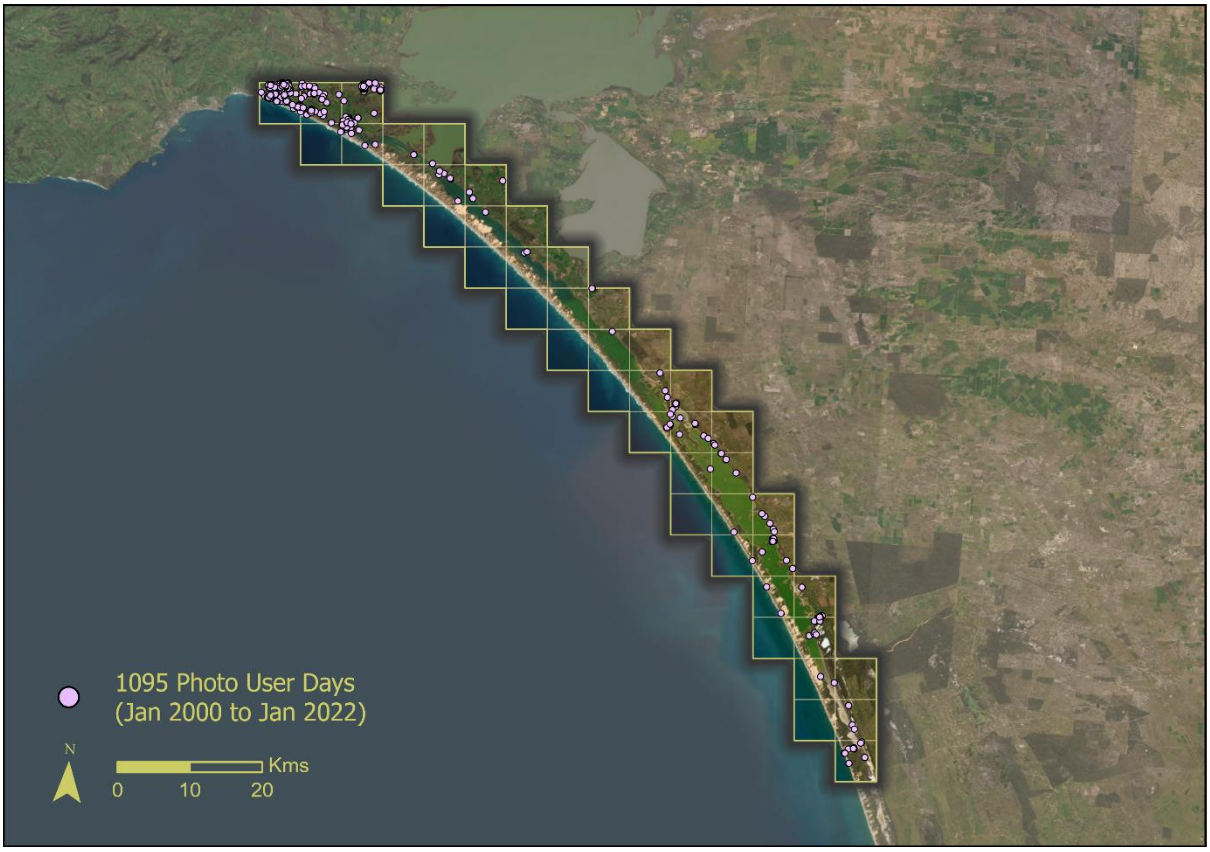

Figure 5: Flickr-derived PuDs in the Coorong, January 2000 to January 2022.

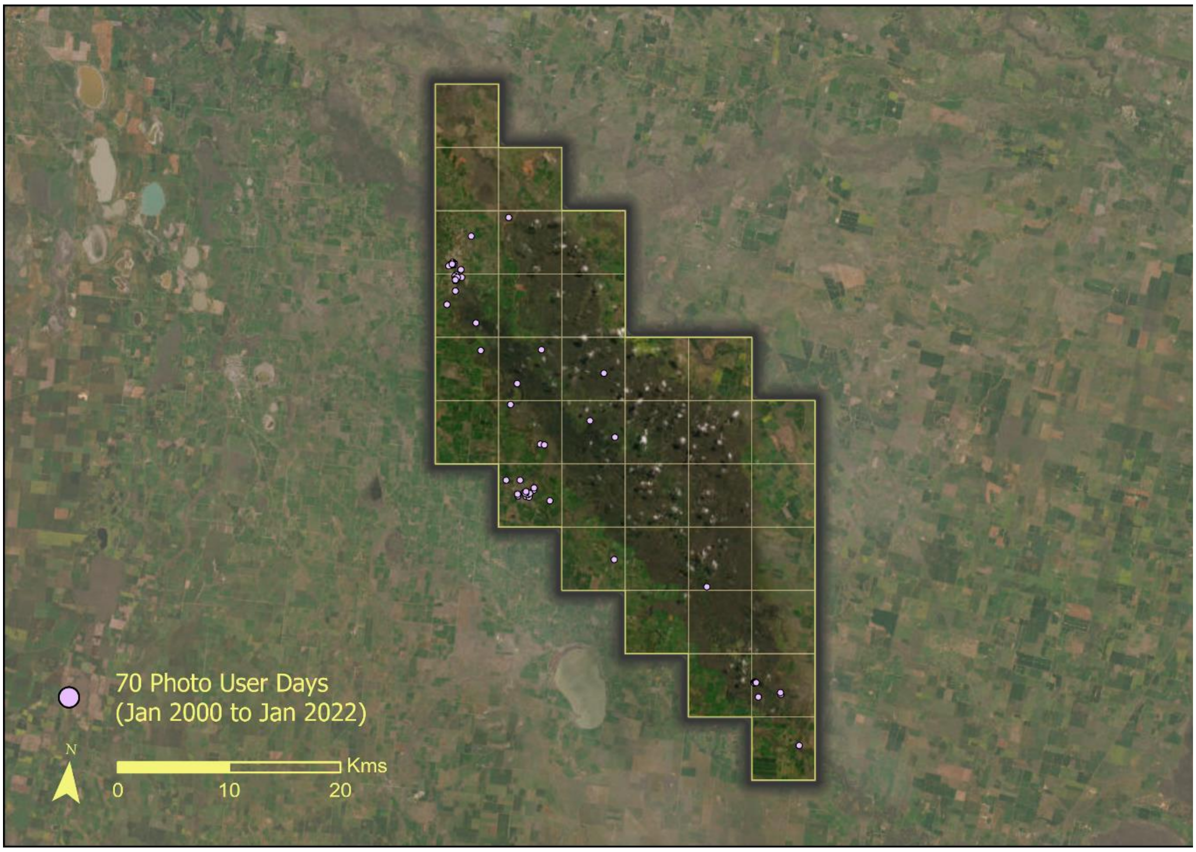

Figure 6: Flickr-derived PuDs in GKP, January 2000 to January 2022.

Figure 7: eBird-derived BuDs in the Coorong, January 2000 to January 2024.

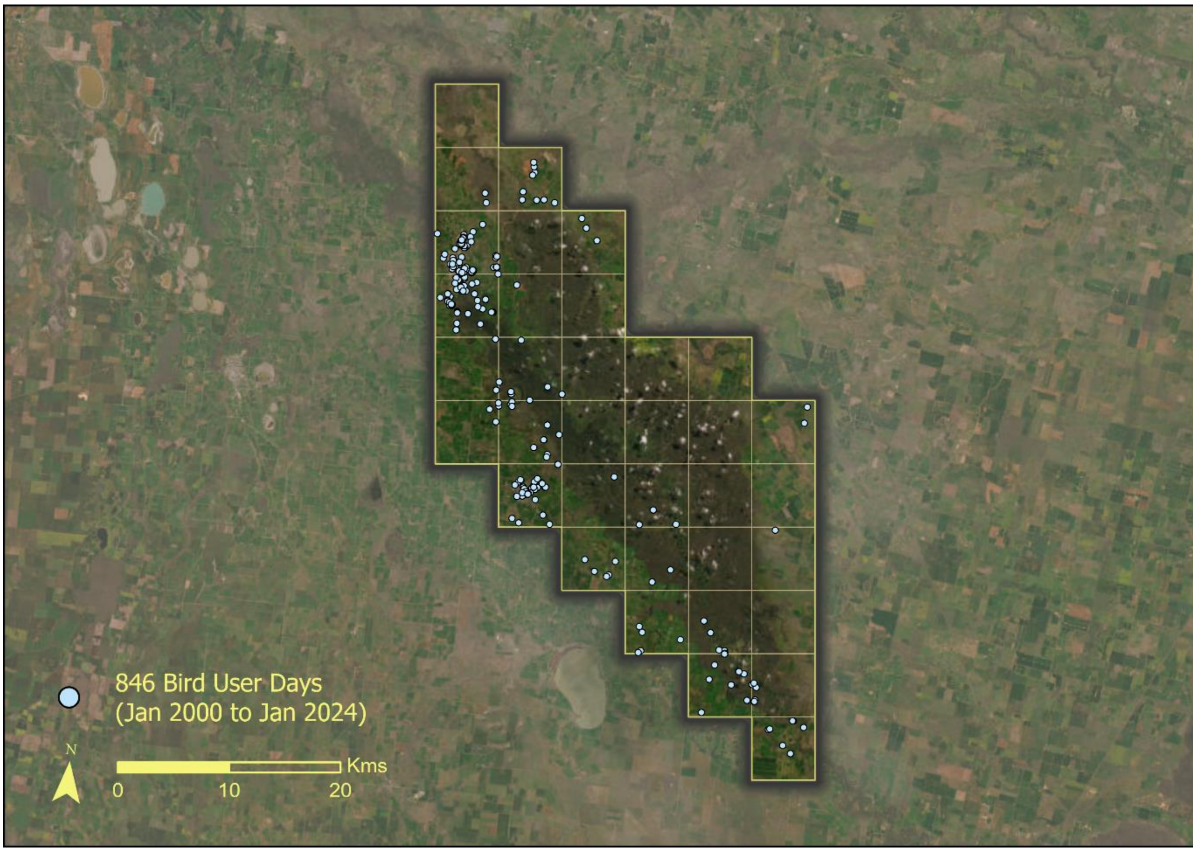

Figure 8: eBird-derived BuDs in GKP, January 2000 to January 2024.

BuD counts are higher than PuD counts at both sites, and BuD and PuD counts are higher at the Coorong than at GKP.

4.2. Global PuD and BuD data from Flickr and eBird posters

Global coverages of 2-year windowed Flickr photo posts and eBird species list posts from Flickr or eBird users who posted from the Coorong or GKP are shown in Figure 9 to Figure 12.

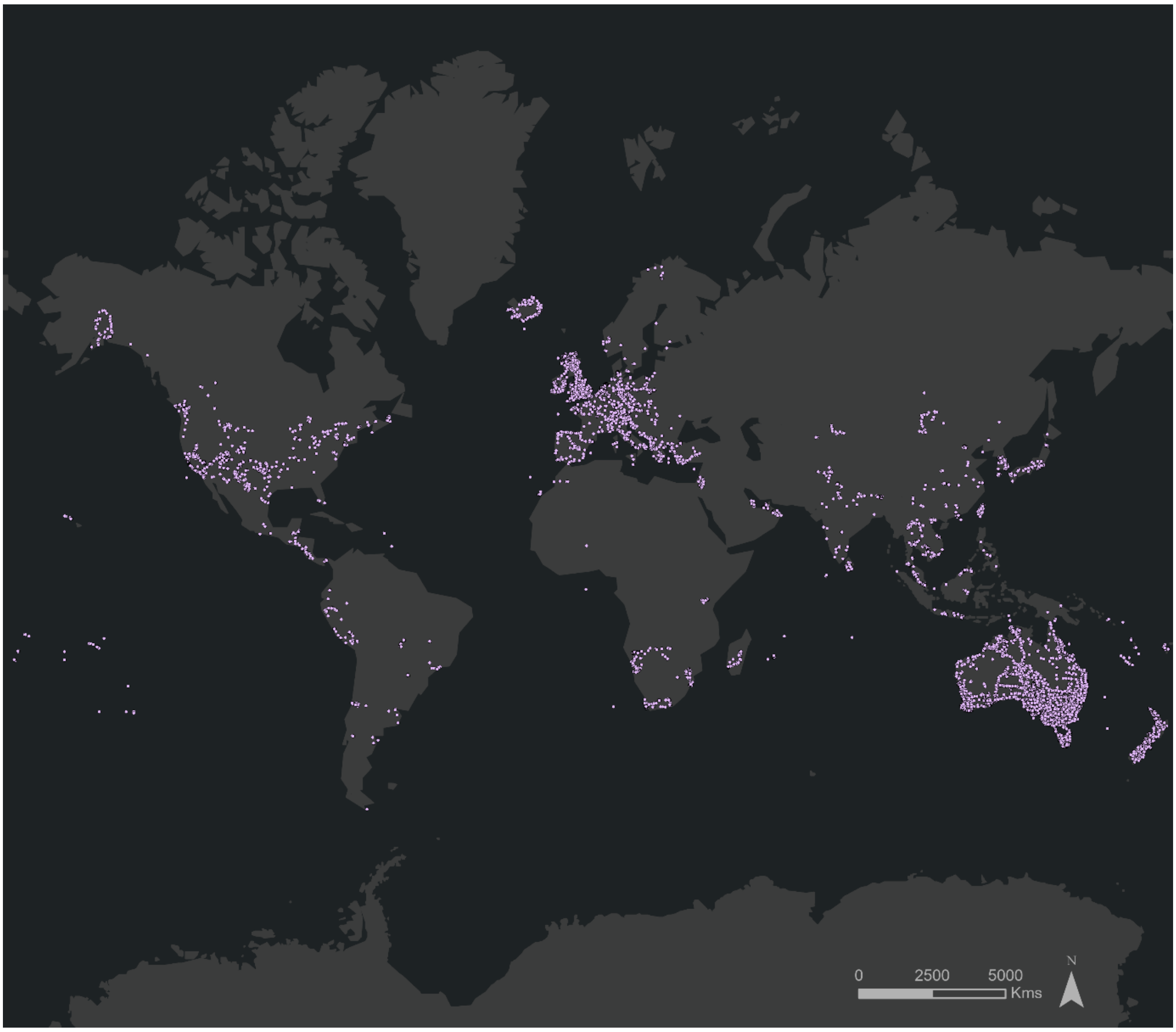

Figure 9: Global locations of Flickr photo posts from Flickr posters who posted from the Coorong between January 2000 and January 2022.
Flickr posts plotted fall within a 2-year time window preceding the individual poster's Flickr post(s) from the Coorong.

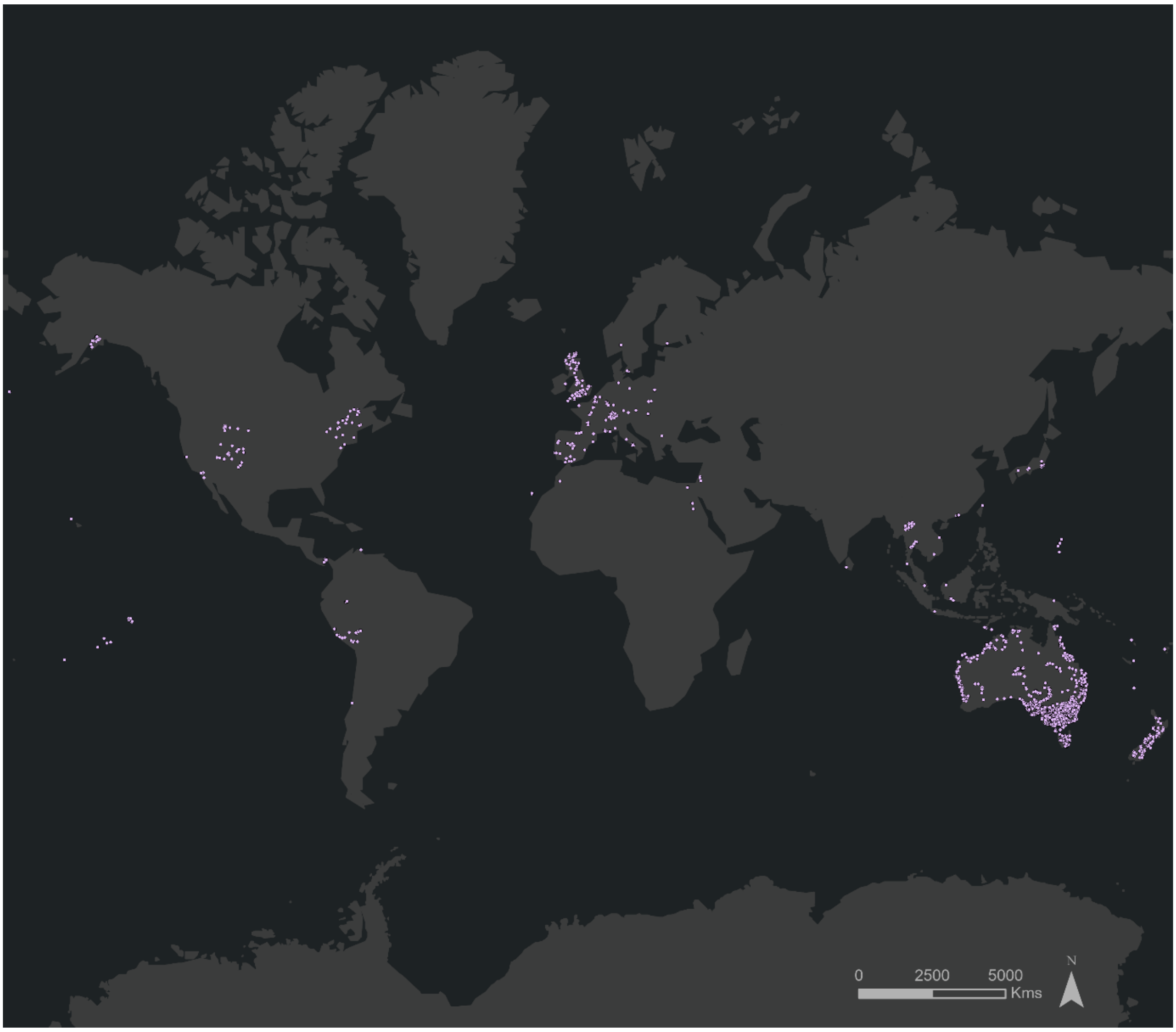

Figure 10: Global locations of Flickr photo posts from Flickr posters who posted from GKP between January 2000 and January 2022.
Flickr posts plotted fall within a 2-year time window preceding the individual poster's Flickr post(s) from GKP.

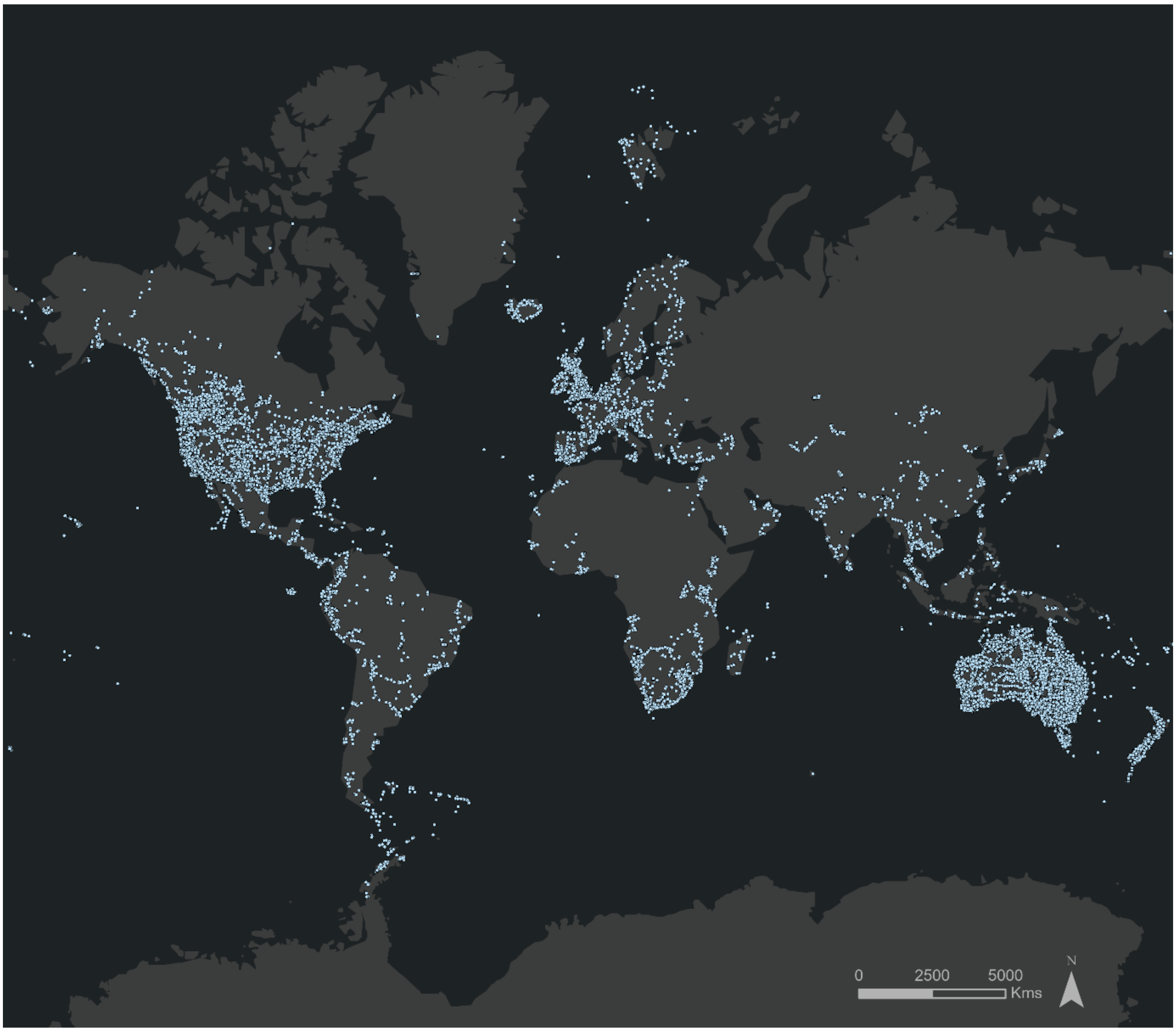

Figure 11: Global locations of eBird species list postings from eBird posters who posted from the Coorong between January 2000 and January 2024.
eBird posts plotted fall within a 2-year time window preceding the individual eBirder's post(s) from the Coorong.

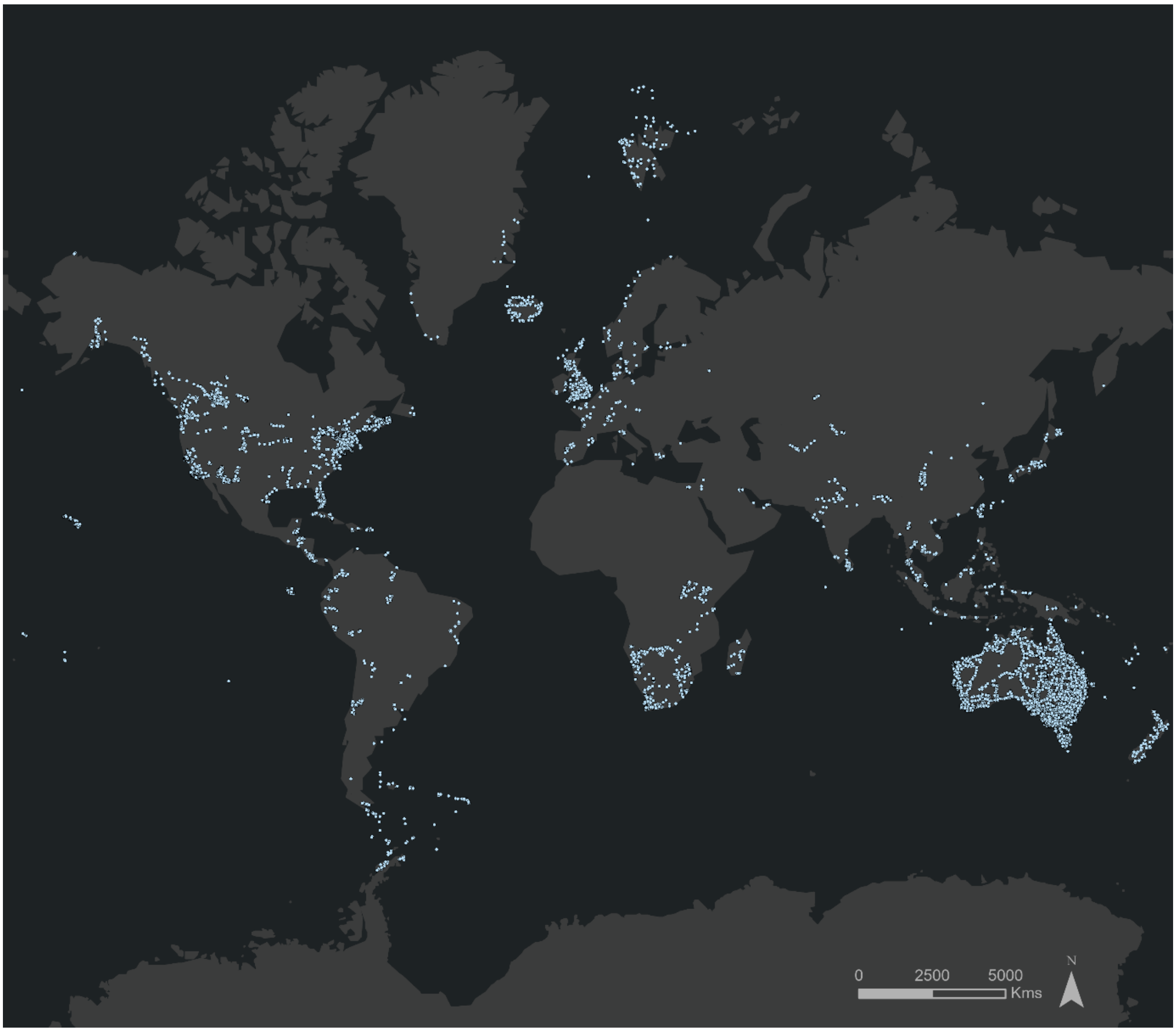

Figure 12: Global locations of eBird species list postings from eBird posters who posted from GKP between January 2000 and January 2024.
eBird posts plotted fall within a 2-year time window preceding the individual eBirder's post(s) from GKP.

4.3. Australian PuD and BuD data from Australia-based Flickr and eBird posters

Coverages of 2-year windowed Flickr photo posts or eBird species list posts within Australia from Australia-based Flickr or eBird users who posted from the Coorong or GKP are shown in Figure 13 to Figure 16. These are used to determine quasi-home locations.

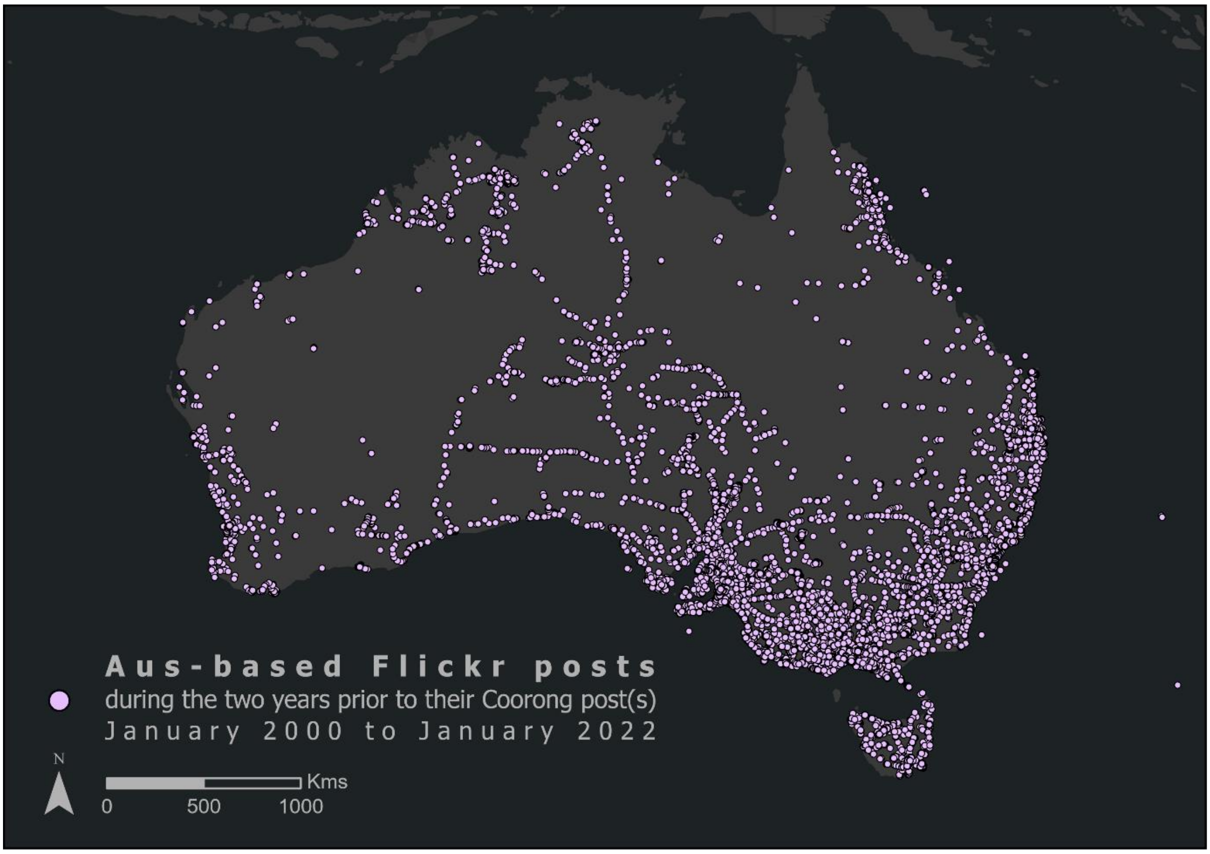

Figure 13: Locations of Flickr photo posts in Australia by Flickr posters who posted from the Coorong between January 2000 and January 2022.
Flickr posts plotted fall within a 2-year time window preceding the individual poster's post(s) from the Coorong.

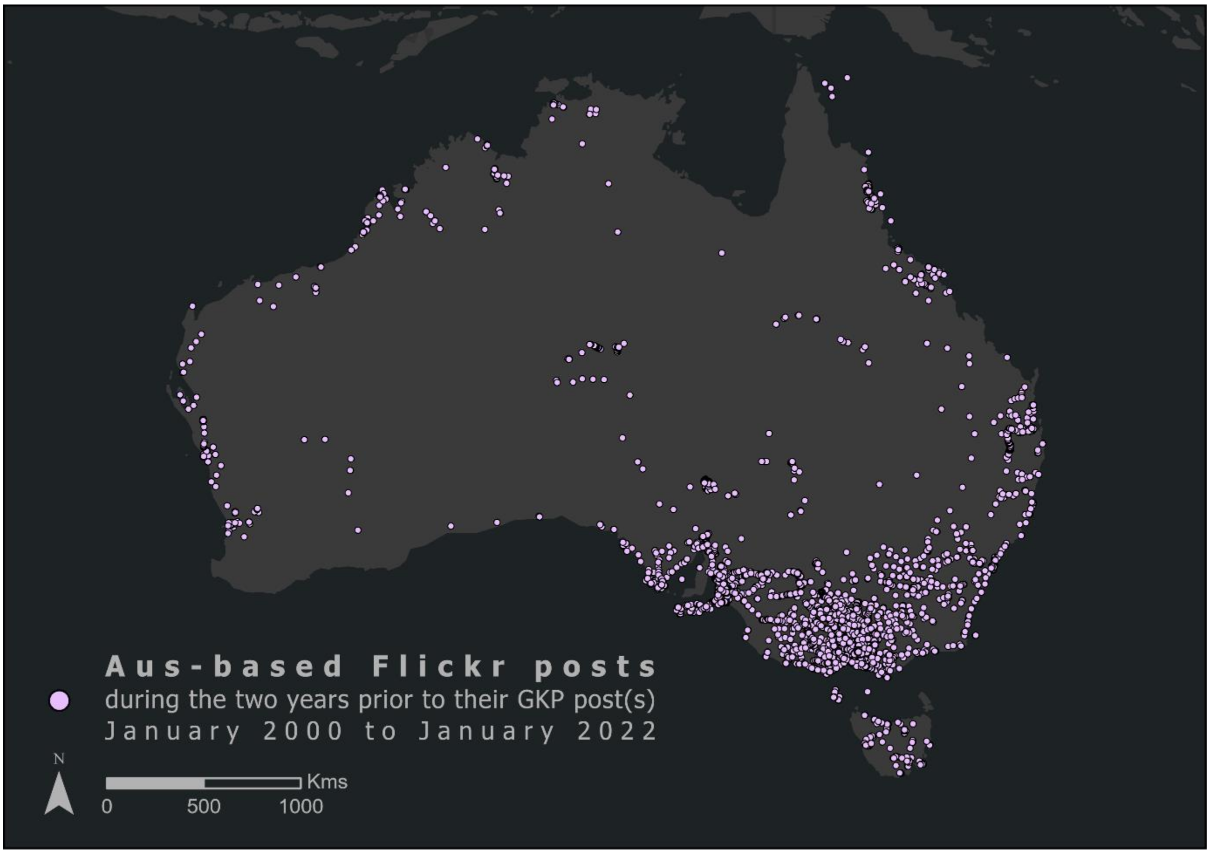

Figure 14: Locations of Flickr photo posts in Australia by Flickr posters who posted from GKP between January 2000 and January 2022.
Flickr posts plotted fall within a 2-year time window preceding the individual poster's post(s) from the Coorong.

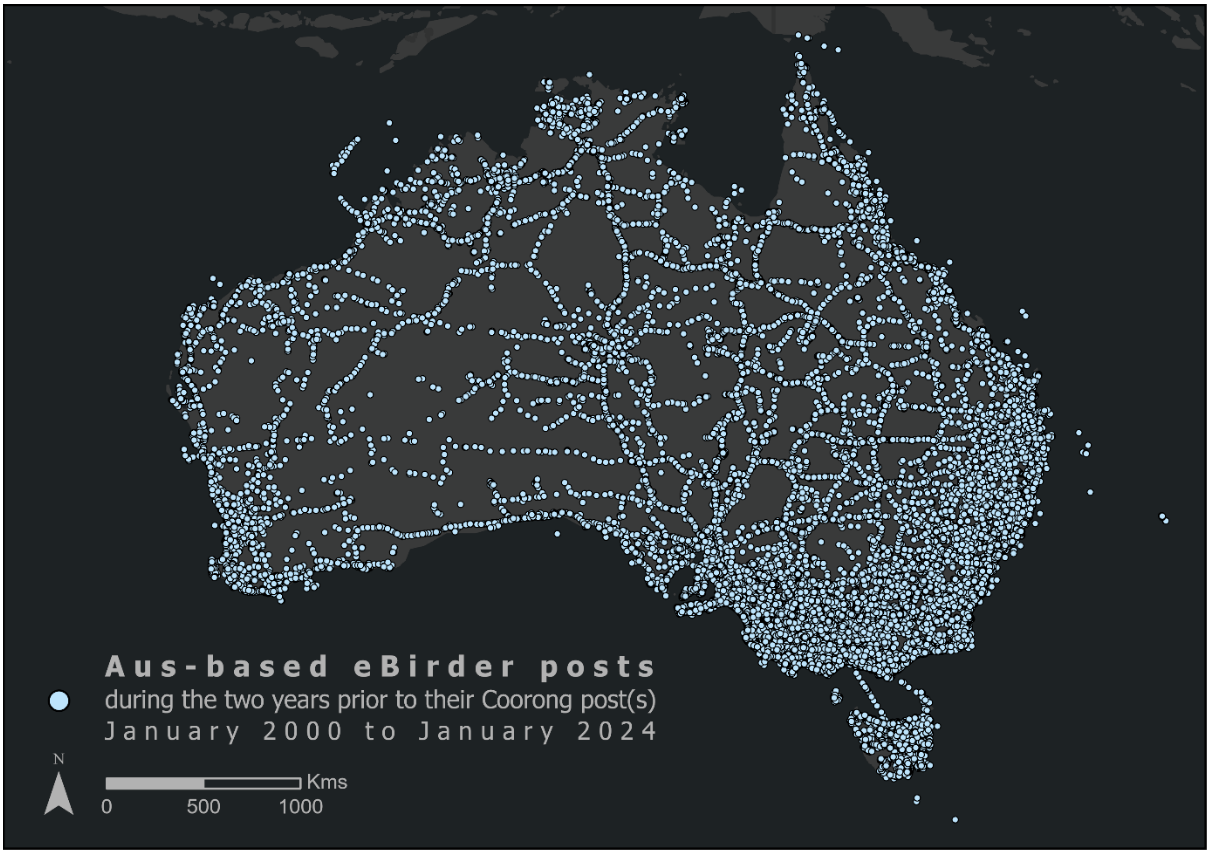

Figure 15: Locations of eBird species list postings in Australia by eBird posters who posted from the Coorong between January 2000 and January 2024.
eBird posts plotted fall within a 2-year time window preceding the individual eBirder's post(s) from the Coorong.

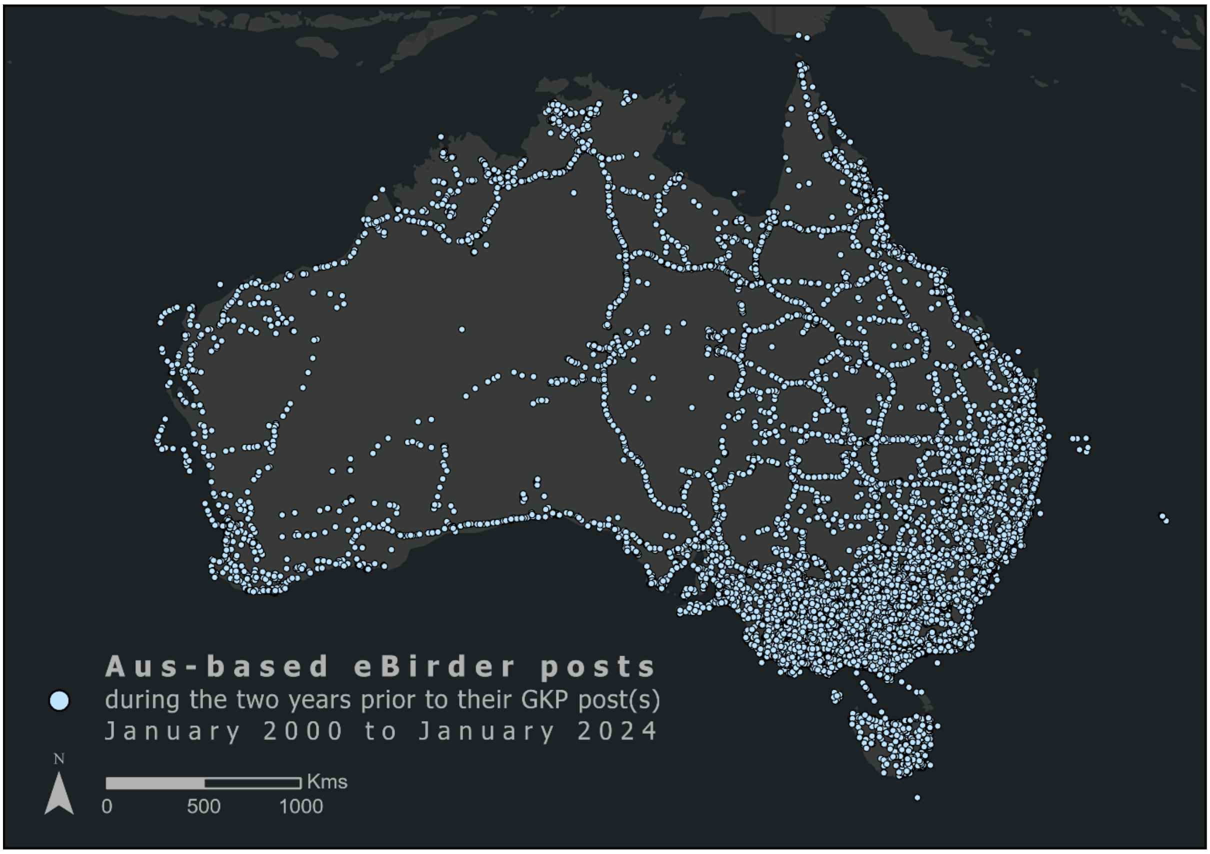

Figure 16: Locations of eBird species list postings in Australia by eBird posters who posted from GKP between January 2000 and January 2024.
eBird posts plotted fall within a 2-year time window preceding the individual eBirder's post(s) from GKP.

5. Results: travel cost method valuations

5.1. The Coorong

5.1.1. Visit data

Applying the data collation and processing methodologies described in Section 3 produced BuD visitation data sets for the Coorong of the sizes reported in Table 2.

Table 2: Sizes of BuD visitation data sets for the Coorong.

Coorong: BuDs						
Number of Coorong BuD posters	794, with 2,087 species lists posted in Coorong					
Australia-based Coorong BuD posters	443, with 90,010 total BuDs in Australia					
Coorong visit days from Australia-based BuD posters with known quasi-home location						
Quasi-home determination using least stringent assignment criteria						
No. Coorong BuD posters with Aus quasi-home	**255** *before* screening for feasible 1d & 2d travel time					
Total number of Coorong visit days	**1107** *before* screening for feasible 1d & 2d travel time					
Distribution of visit days by visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	785	208	63	40	5	6
No. eBirders per visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	232	84	16	9	1	1
No. Coorong BuD posters with Aus quasi-home	**101** *after* screening for feasible 1d & 2d travel time					
Total number of Coorong visit days	**779** *after* screening for feasible 1d & 2d travel time					
Distribution of visit days by visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	549	116	63	40	5	6
No. eBirders per visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	85	38	16	9	1	1
Quasi-home determination using moderately stringent assignment criteria						
No. Coorong BuD posters with Aus quasi-home	**210** *before* screening for feasible 1d & 2d travel time					
Total number of visit days	**990** *before* screening for feasible 1d & 2d travel time					
Distribution of visit days by visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	682	184	69	44	5	6
No. eBirders per visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	181	71	16	10	1	1
No. Coorong BuD posters with Aus quasi-home	**86** *after* screening for feasible 1d & 2d travel time					
Total number of visit days	**722** *after* screening for feasible 1d & 2d travel time					
Distribution of visit days by visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	490	108	69	44	5	6
No. eBirders per visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	68	33	16	10	1	1

Coorong: BuDs (continued)						
Quasi-home determination using most stringent assignment criteria						
No. Coorong BuD posters with Aus quasi-home	**149** *before* screening for feasible 1d & 2d travel time					
Total number of visit days	**717** *before* screening for feasible 1d & 2d travel time					
Distribution of visit days by visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	493	130	51	32	5	6
No. eBirders per visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	127	50	12	8	1	1
No. Coorong BuD posters with Aus quasi-home	**59** *after* screening for feasible 1d & 2d travel time					
Total number of visit days	**497** *after* screening for feasible 1d & 2d travel time					
Distribution of visit days by visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	331	72	51	32	5	6
No. eBirders per visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	43	21	12	8	1	1

As an illustrative example, the quasi-home locations assigned using moderately stringent criteria for Australia-based BuD posters who visited the Coorong are shown in Figure 17.

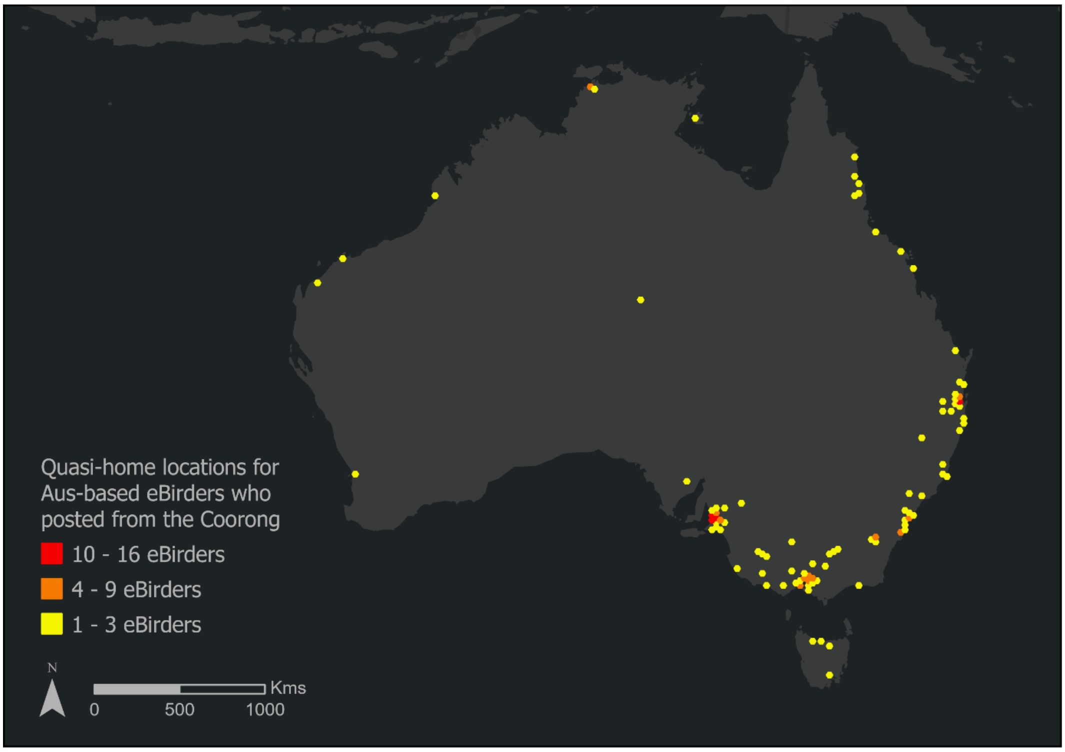

Figure 17: Quasi-home locations for Australia-based eBirders who posted from the Coorong.

Count data regression is used to explore whether per-day visit cost, proxy household income and proxy age (estimated based on median income and age in the quasi-home region) are significant drivers of the number of visit days eBirders chose to make to the Coorong. We recall that, for an individual eBirder, per-day visit cost varies for visits of different durations. Statistics for the input dataset are shown in Table 3, for the dataset with eBirders' quasi-home locations assigned using moderately stringent criteria. Statistics for the input datasets with quasi-home locations determined at the other two levels of stringency are reported in Appendix 2.

Table 3: Statistics for regression input data for Coorong BuDs, with quasi-home location assigned using moderately stringent criteria and feasible limits on round-trip travel time imposed on 1-day and 2-day visits.

Coorong BuDs dataset: Background information						
Total number of visit days	722					
Total number of eBirders	86					
	1d	2d	3d	4d	5d	6d
No. visit days by visit duration	490	108	69	44	5	6
	min	25%ile	median	mean	75%ile	max
Visit duration (days)	1	1	1	1.81	2	6
Travel distance: round trip (km)	6.49	65.72	93.46	254.64	126.45	2038.59
Travel time: round trip (hours)	0.17	0.97	1.42	2.94	1.75	21.48
Dependent variable						
	min	25%ile	median	mean	75%ile	max
No. visit days (days)	1	2	3	5.60	5	39
Independent variables						
	min	25%ile	median	mean	75%ile	max
Per day visit cost* (overall) ($)	13.76	135.63	161.37	268.02	246.65	1394.72
Per day visit cost* (1d visits) ($)	13.76	121.27	141.58	168.38	184.12	512.58
Per day visit cost* (2d visits) ($)	81.88	139.54	167.06	285.84	331.29	771.59
Per day visit cost* (3d visits) ($)	127.02	157.83	270.86	508.45	931.55	1394.72
Per day visit cost* (4d visits) ($)	147.90	158.53	418.16	425.63	497.46	1070.34
Per day visit cost* (5d visits) ($)	896.83	896.83	896.83	896.83	896.83	896.83
Per day visit cost* (6d visits) ($)	403.17	403.17	403.17	403.17	403.17	403.17
Household income proxy ($/week)	900	900	1125	1257.56	1875	1875
Age proxy (years)	26	41	43	42.91	45	59

* Cost per visit day includes the opportunity cost of travel time and – where relevant – accommodation cost.

The initial PuD dataset for the Coorong comprised Flickr posts from 258 Flickr photo posters. This is only 32% of the size of the initial BuD dataset for the Coorong (which comprised 794 eBirders). The data attrition rate for the Coorong BuD dataset was high as only BuDs from Australia-based eBirders (443 eBirders) for whom a quasi-home location could be established convincingly, were retained for regression analysis. This data set was trimmed again to ensure that 1-day and 2-day duration visits were only retained if round-trip travelling times from quasi-home locations were less than 7 hours and 16 hours, respectively. When quasi-home locations were assigned to Australia-based eBirders using moderately stringent criteria (210 eBirders), and feasible round-trip travel times were then imposed on 1-day and 2-day visits, the Coorong BuD dataset contained only 86 eBirders, from the initial 794 (almost 90% data attrition). If the Coorong PuDs dataset suffers a similar attrition rate it is likely that 30 or fewer Flickr posters would remain. This was considered too small for robust regression analysis, so travel cost regression analysis was not attempted on PuD data from the

Coorong. (In the Discussion we describe an alternative approach for data selection that should reduce data attrition rate by making better use of the information provided by VGI.)

5.1.2. Valuation Results: the Coorong

As explained in the Methods section, to account for the zero-truncation inherent in on-site BuD data, Poisson and negative binomial models were run with (number of visit days -1) as the dependent variable, and with per-day visit cost, proxy age and proxy household income as potential drivers. Models were run on data sets constructed with each of the three levels of stringency applied to assignment of quasi-home location, and with a maximum round-trip travel times of 7 hours and 16 hours imposed as selection thresholds for single-day day visits and two-day visits respectively.

Model fit was evaluated using Log-likelihood, Pseudo-R^2 and the Akaike Information Criterion (AIC)[1]. Models were fitted initially with all three dependent variables. The significance of individual dependent variables was then assessed via a Chi-squared test on the difference in residual deviance with variables dropped sequentially from the full model (Zuur et al., 2009).

The per person, per visit consumer surplus is calculated from the best-fitting model as the reciprocal of the estimated parameter for visit cost per day (see Appendix 4 for the mathematical derivation). 95% confidence intervals around the consumer surplus estimate are calculated via non-parametric bootstrapping on 1,000 re-samples from the data set (Kleiber and Zeileis, 2008). Regression results are reported in Table 4 for the dataset with quasi-home range assigned using moderately stringent criteria. Regression results for data sets at the other two stringency levels are reported in Appendix 2.

In Figure 18 the best-fitting model is superimposed on a scatter plot of number of visit days vs. cost per visit day for the data set in which quasi-home locations were assigned using moderately stringent criteria. This is the inverse of the illustrative demand curve sketched in Figure 3 (i.e., the axes are switched over), with the fitted demand curve from the regression superimposed on the data.

[1] Pseudo R^2 for the fitted model is evaluated as the difference between null deviance and residual deviance expressed as a percentage of null deviance (Dobson and Barnett, 2018).

Table 4: Count data regression results from Coorong BuD data with quasi-home location assigned using moderately stringent criteria and maximum feasible travel times imposed on 1-day and 2-day visits.

Coorong: BuDs	Quasi-home location determined using moderately stringent criteria										
	Poisson on (number of visits -1)						NegBin on (number of visits -1)				
Coefficients:	Estimate	Std Err	z-value	Pr(>|z|)			Estimate	Std Err	z-value	Pr(>|z|)	
Intercept	1.301	0.397	3.276	0.001	**		1.619	0.999	1.621	0.105	n.s.
CostPerVisitDay	-1.76E-03	2.74E-04	-6.417	1.39E-10	***		-1.35E-03	4.64E-04	-2.906	0.004	**
HH_Inc	-5.62E-05	9.97E-05	-0.564	0.573	n.s.		-1.97E-05	2.53E-04	-0.078	0.938	n.s.
Age	0.016	0.008	1.941	0.052	•		5.32E-03	0.021	0.255	0.799	n.s.
Null Deviance	895.28	on	128	DoF			148.41	on	128	DoF	
Residual Deviance	819.35	on	125	DoF			136.97	on	125	DoF	
Dispersion	6.55						1.10				
Pseudo R^2	8.48%						7.71%				
LogLik	-579.96						-332.38				
AIC	1167.92						674.75				
NegBin_alpha	n.a.						1.11				

Coorong: BuDs	Quasi-home location using moderately stringent criteria				
	NegBin on (number of visits -1)				
Coefficients:	Estimate	Std Err	z-value	Pr(>|z|)	
Intercept	1.838	0.149	12.322	6.91E-35	***
CostPerVisitDay	-1.40E-03	4.39E-04	-3.196	1.39E-03	**
Null Deviance	148.27	on	128	DoF	
Residual Deviance	136.93	on	127	DoF	
Dispersion	1.08				
Pseudo R^2	7.64%				
LogLik	-332.42				
AIC	670.85				
NegBin_alpha	1.11				
Avg per person per day consumer surplus			$707.49	+95% c.i.	$1058.55
				-95% c.i.	$507.21

Statistical significance indicated via: *** < 0.001, **< 0.01, *<0.05, •<0.10, n.s. = not significant

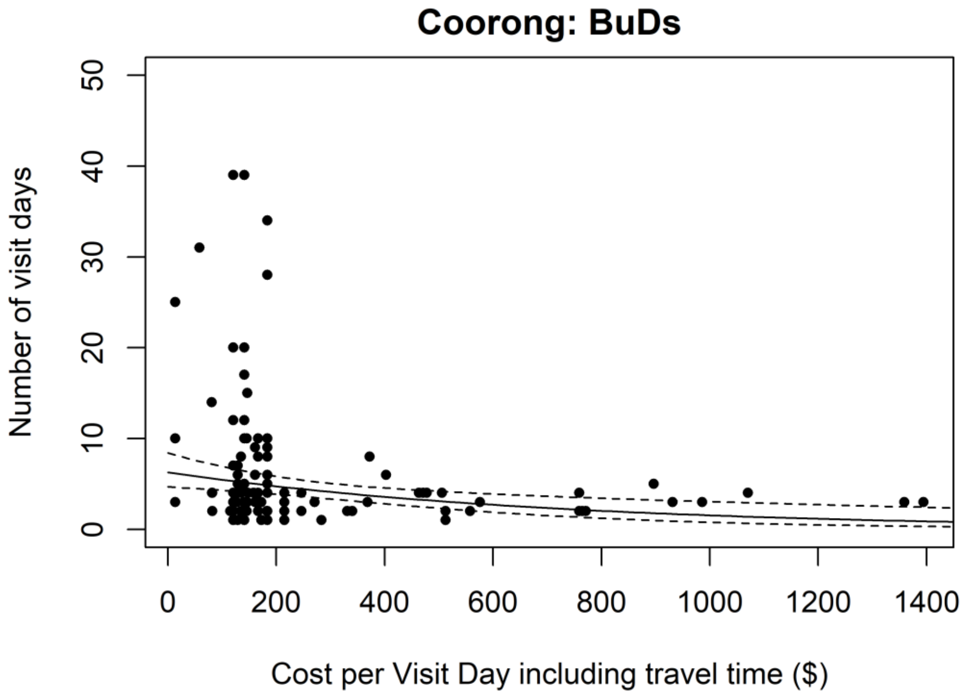

Figure 18: Coorong BuDs: Number of visit days plotted against cost per visit day, showing fitted regression line with 95% confidence intervals.
Cost per visit day includes travel cost, the opportunity cost of travel time and accommodation cost (where relevant).
Data from the data set with quasi-home locations assigned using moderately stringent criteria and feasible limits on round-trip travel time imposed on 1-day and 2-day visits.

5.2. Gunbower – Kondrook - Perrricoota

5.2.1. Visit data

Applying the methodologies described in Section 3 produced BuD visitation datasets for GKP of the sizes shown in Table 5.

Table 5: Sizes of BuD visitation data sets for GKP

GKP: BuDs						
Number of GKP BuD posters	228, with 846 species lists posted in GKP					
Australia-based GKP BuD posters	197, with 52,337 total BuDs in Australia					
GKP visit days from Australia-based BuD posters with known quasi-home location						
Quasi-home determination using least stringent assignment criteria						
No. GKP BuD posters with Aus quasi-home	**124** *before* screening for feasible 1d & 2d travel time					
Total number of GKP visit days	**372** *before* screening for feasible 1d & 2d travel time					
Distribution of visit days by visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	214	66	39	32	15	6
No. eBirders per visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	120	29	8	7	3	1
No. GKP BuD posters with Aus quasi-home	**52** *after* screening for feasible 1d & 2d travel time					
Total number of GKP visit days	**212** *after* screening for feasible 1d & 2d travel time					
Distribution of visit days by visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	60	60	39	32	15	6
No. eBirders per visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	22	26	8	7	3	1
Quasi-home determination using moderately stringent assignment criteria						
No. GKP BuD posters with Aus quasi-home	**110** *before* screening for feasible 1d & 2d travel time					
Total number of visit days	**325** *before* screening for feasible 1d & 2d travel time					
Distribution of visit days by visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	186	54	36	28	15	6
No. eBirders per visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	106	24	7	6	3	1
No. GKP BuD posters with Aus quasi-home	**46** *after* screening for feasible 1d & 2d travel time					
Total number of visit days	**193** *after* screening for feasible 1d & 2d travel time					
Distribution of visit days by visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	58	50	36	28	15	6
No. eBirders per visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	21	22	7	6	3	1

GKP: BuDs (continued)						
Quasi-home determination using most stringent assignment criteria						
No. GKP BuD posters with Aus quasi-home	**98** *before* screening for feasible 1d & 2d travel time					
Total number of visit days	**304** *before* screening for feasible 1d & 2d travel time					
Distribution of visit days by visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	172	54	33	24	15	6
No. eBirders per visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	91	24	6	5	3	1
No. GKP BuD posters with Aus quasi-home	**42** *after* screening for feasible 1d & 2d travel time					
Total number of visit days	**183** *after* screening for feasible 1d & 2d travel time					
Distribution of visit days by visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	55	50	33	24	15	6
No. eBirders per visit duration	*1d*	*2d*	*3d*	*4d*	*5d*	*6d*
	18	22	6	5	3	1

As an illustrative example, the quasi-home locations assigned using moderately stringent criteria for Australia-based BuD posters who visited GKP are shown in Figure 19.

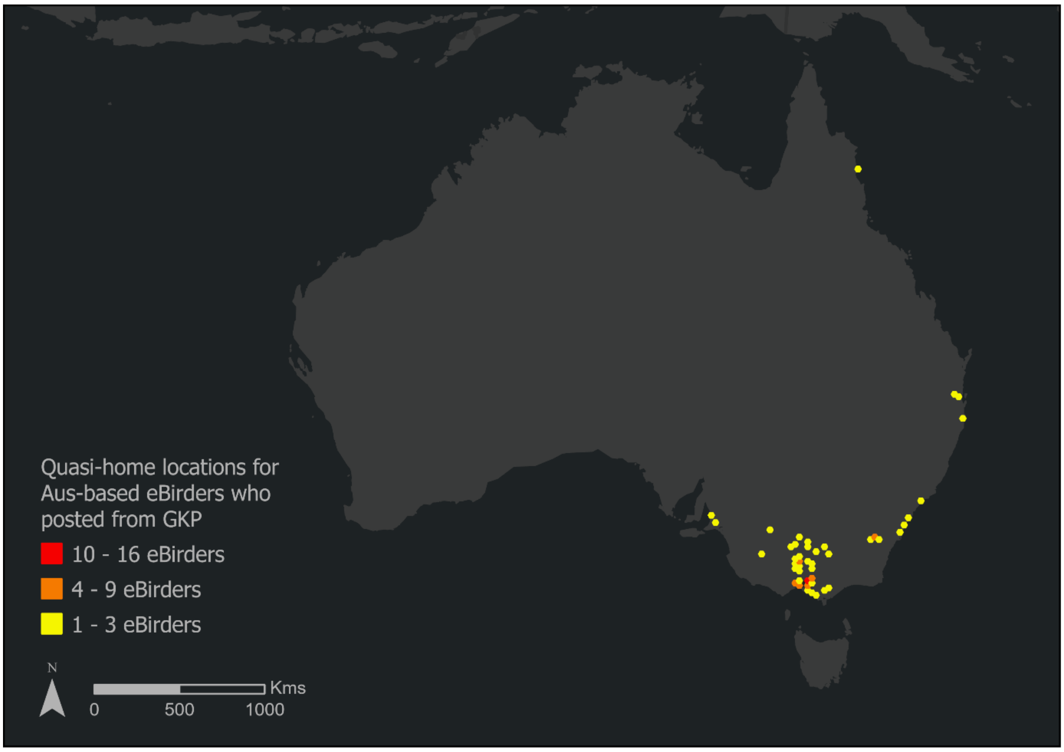

Figure 19: Quasi-home locations for Australia-based Flickr posters who posted from GKP.

Count data regression is used to explore whether per-day visit cost, proxy household income and proxy age are significant drivers of the number of visit days eBirders chose to make to GKP. We recall that, for an individual eBirder, per-day visit cost varies for visits of different durations. Statistics for the input dataset with quasi-home locations assigned using moderately stringent criteria, and feasible travel times imposed for 1-day and 2-day visits, are shown in Table 6. Statistics for input datasets with quasi-home location assigned at the other two stringency levels are reported in Appendix 3.

Table 6: Statistics for regression input data for GKP BuDs with quasi-home location assigned using moderately stringent criteria and feasible limits on round-trip travel time imposed on 1-day and 2-day visits.

GKP BuDs dataset: Background information						
Total number of visit days	193					
Total number of eBirders	46					
	1d	2d	3d	4d	5d	6d
No. visit days by visit duration	58	50	36	28	15	6
	min	25%ile	median	mean	75%ile	max
Visit duration (days)	1	1	1	1.81	2	6
Travel distance: round trip (km)	59.62	178.86	262.71	265.93	312.07	635.94
Travel time: round trip (hours)	1.12	2.51	3.55	3.44	4.07	7.02
Dependent variable						
	min	25%ile	median	mean	75%ile	max
No. visit days (days)	1	2	2	3.22	4	24
Independent variables						
	min	25%ile	median	mean	75%ile	max
Per day visit cost* (overall) ($)	120.40	270.46	333.84	330.56	377.66	505.36
Per day visit cost* (1d visits) ($)	120.40	293.23	337.00	344.26	428.78	497.01
Per day visit cost* (2d visits) ($)	135.20	301.87	350.75	337.29	376.40	493.14
Per day visit cost* (3d visits) ($)	270.46	270.46	324.08	361.19	443.75	505.36
Per day visit cost* (4d visits) ($)	221.58	254.58	273.11	270.05	280.18	321.57
Per day visit cost* (5d visits) ($)	222.27	238.36	254.45	256.93	274.26	294.07
Per day visit cost* (6d visits) ($)	264.38	264.38	264.38	264.38	264.38	264.38
Household income proxy ($/week)	900	1125	1250	1334.17	1625	2250
Age proxy (years)	26	38	40	42.23	50	59

The initial PuD dataset for GKP comprised Flickr posts from only 50 Flickr photo posters. This is only 22% of the size of the initial BuD dataset for GKP (which comprised 228 eBirders). Given the data attrition rate observed for the GKP BuDs dataset, travel cost regression analysis was not attempted on PuD data from GPK because the resulting dataset would inevitable be too small for robust regression analysis.

5.2.2. Valuation Results: GKP

The approach described in Section 5.1.2 for fitting count data models to BuD data from the Coorong was repeated for BuD data from GPK. However, one individual visitor posted species lists within GPK on 324 days over an approximately six and a half-year period between early July 2017 and mid-January 2024. Over this period, this individual posted species lists 203 times on single days, 40 times on two consecutive days, nine times on three consecutive days, twice on four consecutive days, and once on six consecutive days. This is extremely anomalous behaviour as, once the dataset has been trimmed to include only eBirders whose home country and quasi-home location are known, no other individual posted more than 29 BuDs in total from GKP over the full 22-year duration. BuD posts from the anomalous BuD poster were therefore removed from our analysis.

Regression analyses were conducted on the GKP data, following the approach described previously for regressions on the Coorong data. Regression results are reported in Table 4 for the dataset with quasi-home location assigned using moderately stringent criteria, and with maximum feasible travel times imposed on 1-day and 2-day visits. Regression results for GKP data sets with quasi-home locations assigned at the other two stringency levels are reported in Appendix 2.

In Figure 20 the best-fitting model regression is superimposed on a scatter plot of number of visit days vs. cost per visit day for the data set in which quasi-home locations were assigned using moderately stringent criteria and maximum feasible travel times were imposed on 1-day and 2-day visits. This is the inverse of the illustrative demand curve sketched in Figure 3 (i.e., the axes are switched over), with the fitted demand curve from the regression superimposed on the data.

Table 7: Count data regression results for GKP BuDs with quasi-home location assigned using moderately stringent criteria and maximum feasible travel times imposed on 1-day and 2-day visits.

GKP: BuDs	Quasi-home location assigned using moderately stringent criteria										
	Poisson on (number of visits -1)						NegBin on (number of visits -1)				
Coefficients:	Estimate	Std Err	z-value	Pr(>|z|)			Estimate	Std Err	z-value	Pr(>|z|)	
Intercept	0.200	1.294	0.155	0.877	n.s.		0.301	1.815	0.166	0.868	n.s.
CostPerVisitDay	-7.44E-03	1.12E-03	-6.647	2.99E-11	***		-6.63E-03	1.72E-03	-3.842	1.22E-04	***
HH_Inc	7.32E-04	4.03E-04	1.819	0.069	•		7.41E-04	5.59E-04	1.325	0.185	n.s.
Age	0.044	0.019	2.241	0.025	*		0.035	0.027	1.291	0.197	n.s.
Null Deviance	202.89	on	59	DoF			81.87	on	59	DoF	
Residual Deviance	141.66	on	56	DoF			59.26	on	56	DoF	
Dispersion	2.53						1.06				
Pseudo R^2	30.18%						27.62%				
LogLik	-131.34						-110.19				
AIC	270.68						230.37				
NegBin_alpha	n.a.						0.58				

GKP: BuDs	Quasi-home location assigned using moderately stringent criteria					
	NegBin on (number of visits -1)					
Coefficients:	Estimate	Std Err	z-value	Pr(>|z|)		
Intercept	2.769	0.539	5.138	2.78E-07	***	
CostPerVisitDay	-6.51E-03	1.68E-03	-3.869	1.09E-04	***	
Null Deviance	79.23	on	59	DoF		
Residual Deviance	59.85	on	58	DoF		
Dispersion	1.03					
Pseudo R^2	24.47%					
LogLik	-111.39					
AIC	228.77					
NegBin_alpha	0.62					
Avg per person per day consumer surplus			$157.64	+95% c.i.	$306.16	
				-95% c.i.	$104.39	

Statistical significance indicated via: *** < 0.001, **< 0.01, *<0.05, •<0.10, n.s. = not significant

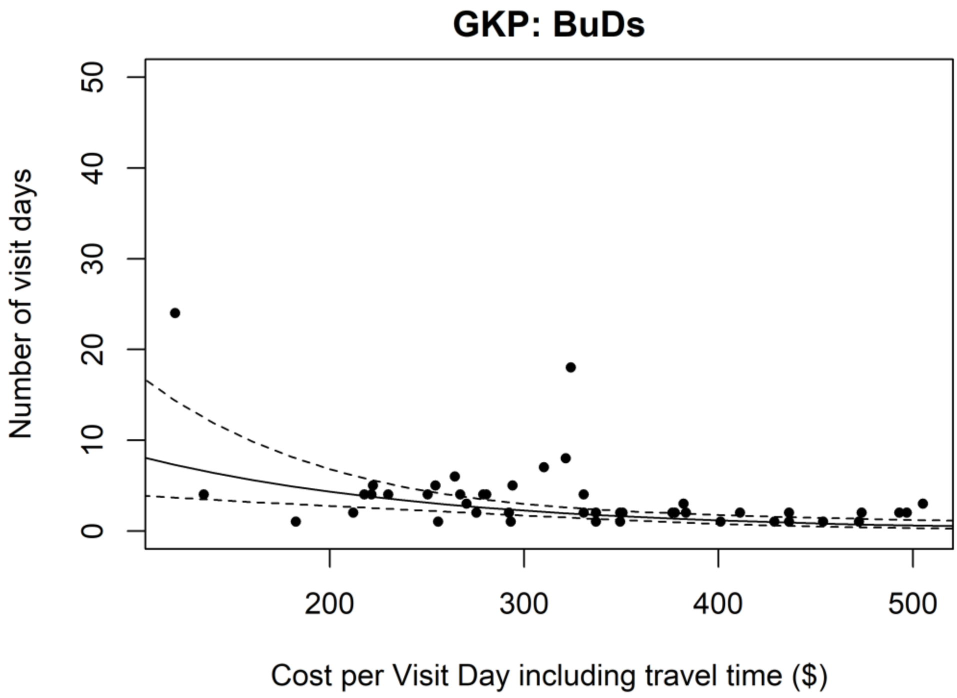

Figure 20: GKP BuDs: Number of visit days plotted against cost per visit day, showing the fitted regression line from single-term regression on full dataset, with 95% confidence intervals.
Cost per visit day includes travel cost, the opportunity cost of travel time and accommodation cost (where relevant).
Data from the data set with quasi-home locations assigned using moderately stringent criteria and feasible limits on round-trip travel time imposed on 1-day and 2-day visits.

6. Discussion

BuDs derived from species postings to the eBird citizen science website, and PuDs derived from photo posts to the Flickr photo posting website are both forms of VGI. Although VGI-derived data have been used for recreational valuation at sites overseas (e.g., Kolstoe et al., 2022; Kolstoe & Cameron, 2017; Sinclair et al., 2018, 2021, 2022; Jayalath et al., 2023), to the best of the authors' knowledge, the research reported here is the first use of VGI-derived data to estimate per visitor, per day consumer surplus from visits to recreation sites in Australia generally, and in the Murray–Darling Basin specifically.

6.1. Valuation comparison

Results from our BuD-derived count data models that regress the number of eBirder visit days to the Coorong and GKP on cost per visit day, along with proxies for age and household income, demonstrate that BuD-derived visitation data shows some promise for estimating the consumer surplus birdwatchers obtain from visiting a recreation site in the Basin. However, the fit of the regression models, and therefore the robustness of the consumer surplus estimates obtained, differed considerably between the two sites. The best-fitting model for predicting the number of eBirder visit days at GKP achieved a Pseudo-R^2 of almost 25% (Table 7), whereas the best-fitting model for the Coorong achieved a Pseudo-R^2 of less than 8% (Table 4). This difference is apparent when comparing the regression fits shown in Figure 20 (GKP) with Figure 18 (the Coorong).

The per person, per day consumer surplus estimates produced from this research are compared with those produced by Rolfe & Dyack (2019) (for the Coorong) and Cheesman et al. (2021) (for GKP) in Table 8. Noting that all valuations in Table 8 are expressed in April 2024 AUD$, the 95% confidence intervals around our BuD-derived consumer surplus estimates for GKP overlap those of Cheesman et al. (2021), although our mid-point estimates are higher by 50% – 60%. This is encouraging, particularly noting the difference in sample sizes (see Section 2.2 compared with Table 5) and that Cheesman et al. used an online survey to sample the general public, whereas our visitation data are derived only from eBirders. By contrast, the 95% confidence intervals for our BuD-derived consumer surplus estimates for the Coorong are considerably higher than those produced by Rolfe and Dyack (2019), with no overlap. This is not surprising, given the poor fit achieved by our Coorong models, even though they were produced from larger VGI datasets than our GKP models.

The reasons for these differences in valuation performance at our two test sites warrant further investigation but may be due partly to the inability of the limited set of driving variables in this iteration of our BuD-derived datasets to adequately represent differences in eBirder visitation behaviour at the two (very different) sites. Suggestions for reducing data attrition and producing additional driving variables by making better use of the information contained in VGI data streams are discussed in following subsections.

Table 8: Comparison of consumer surplus estimates from this research with those in the literature.

The Coorong: Rolfe and Dyack (2019)	Consumer surplus per visit ($)	
Year	Mid-point	95% confidence interval
2006	$134.91	($119.11 – $154.91)
2013	$211.15	($184.18 – $250.73)
2006 & 2013 combined	$139.87	($131.79 – $149.27)
The Coorong: This study	Consumer surplus per visit ($)	
Quasi-home (≥ 40%, < 10d gap)	$769.86	($561.55 – $1115.70)
Quasi-home (≥ 50%, < 7d gap)	$707.49	($507.21 – $1058.55)
Quasi-home (≥ 60%, < 5d gap)	$680.33	($453.94 – $1102.53)
GKP: from Cheesman et al. (2021)		
Gunbower	Consumer surplus per visit ($)	
Year	Mid-point	95% confidence interval
2010	$91.17	($30.39 – $182.34)
2015	$80.20	($26.73 – $160.39)
Koondrook-Perricoota	Consumer surplus per visit ($)	
2010	$94.74	($31.57 – $189.47)
2015	$92.78	($30.93 – $185.57)
GKP: This study	Consumer surplus per visit ($)	
Quasi-home (≥ 40%, < 10d gap)	$232.39	($136.49 – $698.52)
Quasi-home (≥ 50%, < 7d gap)	$157.64	($104.39 – $306.16)
Quasi-home (≥ 60%, < 5d gap)	$159.48	($106.45 – $322.69)

All valuations reported in AUD$ April 2024, converting from the AUD$ valuation years used in the original studies.

6.2. Methodological improvements

The statistician and economist Harold Hotelling first suggested the travel cost method for estimating the value of national parks in a letter to the Director of the U.S National Parks Service in 1947 (Alvarez and Larkin, 2010; Arrow and Lehmann, 2005). The method has since benefited from almost 80 years of development and refinement. The research findings reported here suggest that travel cost-based valuations with VGI-derived data show considerable promise, but there undoubtedly remains considerable scope for further innovation and improvement. The following subsections provide some suggestions.

VGI-derived data on recreational visitation have advantages and disadvantages compared with travel cost data collected by traditional methods of surveying individual recreators either on- or off-site. The effects of these differences have become apparent through this research. Particular challenges that arise when standard travel cost methodologies are applied on VGI data are:

- High rates of data attrition
- Lack of direct information on individual visitor characteristics and behaviour
- No information on the number of individuals travelling as a group and thereby reducing per person travel cost

Here we suggest how each of these challenges might be addressed by modifying data collation and analysis methodologies to make best use of the information provided in VGI data streams.

6.2.1. Data attrition

Traditional methods of data collection for travel cost analysis typically only suffer modest levels of data attrition when, for example, respondents to an internet-administered off-site survey do not answer key questions such as 'Usual origin for your trips to the recreation site?'. Inaccuracies will also typically arise in traditionally collected data through, for example, incorrect recall when on-site survey respondents are asked to state the number of times they visited a focal recreation site over the past five years (Rolfe and Dyack, 2019), or when the same duration of stay or travelling group size are applied to all visits made by an individual visitor over the past five years, even though these features may vary across visits. However, traditionally collected travel cost data generally provide relatively robust information on trip origin with low levels of data attrition. Unfortunately, this is not the case for VGI-derived data for which trip origin is usually assumed to be a home location that must be estimated from the anonymous individual's geo-located posting history (e.g., Sinclair et al., 2022, 2018).

Travel cost is highly influential in estimating per person per visit consumer surplus. This suggests that stringency criteria should be applied when estimating home location to avoid ambiguities propagating through to the consumer surplus estimate. In traditional travel cost analysis home location is usually categorized initially at national level – with international visitors typically being discarded from further analysis (Beal, 1995; Fleming and Cook, 2008; Martínez-Espiñeira and Amoako-Tuffour, 2008) – then again at regional resolution within the country of the focal recreation site. The rate of data attrition increases as more stringent criteria are applied to assignment of home location from VGI-derived data, as shown by the decrease in the number of eBirders and visit days retained in the Coorong and GKP datasets as increasingly stringent criteria are applied to quasi-home location assignment (Table 2 and Table 5). When using VGI-derived visit data a further level of screening is usually applied to restrict trip origins for short duration visits within feasible travel distances or travel times of the focal recreation site (e.g., Martínez-Espiñeira and Amoako-Tuffour, 2008; Sinclair et al., 2022). This introduces further data attrition. For our eBird-derived visit data to the Coorong and GKP, each of these stages – determination of home country, assignment of quasi-home location in Australia, and imposition of feasible travel time limits for 1-day and 2-day visits – caused very substantial levels of data attrition (Table 2 and Table 5).

The overall level of data attrition could, however, be reduced by using VGI data on individual visitors' location(s) in the day(s) immediately prior to their visit to the focal recreation site. When an individual with a distant home location (including home locations overseas) posts a photo or bird species sighting list within one or two days' feasible travelling time of the focal recreation site *one or two days prior* to that individual posting from the focal site, it would be reasonable to assign their location one or two days prior as the origin for their trip to the focal recreation site. Whilst appropriately located prior posts will not be available for all visitors, searching the VGI data stream for relevant prior posts affords real possibilities for reducing data attrition, particularly as this technique could be applied to synthesise relevant trip origin data for international visitors as well as distant domestic visitors. This provides a feasible approach for reducing data attrition that should, all else being equal, increase regression data set size and thus improve the precision of regression estimates and estimated per person, per visit consumer surplus.

6.2.2. Visitor characteristics and behaviour

Travel cost data collected via traditional on-site or off-site surveys typically contain considerable amounts of socio-demographic and socio-economic information on individual visitors (e.g., see Dyack et al., 2007 for a typical list of on-site survey questions). Individual-specific socio-demographic and socio-economic data such as, for example, visitor age, employment status (including retiree), or whether there are school-age children in the family can be included as additional variables in count data regressions to help explain the wide variation that is usually present in visitation rate at any particular level of visit cost per day (see Figure 18 for an example of this variation and Rolfe and Dyack (2019) for examples of using socio-demographic data in travel cost count data regressions). Controlling for individual-specific socio-demographic and socio-economic factors in travel cost regressions aims to improve the precision with which the travel cost parameter can be estimated, and thus increase the precision of the per person, per visit consumer surplus estimate produced.

Unfortunately, individual-specific socio-demographic and socio-economic data are not available directly from VGI data. However, VGI data provide excellent visibility of individual-specific patterns of visitation, which can, for example categorise (anonymous) individuals who visit predominantly at the weekend, or during school holiday periods, or who usually stay for several consecutive days at the focal recreation site. These categorisations of individual-specific visitation behaviour can be included in travel cost regressions with the aim of helping to explain individual-specific variation in the relationship between cost per visit day and the number of visit days a visitor chooses to spend at the recreation site. Using VGI-derived individual-specific patterns of visitation in this way should help to improve the precision of regression estimates and estimated per person, per visit consumer surplus

6.2.3. Travelling as a group

Traditional travel cost data collection will seek to determine whether a visitor usually visits the recreation site as a sole traveler, as a travelling pair, or as part of a larger group. Travelling as a member of a group is assumed to directly affect per person travel cost and will therefore be highly influential over estimated per person, per visit consumer surplus. VGI-derived visitation data provide no information on travelling group size, so a uniform group size is typically assumed for all visitors; visitors were assumed to travel alone in our analysis, whereas Sinclair et al. (2022) assumed that all visitors in their study travelled as a pair.

An online survey of eBird users who are members of Birdlife Australia’s local groups was conducted as part of MD WERP RQ12.2 Extension B. This survey provided data on typical travelling group sizes for birdwatching trips, finding that 58% of birdwatchers surveyed always went on birdwatching trips alone, while 19% usually went birdwatching as a group of two. These percentages could be used to generate Monte-Carlo re-sampled datasets for regression modelling by repeated random re-assignment of a group size variable to individual recreators’ trips, using the prevalence of group sizes from the Extension B birdwatcher survey. Repeated model estimation would then be run on the re-sampled datasets to generate multiple estimates of per person, per visit consumer surplus – each from a data set with a different randomised allocation of group size to an individual visitor’s trips to the recreation site. Mean and median estimates of consumer surplus, together with confidence intervals, could then be determined from the suite of re-sampled results. For our analyses, this approach would act to reduce average cost per visit day (by reducing travel costs when individual visitors were allocated to travelling groups of more than a single person) and thus reduce consumer surplus estimates, potentially bringing them closer to those of Rolfe & Dyack (2019) and Cheesman et al. (2021).

6.3. Opportunities for further research

The foregoing suggestions for methodological improvements when applying the travel cost method to VGI-derived data provide several opportunities for further research:

- Investigate the extent to which the precision of regression parameter estimates in the Coorong and GKP models can be improved by identifying plausible trip origins by using 'away from quasi-home' eBird postings in the days immediately prior to a post from the focal recreation site.
- Investigate whether the precision of consumer surplus estimates in the Coorong and GKP models can be improved by incorporating variables that categorise visit context (weekend, holiday season ….) in the regression models.
- Investigate the extent to which valuation estimates change when group size is incorporated in randomly re-sampled datasets for regression modelling, drawing on group size information from the MD WERP RQ12.2 Extension B birdwatching survey with members of Birdlife Australia's local birdwatching groups.
- Implement VGI data-derived random utility models at multiple wetland sites across the Basin to investigate how differences in site characteristics – such as differences in bird species abundance, diversity and rarity, and inclusion in environmental watering regimes – affect the consumer surplus birdwatchers derive from visiting a site. This ability to assemble visitation data and conduct consumer surplus valuation for multiple sites across the Basin is a key advantage of VGI-derived data, suggesting considerable opportunities for further research in this direction.
- Following the approach suggested by Cameron and Kolstoe (2022a), explore opportunities for using auxiliary population samples to improve sample selection – correction strategies to make eBird-derived valuation results more useful for policy makers.

References

Alvarez, S., L. Larkin, S., 2010. Valuing Ecological Restoration and Recreational Benefits in a Mountain Protected Area: The Case of Los Nevados National Park, Colombia. J Sustain Dev 3. https://doi.org/10.5539/jsd.v3n4p3

Arrow, K., Lehmann, E.L., 2005. Harold Hotelling 1895–1973: A Biographical Memoire. Biographical Memoires 87.

Australian Bureau of Statistics, 2023. Employee Earnings and Hours, Australia. [WWW Document]. URL https://www.abs.gov.au/statistics/labour/earnings-and-working-conditions/employee-earnings-and-hours-australia/latest-release. (accessed 10.16.24).

Beal, D.J., 1995. A travel cost analysis of the value of Carnarvon Gorge National Park for recreational use. Review of Marketing and Agricultural Economics 63, 292–303.

Bhatt, P., Pickering, C.M., 2022. Destination image of Chitwan National Park, Nepal: Insights from a content analysis of online photographs. Journal of Outdoor Recreation and Tourism 37. https://doi.org/10.1016/j.jort.2022.100488

Boardman, A.E., Greenberg, D.H., Vining, A.R., Weimer, D.L., 2001. Cost-benefit analysis: Concepts and practice, Second Edi. ed. New Jersey: Prentice Hall Inc.

Cameron, T.A., Kolstoe, S.H., 2022a. Using Auxiliary Population Samples for Sample-Selection Correction in Models Based on Crowd-Sourced Volunteered Geographic Information. Land Econ 98, 1–21. https://doi.org/10.3368/le.98.1.040720-0050R1

Cameron, T.A., Kolstoe, S.H., 2022b. Using Auxiliary Population Samples for Sample-Selection Correction in Models Based on Crowd-Sourced Volunteered Geographic Information. Land Econ 98, 1–21. https://doi.org/10.3368/le.98.1.040720-0050R1

Cheesman, J., Dawson, L., May, D., Eigenraam, M., Obst, C., McLeod, R., 2021. Technical report on physical and monetary supply and use accounts for the Gunbower-Koondrook-Perricoota Forest Icon Site: a report from the Land and Ecosystem Accounts Project. . Canberra.

Clara, I., Dyack, B., Rolfe, J., Newton, A., Borg, D., Povilanskas, R., Brito, A.C., 2018. The value of coastal lagoons: Case study of recreation at the Ria de Aveiro, Portugal in comparison to the Coorong, Australia. J Nat Conserv 43, 190–200. https://doi.org/10.1016/j.jnc.2017.10.012

Dobson, A.J., Barnett, A.G., 2018. An introduction to generalized linear models. Chapman and Hall/CRC.

Dyak, B., Rolfe, J., Harvey, J., O'Connell, D., Abel, N., 2007. Valuing recreation in the Murray: an assessment of the non-market recreational values at Barmah Forest and the Coorong. .

eBird, 2021. eBird: An online database of bird distribution and abundance [web application]. eBird, Cornell Lab of Ornithology, Ithaca, New York. (Accessed: February 2024)) [WWW Document].

Fleming, C.M., Cook, A., 2008. The recreational value of Lake McKenzie, Fraser Island: An application of the travel cost method. Tour Manag 29, 1197–1205. https://doi.org/10.1016/j.tourman.2008.02.022

Ghermandi, A., 2022. Geolocated social media data counts as a proxy for recreational visits in natural areas: A meta-analysis. J Environ Manage 317. https://doi.org/10.1016/j.jenvman.2022.115325

Ghermandi, A., 2018. Integrating social media analysis and revealed preference methods to value the recreation services of ecologically engineered wetlands. Ecosyst Serv 31, 351–357. https://doi.org/10.1016/j.ecoser.2017.12.012

Goodchild, M.F., 2007. Citizens as sensors: the world of volunteered geography. GeoJournal 69, 211–221. https://doi.org/10.1007/s10708-007-9111-y

Guilfoos, T., Thomas, P., Kolstoe, S., 2023. Estimating habit-forming and variety-seeking behavior: Valuation of recreational birdwatching. Am J Agric Econ. https://doi.org/10.1111/ajae.12422

Haab, T.C., McConnell, K.E., 2002. Valuing environmental and natural resources: the econometrics of non-market valuation. Edward Elgar Publishing.

Hausmann, A., Toivonen, T., Fink, C., Heikinheimo, V., Tenkanen, H., Butchart, S.H.M., Brooks, T.M., Di Minin, E., 2019. Assessing global popularity and threats to Important Bird and Biodiversity Areas using social media data. Science of the Total Environment 683, 617–623. https://doi.org/10.1016/j.scitotenv.2019.05.268

Jayalath, T.A., Lloyd-Smith, P., Becker, M., 2023. Biodiversity Benefits of Birdwatching Using Citizen Science Data and Individualized Recreational Demand Models. Environ Resour Econ (Dordr) 86, 83–107. https://doi.org/10.1007/s10640-023-00788-0

Kleiber, C., Zeileis, A., 2008. Applied econometrics with R. Springer Science & Business Media.

Kolstoe, S., Cameron, T.A., 2017. The Non-market Value of Birding Sites and the Marginal Value of Additional Species: Biodiversity in a Random Utility Model of Site Choice by eBird Members. Ecological Economics 137, 1–12. https://doi.org/10.1016/j.ecolecon.2017.02.013

Kolstoe, S., Cameron, T.A., Wilsey, C., 2018. Climate, Land Cover, and Bird Populations: Differential Impacts on the Future Welfare of Birders across the Pacific Northwest. Agric Resour Econ Rev 47, 272–310. https://doi.org/DOI: 10.1017/age.2018.9

Kolstoe, S., Naald, B. Vander, Cohan, A., 2022. A tale of two samples: Understanding WTP differences in the age of social media. Ecosyst Serv 55, 101420. https://doi.org/10.1016/j.ecoser.2022.101420

Langemeyer, J., Ghermandi, A., Keeler, B., van Berkel, D., 2023. The future of crowd-sourced cultural ecosystem services assessments. Ecosyst Serv 60, 101518. https://doi.org/https://doi.org/10.1016/j.ecoser.2023.101518

Martínez-Espiñeira, R., Amoako-Tuffour, J., 2008. Recreation demand analysis under truncation, overdispersion, and endogenous stratification: An application to Gros Morne National Park. J Environ Manage 88, 1320–1332. https://doi.org/10.1016/j.jenvman.2007.07.006

Parsons, G.R., 2013. Travel cost methods, in: Shogren, J.F. (Ed.), Encyclopedia of Energy, Natural Resource, and Environmental Economics. Elsevier, Amsterdam, pp. 349–358.

Rolfe, J., Dyack, B., 2019. Testing Temporal Stability of Recreation Values. Ecological Economics 159, 75–83. https://doi.org/10.1016/j.ecolecon.2019.01.016

Rolfe, J., Dyack, B., 2011. Valuing Recreation in the Coorong, Australia, with Travel Cost and Contingent Behaviour Models. Economic Record 87, 282–293. https://doi.org/10.1111/j.1475-4932.2010.00683.x

Rolfe, J., Dyack, B., 2010. Testing for convergent validity between travel cost and contingent valuation estimates of recreation values in the Coorong, Australia. Australian Journal of Agricultural and Resource Economics 54, 583–599. https://doi.org/10.1111/j.1467-8489.2010.00513.x

Sinclair, M., Ghermandi, A., Moses, S.A., Joseph, S., 2019. Recreation and environmental quality of tropical wetlands: A social media based spatial analysis. Tour Manag 71, 179–186. https://doi.org/10.1016/j.tourman.2018.10.018

Sinclair, M., Ghermandi, A., Sheela, A.M., 2018. A crowdsourced valuation of recreational ecosystem services using social media data: An application to a tropical wetland in India. Science of The

Total Environment 642, 356–365. https://doi.org/https://doi.org/10.1016/j.scitotenv.2018.06.056

Sinclair, M., Ghermandi, A., Signorello, G., Giuffrida, L., De Salvo, M., 2022. Valuing Recreation in Italy's Protected Areas Using Spatial Big Data. Ecological Economics 200. https://doi.org/10.1016/j.ecolecon.2022.107526

Sinclair, M., Mayer, M., Woltering, M., Ghermandi, A., 2020a. Using social media to estimate visitor provenance and patterns of recreation in Germany's national parks. J Environ Manage 263. https://doi.org/10.1016/j.jenvman.2020.110418

Sinclair, M., Mayer, M., Woltering, M., Ghermandi, A., 2020b. Valuing nature-based recreation using a crowdsourced travel cost method: A comparison to onsite survey data and value transfer. Ecosyst Serv 45. https://doi.org/10.1016/j.ecoser.2020.101165

Sinclair, M., Mayer, M., Woltering, M., Ghermandi, A., 2020c. Valuing nature-based recreation using a crowdsourced travel cost method: A comparison to onsite survey data and value transfer. Ecosyst Serv 45. https://doi.org/10.1016/j.ecoser.2020.101165

Sinclair, M., Vishnu Sagar, M.K., Knudsen, C., Sabu, J., Ghermandi, A., 2021. Economic appraisal of ecosystem services and restoration scenarios in a tropical coastal Ramsar wetland in India. Ecosyst Serv 47. https://doi.org/10.1016/j.ecoser.2020.101236

Sullivan, B.L., Aycrigg, J.L., Barry, J.H., Bonney, R.E., Bruns, N., Cooper, C.B., Damoulas, T., Dhondt, A.A., Dietterich, T., Farnsworth, A., Fink, D., Fitzpatrick, J.W., Fredericks, T., Gerbracht, J., Gomes, C., Hochachka, W.M., Iliff, M.J., Lagoze, C., La Sorte, F.A., Merrifield, M., Morris, W., Phillips, T.B., Reynolds, M., Rodewald, A.D., Rosenberg, K. V, Trautmann, N.M., Wiggins, A., Winkler, D.W., Wong, W.-K., Wood, C.L., Yu, J., Kelling, S., 2014. The eBird enterprise: An integrated approach to development and application of citizen science. Biol Conserv 169, 31–40. https://doi.org/https://doi.org/10.1016/j.biocon.2013.11.003

Sullivan, B.L., Wood, C.L., Iliff, M.J., Bonney, R.E., Fink, D., Kelling, S., 2009. eBird: A citizen-based bird observation network in the biological sciences. Biol Conserv 142, 2282–2292. https://doi.org/https://doi.org/10.1016/j.biocon.2009.05.006

Teles da Mota, V., Pickering, C., Chauvenet, A., 2022. Popularity of Australian beaches: Insights from social media images for coastal management. Ocean Coast Manag 217. https://doi.org/10.1016/j.ocecoaman.2021.106018

Tenkanen, H., Di Minin, E., Heikinheimo, V., Hausmann, A., Herbst, M., Kajala, L., Toivonen, T., 2017. Instagram, Flickr, or Twitter: Assessing the usability of social media data for visitor monitoring in protected areas. Sci Rep 7. https://doi.org/10.1038/s41598-017-18007-4

Wilkins, E.J., Wood, S.A., Smith, J.W., 2021. Uses and Limitations of Social Media to Inform Visitor Use Management in Parks and Protected Areas: A Systematic Review. Environ Manage 67, 120–132. https://doi.org/10.1007/s00267-020-01373-7

Zuur, A.F., Ieno, E.N., Walker, N.J., Saveliev, A.A.,, Smith, G.M., 2009. Mixed effects models and extensions in ecology with R : . Springer., New York, USA.

Appendix 1: Authorisation to use eBird data

Re: Request to use eBird data on a second research project

eBird <help@ebird.org>

Wed 27/03/2024 07:11

To:

Jim Smart <j.smart@griffith.edu.au>

Hi Jim, thank you for notifying us of your use of eBird data for an additional research purpose. This email represents written approval from the Cornell Lab of Ornithology for the use of eBird data in both your initial project and your new project for the Murray Darling Basin. Please let us know if you have any additional questions or if we can be of further assistance.

We wish you all the best in your research.

Sincerely,

Jenna

Jenna Curtis

eBird Project Leader

Cornell Lab of Ornithology

Appendix 2: Coorong BuDs – quasi-home location at other stringency levels

Appendix 2 reports input dataset statistics and regression results for Coorong BuDs with quasi-home location assigned using the lowest and highest levels of stringency.

Table A2-1: Statistics for regression input data for Coorong BuDs with quasi-home locations assigned using the least stringent set of criteria.

Coorong BuDs dataset: Background information						
Total number of visit days	779					
Total number of eBirders	101					
	1d	2d	3d	4d	5d	6d
No. visit days by visit duration	549	116	63	40	5	6
	min	25%ile	median	mean	75%ile	max
Visit duration (days)	1	1	1	1.71	2	6
Travel distance: round trip (km)	6.49	65.72	72.35	248.46	109.75	2038.59
Travel time: round trip (hours)	0.17	0.97	1.03	2.87	1.62	21.48
Dependent variable						
	min	25%ile	median	mean	75%ile	max
No. visit days (days)	1	2	3	5.19	5	39
Independent variables						
	min	25%ile	median	mean	75%ile	max
Per day visit cost* (overall) ($)	13.76	135.63	147.90	266.30	215.52	1394.72
Per day visit cost* (1d visits) ($)	13.76	129.08	141.58	167.77	184.12	512.58
Per day visit cost* (2d visits) ($)	81.88	141.10	156.43	289.02	386.37	771.59
Per day visit cost* (3d visits) ($)	127.02	157.83	319.73	581.49	945.16	1394.72
Per day visit cost* (4d visits) ($)	147.90	158.53	463.75	455.31	506.15	1070.34
Per day visit cost* (5d visits) ($)	896.83	896.83	896.83	896.83	896.83	896.83
Per day visit cost* (6d visits) ($)	403.17	403.17	403.17	403.17	403.17	403.17
Household income proxy ($/week)	900	900	1125	1281.17	1875	1875
Age proxy (years)	26	41	43	42.95	44.75	59

Table A2-2: Count data regression results on Coorong BuD data with quasi-home locations assigned using the least stringent set of assignment criteria.

Coorong: BuDs	Quasi-home location assigned using least stringent criteria										
	Poisson on (number of visits -1)						NegBin on (number of visits -1)				
Coefficients:	Estimate	Std Err	z-value	Pr(>|z|)			Estimate	Std Err	z-value	Pr(>|z|)	
Intercept	1.076	0.390	2.762	5.75E-03			1.427	0.953	1.497	0.134	
CostPerVisitDay	-1.60E-03	2.53E-04	-6.305	2.88E-10			-1.17E-03	4.13E-04	-2.834	4.59E-03	
HH_Inc	-2.28E-04	9.75E-05	-2.334	0.020			-1.72E-04	2.31E-04	-0.746	0.456	
Age	0.023	7.92E-03	2.901	3.72E-03			0.011	0.020	0.557	0.577	
Null Deviance	957.14	on	149	DoF			171.32	on	149	DoF	
Residual Deviance	873.67	on	146	DoF			158.63	on	146	DoF	
Dispersion	5.98						1.09				
Pseudo R^2	8.72						7.41				
LogLik	-628.62						-374.57				
AIC	1265.25						759.14				
NegBin_alpha	n.a.						1.10				

Coorong: BuDs	Quasi-home location assigned using least stringent criteria				
	NegBin on (number of visits -1)				
Coefficients:	Estimate	Std Err	z-value	Pr(>|z|)	
Intercept	1.719	0.137	12.509	6.69E-36	
CostPerVisitDay	-1.28E-03	4.03E-04	-3.185	1.45E-03	
Null Deviance	170.07	on	149	DoF	
Residual Deviance	158.57	on	148	DoF	
Dispersion	1.07				
Pseudo R^2	6.76				
LogLik	-375.12				
AIC	756.23				
NegBin_alpha	1.11				
Avg per person per day consumer surplus			$769.86	+95% c.i.	$ 1115.70
				-95% c.i.	$ 561.55

Statistical significance indicated via: *** < 0.001, **< 0.01, *<0.05, •<0.10, n.s. = not significant.

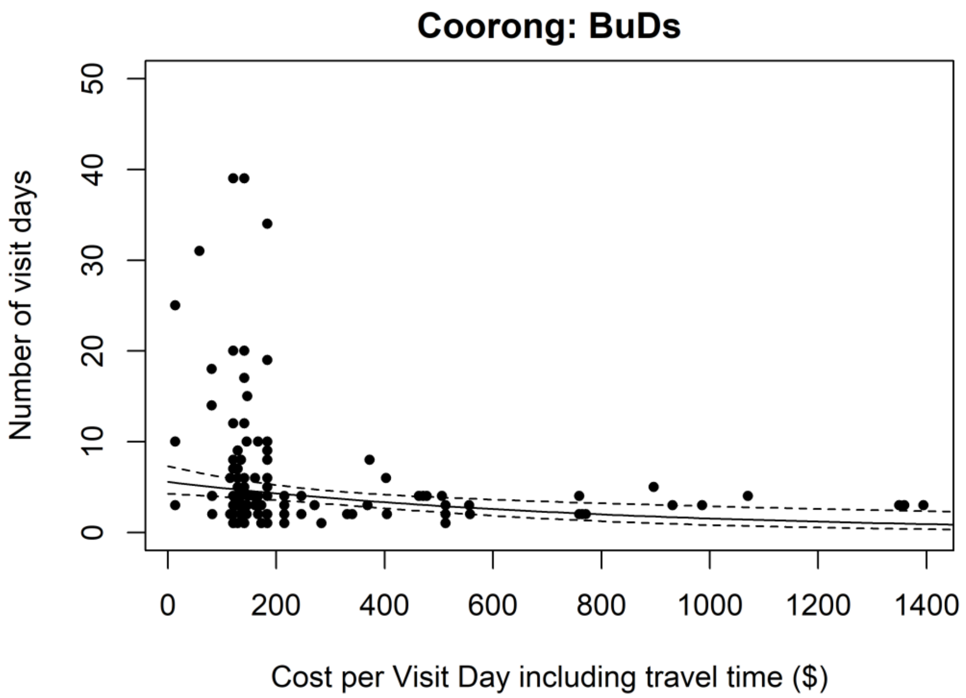

Figure A2-1: Coorong BuDs: Number of visit days plotted against cost per visit day, showing fitted regression line with 95% confidence intervals.
Cost per visit day includes travel cost, the opportunity cost of travel time and accommodation cost (where relevant).
Data from the data set with quasi-home locations assigned using the least stringent set of assignment criteria.

Table A2-3: Statistics for regression input data for Coorong BuDs with quasi-home locations assigned using the most stringent set of criteria.

Coorong BuDs dataset: Background information						
Total number of visit days	497					
Total number of eBirders	59					
No. visit days by visit duration	1d	2d	3d	4d	5d	6d
	331	72	51	32	5	6
	min	25%ile	median	mean	75%ile	max
Visit duration (days)	1	1	1.5	1.91	2.75	6
Travel distance: round trip (km)	6.49	65.72	72.35	282.62	244.93	2038.59
Travel time: round trip (hours)	0.17	0.97	1.03	3.21	2.79	21.48
Dependent variable						
	min	25%ile	median	mean	75%ile	max
No. visit days (days)	1	2	3	5.78	4.75	41
Independent variables						
	min	25%ile	median	mean	75%ile	max
Per day visit cost* (overall) ($)	13.76	135.63	147.90	278.64	280.70	1394.72
Per day visit cost* (1d visits) ($)	13.76	121.27	141.58	169.02	184.12	512.58
Per day visit cost* (2d visits) ($)	81.88	135.63	145.79	275.82	331.29	759.42
Per day visit cost* (3d visits) ($)	127.02	147.19	270.86	489.78	931.55	1394.72
Per day visit cost* (4d visits) ($)	147.90	155.87	467.56	465.65	569.43	1070.34
Per day visit cost* (5d visits) ($)	896.83	896.83	896.83	896.83	896.83	896.83
Per day visit cost* (6d visits) ($)	403.17	403.17	403.17	403.17	403.17	403.17
Household income proxy ($/week)	900	900	1125	1276.74	1875	1875
Age proxy (years)	26	40	43	43.07	45	59

Table A2-4: Count data regression results on Coorong BuD data with quasi-home locations assigned using the most stringent set of assignment criteria

Coorong: BuDs	Quasi-home location assigned with most stringent set of criteria										
	Poisson on (number of visits -1)						NegBin on (number of visits -1)				
Coefficients:	Estimate	Std Err	z-value	Pr(>|z|)			Estimate	Std Err	z-value	Pr(>|z|)	
Intercept	1.285	0.454	2.831	4.64E-03	**		1.911	1.183	1.615	0.106	n.s.
CostPerVisitDay	-1.96E-03	3.23E-04	-6.077	1.22E-09	***		-1.32E-03	5.36E-04	-2.464	0.014	*
HH_Inc	-4.08E-04	1.26E-04	-3.247	1.17E-03	**		-3.10E-04	3.11E-04	-0.997	0.319	n.s.
Age	0.028	9.20E-03	3.051	2.28E-03	**		7.71E-03	0.025	0.314	0.753	n.s.
Null Deviance	665.78	on	85	DoF			100.99	on	85	DoF	
Residual Deviance	582.19	on	82	DoF			90.70	on	82	DoF	
Dispersion	7.10						1.11				
Pseudo R^2	12.56						10.19				
LogLik	-405.63						-223.02				
AIC	819.26						456.05				
NegBin_alpha	n.a.						1.13				

Coorong: BuDs	Quasi-home location assigned with most stringent criteria				
	NegBin on (number of visits -1)				
Coefficients:	Estimate	Std Err	z-value	Pr(>|z|)	
Intercept	1.899	0.186	10.235	1.39E-24	***
CostPerVisitDay	-1.47E-03	5.28E-04	-2.792	5.24E-03	**
Null Deviance	99.60	on	85	DoF	
Residual Deviance	90.68	on	84	DoF	
Dispersion	1.08				
Pseudo R^2	8.95				
LogLik	-223.63				
AIC	453.27				
NegBin_alpha	1.15				
Avg per person per day consumer surplus			$680.33	+95% c.i.	$ 1102.53
				-95% c.i.	$ 453.94

Statistical significance indicated via: *** < 0.001, **< 0.01, *<0.05, •<0.10, n.s. = not significant

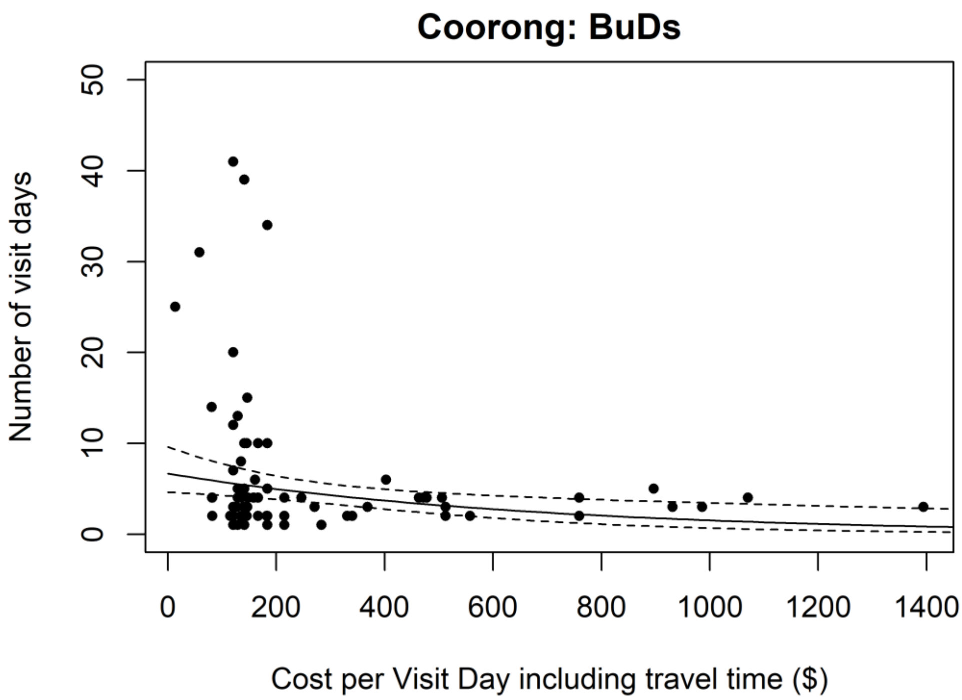

Figure A2-2: Coorong BuDs: Number of visit days plotted against cost per visit day, showing fitted regression line with 95% confidence intervals.
Cost per visit day includes travel cost, the opportunity cost of travel time and accommodation cost (where relevant).
Data from the data set with quasi-home locations using most stringent set of assignment criteria.

Appendix 3: GKP BuDs – quasi-home location at other stringency levels

Appendix 3 reports input dataset statistics and regression results for GKP BuDs with quasi-home location assigned at the lowest and highest levels of stringency.

Table A3-1: Statistics for regression input data for GKP BuDs with quasi-home locations assigned via the least stringent set of criteria.

GKP BuDs dataset: Background information						
Total number of visit days	212					
Total number of eBirders	52					
	1d	2d	3d	4d	5d	6d
No. visit days by visit duration	60	60	39	32	15	6
	min	25%ile	median	mean	75%ile	max
Visit duration (days)	1	1	2	2.19	3	6
Travel distance: round trip (km)	59.62	188.02	262.71	288.91	331.06	959.64
Travel time: round trip (hours)	1.12	2.57	3.55	3.67	4.19	10.11
Dependent variable						
	min	25%ile	median	mean	75%ile	max
No. visit days (days)	1	2	2	3.16	4	24
Independent variables						
	min	25%ile	median	mean	75%ile	max
Per day visit cost* (overall) ($)	120.40	274.97	337.00	343.07	382.74	709.45
Per day visit cost* (1d visits) ($)	120.40	293.23	337.00	341.08	421.88	497.01
Per day visit cost* (2d visits) ($)	135.20	330.68	350.75	346.89	377.66	493.14
Per day visit cost* (3d visits) ($)	270.46	270.46	353.11	404.72	505.36	709.45
Per day visit cost* (4d visits) ($)	221.58	258.78	279.04	312.84	301.06	569.59
Per day visit cost* (5d visits) ($)	222.27	238.36	254.45	256.93	274.26	294.07
Per day visit cost* (6d visits) ($)	264.38	264.38	264.38	264.38	264.38	264.38
Household income proxy ($/week)	900	1125	1125	1327.24	1625	2250
Age proxy (years)	26	38	41	42.30	50	59

Table A3-2: Count data regression results for GKP BuD data with quasi-home location assigned using the least stringent set of criteria.

GKP: BuDs	Quasi-home location assigned using least stringent set of criteria										
	Poisson on (number of visits -1)						NegBin on (number of visits -1)				
Coefficients:	Estimate	Std Err	z-value	Pr(>|z|)			Estimate	Std Err	z-value	Pr(>|z|)	
Intercept	-0.149	1.120	-0.133	0.894			-0.380	1.553	-0.245	0.806	
CostPerVisitDay	-5.56E-03	9.70E-04	-5.734	9.79E-09			-4.09E-03	1.41E-03	-2.900	3.74E-03	
HH_Inc	5.25E-04	3.68E-04	1.427	0.154			4.78E-04	5.08E-04	0.942	0.346	
Age	0.046	0.017	2.770	5.61E-03			0.042	0.023	1.812	0.070	
Null Deviance	206.70	on	66	DoF			84.42	on	66	DoF	
Residual Deviance	156.64	on	63	DoF			67.13	on	63	DoF	
Dispersion	2.49						1.07				
Pseudo R^2	24.22						20.48				
LogLik	-147.13						-124.63				
AIC	302.25						259.27				
NegBin_alpha	n.a.						0.57				

GKP: BuDs	Quasi-home location assigned using least stringent set of criteria					
	NegBin on (number of visits -1)					
Coefficients:	Estimate	Std Err	z-value	Pr(>|z|)		
Intercept	2.128	0.483	4.405	1.06E-05		
CostPerVisitDay	-4.28E-03	1.43E-03	-2.989	2.79E-03		
Null Deviance	80.73	on	66	DoF		
Residual Deviance	67.75	on	65	DoF		
Dispersion	1.04					
Pseudo R^2	16.08					
LogLik	-126.34					
AIC	258.68					
NegBin_alpha	0.62					
Avg per person per day consumer surplus			\$232.39	+95% c.i.	\$698.52	
				-95% c.i.	\$136.49	

Statistical significance indicated via: *** < 0.001, **< 0.01, *<0.05, •<0.10, n.s. = not significant.

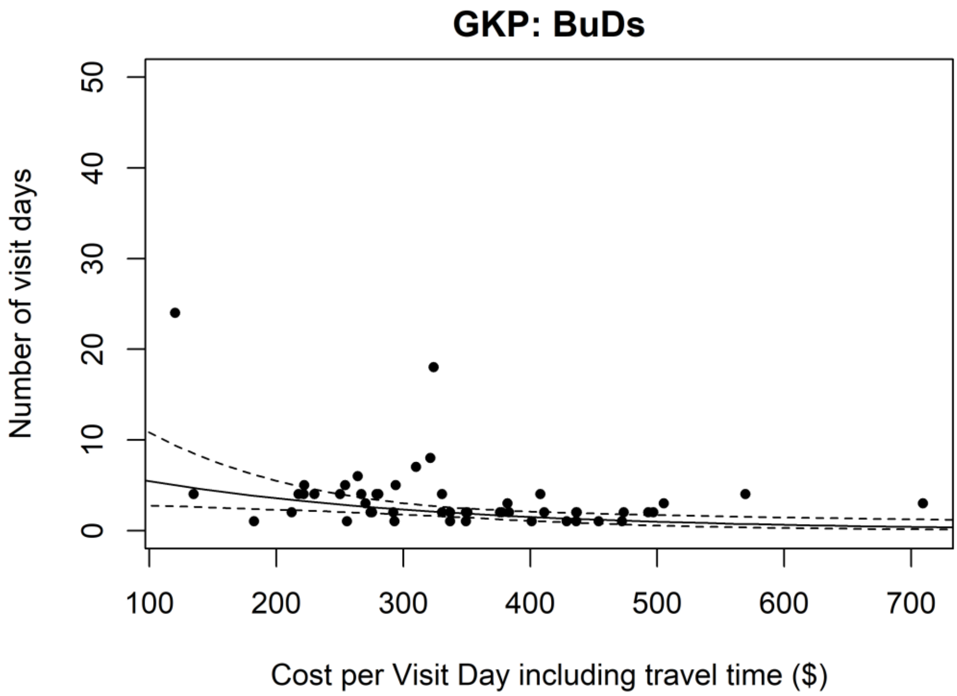

Figure A3-1: GKP BuDs: Number of visit days plotted against cost per visit day, showing fitted regression line with 95% confidence intervals.
Cost per visit day includes travel cost, the opportunity cost of travel time and accommodation cost (where relevant).
Data from the data set with quasi-home locations assigned using least stringent set of criteria.

Table A3-3: Statistics for regression input data for GKP BuDs with quasi-home locations assigned with most stringent set of criteria.

GKP BuDs dataset: Background information						
Total number of visit days	183					
Total number of eBirders	42					
	1d	2d	3d	4d	5d	6d
No. visit days by visit duration	55	50	33	24	15	6
	min	25%ile	median	mean	75%ile	max
Visit duration (days)	1	1	2	2.20	3	6
Travel distance: round trip (km)	59.62	188.02	262.71	269.37	312.07	635.94
Travel time: round trip (hours)	1.12	2.57	3.55	3.47	4.07	7.02
Dependent variable						
	min	25%ile	median	mean	75%ile	max
No. visit days (days)	1	2	2	3.33	4	24
Independent variables						
	min	25%ile	median	mean	75%ile	max
Per day visit cost* (overall) ($)	120.40	270.46	337.00	331.70	377.66	505.36
Per day visit cost* (1d visits) ($)	120.40	316.96	343.21	343.84	421.88	497.01
Per day visit cost* (2d visits) ($)	135.20	301.87	350.75	337.29	376.40	493.14
Per day visit cost* (3d visits) ($)	270.46	283.86	353.11	376.31	474.56	505.36
Per day visit cost* (4d visits) ($)	221.58	250.38	267.18	268.25	280.56	321.57
Per day visit cost* (5d visits) ($)	222.27	238.36	254.45	256.93	274.26	294.07
Per day visit cost* (6d visits) ($)	264.38	264.38	264.38	264.38	264.38	264.38
Household income proxy ($/week)	900	1125	1125	1312.27	1625	2250
Age proxy (years)	26	37.5	42	42.15	50	51

Table A3-4: Count data regression results on GKP BuD data with quasi-home location assigned using most stringent set of criteria.

GKP: BuDs	Quasi-home location assigned using most stringent set of criteria										
	Poisson on (number of visits -1)						NegBin on (number of visits -1)				
Coefficients:	Estimate	Std Err	z-value	Pr(>|z|)			Estimate	Std Err	z-value	Pr(>|z|)	
Intercept	-0.863	1.520	-0.568	0.570	n.s.		-0.193	1.930	-0.100	0.920	n.s.
CostPerVisitDay	-7.36E-03	1.11E-03	-6.652	2.88E-11	***		-6.75E-03	1.70E-03	-3.963	7.39E-05	***
HH_Inc	1.11E-03	4.34E-04	2.556	0.011	*		1.00E-03	5.77E-04	1.737	0.082	n.s.
Age	0.058	0.024	2.460	0.014	*		0.041	0.030	1.387	0.165	n.s.
Null Deviance	189.03	on	54	DoF			76.54	on	54	DoF	
Residual Deviance	127.19	on	51	DoF			52.73	on	51	DoF	
Dispersion	2.49						1.03				
Pseudo R^2	32.71						31.11				
LogLik	-121.30						-102.03				
AIC	250.60						214.06				
NegBin_alpha	n.a.						0.53				

GKP: BuDs	Quasi-home location assigned using most stringent set of criteria					
	NegBin on (number of visits -1)					
Coefficients:	Estimate	Std Err	z-value	Pr(>|z|)		
Intercept	2.790	0.537	5.192	2.08E-07	***	
CostPerVisitDay	-6.41E-03	1.67E-03	-3.833	1.26E-04	***	
Null Deviance	72.55	on	54	DoF		
Residual Deviance	53.77	on	53	DoF		
Dispersion	1.01					
Pseudo R^2	25.89					
LogLik	-103.88					
AIC	213.75					
NegBin_alpha	0.59					
Avg per person per day consumer surplus			$159.48	+95% c.i.	$322.69	
				-95% c.i.	$106.45	

Statistical significance indicated via: *** < 0.001, **< 0.01, *<0.05, •<0.10, n.s. = not significant

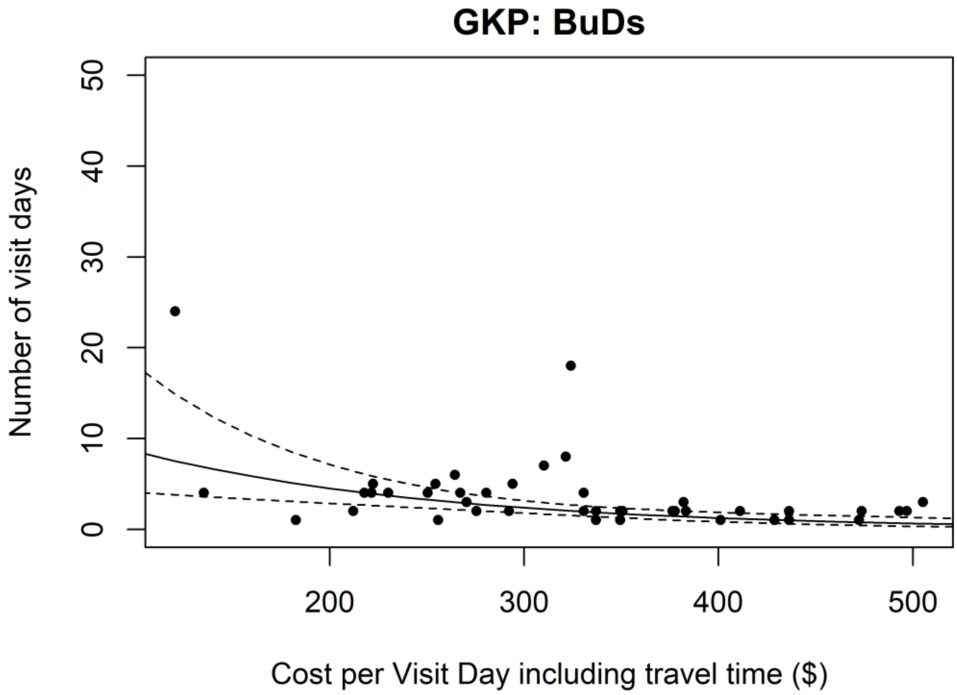

Figure A3-2: GKP BuDs: Number of visit days plotted against cost per visit day, showing fitted regression line with 95% confidence intervals.
Cost per visit day includes travel cost, the opportunity cost of travel time and accommodation cost (where relevant). Data from the data set with quasi-home locations assigned using most stringent set of criteria.

Appendix 4: Mathematical derivation of consumer surplus result

Following explanations in Haab and McConnell (2002),this appendix provides a mathematical derivation of the estimation of consumer surplus for a recreation site from Poisson-form count data regression results.

Figure A4-1 shows the form of an estimated demand curve for individual visitor *i* who incurs cost per visit day tc_i in visiting the focal recreation site. Facing cost per visit day tc_i, visitor *i* would be expected to make x_i visits to the recreation site.

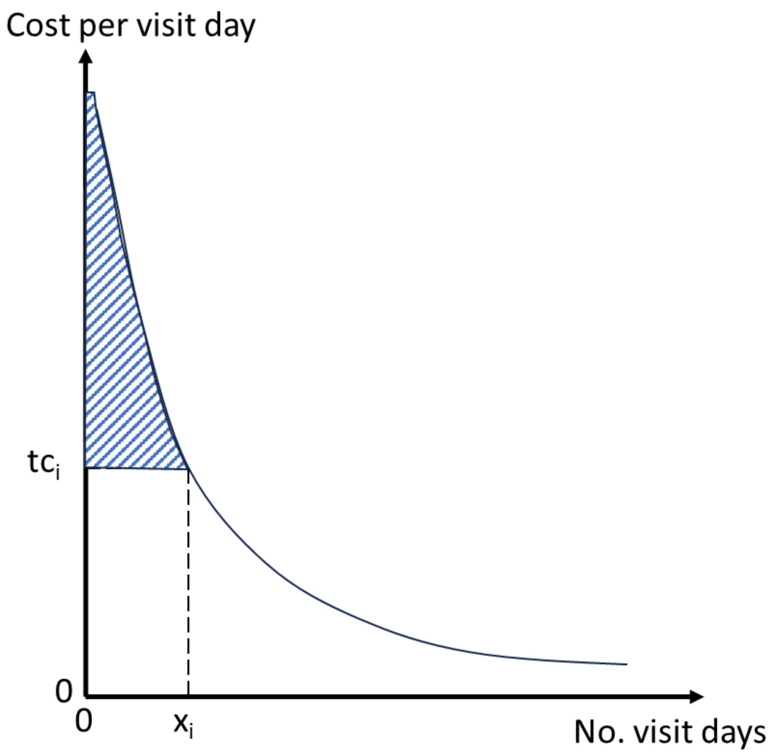

Figure A4-1 An estimated demand curve for individual visitor I who incurs cost per visit day tc_i in visiting a recreation site.

The individual consumer surplus which visitor *i* accrues from making x_i visits to the recreation site is shown by the blue hatched area. This area can be calculated by integration up the vertical axis from tc_i to tc = ∞. Thus:

$$\text{Individual consumer surplus for site access} = \int_{tc_i}^{tc=\infty} E(x_i)\ \ dtc$$

where $E(x_i)$ denotes the number of visits individual *i* would be expected to make to the site (at different costs per visit day).

If, as in the Poisson count data model, we assume an exponential form for $E(x_i)$, driven by travel cost and individual-specific characteristics such as age and income, the integral for consumer surplus can be calculated knowing estimated regression parameters β_1, β_2 and β_3 for individual-specific travel cost tc_i, age age_i , and income inc_i as:

$$\text{Individual consumer surplus for site access} = \int_{tc_i}^{tc=\infty} E(x_i)\ \ dtc = \int_{tc_i}^{tc=\infty} e^{\beta_0+\beta_1 tc_i+\beta_2 age_i+\beta_3 inc_i}\, dtc$$

$$= \left[\frac{e^{\beta_0+\beta_1 tc_i+\beta_2 age_i+\beta_3 inc_i}}{\beta_1}\right]_{tc\ =\ tc_i}^{tc\ =\ \infty}$$

$$= \left(\frac{0}{\beta_1} - \frac{e^{\beta_0+\beta_1 tc_i+\beta_2 age_i+\beta_3 inc_i}}{\beta_1}\right)$$

$$= \left(\frac{0}{\beta_1} - \frac{E(x_i)}{\beta_1}\right) = \frac{-x_i}{\beta_1} = \frac{-1}{\beta_1} \cdot x_i$$

Thus individual-specific consumer surplus from accessing the recreation site is given by $\frac{-1}{\beta_1}$ multiplied by the number of visits the individual is expected to make to the recreation site x_i.

The *per visit* consumer surplus for individual *i*, and for all other individuals, is thus given by:

$$\frac{\left(\frac{-1}{\beta_1} \cdot x_i\right)}{x_i} = \frac{-1}{\beta_1}$$

Where β_1 is the estimated regression parameter for travel cost tc, or in our terminology 'cost per visit day'.