




RESEARCH ARTICLE

Integrated SDM database: Enhancing the relevance and utility of species distribution models in conservation management

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Abstract

1. Species' ranges are changing at accelerating rates. Species distribution models (SDMs) are powerful tools that help rangers and decision-makers prepare for reintroductions, range shifts, reductions and/or expansions by predicting habitat suitability across landscapes. Yet, range-expanding or -shifting species in particular face other challenges that traditional SDM procedures cannot quantify, due to large differences between a species' currently occupied range and potential future range. The realism of SDMs is thus lost and not as useful for conservation management in practice. Here, we address these challenges with an extended assessment of habitat suitability through an *integrated SDM database (iSDMdb)*.
2. The *iSDMdb* is a spatial database of predicted sites in a species' prediction range, derived from SDM results, and is a single spatial feature that contains additional, user-friendly data fields that synthesise and summarise SDM predictions and uncertainty, human impacts, restoration features, novel preferences in novel spaces and management priorities. To illustrate its utility, we used the endangered New Zealand sea lion *Phocarctos hookeri*. We consulted with wildlife rangers, decision-makers and sea lion experts to supplement SDM predictions with additional, more realistic and applicable information for management.
3. Almost half the data fields included in this database resulted from engaging with these end-users during our study. The SDM found 395 predicted sites. However, the *iSDMdb's* additional assessments showed that the actual suitability of most sites (90%) was questionable due to human impacts. >50% of sites contained unnatural barriers (fences, grazing grasslands), and 75% of sites had roads located within the species' range of inland movement. Just 5% of the predicted sites were mostly (>80%) protected.
4. Integrating SDM results with supplemental assessments provides a way to address SDM limitations, especially for range-expanding or -shifting species. SDM products for conservation applications have been critiqued for lacking transparency and interpretation support, and ineffectively communicating uncertainty.

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The *iSDMdb* addresses these issues and enhances the practical relevance and utility of SDMs for stakeholders, rangers and decision-makers. We exemplify how to build an *iSDMdb* using open-source tools, and how to make diverse, complex assessments more accessible for end-users.

KEYWORDS

anthropogenic impacts, ecological niche model, multi-criteria decision analysis, multi-state species distribution model, *Phocarctos hookeri*, qualitative decision-making, range shift, recolonisation

1 | INTRODUCTION

Species' geographical ranges are changing at accelerating rates, largely due to climate change, anthropogenic pressures and anthropogenic introductions of non-native species (Doherty et al., 2021; Pecl et al., 2017). In some cases, species are expanding their ranges due to successful conservation and management, often recolonising ranges from which they were once extirpated (Le Boeuf et al., 2011; Smeraldo et al., 2017). To inform the conservation of reintroduced, range-shifting or range-expanding species, scholars and practitioners often map habitat suitability or probability of occurrence across a species' potential range using methods such as expert opinion (Adem Esmail & Geneletti, 2018), statistical models (Smeraldo et al., 2017) or machine-learning algorithms (Phillips et al., 2006). These approaches help rangers and decision-makers designate or restore protected areas (Angelieri et al., 2016; Villero et al., 2017), assess threats posed by invasive species (Rodríguez-Merino et al., 2017) and assess habitat availability under changing anthropogenic or environmental conditions, among other purposes (Engler et al., 2017; Schwartz, 2012).

While many studies acknowledge the importance of predictive habitat models for conservation management (Villero et al., 2017), practical, comprehensive results for decision-makers are needed (Araújo et al., 2019; Sofaer et al., 2019). Rangers and decision-makers have additional considerations when working with range-shifting or -expanding species compared to species whose ranges are relatively stable or shrinking. For example, new biotic (interspecific) interactions could arise and negatively impact a range-shifting or established species, or native populations could be threatened by an expanding invasive species. For species recolonising their historic ranges, high population densities in new colonies could be at greater disease risk (Lavigne & Schmitz, 1990). Reintroduced species could expand outside the protected areas where they were introduced (Smeraldo et al., 2017), requiring rangers and decision-makers to engage with local communities to generate awareness and support (Karamanlidis et al., 2016). Natural and unnatural barriers, such as topographic changes or roads, could inhibit a reintroduced species' expansion (Engler et al., 2012; McFadden-Hiller & Belant, 2018). Furthermore, mapping a species' potential range requires understanding and proper handling of predictive model limitations, for example, how much extrapolation to allow into new regions

(Elith et al., 2010) or a model's inability to account for environmental conditions that are non-existent in a species' current range but become important as the species expands its range (Leroux et al., 2017; Swinnen et al., 2017). Besides accurate mapping of potential habitats, rangers and decision-makers need to assess additional circumstances for species dispersing into ranges with novel conditions, and such information has to be accessible, concise and practical.

We demonstrate a decision-support tool to address such challenges for range-shifting or -expanding species by creating an *integrated species distribution model database (iSDMdb)*. Species distribution models (SDMs) are statistical or machine-learning models that predict probabilities of occurrence or habitat suitability in novel (unsampled or unoccupied) areas. They compare environmental conditions (e.g. climate, land cover) at species presence locations with conditions where the species is absent or location data are lacking. The *iSDMdb* is a spatial, descriptive database of predicted sites in a species' predicted range, derived from SDM results, that contains additional data fields that synthesise and summarise SDM predictions and uncertainty, potential human impacts, restoration features, novel preferences in novel spaces and management priorities. Data fields are generated using a wide range of assessments outside traditional SDM procedures, resulting in an enhanced, practical and accessible decision-making database to guide management.

We demonstrate how the *iSDMdb* can be created and assessed for informing decision-making at a national scale, using the New Zealand sea lion (*Phocarctos hookeri*; NZSL). We predicted the NZSL's potential breeding colony range and engaged with wildlife rangers, NZSL experts, and decision-makers to supplement SDM predictions with additional assessments to address SDM limitations in the species' predicted range. We discuss how this example can be applied for informing the management of other range-shifting or -expanding species, and provide exemplary materials to create an *iSDMdb* using open-source tools.

2 | MATERIALS AND METHODS

2.1 | Case study species and *iSDMdb* framework

The NZSL was once found throughout mainland New Zealand's coasts (Collins et al., 2014). Human exploitation extirpated them

from the mainland and restricted their population to islands in the Subantarctic (Childerhouse & Gales, 1998; Figure 1). Since the 1990s, multiple recolonisation events have occurred on the mainland (Department of Conservation, 2017; Figure 1). Yet, their range expansion presents new challenges. Local residents do not always welcome recolonising NZSLs, and NZSLs have been hit by cars on roads or deliberately killed (Lalas, 2008). Mainland habitats also differ from their Subantarctic habitat, with new habitat features such as commercial pine forests, or anthropogenic features such as live-stock fencing (McConkey et al., 2002). Decision-makers need to determine where human interactions would most likely occur, and engage with communities to generate awareness (Department of Conservation, 2017). Finally, SDM assumptions and uncertainties need to be made explicit so rangers and decision-makers can determine their confidence in, and gauge the potential effectiveness of, alternative management options.

The *iSDMdb* can address these challenges as this species recolonises. Its methodology has five main components: (a) *SDM prediction*, (b) *human impacts*, (c) *novel preferences in novel spaces*, (d) *locations of inquiry* and (e) *integration* (Figure 2). Throughout this process, engagement with decision-makers, rangers and experts (hereafter, *end-users*) can identify the most important assessments and features to include while also minimising misinterpretations of these complex methods.

In *SDM prediction*, an SDM (any algorithm or an ensemble) is trained in the species' current range and projected to a different or expanded range. A multi-state SDM (*sensu* Frans et al., 2018b) then uses SDM predictions and statistical thresholds to map potential suitable sites for a minimum number of individuals, as defined by end-users. A multi-state SDM is an SDM framework that accounts for multiple distinct habitat types due to a species' changes in movement, behavioural states or life-cycle stages. It transforms SDM predictions into minimum habitat patches (polygons) for minimum numbers of individuals, which we adapted to form the main, simple structure of the *iSDMdb*. SDM uncertainties and limiting factors impacting predictions are also assessed via coefficient of variation (CV), multivariate environmental similarity surface (MESS), most dissimilar variable (MOD) and limiting factor mapping (*sensu* Elith et al., 2010). CV informs on the spread of the prediction from the mean predicted value within a given pixel across SDM runs, where relatively high CV percentages show caution for higher uncertainty in a prediction. MESS and MOD help determine potential extrapolation errors when evaluating and prioritising among predicted sites, indicating locations to consider with caution (i.e. less reliable if high extrapolation). Limiting factor grids indicate which variables within a pixel would increase suitability if its values were changed, highlighting potential variables that could be ground-truthed or prioritised for habitat restoration.

In *human impacts*, expert opinion informs a multi-criteria decision analysis (MCDA) on potential threats from novel anthropogenic features. MCDA groups criteria by objectives, assigns weights based on expert-opinion-based judgements of relative importance and combines the criteria to reach a final output of suitability (Adem Esmail

& Geneletti, 2018). The *human impacts* step can additionally include feature summaries, for example, presence of unnatural barriers to species' movement.

Novel preferences in novel spaces assesses the availability of habitat features important to the species in their predicted range but unable to be modelled sufficiently within their current range. In *locations of inquiry*, other important features are included to, for example, identify protected areas overlapping predicted sites of species' presence or estimate predicted sites' proximity to known occurrence locations within the predicted range. Finally, in *integration*, the assessments' outputs are summarised into a spatial database and appended to the SDMs' predicted sites. The *iSDMdb* is convertible into multiple formats to facilitate end-users' use.

2.2 | Study area, data collection and preparation

This study covers the entire coastline of mainland New Zealand and Stewart Island, from the shoreline to 2.5 km inland, totalling an area of approximately 209,000 km² (Figure 1).

We prepared 19 environmental, anthropogenic and management-related spatial layers (variables) at a 25-m resolution. Table 1 provides details on their correspondence to each *iSDMdb* step, purpose and assumptions for their use, data sources and derivation. We used ArcGIS (ESRI, 2019) and R (R Core Team, 2021) for data preparation, extraction and modelling.

2.3 | Predictive modelling: Multi-state SDM prediction

We previously used Maxent (Phillips et al., 2006) to build and train a multi-state SDM from breeding females on Sandy Bay, Auckland Islands (Figure 1; Frans et al., 2018b), which we used to predict potential terrestrial habitats for breeding colonies across the mainland. Multi-state SDMs were necessary because breeding female NZSLs undergo three states of inland movement in the breeding season (breeding state, S1; transition state, S2; dispersion state, S3), preferring three distinct habitat types that cannot be modelled in a single SDM (Augé et al., 2012; Frans et al., 2018b); three separate SDMs needed to be modelled and combined. This methodology is also later used to form the *iSDMdb*'s main, simple structure for data integration.

For model training, we used 2,247, 1,333 and 293 Sandy Bay breeding female occurrences for S1, S2 and S3, respectively. We randomly selected 133 occurrences for 75/25% training/testing against 10,000 background points for 100 Maxent iterations per state, using eight environmental variables (Table 1). In Frans et al. (2018b), we assessed variable responses and model performance (Appendix S1). All state SDMs had mean area under the Receiver Operating Characteristic curve (AUC) test scores >0.99 and True Skill Statistic (TSS) test scores >0.92, which were expected given the NZSL's small, restricted breeding range (Lobo et al., 2008). Sørensen's similarity

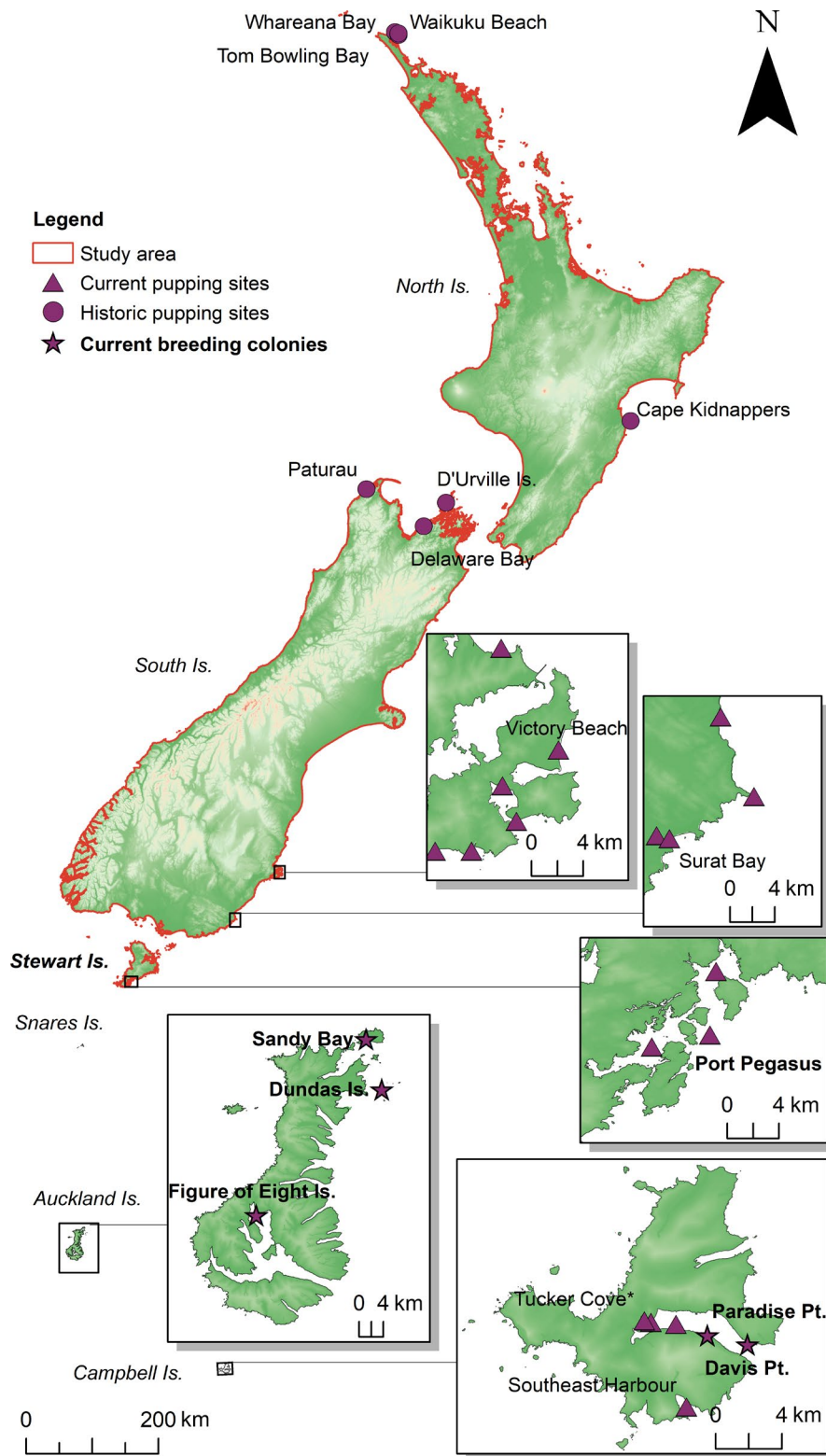


FIGURE 1 Study area with known historic and current (1990–2019) New Zealand sea lion pupping sites and current breeding colony locations (sources: Childerhouse & Gales, 1998; Collins et al., 2014; New Zealand Department of Conservation; Dragonfly Database, <https://sealions.dragonfly.co.nz/demographics/sighting>)

index, an accuracy metric that avoids inflation from true negatives (Leroy et al., 2018), indicated good performance (mean \pm SD of 0.82 ± 0.13 , 0.58 ± 0.09 , 0.59 ± 0.08 for S1, S2 and S3, respectively; Appendix S1).

For model prediction, we used Maxent-generated training information data (*lambda* files) to predict habitat suitability across the mainland (Appendix S2). We calculated the mean prediction

per state and used Maxent's maximum sum of sensitivity and specificity threshold to generate binary suitable/unsuitable maps per state. We used the multi-state SDM framework to define predicted sites for a breeding colony of ≥ 35 females (minimum requirement to designate Stewart Island as a breeding colony; Department of Conservation, 2017), estimated using the minimum mapping unit (MMU) formula from the framework (*mmu.calc* function;

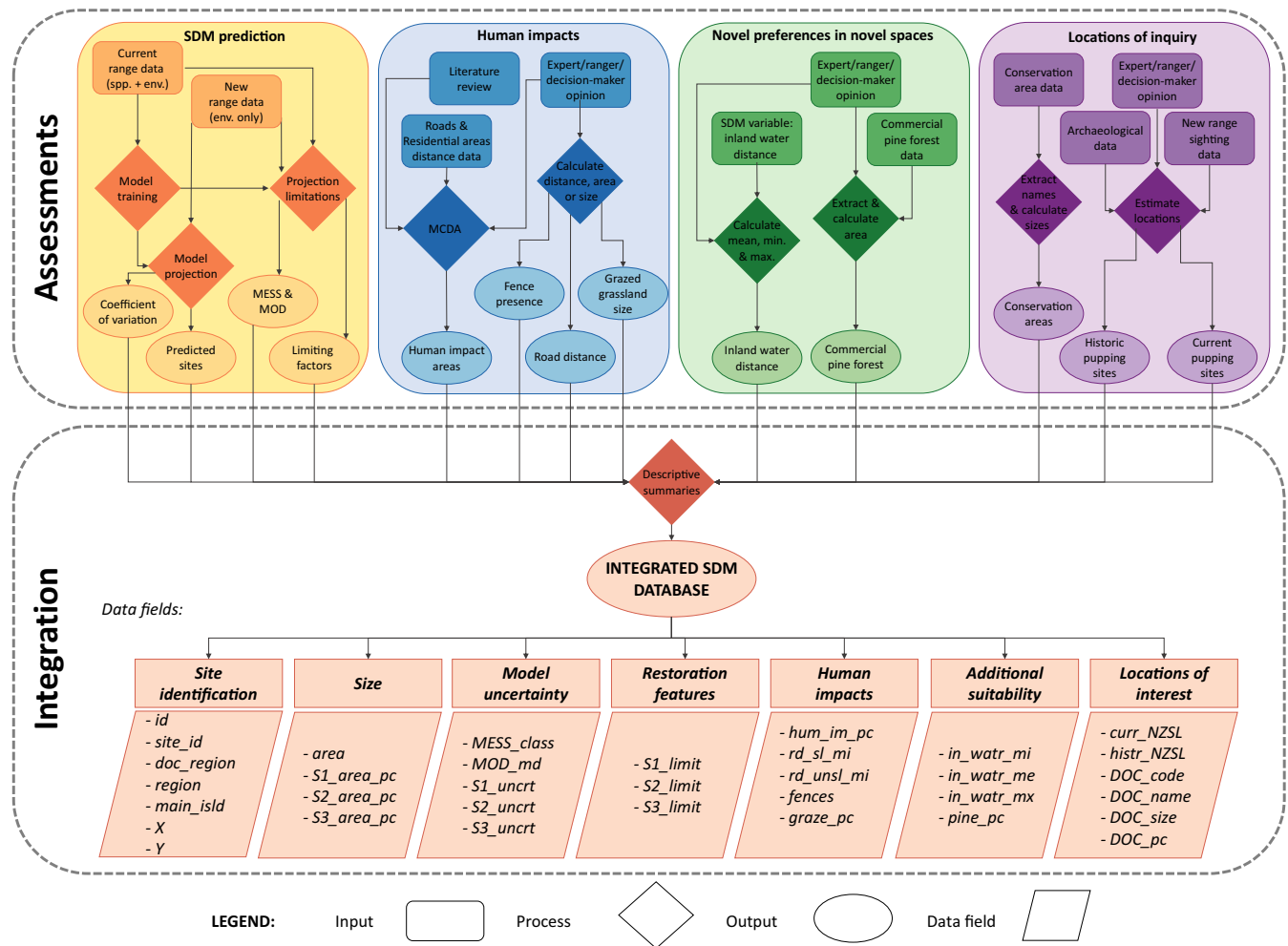


FIGURE 2 Workflow for building an *iSDMdb* for the New Zealand sea lion (NZSL). *SDM prediction* refers to a species distribution model (SDM) and an analysis of uncertainties and limitations; *human impacts* refers to a multi-criteria decision analysis (MCDA) of impacts and evaluating unnatural barriers; *novel preferences in novel spaces* assesses preferred variables in the predicted range that the SDM is lacking in the SDM training range; *locations of inquiry* estimates locations of pupping sites and sizes of conservation areas; and *integration* summarises the outputs from these first four steps into a spatial database with data fields addressing seven main categories (in bold italic) to assist in decision-making. The abbreviated data field names correspond to the data field summaries in Table 2. (Abbreviations: spp.: species occurrences; env.: environmental variables; MESS: multivariate environmental similarity surface; MOD: most dissimilar variable)

Appendix S2). With female NZSL densities of 85 per 100 m² in S1, 30 per 100 m² in S2 and 1 per 10,000 m² in S3 (Augé et al., 2009), and a 25-m resolution, suitable breeding sites for ≥35 females needed to be ≥0.35 km² (MMU ≥ 562 pixels). From each state prediction, we removed non-contiguous pixels <MMU per state. We summed these maps and extracted all contiguous predicted areas ≥MMU. This gave us the final predicted breeding sites for the study, which we converted into vector polygons for the *iSDMdb* (Appendix S2).

2.4 | Assessing SDM uncertainties and limitations

We generated MESS, MOD and three limiting factor grids (one per behavioural state) in Maxent, and calculated CV. These were essential for evaluation since the prediction area (mainland) was

not included in model training and differed from the training area (Auckland Islands).

We calculated MESS and MOD using Maxent's *density.tools*. *Novel* command (see Appendix S3). We inputted the training area variables from Frans et al. (2018b) to contrast with the mainland variables' values at each pixel and produce the two maps. MESS values range from positive (no extrapolation) to negative (extrapolation). MOD corresponds with MESS and indicates the most dissimilar variable at a pixel that affected the MESS score.

To generate limiting factor grids, we used Maxent's *density.tools*. *LimitingFactor* command to input the *.lambda* and *sampleAverages*. *csv* files generated from model training for 100 iterations per state. These were compared against each of the mainland variables' pixels to produce 100 limiting factor grids per state. We calculated the mode for each state to evaluate the most frequent limiting factors across predictions (Appendix S3).

TABLE 1 Variables used in this study, reasoning for their use, data sources and their derivation

Variable	Purpose/Assumptions	Source	Preparation steps (25-m resolution)
Species distribution model (SDM) prediction and limitations (Augé et al., 2009, 2012; Frans et al., 2018b; McNally et al., 2001)			
Cliff edges	Avoidance of cliffs	NZ Mainland Topo 50 (LINZ 2013, http://data.linz.govt.nz)	Rasterisation of cliff edge polygons
Coastline distance	Accounting for female inland movement	NZ Mainland Topo 50; LCDB4 (Landcare NZ 2014, https://lris.scinfo.org.nz)	Euclidean distance from coastline polygons
Forest distance	Movement into forests towards the end of the breeding season	LCDB4	Euclidean distance from forest polygons
Grass distance	Movement from the beach to high sward after having the pups	LCDB4	Euclidean distance from grass polygons
Inland water distance	Water for thermoregulation	LCDB4	Euclidean distance from water polygons
Land cover	Differentiating between land cover types, whether preferred by the NZSL or not	NZ Mainland Topo 50; LCDB4	Simplification of LCDB land cover classifications (12 categories); merged with Topo 50 sand polygons to extend the beach and match satellite imagery
Sand distance	Beaches required for all states; implies access to forests, grass and areas for foraging	NZ Mainland Topo 50; LCDB4	Euclidean distance from sand polygons
Slope	Female NZSLs tend to prefer areas with slopes of less than 20°	NZ DEM (Landcare NZ 2010, https://lris.scinfo.org.nz)	Calculated slope from NZ DEM
Human impacts (Lalas & Bradshaw, 2003; MacMillan et al., 2016; consultation with experts, managers and meeting attendees)			
Residential areas distance	Accounting for areas with potentially more human-NZSL interactions, and development in or near suitable sites may also imply that environmental suitability (the SDM prediction) will have to be further examined	LCDB4	Three-dimensional (path) distance from LCDB residential area polygons
Sealed roads distance	History of NZSLs on the mainland being hit by cars as they move inland; sealed roads are assumed more of a threat than unsealed roads, due to the density of cars that use them	NZ Mainland Topo 50	Three-dimensional (path) distance from sealed road centrelines
Unsealed roads distance	History of NZSLs on the mainland being hit by cars as they move inland; unsealed roads are assumed to be less of a threat than sealed roads, due to a potentially lower density of cars that use them	NZ Mainland Topo 50	Three-dimensional (path) distance from unsealed road centrelines
Fences	Presence of fences could create barriers to NZSL inland movement on the mainland, making less suitable areas available; can also imply potential human-NZSL conflict	NZ Fence Centrelines Topo 50 (LINZ 2019, http://data.linz.govt.nz)	Rasterisation of fence centrelines, with 1 for presence and 0 for absence
Grazed grasslands	Not all fence lines may be accounted for in the Topo50 dataset. Pasture for grazing can have fences, creating barriers to NZSL inland movement, lessening the number of suitable areas available and posing potential human-NZSL conflict	LUCAS NZ Land Use Map 1990 2008 2012 2016 v006 (Ministry for the Environment 2016)	Extraction of high- and low-producing grassland polygons, for the subclasses '502 - Grazed - dairy' and '503 - Grazed - non-dairy'
Novel preferences in novel spaces (Consultation with experts, managers and 2019 meeting attendees)			
Inland water distance	See SDM data; added as a searchable feature in the database	See <i>SDM data</i>	See <i>SDM data</i>

(Continues)

TABLE 1 (Continued)

Variable	Purpose/Assumptions	Source	Preparation steps (25-m resolution)
Planted pine forests (<i>Pinus radiata</i>)	NZSL females on the mainland have been dispersing into pine forests, making them key habitats at some newly recolonised sites; as commercial, privately owned forests, this can highlight areas for community engagement and outreach	LUCAS 2016	Extraction of <i>Pinus radiata</i> planted pine forest polygons, subclass '201 - Pinus radiata'
Conservation regions (Consultation with experts, managers and 2019 meeting attendees)			
Region names	To facilitate suitable site queries in the database	Regional Council 2019 Clipped (generalised; Stats NZ 2019, https://data.mfe.govt.nz/)	Rasterisation of polygons by region name
DOC public conservation areas	To query sites by protected areas; to calculate the proportion of a site that is protected	DOC Public Conservation Areas (DOC 2017, https://koord.inates.com/)	None
DOC operation regions	To facilitate suitable site queries in the database; used to assign unique site IDs	DOC Operations regions (DOC 2017, https://koordinates.com/)	Rasterisation of polygons by region name
Known breeding areas (Consultation with experts, managers and 2019 meeting attendees)			
Current female/pup mainland sightings (1990–2019)	To compare predicted sites with areas where female NZSLs or pups have been sighted since the 1990s	Department of Conservation South Island Sighting Data; Dragonfly database sightings (Stewart Island and South Island, https://sealions.dragonfly.co.nz/demographics/); NZ Geographical Names Topo 50 (LINZ 2019, http://data.linz.govt.nz)	Subsetting female/pup (alive) sightings only; extraction of unique location fields and text mining (keyword/pattern searching) of sighting comments to extract location names from the database; matching of location names to geographical names in LINZ shapefile to approximate XY coordinates; 10 km buffer around the points
Archaeological evidence of breeding sites	To compare predicted sites with known historic breeding sites from before their extirpation from the mainland	Childerhouse & Gales, 1998 and Collins et al., 2014; NZ Geographical Names Topo 50 (LINZ, 2019, http://data.linz.govt.nz)	Matching of location names to geographical names in LINZ shapefile to approximate XY coordinates; 10 km buffer around the points

Abbreviations: DEM, digital elevation model; LCDB, Land Cover Database; LINZ, Land Information New Zealand.

To assess uncertainty in the SDM predictions, we calculated CV ($SD/\text{mean} \times 100$) across the 100 predictions for each behavioural state (Appendix S3).

2.5 | Human impacts: Multi-criteria decision analysis

To include human impacts on the mainland (Department of Conservation, 2017; Lalas, 2008; MacMillan et al., 2016), we used an expert opinion-based evaluation via the Analytic Hierarchy Process (Saaty, 1990), a weighted MCDA. Using pairwise comparisons, we determined criteria weights for three human impact variables (residential areas, sealed and unsealed road distances; Table 1), with

relationship values ranging from 1 (equal importance) to 9 (extreme importance; Saaty, 1990). While MacMillan et al.'s (2016) previous work ranked residential areas as two times more of a potential disturbance to NZSLs than roads, road types were not evaluated. We updated this evaluation based on further expert opinion and ranked sealed roads as two times more of a threat than unsealed roads. Pairwise values for residential areas relating to both sealed and unsealed roads were thus 4; sealed roads' relation to residential areas and unsealed roads was $\frac{1}{4}$ and 2; and unsealed roads' relation to residential areas and sealed roads was $\frac{1}{4}$ and $\frac{1}{2}$. We put these values into a pairwise matrix, added each variable's row, and divided them by the total variables compared ($n = 3$; Saaty, 1990), yielding weights of 0.655, 0.211 and 0.134 for residential areas, sealed roads and unsealed roads, respectively. To check uncertainty, we calculated the

matrix's consistency ratio (CR) to objectively validate the weights (Saaty, 1990) and determined judgements were consistent at CR = 6.87% (pairwise comparisons are consistent when CR < 10%). We demonstrate all calculations in Appendix S4.

Next, we standardised the three distance variables to a 0 to 1 scale using fuzzy membership in ArcGIS (ESRI, 2019). Fuzzy standardisation reclassifies a variable by following an increasing linearised sigmoidal function along three main values, *A*, *B*, *C*. Values < *A* are reclassified to 0; values between *A* and *B* gradually increase to 1, following $((x - A)/(B - A))$, where x = value; *C* is the maximum value (*B* to maximum were reclassified to 1). Here, *A* for sealed roads, unsealed roads and residential areas were 200, 100 and 0 m, respectively (sensu MacMillan et al., 2016); *B* was 5 km for all variables; *C* was each variable's maximum distance. We multiplied these standardised layers by their corresponding weights and summed them, yielding a map of suitability scores ranging from 0 to 1. We reclassified this grid to indicate presence or absence of human impacts, according to a 0.4 threshold. We derived this threshold by visually inspecting the values around Otago Peninsula (45°51'S, 170°39'E), where some recolonising females have been breeding in an area near potential human impacts since 1993 (McConkey et al., 2002), and by verifying with experts from the New Zealand Department of Conservation (DOC).

2.6 | Supplemental features, consultation and integration into an *iSDMdb*

To create a list of additional assessments and data to include with the predicted sites identified in the SDM prediction step (Table 1), we reviewed government reports and publications (Table 1), and, from July 2018 to October 2019, consulted with DOC end-users and attendees at DOC New Zealand Sea Lion/Rāpoka Conservation Services Programme and Threat Management Plan Technical Working Group Meetings. Based on end-users' relevant concerns, we added supplemental assessments or data (Table 1) and simplified model results to improve accessibility and ensure their practical use.

We summarised the SDM, MCDA, supplemental assessments and data into seven categories: *site identification*, *size*, *model uncertainty*, *restoration features*, *human impacts*, *additional suitability* and *locations of interest* (Figure 2). We created custom functions in R to extract these categorised features within predicted site polygons and append them to a data frame. They extract the mean, minimum and maximum values (*get.mmm*), mode (*get.mode*), percent coverage of suitable or unsuitable pixels (*get.perc1* and *get.perc0*, respectively), presence or absence of a feature (*get.pa*) and lists of place names (*get.text*; see Appendix S5). We merged these extracted data to the predicted site polygons to create the *iSDMdb*, with data fields corresponding to these extractions. The final *iSDMdb* was a polygon shapefile of predicted sites harbouring ≥35 females, with the accompanying data fields as attributes for each polygon.

To increase accessibility, we created other formats, such as printed maps, spreadsheets and an interactive HTML map (Appendix S6). The interactive map was made using the TMAP package (Tennekes, 2018). This map includes areas of reference with the predicted sites for easier navigation, such as DOC conservation regions, Open Street Map (www.openstreetmap.org), known historic and current pupping locations, and human impact areas identified from the MCDA. The predicted sites were set to have pop-ups containing data for each site, corresponding to the seven data field categories.

3 | RESULTS

3.1 | *iSDMdb* and selected data fields

Our resulting *iSDMdb* for the NZSL has 34 data fields (Table 2). Almost half of these data fields ($n = 15$) were included in response to end-users' recommendations, while the rest ($n = 19$) were based on literature review and studies. The data fields summarise the *SDM prediction*, *human impacts*, *novel preferences in novel spaces* and *locations of inquiry* outputs from Figure 2. To address end-users' concerns about model uncertainty and their desire to identify variables that could improve habitat suitability, we included MESS, MOD, limiting factors and CV in the *iSDMdb*. While some variables were used within the SDM and MCDA, end-users requested that they also be readily available for query (e.g. road or inland water distances). Upon incorporating these and other assessments beyond the SDM, we found that the actual availability of ~90% of the predicted sites was conditional on these additional features included in the *iSDMdb*.

The resulting *iSDMdb* had multiple formats to suit application needs. We exemplify the interactive map in Figure 3.

3.2 | Predicted sites, uncertainty and limitations

The multi-state SDM identified 395 breeding sites for ≥35 females, covering 798.2 km² of the mainland (0.38% of the study area). There were more predicted sites on North Island ($n = 227$; 490 km²) than South Island ($n = 168$; 308.2 km²; Figure 4a; Appendix S7).

Most sites had low levels of extrapolation (MESS -100 to 0; 308 sites; ~78%; Figure 4b), indicating that most predicted sites were similar to the model training area (Auckland Islands). Only one site, located on North Island, was strongly extrapolated (MESS -1,000 to -500). Slope was the most dissimilar variable among sites ($n = 132$; Figure 4c), followed by land cover on North Island (56 sites) and sand distance on South Island (59 sites).

The most limiting variables across the three state predictions were grass and sand distance (Figure 4d-f). Grass distance was the most limiting for over half the sites for all three states (212, 306 and 312 sites for S1, S2 and S3, respectively). Sand distance was the most limiting for almost half of the S1 sites ($n = 183$), but not as

TABLE 2 Names and descriptions of *iSDMdb* data fields, and how they apply to NZSL management. Fields marked with an asterisk (*) were added to the study based on comments from sea lion experts, wildlife rangers and decision-makers

Data field name	Description	Management application
Site identification		
id	Numerical ID, corresponding to the row number	To differentiate among sites; site queries
site_ID (site identification number)	Three-letter + number-coded ID for each site	See <i>id</i>
DOC_region	DOC operations region where a majority of the site is located	To query and locate sites by management region
region	Name of the New Zealand region where the site is located	See <i>DOC_region</i>
main_isld (main island)	North or South Island (includes Stewart Island)	See <i>DOC_region</i>
X	X centrepoint coordinates (UTM)	To map sites
Y	Y centrepoint coordinates (UTM)	see X
Size		
Area	Area of the site in km ²	To prioritise or evaluate sites by size or capacity
S1_area_pc (S1 suitable area coverage (%))	Proportion of a site (in percent) that is environmentally suitable for the first behavioural state in the breeding season, S1 (breeding), based on the multi-state SDM	To assess the availability of a habitat for each behavioural state
S2_area_pc (S2 suitable area coverage (%))	Proportion of a site (in percent) that is environmentally suitable for the second behavioural state in the breeding season, S2 (transition), based on the multi-state SDM	See <i>S1_area_pc</i>
S3_area_pc (S3 suitable area coverage (%))	Proportion of a site (in percent) that is environmentally suitable for the third behavioural state in the breeding season, S3 (dispersion), based on the multi-state SDM	See <i>S1_area_pc</i>
Model uncertainty		
MESS_class* (multivariate environmental similarity surface grid mean value class)	Classified mean multivariate environmental similarity surface grid value. A measure of extrapolation impact on an area's prediction, based on similarity comparisons with the SDM training area (Auckland Islands). Five classes describe extrapolation levels as follows: 1. none (values 0 to 100) 2. low (values -100 to 0) 3. intermediate (values -500 to -100) 4. strong (values -1,000 to -500) 5. very strong (values -1,600 to -1,000)	To critically review predicted sites; sites with MESS class of 'none' to 'low' have qualities that are most similar to the Auckland Islands; sites with 'intermediate' to 'very strong' MESS classes have qualities that are dissimilar to the Auckland Islands, so there could be errors in the predictions
MOD_md* (mode of the most dissimilar variable)	Mode (most common) of the most dissimilar variable for a site, corresponding to the MESS grid	To determine the variable that is the most dissimilar from the training area (Auckland Islands), which caused extrapolation
S1_uncrt (uncertainty for the S1 prediction (%))	Coefficient of variation (CV) value (in percent) for the S1 prediction, estimating how far a prediction at a site deviates from the average prediction in the model-building process	To gauge uncertainty in the SDM's prediction of habitat suitability. Relatively low percentages indicate low uncertainty (more reliable predictions), and relatively high percentages indicate high uncertainty (less reliable predictions)
S2_uncrt (uncertainty for the S2 prediction (%))	Coefficient of variation (CV) value (in percent) for the S2 prediction, estimating how far a prediction at a site deviates from the average prediction in the model-building process	See <i>S1_uncrt</i>

(Continues)

TABLE 2 (Continued)

Data field name	Description	Management application
S3_uncrt (uncertainty for the S3 prediction (%))	Coefficient of variation (CV) value (in percent) for the S3 prediction, estimating how far a prediction at a site deviates from the average prediction in the model-building process	See <i>S1_uncrt</i>
Restoration features		
S1_limit* (mode of limiting factor for the S1 prediction)	Mode (most common) of limiting factor (or, model variable) for the S1 prediction	To evaluate the variable that limits the suitability of a site for that behavioural state; if this variable's values are improved, then site suitability can improve
S2_limit* (mode of limiting factor for the S2 prediction)	Mode (most common) of limiting factor (or, model variable) for the S2 prediction	See <i>S1_limit</i>
S3_limit* (mode of limiting factor for the S3 prediction)	Mode (most common) of limiting factor (or, model variable) for the S3 prediction	See <i>S1_limit</i>
Human impacts		
hum_im_pc (potential human impacts coverage (%))	Proportion (in percent) of a site that has potential human impacts, based on the multi-criteria decision analysis of 3D distances from sealed/unsealed roads and residential areas	To examine the degree or potential NZSL interactions with humans by roads and residential areas; to prioritise areas for community engagement and outreach
rd_sl_mi* (minimum sealed roads distance (3D; km))	Minimum 3D path distance (in km) of a site from sealed (paved) roads	To expand on the information from the multi-criteria decision analysis; vehicle collisions are a threat to NZSLs
rd_unsl_mi* (minimum unsealed roads distance (3D; km))	Minimum 3D path distance (in km) of a site from unsealed (unpaved) roads	See <i>rd_sl_mi</i>
fences	The presence or absence of fences within a site	To assess barriers that could not be included in the SDM; presence of fences implies that there is less suitable area available for the NZSL than predicted
graze_pc* (grazing grasslands (%))	Proportion (in percent) of a site that has high-/low-producing grasslands for dairy and non-dairy grazing	See <i>fences</i>
Additional suitability		
in_watr_mi* (minimum inland water distance (km))	Minimum Euclidean (straight line) distance of a site from inland water bodies (lakes, ponds, streams; excludes inlets)	To ground-truth the predicted sites; this SDM variable is limited because it is lacking inlets, which are also important for thermoregulation
in_watr_me* (mean inland water distance (km))	Mean Euclidean (straight line) distance of a site from inland water bodies (lakes, ponds, streams; excludes inlets)	See <i>in_watr_mi</i>
in_watr_mx* (maximum inland water distance (km))	Maximum Euclidean (straight line) distance of a site from inland water bodies (lakes, ponds, streams; excludes inlets)	See <i>in_watr_mi</i>
pine_pc* (pine forest (%))	Proportion (in percent) of a site that contains planted pine <i>Pinus radiata</i> forest (as of 2016)	To account for additional, non-native forest types that are preferred by recolonising NZSLs on the mainland
Locations of interest		
curr_NZSL* (current New Zealand sea lion sites)	Names of known current (1990–2019) sites where females and/or pups have been sighted during the breeding season (December–March) that are within a 10 km Euclidean (straight line) distance from a site	To investigate or ground-truth areas near where current management actions are taking place; optional suitable locations where NZSLs are likely to be found due to proximity to existing pupping sites

(Continues)

TABLE 2 (Continued)

Data field name	Description	Management application
histr_NZSL* (historic New Zealand sea lion sites)	Names of known historic (archaeological) breeding sites identified in Childerhouse & Gales, 1998 and Collins et al., 2014 that are within a 10 km Euclidean (straight line) distance from a site	To use as reference if future actions lead to proactive measures such as reintroductions
DOC_code (DOC conservation area codes)	List of DOC conservation area codes within a site	To query if sites are found within an area under other management priorities
DOC_name (DOC conservation area names)	List of DOC conservation area names within a site	see <i>DOC_code</i>
DOC_size (DOC conservation areas size (km ²))	Total size of DOC conservation areas within a site	To assess how much of a site is already being managed for other purposes
DOC_pc (DOC conservation area coverage (%))	Proportion (in percent) of a site that is a DOC conservation area	See <i>DOC_size</i>

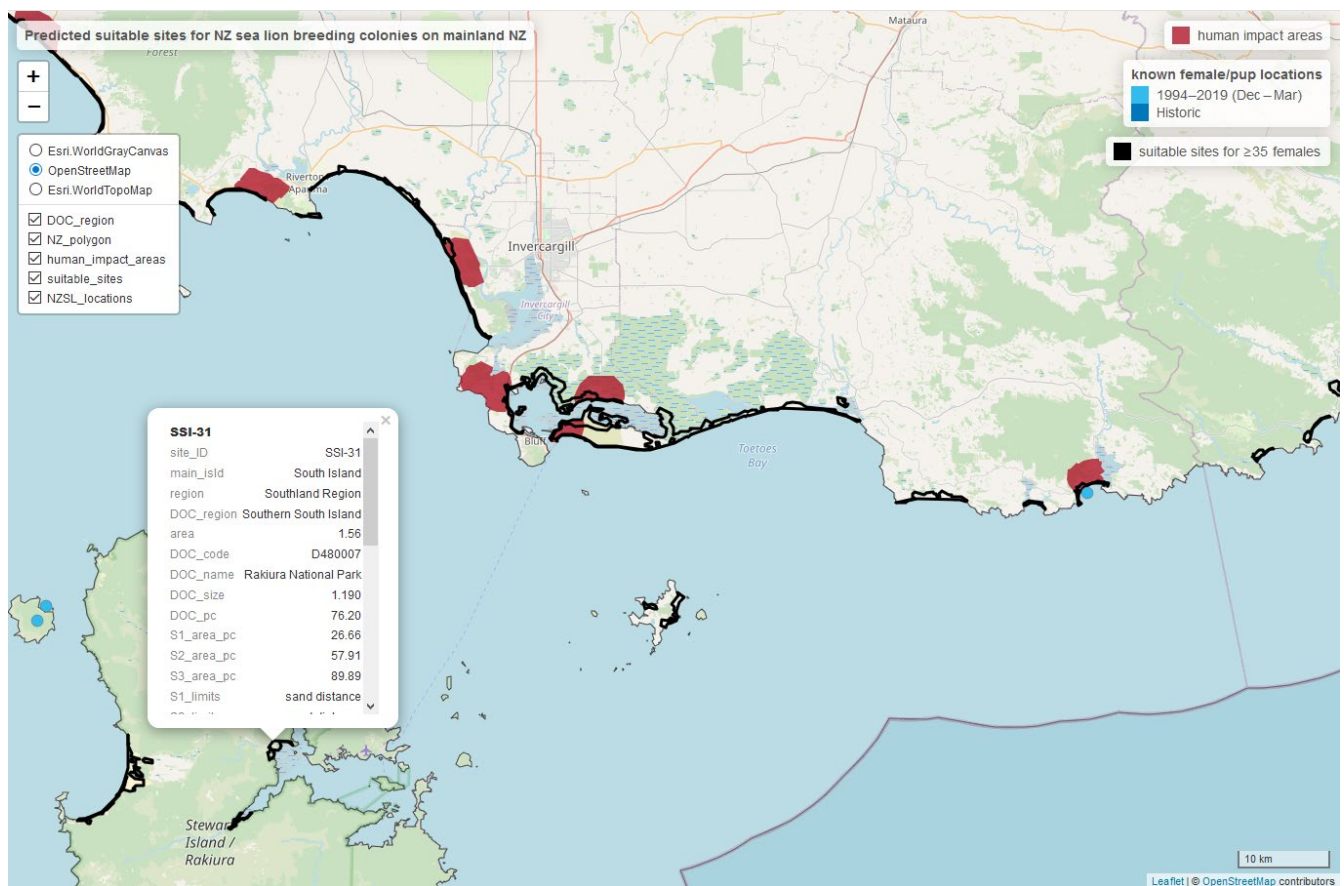


FIGURE 3 Example screenshot of the interactive *iSDMdb* map and how to retrieve summaries for each predicted site, with data fields corresponding to descriptions in Table 2

limiting across S2 ($n = 71$) and S3 ($n = 15$) sites. S1 had a larger variety of limiting factors across sites compared to S2 and S3, which included inland water distance (39 sites), coastline distance (27 sites), sand distance (15 sites) and slope (2 sites).

Across all predicted sites and state models, uncertainty in these predictions was low. CV ranged from 0.01% to 3.25%, with a mean \pm SD of $1.11 \pm 0.38\%$, $0.46 \pm 0.12\%$ and $0.59 \pm 0.28\%$ for S1, S2 and S3, respectively (Appendix S6).

3.3 | Human impacts and supplemental evaluation features

Almost a third of the sites had the highest potential for human impacts from residential areas and roads (MCDA score >0.4 ; 122 sites; Figure 5a), making the actual suitability of the predicted sites questionable. Only 69% of the sites were suitable for breeding colonies after these impacts were considered. South Island had fewer sites

with potential human impacts than North Island (58 vs. 64 sites, respectively). However, this accounted for 18% (56 km²) of the total predicted area in South Island, compared to 9% (42 km²) of the total predicted area in North Island.

Over half the predicted sites had unnatural barriers, containing grazing grasslands ($n = 268$; Figure 5b), fences ($n = 191$; Figure 5c) or both ($n = 189$). With these features considered, the estimated sizes of at least 48% of these sites were thus potentially less than predicted by the SDM. Grazing grasslands covered as much as 92% of a site's area in North Island (mean \pm SD: $19 \pm 18\%$), and 60% of a site's area in South Island (mean \pm SD: $21 \pm 16\%$).

Seventy-five percent of sites ($n = 297$) had sealed roads within 2 km of them (Figure 5d). North Island had more sites with nearby sealed roads than South Island (177 and 120 sites, respectively). Most sites (86%; $n = 341$) were within 2 km of unsealed roads (Appendix S7).

Although almost two-thirds of the total predicted sites contained some conservation areas ($n = 251$), the amount of coverage per site ranged from 0.01% to 100% (median 12.20%; Figure 5e). Only 18 sites (5 and 13 in North and South Island, respectively) were mostly (80%–100%) protected.

3.4 | Sites near current breeding locations

We found 19 sites within 10 km of known current pupping locations (Figure 6), ranging from 0.4 to 3.76 km² in size (Table 3). All areas had little to no uncertainty (CV < 1.85%) or extrapolation (MESS values between -100 and 100), except for site SSI-36 on Stewart Island. Most sites had sand distance as the most dissimilar variable, followed by slope. The most limiting factors across behavioural state models were sand and grass distances. Only three sites had potential human impacts according to the MCDA (ESI-21, ESI-24 and SSI-24), but most sites contained unnatural barriers. All except five sites were partially protected.

4 | DISCUSSION

4.1 | Wider applications for an *iSDMdb*

We demonstrated how to create an *iSDMdb* that can be used by managers to inform their actions. SDMs alone can provide useful information to guide conservation efforts, but in practice, enabling their use by rangers and decision-makers is challenging. End-users

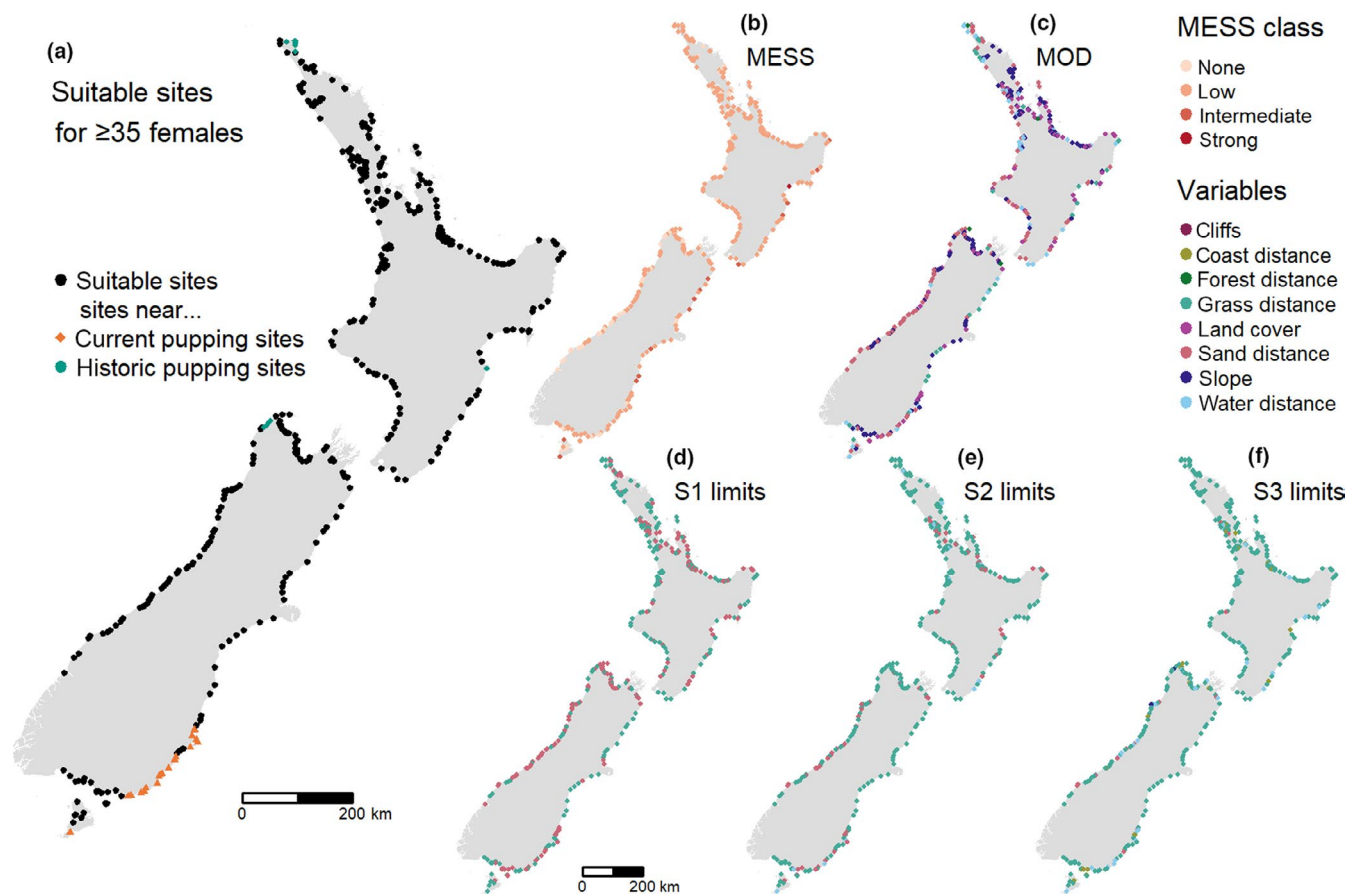


FIGURE 4 *iSDMdb* output of predicted breeding sites (a), and multivariate environmental similarity surface (MESS) classifications (b), most dissimilar variables (MOD) (c) and state model limiting factors (d–f) for each site. Predicted sites found within 10 km of known pupping locations are also indicated (a). See Table 2 for data field descriptions and interpretations

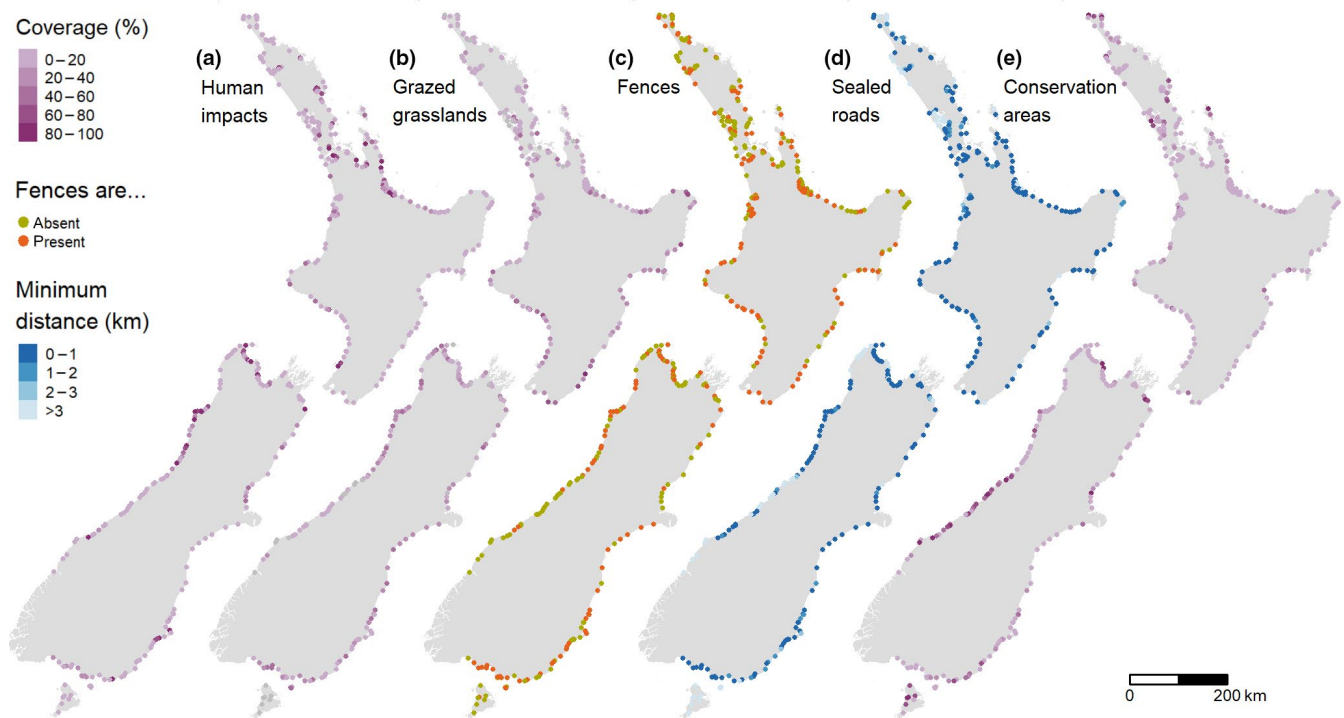
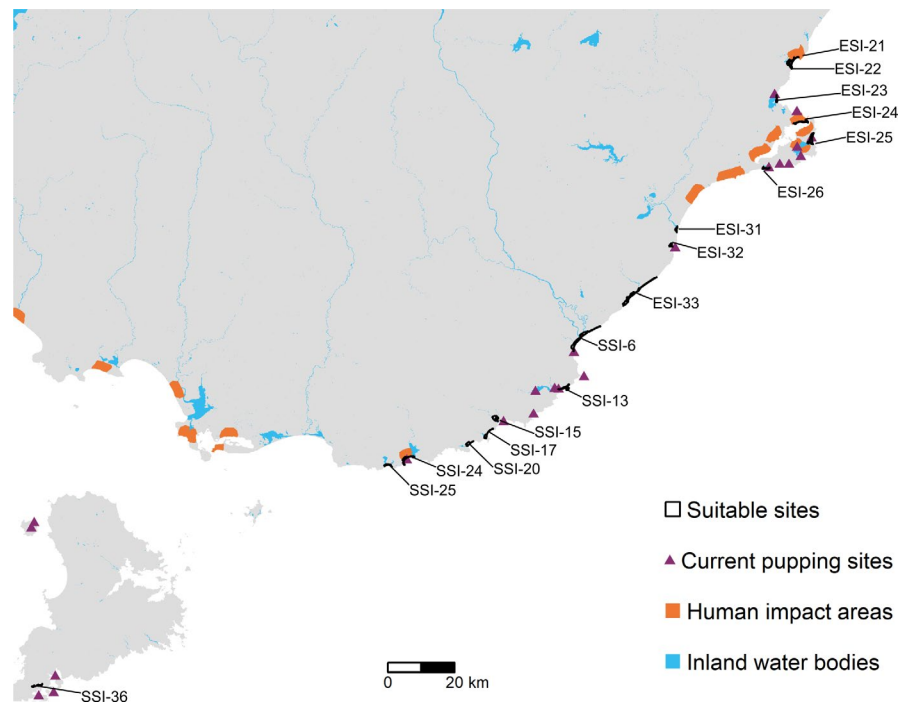


FIGURE 5 *iSDMdb* output of predicted sites, with percent cover of human impacts (a) and grazed grasslands (b), presence of fences (c), minimum sealed road distance (d) and percent cover of conservation areas (e). See Table 2 for data field descriptions and interpretations

FIGURE 6 *iSDMdb* subset of predicted sites located within 10 km of known current pupping locations, and areas of potential human impact from roads and residential areas (MCDA scores > 0.4)



may want to delineate manageable sites and systematically prioritise among them, which is difficult when providing only raw SDM predictions. Uncertainty also tends not to be brought to the forefront (either in model training or prediction), but is necessary for identifying habitat limitations and restoration targets. Furthermore, human activities and barriers limiting predicted area availability cannot be

sufficiently modelled in traditional SDMs for cases where training occurrences capturing these circumstances are lacking. Similarly, newly emerging habitat preferences or adaptations may not be accountable in SDM training, but instead need to be considered post-hoc. The *iSDMdb* incorporates such essential considerations and makes them easily accessible.

We also demonstrated the *iSDMdb*'s use for a recolonising species. The *iSDMdb* should be tested for species whose ranges are shifting due to climate change or other anthropogenic pressures, or expanding into historic or novel regions via natural or human-mediated introductions. In climate change cases, for example, species may not always change their geographical range, but rather their realised niche; as opposed to MESS/MOD, which better inform on extrapolation to novel geographical spaces, mechanistic, cause-effect models may be used and integrated into the *iSDMdb*. In many conservation cases, species' ranges are shrinking. For such species, and considering that SDM training and prediction areas may be equivalent, the *iSDMdb* may be helpful in the following ways: (a) monitoring extrapolation errors if species are rare, elusive or few occurrences are available (MESS/MOD); (b) supplementing SDMs with expert opinion on human impacts or with local ecological knowledge (MCDA); (c) instead of highlighting new behaviours in the *novel preferences in novel spaces* step, making other habitat features of interest accessible for decision-making; and (d) extracting habitat patches from the SDM step, in conjunction with the *restoration features* data field, to examine possibilities for increasing population densities. In other applications, the *iSDMdb* can also be integrated with outputs from additional models, such as those that limit predicted suitable habitat extents due to dispersal or barriers (Engler et al., 2012), or statistical or simulated models of human interactions (Arenas-Castro & Sillero, 2021). As an open-source tool, there are many possibilities, so we encourage using only relevant portions or expanding the *iSDMdb* as needed.

Our example of the *iSDMdb* process and its evaluation demonstrates the value of discussing SDM development steps with conservation decision-makers and rangers. We supplemented our SDM prediction with evaluations we would not have otherwise included (e.g. MESS, limiting factors, barriers that could restrict the predicted sites' actual size), providing more practical results to conservation practitioners than many previous SDM studies. Syntheses of SDM studies remark that many SDM products for conservation or management applications lack transparency and interpretation support, and do not effectively communicate uncertainty (Araújo et al., 2019; Guisan et al., 2013; Sofaer et al., 2019; Villero et al., 2017). Our study demonstrates how to, respectively, address these issues by providing a clear guide on how the database was created and could be evaluated (Table 1; Appendices S1–S8), explaining how each data field applies to the management of our case study species (Table 2), and by incorporating model uncertainty and restoration features within the database (Figure 2). Interpretation support was especially paramount, as understanding each assessment's purpose, assumptions and raw outputs could be incredibly time-consuming. We demonstrate these simplifications in R (Appendices S5 and S6) and encourage future studies to follow suit. Appendix S8 demonstrates how the *iSDMdb* could be queried and further analysed. As the *iSDMdb* was created using flexible, open-source tools, additional assessments can be appended to it over time as other data become available and priorities or concerns shift (e.g. prey availability).

The most successful conservation outcomes from research build trust, collaborate, embrace different perspectives and diversify communication with stakeholders (Gerber et al., 2020). Our *iSDMdb* inherently requires engagement with rangers and decision-makers through multiple steps in the database-building process. Efforts should also be made to prepare results in multiple, accessible formats, and researchers should be aware of end-users' varying levels of experience in using such formats. Here, we presented the *iSDMdb* to our end-users as GIS shapefiles, spreadsheets, printed maps and an interactive map, along with an interpretation guide. A variety of formats allows for a range in exploration, from a general overview (Figures 3–6) to a more detailed analysis (Appendix S8).

There are limitations to the simplifications used to construct the final database. The first is converting SDM predictions into polygons of predicted sites. These polygons were created by identifying contiguous suitable pixels to meet the minimum area sizes. If species' movement does not require habitat contiguity, other ways of creating polygons can be used, such as a moving window analysis within a given dispersal distance (e.g. *range module* in Frans et al., 2018b). The boundaries, sizes and existence of these sites for ≥ 35 females depended on SDM threshold choice. As an exploratory study, we chose a conservative threshold, allowing us to identify more sites. Where the management intention is to specifically allocate resources or efforts to all identified sites, stricter or multiple thresholds should be used (Liu et al., 2005, 2013). These polygons should also be validated with the best available information, local knowledge or ground-truthing with experts on species' behaviours. For the human impact areas, we used thresholds based on expert opinion; when possible, statistical thresholds are preferred, especially if statistical or simulation models of human interactions are implemented (e.g. Arenas-Castro & Sillero, 2021).

Some information from the other assessments was also lost when integrated into the predicted site polygons. The multi-state SDM, MESS, MOD, limiting factors, CV, MCDA and distance features were all raster analyses, having gradients of values at every pixel. These assessments for each site thus had ranges of values that we summarised as means, minima, maxima and/or modes. To our advantage, however, this format ensured the *iSDMdb*'s accessibility to all end-users. The simplifications allow for end-users to easily view results at the national scale (Figures 4 and 5), and, when accompanied with a guide (Table 2), easy interpretation without requiring that end-users have technical understandings of SDMs, MCDAs or any of the other methods. For sites where further raster evaluations are needed (especially in determining the spatial extent of limiting factors within sites, or ground-truthing), raw outputs can be made available to end-users by appending them to the HTML version of the *iSDMdb*.

While we listed some limitations in the *iSDMdb*'s simple format, from the practical conservation and management perspective, these same limitations become strengths, as they bring SDM outcomes closer to real-life applications. Continuous SDM predictions—especially at large, national scales and fine resolutions—can be difficult to interpret, and choices in how continuous values are

TABLE 3 Summary of size, management priority, human impact, restoration and model uncertainty features for predicted sites within 10 km of current mainland pupping locations. Data field descriptions are provided in Table 2

Identification	Size	Management		Human impacts		Restoration features			Model uncertainty					
		Area (km ²)	% conservation area	% human impacts	% grazing grassland	Fences	S1 limits	S2 limits	S3 limits	MESS class	MOD	S1 CV (%)	S2 CV (%)	S3 CV (%)
ESI-21	1.76	3.43	0	33.82	10.69	N	Sand	Grass	Coast	Low	Slope	1.27	0.36	0.26
ESI-22	0.71	0	0	0	35.16	N	Sand	Sand	Coast	Low	LC	1.28	0.28	0.38
ESI-23	0.45	0	0	0	0.07	N	Grass	Grass	Grass	None	Slope	0.75	0.57	0.74
ESI-24	0.79	0	100	0	0.55	Y	Grass	Water	Water	Low	Water	0.63	0.58	0.82
ESI-25	2.11	0	0	0	1.78	Y	Sand	Sand	Grass	Low	Slope	1.4	0.43	0.36
ESI-26	0.37	5.83	0	0	16.12	N	Grass	Grass	Grass	Low	Sand	0.96	0.4	0.59
ESI-31	0.48	0.84	0	0	9.99	Y	Sand	Grass	Grass	Low	Sand	1.35	0.32	0.52
ESI-32	0.57	20.95	0	0	12.40	Y	Sand	Sand	Sand	Low	Sand	1.42	0.38	0.22
ESI-33	3.79	3.49	0	0	41.40	Y	Sand	Grass	Grass	Low	LC	1.31	0.38	0.51
SSI-5	0.40	0	0	0	7.31	N	Grass	Grass	Grass	None	Sand	0.68	0.52	0.78
SSI-6	1.48	4.52	0	0	36.75	Y	Sand	Grass	Grass	Low	LC	1.32	0.43	0.39
SSI-8	2.26	61.29	0	0	15.23	Y	Sand	Sand	Water	Low	Sand	1.35	0.23	0.34
SSI-13	1.13	12.20	0	0	13.40	N	Grass	Water	Water	Low	Water	1.08	0.44	0.57
SSI-15	1.49	54.33	0	0	4.81	Y	Sand	Sand	Water	Low	Slope	1.61	0.36	0.3
SSI-17	0.86	23.88	0	0	16.55	N	Grass	Grass	Grass	None	Sand	1.19	0.42	0.52
SSI-20	0.84	59.57	0	0	7.32	N	Sand	Sand	Grass	None	Sand	1.85	0.48	0.34
SSI-24	1.24	5.47	83.86	0	41.56	Y	Grass	Grass	Grass	Low	LC	1.12	0.43	0.55
SSI-25	0.46	61.74	0	0	0.53	N	Grass	Grass	Grass	None	Sand	0.61	0.43	0.78
SSI-36	0.51	16.17	0	0	0	N	Grass	Water	Water	Intermediate	Water	0.58	0.64	0.98

Abbreviation: LC, land cover.

visualised (e.g. value breaks, colour schemes) can mislead an end-user (Brewer & Pickle, 2002; Crameri et al., 2020). Thus, a simplified format, along with an interpretive guide and direct engagement with species experts, rangers, and decision-makers, enhances the database's ultimate utility.

4.2 | The *iSDMdb*'s place among other decision-support tools

While similar to other spatial, integrative conservation decision-support tools (e.g. Marxan, Zonation), the *iSDMdb* differs in multiple ways. First, previous studies emphasise advantages in using SDMs for delineating conservation prioritisation areas (Di Febbraro et al., 2018; Domisch et al., 2019). Many decision-support tools and integrative modelling processes use custom algorithms that may or may not use species occurrence data to determine important sites, and others require that conservation units be defined prior to assessment (Domisch et al., 2019; Regos et al., 2021; Williams & Hooten, 2016). The *iSDMdb*, however, centres conservation units on the species of interest's occurrences and ecological niche (also see Johnson & Gillingham, 2005). It can be used with any SDM algorithm, allowing for robust model selection procedures and other tests to take place prior to input. Ensemble models can also be used.

Second, as an extended assessment of habitat suitability, the *iSDMdb* is easily customisable. Our example case resulted in 34 data fields, but more data fields can be added in future studies. For example, the *iSDMdb* can bring attention to multiple kinds of uncertainty. Here, we used CV, MESS and MOD, but other SDMs such as generalised linear models or Bayesian hierarchical models (e.g. occupancy models, spatial abundance models; Kéry & Royle, 2018) can report uncertainties such as confidence or credible intervals, sample bias grids, detection probability or other extrapolation assessment methods (Conn et al., 2015) into the *iSDMdb* (Burgman et al., 2005; Elith & Leathwick, 2009; Nicholson & Possingham, 2007). Minimum and maximum probabilities across multiple SDM iterations can also be integrated. If an ensemble SDM is used, areas of disagreement among SDMs can be highlighted.

Finally, combined SDM/expert-opinion methods are available (e.g. Anadón et al., 2010; Bélisle et al., 2018; Luizza et al., 2016); however, such existing frameworks are designed for scenarios where habitat features of concern exist within the model training area (where the species is currently present). Here, we demonstrated a way for the *iSDMdb* to help when features in a model prediction area vastly differ from or are non-existent in a model training area, which can apply to the circumstances of many range-shifting or -expanding species.

4.3 | The case of the NZSL and recommendations for management

As the NZSL recolonises the mainland, there are many concerns decision-makers must address. Among them, predicting sites where

the NZSL could recolonise seems simple, given the robust amount of existing habitat suitability modelling methodologies. However, traditional SDMs need to be supplemented to make them more practical because anthropogenic variables are absent from current breeding colonies but will impede NZSLs in their predicted range (e.g. roads, fences, residential areas), and because non-native habitat variables are absent from current breeding colonies but are potentially beneficial in the predicted range due to the unavailability of native habitat in some areas (e.g. pine forests).

Providing end-users with only the resulting mapped sites from the SDM step would have been insufficient for informing this species' conservation. End-users were concerned about model uncertainty, whether the SDM gives guidance for habitat restoration priorities, and human impacts that could not be modelled in the SDM. Incorporating such features showed that the actual availability of almost 90% ($n = 358$) of the predicted sites was conditional on these additional *iSDMdb* features.

There were many predicted sites on North Island (Figure 4), despite this number being lowered by human impacts (Figure 5). Current management efforts focus on known, newly existing pupping sites on South Island and Stewart Island (Department of Conservation, 2017). Including North Island provides information for future measures that have not yet been considered (e.g. reintroductions).

The MESS evaluation indicates little to no risk of extrapolation in SDM predictions for the current areas of focus in South Island and Stewart Island; most predicted sites were similar to the model training area (Table 3). Across behavioural states, distance from grasslands was the most limiting variable for most South Island sites. Yet, the importance of grass or sward for S2 may be unique to Sandy Bay, and perhaps not worth emphasis for restoration. Site limitations for S1 and S3 should thus be the focus of restoration activities. Management should especially focus on areas where sand distance and slope are the most limiting variables, as invasive plants (e.g. marram grass *Ammophila arenaria*) are altering sand dunes across New Zealand (Hilton, 2006).

Another utility of our results lies in community engagement and outreach. While we found many predicted sites throughout the mainland, the true *availability* of most sites relies on the NZSL's reception by surrounding communities. Fencing from grazed grasslands could limit females' inland movement into forests, and females' damage of fences to gain access could cause conflicts with landowners. Privately-owned coastal pine forest plantations are currently an important habitat on the mainland because there is very little remnant coastal native forest. When these plantations are cut, they will be unavailable for any establishing NZSLs during S3. Rangers and decision-makers should therefore engage with landowners about the NZSL as it recolonises, and a focus on restoring native coastal forests at key sites should be investigated.

5 | CONCLUSIONS

As species' ranges change, management-oriented studies and results are needed to aid conservation practitioners in biodiversity

protection and recovery efforts. Using habitat suitability models such as SDMs can be challenging when landscapes have natural or unnatural features that vastly differ from their current range. As a result, SDM realism becomes questionable. We demonstrate how additional assessments consolidated into an *iSDMdb* can account for such issues in predicted ranges. In such cases, including stakeholders, rangers and decision-makers is invaluable for identifying and integrating components that traditional SDMs may omit and for providing that information in a practical, accessible manner.

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AUTHORS' CONTRIBUTIONS

V.F.F. and A.A.A. conceived the ideas for this study; V.F.F. designed the methodology and prepared and analysed the data, with support from A.A.A., J.O.E. and H.E.; V.F.F., A.A.A., J.F., J.O.E. and N.M. evaluated the results; V.F.F. drafted the manuscript, with critical revisions by A.A.A., J.O.E., Y.Z., N.B. and J.F. All authors contributed to the drafts and gave final approval for publication.

PEER REVIEW

The peer review history for this article is available at <https://publons.com/publon/10.1111/2041-210X.13736>.

DATA AVAILABILITY STATEMENT

All data sources are listed in Table 1 of the manuscript. Data used in this study were obtained from Land Information New Zealand (<http://data.linz.govt.nz>), Stats New Zealand (<https://data.mfe.govt.nz>), New Zealand Department of Conservation (DOC), <https://koordinates.com>, Ministry for the Environment, and Landcare New Zealand (<https://iris.scinfo.org.nz>), under New Zealand Creative Commons Attribution 3.0 and Landcare Data Use licensing. New Zealand sea lion location data were obtained from DOC via Dragonfly Data Science (<https://sealions.dragonfly.co.nz/demographics/>) and Frans et al. (2018a; <https://doi.org/10.5061/dryad.14mt7>). R scripts and summary results for this study are provided in Appendices S1–S8, <https://github.com/vffrans/iSDMdb>, Zenodo (Frans et al., 2021a; <https://doi.org/10.5281/zenodo.5535797>), and the Dryad Repository (Frans et al., 2021b; <https://doi.org/10.5061/dryad.t1g1jw33>).

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