A CONTINENTAL-SCALE ASSESSMENT OF DENSITY, SIZE, DISTRIBUTION, AND HISTORICAL TRENDS OF AUSTRALIAN FARM DAMS

Running Title: Impacts of farm dam urbanization in Australia

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Abstract

Australia is the second driest continent on Earth and freshwater is, therefore, a critical policy concern. Farm dams are ubiquitous and drive AU$17.7 billion of agricultural value, yet there has never been a formal census of Australian dams. In this study, we present a continental-scale assessment on density, distribution, and historical trends of farm dams in each State and Territory of Australia. We estimated that Australia has 1,838,052 dams occupying an area of 5,001 Km^2 and storing 11,922 GL of water. The State of New South Wales recorded the highest number of dams (642,714, 35% of the total) and Victoria the highest overall density (1.67 dams Km^{-2}). We also estimated that 284,820 dams (15%) remain unreported across Australia, especially in South Australia, Western Australia, and the Northern Territory. Three decades of historical records revealed an ongoing decrease in the rate of farm dam accumulation, from >3% per annum before 2000, to ~1% after 2000, to <0.05% after 2010 – except in the Australian Capital Territory where rates have remained relatively high. To facilitate sharing information with the Government, scientists, managers, and the local community, we developed AusDams.org: a free interactive portal to visualise the distribution of farm dams and generate statistics for any area of Australia. We hope that this work will encourage future research and outreach on the effects of sprawling farm dams on freshwater resources, food security, and the environment.

Introduction

Dams are a ubiquitous feature of urbanised landscapes and a cornerstone of farming and industrial practices. These artificial water bodies collect water for livestock and irrigation, recycle runoff, protect against fires or extreme weather, and more (Clifford & Heffernan, 2018; Tisdell & Ward, 2002). Escalating water prices, diminishing rainfalls, and increasing temperatures are stimulating the development of new dams, increasing worldwide at 0.7% to 60% per annum (Downing, 2010). This specific type of urbanisation is having intensifying effects on biodiversity (Brainwood & Burgin, 2009; Hazell et al., 2001), nutrient cycling (Stone et al., 2005), soil erosion (Stenberg et al., 2015), greenhouse gases (Grinham et al., 2018; Ollivier et al., 2019a), and pest control (Cowley et al., 2007). However, there are many countries where the accumulation of farm dams has gone mostly unquantified.

Australia is a dry country, covering 5.6% of the World's landmass, but only containing 1% of its total freshwater (Lehane, 2014; Taylor, 2019). Water is, therefore, a limited resource and a critical policy concern. In Australia, there has never been a census of farm dams, with only ballpark estimates ranging from "half a million" to "several million" reported by Federal documents and scientific articles (see quotes in Table S1). The Australian Government (i.e. Geoscience Australia) has previously invested in a Water Observation from Space program (Mueller et al., 2016). However, the minimum detection is limited to water bodies larger than half a soccer field (50 x 50 m), which excludes the majority of farm dams. The absence of basic information on farm dams is surprising, given that agriculture accounts for 70% of the total water use in Australia (Chartres & Williams, 2006; Taylor, 2019).

In Australia, States and Territories manage their water supplies independently (Australian Government Productivity Commission, 2017; Taylor, 2019; Tisdell & Ward, 2002). As a result, a census of farm dams across Australia requires overcoming several challenges. *First*, only medium/large dams (typically $>10^3$) need a license and the minimum requirements for licensing vary among jurisdictions are poorly comparable, with thresholds based on size, capacity, age, or local rainfall (Baillie, 2008; Department of Natural Resources Mines and Energy, 2018; Water NSW, 2017). *Second*, most States and Territories complement licensing data with remote sensing. Still, the image resolution varies by 50-fold among jurisdictions – from 25 m (e.g. Landsat data) to 0.5 m (e.g. WorldView) – causing widely different minimum detection sizes for surface water among regions. *Third*, States and Territories updated their datasets at different frequencies – often once a decade – and historical rates of dam proliferations are poorly documented. Before this study, there has never been a nation-wide assessment of Australian farm dams (Australian Bureau of Statistics, pers. comm.). The only dataset of Australian farm dams is by Geoscience Australia (Crossman & Li, 2015a, 2015b), but only a subset of dams feature in this map. For example, the number of dams reported by Geoscience Australia for the State of Tasmania (726) is a mere 1% of the dams reported by regional authorities (62,288 – see Methods).

In this article, we present a census of density, distribution, water capacity, and historical trends of Australian dams. *First*, we compiled all available information from Federal, State and local authorities on Australian farm dams and similar artificial water bodies (e.g. tailings ponds, sewage ponds, settling ponds). *Second*, we designed an independent algorithm to detect dams from satellite images that we used to examine and standardise records among sources. *Third*, we quantified historical trends in the rate of development of new dams from each State and Territory in Australia.

Methods

1. Mapping dams in Australia

Please refer to Table S2 for details on curators, geographical extents, sample sizes, data types, filters, access dates, and sources for all datasets used in this study. Briefly, we sourced data on 1,696,321 farm dams from (1) the Surface Water map by Geoscience Australia (N = 932,810), (2) the Department of Environment, Land, Water & Planning of the Victorian Government (N = 429,651), (3) the Department for Environment and Water in South Australia (N = 105,361), (4) the Department of Primary Industries and Regional Development in Western Australia (N = 165,571), (5) the Department of Primary Industries, Parks, Water and Environment in Tasmania (N = 62,075), and (6) the Environment & Planning Directorate in the Australian Capital Territory (N = 853). We inspected all large dams (>10^5 m^2 in surface area) and removed those that appeared of relatively natural origin (i.e. complex shapes, jiggered borders) by retaining only dams with circularity (calculated as $4 \times Area \times [\pi \times Perimeter^2]^{-1}$) above 0.5. For dams reported as points (as opposed to polygons), we used the minimum detection area for polygons reported in the metadata, and we calculated the perimeter assuming circular shape. We ensured there were no repeated or overlapping entries in our data. Finally, we estimated the volume of stored water (ML) in each dam as the average from two calibration curves, one developed by Sinclair Knight Merz (2012a) with dams in Queensland ($Dam\ volume\ = 1.9 \times 10^{-4} \times Surface\ area^{1.24}$, R^2 = 0.91) and another developed by Sinclair Knight Merz (2012b) with dams in Victoria ($Dam\ volume\ = 1.45 \times 10^{-4} \times Surface\ area^{1.32}$, R^2 = 0.95).

2. Quantifying uncertainty

To account for different uncertainties among jurisdictions, we developed an independent water detection algorithm that we could use as ground truth for each map. Specifically, we derived statistical models to estimate the probabilities of false positive (i.e. entries that are falsely identifying as a dam) and false negative (i.e. undocumented dams) in each State and Territory in Australia.

2.1. Deep learning detection model

We trained a convolutional neural network model to detect dams in the Python programming language using the open-source library “fastai” version 1 (https://github.com/fastai/fastai; Howard & Gugger, 2020). We downloaded RGB satellite imagery of 7,362 Australian locations from three different repositories (i.e. http://ecn.t3.tiles.virtualearth.net, https://api.mapbox.com, and https://server.arcgisonline.com). We sampled 75% of these images from our dam dataset and the remaining 25% from randomly selected locations within Australia. These images had varying sizes and aspect ratios and the pixel resolution was mostly 0.45 m, but when unavailable we also used lower resolutions (e.g. 1-5 m).

To avoid manually labelling of all 7,362 downloaded images, we took a random subsample of 400 images and labelled them into ‘dam’ or ‘not dam’ and we trained a classification model on the labelled data. We utilised transfer learning by initialising a ImageNet-pretrained ResNet34 model (Howard & Gugger, 2020). We applied an 80-20% split for training and validation datasets, respectively. To help generalise the model, we used data augmentation with the fastai get_transforms function (Howard & Gugger, 2020) and the following arguments: ‘flip_vert=TRUE’ to allow for vertical flipping of images, ‘max_lighting=0.02’ to limit overly exposing the images, ‘max_zoom=1’ to disable the zooming augmentation, and ‘to_fp16 = TRUE’ to reduce the memory load on the graphical processing unit (GPU). We set the batch size to 300 images and trained the model with a learning rate of 10-3 for 10 epochs. At epoc 5, we achieved an error rate of 0.1538 (15.38%) a validation loss of 0.4211 and a training loss of 0.8287. We used the trained model to automatise the classification of 500 more images from the unlabelled training dataset and we manually fixed any mistakes. We repeated this process of training, classification and checking until all of the 7,362 downloaded images were labelled.

We trained the model using all 7,362 labelled images using the same parameters detailed above and we achieved an error rate of 0.1195 (11.95%) with a training loss of 0.3462 and a validation loss of 0.2847. We further fine-tuned the model by unfreezing the entire model and training at a 10-fold lower learning rate (10^{-4}). The final model achieved an accuracy of 94.8% (error rate of 5.2%) with a training loss of 0.1397 and a validation loss of 0.1446 with 10 epocs (see confusion matrix in Fig. S1).

2.2. Detection reliability assessment

Locations falsely classified as containing a dam (i.e. false positives) act to overpredict the real number of dams in Australia. So, we calculated the probability of false positives by using our deep learning model to analyse and validate 2000 dams in each State and Territory sampled from our compiled database. To do so, we downloaded RGB satellite imagery of the surrounding area from the same three repositories mentioned above and combined their predictions to generate an outcome for each location.

We corrected our dataset for false positives using generalised linear models. We used the classification outcome from our deep learning model (binomial distribution, either "dam correctly verified" or "dam being a false positive") as the response variable, and we used the State or Territory identity (categorical), dam surface area (continuous), and their interaction as the covariates in the analysis. The rationale is that jurisdictions using outdated or low-definition satellite images to map water bodies will have a higher probability of missrecording smaller dams (i.e. low reliability). We used our best-fitting statistical model (following Akaike information criterion; Burnham & Anderson, 2004) to predict the reliability (i.e. probability of true positives) for each dam in our dataset. Finally, we corrected our data by removing all entries that recorded less than 75% reliability of being a true positive, which we verified to be an appropriate threshold to filter out the large majority of false positives.

2.3. *Undocumented dams*

We estimated the fraction of undocumented dams (i.e. false negatives) in each State and Territory by conducting an independent exploration using our deep learning model in areas supposedly free of dams. We randomly sampled locations in each State and Territory and downloaded RGB images at 0.5 m resolution from http://ecn.t3.tiles.virtualearth.net/. Given that the probability of encountering a dam by randomly sampling a site around Australia is very low, we maximised our sampling efforts by sampling only land types with high dam densities. To do so, we overlapped our compiled dataset of Australian dams with the 2016 Australian Land Use and Management Classification developed by the Australian Bureau of Agricultural and Resource Economics and Sciences (see Table S2) to identify the 19 land types with the highest dam densities (>5 dams km^{-2}) across Australia (see Fig. S2 for the list of land types). We used our deep learning model to search for unreported dams in random sites inside the 19 land-use types. The number of investigated sites depended on the available sampling area in each region and was typically between 13,000 to 27,000 – although we could only sample fewer sites in the Northern Territory (N = 5,400) and Australian Capital Territory (N = 62). We calculated the relative density of unreported dams (i.e. false negative) compared to the density of reported dams (true positives) to calculate a probability of false negatives per area for each land-use type in each State and Territory. Finally, we used the mean probability of false negatives across all land-use types to estimate the total number of undocumented dams across each State and Territory. As an example, suppose there are 100 dams documented for a specific land-use type of 100 km^2 (i.e. reported density of 1 dam per km^2), from which we removed 5 dams because deemed as unreliable entries (i.e. density after correcting for false positives of 0.95 dam per km^2). Were we to find 5 undocumented dams by searching 10 km^2 of randomly sampled locations, we would infer a density of undocumented dams of 0.5 dam per km^2. Hence, we would conclude that undocumented dams in this land-use type are (0.5/0.95 =) 53% of the documented dams. By repeating these operations for all 19 land-use types, we could calculate an overall percentage of false negatives that we used to correct all densities of documented dams to infer the total number of documented+undocumented dams in each State or Territory. Our approach assumes that the probability of a dam being unreported is constant across all land-use types, which reasonable when using the same mapping techniques across the landscape. Finally, we manually traced the area of 221 randomly selected unreported dams to estimate the average surface area (m^2) of undocumented dams in each State and Territory (Fig. S2), which we used to estimate the total surface area covered by documented+undocumented dams.

2.4. *Compounding sources of uncertainties*

We quantified the overall uncertainty for all our metrics using bootstrapping procedures (Efron & Tibshirani, 1998). Specifically, we sampled with replacement the datasets to quantify false positives and false negatives. For each simulated dataset, we repeated the steps detailed above to calculate all statistics after correcting for false positives and false negatives. By simulating 1,000 datasets, we obtained a bootstrap distribution of each estimate from where we extracted the median and the 95% confidence intervals.

3. Historical trends

We used data from the Water Observations from Space (WOfS) to quantify historical changes in surface water in Australia from 1988 to present (Mueller et al., 2016). Data from WOfS are elaborations of Landsat 5 and Landsat 7 satellite images to display surface water at a 30 m grid size across Australia at an approximate bi-weekly frequency. We selected ca. 1,000 dams in our dataset from each State and Territory – excluding the Northern Territory that had too few documented dams. At each dam, we monitored water detection over time by tracking the relative number of pixels identified as water from 1988 to 2015. We recorded the year when water started being consistently detected in at least 25% of the farm dam area. Finally, we computed the relative and absolute cumulative distribution in farm dams over time in each State and Territory and used linear models to analyse trends.

4. Statistical analyses

We used Python (Python Software Foundation) and fastai (Howard & Gugger, 2020) for developing the deep learning detection model. We used R (R Core Team, 2019) for all statistical analyses, using packages ncdf4 (Pierce, 2017) and raster (Hijmans, 2016) for data manipulation; ggplot2 (Wickham, 2009), rasterVis (Lamigueiro & Hijmans, 2016), and cowplot (Wilke, 2016) for plotting. We also use R for designing the website AusDams.org, using Shiny (Chang et al., 2020), Leaflet (Cheng et al., 2019), Plotly (Sievert, 2020), and using Joe Cheng's Superzip template (https://shiny.rstudio.com/gallery/superzip-example.html).

Results

Reported dams

There are 1,696,317 dams reported by regional and Federal authorities in Australia. The majority of dams were in New South Wales (36%), Victoria (26%), Queensland (17%), and Western Australia (11%; Table S2). Around three-quarters of Australia recorded at least 1 dam per 2,000 Km^2, but the typical density near urban centres was 2-5 dams per Km^2 (Fig. 1). The average size of a dam is ca. 1,000 m^2, ranging from 100 m^2 to 10^5 m^2 (Fig. 2).

Data reliability

Our results showed that reports of larger (>1000 m^2) dams were reliable, with a probability of a successful verification ranging from 78 $\pm$ 1.2% in Queensland to 92$\pm$ 0.7% (S.E.) in Victoria (Fig. 2). Instead, reports of smaller dams (<100 m^2) were only verified in 9$\pm$3% (in Western Australia) to 73$\pm$ 2% S.E. (in South Australia) of cases (Fig. 2 and Fig. S3). Overall, we corrected for false positives in the data by removing 50,056 dams (2.9% of the total), ranging from 22,968 (5.18%) in Victoria to 54 (2.6%) in the Australian Capital Territory (Fig. 2 and S3). The State with the largest percentage of removed dams was Tasmania (13%). Notice that in the Northern Territories there were too few documented dams to carry out a formal probability assessment, so we assumed 100% of the 2,040 documented dams were successfully verified – although our analysis suggests the real value is around 37%.

Unreported dams

We estimated that 284,820 dams are unreported in Australia. Dams in Tasmania, Queensland, New South Wales, Victoria, and the Australian Capital Territory contributed to 83.8% of all documented dams and recorded the lowest percentages (<6%) of unreported dams, corresponding 56,551 unreported dams across the five regions (Fig. 3). We recorded higher percentages of unreported dams in South Australia (12.5%) and Western Australia

(54.4%), for an estimated 218,499 unreported dams (Fig. 3). Finally, the Northern Territory recorded the highest percentage (83%) of unreported dams (Fig. 3).

Total dams in Australia

Overall, we inferred that in Australia there are 1,838,052 dams (95% C.I.: 1,738,453; 1,986,236). New South Wales recorded the highest number of dams (642,714, 35% of the total) and Victoria the highest overall density (1.67 dams Km^{-2}; Fig. 4 A, B). Conversely, the Australian Capital Territory recorded the lowest dam counts (2,047, 0.01% of the total) and the Northern Territory the lowest dam density (0.0075 dams Km^{-2}). In total, farm dams in Australia occupy an area of 5,001 km^2 (95% C.I.: 4,663; 5,592).

In all regions, most (>84%) dams were documented (see green bars in Fig. 4D), except Western Australia and Northern Territory where reported dams were only 46% and 17% of the total, respectively (see red bars in Fig. 4D). Finally, false positives were generally a small fraction (<5%) of the total number of documented dams, with only Tasmania recording a relatively high value (11%; see blue bars in Fig. 4D).

Total water stored in dams

We estimated that the total water stored in Australian dams is 11,922 GL (95% C.I.: 11,227; 13,190; Fig. 4D). New South Wales recorded the greatest amount of water stored in dams (4,669 GL, 39% of the total), followed by Queensland (2,548 GL, 21%) and Western Australia (2,219 GL, 19%; Fig. 4D). Overall, unreported dams store 1,737 GL of water (14.6% of the total). Importantly, water from unreported dams contributed to 94% (38 GL) of the total stored water in the Northern Territory and 45.6% (1,012 GL) in Western Australia.

Historical trends

The years between 1988 and 2000 recorded the fastest increases in dam numbers across all regions (>2% per annum; see steep lines in Fig. 5 before vertical dashed line). In these years, the Australian Capital Territory recorded the fastest rate of growth (3.4% per annum) and New South Wales recorded the highest number of new dams built per year (15,019; Fig. 5 and Fig. S4).

After 2000, the development of new dams slowed down across Australia to <1.5% per annum, except in the Australian Capital Territory where rates remained relatively high (2.6% per annum; see lines in Fig. 5 after vertical dashed line). We found that Queensland recorded the highest number of new dams built each year (4,014), followed by Victoria (2,270) and New South Wales (2,011; see Fig. S4 for all absolute and relative rates).

Discussion

We estimated that in Australia there are 1,838,052 dams, of which 284,820 (15% of the total) are undocumented. Freshwater provides an essential service to Australia's economy, with the total value of irrigated agriculture estimated at AU$17.7 billion, mostly in Victoria ($4.9 billion), Queensland ($4.5 billion), and New South Wales ($4.4 billion; Australian Bureau of Statistics, 2018a). Of the total water used in Australian agriculture (9,968 GL), 13.3% comes from dams or tanks (1,324 GL; Australian Bureau of Statistics, 2018b). Nonetheless, we showed that no information exists on nearly 1 out of 6 Australian dams. Using the percentages of undocumented dams calculated here for each State and Territory (i.e. red bars in Fig. 4D), we can approximate that undocumented dams on average are associated with ($17.7 \times 15\% \times 13.3\%$ =) AU$353 million of Australia's revenue: Western Australia ($61 million), South Australia ($31 million), Queensland ($27 million), New South Wales ($23 million), Victoria ($19 million), Northern Territory ($12 million), Tasmania ($7.7 million) and ACT ($0.008 million). Hence, there are substantial economic benefits to monitoring and ensuring appropriate management for farm dams across the country.

Perhaps the most important reason for increasing investments into monitoring Australian farm dams is water security. We estimated that farm dams in Australia hold 11,922 GL and we showed where these freshwater reserves are. Trends in available freshwater are becoming of increasing concern under anthropogenic climate change. Rainfalls in Australia have declined by 11-20% since the 1990s (Steffen et al., 2019), with evaporation removing up to 2.88 GL (~3.5%) of freshwater from dams every year (Baillie, 2008). Worldwide population growth will nearly double food consumption by 2050 and current water availabilities in Australia are unlikely to meet future demands (Lehane, 2014). Given the increasing frequencies of droughts, we would expect an overall reduction in the available water in farm dams, but there is no data to test this prediction. Hence, a promising and (relatively) easy next-step would be to complement our study with satellite tools to track interannual trends in water availability within farm dams.

Investing now in better monitoring techniques for farm dams is most cost-effective than ever before. We analysed historical trends in rates of dam development among States and Territories and we found a monotonic decline: from 2-3.4% before 2000, to 0.5-1.5% after 2000, to 0.05-0.8% after 2010. We are unaware of any specific policy intervention or natural event that could explain this plateau, possibly indicating saturation of available space or farm dam demand. Regardless of the underlying drivers, if this trend continues, dam numbers will nearly stabilise by 2020, which means investing now into a national farm dam database would require fewer updates than in the past.

AusDam.org: a portal for data on Australian dams

We created a free interactive website (AusDam.org) to share our findings on density, size, distribution, and historical trends on Australian dams with the Government, farmers, scientists, and the general community (Fig. 6). We designed this portal to ensure maximum simplicity: the user only needs to navigate on a map to any area of Australia to generate tailored statistics, plots and tables on various aspects of farm dams (e.g. count, density, total surface area, size distribution, water capacity; see Fig. 6). Moreover, we incorporated in our portal all information on the sources of uncertainty detected in our analyses – including the expected number of unreported dams or the reliability of each entry – which can be essential to inform where to prioritise new investments. Specifically, policymakers can decide to focus on the region with the highest number of unreported dams (Western Australia), or with the most significant percentage of unreported dams (Northern Territory), or with the highest overall agricultural value (New South Wales), or with the highest cost of water (Northern Territory).

There are several ways in which our portal can support new research. For example, farm dams have unique properties that make them a hotspot for methane emissions – a greenhouse gas that is 34 times more potent than carbon dioxide (Grinham et al., 2018; Ollivier et al., 2019a; Ollivier et al., 2019b). Given Australia's commitment to reach net-zero emissions by 2050, the contributions of farm dams to climate change must be monitored and regulated – as recommended by the 2019 Refinement of IPCC Guidelines (IPCC, 2019). The size and location of farm dams can help government agencies (e.g., Dept. of Agriculture, Water and the Environment) to include their greenhouse gas emissions in the Australian National Greenhouse Gas Inventory. As another example, our portal can help manage biological invasions. In arid habitats, farm dams provide a refuge that pests can use as stepping-stones to spread across the country (e.g. the cane toad *Rhinella marina* in north Australia; Letnic et al., 2015). Knowing where farm dams are can, therefore, inform on invasion fronts. Moreover, our portal could help to predict species richness and distribution across Australia (Brainwood & Burgin, 2009; Hazell et al., 2001), managing water quality (Brainwood et al., 2004), soil erosion, runoffs, or sediment delivery (Callow & Smettem, 2009; Verstraeten & Prosser, 2008). Our portal can also facilitate managing licenses or help developing new dams. To support all these applications, we are committed to keeping expanding the data in AusDam.org as they become available.

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Figures

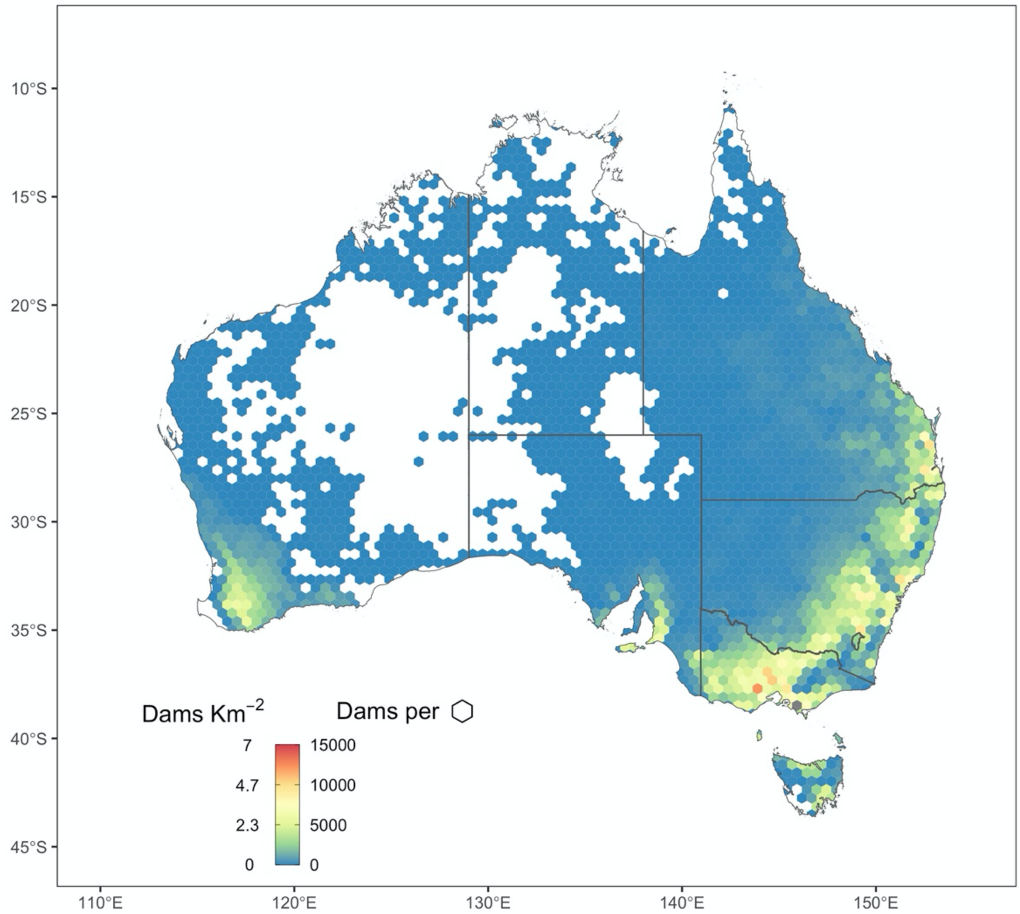

Figure 1: Distribution of documented dams in each Australian State and Territory. The colour indicates both total counts (dams per hexagon) and density (dams Km^{-2}), with empty hexagons indicating no reports of dams in the area. Total counts are exact, whereas dam densities are approximated (±10%) using the latitude in the centre of Australia (hexagon area of 2131.683 Km^2 at 27.61°S).

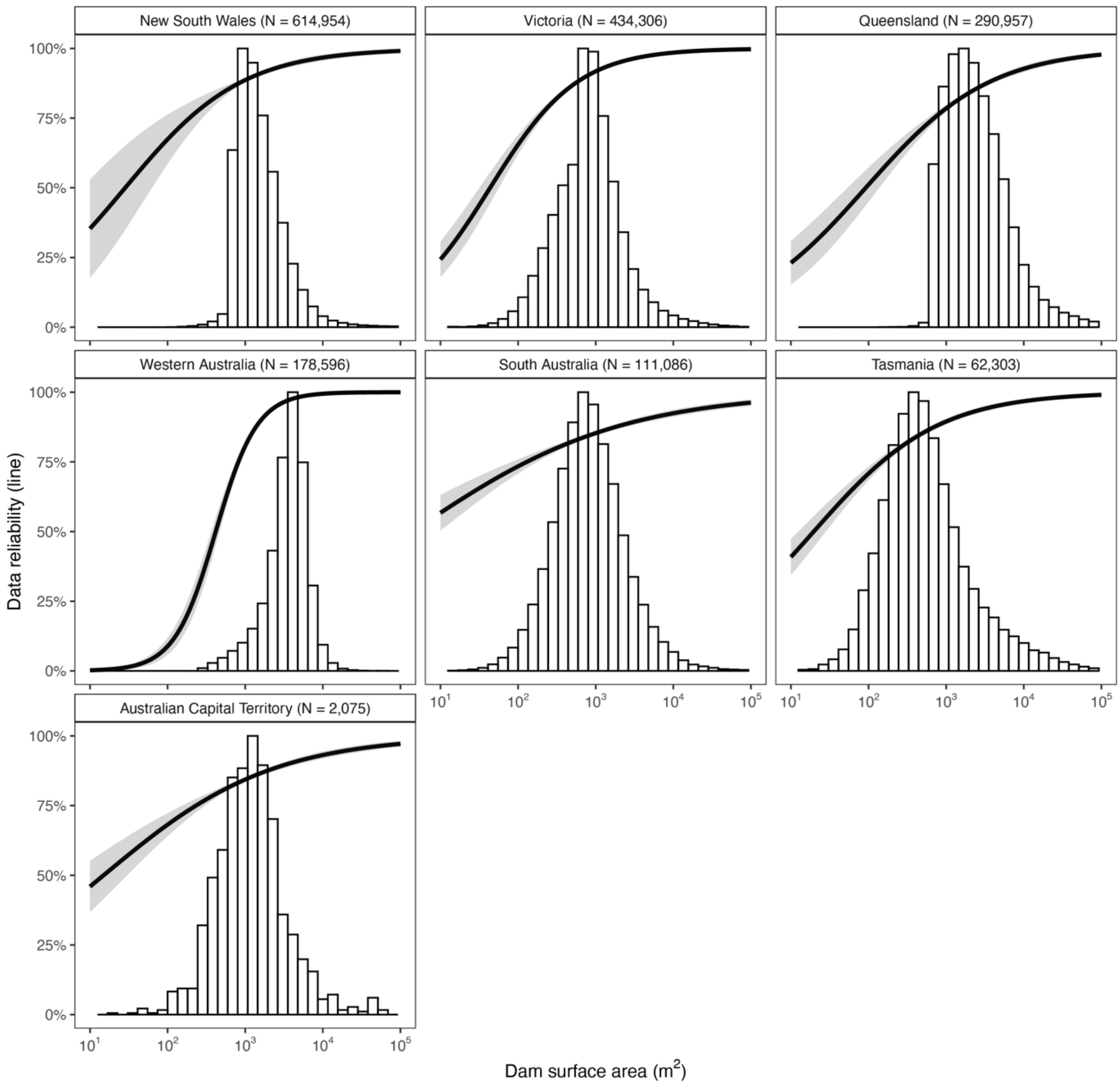

Figure 2: Dam detection reliability as a function of geographic region and dam surface area (m^2). Histograms and x-axes represent the distribution of all documented dam sizes, while faceting represent States and Territories in Australia (with sample size reported in the facet titles). Lines ($\pm$95% C.I) indicate the probability of a reliable entry extracted from the best-fitting generalized linear model following Akaike Information Criterion. Low probabilities indicate high frequencies of entries wrongly classified as dams (false positives), whereas high probabilities indicate high frequencies of dams correctly documented (true positives). We omitted data for the Northern Territories because there were too few documented dams to carry out a formal probability assessment.

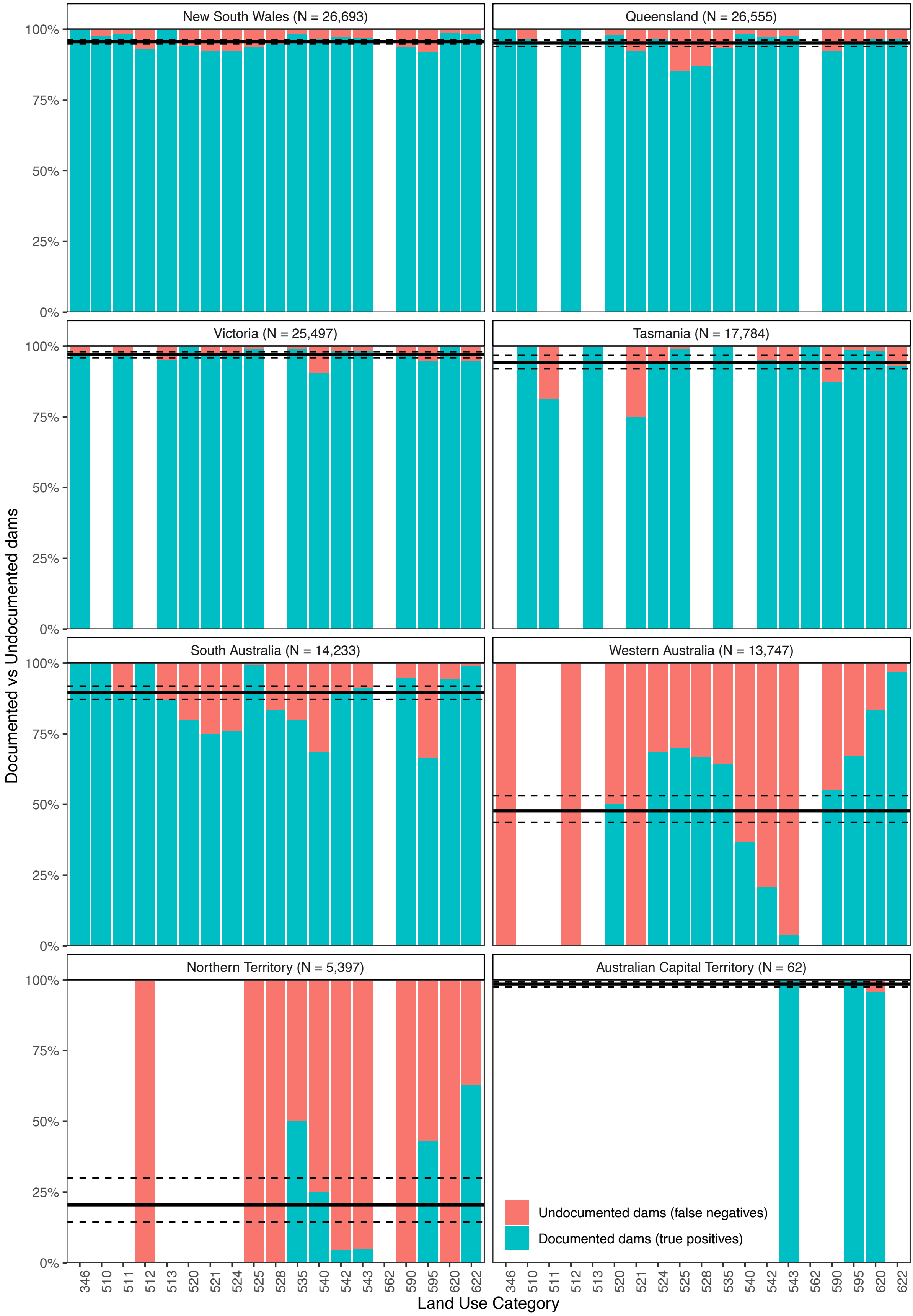

Figure 3: Frequency of undocumented artificial water bodies (false negatives) encountered in the top 19 land types with the highest farm dam densities (>5 dam km^{-2}) across Australia (see Fig. S2 for the legend of land use categories). We searched for dams by randomly sampling

sites among the 19 land use types that recorded the highest dam densities (>5 dam km^{-2}) across Australia. The number of searched sites in each region is reported in the facet title. Horizontal lines indicate overall percentages of detected dams across all land use types over the total ($\pm$ bootstrapped 95% confidence intervals). Missing columns indicate land use categories that are absent from the State or Territory.

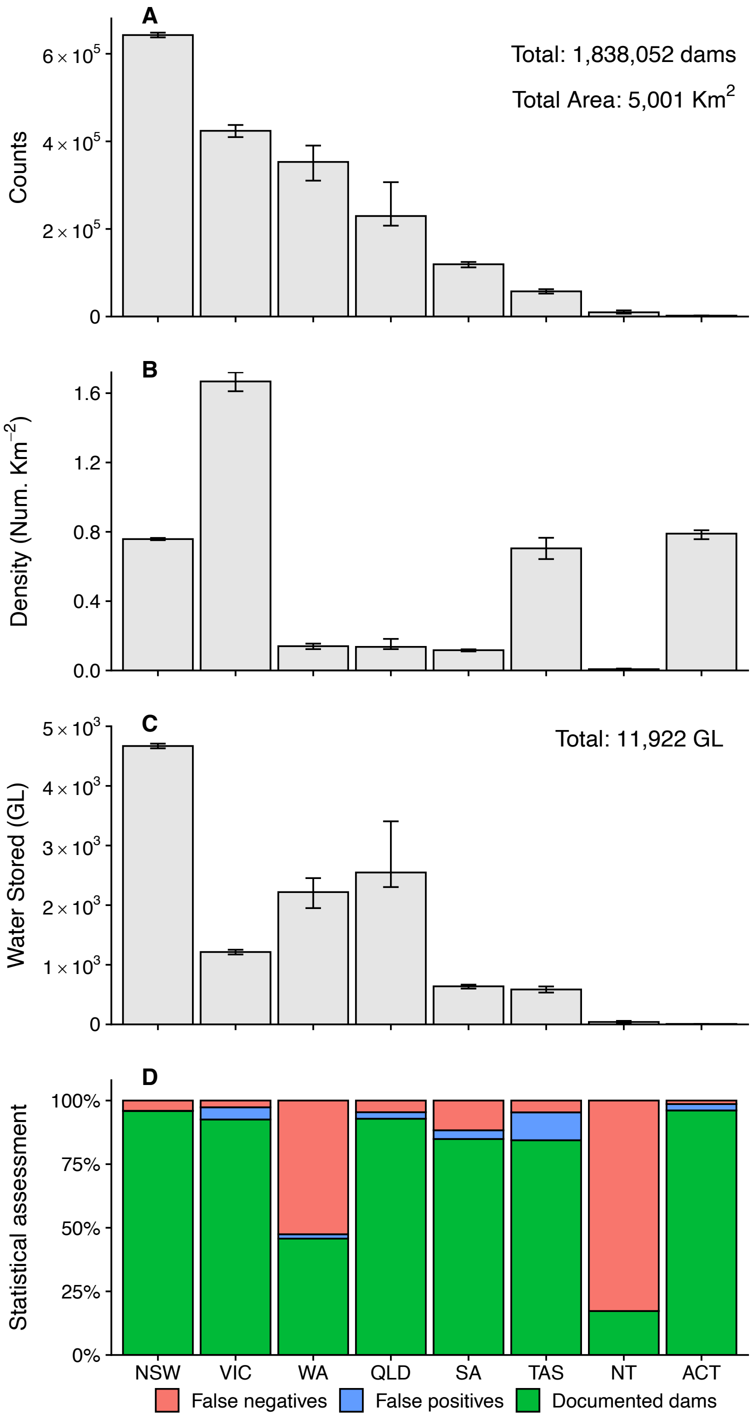

Figure 4: Overall statistics for Australian dams in each State and Territory. (A) Total counts and (B) overall densities are calculated after removing unreliable entries (false positives) and adding expected undocumented dams (false negatives). (C) Cumulative water capacity (GL) of farm dams. (D) Relative contributions of false positives and false negatives compared to the total documented dams in each State and Territory. Grey bars indicate medians, while error bars represent the bootstrapped 95% confidence intervals.

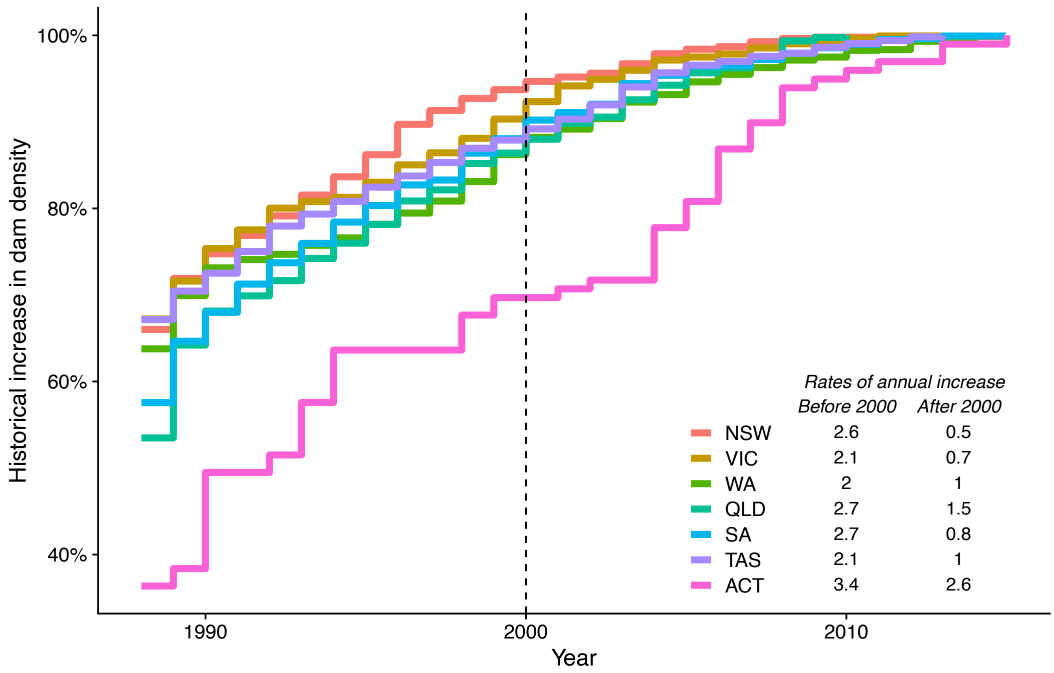

Figure 5: Historical trends in dam density between the years 1988 and 2015 in each State and Territory of Australia. The embedded table shows annual rate of proportional increase in dam density, both before 2000 and after 2000 (dashed line). There were too few data to calculate historical rate for dams in the Northern Territory.

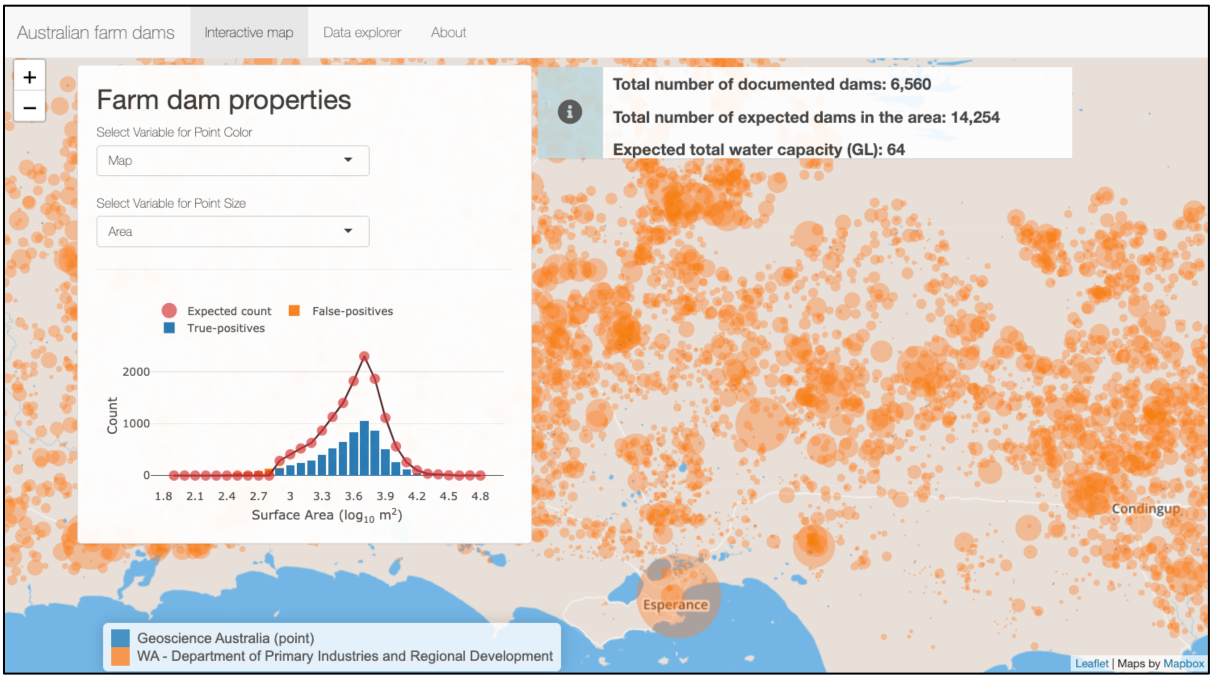

Figure 6: The online guided user interface of AusDam.org. Dots in the map indicate the distribution of dams in the region near Esperance (Western Australia). The panel on the left allows the user to choose the variables to represent as point colour (e.g. the region, data source) and point size (e.g. surface area, perimeter). The histogram shows expected counts (dots), documented dams (blue bars), and the expected false positives (orange bars). The banner at the top summarizes the overall statistics. The two tabs at the top allows the user to access the raw data (Data explorer) or to read about the project and the methods (About).