**Supplementary Material Appendix A: Method to predict continental carp biomass**

Carp biomass was estimated by using models that linked historic and contemporary catch data with catch efficiency rates for different aquatic habitat types. The eight-step methodological approach for rivers, wetlands, lakes and storages (i.e. including impoundments and reservoirs) is summarised in Supplementary Table A1, with major methodological assumptions recapped in Supplementary Table A2, and further details below.

*Step 1: Classify aquatic habitat types and develop a map of carp-occupied habitats*

A map of aquatic habitats across the range of carp in Australia was built using GIS to integrate existing spatial data, including the Australian National Aquatic Ecosystem mapping of the Murray-Darling Basin, the Australian Geofabric, and jurisdictional wetland mapping (Aquatic Ecosystems Task Group, 2012; BOM 2014; Brooks et al., 2014; Brooks 2017; Geosciences Australia, 2018). Where data gaps were identified, habitat area was estimated using imagery from Google Earth to measure the wetted channel width at 1,233 randomly selected locations across 28 irrigation districts. The distribution of wetted widths and mapped length was then used to calculate the surface area of each channel. Two new GIS layers were developed: (i) rivers (including estuaries) and (ii) standing waterbodies, that each mapped carp-occupied habitat and enabled an estimation of their surface areas. Rivers were divided into Geofabric segments that typically represented sections between river junctions (BOM, 2014).

We categorised eight aquatic habitat types: (i) non-perennial rivers, (ii) perennial rivers, (iii) waterholes, (iv) estuaries, (v) lakes, (vi) storages, (vii) wetlands and (viii) irrigation networks (Supplementary Table A3). The area of each habitat type was considered to be indicative of an ‘average’ hydrological year (Supplementary Table A2). A comparative carp biomass estimate for a ‘wet’ hydrological scenario was also modelled, by including additional area of ephemeral floodplain lakes and wetlands (Todd et al., 2019).

*Step 2: Assemble carp database and undertake contemporary sampling*

A carp database was compiled from the literature, jurisdictional databases and from carp density records from wetland and lake management projects (e.g. lakes and wetlands that were temporarily drained to eliminate carp). The resulting database comprised data from 153 projects and 4831 individual sites collected over a 24-year period in six Australian states and territories. Data included relative abundance (CPUE data from electrofishing: *ef*CPUE, standardised to no/h), fish length (fork length; FL, mm), individual mass (g), and estimates of absolute carp density (e.g. from wetland drying events and mark-recapture data). These maps were then checked by jurisdictional experts to ensure accuracy and examination of the spatial distribution of carp data revealed some data-poor areas, particularly within estuarine habitats and in isolated far western rivers of Victoria and NSW. Hence, contemporary sampling using the Sustainable Rivers Audit (SRA) boat electrofishing protocol (Davies et al., 2010) was undertaken to supplement the catch database.

*Step 3: Model and map predicted efCPUE and the average individual carp mass*

Carp sampling locations were matched to the habitat mapping by using GIS. For each fish record, the closest river segment (if a river site) or waterbody (if a waterbody site) within 500 m was identified. Fish catch records with location data that mapped more than 500 m from any mapped habitat feature were excluded as they could not reliably be assigned to a habitat class. Overall, there were 4831 sites in the database, and 73.8% were linked to an aquatic spatial object.

For river sites, two analyses were conducted to predict *ef*CPUEs and average body mass of carp in the mapped habitats. For *ef*CPUE, a boosted regression tree (BRT) approach was implemented which uses machine learning to improve predictions (Elith et al., 2008). The response variable was *ef*CPUE (no/h) for carp > 150 mm FL. Predictor variables in the models were river attributes (relating to climate, flow, terrain), time (year and month) and major spatial region (Murray, Darling, Northern Basin (waterhole), Lachlan systems, and coastal areas; Supplementary Table A4, Supplementary Fig. A1).

For individual carp mass in rivers, a Bayesian general additive mixed model (bGAMM) was fitted assuming a Gaussian distribution. The response variable was the average mass of individual fish per survey (log-transformed; for carp ≥ 150 mm FL, length was converted to mass). The final model included: river attributes relating to climate, flow and terrain which were all continuous factors as splines; time as year and month also as splines; and major spatial region as a fixed effect. As yearly patterns may differ for different spatial regions, yearly trends were modelled for the major spatial regions and river basin was included as a random effect. Site was also included as a random effect if there were repeated measures at multiple sites. The model for average individual fish mass also included *ef*CPUE as a predictor, because we expected a higher *ef*CPUE to reflect high recruitment and hence low average mass.

For waterbodies, a similar approach was used in which bGLMM were conducted for both *ef*CPUE and average individual fish mass, except that the predictor variables were waterbody type (lake, storage, wetland; fixed factors), spatial region (fixed), river basin (random), and year (spline). Again, *ef*CPUE was included for the fish mass model. For all models, a 10-fold cross-validation approach was performed to assess predictive performance and we calculated the Pearson correlation between model predictions and test data for each run.

*Step 4: Convert predicted efCPUE to density (no/ha)*

As *ef*CPUE is a relative abundance measure, a conversion factor (i.e. a calibration approach: Driver et al., 2005) was developed to convert *ef*CPUE (no/h) to carp density (no/ha) for the suite of aquatic habitat types. As sampling efficiency likely varies by habitat and spatial regions, a series of 31 field studies were carried out across five states/territories (QLD, NSW, VIC, SA and ACT), including 20 riverine sites in rivers of various sizes (4 m to 170 m wide) and 11 wetland sites (up to 12 ha) and spanning various depths and turbidity conditions. For each of these sites, the standard SRA electrofishing protocol (Davies et al., 2010) was used to obtain *ef*CPUE (fish ≥ 150 mm FL) and the density of carp ≥ 150 mm FL was estimated by using one of four methods: mark-recapture (mid-size rivers, waterholes, and large wetlands), depletion sampling (small rivers), mark-recapture (i.e. radio-tags in large rivers – see below), and for small wetlands there was chemical treatment (rotenone) or draining (Supplementary Table A5). In mid-sized rivers and large wetlands, to ‘close’ the site, stop-nets (or natural barriers) were deployed to preclude fish movement. The SRA standard boat or backpack electrofishing protocol was then implemented to obtain *ef*CPUE (Davies et al., 2010). Subsequently, to catch and tag as many fish as possible, a minimum of three high-intensity electrofishing passes were conducted over multiple days. All passes had similar sampling effort with all carp removed. Power analysis indicated that, after three passes, if the percentage of tagged fish exceeded 40% of the total catch the population estimate should have a %CV less than 20%. Thus, sampling was terminated when the catch was >40% tagged fish or sampling time was five days. For isolated water holes, there was a slightly modified technique whereby fish were tagged in the first week and recaptured in the second.

To estimate site density, an estimated population size was needed, state-space models were used which provide flexibility in structure to manage time-varying catchabilities and incorporation of factors that affect catchability (Kéry and Schaub, 2011). Models were constructed using JAGS software (Plummer 2003) in junction with the R2jags package (Su and Yajima, 2015). Population size estimation was obtained through data augmentation whereby the models assumed constant catchability between mark and re-capture sessions which were compared with models assuming time-varying catchability. The waterhole models had a single mark and single recapture period. Posterior sampling was used to obtain credible estimates for population size and catchability. Density was obtained by dividing the total estimated population size by total area sampled (i.e. fish/ha). Four models were compared: null model, the avoidance model, the effort model, and the avoidance and effort model. The model with the lowest deviance information criterion was selected, and to assess model fit we used a Freeman-Tukey statistic (Kéry and Schaub, 2011) as a goodness-of-fit statistic and we then compared the fit of the real data to the simulated data from the model.

For large permanent rivers, it was not possible to close the site to fish movement. Therefore, a 1-km case-study site immediately downstream of Lock 10 on the lower Murray River was sampled using the SRA boat electrofishing protocol (Davies et al., 2010). A total of 64 carp were radio-tagged and released, and the reach was re-sampled a total of four times (e.g. at 1 week, 2 weeks, 3 weeks, 8 weeks after tagging). During each re-sampling event, an independent radio-tracking team first determined how many radio-tagged carp were within the sample reach (Lyon et al., 2014). This was followed by a standard boat electrofishing protocol without knowledge of the number of tagged fish present, and the number of radio-tagged fish caught were recorded. Due to very low recapture rates, the approach used by Lyon et al. (2014) to estimate density could not be replicated and so a simple Bayesian General Linear Model (bGLM) was performed assuming a binomial distribution. For each week, the total number of tagged carp caught were summed in relation to the number of tagged fish counted by radio-tracking. No predictors were included in the model and the density estimate was the inverse of the detection probability estimate from the model.

Using the *ef*CPUE and density estimate at each of the field-study sites, a conversion factor was calculated as the ratio of density to *ef*CPUE (i.e. conversion factor = density / *ef*CPUE). The relationship between the conversion factor and habitat groups was then modelled using a Bayesian generalised linear model (bGLM). The response variable was the natural log of the conversion factor and a Gaussian distribution was assumed for the error distribution. Four habitat groupings were used: (1) rivers with river width ≤ 50 m, (2) rivers with width > 50 m, (3) waterholes, and (4) wetlands and large estuaries, and these were included as a predictor in the model. Model fit was assessed through graphical plots of model residuals and posterior predictive plots, and significant differences defined where the 95% credible interval (95%CrI) of the difference between habitat types did not overlap with zero. An assumption was that the conversion factor for fish <150 mm FL was the same as for fish ≥150 mm FL.

The methods outlined above enabled estimates of: (i) area of carp-occupied habitat, and (ii) biomass density (kg/ha) for every mapped river segment and waterbody. Biomass density (kg/ha) for each spatial object was then posterior calculated by multiplying density (no/ha) by predicted average fish mass.

*Step 5: Estimating carp habitat use in lakes and storages to correct biomass density for offshore zones*

In lakes and storages, existing *ef*CPUE data were mainly collected from the shallow littoral zone because electrofishing is less efficient at greater depths (Bayley and Austen, 2002; Lyon et al., 2014). During spring and summer, carp density is often lower in offshore zones compared to vegetated littoral zones where there are greater feeding and spawning resources (Penne and Pierce, 2008; Taylor et al., 2012). Consequently, for every lake and storage, data were corrected by estimating the proportions of littoral and offshore habitat area using water permanency as a surrogate in the absence of bathymetry data. Water Observations from Space (WOfS; Mueller et al., 2016) was used to map where water was recorded >80% of the time over the past 30 years as an estimate of the deep offshore habitat area, with the remaining shallow waterbody area to the shoreline allocated as littoral habitat. The 80% cut-off was arrived at by consensus of jurisdiction experts for a range of example storages.

Next, we estimated the difference in carp relative density between littoral and offshore zones by investigating the changes in gill-net CPUE (*net*CPUE) from littoral to offshore zones in four lakes and three storages, and with increasing depth in storages. For lakes, gill-nets were set at three locations: edge (about 5 m from the lake edge); midway (about 50 m from the edge); and offshore (about 200 m from the edge). For storages, depth often changes more quickly than in lakes; therefore, we used depth rather than distance. Gill-nets were set at varying depth zones (2 m, 6 m, 12 m, 18 m, 24 m) in the storage. Within each depth zone, gill-nets were set at different water depths (surface, midway, or bottom) depending on the depth zone (Stuart et al., 2019).

Two separate analyses (lake and storage) were performed using Bayesian generalised linear mixed models (bGLMM), assuming a negative binomial distribution. For the lake data, *net*CPUE (no/h) was compared across the three sampling locations (edge, midway, offshore) with bGLMM. The response variable was the number of fish caught and a negative binomial distribution was assumed. The fixed effect was lake location, and random effects were lake and lake site (nested within lake). Sampling effort (log-transformed) was included as an offset. All analyses were performed using R v3.4.1 and the *brms* package (Bürkner 2017). All models were checked for fit by using posterior predictive checks and ensuring they converged through graphical examination and Gelman-Rubin statistics. Estimates are shown with 95% credible intervals (95%CrI).

For storages, the same GLMM model was performed using a Bayesian framework, except that the fixed effect was the combination of net depth (surface, midway, bottom) and depth zone (2 m, 6 m, 12 m, 18 m, 24 m) as the design was not fully crossed (e.g. only one depth at 2 m contour and only bottom nets for 18 and 24 m depth zones. All comparisons were with the 2 m depth zone net as the reference category.

*Step 6: Model and map the biomass of juvenile carp*

To estimate the biomass of juvenile carp (<150 mm FL), a slightly simplified version of the method was used. From the database, the average juvenile biomass (kg) was modelled in relation to *ef*CPUE for fish ≥150 mm FL, habitat attributes, space and time. Thus, we could predict average juvenile biomass (kg) for a sampling event based on the predicted *ef*CPUE for fish ≥150 mm FL and habitat attributes. We refer to this juvenile biomass (kg) in relation to *ef*CPUE as the juvenile fish biomass rate (i.e. juvenile biomass per *ef*CPUE).

To model and map juvenile fish biomass rate, we used the same *ef*CPUE data used for fish ≥150 mm FL. For every sampling event, we calculated the total mass of fish <150 mm FL. For sampling events in which all fish were measured, we used the total juvenile biomass. However, some sampling events only measured a fraction of all juvenile carp collected and so to maximise spatial coverage we adjusted the juvenile biomass by the proportion of the total catch that was measured (e.g. if only 25% of fish were measured, then we multiplied the juvenile biomass by 4). For simplicity we did not include any uncertainty in those conversions into the model. We used juvenile biomass rate (i.e. juvenile biomass per *ef*CPUE) as the response variable (log-transformed + 0.1 kg).

We performed a single bGAMM assuming a normal distribution. As the response variable was juvenile biomass rate, we only needed a biomass model (i.e. we did not need separate models for CPUE and average mass, as for adult carp). To further reduce model complexity, we combined river and waterbody data into a single model. After expert consultation about river attributes, we decided that river attributes should focus only on-stream slope, because spawning areas are known to be in areas of low slope near wetlands, and the slope of the stream provides a useful proxy for such areas. We gave the waterbodies a slope of zero (and tested the effect by re-running the model, setting waterbody slope to the mean river slope and no substantial differences were found). The predictors in the model were *ef*CPUE for fish ≥150 mm (log-transformed + 1; thin-plate spline), aquatic habitat class (categorical: wetland, lake, river), stream slope (thin-plate spline), year (thin-plate spline, and month (cyclic cubic spline). The *ef*CPUE for ≥150 mm FL fish was included because a high *ef*CPUE often reflected more juveniles in the catch. As in Step 3, a 10-fold cross-validation approach was implemented to assess model fit.

*Step 7: Estimate total carp biomass*

The prior steps enabled estimates of: (i) area of carp-occupied habitat, and (ii) biomass density (kg/ha) for every mapped river segment and waterbody. We then estimated carp biomass for each river/waterbody by multiplying the mapped area by biomass density (kg/ha), incorporating the separate littoral and offshore components of lakes and storages (Supplementary Table A1) The estimates for individual rivers (perennial, non-perennial and estuaries) and standing waterbodies (wetlands, lakes and storages) were then summed to derive a total carp biomass (metric tonnes).

To assess the uncertainty in our total biomass estimate, we assumed that a spatial object’s area (i.e. a river, wetland or lake) was constant and treated the other variables (predicted CPUE, average carp mass, juvenile biomass rate, conversion factor and habitat utilisation variable) as random variables. An estimate of variation in carp biomass was then obtained by sampling from the distributions of each random variable 10,000 times. After this, data from each segment were summed, to obtain values of Australian state and total continental biomass. From these replicates, we calculated the mean biomass with 95%CrI.

*Step 8: Model validation*

Predictions of carp biomass were compared with nine known estimates of absolute biomass for lakes and storages from drying and dewatering events. These biomass data had no measures of uncertainty and were treated as being ‘known’ for the validation. For the validation, we compared the predicted range of biomass for each waterbody with a known estimate of absolute biomass and determined whether the known biomass was within the 95%CrI of our estimate.

*Biomass estimates for irrigation channels and for aquatic habitats in Western Australia*

There were too few carp records for irrigation channels in south-eastern Australia or for aquatic habitats in Western Australia to model carp density as described above. For irrigation channels, carp biomass was estimated by: 1) estimating the area of irrigation channel habitat using a combination of the length of mapped channel lines and observations of wetted width in aerial imagery; 2) multiplying the total wetted channel area by three potential biomass density levels (low = 50 kg/ha, medium = 150 kg/ha, and high = 300 kg/ha). An estimate for aquatic habitats in Western Australia followed a similar approach except that river areas were predicted from the eastern Australia river width model, and the total water area was the sum of both river and waterbody areas with no separation of habitats. The geographic distribution of carp (i.e. presence/ absence) in aquatic habitats in Western Australian was verified with local experts. For both estimates, no attempt was made at quantifying uncertainty in biomass estimates. We consider these to be negligible sources of error as they comprise only small components of the continental-scale biomass.

**Table A1.** Process for estimating carp biomass by using models that link historic and contemporary catch data with catch efficiency rates for different aquatic habitat types, including rivers (including estuaries), wetlands, lakes and storages (i.e. impoundments and reservoirs).

|  |  |  |  |
| --- | --- | --- | --- |
| **Step** | **Rivers** | **Wetlands** | **Lakes and storages** |
| **1** | Compile a national map of aquatic ecosystems and calculate the spatial extent (i.e. total area) of each habitat type. | | |
| **2** | Assemble a national database of existing site-based estimates of carp relative density (catch-per-unit-effort; CPUE) and associated environmental co-variates (e.g. depth, turbidity, electrical conductivity) and conduct contemporary sampling in data-poor habitats. | | |
| **3** | Predict *ef*CPUE (no/h) and average individual carp mass for every river segment using the river CPUE model. | Predict the *ef*CPUE and average individual carp mass for every waterbody using the wetland CPUE model. | Predict littoral *ef*CPUE and average individual carp mass from the waterbody model. |
| **4** | Determine the relationship between CPUE and carp density (no/ha). Multiply each *ef*CPUE by the appropriate conversion factor to obtain density (no/ha) for every mapped river segment and waterbody. Calculate biomass density (kg/ha) for each spatial object by multiplying density (no/ha) by predicted average fish mass. | Determine the relationship between CPUE and carp density (no/ha). Multiply each CPUE by the appropriate conversion to obtain density (no/ha). Calculate biomass density (kg/ha) for each spatial object by multiplying density (no/ha) by predicted average fish mass. | Predict offshore CPUE from the habitat utilisation estimate. Multiply each *ef*CPUE by the conversion factor and predicted average individual carp mass to obtain littoral and offshore biomass density (kg/ha). |
| **5** |  |  | Correct carp biomass for habitat utilisation preferences in lakes and storages. |
| **6** | Add juvenile biomass (fish <150 mm FL) by using the predicted juvenile biomass rate from the predicted CPUE for fish ≥150 mm FL to predict juvenile biomass rate for each river segment. Multiply this rate by the conversion factor and spatial object area to determine juvenile biomass. | Add juvenile biomass (fish <150 mm FL), by using the predicted juvenile biomass rate from the predicted CPUE for fish ≥150 mm FL to predict juvenile biomass rate for each wetland polygon. Multiply this rate by the wetland conversion factor and total area to determine juvenile biomass. | Sum total biomass from littoral total biomass and offshore total biomass. |
| **7** | Estimate carp biomass for each river/waterbody by multiplying the total area (ha) by biomass density. Lakes and storages had littoral and offshore components which were included in the calculations. Estimate continental total biomass (tonnes) by summing individual rivers (perennial and non-perennial) and standing waterbodies (wetlands, lakes and storages).  Assess uncertainty in the total biomass estimate by sampling from the distributions of each random variable 10,000 times. For each replicate, data from each segment were summed, to obtain values of state and continental biomass. From these replicates, we calculated the mean biomass with 95%CrI. Random variables included: predicted CPUE, average individual carp mass, juvenile biomass rate, conversion factor and habitat utilisation. | | |
| **8** | To validate the biomass model, predict carp biomass for waterbodies with a known estimate of absolute biomass, and determine whether the known biomass was within the 95%CrI of the modelled estimate. | | |
| **9** | Irrigation channels in SE Australia and aquatic habitats in Western Australia lacked sufficient data (GIS and CPUE) and were not included in the formal biomass modelling described above. For irrigation channels, a coarse biomass estimate was undertaken by: 1) estimating irrigation channel area using mapped length combined with the probability of having water and, if water is present, estimated channel width calibrated from aerial imagery; and 2) multiply total wetted channel area by three biomass density levels (i.e. low = 50 kg/ha, medium = 150 kg/ha, and high = 300 kg/ha). For Western Australian rivers, the process was the same except width was predicted from an eastern Australia river width model and total water area was the sum of river and waterbody area with no separation of habitats. For both estimates, no attempt was made to quantify uncertainty in biomass estimates. | | |

**Table A2.** A summary of major assumptions and limitations made during this estimate of the continental biomass of carp.

|  |  |
| --- | --- |
| **Assumption** | **Justification** |
| *Database assumption* | |
| Surveys in which no carp were caught were under-represented in the database | Missing zeros would lead to an overestimation of catch per unit effort (CPUE); though this is most likely to have occurred in lower density areas, mitigating some of the potential bias. |
| *Spatial limitations* | |
| Few environmental attributes were available for waterbodies compared with rivers, for use in predictive models of CPUE and average individual fish mass. | Little other information was available with which to adjust estimates of biomass for waterbodies. Predictions of carp biomass for waterbodies were based primarily on habitat class (lake, wetland, or storage) and spatial region. |
| Modelled river area (ha) fits were moderate with some over and under-estimation of the total area. | Data on river widths were unavailable. |
| Few GIS and CPUE data were available for aquatic habitats in Western Australia and irrigation channels in SE Australia. | GIS layers were built for irrigation channels and for Western Australian rivers and a coarse estimate of carp biomass density was applied (low =50 kg/ha, medium = 150 kg/ha and high = 300 kg/ha). |
| The GIS spatial area of rivers and waterbodies was treated as a constant. | Average and wet hydrological scenarios were modelled as static areas, but the area of aquatic habitats is substantially different under flood, average and drought conditions (Todd et al., 2019). |
| Spatial area (ha) is a less accurate habitat metric compared with volume (m3). | Carp occupy three-dimensional habitats and hence volume may be a superior spatial metric. However, there are no GIS bathymetry layers for standing waterbodies or rivers and depth is even more temporally dynamic than spatial area. Hence, carp density by area (ha) is the most commonly used metric (Bajer and Sorensen 2012; Farrier et al., 2018). |
| *Model assumptions* | |
| Conversion factor for young-of-the-year (YOY) fish <150 mm FL was the same as for fish ≥150 mm FL. | Small fish are difficult to electro-fish for reliable estimates of density (Dolan and Miranda 2003). Without any available information on detection rates, a conservative approach of using the conversion factor for fish ≥150 mm fork length (FL) was adopted. Juvenile carp biomass is likely underestimated. |
| Constant length-mass relationship for carp across the entire geographic range. | Carp length (FL, mm) and mass (g) were extracted from the database and a general linear model (GLM) applied with mass (log10-transformed) as the response variable and length (log10 transformed) as the predictor. From this model, a constant length-mass relationship was established across the entire geographic distribution of carp. |
| *Model limitations* |  |
| Exclusion of farm dams (<4 ha) from the carp biomass estimate. | No data were available as to carp presence in farm dams. |
| Estimates of conversion factors may underestimate the true conversion factor for standard boat electrofishing protocols. | Standardised electrofishing protocols are the most widely applied in eastern Australia (Davies et al., 2010). During the conversion factor experiments, there was likely a higher detection probability than for historic surveys. This effect may contribute to an underestimation of the total carp biomass. |

**Table A3**. Aquatic habitat types occupied by carp in Australia with rules developed for classifying each type.

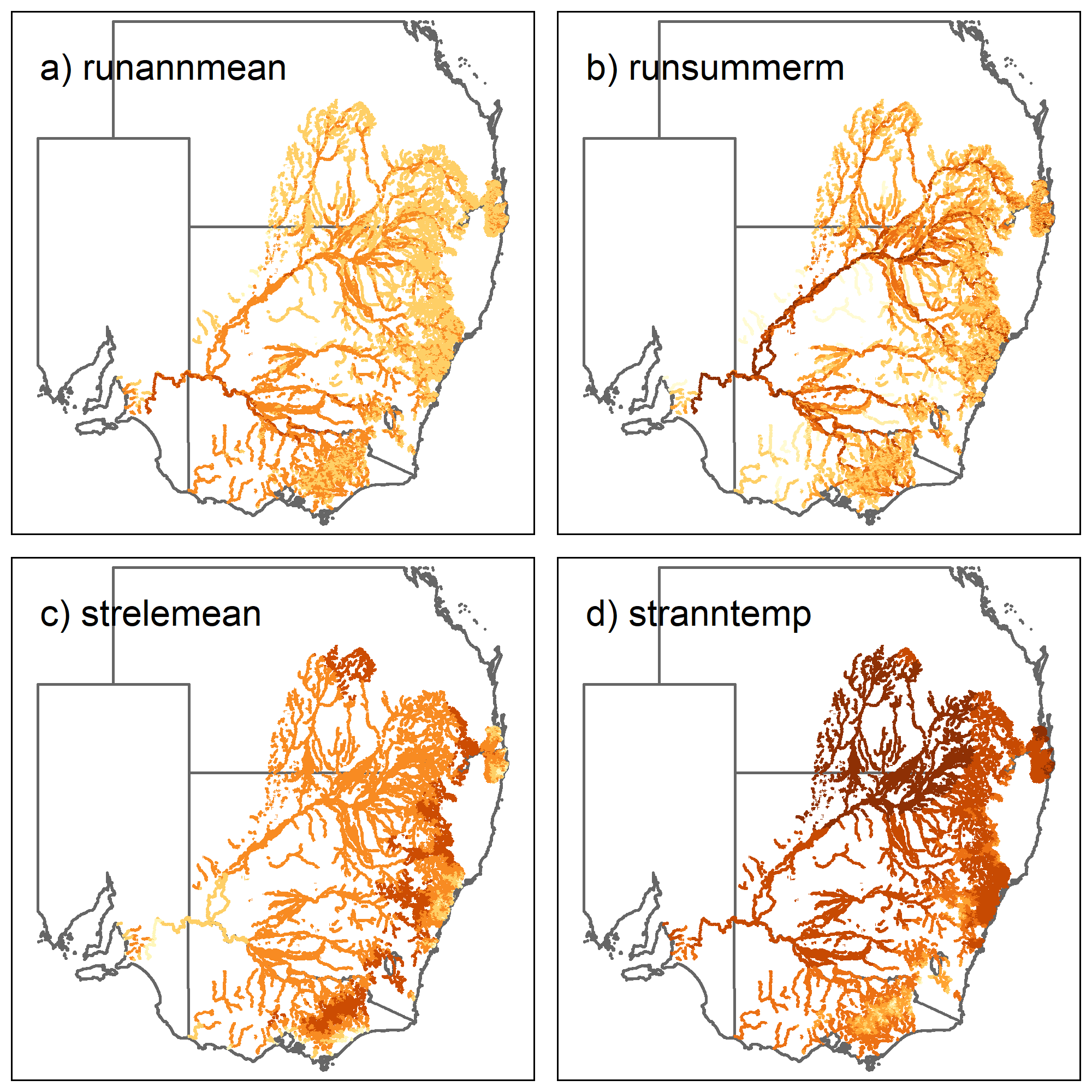
|  |  |
| --- | --- |
| **Carp-occupied aquatic habitat type** | **Rules developed for aquatic habitat types** |
| Perennial rivers | For any river for which width/area was mapped as surface hydrology polygons, the polygon area was used. For major rivers in Victoria with no surface hydrology polygons, river widths were predicted by using the wetted river width from LIDAR data used to map riverbeds. For the remaining rivers (mainly in NSW), river widths were predicted by randomly sampling rivers from aerial maps across the whole river network combined with field measurements. Widths were then predicted based on models of catchment hydrological metrics. Rivers were designated as permanent or temporary using the Geofabric perennialism attribute. Ephemeral headwater streams that flow too infrequently to support carp populations (stream order <5 with summer month flow rates <100 ML/day) were removed to improve model performance. These thresholds were chosen arbitrarily and the resulting maps were checked by jurisdictional experts against catch data to ensure streams with carp were not removed prematurely. |
| Non-perennial rivers and waterholes | In the northern Murray–Darling Basin, many rivers recede to pools in the dry season, which is the time when fish surveys and monitoring typically occur. For these intermittent and ephemeral rivers, the estimate of potential carp habitat at the time of sampling was improved by using the summed area of mapped waterholes within each river segment, instead of the total channel area (width × length), which can overestimate habitat availability in these ephemeral arid-zone rivers. Spatial data were lacking for the isolated Paroo and Warrego river regions, whose waterhole area was predicted from local waterhole mapping. |
| Estuaries | Estuarine surface area was available from ANAE and Geofabric waterbody mapping. |
| Wetlands | Wetlands were assigned to permanent and temporary categories using the relevant hydrological regime attributes from state classifications and the ANAE water regime attribute. Habitat area was calculated in GIS from the mapped extent. Wetland ecosystems that regularly dry out and that were unlikely to support carp populations were excluded including: salt lakes, clay pans, ephemeral freshwater meadows, temporary marshes, peat bogs and springs. |
| Lakes | Lakes are open-water systems characterised by deep, standing or slow-moving water with little or no emergent vegetation. Temporary lakes that periodically dry out were included. Temporary lakes were included only if they were within 250 m of a waterway or floodplain. Large temporary lakes >10 ha were removed if the WOfS (Geoscience Australia) data set showed water was not detected at any location in at least 40% of Landsat views since 1987. Lake area was divided into offshore and littoral zones using WOfS to define deep offshore habitat as the area that recorded water at least 80% of the time. |
| Storages | Storages are artificially constructed reservoirs, town water storages, impoundments and large irrigation storages. They are similar to lakes with highly regulated hydrological regimes. Storages were included as permanent waterbodies, unless data or jurisdiction experts nominated them as not supporting carp. Deep-water zones were classified as the area containing water in >80% of satellite views since 1987 (WOfS), including areas that retained water in the Millennium drought (i.e. 1996-2010). The area of the littoral zone was calculated by subtracting the area of the deep-water zone from the mapped storage area. |
| Irrigation channels | For irrigation channel networks, GIS layers were built where data were available, focusing on larger supply channels that typically held permanent water to sustain carp populations. Irrigation channel area was estimated using aerial imagery from Google Earth to measure the wetted width of channels at 1233 randomly selected spot locations spread over 28 irrigation districts. Then mixture modelling was applied to estimate probability of having water and if water was present, the estimated channel width. There were few jurisdictional carp electrofishing survey data (i.e. CPUE) so total channel area was multiplied by three density levels (low=50 kg/ha, medium=150 kg/ha, and high=300 kg/ha). No attempt was made at quantifying uncertainty in estimates. |
| Western Australia | For Western Australia, river width was predicted from the eastern Australian river width model to calculate total aquatic habitat area with no separation of habitats. As for irrigation channels, there were few CPUE data and hence the coarse three density estimate was applied with no quantification of uncertainty. |
| Farm dams | Small farm dams (<4 ha) typically used for watering stock were excluded from the biomass model due to lack of fish survey data and hydrological information to determine those which might support carp. |

##### Table A4. Environmental attributes considered for river models.

| **Type** |  | **Variable** | **Description** | **Units** |
| --- | --- | --- | --- | --- |
| Climate |  | strannrain | Stream and environs average annual mean rainfall | mm |
|  | stranntemp | Stream and environs average annual mean temperature | °C |
|  | strcoldmthmin | Stream and environs average coldest month minimum temperature | °C |
|  | strdryqrain | Stream and environs average driest quarter rainfall | mm |
|  | strhotmthmax | Stream and environs average hottest month maximum temperature | °C |
| Flow |  | runannmean | Annual mean accumulated soil water surplus | ML |
|  | runmthcofv | Coefficient of variation of monthly totals of accumulated soil water surplus |  |
|  | runperenia | % contribution to mean annual discharge by the six driest months of the year | % |
|  | runsummermean | Summer means of accumulated soil water surplus | ML |
|  | runspringmean | Spring means of accumulated soil water surplus | ML |
| Habitat |  | habitatcla | Habitat class |  |
|  | hierarchy | Major or minor stream classification |  |
|  | perennial | ANAE permanent or temporary |  |
| Terrain |  | catarea | Catchment area | km2 |
|  | d2outlet | Distance to outlet | km |
|  | downavgslp | Average slope of downstream flow path | % |
|  | strahler | Strahler stream order |  |
|  | strelemean | Mean segment elevation | m |
|  | subarea | Sub-catchment area | km2 |
|  | upsdist | Distance to source | km |
|  | valleyslope | Stream segment slope | % |

**Table A5.** A summary of sample sizes for the conversion factor experiment to determine the relationship between CPUE and true density of carp (kg/ha).

|  |  |  |  |
| --- | --- | --- | --- |
| **Type** | **Method** | **River** | **Waterbody** |
| **Designed** | Depletion | 2 | 0 |
| Mark-recapture | 17 | 7 |
| Acoustic tagging | 1 | 0 |
| **Opportunistic** | Pump-out | 0 | 2 |
| Rotenone | 0 | 2 |
| **Total** |  | **20** | **11** |



**Fig. A1.** Mapping of four examples of river attributes. Each panel shows the spatial pattern for a river attribute, with redder colours indicating higher levels. Note - attributes are on a log-scale. A definition of each river attribute is given in Supplementary Table A4.

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