Including Indigenous knowledge in species distribution modelling for increased ecological insights

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Running head

Indigenous knowledge

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Article impact statement

Indigenous knowledge systems hold detailed environmental data that can be used to model species' distributions to assist with management.

Abstract

Indigenous knowledge systems hold detailed information on current and past environments that can inform ecological understanding as well as contemporary environmental management. Despite its applicability, there are limited examples of Indigenous knowledge being incorporated in species distribution models, which are widely used in the ecological sciences. We describe a collaboratively designed project that applied a structured elicitation process and statistical framework to combine Indigenous knowledge with survey data to model the distribution of a threatened and culturally significant species (mankarr; greater bilby; *Macrotis lagotis*). We used Martu (Indigenous) occurrence knowledge and presence data from track-based surveys to create predictive species distribution models using the Maxent program. We found that predictions of species distribution using Indigenous knowledge suggested a broader distribution to those created with survey data and together the models implied potential local declines, which were supported by Martu observation. Both data types were influenced by sampling bias that appeared to influence model predictions and performance. Further ecological insights were provided by Martu knowledge of habitat associations, locations of decline, plus descriptions of the ecosystem dynamics and disturbance regimes that influence occupancy. We conclude that intercultural approaches that draw on multiple knowledges and information types can be beneficial for species distribution

modelling, and for gaining understanding to manage threatened or culturally significant species.

Introduction

Developing collaborative opportunities which combine the insights from Indigenous Knowledge (IK) and Western science to improve contemporary environmental management is a priority for many conservation organizations, governments and Indigenous people (Mistry & Berardi 2016). Central to this endeavour is the development of frameworks that facilitate coproduction by Indigenous and non-Indigenous partners, where Indigenous rights, values and socioeconomic realities are considered, and where IK and Indigenous priorities are applied (Hill et al. 2012). The knowledge systems of Indigenous people hold detailed information on the current and past environment, as well as the dynamics that shape the condition and diversity of the natural world (Agrawal 1995; Houde 2007). IK emerges from long periods of shared human observation and experimentation and contains intimate understanding of species distributions, animal behaviour, habitat relationships and the complex feedback loops between humans and nature (Agrawal 1995; Huntington 2000; Brennan et al. 2012). Although there may be cultural differences in worldviews and priorities, Indigenous and non-Indigenous managers often have related questions and goals with regard to natural resource management (Lynch et al. 2010).

The conservation and recovery of the mankarr (greater bilby/ *Macrotis lagotis* Reid, 1837) is of national significance in Australia (Bradley et al. 2015) and a priority for Martu, the

Traditional Custodians of the Martu Native Title Determination Area in Western Australia (Jupp et al. 2015), and other Aboriginal Australians who are custodians of this species (Walsh & custodians of the Bilby 2016). The mankarr is the last of the extant desert bandicoots, once found across most of the interior of Australia, the species' distribution has contracted to the north-western parts of its former range (which are largely Indigenous estates), and a continuing decline in distribution suggests populations are far from secure (Woinarski et al. 2014). It is one of many small mammal species that have experienced a precipitous decline over the last 100 years, as at least a third of all central desert mammals have become extinct (Woinarski et al. 2015). To the Indigenous people living in these deserts, these mammals form an integral part of culture and Jukurrpa (Dreaming/Law) and historically provided important sources of food (Burbidge et al. 1988; Walsh 2008). The knowledge of Indigenous people reveals crucial ecological insights into these extinct species, and establishes historical distributions and timelines of declines (Burbidge et al. 1988; Ziembicki et al. 2013).

The recovery of the mankarr is challenged by limited understanding of its current extent of occurrence, its abundance, and location of suitable habitat (Cramer et al. 2016) across the remote and expansive Indigenous lands where extant populations chiefly occur. Species distribution models (SDMs) offer methods to identify environmental correlates of occurrence to predict species distribution (Guisan & Thuiller 2005; Elith & Leathwick 2009), and methods are being developed where IK or local knowledge can be applied in ecological modelling to fill survey gaps or provide novel insights (Bélisle et al. 2018). However there are challenges to using IK in SDMs which include eliciting reliable knowledge (Kuhnert et al. 2010), developing methods to integrate different geographical data types (beyond the most commonly used point-level presences) in SDMs (Merow et al. 2017), and gaining an understanding of how the observation and cultural transmission process associated with IK may impact on predictions and interpretations (for instance Polfus et al. 2014).

The aim of this study was to develop a modelling approach that incorporates Indigenous (Martu) knowledge (IK) of mankarr ecology and occurrence along with geo-referenced track-based survey data to assist with understanding mankarr distribution in the Martu Determination. We elicited Martu knowledge of mankarr distribution and ecology through semi-structured interviews, and applied this information in two ways: 1) building a model to predict spatial distribution, and 2) adding contextual understanding of the ecological processes that influence mankarr occurrence (Fig. 1). We present probabilistic maps of mankarr occurrence and test whether data from SDMs incorporating IK or presence data generate similar predictions. We consider the contributions of both IK and survey data in understanding distribution patterns and in assisting management and recovery planning.

FIGURE 1 near here

Methods

Background and study area

The study area comprised the 13.6 million hectare Martu Native Title Determination Area in Western Australia. Martu is used as a self-reference for a set of Aboriginal Australian dialect groups whose traditional estates encompass parts of the Great Sandy, Little Sandy and Gibson Deserts including the Karlamilyi River and Percival Lakes (Fig. 2). Martu are seeking ways to incorporate new technologies to achieve their priorities for caring for Country and culture (Jupp et al. 2015).

Elicitation of Indigenous knowledge

The knowledges of Aboriginal Australians in the deserts is complex and holistic; including major domains of Country, People and the Law (Walsh et al. 2013). Here we focused on gaining a sample of open information that could be used for mapping and natural resource management. We conducted elicitations in Parnngurr and Punmu communities in 2016 with ten Martu who were identified by the community as holding knowledge on mankarr and country, endorsed to speak on these topics and willing to participate. The interview process was developed in collaboration between the authors, Martu and staff at Kanyirninpa Jukurrpa (KJ; a Martu organisation), who provided guidance in making interviews respectful and culturally appropriate. Martu interviewees requested to participate in self-designated family groups rather than individually (6 independent groups with 1-3 people), with younger family members often present to help with translation and thereby add knowledge. Prior to seeking consent, we discussed the purpose of data collection, and how the data would be stored and used.

FIGURE 2 near here

Interviews were conducted in a semi-structured manner, with open-ended questions to encourage discussion (Table 1). We had photos of animals (including their tracks, scats and other sign) to aid with identification. A mixture of English and Martu languages were used. Groups were seated around large maps (AO size), which were annotated with spatial information as discussions progressed. We sought three types of information: 1) spatial data indicating where mankarr are likely to be present, 2) indications of whether distribution has been changing, and 3) information on habitat suitability (Table 1). The interviewees provided spatial information by drawing polygons around areas where mankarr activity was known. For each polygon we recorded when mankarr were last considered to be active there. Elders elected to only provide spatial information for their specific family lands, and we were unable to elicit information on areas that the mankarr is absent, as interviewees could only speak of the location where they knew of mankarr encounters.

The study was carried out with approvals from the Kanyirninpa Jukurrpa board and the University of Melbourne Human Research Ethics (UoM : 1646700).

TABLE 1 near here

Preparation of spatial IK for analysis

We digitized the hand-drawn maps using ArcMap 10.2 (Esri) to create spatial polygons of Martu knowledge of mankarr occurrence. One Elder was uncertain about the map placement of two locations where sign was witnessed several decades before, and we decided not to include these areas in the analysis to reduce the potential for false positives. As the combined knowledge from Elders covered only a subsection of the Native Title Area, we decided to constrain model parameterization to the area that encapsulated the IK, which we call the "IK boundary" (Lat: 121.82 to 123.87, Lon: -23.44 to -21.51; Fig. 2). We recognize that mankarr (and IK) occur on other Martu family lands (and other Indigenous lands), and that SDMs could be applied to extrapolate to these lands.

Survey data

Records of mankarr presence are also provided by surveys carried out by KJ ranger teams for arid fauna between 2008 and 2015. Surveys were conducted by searching a 2ha area for signs (including tracks, scats, diggings and burrows) to indicate the recent presence of animal species including mankarr (following methods of Moseby et al. 2012). We screened the data and removed two presence points that appeared to be erroneous, leaving 144 presences. The survey work did not have a strict sampling framework; some sites were visited once, while others had multiple surveys, and at times a series of surveys were located within 1km of others. We therefore designated presence at the scale of the 1km environmental layers, where the centre of any cell that had one (or more) mankarr detections was included as a presence point, resulting in 93 presence points.

Environmental variables

A set of 10 environmental variables were chosen as potential predictors of mankarr distribution (Table 2). Mankarr distribution is reliant suitable substrate for burrowing (Moseby & Donnell 2003), so to characterize substrate at a scale relevant to mankarr, we used polygon-based regolith data to create a separate raster layer (1km resolution) for each regolith type (sand, lacustrine, exposed rock, alluvium and calcrete) which depicted the percentage cover of this substrate within a 2km radius of each raster cell. Maps of vegetation pre-European settlement (Geoscience Australia) were collapsed from 26 categories into seven broad vegetation classes (Supporting information). We did not include climate variables (i.e. maximum temperature, precipitation) because the study area has extremely poor coverage by weather stations. We could not include radiometric data (relative potassium, thorium and uranium), which is a predictor of other arid vertebrate species occurrence, due to gaps in coverage (Pert & Norton 2011). Salt lakes were removed from consideration in analyses as they are unsuitable. All data preparation and analyses were undertaken in R (version x64 3.2.4) unless specified.

The continuous candidate environmental predictors (Table 2) were assessed for co-linearity with tests of Pearson correlation coefficients. There was strong pairwise correlation between three predictors (roughness & relief 0.97; roughness & rock 0.7; relief and rock 0.65). We retained relief and exposed rock because they may directly limit habitat suitability for the mankarr which is a burrowing animal, so we considered them *proximal* predictors of mankarr habitat suitability (sensu Austin 2002). After correlation analysis and screening, we arrived at a final set of 9 environmental predictors.

TABLE 2 near here

Considering sampling bias

As the study area is remote with few roads, records (both survey and IK) may be biased towards areas that are more accessible, which may lead to problems in estimation of environmental relationships if observer bias is aligned with a biased sampling of environmental conditions (Merow et al. 2013; Fourcade et al. 2014). In our case, we did not know observer bias *a priori*, and there was limited survey effort or data for taxonomically related species to infer sampling probability across the landscape for modelling bias. We therefore used a model-based method (following Warton et al. 2013) where distance to roads (km) was used as a covariate to model sampling bias in both survey and IK models, as both may be biased to the roads which are > 20 - 30 years old. Bias was corrected for prior to model prediction (see below). Pearson correlation coefficients between distance to roads and environmental variables were all $R < 0.2$.

Generating models

As the IK we elicited consisted of polygons of species presence (no absence data), and our aim was to predict geographic distribution of the mankarr, we decided to generate SDMs using Maxent 3.4.1 (Steven J. Phillips et al. 2018) as implemented in *dismo* (1.1.4; Hijmans et al. 2017). Maxent uses machine learning methods to estimate species habitat preferences by comparing the environmental conditions where a species was detected with the frequency of these conditions in the landscape, thereby providing an estimate of relative likelihood of occurrence (Elith et al. 2011).

Before commencing modelling, we needed to generate point data from the IK polygon data. We did this by sampling random points (using 'spsample' in the sp 1.2-6 package; Pebesma & Bivand 2005) within the IK polygons. Our default approach was to use the same total number of randomly generated IK points as we had survey data (~100). However, to ensure that this provided a reasonable representation of the IK, we generated models using four replicate data sets with sample sizes ranging from 100 to 2000 points (at increments of 100). Maxent was set to include only linear, quadratic and product features, with regularization set to 1 and duplicate points within 1km scale of environmental predictors removed. For each sample size, we checked for model performance and stability in the importance of environmental predictors in the model output between replicates and sample sizes. This allowed us to ascertain the minimum sample size at which model fits did not change appreciably between sample replicates. At a sample size of approximately 1000, the variables selected by Maxent as highly important and their functional forms became broadly consistent (Supporting information). We used this sample size for all ensuing model analysis.

Evaluating model performance

We ran two Maxent models which used: 1) IK, and 2) survey data. We first generated separate 10 folds sets of the data sets for model evaluation. We used BlockCV (Valavi et al. 2018) to assess the effective range of spatial autocorrelation in the environmental predictors, and then used the median of the spatial autocorrelation ranges (21 km) as the block size for creating spatially separated testing and training folds for model evaluation. Both occurrences and background localities were assigned to each of the 10 bins, with the intention to reduce spatial-autocorrelation between testing and training points, which if present, can overinflate model performance (Hijmans 2012; Roberts et al. 2017).

We used ENMeval (Muscarella et al. 2014) to run successive Maxent models using different combinations of parameters to select the settings that optimize the trade-off between goodness-of-fit and overfitting for each data source, and carry out cross-validation with 9 bins for training and the withheld bin for testing. We created a suite of models with the following feature classes: linear, linear + quadratic, linear + quadratic + product. For each feature class combination, we built models across a range of regularization multipliers (0.5 – 4 with 0.5 steps), resulting in a suite of 24 models for each data type. All models used the same sample of 10 000 random background points. We retained the model with the lowest corrected Akaike Information Criterion (Burnham & Anderson 2002). Models were evaluated using Area Under the Receiver Operating Curve (AUC), where a score of 0.5 indicates randomness, whilst a ranking of 1.0 indicates perfect model performance. For Maxent presence-background models, AUC quantifies the probability that the model correctly ranks a random presence locality higher than a random background pixel (Phillips et al. 2006). We also recorded the 10% omission rate which provides a measure of overfitting (Muscarella et al. 2014).

Model predictions

We created predictive maps of mankarr distribution for the two models using ‘predict’ in the raster package with the cloglog transformation (Hijmans 2017). To correct for observer bias, we made predictions with distances from roads conditioned on a common level of at all locations, giving predictions an interpretation as the relative likelihood of observing the species if all places had the same accessibility (Warton et al. 2013).

Results

Martu knowledge of mankarr occurrence

Elders had knowledge of mankarr occurrence from a > 50 year period, including when Martu were living traditional lifestyles prior to contact with non-Indigenous people until the present day. This knowledge was obtained by interviewees through a combination of direct experience, shared information (between Martu, other Indigenous groups, and ecologists), and childhood tutelage by Elders and parents. In total, 39 polygons with mankarr occurrence were designated (ranging from 2.8 km^2 - 504 km^2; mean 89 km^2; total 3500 km^2). As Elders elected to only provide spatial information for their specific family lands, we had little spatial overlap between interviewees groups, and could not undertake verification procedures as used elsewhere (for instance Zhang & Vincent 2017), although congruence between track-based surveys and data provided by Elders could be assessed. Areas where mankarr were encountered were clustered around Punmu and Parnngurr communities (where interviewees were based). The IK boundary we drew to encapsulate the areas Martu spoke for was approximately 45 000 km^2 (28 % of the Martu Determination; Fig. 2), of this 7.8 % was designated by Elders as places where mankarr sign had been observed. Of the IK polygons, 25 (of 39) had track-based surveys located within them. In total 47 % of surveyed mankarr detections fell within IK polygons.

Habitat knowledge

Mankarr were described as most likely to be found in six types of habitat: verges of salt lakes, mulga, laterite, sandplain, claypan and dune fields. Martu described suitable habitat as having the correct soil properties for burrow formation with low numbers of feral predators (foxes and cats), and detailed the right combination of fire and rain to make food resources available depending on habitat. Martu fire practices, which create a patchy mosaic of seral stages and old growth vegetation, were indicated as important to maintain habitat suitability. All interviewees from Parnngurr (N = 5) reported local declines, suggesting the species was less common and had restricted distribution in the last decades. Punmu Elders described that mankarr shift distribution with environmental conditions (N = 3/5), and that mankarr usually return to areas when the fire regimes and predator pressure improve. Elders suggested that patterns of regional and local declines were influenced by Martu movement off their lands in the 1960s with the associated cessation of traditional practices and ceremonies, resulting changes in land management practices, rainfall and compounded by introduced predators.

Importance of environmental predictors in models

The importance of predictors within Maxent models changed depending on the data source used (Fig. 3). Biased sampling towards roads was evident in all models, however roads had the strongest permutation importance in the survey model (80.4), compared with the IK (22.5) and joint (25.8) models. In the IK model the predictors with the highest permutation importance were lacustrine (16.8), sand (13.9), alluvium (12.8), calcrete (12) followed by roughness (7.4). In the model fitted to the survey data, the environmental predictors had small importance once the road bias was included, the highest permutation importance was lacustrine (4.7) followed by elevation (4.5). As distance to roads was an important predictor in all models this supported the need to correct for bias in sampling.

TABLE 3 near here

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Model performance

The survey model had a higher test AUC (0.85) compared with the IK (AUC = 0.7) and joint (AUC = 0.74) models (Table 3). However, the 10% high omission rate of the survey model (0.34; Table 3) suggests this model is overfitting at a higher rate than the IK (10%OR = 0.18) model (Table 3). The predictive maps of mankarr habitat suitability differed between the data types (Fig. 3). The IK model suggested that suitable areas are found in diffuse patches across much of the study area, in particular the country surrounding salt lakes and where there is sandy substrate. In comparison the survey model predicts suitable habitat is largely restricted to the vicinity of salt lakes in the central north. Both the IK and survey models suggest the rocky ranges to the west provide lower habitat suitability.

Discussion

Our study applies Martu Indigenous knowledge and western science to model the distribution of the mankarr, and considers the broader ecological knowledge elicited from Martu to gain a fuller understanding of the distribution and ecology of this threatened and culturally important species. By comparing the insights from the IK and survey data models, we develop understanding of the limits and strengths of the two approaches and gain a more holistic understanding of what drives and limits mankarr distribution. Our findings emphasize the importance of understanding the context and observational process underlying IK and other data sources to interpret the predictions produced by SDMs based on either IK or biological surveys.

Modelling mankarr distribution

In our study, both the IK and survey data models suggested that the highest relative habitat suitability for mankarr was associated with lacustrine landforms (relating to lakes - in this case salt-lakes and paleo-drainages). However, the IK model suggested a broader habitat suitability extending to sandy, alluvium (clay), and calcrete substrates (Fig. 3). As the two models are based on data from differing observational processes (Fig. 1), and AUC cannot be used for comparison of models using different test data (Elith et al. 2011), it is challenging to ascertain whether one model is closer to the truth. However, the differing insights offered by the two models, along with additional ecological context, can help us to piece together a fuller understanding of mankarr distribution.

The differences in the models may signal evidence of a shift in local relative habitat suitability for the mankarr over the past decades, which was described by Martu and other studies from deserts to the east (Southgate et al. 2007). IK data contained locations of mankarr distribution over a long temporal scale (> 50 years vs 8 years of survey) and included polygons for areas where Martu assume the species has locally declined based on lack of recent observations. From Martu descriptions, these areas of local decline are mainly in sand plain country where populations are low density and transient due to disturbance, and that populations near salt-lakes tend to be more resident and are easier to detect. The same pattern has been found to the east where mankarr have become increasingly restricted in occurrence to residual and fluvial landforms and less prevalent on the sand plains or dune fields (Southgate et al. 2007).

It is important to consider how the observation and cultural transmission process associated with IK may impact on predictions and interpretations (Fig 1). Martu observation of distribution seemed to be related to species behaviour: the polygons for populations near salt-lakes were smaller and more precise, while polygons in sand plain country encompassed larger areas signalling the mobile nature of the species (Fig. 2). This bias towards larger polygons in sand plain country would result in an overestimate of the relative importance of those environmental conditions (Guillera-Arroita et al. 2015). These larger polygons may also include more false presences at the modelling scale, making it harder for the model to distinguish presences from background. On the other hand, there is likely to be shared community knowledge of where mankarr reliably occur, and at least a subset of the surveys were directed to places where Martu knew that mankarr were present and easy to detect (i.e. salt-lakes and fluvial landforms), suggesting the survey data may overestimate the importance of salt-lakes, thereby enhancing model differences. Ascertaining the current status of mankarr ultimately needs further monitoring effort to investigate the impact of landform, fire and food resources on mankarr occupancy and detectability, with attention to differences between sandplain and salt-lake country as suggested by the SDMs and IK.

Incorporating IK in SDMs

There are multiple reasons to incorporate IK into SDMs, including access to unique insights such as understanding of habitat associations that are overlooked by other data sources (Polfus et al. 2014), or observations that pre-date scientific exploration (Burbidge et al. 1988). In co-designed or participatory Indigenous projects, inclusion of IK can make research more relevant, establish equality between knowledges (Koster et al. 2012), and support the maintenance and conservation of language and culture (Wilder et al. 2016). To apply IK ethically requires collaborative partnerships that give time to relationship building, respect

Indigenous priorities, are conscious of Indigenous culture and protect intellectual property (Huntington 2000). IK should be applied within SDMs based on its validity within the constraints and context of the modelling objective, plus the difference it makes to the quality of the research, effectiveness of management or the involvement of the resource users in the decisions that affect them.

There will be no one SDM technique that will be optimal for all IK models, but will depend on the research question and application (Elith & Graham 2009). There may be opportunities to incorporate IK in SDM methods that use local spatial knowledge, such as guidance in the collection of GPS presences points for wildlife (Luizza et al. 2016; Evangelista et al. 2018), local knowledge of species distribution patterns (Zhang & Vincent 2017), and application of expert understanding of species range boundaries to constrain the predictions of a SDMs that are parameterized with point occurrence records (Merow et al. 2017). There are also opportunities for non-spatial IK to contribute to ecological modelling that incorporates expert knowledge, such as guiding data cleaning, approximation of distributions and model validation (Calixto-Pérez et al. 2018), or in construction of habitat suitability indexes (Polfus et al. 2014; Tendeng et al. 2016), or Bayesian models (Kuhnert et al. 2010). These methods are dependent on multiple experts providing qualitative or quantitative scores to represent the importance of environmental attributes to a focal species (Johnson et al. 2012). In some cross-cultural contexts where there are language barriers and varied literacy and numeracy skills, it could be challenging to elicit some of the common metrics used in HSIs or Bayesian ecological metrics – such as probability, frequency, quantity or weighting/rank (Kuhnert et al.

2010). In all cases, care must be taken in the elicitation process to be culturally sensitive and avoid misinterpretations. There are frameworks to assist with transparent and repeatable data elicitation (Johnson et al. 2012; Martin et al. 2012), and methods for validation if required (Gratani et al. 2011).

We conclude that an intercultural approach to eliciting and modelling with IK can provide an important role in understanding species distribution on Indigenous lands. Our results add to examples that Indigenous knowledge and perspectives can provide its own source of ecological insights that improves the impact of research (Ban et al. 2018). Collaborations that combine multiple knowledges may play an increasing role in enhancing our capacity to have a more holistic understanding of ecology (Ens et al. 2015), improve recovery planning, and ultimately halt the loss of biodiversity and cultural knowledge (Wilder et al. 2016).

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Supporting information

Appendix S1 is available online. The authors are solely responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author.

Literature cited

Agrawal A. 1995. Dismantling the divide between indigenous and scientific knowledge. Development and change **26**:413-439.

Austin M. 2002. Spatial prediction of species distribution: an interface between ecological theory and statistical modelling. Ecological modelling **157**:101-118.

Ban NC, Frid A, Reid M, Edgar B, Shaw D, Siwallace P. 2018. Incorporate Indigenous perspectives for impactful research and effective management. Nature Ecology & Evolution **2**:1680-1683.

Bélisle AC, Asselin H, LeBlanc P, Gauthier S. 2018. Local knowledge in ecological modeling. Ecology and Society **23**.

Bradley K, Lees C, Lundie-Jenkins G, Copley P, Paltridge R, Dziminski M, Southgate R, Nally S, Kemp L. 2015. Greater Bilby Conservation Summit and Interim Conservation Plan: an Initiative of the Save the Bilby Fund. Apple Valley, MN.

Brennan KEC, Twigg PJ, Watson A, Pennington A, Sumner J, Davis R, Jackson J, Brooks B, Grant F, Underwood R. 2012. Cross-cultural systematic biological surveys in Australia's Western Desert. Ecological Management and Restoration **13**:72-80.

Burbidge AA, Johnson KA, Fuller PJ, Southgate R. 1988. Aboriginal knowledge of the mammals of the central deserts of Australia. Australian Wildlife Research **15**:9-39.

Burnham KP, Anderson DR 2002. Model selection and multimodel inference: a practical information-theoretic approach. Springer, New York, New York.

Calixto-Pérez E, et al. 2018. Integrating expert knowledge and ecological niche models to estimate Mexican primates' distribution. Primates **59**:451-467.

Cramer VA, Dziminski MA, Southgate R, Carpenter F, Ellis RJ, van Leeuwen S. 2016. A conceptual framework for habitat use and research priorities for the greater bilby (*Macrotis lagotis*) in the north of Western Australia. Australian Mammalogy **39**:137-151.

Elith J, Graham CH. 2009. Do they? How do they? WHY do they differ? On finding reasons for differing performances of species distribution models. Ecography **32**:66-77.

Elith J, Leathwick JR. 2009. Species Distribution Models: Ecological Explanation and Prediction Across Space and Time. Annual Reviews **40**:677-697.

Elith J, Phillips SJ, Hastie T, Dudík M, Chee YE, Yates CJ. 2011. A statistical explanation of MaxEnt for ecologists. Diversity and Distributions **17**:43-57.

Ens EJ, et al. 2015. Indigenous biocultural knowledge in ecosystem science and management: Review and insight from Australia. Biological Conservation **181**:133-149.

Evangelista PH, Mohamed AM, Hussein IA, Saied AH, Mohammed AH, Young NE. 2018. Integrating indigenous local knowledge and species distribution modeling to detect wildlife in Somaliland. Ecosphere **9**:e02134.

Fourcade Y, Engler JO, Rödder D, Secondi J. 2014. Mapping Species Distributions with MAXENT Using a Geographically Biased Sample of Presence Data: A Performance Assessment of Methods for Correcting Sampling Bias. PLOS ONE **9**:e97122.

Geoscience Australia. http://www.ga.gov.au/; Accessed 1/10/2016.

Gratani M, Butler JR, Royee F, Valentine P, Burrows D, Canendo WI, Anderson AS. 2011. Is validation of indigenous ecological knowledge a disrespectful process? A case study of traditional fishing poisons and invasive fish management from the Wet Tropics, Australia. Ecology and Society **16**:25.

Guillera-Arroita G, Lahoz-Monfort JJ, Elith J, Gordon A, Kujala H, Lentini PE, McCarthy MA, Tingley R, Wintle BA. 2015. Is my species distribution model fit for purpose? Matching data and models to applications. Global Ecology and Biogeography **24**:276-292.

Guisan A, Thuiller W. 2005. Predicting species distribution: offering more than simple habitat models. Ecology Letters **8**:993-1009.

Hijmans RJ. 2012. Cross-validation of species distribution models: removing spatial sorting bias and calibration with a null model. Ecology **93**:679-688.

Hijmans RJ. 2017. raster: Geographic Data Analysis and Modeling. R package version 2.6-7.

Hijmans RJ, Phillips S, Leathwick JR, Elith J. 2017. dismo: Species Distribution Modelling. R package version 3.2.0

Hill R, Grant C, George M, Robinson CJ, Jackson S, Abel N. 2012. A Typology of Indigenous Engagement in Australian Environmental Management: Implications for Knowledge Integration and Social-ecological System Sustainability. Ecology and Society **17**.

Houde N. 2007. The six faces of traditional ecological knowledge: challenges and opportunities for Canadian co-management arrangements. Ecology and Society **12**.

Huntington HP. 2000. Using Traditional Ecological Knowledge in science: methods and applications Ecological Applications **10**:1270-1274.

Johnson CJ, Hurley M, Rapaport E, Pullinger M. 2012. Using Expert Knowledge Effectively: Lessons from Species Distribution Models for Wildlife Conservation and Management in Perera A, Drew C, and Johnson C, editors. Knowledge and Its Application in Landscape Ecology. Springer, New York, NY.

Jupp T, Fitzsimons J, Carr B, See P. 2015. New partnerships for managing large desert landscapes: experiences from the Martu Living Deserts Project. The Rangeland Journal **37**:571-582.

Koster R, Baccar K, Lemelin RH. 2012. Moving from research ON, to research WITH and FOR Indigenous communities: A critical reflection on community-based participatory research. The Canadian Geographer / Le Géographe canadien **56**:195-210.

Kuhnert PM, Martin TG, Griffiths SP. 2010. A guide to eliciting and using expert knowledge in Bayesian ecological models. Ecology Letters **13**:900-914.

Luizza MW, Wakie T, Evangelista PH, Jarnevich CS. 2016. Integrating local pastoral knowledge, participatory mapping, and species distribution modeling for risk assessment of invasive rubber vine (Cryptostegia grandiflora) in Ethiopia’s Afar region. Ecology and Society **21**.

Lynch AJJ, Fell DG, McIntyre-Tamwoy S. 2010. Incorporating Indigenous values with 'Western' conservation values in sustainable biodiversity management. Australasian Journal of Environmental Management **17**:244-255.

Martin TG, Burgman MA, Fidler F, Kuhnert PM, Low-Choy S, McBride M, Mengersen K. 2012. Eliciting Expert Knowledge in Conservation Science

Obtención de Conocimiento de Expertos en Ciencia de la Conservación. Conservation Biology **26**:29-38.

Merow C, Smith MJ, Silander JAJ. 2013. A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. Ecography **36**:1058-1069.

Merow C, Wilson AM, Jetz W. 2017. Integrating occurrence data and expert maps for improved species range predictions. Global Ecology and Biogeography **26**:243-258.

Mistry J, Berardi A. 2016. Bridging indigenous and scientific knowledge. Science **352**:1274-1275.

Moseby K, Nano T, Southgate R 2012. Tales in the Sand; a guide to identifying Australian arid zone fauna using spoor and other signs. Ecological Horizons, South Australia.

Moseby KE, Donnell E. 2003. Reintroduction of the greater bilby, *Macrotis lagotis* (Reid) (Marsupialia : Thylacomyidae), to northern South Australia: survival, ecology and notes on reintroduction protocols. Wildlife Research **30**:15-27.

Muscarella R, Galante PJ, Soley-Guardia M, Boria RA, Kass JM, Uriarte M, Anderson RP. 2014. ENMeval: An R package for conducting spatially independent evaluations and estimating optimal model complexity for Maxent ecological niche models. Methods in Ecology and Evolution **5**:1198-1205.

Pebesma EJ, Bivand RS. 2005. Classes and methods for spatial data in R. R News 5 (2), https://cran.r-project.org/doc/Rnews/.

Pert PL, Norton TW. 2011. Potential Use of Radiometric Data for Wildlife Habitat Modelling. Geographical Research **49**:153-170.

Phillips SJ, Anderson RP, Schapire RE. 2006. Maximum entropy modeling of species geographic distributions. Ecological Modelling **190**:231-259.

Polfus JL, Heinemeyer K, Hebblewhite M, Taku River Tlingit First N. 2014. Comparing traditional ecological knowledge and western science woodland caribou habitat models. The Journal of Wildlife Management **78**:112-121.

Roberts DR, et al. 2017. Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. Ecography **40**:913-929.

Southgate R, Paltridge R, Masters P, Carthew S. 2007. Bilby distribution and fire: a test of alternative models of habitat suitability in the Tanami Desert, Australia. Ecography **30**:759-776.

Steven J. Phillips, Miroslav Dudík, Schapire. RE. 2018. Maxent software for modeling species niches and distributions (Version 3.4.1). Available from url: http://biodiversityinformatics.amnh.org/open_source/maxent/. Accessed on 2018-8-23.

Tendeng B, Asselin H, Imbeau L. 2016. Moose (Alces americanus) Habitat Suitability in Temperate Deciduous Forests Based on Algonquin Traditional Knowledge and on a Habitat Suitability Index. Ecoscience **23**:77-87.

Valavi R, Elith J, Lahoz-Monfort JJ, Guillera-Arroita G. 2018. blockCV: an R package for generating spatially or environmentally separated folds for k-fold cross-validation of species distribution models. bioRxiv.

Walsh FJ. 2008. To hunt and to hold: Martu Aboriginal people's uses and knowledge of their country, with implications for co-management in Karlamilyi (Rudall River) National Park and the Great Sandy Desert, Western Australia. School of Social and Cultural Studies (Anthropology) and School of Plant Biology (Ecology). The University of Western Australia.

Walsh FJ, custodians of the Bilby. 2016. Bilby is Part of This Country and for Everybody: Cultural report about Bilbies and the Ninu Festival Kiwirrkura, 2016. Report to Central Desert Native Title Services, Alice Springs, 70 pages.

Walsh FJ, Dobson PV, Douglas JC. 2013. Anpernirrentye: a Framework for Enhanced Application of Indigenous Ecological Knowledge in Natural Resource Management. Ecology and Society **18**.

Warton DI, Renner IW, Ramp D. 2013. Model-Based Control of Observer Bias for the Analysis of Presence-Only Data in Ecology. PLOS ONE **8**:e79168.

Wilder BT, O'Meara C, Nabhan GP, Monti L. 2016. The Importance of Indigenous Knowledge in Curbing the Loss of Language and Biodiversity. BioScience **66**:499-509.

Woinarski JC, Burbidge AA, Harrison PL 2014. The action plan for Australian mammals 2012. CSIRO Publishing, Melbourne.

Woinarski JC, Burbidge AA, Harrison PL. 2015. Ongoing unraveling of a continental fauna: decline and extinction of Australian mammals since European settlement. Proceedings of the National Academy of Sciences **112**:4531-4540.

Zhang X, Vincent ACJ. 2017. Integrating multiple datasets with species distribution models to inform conservation of the poorly-recorded Chinese seahorses. Biological Conservation **211**:161-171.

Ziembicki MR, Woinarski JCZ, Mackey B. 2013. Evaluating the status of species using Indigenous knowledge: Novel evidence for major native mammal declines in northern Australia. Biological Conservation **157**:78-92.

Tables

Table 1. Lines of questioning that were attempted to elicit knowledge of mankarr, with example questions shown in italic.

1. Establish the geographic region participants know. *Where is your country, and country you know well?*	
2a) Identify areas of suitable habitat *Where do mankarr live on Martu country?* *Where have you seen mankarr?*	3a) Identify areas of unsuitable habitat *Where are places mankarr do not live?* *Where are places mankarr is not found?*
2b) Whether distribution has changed *When did you see mankarr there?* *Are mankarr still there today?* *No? When was mankarr last there?*	3b) Whether distribution has changed *Did mankarr ever live there?*
2c) Population size/habitat suitability *How often did you see mankarr there?* *How many mankarr were living there?*	
2d) Environmental factors *What makes this place "good" for mankarr?*	3c) Environmental factors *Why don't mankarr live in this place?*

* Questions relating to identifying unsuitable habitat were unsuccessful in gaining responses and discontinued.

Table 2. Environmental predictors used in models of mankarr occurrence.

Variables	Description	Source Type	Source	Native resolution	Modification
Elevation	Geodata 9 Second DEM	Continuous	GeoScience Australia	250 m	Aggregated mean at 1km
Roughness	Coefficient of variation in elevation	Continuous	ANUCLIM	1km	-
Relief	Elevation range within grid cell	Continuous	ANUCLIM	1km	-
Fertility	Index of inherent rock fertility	Continuous	GeoScience Australia	1km	-
Sand	Regolith category	Categorical	Geoscience Australia	1km	% sand in 2km radius
Lacustrine	Regolith category,	Categorical	GeoScience Australia	1km	% lacustrine in 2km radius
Rock	Regolith category	Categorical	Geoscience Australia	1km	% exposed rock in 2km radius
Alluvium	Regolith category	Categorical	Geoscience Australia	1km	% alluvium in 2km radius
Calcrete	Regolith category	Categorical	Geoscience Australia	1km	% calcrete in 2km radius
Vegetation	Major groups of pre-European vegetation	Categorical	Geoscience Australia	1km	Aggregation

Table 3. Model parameterization and performance evaluation of the final models for each data source.

Model	Features *	Regularization multiplier	Training AUC	Average test AUC	Variation test AUC	10% omission rate
IK	LPQ	0.5	0.79	0.70	0.08	0.18
Survey	LQ	0.5	0.92	0.85	0.08	0.34

* L = linear, P = product, Q = quadratic

Figures

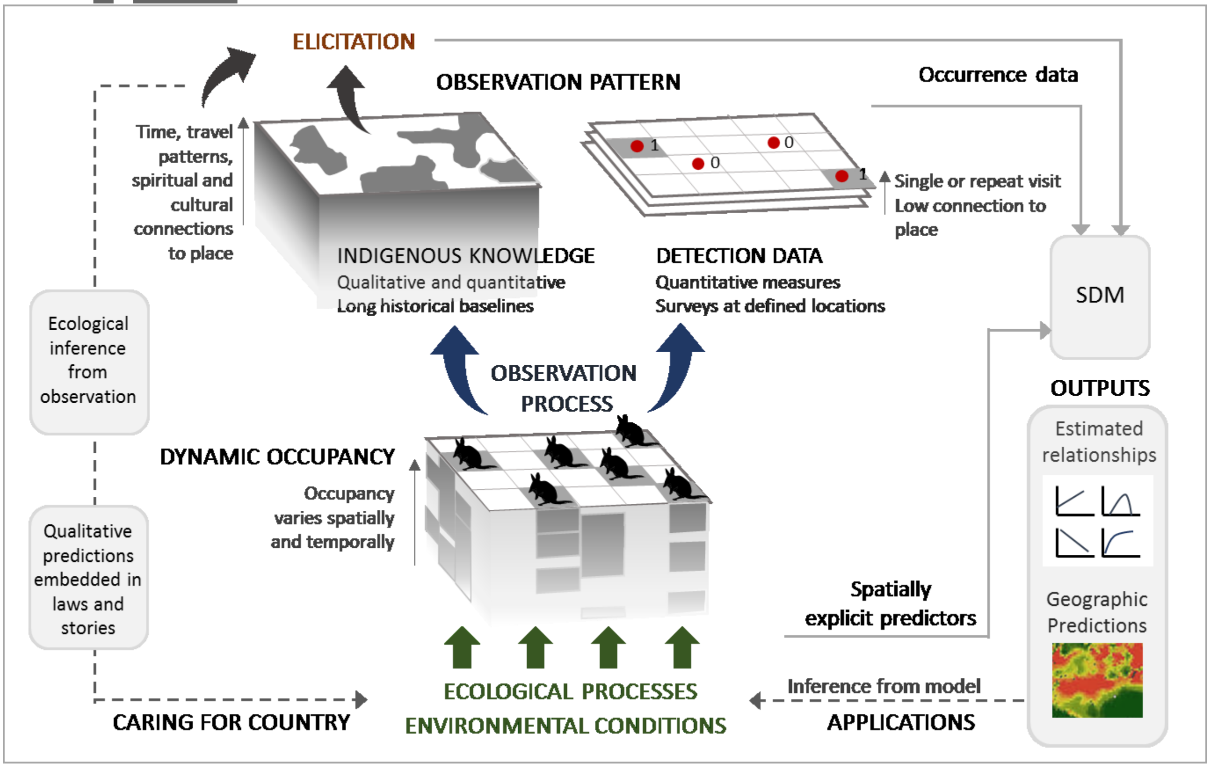

Figure 1. Species distribution modelling incorporating observation data arising from western science and Indigenous methodologies. Western science detection data is derived from surveys at defined locations with observation influenced by the characteristics of the survey design. Indigenous knowledge of species occurrence (e.g. presences, distributions, ranges, habitat suitability) is developed as part of the biocultural knowledge of a place-based culture that can be connected to caring for country practices. The SDM describes the distribution of the species as a function of the observation pattern and environmental covariates and should

be constructed based on the data available and modelling objectives. Building on Guillera-Arroita (2017).

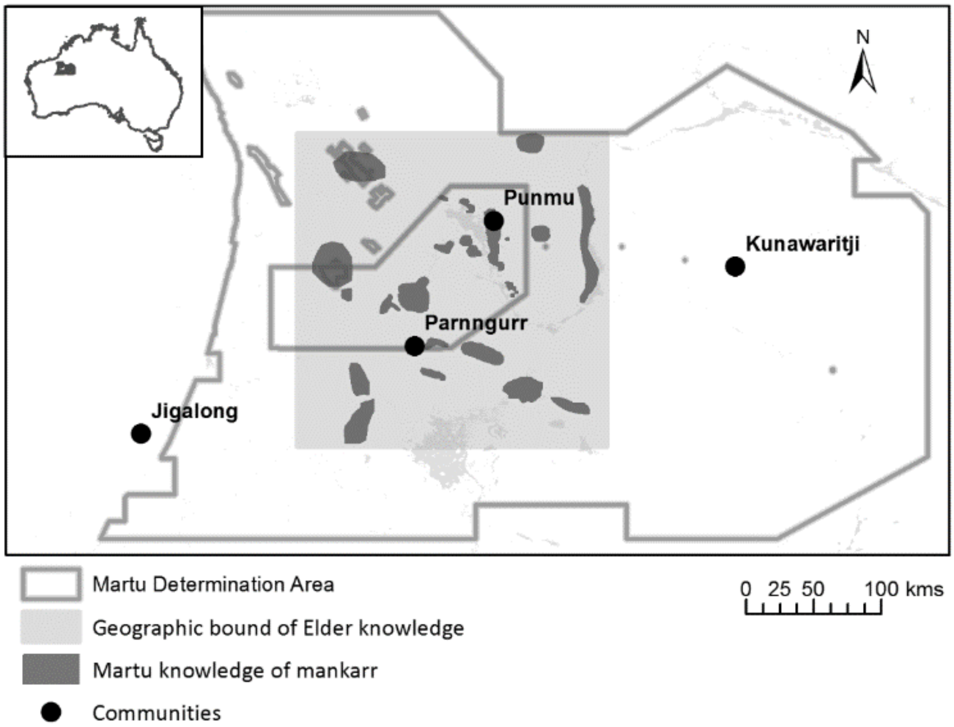

Figure 2. The Martu Determination with the location of IK polygons of mankarr occurrence and salt-lakes in light grey. The geographic bound of Elders' knowledge captures the area that interviewees from Punmu and Parnngurr communities spoke about. These communities sit in the Karlamilyi National Park, which is excised from the Martu Determination along with small areas under mining tenure but are recognized by Martu as their traditional lands.

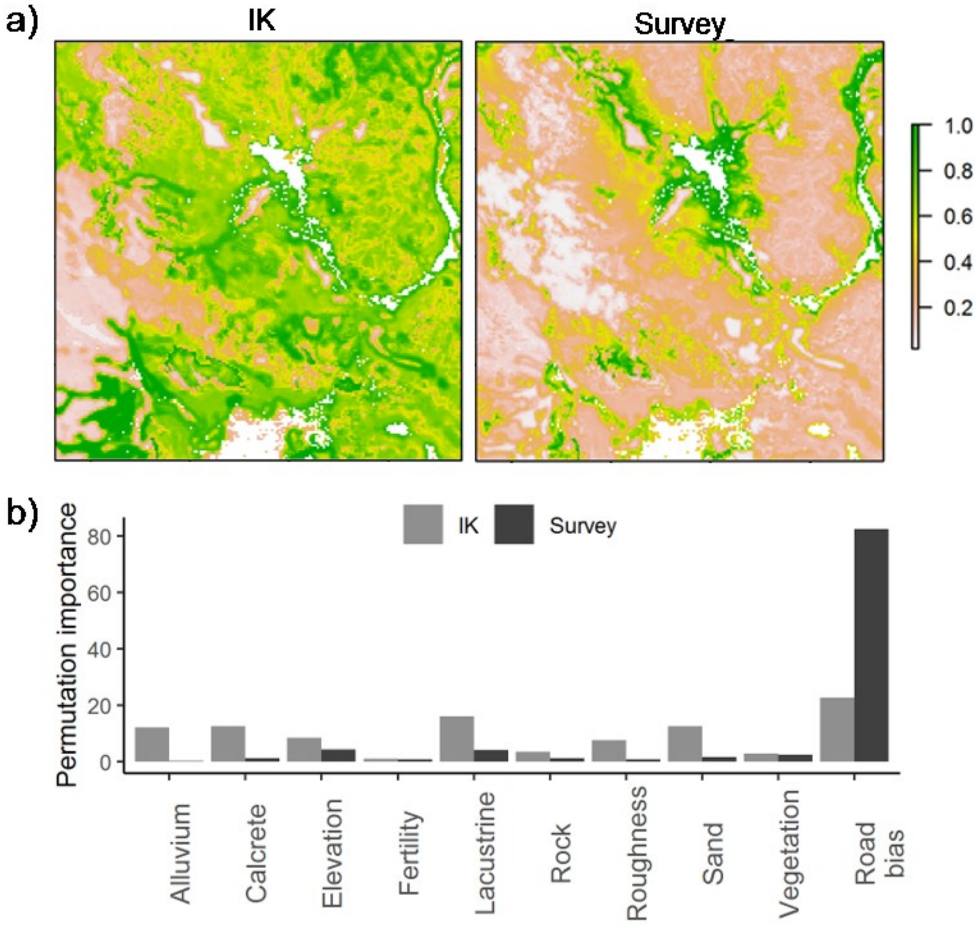

Figure 3. Comparison of predictive maps and importance of environmental variables to forming the Maxent models of mankarr occurrence within the geographic bounds of Elder knowledge. a) Maps plotted on cloglog scale where predictions are conditioned on a uniform value of road bias across the landscape; b) the permutation importance of the environmental variables and distance to roads which was used to model sampling bias.