Modelling complex habitat use for threatened bat species decision-making in landscapes with competing priorities

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Abstract

Species distribution models (SDMs) provide valuable information to aid conservation decisions, particularly in landscapes where economic and biodiversity priorities compete. Generating SDMs for species that rely on discrete habitat types for different activities (e.g. roosting or foraging) can be challenging, and result in outputs that are not appropriately tailored for end use. We collated expert-validated occurrence records for ghost bats (*Macroderma gigas*) and Pilbara leaf-nosed bats (*Rhinonicteris aurantia*), two threatened species in a region of intensive mineral extraction in north-western Australia. We generated spatial layers describing roosting and foraging habitat separately through literature review, expert consultation, and a novel neighborhood approach that inferred foraging habitat around roosts using summary metrics of key environmental predictors. Habitat suitability was then predicted using an ensemble SDM (averaging tuned-Maxent, Boosted Regression Trees, and Random Forest models). Through iterative consultation and co-design with end-users, outputs were refined into a spatial tool tailored for conservation decision-making. Roosting habitat for both species was largely predicted by moderately complex terrain and presence of major iron formations, as well as moderate terrain complexity and high vegetation diversity in the surrounding foraging neighborhood. Only 5–6% of predicted habitat occurred within conservation estate, while over 70% overlapped areas under mining tenure, with many known roosts located close to operational mines. Our approach demonstrates how explicitly modelling complex habitat use and co-designing SDMs with end-users can produce tools that better support landscape-scale habitat assessments across a region with competing priorities.

Introduction

Species distribution models (SDMs) are well-established tools in biodiversity research with a diversity of conservation applications (Zurell et al., 2022). Despite the increasing availability of SDMs, evidence of their use in on-ground decision-making remains limited (Guisan et al., 2013; Zurell et al., 2022). This is partly due to the difficulty non-specialists face in interpreting model outputs, and because models are often developed without a clear understanding of the decision-making context in which they are applied (Guisan et al., 2013; Villero et al., 2017). Various frameworks have been proposed to create SDMs that are fit for purpose by involving end-users, such as species experts and environmental policy-makers, in all aspects of the modelling process (Sofaer, Jarnevich, et al., 2019; Villero et al., 2017). This is important when managing threatened species, where well informed SDMs can aid in effective decisions for conservation that minimize impacts on population viability.

Threatened species management can benefit from SDMs that help identify habitat critical to survival, although modelling this habitat can be complex when species use multiple, distinct habitat types for different purposes across large spatial scales (Lamb et al., 2020). While intense field surveying and telemetry can be used to explore habitat use (Crispim-Mendes et al., 2024), the time and resources required to generate such fine-scale, spatially and temporally resolved data often lag behind the urgent timelines of conservation decision-making. When habitat requirements shift seasonally, occurrence data can be partitioned to understand temporal change (e.g., Vignali et al., 2021), as implemented in multi-state SDMs which have been used to model suitable breeding and non-breeding habitat (Frans et al., 2018). However, in practice, decision-making often relies on integrating existing occurrence records from multiple projects, time periods, and sources (Sofaer, Jarnevich, et al., 2019). In these cases, the time-series data required for modelling shifting habitat are rarely available, especially for species that rely on distinct habitat types daily.

Bat species rely on distinct habitat for diurnal roosting and nocturnal foraging. Roosts can be limited and patchily distributed throughout the landscape (Cramer et al., 2016), while nocturnal foraging can take individuals many kilometers from roosts to feed and rehydrate (Lundy et al., 2012). Foraging habitat may also be limited, patchy and only accessible if within bats nightly flight distance (Fonderflick et al., 2015). Little is known of the impact on bat population dynamics when roost or foraging habitat is removed or fragmented, particularly for species with high dispersal capacity (Umbrello et al., 2022).

Two threatened bat populations occur in the Pilbara bioregion (Cramer et al., 2016, 2022), a biologically diverse and distinctive region in north-western Australia. The ancient and complex geology of the Pilbara (Pepper et al., 2013) has resulted in rich mineral deposits, particularly of iron ore, leading to rapid expansion of the mining industry over the past 60 years (McKenzie et al., 2009), with 84% of this area currently under mining tenure (Department of Energy, Mines, Industry Regulation and Safety, 2024a). The ghost bat (*Macroderma gigas*) and the Pilbara leaf-nosed bat (*Rhinonicteris aurantia* Pilbara form) roost in caves that overlap with economically valuable ore deposits in the Pilbara. Both are listed as Vulnerable under the Western Australian *Biodiversity Conservation Act 2016* and Federal *Environment Protection and Biodiversity Conservation Act 1999* (EPBC Act), where they are recognized as Matters of National Environmental Significance. Both species are predicted to decline over the next 20–40 years due to increased disturbance, alteration or removal of roost caves by mining operations (Woinarski et al., 2014). Multiple stakeholder workshops have identified that a better understanding of species' distributions, and the location of critical roosting and foraging habitats, are key priorities to effectively conserve and manage populations of these species (Bradley et al., 2024; Cramer et al., 2016, 2022).

Here, we applied a co-design approach to develop habitat suitability models for *M. gigas* and *R. aurantia* in the Pilbara. Expert-validated roost records were used as anchor points to define species-specific 'foraging neighborhoods' based on known nightly foraging distances. We then characterized the environment at roost sites and within surrounding neighborhoods to identify attributes associated with roosting and foraging habitat, guided by ecologically grounded hypotheses (Table 1, Table S1). This approach allowed us to infer key environmental requirements for both habitat types, even in the absence of fine-scale movement data. With end-user input, we refined the SDMs into a practical decision-support tool to inform environmental impact assessments, survey design, threatened species management, and conservation prioritization; key priorities in a region undergoing intensive resource development.

Methods

Study species and location

Our study focused on two obligate cave roosting species, *M. gigas* (150 g) and *R. aurantia* (8.4 g), which both have disjunct distributions in the Pilbara, separated from northern populations in the Kimberley by over 450 km of sand dune habitat lacking suitable roost caves. Both species have narrow physiological tolerance to variation in temperature and humidity and, as such, must shelter in deep, humid caves during the day which maintain stable temperature (Baudinette et al., 2000; Kulzer et al., 1970). In the Pilbara, suitable natural roosts occur in ore-bearing strata and 'artificial' roosts in historical 20th century mine shafts (Cramer et al., 2016, 2022). Both roost types are limited, and subject to disturbance, collapse (in the case of historical mines) and future destruction from mining development (Woinarski et al., 2014).

Occurrence records

Cleaning and expert consultation – we obtained occurrence records for both species from multiple sources, including the Western Australian Threatened Species database (Department of Biodiversity, Conservation and Attractions, 2019) (downloaded in 2019–2020), the Department of Biodiversity, Conservation and Attractions (DBCA) Species and Communities Program (2022), the DBCA *M. gigas* scat database (obtained from genetic monitoring, 2015–2023; see Thavornkanlapachai et al. 2024; Umbrello et al. 2025) and *R. aurantia* roost locations provided by R. Bullen. We excluded: 1) records collected prior to 2000 due to potential inaccuracy of coordinates; 2) records from outside of the Pilbara (defined by the bioregional boundary, see DCCEEW 2020); 3) records found in carparks, likely to be road strike bats that have been moved from their natural habitat; 4) records with accuracy greater than 1 km or fewer than four decimal points; and 5) duplicate records within the same 1 km^2 pixel (based on rasters described below) to reduce the effects of sampling bias (Reddy & Dávalos, 2003). We then used expert consultation and information about survey methodology to determine whether records represented roosting or non-roosting individuals, assuming non-roosting individuals were foraging or in transit between roosts.

Macroderma gigas – most confirmed records meeting the criteria above were identified as roosting sites (*n* = 156; Figure S1); acoustic detections are rare due the species low intensity calls (Pettigrew et al., 1986). We excluded non-roosting records from our main dataset (*n* = 41) but retained this 'foraging' subset (*n* = 36 after cleaning) for qualitative validation of our model, described below. Given our primary goal was to identify potential natural roosting habitat for this species, we excluded records found in artificial caves, i.e. historical mine shafts or rail culverts (*n* = 15) resulting in 141 expert-confirmed roosting records in naturally forming caves for subsequent modelling.

Rhinonicteris aurantia – Most of the records were foraging individuals as *R. aurantia* roost caves are cryptic and difficult to locate; only 64 are known, 50 of which have been located within an accuracy of <1 km (Figure S1). As described above, we excluded non-roosting records (*n* = 517) and retained 291 records obtained through acoustic detections as a 'foraging' subset, assuming that these represent bats in flight that are foraging, travelling to forage or disperse. We excluded records found in artificial caves (*n* = 11), resulting in 39 expert-confirmed roosting records in naturally forming caves for subsequent modelling. Of these, most are considered permanently occupied roosts (*n* = 28). The remaining 11 records, located in the northern Pilbara, may not be occupied year-round but were retained to balance confidence in roost status with the need for an adequate sample size for modelling.

Spatial layers

We obtained or derived rasters that represent two functionally discrete habitat requirements: roosting and foraging habitat. We defined *a priori* biological hypotheses based on species life history for how environmental variables may influence roosting and/or foraging habitat suitability (Table 1; Table S1), including aridity, temperature, precipitation, soil moisture, elevation, geology, landform, terrain, vegetation, water and wind speed.

Roosting habitat – We prepared rasters by reprojecting them to UTM50S, cropping to the smallest raster extent (which encompassed the Pilbara bioregion), resampling to the same pixel size and origin, then aggregating by mean to a 1 km^2 resolution (for more detail see Shaw et al., 2023). Spatial layers available as vector data (i.e., polygons) were also rasterized to this extent and resolution.

Foraging habitat – Rasters were prepared as described above, and then further processed to describe the 'foraging neighborhood' using moving window calculations with the *focal* function in the *raster* package (Hijmans, 2024a). We defined this as a 12 or 20 km radius around the focal cell, for *M. gigas* and *R. aurantia* (respectively). This distance is based on recorded nightly flight distances travelled in one direction from roosts and represents a 'likely' average maximum foraging distance for each species (Augusteyn et al., 2018; Bat Call WA, 2021; Bullen et al., 2023).

For continuous climate and vegetation variables, we calculated the neighborhood mean and standard deviation to describe the average and the heterogeneity across the foraging area. We also used categorical vegetation data, summing the total amount of preferred and non-preferred vegetation (i.e., sum of cells containing specified vegetation type) and the Shannon diversity index of different vegetation types across the foraging neighborhood, calculated in the R package *vegan* (Oksanen et al., 2024). We described terrain complexity as the proportion of highly rugged terrain (ruggedness) and steep cliffs (relative elevation) in the foraging neighborhood by summing the total number of cells with values in the top percentiles (we tested three options: the 5th, 10th, or 20th percentile). Finally, the total availability of potential riparian habitat and water was described by summing the number of cells within 1 km of a watercourse within the foraging neighborhood.

Modelling approach

We modelled habitat suitability for both species with three widely used approaches that were among the top performing models identified by Valavi et al. (2022): tuned MaxEnt v3.4.1 (Phillips et al., 2006, 2017), boosted regression trees (BRT; Friedman, 2002; Elith et al., 2008), and random forests with down-sampling (RF; Breiman, 2001) in R 4.4.0 (R Core Team, 2024). We generated 10,000 random background points per species and split occurrence roost records into three data subsets (60% for model training, 20% for hyperparameter tuning, and 20% for evaluation and testing) to avoid overfitting and enable model validation on independent datasets (Hastie et al., 2009; Phillips & Dudík, 2008). The same background points and data partitions were used across all algorithms. We also trialed generating background points that accounted for bias by using other bat species' occurrence records to represent sampling effort (e.g. see von Takach et al. 2020), but this yielded results similar to the random background approach and is not presented here.

MaxEnt models were tuned using the R package *SDMtune* (Vignali et al., 2020), and following the methods described in Shaw et al. (2023). In brief, the *M. gigas* training dataset was split into four cross-validation folds to account for spatial nonindependence with the 'checkerboard2' method in *ENMeval* (Muscarella et al., 2014; Radosavljevic & Anderson, 2014). We did not split the *R. aurantia* training data into cross-validation folds, as we had a limited sample size of occurrence records and preliminary results suggested that further sub-setting resulted in a poorly calibrated model. We removed correlated variables (Spearman's |rs| > 0.7), tuned model hyperparameters, and then performed further variable reduction by optimizing for the best model based on the area under the receiver operating characteristic curve (AUC_{ROC}) (Fielding & Bell, 1997). Although we used a data-driven approach to variable selection, we only included variables for which we had *a priori* biological hypotheses for how they influence habitat suitability (Table 1; Table S1).

The selected variables were then used to fit BRT and RF models in the R packages *gbm* v2.2.2 (Ridgeway, 2024) and *randomForest* v4.7-1.1 (Liaw & Wiener, 2002), using R code adapted from Valavi et al. (2022). For RF, we converted the response variable to a factor (presence/absence) for classification, using 5000 trees and default settings for other parameters. We applied down-sampling to account for the known sensitivity towards low ratios of presence to background points (Chen et al., 2004; Valavi et al., 2021). BRT models were implemented using stochastic gradient boosting (Friedman, 2002), with tree complexity set to 1 for *R. aurantia* and 5 for *M. gigas* (i.e., to account for small versus larger sample sizes), a learning rate of 0.001, a bag fraction of 0.75, and five cross-validation folds. Background points were down weighted to have a total weight equal to the sum of presences weights.

To generate the final model, predictions from the tuned MaxEnt, RF, and BRT models were rescaled between 0 and 1 and an unweighted average was calculated to create an ensemble model. Only models with $\mathrm{AUC}_{\mathrm{ROC}}$ values of ≥ 0.7 were included in the ensemble. The ensemble predictions and associated variance were calculated for evaluation and the former was mapped across the study area.

Model evaluation

We evaluated continuous model predictions for the tuned MaxEnt, RF, BRT and ensemble using three threshold-independent metrics that capture different elements of model performance: $\mathrm{AUC}_{\mathrm{ROC}}$, area under the precision-recall gain curve ($\mathrm{AUC}_{\mathrm{PRG}}$), and Pearson correlation (COR) between predicted likelihood and presence-absence testing data. Using a range of metrics provides information relevant to different ecological applications (Valavi et al., 2022). Note that predictions based on presence-only models are not expected to be well calibrated, as shown in a large multi-species dataset, where most models achieved a COR <0.225 (Valavi et al., 2022).

Thresholding continuous model predictions to produce binary maps is often necessary in conservation, for example, to identify important habitat (Guillera-Arroita et al., 2015). To convert the ensemble model's continuous predictions into a binary presence-absence layer, we applied the maximum sensitivity plus specificity thresholding method. This approach optimizes the trade-off between these features, ensuring a balanced rate of true positives and true negatives and minimal misclassification errors. We then evaluated the binary ensemble predictions using the True Skill Statistic (TSS; Allouche et al., 2006), which provides a measure of model performance by balancing true positive and true negative rates. Because background data were used as pseudo-absences, they only provide an approximation of true absence, which can influence the accuracy of estimates. Therefore, TSS was reported alongside threshold-independent metrics described above, which are well-suited to presence-only models; together providing a comprehensive assessment of the ensemble model’s performance.

To characterize uncertainty in the final decision support layers, we assessed model agreement across the three ensemble components (tuned MaxEnt, RF, and BRT). Binary presence–absence maps for each model were generated using the approach described above. We then treated the ensemble binary layer as the reference and compared each individual model’s binary predictions to it, calculating the number of models that agreed with the ensemble prediction (presence or absence) at each grid cell. This agreement layer allowed us to identify areas where predictions were consistently supported across all models (low uncertainty) versus areas where ensemble predictions were driven primarily by one or two models (moderate to high uncertainty). This approach provided a spatially explicit indicator of confidence in ensemble predictions and helped identify locations where conservation recommendations should be interpreted with caution.

Descriptive statistics

To further evaluate our model predictions and validate assumptions about foraging behavior, we compared the location of records in the 'foraging' data subsets to the predicted roosting habitat in our binary presence-absence map. We calculated the distances between foraging records and the nearest predicted roost locations to explore whether foraging individuals were largely found within our pre-designated foraging neighborhoods as defined above.

To understand how known roost locations and predicted habitat for threatened bats are distributed across mining land tenures in the Pilbara (a potentially threatening process), we sourced and combined spatial information about mining tenements (Department of Energy, Mines, Industry Regulation and Safety, 2024a) and protected areas (Department of Climate Change, Energy, the Environment and Water 2022) (see Appendix S1 for details). We calculated the percentage of predicted roosting habitat within each tenure type using the 'ratioOverlap' function from the *changeRangeR* v 1.1.0 (Galante et al., 2024) package by overlaying the binary presence-absence and the land-use layer. To compare model predictions with actual roosting locations, we also calculated the percentage of known roosting locations, both natural and artificial, within each tenure type. Roost locations were thinned to one point per roost, so that percentages represent roost locations rather than individuals.

To quantify how many roosts are potentially impacted by mining activities, we sourced information on the location of both operating mines and those under development (Department of Energy, Mines, Industry Regulation and Safety, 2024b). We first counted the number of mines within the foraging neighborhood of each species. This distance represents the 'potential impact zone' which would plausibly impact bats by restricting or disturbing foraging or roosting habitat. Next, we generated a raster using the 'distance' function in *terra* (Hijmans, 2024b), where each pixel represents the distance to the nearest mine. Known *M. gigas* and *R. aurantia* roost locations were then overlaid to determine the distance of each roost to the nearest mine. For visualization, we masked out distances beyond 20 km, as areas further than this are less likely to affect either species' daily activities.

Decision support tool development

To enhance the interpretability and accessibility of model outputs for conservation decision-making, we developed a categorical map layer based on the ensemble model binary predictions for each species. The goal of this tool was to integrate expert-validated roost records, modelled habitat suitability, and species-specific foraging neighborhoods to provide a spatial overview of habitat use by the two threatened bats species across the Pilbara. Maps were shared as a QGIS v3.32.3-Lima (QGIS Development Team, 2025) project with a written guidance document and short explanatory video to assist stakeholders with interpretation and application.

To refine and evaluate the applicability of the tool, we sought targeted feedback from invited stakeholders involved in conservation planning and environmental regulation for these species within the Pilbara region, including staff from consultancies and three regulatory agencies, DBCA, Western Australian Department of Water and Environment (DWER) and the Australian Department of Climate Change, Energy, the Environment and Water (DCCEEW). Participants were asked to assess the relevance of the outputs to their decision-making contexts, how they interpreted the habitat categories, and whether any aspects could be misused or misinterpreted. Feedback was gathered through a structured form (Table S2) and subsequent in-person and online meeting, and contributors were invited to co-author the final publication. Revisions were made to both the spatial outputs and supporting guidance material in response to this consultation, reported below.

Results

Variable selection

Macroderma gigas – Five variables were retained in the final MaxEnt model after tuning and variable reduction, including terrain ruggedness (VRM; percent contribution = 41.9%), iron ore formation (percent contribution = 36.4%), and annual precipitation (percent contribution = 6.0%) for roosting habitat, and vegetation diversity (percent contribution = 12.4%) along with the total amount of steep terrain (the top 5^{th} percentile of relative elevation; percent contribution = 3.3%) within the foraging neighborhood (Figure 1a). Univariate response curves indicated habitat suitability at roosting sites was driven by moderate terrain ruggedness, the presence of major iron ore formations, and annual precipitation within the mid-range for the Pilbara (Figure 1b). Foraging habitat suitability was driven by high vegetation diversity and a moderate amount of steep terrain in the foraging neighborhood (Figure 1b). However, it is important to note that univariate response curves do not account for interactions between variables, which may influence these preferences.

Rhinonicteris aurantia – Fourteen variables were retained in the final, tuned *R. aurantia* bat MaxEnt model, though nine of these contributed less than 5% to the model. Roosting habitat variables included iron ore formation (percent contribution = 43.5%), terrain steepness (relative elevation; percent contribution = 15.0%), elevation (percent contribution = 11.0%), and weathering intensity (percent contribution = 2.0%) (Figure 1c). Foraging habitat suitability was influenced by the total amount of rugged terrain (the top 5th percentile of VRM; percent contribution = 8.4%), vegetation diversity (percent contribution = 6.9%), variation in the minimum temperature of the coldest month (percent contribution = 3.6%), total amount of low/poor vegetation (percent contribution = 3.0%), variation in isothermality (percent contribution = 2.4%), moisture seasonality (percent contribution = 1.2%), total amount of water/riparian habitat (percent contribution = 1.0%), variation in forest cover (percent contribution = 0.9%), average wind speed at 10 km altitude (percent contribution = 0.7%), and average amount of spinifex (percent contribution = 0.45%) in the foraging neighborhood (Figure 1d). Univariate response curves suggested that *R. aurantia* habitat suitability was primarily driven by presence of major iron ore formations, moderate terrain steepness, higher elevations, and, to a lesser extent, less weathered roost sites indicative of rocky outcrops (Figure 1d; Figure S2). Foraging suitability was associated with a moderate amount of highly rugged terrain and high vegetation diversity (Figure 1d; Figure S2). Although the remaining variables had low individual contributions, their inclusion emphasizes the role of diverse vegetation, moderate climate variation, and consistent forest cover in foraging areas. As above, interactions between variables were not considered in the univariate response curves.

Model evaluation

All models demonstrated strong predictive performance ($AUC_{ROC} > 0.9$; Table 2). For *M. gigas*, RF and BRT models were slightly better at discriminating between presence and absence locations than the tuned MaxEnt model (AUC_{ROC} = 0.919 [tuned Maxent]; 0.960 [RF]; 0.962 [BRT]) whereas *R. aurantia* models showed similar performance (AUC_{ROC} = 0.970 [tuned Maxent]; 0.977 [RF]; 0.961 [BRT]) (Table 2). The *M. gigas* models showed higher precision when predicting presences (AUC_{PRG} = 0.927 [tuned Maxent]; 1.000 [RF]; 0.913 [BRT]) than the *R. aurantia* models; with the latter showing higher performance when using the tuned MaxEnt and RF models compared to the BRT model (AUC_{PRG} = 0.875 [tuned Maxent]; 0.812 [RF]; 0.624 [BRT]) (Table 2). The *M. gigas* models were also better calibrated than the *R. aurantia* models (*M. gigas*: COR = 0.212 [tuned Maxent]; 0.183 [RF]; 0.186 [BRT], *R. aurantia*: COR = 0.158 [tuned Maxent]; 0.085 [RF]; 0.083 [BRT]) (Table 2), with the tuned MaxEnt models performing best for both species and within the range expected when using presence-only data.

All models met criteria for inclusion in the ensemble (Table 2), resulting in high performing ensemble models for *M. gigas* (AUC_{ROC} = 0.960, AUC_{PRG} = 1.000, COR = 0.198) and *R. aurantia* (AUC_{ROC} = 0.973, AUC_{PRG} = 0.937, COR = 0.105). Ensemble predictions for both species highlighted high habitat suitability across the southern Pilbara, variable suitability in the northern Pilbara, and low suitability in the central valley and coastal lowlands (Figure S3). Concordance across model predictions for the three component models was generally high for *M. gigas* (variance: maximum = 0.19; mean = 0.005), while model predictions were slightly more variable for *R. aurantia* (variance: maximum = 0.26; mean = 0.02). Using the maximum sensitivity plus specificity thresholding method, ensemble models were converted to binary presence-absence maps (Figure 2a–b) using thresholds of 0.3 for *M. gigas* and 0.45 for *R. aurantia*. The binary layers also performed well (TSS: *M. gigas* = 0.917; *R. aurantia*: 0.943; Table 2).

Descriptive statistics

Analyses to determine the distance between foraging records and nearest predicted roost locations confirmed that foraging bats were largely found within the expected foraging neighborhood, with *M. gigas* averaging 2.87 km from the nearest predicted roosts and *R. aurantia,* 3.43 km (Figure 2a–b). Maximum distances observed were 16.56 km for *M. gigas* and 53.73 km for *R. aurantia*, with 8% versus 1% of foraging records falling outside of the foraging neighborhood, respectively. This suggests that these may have been dispersing individuals (rather than foraging), that some suitable roosting habitat was not identified by our models, or that these represent outliers. Most of the modelled area was classified as potential dispersal habitat (44%) or foraging habitat (30%) for both species. Habitat suitable for both species (5%) was more extensive than habitat unique to either species (*M. gigas* = 3%; *R. aurantia* = 2%). Known roost sites, including natural and artificial caves, represented less than 0.1% of the total area.

Macroderma gigas and *R. aurantia* roosts substantially overlapped areas under mining tenure (Figure 3a), and many roosts fell within the 'potential impact zone' of operating mines (Figure 3b–c). For *M. gigas*, predicted habitat was primarily located within exploration licenses (44.3% live, 20.3% pending), with lower percentages in conservation areas (5.4%), mining leases (4.3% live, 1.5% pending) and other mining tenure (4.2% live, 1.8% pending). Actual roost locations, however, were predominantly within live mining leases (78.8%, with an additional 7.1% pending), exploration licenses (11.5% live, 3.8% pending) and other mining tenure (1.3% live, 1.3% pending), with a smaller fraction in conservation areas (0.6%). *Rhinonicteris aurantia* showed a similar pattern, with the majority of predicted habitat found within exploration licenses (44.7% live, 20.5% pending), followed by conservation areas (5.5%), mining leases (4.4% live, 1.5% pending), and other mining tenure (4.2% live). Actual *R. aurantia* roost locations were mainly found within live mining leases (60.0%, with an additional 16.0% pending) and exploration licenses (24.0% live, 4.0% pending), followed by other mining tenure (4% live) and only 2% in conservation areas.

Most mines within the study area were open pit (open pit = 269; pond = 15; decline = 1) and operational (operating = 260; under development = 25). The average distance of *M. gigas* roosts to mine sites was 14.1 km, with a median distance of 5.7 km (range: 0.2–96.2 km). For *R. aurantia*, the average distance was 16.2 km, with a median of 9.7 km (range: 0.6–96.6 km) (Figure 3c). On average, *M. gigas* roosts had 3 mines within their 'potential impact zone' (median = 1, range = 1–12), while *R. aurantia* roosts had 3.54 mines on average (median = 2.5, range = 1–12).

Decision support tool development

Qualitative stakeholder feedback

Stakeholders agreed that SDM outputs will complement their existing risk assessment workflows for each species. Most participants had not built SDMs themselves, although many had previously used model products to design ecological surveys, assess development proposals and support decisions under environmental legislation. Feedback highlighted four principal needs: understanding potential cumulative impacts, identifying survey or conservation priorities, estimating habitat availability and risk, and guiding landscape-scale planning. Stakeholders emphasized the importance of species-specific layers, explicit uncertainty classes and terminology that avoids unintended regulatory triggers or risks misinterpretation (Table 3). Because roost locations are sensitive, they acknowledged the need for a balance between data sharing and protecting threatened species location information and asked that model confidence and limitations be stated plainly. Terms such as 'critical habitat', 'predicted absence' or 'predicted presence' were considered misleading unless clearly defined.

Tool revisions

To meet these needs, we produced 1 km² decision support maps (Figure 2) containing four habitat layers: known roosts, potential roosting habitat, potential foraging habitat and potential dispersal habitat. Each was labelled low, moderate or high uncertainty according to ensemble agreement. Artificial roosts omitted from model training were added to the known-roost layer. Language was standardized to 'potential roosting/foraging/dispersal habitat' to reflect uncertainty, and the phrase 'critical habitat' was removed. Although species-specific layers are required for regulatory assessments, a combined map was retained for strategic conservation planning.

We also supplied additional tools in the final QGIS project to support decision-making, such as obscured point layers for natural and artificial roosts, rasters showing distance to roosts and to mining infrastructure, tenure delineating Conservation Reserve System boundaries and mining tenements, and the continuous habitat suitability ensemble SDMs for users who wish to set their own thresholds.

Additionally, we provide geoPDFs so that users without specialist software can access the information.

Discussion

We used a novel neighborhood-based SDM approach for two threatened bat species to capture distinct habitat uses (roosting and foraging). By pairing this with an iterative co-design process, we generated outputs that deliver ecological insight and meet the practical needs of end-users, ensuring our SDMs are truly fit-for-purpose in a landscape with competing conservation and economic priorities. Even with limited data, our models performed well and showed that most known and predicted roosting and foraging habitat occurs on active or pending mining tenure, underscoring the urgency of better planning tools. Stakeholder feedback indicated that the tool we developed will help to streamline environmental impact evaluations and enable more proactive, evidence-based decisions. This will support strategic conservation planning for bats that are sensitive to landscape scale threats in the Pilbara. We outline the ecological insights, management implications, and remaining challenges below.

Model performance and biases

Despite the difference in sample size, ensemble models for *M. gigas* and *R. aurantia* both performed well ($AUC_{ROC} \geq 0.96$). Rigorous data screening likely contributed to this outcome, with expert validation ensuring that each retained record genuinely represented a roost, minimizing early misclassification noise. The large *M. gigas* dataset resulted in parsimonious models with tight agreement across algorithms, indicating a high confidence ensemble model. For *R. aurantia*, the limited number of validated roost records (n = 39) fell well below the recommended threshold of 100 presences (Van Eupen et al., 2021), increasing the risk of overfitting. To mitigate this, we applied multiple safeguards: highly correlated variables were removed prior to tuning, non-informative variables were excluded, and models were averaged across three algorithms in an ensemble framework. This ensemble approach helps reduce model-specific variance and improve generality, particularly with small or noisy datasets (Dormann et al., 2018),and has been demonstrated to perform well when using tuned and/or high-performing component models (Valavi et al., 2021). Until more validated *R. aurantia* records are detected, this integrated approach, combining expert screening, variable reduction, model tuning, and model averaging, provides the most robust path forward. In the meantime, areas predicted to have no suitable habitat for *R. aurantia* should be interpreted with caution, as limited data may constrain the model's ability to extrapolate to novel or underrepresented environments.

There was a strong geographic bias in where the input data was collected, as most records were collected near mines during environmental impact assessment surveys associated with developments. With no adjustment for a strong sampling bias, presence-background models will model a combination of environmental suitability and sampling intensity, as the two cannot be untangled (Fithian et al., 2015; Phillips et al., 2009; Valavi et al., 2022). However, our preliminary exploration into using bias layers based on sampling intensity did not improve model performance. This suggests that the strong ecological dependence on iron-bearing geology (Armstrong, 2001; Armstrong & Anstee, 2000), which also drives survey effort, overwhelms artefacts introduced by spatial sampling bias. This result aligns with broader modelling studies showing that species with narrow ecological requirements are more reliably predicted from presence-only data than generalists, whose distributions are more sensitive to the way absences are generated (Brotons et al., 2004). Without independent absence data, presence-background models based on these key geophysical predictors, and further refined with foraging variables, appear to provide a good approximation of habitat suitability for both species.

Ecological insights

For both species, roosting habitat suitability was driven by rugged or steep terrain, and iron-rich strata, indicative of the deep, cave systems where these species are known to occur (Armstrong, 2001; Armstrong & Anstee, 2000). Elevation and precipitation also contributed to habitat suitability for both species, possibly because areas with higher rainfall and elevation may offer cooler, more humid cave environments that reduce the risk of desiccation (Baudinette et al., 2000; Kulzer et al., 1970). These key variables aligned very strongly with previous knowledge of the species (Table 1; Table S1) and demonstrates the degree of overlap in 'niche space' between them.

While our understanding of roosting habitat is comparatively comprehensive, knowledge of foraging ecology of either species has been lacking (Cramer et al. 2016, 2022). By embedding 'foraging neighborhoods' around each roost, our neighborhood-SDM provides the first landscape-scale view of key environmental characteristics of likely foraging areas. Across both species, the most important foraging variable was high vegetation diversity: heterogeneous mosaics of riparian habitat, mulga vegetation, open woodlands and spinifex out-performed any single vegetation class or variables describing proximity-to-water. For *R. aurantia*, dense and structured vegetation, particularly riparian vegetation (Bat Call WA, 2021; McKenzie & Bullen, 2009), is considered high quality foraging habitat presumably due to the increased biomass of flying insects (Fukui et al., 2006). *Macroderma gigas* are thought to prefer to forage in more open areas with an availability of perching trees (Bullen et al., 2023; Tidemann et al., 1985). Our modelling suggests a mosaic of vegetation types may supply both prey biomass and vantage points during long commuting flights. Moderate amounts of rugged terrain within the neighborhood also increased suitability, possibly because a heterogeneous landscape also supports diverse habitats and offers both shelter and open space for foraging and dispersal. While water availability is thought to be a vital component of foraging habitat for *R. aurantia* (Bat Call WA, 2021), it did not emerge as a strong predictor in our models. Water variables were moderately correlated with other retained variables such as terrain and weathering intensity, suggesting that water may be indirectly captured. Alternatively, our spatial summaries of water may not fully reflect its functional role for this species. Nonetheless, these high-level insights provide a baseline for further fine-scale studies, providing spatial hypotheses to be tested.

Both bats share extensive suitable habitat around banded-iron formations and the ensemble for *M. gigas* aligns closely with the species confirmed Pilbara range, whereas the *R. aurantia* model highlights several high-uncertainty hotspots, most notably in the north-west Pilbara. These outliers mark priority targets for surveys to confirm whether *R. aurantia* is truly absent from these areas (the current expert view), or whether unmodelled factors explain the mismatch. Adopting a 'survey-and-refine' loop, where yearly presences-absence records are used to validate and update models, would help improve accuracy and support better decision-making into the future. Integrated species distribution models (iSDMs), which combine opportunistic presence-only records with even small amounts of survey-derived absence data, are a promising approach for this purpose and have been shown to outperform presence-only models in cross-validation (Mäkinen et al., 2024).

Implications

Our modelled predictions indicated suitable habitat in conservation reserves within the Pilbara, especially Karijini National Park, despite very few known roosts in this location. This suggests that either, the current reserve system is inadequate at protecting preferred bat habitat, or that these areas are under-surveyed. Our spatial tool could help target survey effort to locate roosts within conservation estate. SDMs have a proven track record in guiding population discovery, for example, field validation of an SDM for the federally threatened herb *Macbridea alba* uncovered six previously unknown populations in the south-eastern United States (Johnson et al., 2023).

The mainland Pilbara bioregion is ~178,500 km^2 (McKenzie et al., 2009) and 84% of this is under mining tenure (Department of Energy, Mines, Industry Regulation and Safety, 2024a). Our results confirm that a significant proportion of known and predicted bat habitat is under active mining lease, with much more under exploration licenses, meaning these areas could be mined in the future (Woinarski et al., 2014). Under the Commonwealth EPBC Act, proponents must show they have avoided and minimized significant impact on matters protected under national environment law before a development can be approved. Current guidance recommends mapping known roosts and ‘likely foraging habitat’ to help determine if the impact is significant (Threatened Species Scientific Committee, 2016). By incorporating known and potential roost habitat alongside the foraging neighborhood, our tool can help inform targeted surveys, identify locations where development may be more appropriate (i.e. where habitat suitability is low, pending on-ground validation), and support the implementation of avoidance and mitigation measures. The mapped foraging areas broadly encompass the potential foraging records we identified, suggesting that the models effectively capture this important habitat type, enabling better informed decision-making for these species.

The integration of SDMs into decision support tools is most effective when they are co-designed with end-users (Sofaer, Jarnevich, et al., 2019; Villero et al., 2017). In our context, this includes stakeholders recommending decisions in relation to environmental approvals, offset strategies, and management plans, and we were able to build on a wealth of prior engagement focused on the region and target species (Bradley et al., 2024; Cramer et al., 2016, 2022). Such collaborative approaches align with best practice in conservation planning, where stakeholder participation is important to maximize the usefulness of decision support tools and encourage the uptake of scientific knowledge (Cvitanovic et al., 2016). Through our engagement process, several issues were identified that we would not have anticipated without stakeholder involvement. For example, stakeholders advised caution around terminology, with terms like ‘critical habitat’ having specific regulatory meaning, and ‘predicted absence’ and ‘predicted roosting habitat’ carrying potential interpretive risks if not clearly defined. For example, end-users may overinterpret model outputs and incorrectly assume that predicted habitat equates to species presence (and thereby suitable for locating conservation ‘offset’ areas to mitigate species impacts without on ground validation) or that areas of predicted absence require no further survey or no consideration of potential impact to species. This feedback directly informed the final content provided as guidance material to users with clear guidance on the tool’s limitations and appropriate use. This feedback strongly aligns with the recommendations of Sofaer et al. (2019a), who stress the importance of transparent communication and targeted guidance when delivering SDMs to support conservation decision-making. Our experience reflects broader calls to incorporate user needs and policy and or regulation context from the outset to improve the uptake, relevance, and trust in decision support tools (Rose et al., 2016).

Future directions

Our co-designed SDMs provide high level information to support decision-makers assessing impacts on both threatened bat species in the Pilbara, but tools to assess or quantify the effects of the cumulative impacts of development activities at a landscape scale are sorely needed. Because environmental impact assessment occurs on a project-to-project basis, decision-makers often lack up-to-date and integrated information on activities occurring across multiple sites. This makes it difficult to evaluate how localized impacts (e.g., dust, noise, vibration) affect the regional population. Assessing cumulative impact will require information and spatial data that captures the footprint of development, and real-time information on which roosts and surrounding foraging habitat have been affected or lost. Finer ecological knowledge, such as seasonal patterns of roost use and foraging, and sex-specific differences in roost occupancy, will also improve understanding of how disturbance influences meta-population dynamics. While our decision support tool is a first step towards more informed planning in the region, fragmentation indices and population viability models (PVAs) will be critical to assess whether new developments could trigger local extinction or severely limit bat movement in specific areas (López-Wilchis et al., 2021; Theobald et al., 2020). Furthermore, updating models with new data, or adopting a 'survey-and-refine' loop, will ensure that this tool remains useful into the future.

Conclusion

Our results demonstrate that robust SDMs that capture complex habitat use can be developed even with limited data, particularly when expert-validated records and ecologically meaningful variables are used. High model performance for both threatened bat species supports the reliability of these predictions, despite geographic sampling biases. Model results suggest that iron ore, complex or steep terrain and vegetation diversity are important characteristics of roosting and foraging habitat for these species. While the models identify potentially suitable habitat, they are not occupancy models and should not be used as a proxy for species presence without validation. The primary value of these outputs lies in their ability to guide targeted surveys, inform impact assessments, and support more strategic conservation planning. By integrating species ecology, expert review, and co-design with decision-makers, this work advances the application of SDMs as practical decision support tools, applicable to other taxa facing overlapping development pressures within the Pilbara and in similar resource-driven landscapes globally.

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Tables and Figures

Table 1. Roosting and foraging environmental variables for *Macroderma gigas* and *Rhinonicteris aurantia* (see Table S1 for species specific hypotheses).

Environmental variables	**Habitat type**	**Spatial layer/s**
Aridity	Roosting, foraging	Aridity indices (ADI, ADM, and ADX)[1]
Elevation	Roosting	Digital elevation model (DEM)[2]
Geology	Roosting	Iron ore[3] (rasterized polygon data using the following iron formation hierarchy: major, minor, not present)
Landform	Roosting	Weathering intensity index (WII)[4,5]
Precipitation	Roosting, foraging	BIOCLIM precipitation variables (B12-B17)[6]
Soil moisture	Foraging	BIOCLIM soil moisture variables (B29-B33)[6]
Temperature	Roosting, foraging	BIOCLIM temperature variables (B03-B07 and B10-B11)[6]
Terrain	Roosting, foraging	Vector ruggedness measure (VRM)[4,7], relative elevation at 250 m[4,8]
Vegetation	Foraging	Mulga vegetation[9], low/poor vegetation[9] (bare/open ground/plains) and vegetation diversity[9,10], persistent forest cover[11,12], Spinifex density[13]
Water	Foraging	Natural perennial water availability[14-16] (i.e. excluding artificial water points, and inland flats subject to inundation or flooding)
Wind	Foraging	Windspeed at 10 m and 50 m altitude[17]

Data sources: [1]Harwood et al. (2016); [2]Gallant et al. (2011); [3]Department of Mines, Industry Regulation and Safety (2020); [4]Wilford (2012); [5]Wilford & Roberts (2018); [6]Harwood (2019); [7]Evans et al. (2023); [8]ESRI (2018); [9]Department of Primary Industries and Regional Development (2019); [10]Oksanen et al. (2024); [11]Furby et al. (2007); [12]Furby (2018); [13]Rampant et al. (2019); [14]Landgate (2012) ; [15]Landgate (2017) ; [16]Landgate (2019); [17]Davis et al. (2023).

Table 2. Threshold independent evaluation metrics providing measures of predictive performance for each model algorithm, including area under the receiver operating characteristic curve (AUC_{ROC}), area under the precision-recall gain curve (AUC_{PRG}), Pearson correlation between the predicted likelihood of presence and the presence-absence testing data (COR), the maximum sensitivity plus specificity threshold used to convert continuous predictions into binary presence-absence layers, and the resulting True Skill Statistic (TSS).

Model	**AUC_{ROC}**	**AUC_{PRG}**	**COR**	**TSS**	**Threshold**
M. gigas					
Maxent (tuned)	0.919	0.929	0.212	-	-
Random Forest (down-sampled)	0.960	1.000	0.183	-	-
Boosted Regression Trees	0.962	0.913	0.186	-	-
Ensemble	0.960	1.000	0.198	0.917	0.300
R. aurantia					
Maxent (tuned)	0.970	0.875	0.158	-	-
Random Forest (down-sampled)	0.977	0.812	0.085	-	-
Boosted Regression Trees	0.961	0.624	0.083	-	-
Ensemble	0.973	0.937	0.105	0.943	0.450

Table 1. Summary of main feedback themes from end-users with detail on the action taken to address the feedback.

Feedback theme	Detail	Change implemented
Timeframe of input data	Be explicit with date range of input data as roosts continue to be discovered	In spatial metadata and tool materials clearly state the date range on input occurrence and environmental data
Visualize each species separately	Decisions are made on each species independently, and they need to be separated in the tool	Re-processed the binary raster to have a predicted roosting and foraging layer for each species
Use of 'critical habitat'	The phrase 'critical habitat' has specific meaning under different legislation (e.g., BC Act vs. the EPBC Act)	Ensure all terminology for output layers does not include legislated phrases or words if it does not encompass those categories. Rename binary layer as 'potential roosting' and 'potential foraging' habitat
Accessibility	Difficulty with downloading files, installing QGIS or using QGIS. Color consistency – prefer same for both species. Color contrast - increase	Ensure spatial tool is publicly accessible in different formats (e.g., spatial package and geoPDF). Other opportunities to make the tool more accessible and interactive will be investigated in the future. Adjust color schemes and for separated species ensure the colors are the same.
Potential foraging habitat and predicted absence	Areas outside of the foraging neighborhood (12 or 20 km) that are considered high value (e.g., riparian vegetation, watercourses etc.) are not captured. These areas could be important for foraging by dispersing bats. Further, categorizing areas as 'predicted absence' suggests these areas provide no value, but they are likely to be important for dispersal.	Updated guidance document to emphasize that the foraging neighborhood represents the most 'likely' foraging areas, and rename 'predicted absence' to 'potential dispersal habitat'.

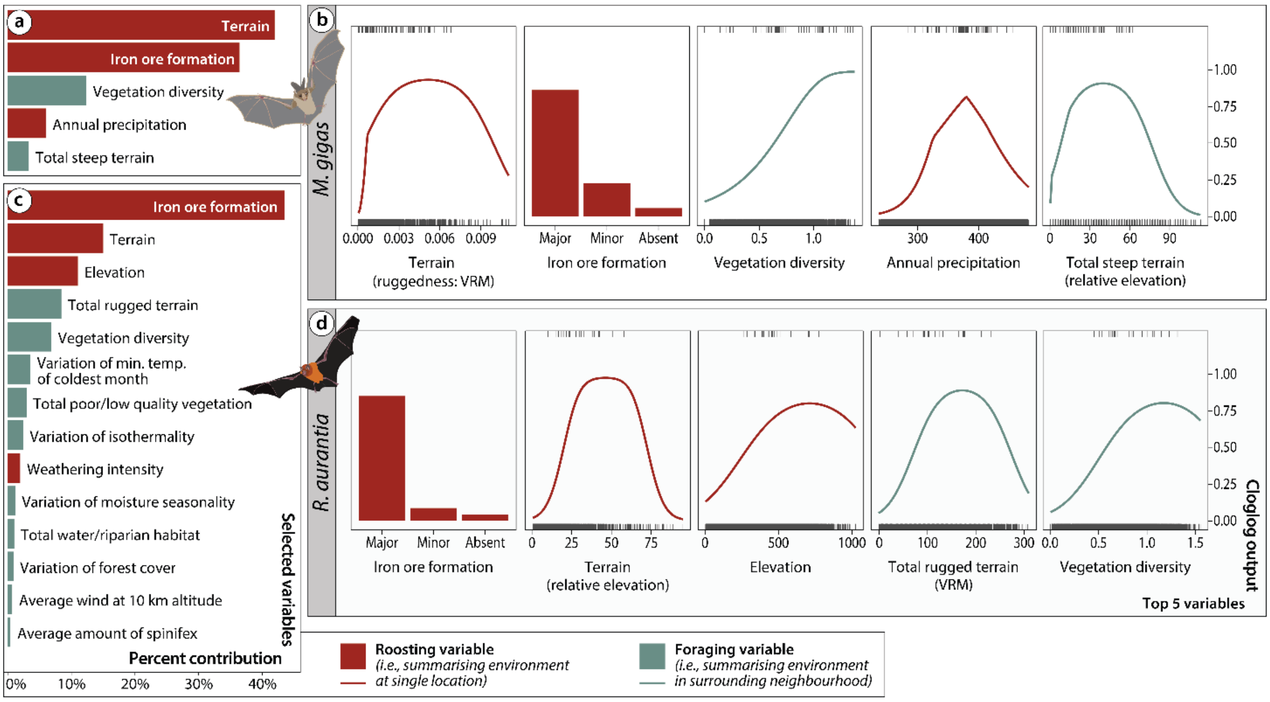

Figure 1. Contribution of the full variable set (refer to Table 1 for variable descriptions) towards the final tuned MaxEnt model (a) and univariate response curves for the top 5 ranked variables (b) for *Macroderma gigas;* and for *Rhinonicteris aurantia* (c-d; see Figure S2 for remaining *R. aurantia* response curves). Roosting variables (in red) represent the environment at the focal location, whereas foraging variables (teal) represent the environment in the surrounding ‘foraging’ neighborhood. Vertical tick marks in b and d (rug plots) represent presence (top) and background (bottom) locations.

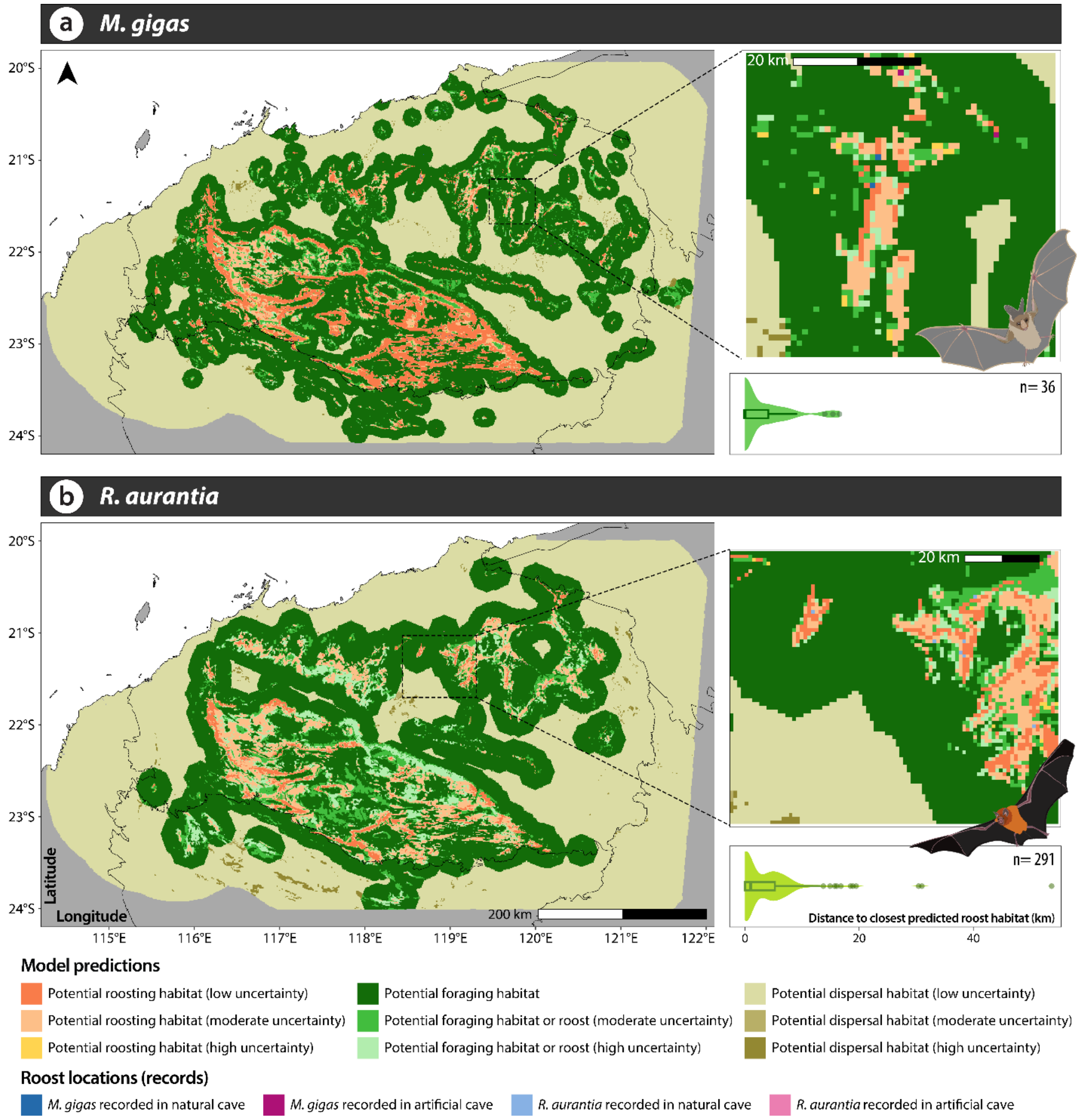

Figure 2. Decision support tools for a) *Macroderma gigas* and b) *Rhinonicteris aurantia*, based on modified presence–absence maps derived from ensemble model binary layers. Maps integrate known roost locations, foraging neighborhoods, and model uncertainty (grey = outside of the study area). Insets show high-resolution detail (pixel size = 1 km^2) for a selected area. Violin plots with overlaid boxplots display the distribution of distances from foraging records (n) to the nearest predicted roosting habitat for each species. Note that x-axis labels are shown in panel b.

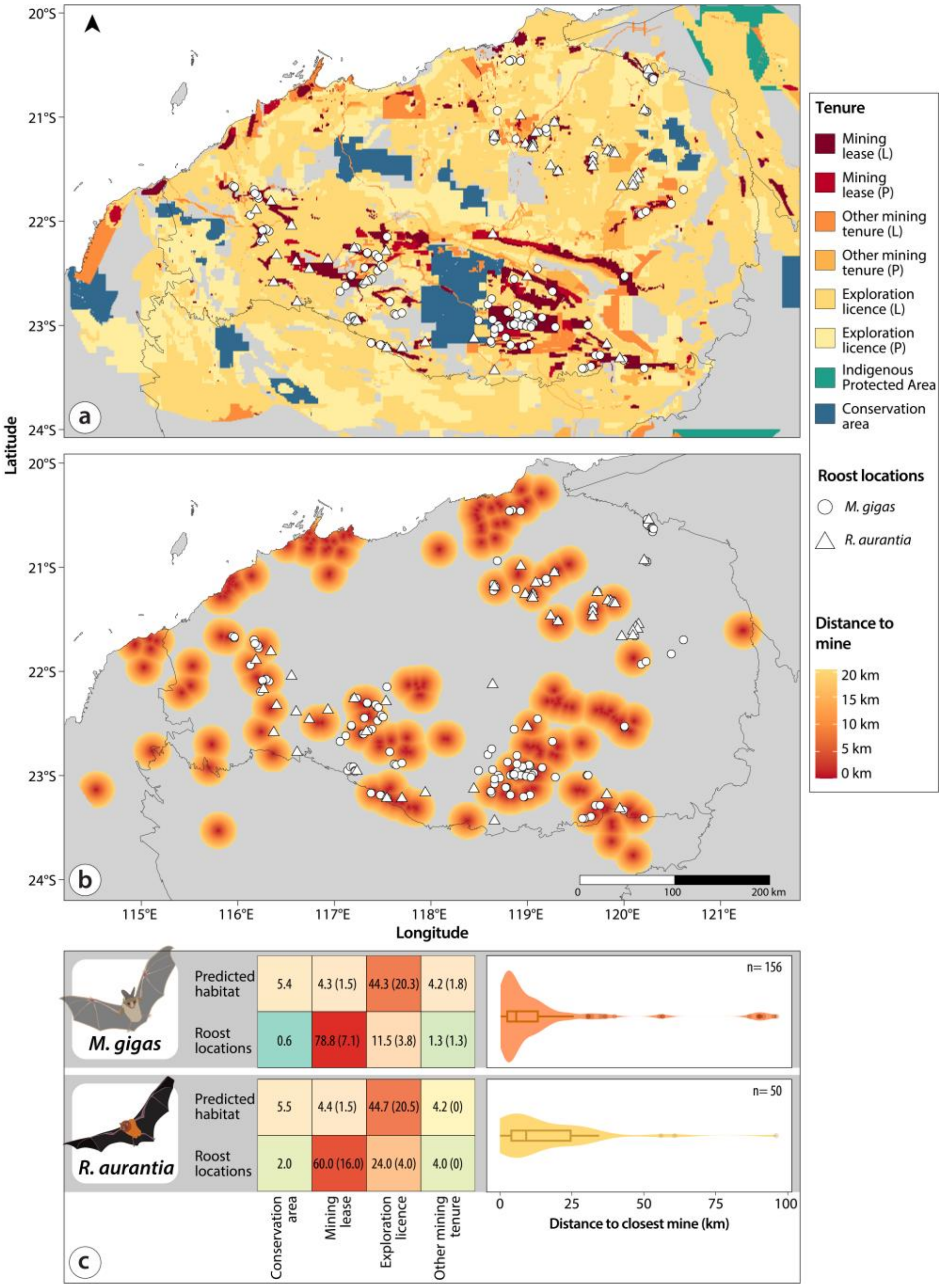

Figure 3. a) Map displaying different land-use tenure types across the Pilbara, where L = live and P = pending, with known roost locations represented by white circles (*Macroderma gigas*) and triangles (*Rhinonicteris aurantia*); b) map with known roost locations (as previously described) displaying the distance to nearest mine (operational and in development) up to a 20 km 'impact zone', which includes the foraging range of both species; and c) heat maps illustrating the percentage of predicted roosting habitat and known roost locations within different tenure types (live, with pending in brackets for mining tenure), and violin plots (with overlayed boxplots) showing the distribution of distances to the nearest mine site for known roost locations for each species.

Supporting Information

Appendix S1.

Land-use tenure data were sourced on the 5th of February 2024 from two primary spatial layers: mining tenements (Department of Energy, Mines, Industry Regulation and Safety, 2024) and protected areas (Dept of Climate Change, Energy, the Environment & Water, 2022). To generate a single tenure classification layer suitable for analysis, categories within the mining tenement dataset were first standardised by merging similar tenement types. Specifically, general purpose leases included both '*General purpose lease*' and '*General purpose lease S.A.*'; mining leases included '*Mining lease*', *'Mineral lease S.A.*' and '*Mining lease S.A.*'; and miscellaneous licences included both '*Miscellaneous licence*' and '*Miscellaneous licence S.A.*'.

A hierarchical scheme was then applied to resolve overlapping tenure types, retaining only the category likely to have the highest potential for disturbance to threatened bat habitat within each overlapping area. The hierarchy, from highest to lowest impact, was: The hierarchy, from highest to lowest impact, was: mining lease, general purpose lease, miscellaneous licence, retention licence, exploration licence, prospecting licence, conservation area (including reserves, national parks, conservation parks, Indigenous Protected Areas), and temporary reserves or pending additions to the National Reserve System.

Mining tenements were split into 'Live' and 'Pending' based on their current approval status. To reduce complexity, several tenement types were grouped under a single category, called 'Other mining tenure'. This included: General Purpose Lease, Miscellaneous Licence, Prospecting Licence, Retention Licence, and Temporary Reserve. We processed spatial data using the R packages *terra* v 1.7-71 (Hijmans, 2024), *sf* v 1.0-16 (Pebesma, 2018; Pebesma & Bivand, 2023), and *rmapshaper* v 0.5.0 (Teucher et al., 2023).

The resulting layer provides a simplified representation of tenure by retaining only the most relevant tenure type per location.

Table S1. Roosting and foraging environmental variables for *Macroderma gigas* and *Rhinonicteris aurantia* (see Table 1 for description of spatial layers).

Environmental variables	**Habitat type**	***Macroderma gigas* hypotheses**	***Rhinonicteris aurantia* hypotheses**
Aridity	Roosting, foraging	Unlikely to prefer highly arid areas due to physiological constraints[1] and lower prey abundances	Their preferred temperature and humidity for roosting is ~28–32°C and 85–100% respectively due to physiological constraints[1,6,7]. The risk of desiccation increases the longer foraging bats are outside of their preferred conditions
Elevation	Roosting	Unlikely to roost in low-lying areas that lack caves[2]. Where caves occur, they may roost within a range of elevations	Unlikely to roost in low-lying areas that lack caves. Where caves occur, they may roost within a range of elevations[8,9]
Geology	Roosting	Known to roost in caves that naturally occur in iron ore formations[2], compared to other geological types in the Pilbara	Roosts are closely tied to areas rich in iron ore as these deposits form natural caves that are deep/complex enough to provide the microclimate conditions that the species depend on[8]
Landform	Roosting	Unlikely to roost in highly weathered areas, but rather in areas with exposed bedrock that form caves and overhangs[2]	More likely to roost in areas of complex terrain (gorges and breakaways) with caves and overhangs[8,9]
Precipitation	Roosting, foraging	Likely to prefer areas with lower seasonality of precipitation indicating more stable prey abundances and humidity levels[1]. Unlikely to prefer very dry areas	Likely to prefer areas with more stable precipitation and high humidity due to desiccation risk[1]. Unlikely to prefer very dry areas
Soil moisture	Foraging	If soil moisture indicates habitat productivity, then lower values would indicate less preferred habitat and lower seasonality of soil moisture could result in more constant productivity and more persistent prey abundance throughout the year if the soil moisture is high	Seem to prefer to forage in riparian or more productive environments where soil moisture would be higher. Unlikely to forage in areas with low soil moisture due to lower prey abundances and desiccation risk
Temperature	Roosting, foraging	Prefer areas with temperatures within their thermal tolerance limits (between 20–38°C)[3]	Prefer areas within their thermal tolerance limits (between ~28–32°C)[1,6]
Terrain	Roosting, foraging	Likely to roost in areas of complex terrain (gorges and breakaways) with caves and overhangs[2]. Seem to prefer not to forage in complex terrain[4]	Likely to roost in areas of complex terrain (gorges and breakaways) with caves and overhangs[8]. Seem to prefer to forage in areas with complex geology and steep areas, less preferred are more open gullies with gentler sloped sides and open flat plains[9]
Vegetation	Foraging	Use trees to perch and feed, but dense vegetation could be difficult for them to navigate through and spot terrestrial prey items. Bare ground may not support enough prey items.	Preferred foraging habitat is thought to include complex 3-layered vegetation structure that includes canopy (e.g. tree-lined watercourses or scattered shrubs and trees in gullies[8]). Denser vegetation is preferred[4]

Environmental variables	**Habitat type**	***Macroderma gigas* hypotheses**	***Rhinonicteris aurantia* hypotheses**
Water	Foraging	Have been recorded to forage along ephemeral drainage lines[5] and water may give an indication of general productivity of an area that could yield higher quality foraging habitat.	Known to visit water sources shortly after emerging from roosts at night, which occur 0–8.7 km from diurnal roosts. All known permanent roosts occur within the species flight distance to permanent water[9]
Wind	Foraging	Areas with high winds may make foraging difficult, through increasing energy expenditure during daily movements	Areas with high winds may make foraging difficult, through increasing energy expenditure during daily movements

Data sources: [1]Baudinette et al. (2000); [2]Armstrong & Anstee (2000); [3]Leitner & Nelson (1967); [4]McKenzie & Bullen (2009); [5]Bat Call WA (2021b); [6]Kulzer et al. (1970); [7]Armstrong (2000); [8]Armstrong (2001); [9]Bat Call WA (2021a)

Table S2. Feedback questions sent to decision-makers to refine model outputs and understand end-user's experience and familiarity with interpreting and using SDMs.

Number	Question
1	Do you have experience with Species Distribution Modelling, and have you ever used the model outputs in decision-making before (if yes, please provide some brief examples of the decision-making context and your confidence level with interpreting the model outputs to make decisions)?
2	What specific assessment or other decision-making processes would you use this tool for? Would it improve these existing processes beyond information that is currently available to you?
3	Please provide a brief description of how you interpret the "potential habitat" categories that form the main model output (i.e. the PresAbs_RecordsForaging layer) and how these might inform your decision-making?
4	How could we refine this tool to improve interpretation and its relevance to the processes identified in question 1? (e.g., different categories, explanation for interpretation in the guidance document and video, etc.)
5	Given your area of experience, would you be concerned that this tool may be used or interpreted in ways that may be adverse to its intended use to aid bat conservation? Do you see this tool being used/interpreted differently to the processes you identified in question 1?
6	Do you have any further feedback to provide on how the tool is presented or the support materials?

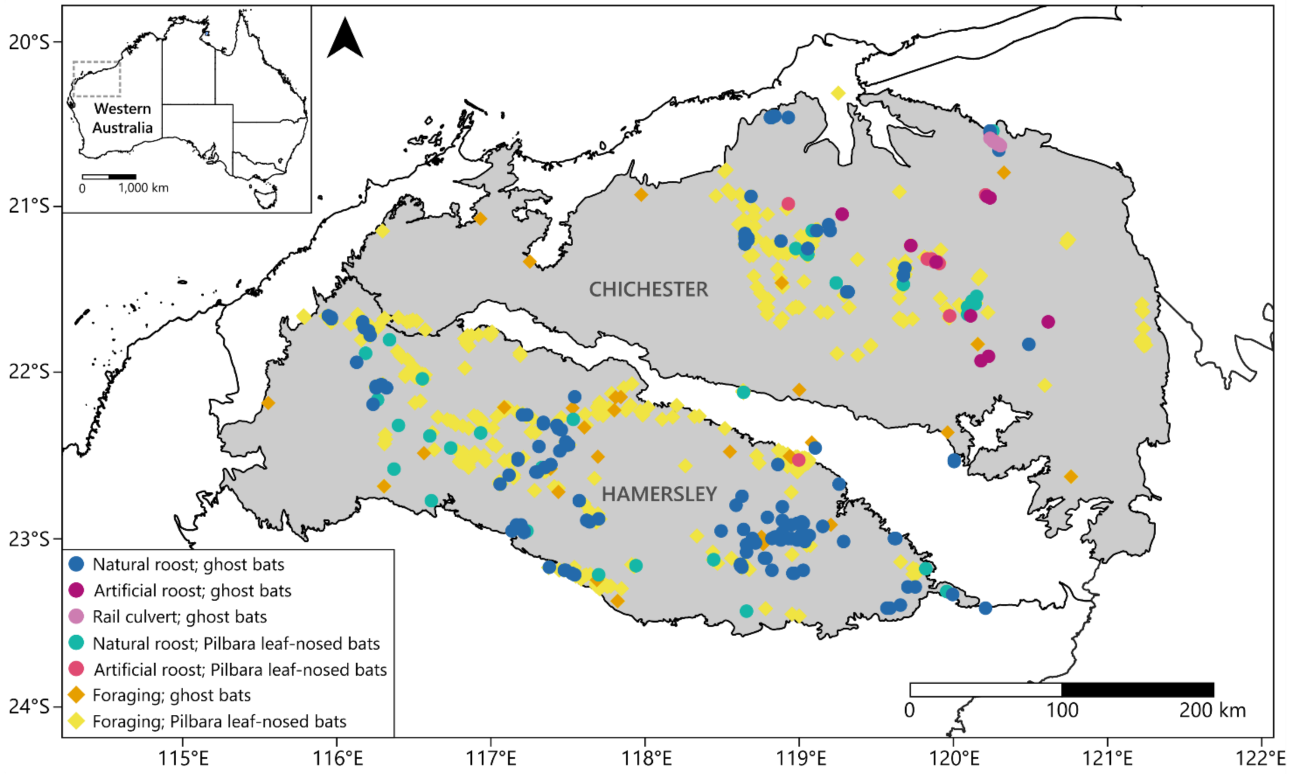

Figure S1. Expert validated *Macroderma gigas* and *Rhinonicteris aurantia* occurrence records from the Pilbara used in this study. Two major bioregions of the Pilbara, the Chichester and Hamersley, shaded grey. Echolocation (assumed to be foraging or dispersing bats) and artificial/rail culvert roost records for both species are shown, but were excluded from the modelling.

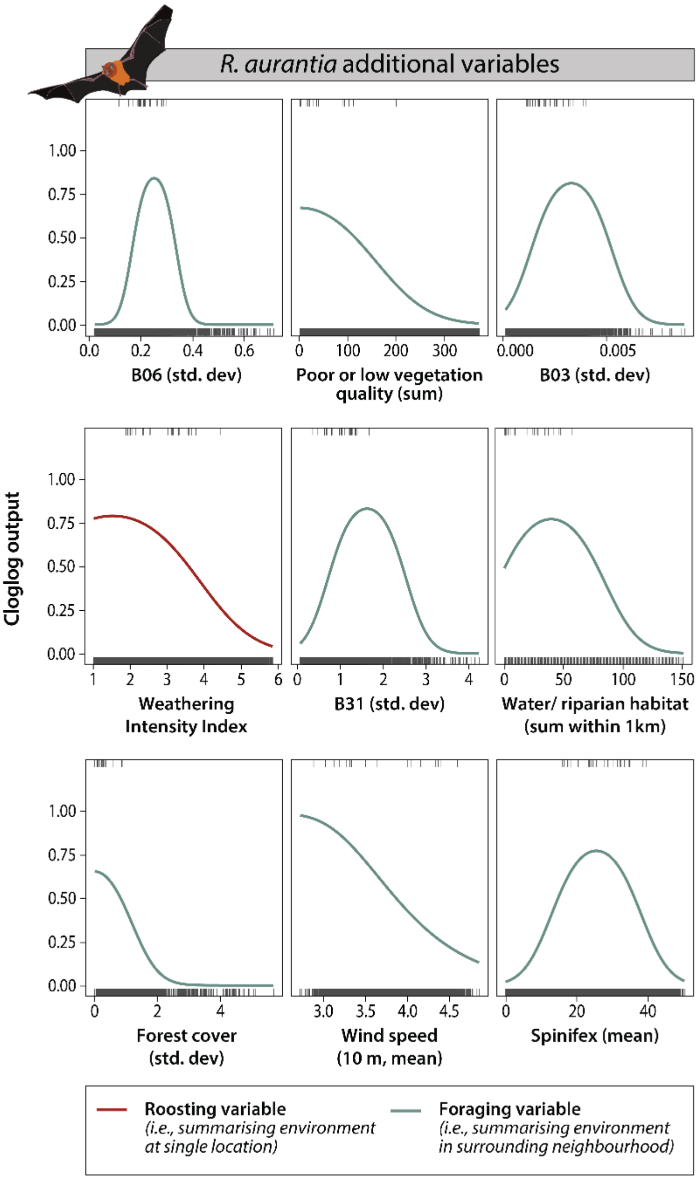

Figure S2. *Rhinonicteris aurantia* response univariate response curves for the remaining nine variables selected during MaxEnt modelling (note that all *Macroderma gigas* variables are presented in Figure 1). Roosting variables (in red) represent the environment at the focal location, whereas foraging variables (teal) represent the environment in the surrounding 'foraging' neighbourhood. Vertical tick marks in (rug plots) represent presence (top) and background (bottom) locations. BIOCLIM variables are as follows: B06 = minimum temperature of coldest month; B03 = isothermality; B31 = moisture index seasonality.

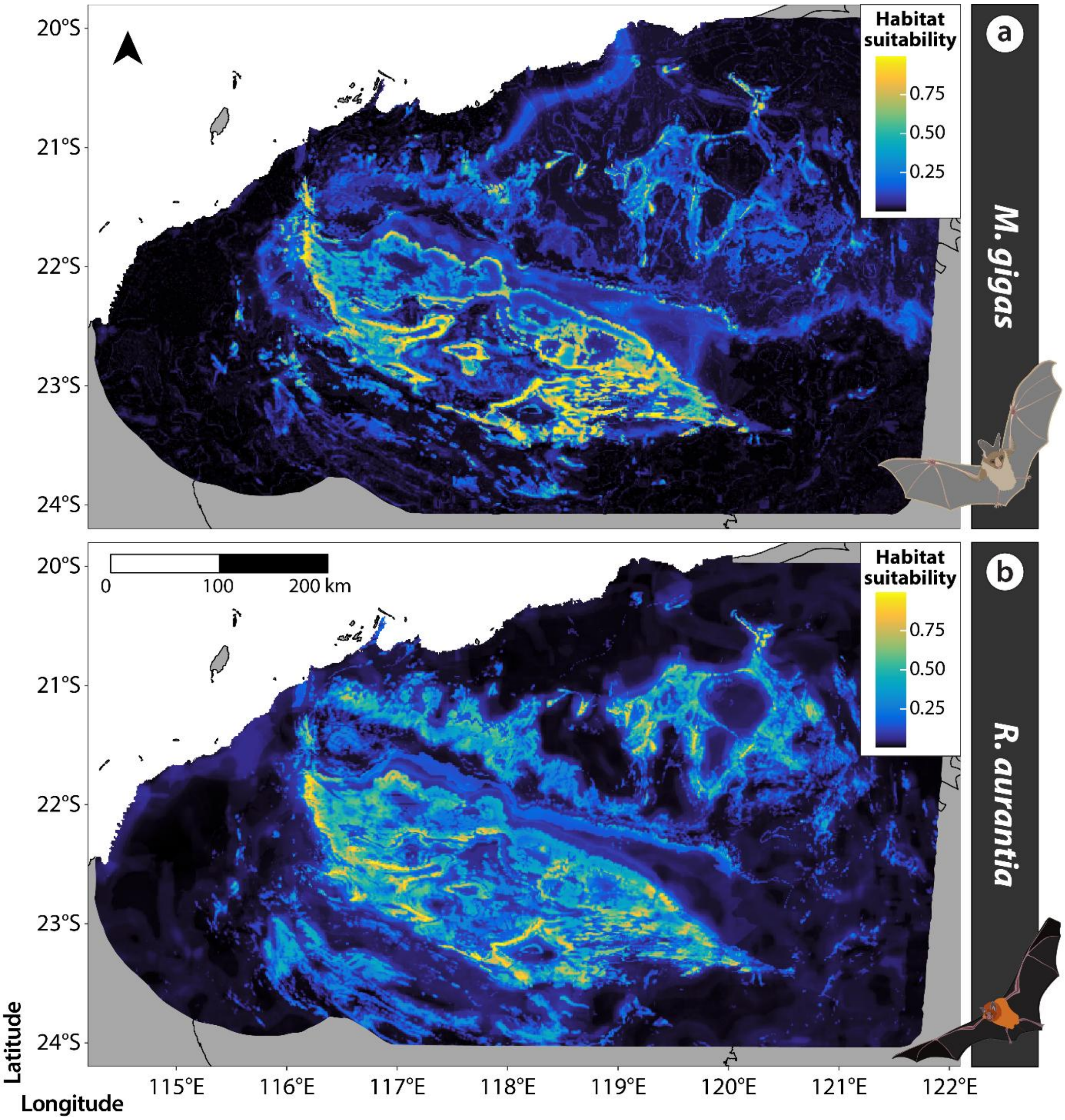

Figure S3. Ensemble model projections showing continuous habitat suitability for a) *Macroderma gigas*; and b) *Rhinonicteris aurantia* across the Pilbara region. Warmer colours indicate higher predicted suitability based on environmental and landscape features of each grid cell and its surrounding foraging neighbourhood.

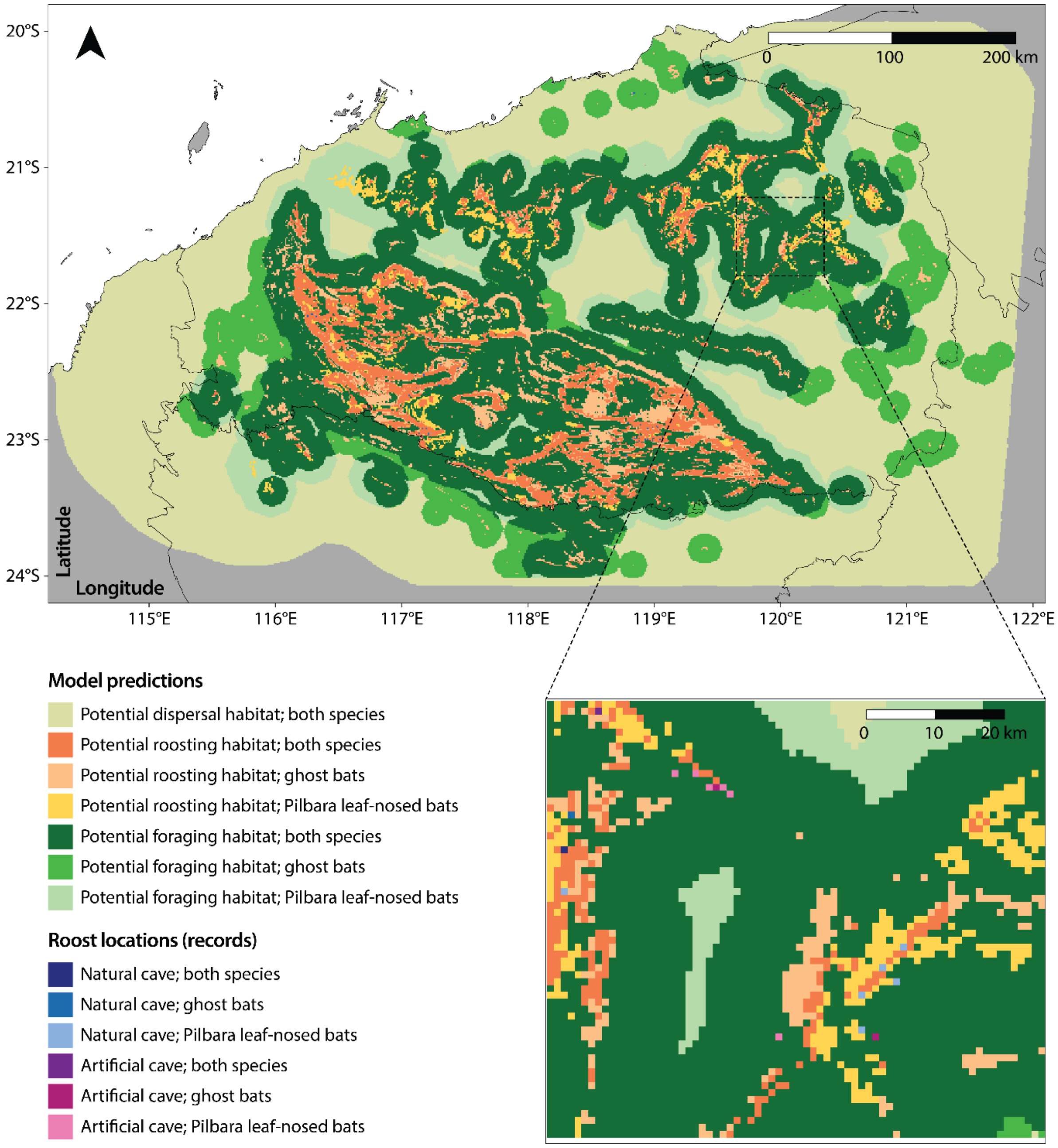

Figure S4. Combined decision support map for *Macroderma gigas* and *Rhinonicteris aurantia*, integrating roosting and foraging habitat predictions and known roosting locations for both species. The map is based on ensemble model binary layers and shows areas with different habitat uses (known or predicted) for each species, and where these overlap. The zoomed inset shows high-resolution detail (pixel size = 1 km^2) for a selected area.

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