Date of publication: 30 May 2016

The Borneo carnivore database and the application of predictive distribution modelling

Stephanie Kramer-Schadt^{1*}, Vanessa Reinfelder, Jürgen Niedballa, Jana Lindenborn, Milena Stillfried, Ilja Heckmann and Andreas Wilting^{1*}

Abstract. South-east Asian mammals face a particularly severe threat of extinction. Borneo, the third largest island in the world, is located in the centre of South-east Asia. It harbours more endemic carnivores than does any other island except Madagascar. Almost half the Bornean carnivore species have been classified by The IUCN Red List of Threatened Species as threatened. Because little is known about most Bornean carnivores, predicting their spatial distribution is important for management strategies to improve the conservation of these species. As a part of the 1st Borneo Carnivore Symposium (BCS) we started to assemble a knowledge base of Bornean carnivores. We established the Borneo Carnivore Database which contains the previously largely fragmented occurrence records of carnivores on the island and then used these records to predict the distribution of 20 Bornean carnivores (all native species except sun bear Helarctos malayanus and the four otter species, Eurasian otter Lutra lutra, Asian smallclawed otter Aonyx cinereus, hairy-nosed otter Lutra sumatrana and smooth-coated otter Lutrogale perspicillata). We describe general considerations – the underlying assumptions, advantages, and most importantly the limitations and constraints - of species distribution modelling. We then summarise the methodological framework of our modelling approach and results of the sensitivity analyses. We emphasise that despite the extensive efforts to compile existing information, so few or spatially biased occurrence records exist for some species that the model outcomes presented in this journal issue must be interpreted cautiously. We recommend using new data as they become available to test our projections and improve our understanding of carnivore distributions on Borneo.

Key words. Borneo, mammals, MaxEnt, sampling bias, spatial locations, species distribution models, uneven search-effort

Abstrak (Bahasa Indonesia). Mamalia Asia Tenggara menghadapi ancaman dari kepunahan yang demikian tinggi. Borneo, sebagai pulau ke tiga terbesar di dunia yang terletak di tengah wilayah Asia Tenggara, menjadi tempat bagi banyak karnivora endemik dibandingkan pulau lainnya, terkecuali Madagaskar. Hampir setengah dari karnivora Borneo masuk klasifikasi Terancam dalam daftar IUCN Red List of Threatened Species. Mengingat masih sangat terbatasnya pengetahuan mengenai kebanyakan jenis karnivora Borneo, pendugaan penyebaran wilayah menjadi penting dalam strategi pengelolaan untuk peningkatkan konservasi dari jenis-jenis yang ada. Sebagai bagian dari hasil Simposium Karnivora Borneo Pertama (the 1st Borneo Carnivore Symposium; BCS) kami mulai menyusun pengetahuan dasar yang ada mengenai karnivora tersebut. Kami membangun Pangkalan Data Karnivora Borneo yang memuat sebagain besar informasi perjumpaan yang terpencar mengenai karnivora di Borneo dan menggunakan catatan tersebut untuk memperkirakan penyebaran 20 karnivora Borneo (semua satwa asli setempat terkecuali Beruang Madu Helarctos malayanus dan empat jenis berang-berang/sero yaitu Berang-Berang Pantai Lutra lutra, Sero Ambrang Aonyx cinereus, Berang-Berang Sumatera Lutra sumatrana serta Berang-Berang Wregul Lutrogale perspicillata. Kami menjelaskan pertimbangan umum – asumsi yang menjadi dasar, keuntungan, dan terpenting keterbatasan dan tantangan - pemodelan persebaran jenis tersebut. Kami kemudian menyimpulkan kerangka metode dari pendekatan pemodelan kami dan hasil dari analisa kesensitifitasan. Kami tekankan, walaupun usaha besar untuk mengumpulkan informasi yang ada telah berjalan, ada sedikit atau terdapat data spasial catatan keberadaan yang bias pada beberapa jenis, sehingga model yang disajikan dalam jurnal ini harus diinterpretasikan dengan kehatihatian. Kami merekomendasikan penggunaan data baru, ketika sudah tersedia, untuk menguji kembali proyeksi kami dan meningkatkan pemahaman kita mengenai persebaran karnivora di Borneo.

Abstrak (Bahasa Malysia). Mamalia Asia Tenggara menghadapi ancaman kepupusan yang begitu tinggi. Borneo, sebagai pulau ketiga besar di dunia dan terletak di pertengahan Asia Tenggara, adalah tempat di mana terdapat paling banyak karnivora endemik (tidak didapati di tempat lain) dibandingkan kepulauan lain di dunia kecuali Madagascar. Hampir separuh daripada karnivora ini tersenarai sebagai terancam di atas IUCN Red List of Threatened Species. Oleh kerana pengetahuan kami sangat terhad mengenai kebanyakan karnivora Borneo, ramalan tentang penyebaran spesis-spesis ini adalah penting untuk pembentukan strategi pengelolaan dan meningkatkan usaha pemuliharaan mereka. Sebagai satu hasil dari Simposium Karnivora Borneo Pertama (1st Borneo Carnivore Symposium), kami mula berkumpul pengetahuan asas tentang karnivora ini. Kami mewujudkan satu Pangkalan Data Karnivora Borneo (Borneo Carnivore Database) untuk berkumpul maklumat tentang karnivora Borneo dan meramalkan penyebaran bagi 20 spesis karnivora Borneo (semua spesis yang didapati di Borneo kecuali Beruang Madu *Helarctos malayanus* dan empat spesis memerang iaitu Memerang 'Eurasian' *Lutra lutra*, Memerang Kecil *Aonyx cinereus*, Memerang Kumis *Lutra sumatrana* dan Memerang Licin *Lutrogale perspicillata*. Kami menjelaskan pertimbanganan am – penyangkaan dasar, faedahnya, dan yang paling penting, kebatasan dan masalah – menggunakan cara pemodelan penyebaran spesis jenis ini. Kami kemudian meringkaskan cara bagaimana pendekatan pemodelan ini dilakukan dan keputusan analisa kepekaan (sensitivity analysis). Kami menekankan bahawa walaupun usaha besar telah dilakukan

untuk mengumpulkan maklumat terkini, rekod-rekod yang sedia ada terlalu sedikit atau terdapat kecondongan setempat (spatial bias) untuk beberapa spesis sehingga keputusan model yang dikemukakan di dalam terbitan jurnal ini harus diinterpretasikan dengan hati-hati. Kami cadangkan agar bila data baru sudah ada, ianya digunakan untuk menguji peramalan model kami dan meningkatkan pemahaman mengenai penyebaran karnivora di Borneo.

PROJECT BACKGROUND

The 2008 Global Mammal Assessment of the threat status of the world's mammal species by the International Union for Conservation of Nature (IUCN) revealed that South-east Asian mammals face a particularly severe threat of extinction (Schipper et al., 2008; Hoffmann et al., 2011). On Borneo, almost 50% of carnivore species are listed as threatened on The IUCN Red List of Threatened Species. Because little is known about most Bornean carnivores, predicting their spatial distribution is important for developing management strategies to conserve these species (e.g., Kanagaraj et al., 2013). Species distribution models (SDM) relate environmental variables and species occurrence records to predict the distribution of species across large spatial scales (e.g., Elith & Leathwick, 2009). While spatial modelling studies stress the importance of predicting future species distributions in changing environments (e.g., Struebig et al., 2015a, b), it is also important to establish historical distributions of species to provide baseline conditions for understanding recent shifts in distributions (Louzao et al., 2013).

Our aim was to assist conservation efforts for Bornean carnivores by predicting potential historical and current distributions of carnivores (all native species except sun bear Helarctos malayanus (Raffles) and the four otter species Eurasian otter Lutra lutra (Linnaeus), Asian smallclawed otter Aonyx cinereus (Illiger), hairy-nosed otter Lutra sumatrana (Gray) and smooth-coated otter Lutrogale perspicillata (Geoffroy Saint-Hilaire)) throughout the island and the effects of human-dominated landscapes (habitat suitability). This is necessary to assess areas in which suitable habitat has potentially been lost. To this end, we first assembled the available species occurrences in a digital database. We then followed the hierarchical modelling approach by Wilting et al. (2010) where we estimated the potential historical distributions of 20 carnivore species based on environmental data and the suitability of current land area (land-cover class and human population density) using respondents' knowledge and thoughts to calculate the current potential distribution based on a habitat suitability index (HSI) integrating historical distributions and current land-cover (Fig. 1). The modelling methods are also published in Kramer-Schadt et al. (2013) and Struebig et al. (2015a, b).

GENERAL CONSIDERATIONS REGARDING SPECIES DISTRIBUTION MODELS (SDMS)

Maximum entropy modelling (program MaxEnt; Phillips et al., 2006) has become popular for predicting distributions of rare and threatened species as it purportedly accommodates sparse data irregularly observed or sampled or low locational precision, typical for rare and elusive species, museum data, or species occurring in difficult terrain and climate (Elith et al., 2006, 2011). Because systematic surveys for carnivores across Borneo have not been conducted, we used MaxEnt to estimate distributions that would account for spatially uneven data, i.e. data where the survey or search effort, respectively, was not equal everywhere.

Despite the advantages of MaxEnt, there are several limitations of SDMs (Araujo & Guisan, 2006; Yackulic et al., 2013). Researchers must be mindful of study design and biases inherent in presence data, and be cautious when interpreting model predictions (Pearce & Boyce, 2006). That is, MaxEnt is a presence-only approach (Li & Guo, 2011; Royle et al., 2012) that because of methodological constraints (see Yackulic et al., 2013) precludes the comparison of MaxEnt outputs across species. The output of MaxEnt models is a relative occurrence probability in relation to a default occupancy probability and cannot be compared across species observed during different temporal and spatial scales (Elith et al., 2011), because occupancy probability differs across species. A second limitation using presence-only data is that sample selection bias, i.e., bias created by uneven search-efforts or non-systematic surveys, has a stronger effect on presence-only models than on presence-absence models (Phillips, 2008; Phillips & Dudik, 2008; Phillips et al., 2009; Elith et al., 2011). Sample selection bias occurs when outside a structured survey framework some areas in the landscape are surveyed more intensively than are others, as is common with museum data or opportunistic occurrence records such as sightings or road kills (Graham et al., 2008). This uneven search-effort is often termed 'sampling bias'.

Our occurrence dataset was strongly biased to a few areas in Sabah, north-eastern Borneo, making the modelled relative probability of occurrence partly dependent on searching or surveying intensity (see Kramer-Schadt et al. (2013) for a detailed discussion on the effects of sampling bias). Although we reduced search-effort bias by filtering the occurrence records spatially and adjusting the background maps (see below and Kramer-Schadt et al., 2013; Struebig et al., 2015a), this bias still affected model results. Consequently, we describe how results in the following papers of this supplementary issue should be interpreted. Models derived from data with large search-effort biases (e.g., few and

¹Leibniz Institute for Zoo and Wildlife Research, Alfred-Kowalke-Strasse 17, D-10315 Berlin, Germany; Email: kramer@izw-berlin.de (SK-S); wilting@izw-berlin.de (AW) (*corresponding authors)

[©] National University of Singapore ISSN 2345-7600 (electronic) | ISSN 0217-2445 (print)

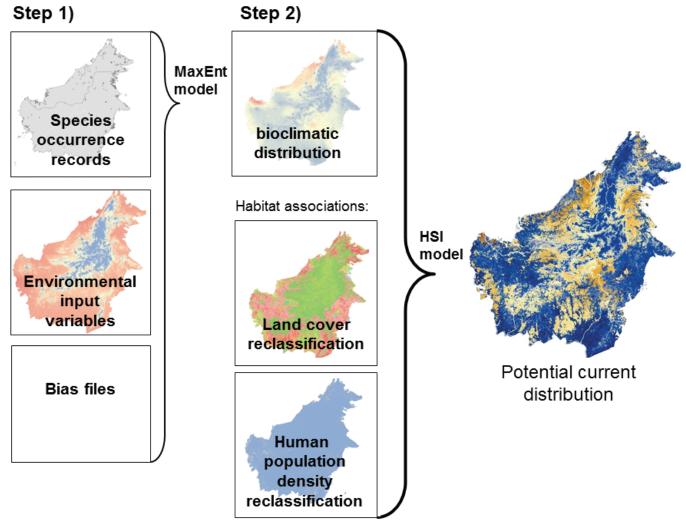


Fig. 1. Overview of the hierarchical modelling approach to develop distribution models for Bornean carnivores. In step one, the species occurrence records, environmental input layers and bias files representing record densities were used in a MaxEnt modelling approach to derive historical habitat suitability or possible bioclimatic distribution. In step two, the historical habitat suitability map was integrated with reclassified land-cover and human population density suitability scores (habitat associations) in a habitat suitability index model to yield relative current habitat suitability probability or potential current distribution.

spatially clumped records for some species in Sabah; see Fig. 2), generally produce reliable predictions for areas intensively surveyed but not for other areas. Large areas with few records (e.g., parts of West Kalimantan) should be regarded as unstudied and areas with low predicted probability of occurrence in these areas should not be considered necessarily to be unsuitable. Underrepresentation of non-surveyed areas in the respective species' distribution maps can further be reinforced when the climatic conditions are very much different from areas from whence locations stem. Hence, areas in Brunei, being similar to climatic conditions in Sarawak and Sabah, might be predicted correctly, whereas data-poor areas that are climatically different from areas with records, e.g., in South Kalimantan (Fig. 3A), cannot be predicted as suitable. Thus, care must be taken when discussing low suitability in the predictions as to whether this is because of methodological issues, climatic differences or because large areas have been transformed into unsuitable land-cover, e.g., oil palm plantations (Fig. 3B). Here, a careful evaluation of the model results in the context of survey effort and the individual species's biology is needed.

Also, because of search-effort bias the comparison of absolute model prediction values across regions for the same species is not meaningful. That is, a relative probability of occurrence of 0.4 in Kalimantan (few records) could be equivalent to value of 0.7 in Sabah (many records). Finally, because each model is based on the records of the respective species, model predictions are based on a species-specific scaling. However, the detection probability is fixed at the same threshold for each species. Thus, comparisons across species are not possible, i.e. species A is not necessarily more likely to occur within a certain area than does another species B even if species A's modelled relative occurrence probability in that area is higher than that for the species B.

Despite these limitations, the SDMs provide an important contribution towards knowledge of Bornean carnivores. This is the first time that distribution records about all Bornean carnivores (except sun bear and otters) were assembled and processed (i.e., modelled) in a standardised framework; this provides a baseline for compiling additional data. The SDMs provide an explicit quantification of habitat suitability

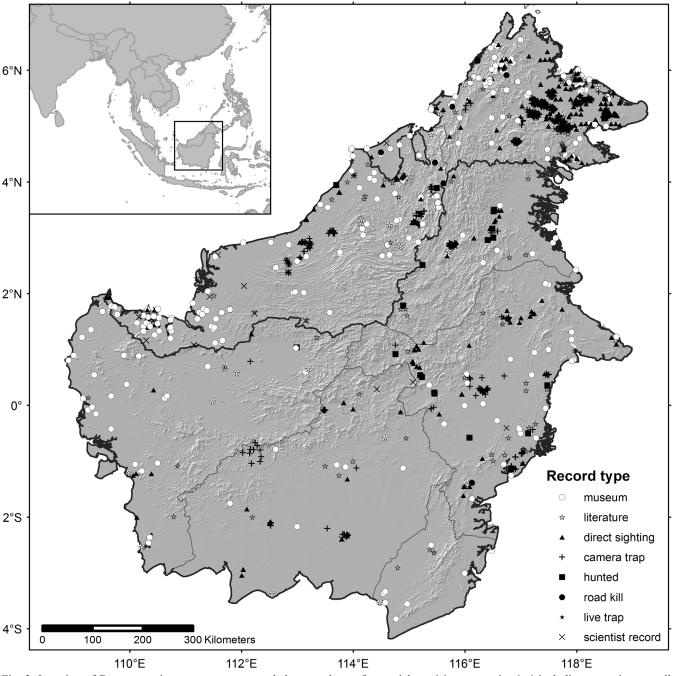


Fig. 2. Location of Borneo carnivore occurrence records by record-type for spatial precision categories 1-4 including countries as well as state boundaries.

assessments, can be refined with new records, and can serve to facilitate discussion of species conservation in a spatial context. Further, they can be used to identify areas with limited information for further research as well as conservation areas and potential corridors. Finally, SDMs can function as a tool to test ecological hypotheses about species' distributions and niches and to help synthesise existing knowledge.

METHODOLOGICAL APPROACH

I: THE BORNEO CARNIVORE DATABASE

The Borneo Carnivore Database was created to assemble occurrence records for the 20 Bornean carnivores, the subject

of this proceedings issue (see also Table 2). All records with uncertain species identification or with uncertain or missing geographic information were excluded from the database. We collected and assembled occurrence records from scientists, wildlife observers, museums and literature (Table 1). We also reviewed the Indo-Australian Mammal Atlas (van Strien, 2001) for occurrence records. Data types included museum specimens found in the Mammal Networked Information System (MaNIS) and Global Biodiversity Information Facility (GBIF) non-fossil museum databases or provided by the museums directly, road kills, hunters' relicts like skins and skulls where the spatial origin was established, cameratrapping data and direct sightings. Indirect information in the forms of tracks and other local people was excluded because of

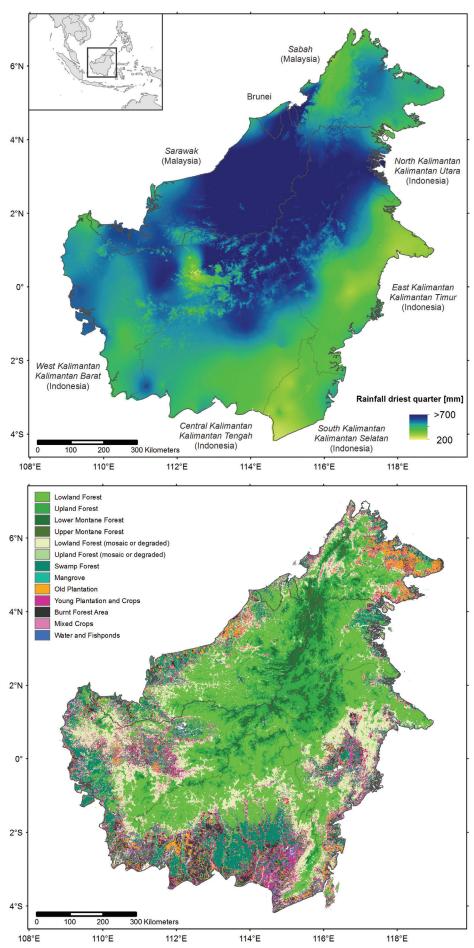


Fig. 3. A, climatic differences in Borneo expressed here as the Driest Quarter (Hijmans et al, 2005; www.worldclim.org/bioclim; bioclim 17). B, land-cover map used for habitat associations.

the high potential of species misidentification (e.g., Mohd-Azlan et al., 2013).

Each occurrence record was validated with other records and those in question were discussed with respective contributors. Contributors were asked to provide only records of high certainty and camera-trapping photographs were shared with a broader community for species identification as required. Due to our careful review of the records and our strict criteria, most uncorroborated records from public databases such as MaNIS, GBIF and the Indo-Australian Mammal Atlas were excluded from modelling because of missing or uncertain information, but kept as entry in the database.

Each record included the following information when available: species, geographic coordinates in decimal degrees, location name, collector or observer, date, type of record, museum identification, museum name, habitat as provided by the observer, altitude as provided by the observer, reference and remarks. When geographic coordinates were not available, we assigned coordinates using maps of Kalimantan (CV. Indo Prima Sarana; http://www.indoprimasarana.com/), Google Earth and knowledge from researchers working in those regions.

We categorised records based on spatial precision provided by the contributors of (1) within 0.5 km, (2) 0.5-2.0 km, (3) 2.0-5.0 km, (4) over 5.0 km and (5) unknown radius (Table 2, Fig. 2). Overall, we had compiled 3979 records by September 2011, of which 1151 were from 36 museums, 2290 were from 46 field studies, 126 were from online databases, and 412 were found in 67 of 270 documents published from 1845 to 2011 (Tables 1, 2). Duplication of records was avoided by cross-validating the collector's name or location specification. However, if there were differences in the sources, i.e., entry in a museum list, book or database, we could not distinguish the record at this stage. However, if this occurred, it would not have affected the modelling procedure because such records would have been spatially too imprecise or spatially filtered (see below). Of these, 1850 records were gathered before 2001, 2078 records were from 2001 or later, and 51 lacked the date. From field sources, 741 records were sightings and 1615 were camera-trap photographs. From a total of 3581 records in categories 1-4 we compiled 2464 (69%) records from Malaysian Borneo (578 [16%] from Sarawak and 1886 [53%] from Sabah), 1100 (31%) from Indonesian Kalimantan (West Kalimantan 177 [5%], South Kalimantan 29 [1%], Central Kalimantan 336 [9%], East Kalimantan 389 [11%], North Kalimantan 169 [5%]) and 17 (0.5%) from Brunei Darussalam.

Species occurrence records used for modelling. We only used records with spatial precision categories 1–3 for generating SDMs because of potential spatial inaccuracy of records with precision categories 4 and 5. To reduce inaccuracy in model projections associated with spatial autocorrelation in model residuals because of a clustered, dependent data structure (cf. Dormann et al., 2007; Veloz, 2009), we applied further spatial filtering and used only one record within a radius of 2 km (greater than the approximate

home range radii of many small carnivores) for each species. For species with a greater number of records this radius was extended to 5 or 10 km (Table 3), to reduce possible search-effort bias without removing too many data points. We retained records with greatest location accuracy; when data clusters included two or more records of equal accuracy, we selected the record to be retained randomly. This spatially filtered dataset (M₂ in Tables 1 of the respective species papers) was used to model only the distribution within the Malaysian state of Sabah (referred to as 'spatial filtering model' M₂). However, even after spatial filtering, the Malaysian State of Sabah, which represents 10% of the area of Borneo, still contained over 50% of all records. To model the distribution outside Sabah appropriately, we further reduced the number of records for each species by selecting randomly the number of records in Sabah which corresponded by areal proportion to the number of records outside Sabah (balanced dataset M₁ in Tables 1 of the respective species papers in this supplementary issue, referred to as 'balanced model' M₁). For example, if 90 records of a species were detected outside Sabah, we included 10 records of that species from Sabah from the respective species database (see Kramer-Schadt et al., 2013, for sensitivity analyses of spatial filtering effects).

II: THE BORNEO GEODATABASE

All analyses were done using ArcInfo 9.3 and ArcGIS v. 9.3.1 (ArcView, Spatial Analyst, 3D Analyst, Geostatistical Analyst) by Environmental Systems Research Institute (ESRI) and R 2.10.1 (R Development Core Team 2009). All maps were geo-referenced, clipped or shifted to the same extent with a cell size of 30 arc seconds (~ 1 km²). We filled missing data in the Bioclim maps (see below) by applying mean values of surrounding cells using a moving window approach across a radius of eight cells around the focal cell (procedure 'focalmean' in ArcInfo).

Environmental input variables: maps for modelling the potential historical distribution. We used 19 global climate data maps including temperature and precipitation parameters calculated from long-term time series (1950-2000) of monthly values (Hijmans et al., 2005; http://www.worldclim. org/bioclim; Fig. 3A; for a detailed list see Table SM1 subtext). We also created maps that contained information on landscape attributes such as aspect, terrain ruggedness and distance to water courses, which are important for some species such as flat-headed cat Prionailurus planiceps Vigors & Horsfield (Wilting et al., 2010). Aspect and terrain analyses were based on a digital elevation model (DEM, 90m raster resolution; http://srtm.csi.cgiar.org). Aspect was calculated using the extension Spatial Analyst in ArcView 9.3.1. The Topographic Ruggedness Index (TRI, Riley et al., 1999) expresses the elevational difference between each cell of the DEM and its eight nearest neighbours (Moore neighbourhood), with ruggedness classes ranging from one (level) to seven (extremely rugged). Hydrologic analyses (Hydrologic Analysis in Spatial Analyst) included flow directions calculated to derive a subsequent river net. We used a single flow direction approach, that is, the flow

Table 1. Reference numbers for museums and for individual contributors. There is no connection between the Museums (left) and the individual (right).

Museum Name	Scientists
American Museum of Natural History, New York, U.S.A. (AMNH)	Amanda Peter
Museum für Naturkunde, Berlin, Germany (ZMB)	Andjar Rafiastanto
Bernice P. Bishop Museum, Honolulu, Hawaii, U.S.A. (BPBM)	Andrew J. Marshall
Natural History Museum, London, U.K. (BMNH)	Azlan Mohamed & Andreas Wilting*
Museum Zoologicum Bogoriense, Bogor, Java, Indonesia (MZB)	Ben Wielstra & Sander Pieterse*
Zoologisches Forschunginstitut und Museum Alexander König, Bonn, Germany (ZFMK)	Brent Loken
Brunei Forest Center, Sungai Liang, Brunei, Darussalam	Craig Robson
Brunei Museum, Bandar Seri Begawan, Brunei Darussalam	Danielle Kreb
Institut Royal des Sciences Naturelles de Belgique, Brussels, Belgium (IRSNB)	Dave Augeri
Staatliches Museum für Tierkunde, Dresden, Germany (MTKD)	Edward Pollard
Field Museum of Natural History, Chicago, Illinois, U.S.A. (FMNH)	Erik Meijaard
Naturmuseum und Forschungsinstitut Senckenberg, Frankfurt, Germany (SMF)	Gabriella Fredriksson
Zoological Survey of India, Calcutta, India (ZSI)	Godwin Limberg
University of Kansas Museum of Natural History, Lawrence, Kansas, U.S.A. (KU)	Gono Semiadi & Hiromitsu Samejima*
University of Malaya, Kuala Lumpur, Malaysia (UMKL)	Hans Skotte Moeller
Musée National d'Histoire Naturelle, Paris, France (MNHN)	Henry Bernard
Museo Civico di Storia Naturale Giacomo Doria, Genova, Italy (MSNG)	Hiromitsu Samejima
	•
Museum of Comparative Zoology, Harvard University, Cambridge, Massachusetts. U.S.A. (MCZ)	Hiroshi Sasaki
University Museum of Zoology, University of Cambridge, U.K. (UMZC)	J. W. Duckworth
National Museums of Scotland, Edinburgh, Scotland (NMSZ)	James Eaton
Universitetets I Oslo, Zoologisk Museum, Oslo, Norway (ZMUO)	Jason Hon
Rijksmuseum van Natuurlijke Historie 'Naturalis', Leiden, Netherlands. (RMNH)	Jedediah Brodie & Anthony Giordano*
Naturhistorisches Museum Basel, Basel, Switzerland (NMBA)	Joanna Ross & Andrew Hearn*
Naturhistorisches Museum, Vienna, Austria (NMW)	John D. Pilgrim
OZCAM (Online Zoological Collections of Australian Museums) Provider	John Howes
Sabah Museum, Kota Kinabalu, Sabah, Malaysia (SBM)	John Mathai
Collection of Sabah Parks, Sabah, Malaysia	Jon Hall
Sarawak Museum, Kuching, Sarawak, Malaysia (SMK)	Konstans Wells
National Museum of Natural History, Washington D.C., U.S.A. (USNM)	Lim Boo Liat
Staatliches Museum fuer Naturkunde in Stuttgart, Germany (SMNS)	Mark Bezuijen
Naturhistoriska Riksmuseet, Goteborg, Sweden (NHMG)	Martjan Lammertink
National Museum of Victoria, Melbourne, Victoria, Australia (NMV)	Matt Heydon
Universiteit van Amsterdam, Zoologisch Museum, Amsterdam (ZMA)	Miyabi Nakabayashi
Zoological Museum, University of Copenhagen, Copenhagen, Denmark (ZMUC)	Norman Lim
Zoological Reference Collection, National University of Singapore, Singapore. (ZRC)	Ramesh Boonratana
Zoologische Museum Staatssammlung, München, Germany (ZSM)	Rob Stuebing
20010gisene iviuseum suaussammung, iviunenen, Germany (2014)	Roger Wilkinson
	Rustam
	Shai Meiri
	Sophie Persey
	Susan Cheyne
	Tim van Berkel
	Tjalle Boorsma
	Vladimir Dinets
	William J. McShea & Peter L. Erb* Yoshishiro Nakashima

^{*} records were collected in a joint effort

Table 2. Borneo carnivore occurrence records with spatial precision categories 1–3 (< 5 km radius) collected before 2001 and during 2001–2011; for 29 records no date could be assigned (abbreviations: ct = camera-trapping, ds = direct sighting, hr = hunters' relic, rk = road kill). Literature included the van Strien (2001) database; scientist records include verified records collected in local communities and villages. Individual species localities provided by multiple sources were treated as described in the text.

								Type of record	record									
	Mus	Museum	Liter	Literature	Direct Sighting	ighting	Camera-trap	a-trap	Hunted	ted	Road Kill	Kill	Live-trapped	apped	Scientist	ntist	Sum	Е
Species	before 2001	2001– 2011	before 2001	2001– 2011	before 2001	2001– 2011	before 2001	2001– 2011	before 2001	2001– 2011	before 2001	2001– 2011	before 2001	2001– 2011	before 2001	2001– 2011	before 2001	2001– 2011
Mustelidae																		
Martes flavigula	29		3	7	23	16		79							3		28	26
Mustela nudipes	27	1	1		22	29	1	~	1		7	7		1			54	41
Melogale everetti	21	П				_								_			21	3
Mephitidae	-		r	-	0	٥		00	-			6			-		7.0	101
Myaaus Javanensis	13		n	-	13	0		69	-			n			-		2/	101
Prionodintidae Prionodon linsang	21	2	3		10	12		37								2	34	53
Viverridae																		
Viverra tangalunga	52		3	3	42	34		249					7	П	4	4	103	291
Paradoxurus	58	1	7	4	52	27		143						1	7	7	114	178
hermaphroditus																		
Paguma larvata	28		7	т	14	13		37									44	53
Arctictis binturong	19		7	3	26	15		50		-					-	-	48	70
Arctogalidia	78	-	4	3	23	20		9		-						2	105	33
trivirgata																		
Hemigalus derbyanus	09		_	_	36	19		188		\mathcal{C}							97	212
Diplogale hosei	11		П	3		_		17						1			12	22
Cynogale bennettii	22		7		12	3		38									36	41
Herpestidae																		
Herpestes	42		2	4	14	11		129					2	1	2		62	145
brachyurus	-		t			,		7								,	ç	Ġ
Herpestes semitorquatus	10		_		٥	4		5/								2	C7	08
•																		

Table 2. Continued																		
								Type of record	record									
	Museum	mne	Literature	ıture	Direct S	Direct Sighting	Camera-trap	a-trap	Hunted	ted	Road Kill	Kill	Live-trapped	pbddı	Scientist Record	ntist	Sum	8
Species	before 2001– 2001 2011	2001– 2011	before 2001– 2001 2011	2001– 2011	before 2001– 2001 2011	2001– 2011	before 2001– 2001 2011		before 2001– 2001 2011	2001– 2011								
Felidae																		
Neofelis diardi	~		14	7	20	14	7	145		11					1	2	45	174
Pardofelis	9	7	5	_	9	3		53					-	П	_		19	09
Catopuma badia	ъ		П	11	S	2		25									6	38
Prionailurus	14		3		12	13		48		7			7				31	63
prunneeps Prionailurus bengalensis	34	С	11	8	34	24		178		8		-	3			7	82	214
Total per record type	556	11	70	4 4	376	269	3	1592	2	21	2	9	10	7	15	19	1034	1969
Total	267	7:	114	4	645	Š	1595	35	23	3	8		17		34	4	3003)3

from each cell was directed only to the steepest down-slope neighbouring cell. The cells in which flow accumulated were considered rivers according to the number of accumulated cells. We established flow accumulation cut-offs to 5000, 100,000 and 500,000 cells for small, medium and large perennial river systems, respectively. Corresponding catchment sizes were about 42 km², 850 km² and 4230 km², respectively. By combining the three river net maps with a map of the water bodies of Borneo (i.e., lakes and large rivers; country inland water data of the Digital Chart of the World, downloaded from: http://www.diva-gis.org) three distance-to-water maps were created.

Accounting for search-effort bias. Spatial distributions of records across Borneo were heterogeneous, therefore, we developed species-specific 'bias files' representing relative search efforts. We first mapped species records on our raster-based grid, and then assigned each cell with a score of 1 for species presence or 0 for absence. We summed the values within each cell's Moore neighbourhood to generate a map of search-effort density. We assigned the value 0.1 to cells with scores of 0, representing a 10-fold lower search effort than cells with a value of 1 (Kramer-Schadt et al. (2013) gave a detailed sensitivity analysis regarding bias file background values).

Habitat associations: maps for modelling the potential recent distribution. For each species, the suitability of land-cover classes and human population density to serve as each species's habitat was classified from 0 to 4 based on respondents' opinions, then rescaled from 0 to 1 (see below and Tables 2 in respective species papers). The respondents were scientists and conservationists working on carnivores and other species on Borneo. We calculated mean suitability score values from the respondents' scoring per map and species. From these averaged respondents' rankings we reclassified the land-cover attributes for species-specific (i) land use (L_i) and human population density (P_i) suitability maps.

Human population density (LandScan 2007TM High Resolution Global Population Data Set, Oak Ridge National Laboratory, UT-Battelle, LLC) was categorised as 0 = population densities too high for the species to occur regularly and therefore unsuitable, 0.25 = large negative effects, 0.5= medium effects, 0.75 = little impact and 1 = no effect on the species. Then, the mean values were calculated using the respondents' rankings. Despite some differences between respondents in ranking human population density as suitable habitat for each species, the influence of this variable on model results was quite low because high human population density was strongly associated with modified land-cover classes such as plantations, mixed crops, degraded forests, bare areas and burnt areas. Thus, information about respondents' reclassifications of human population density is omitted from the single-species papers, which focus on land-cover reclassification instead.

For land-cover, we used the PALSAR land-cover map validated for Borneo (Hoekman et al., 2009) from 2007

column 5) of spatial precision categories 1-3 (< 5 km radius; note that in species papers the total number of records includes categories 4 and 5). The difference between total number here and in Table 2 (3032 vs. 3003 records) is because for 29 records no date could be assigned. Record reduction (%) is shown for the balanced design (M₁ models in respective species papers, except for Bornean ferret badger *Melogale everetti* and Sunda Stink-badger *Mydaus javanensis* for which the reduction is shown for the Spatial Filtering M₂ model because of the range restriction of these Table 3. Number of Borneo carnivore occurrence records without reduction (column 2), after spatial filtering (distances of 2, 5, 10 km; column 3) and after geographic correction (Sabah reduction, species) compared with the full dataset (no reduction). AUCPO refers to scenarios based on all environmental layers including the bias file.

Species	No Reduction	Spatial Filtering (M ₂ models)	Filter Radius (km)	Sabah Reduction (balanced design) (M ₁ models)	Record Reduction (%)	AUC _{PO} Spatial Filtering	AUC _{PO} Balanced
Mustelidae							
Martes flavigula	156	94	5	99	64	0.735	0.67
Mustela nudipes	86	84	2	56	43	908.0	0.763
Melogale everetti	24	14	2	NA	42	0.995	NA
Mephitidae							
Mydaus javanensis	138	77	5	NA	44	0.912	NA
Prionodintidae							
Prionodon linsang	87	70	2	38	56	0.781	0.65
Viverridae							
Viverra tangalunga	394	115	10	69	82	0.747	0.661
Paradoxurus hermaphroditus	294	113	10	29	77	0.691	0.64
Paguma larvata	66	72	2	49	51	0.768	69.0
Arctictis binturong	118	83	2	47	09	0.807	0.701
Arctogalidia trivirgata	138	82	2	48	65	0.729	0.645
Hemigalus derbyanus	309	104	10	65	79	0.751	0.642
Diplogale hosei	34	24	2	20	41	0.942	0.957
Cynogale bennettii	83	64	2	23	72	0.794	0.495
Herpestidae							
Herpestes brachyurus	209	98	10	53	75	0.742	899.0
Herpestes semitorquatus	103	77	2	27	74	0.863	0.709
Felidae							
Neofelis diardi	219	94	5	48	78	0.772	0.569
Pardofelis marmorata	80	69	2	27	99	0.838	0.589
Catopuma badia	47	40	2	23	51	0.775	0.687
Prionailurus planiceps	105	92	2	50	52	0.789	0.713
Prionailurus bengalensis	297	102	10	63	79	0.701	0.645
Total	3032	1540		829			

NA = Not Applicable

Kramer-Schadt et al.: Methods for BCS distribution modelling

Table 4. Reclassification of the PALSAR land-cover map incorporating a digital elevation model (DEM) (see also Fig. 3 B).

Original Classification	Amended Classification
Tropical lowland forest	Lowland forest 0–500 m Upland forest 501–1000 m
Tropical mountain forest	Lower montane forest 1001–1500 m Upper montane forest above 1500 m
Forest mosaics / fragmented or degraded forests	Lowland forest: Forest mosaics/fragmented or degraded forests 0–500 m Upland forest: Forest mosaics/fragmented or degraded forests 501–1000 m *Lower montane forest: Forest mosaics / fragmented or degraded forests; 1001–1500 m *Upper montane forest: Forest mosaics / fragmented or degraded forests; above 1500 m
Riverine forest	Swamp forest
Swamp forest	
Peat swamp (pole) forest	
Peat swamp (padang) forest	
Mangrove forest	Mangrove
Nipah mangrove forest	
Plantations	Old plantations
High shrub	Young plantations and agriculture
Medium shrub	
Ferns/grass	Burned forest area
Grasslands	
Tree cover, burnt	
Cropland (upland)	Mixed crops
Cropland (irrigated)	Water and fishponds **
Water bodies	Water bodies
No data	No data

^{*}Categories not applicable to the reclassified map.

^{**}Groundtruthing revealed irrigated cropland to be mainly fishponds or other human-modified wetlands and was therefore reclassed to 'water and fishponds'.

with an original resolution of 50 m and resampled to the cell-size of the bioclimatic predictors using the 'majority' approach in ArcGIS 9.3.1. We modified it with height information from the DEM in 500 m steps to allow a finer grain of land-cover classification (Table 4, Fig. 3 B). The respondents then assigned one of five categories to each land-cover type ranging from 0 to 1 with 0 = unsuitablehabitat, 0.25 = low suitability, 0.5 = medium suitability (e.g., potential use as corridor), 0.75 = high suitability and 1 =very high suitability. For certain species some respondents ranked particular land-cover classes as unsuitable whereas others ranked them as highly suitable. This indicates how little is known for some Bornean carnivores. Table 2 in each species paper of this supplementary issue gives the scoring of the land-cover classifications and including the range of the ranking as an indicator of consistency among the respondents.

III: THE BORNEO CARNIVORE DISTRIBUTION MODELLING

Modelling the potential bioclimatic distribution. We used MaxEnt v. 3.3.3a (www.cs.princeton.edu/~schapire/ maxent; Elith et al., 2006; Phillips et al., 2006) to associate occurrence records with abiotic environmental conditions. We ran MaxEnt with the default settings and evaluated the percentage contribution of each variable with a jackknife procedure. We ran 10 replicates and used mean probabilities predicted for further analyses. As a measure of SDM accuracy or discriminative power, respectively, generally the threshold independent and prevalence insensitive presence-only (PO) area under the curve (AUC_{PO}) produced by MaxEnt classifying background versus presence points are used (Yackulic et al., 2013). Models with an AUC > 0.7 are said to have fair discriminative power (Hosmer & Lemeshow, 1989); however, this is a statistical measure of how well the model could discriminate spatial variables depending on the input data. AUC and AUC_{PO} are not always good predictors of model quality in terms of ecological plausibility (Lobo et al., 2007; Kramer-Schadt et al., 2013; Yackulic et al., 2013). Therefore AUC_{PO} are presented only in Table 3 and are used for our sensitivity analysis (see below) to compare model performance, but are not used as a measure of model quality.

Habitat Suitability Index (HSI): modelling potential current distributions. Using MaxEnt, we produced a map estimating the relative probability of occurrence of each species i per grid cell (M_i) that was updated using the current species-specific land-cover (L_i) and population density (P_i) maps to derive a habitat suitability index (HSI_i) for potential recent distributions (Fig. 1) following a modified equation of Wilting et al. (2010) that places greater weight on the current land-cover map:

$$HSI_i = (M_i^2 * L_i^3 * P_i)^{1/6}$$
 (1).

We placed lesser weight on the human population density map as species' responses to human population densities are largely unknown for Bornean carnivores. However, by including the human population density map with a lower weight in analyses we attempted to account for this potential effect.

Sensitivity analysis of the MaxEnt model. We conducted uncertainty analyses on the MaxEnt potential bioclimatic distribution layer to account for potential effects of clumping of species records because of search-effort bias, background adjustment with bias files and multicollinearity of environmental input layers. To this end, we compared model runs conducted with the full set of input records (termed 'no reduction') with systematically filtered species records (i.e. 2-10 km reduction termed spatial filtering and reduction proportionally to the size of Sabah termed balanced design). Additionally, we assessed the sensitivity of model outputs by omitting the bias files and we ran all models with a reduced set of uncorrelated (Pearson's moment correlation |r| < 0.75) environmental input layers (see Table SM2 subtext for the reduced set).

We evaluated sensitivity based on changes in the AUC_{PO} values and applied two cut-off values based on the relative probability of occurrence (>0.5 and >0.7) and calculated the total area above these thresholds in relation to the total area of Borneo. These cut-off values were used only to assess relative changes in spatial model predictions within the same data set, and not used as thresholds to categorise suitable and unsuitable areas (Tables SM1, SM2; see also Kramer-Schadt et al., 2013).

Results of the sensitivity analysis. Multicollinearity of input layers did not strongly affect model outputs, because the predicted areas increased only marginally (Table SM2; see also Kramer-Schadt et al., 2013). The use of a bias file did not affect AUC_{PO}s (Table SM1), though the extent of spatial predictions increased with the use of a background bias file in sensitivity scenarios (Table SM2). This increase was negligible in the balanced scenarios and core areas (areas above cut-off with relative occurrence probability >0.7). Reducing clumping of records using spatial filtering also did not affect model AUCPOS for most species compared with model results using the full data set (Table SM1). By contrast, balancing the number of records in Sabah relative to the total survey effort in Borneo reduced AUCPOS for most species up to one order of magnitude (Table 3). However, Kramer-Schadt et al. (2013) demonstrated that model quality, despite the reduced AUC_{PO} in the balanced model, was actually higher in these models because they showed lower omission and commission errors than did models based on the full dataset. For well-surveyed areas such as Sabah the models with spatial filtering showed the lowest number of omission and commission errors (Kramer-Schadt et al., 2013). Therefore, we divided our analyses. Fig. 2 in most of the specific species papers (excepting those species recorded solely or very largely from Sabah) shows an insert (Figure 2A) for Sabah, which is based on the spatial filtering model, whereas Figure 2B is based on the balanced model. Each species distribution map in the respective species papers shows the protected area network, consisting of fully protected areas as well as, for Indonesia, forest reserves (such information was not available for

Brunei and Malaysia), because forests still can contribute to conservation if well managed (http://gislab.cifor.cgiar.org/wm/borneo/; Struebig et al., 2015a). We updated this map with latest information on recently protected areas in Sabah, Malaysia, provided by the Sabah Forestry Department, Forest Resource Management (FRM) Division.

Threshold maps for delineating possible conservation hotspots. To be able to compare all species models with their relative probabilities of occurrence (HSI value), we standardised all maps by converting the HSI values into binary maps separating the predictions into suitable and unsuitable. We used the commonly applied 10% and 25% omission error thresholds to yield a liberal and a conservative suitability prediction, respectively, allowing for some leeway in interpreting model results. These binary threshold maps were then combined in Mathai et al. (2016) to map those areas with the highest possible occurrence probability of selected (as indicated by the respective map) carnivore species. These combined overlays were used to discuss and delineate areas of conservation priorities.

SYNTHESIS AND DISCUSSION

To map predictions of the potential bioclimatic distributions (MaxEnt projections), we used the results of the balanced design M₁ (for Sabah, the spatial filtering design M₂) together with the bias file. The uncertainty analyses revealed that model AUC_{PO}s were robust to multicollinearity and the use of bias files, however, AUC_{PO}s were reduced below 0.7 for some species. This does not mean that models do not project species distributions effectively, because a perfect model can have a low AUC_{PO} value if the species's detection probability is low in a certain area or if it experiences frequent local extinctions (Yackulic et al., 2013). Although we considered potential sources of bias in our modelling approach and balanced our design as much as possible, spatial searcheffort bias still affected model performance. That is, relative probability of occurrence produced by MaxEnt is partly related to search effort (see Kramer-Schadt et al., 2013). However, it is not possible with available data to account further for spatial bias. Consequently, species distribution maps should be interpreted with caution.

To aid model validation and interpretation, a threshold is usually applied to develop binary maps of suitable and unsuitable areas (Liu et al., 2005). Severe variation in predicted suitable areas using varying thresholds can occur; thus the selection of a threshold can have a strong effect on results (Liu et al., 2005). To avoid this shortcoming, we used continuous relative probability measures to estimate species habitat suitability and used fixed thresholds only for sensitivity analyses (Table SM2). For the summarising map overlays (as in Mathai et al. 2016) we used the commonly applied thresholds (see above).

The MaxEnt distribution was one of three factors we used to predict potential species distributions. A strength of our modelling approach is that we considered multiple sources of information to estimate habitat suitability. We placed greatest emphasis on current land-cover class that was refined by respondents' knowledge. In doing so, we ameliorated model accuracy by updating predictions with rule-based models (Yamada et al., 2003). In line with our approach, Beck et al. (2014) showed that spatial filtering provided more accurate projections.

Discussions regarding projected distributions, habitat associations and conservation needs of each species follow in the species-specific papers, where modelled relationships are examined using our current state of knowledge. That speaking, the maps do not predict the actual distribution of the species, they predict conditions suitable for the species in respect of the modelled attributes. Other non-modelled aspects like dispersal barriers and targeted overhunting may mean the species is not there. These aspects are thoroughly discussed in the single species papers. Our intent is that results of this effort will assist with future prioritisation of conservation and research efforts for carnivores on Borneo. New data, particularly additional occurrence records, can be used to refine the projected species distributions and provide independent assessments of projections presented in this initial effort.

ACKNOWLEDGEMENTS

We thank Klara Strube, Lena Katharina Schmidt, Anne K. Scharf and Moritz Wenzler for help compiling the data. We are grateful to J. L. Belant and J. W. Duckworth for providing helpful comments to improve the manuscript.

LITERATURE CITED

Araujo MB & Guisan A (2006) Five (or so) challenges for species distribution modelling. Journal of Biogeography, 33: 1677–1688

Beck J, Böller M, Erhardt A & Schwangart W (2014) Spatial bias in the GBIF database and its effect on modelling species' geographic distributions. Ecological Informatics, 19: 10–15.

Dormann CF, McPherson JM, Araujo MB, Bivand R, Bolliger J, Carl G, Davies RG, Hirzel A, Jetz W, Kissling WD, Kuehn I, Ohlemueller R, Peres-Neto PR, Reineking B, Schroeder B, Schurr FM & Wilson R (2007) Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. Ecography, 30: 609–628.

Elith J, Graham CH, Anderson RP, Dudik M, Ferrier S, Guisan A, Hijmans RJ, Huettman F, Leathwick JR, Lehmann A, Li J, Lohmann L-G, Loiselle BA, Manion G, Moritz C, Nakamura M, Nakazawa Y, Overton JM, Peterson AT, Phillips SJ, Richardson K, Scachetti-Pereira R, Schapire RE, Soberon J, Williams S, Wisz MS & Zimmermann NE (2006) Novel methods improve prediction of species' distributions from occurrence data. Ecography, 29: 129–151.

Elith J & Leathwick JR (2009) Species distribution models: ecological explanation and prediction across space and time. Annual Review of Ecology and Systematics, 40: 677–697.

Elith J, Phillips S, Hastie T, Dudik M, Chee YE & Yates C (2011) A statistical explanation of MaxEnt for ecologists. Diversity and Distributions, 17: 43–57.

Graham CH, Elith HJ, Hijmans RJ, Guisan A, Peterson AT, Loiselle BA & the NCEAS Predicting Species Distributions Working Group (2008) The influence of spatial errors in species occurrence data used in distribution models. Journal of Applied Ecology, 45: 239–247.

- Hijmans RJ, Cameron SE, Parra JL, Jones PG & Jarvis A (2005) Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology, 25: 1965–1978.
- Hoekman D, Vissers M & Wielaard N (2009) PALSAR land cover mapping methodology validation study Borneo. Wageningen University, Wageningen, the Netherlands, 112 pp.
- Hoffmann M, Belant JL, Chanson JS, Cox NA, Lamoreux J, Rodrigues ASL, Schipper J & Stuart SN (2011) The changing fates of the world's mammals. Philosophical Transactions of the Royal Society B, 366: 2598–2610.
- Hosmer DW & Lemeshow S (1989) Applied logistic regression. Wiley, New York, U.S.A., 307 pp.
- Kanagaraj R, Wiegand T, Mohamed A & Kramer-Schadt S (2013) Modelling species distributions to map the road towards carnivore conservation in the tropics. Raffles Bulletin of Zoology, Supplement 28: 85–107.
- Kramer-Schadt S, Niedballa J, Pilgrim JD, Schröder B, Lindenborn J, Reinfelder V, Stillfried M, Heckmann I, Scharf AK, Augeri DM, Cheyne SM, Hearn AJ, Ross J, Macdonald DW, Mathai J, Eaton J, Marshall AJ, Semiadi G, Rustam R, Bernard H, Alfred R, Samejima H, Duckworth JW, Breitenmoser-Wuersten C, Belant JL, Hofer H & Wilting A (2013) The importance of correcting for sampling bias in MaxEnt species distribution models. Diversity and Distributions, 19: 1366–1379.
- Li W & Guo QEC (2011) Can we model the probability of presence of species without absence data? Ecography, 34: 1096–1105.
- Liu C, Berry PM, Dawson TP & Pearson RG (2005) Selecting thresholds of occurrence in the prediction of species distributions. Ecography, 28: 385–393.
- Lobo JM, Jimenez-Valverde A & Real R (2007) AUC: a misleading measure of the performance of predictive distribution models. Global Ecology & Biogeography, 17: 145–151.
- Louzao M, Aumont O, Hothorn T, Wiegand T & Weimerskirch H (2013) Foraging in a changing environment: habitat shifts of an oceanic predator over the last half century. Ecography, 36: 57–67.
- Mathai J, Duckworth JW, Meijaard E, Fredriksson G, Rustam, Hon J, Sebastian A, Ancrenaz M, Hearn A, Ross J, Cheyne S, Borneo Carnivore Consortium & Wilting A (2016) Carnivore conservation planning on Borneo: identifying key carnivore landscapes, research priorities and conservation interventions. Raffles Bulletin of Zoology, Supplement 33: 186–216.
- Mohd-Azlan J, Belant JL & Meijaard E (2013) Can secondary information inform about population trends of carnivores in Borneo? Raffles Bulletin of Zoology, Supplement 28: 1–8.
- Pearce JL & Boyce MS (2006) Modelling distribution and abundance with presence-only data. Journal of Applied Ecology, 43: 405–412
- Phillips SJ (2008) Transferability, sample selection bias and background data in presence-only modelling: a response to Peterson et al. (2007). Ecography, 31: 272–278.
- Phillips SJ, Anderson RP & Schapire RE (2006) Maximum entropy modeling of species geographic distributions. Ecological Modelling, 190: 231–259.
- Phillips SJ & Dudik M (2008) Modeling of species distributions with MaxEnt: new extensions and a comprehensive evaluation. Ecography, 31: 161–175.
- Phillips SJ, Dudik M, Elith J, Graham CH, Lehmann A, Leathwick J & Ferrier S (2009) Sample selection bias and presence-only distribution models: implications for background and pseudoabsence data. Ecological Applications, 19: 181–197.
- Riley SJ, De Gloria SD & Elliot R (1999) A terrain ruggedness that quantifies topographic heterogeneity. Intermountain Journal of Science, 5: 23–27.

- Royle JA, Chandler RB, Yackulic C & Nichols JD (2012) Likelihood analysis of species occurrence probability from presence-only data for modelling species distributions. Methods in Ecology and Evolution, 3: 545–554.
- Schipper J, Chanson JS, Chiozza F, Cox NA, Hoffmann M, Katariya V, Lamoreux J, Rodrigues ASL, Stuart SN, Temple HJ, Baillie J, Boitani L, Lacher TE, Mittermeier RA, Smith AT, Absolon D, Aguiar JM, Amori G, Bakkour N, Baldi R, Berridge RJ, Bielby J, Black PA, Blanc JJ, Brooks TM, Burton JA, Butynski TM, Catullo G, Chapman R, Cokeliss Z, Collen B, Conroy J, Cooke JG, da Fonseca GAB, Derocher AE, Dublin HT, Duckworth JW, Emmons L, Emslie RH, Festa-Bianchet M, Foster M, Foster S, Garshelis DL, Gates C, Gimenez-Dixon M, Gonzalez S, Gonzalez-Maya JF, Good TC, Hammerson G, Hammond PS, Happold D, Happold M, Hare J, Harris RB, Hawkins CE, Haywood M, Heaney LR, Hedges S, Helgen KM, Hilton-Taylor C, Hussain SA, Ishii N, Jefferson TA, Jenkins RKB, Johnston CH, Keith M, Kingdon J, Knox DH, Kovacs KM, Langhammer P, Leus K, Lewison R, Lichtenstein G, Lowry LF, Macavoy Z, Mace GM, Mallon DP, Masi M, McKnight MW, Medellin RA, Medici P, Mills G, Moehlman PD, Molur S, Mora A, Nowell K, Oates JF, Olech W, Oliver WRL, Oprea M, Patterson BD, Perrin WF, Polidoro BA, Pollock C, Powel A, Protas Y, Racey P, Ragle J, Ramani P, Rathbun G, Reeves RR, Reilly SB, Reynolds JE, Rondinini C, Rosell-Ambal RG, Rulli M, Rylands AB, Savini S, Schank CJ, Sechrest W, Self-Sullivan C, Shoemaker A, Sillero-Zubiri C, De Silva N, Smith DE, Srinivasulu C, Stephenson PJ, van Strien N, Talukdar BK, Taylor BL, Timmins R, Tirira DG, Tognelli MF, Tsytsulina K, Veiga LM, Vie JC, Williamson EA, Wyatt SA, Xie Y & Young BE (2008) The status of the world's land and marine mammals: diversity, threat, and knowledge. Science, 322: 225-230.
- Struebig MJ, Wilting A, Gaveau, DLA, Smith RJ, the Borneo Mammal Distribution Consortium, Fischer M, Metcalfe K & Kramer-Schadt S (2015a) Targeted conservation to safeguard a biodiversity hotspot from climate and land-cover change. Current Biology, 25: 372–378.
- Struebig MJ, Fischer M, Gaveau DL, Meijaard E, Wich SA, Gonner C, Sykes R, Wilting A & Kramer-Schadt S (2015b) Anticipated climate and land-cover changes reveal refuge areas for Borneo's Orang utans. Global Change Biology, 21: 2891–2904.
- van Strien N (2001) Indoaustralian mammals. A taxonomic and faunistic reference and atlas. ETI, Amsterdam, the Netherlands, non-paginated CD format.
- Veloz SD (2009) Spatially autocorrelated sampling falsely inflates measures of accuracy for presence-only niche models. Journal of Biogeography, 36: 2290–2299.
- Wilting A, Cord A, Hearn A, Hesse D, Mohamed A, Traeholdt (sic)
 C, Cheyne SM, Sunarto S, Mohd-Azlan J, Ross J, Shapiro AC,
 Sebastian A, Dech S, Breitenmoser C, Sanderson J, Duckworth
 JW & Hofer H (2010) Modelling the species distribution of
 Flat-headed Cats (*Prionailurus planiceps*), an Endangered
 South-east Asian small felid. PLoS One, 5(3): e9612.
- Yackulic CB, Chandler R, Zipkin EF, Royle JA, Nichols JD, Campbell Grant EH & Veran S (2013) Presence-only modelling using MaxEnt: when can we trust the inferences? Methods in Ecology and Evolution, 4: 236–243.
- Yamada K, Elith J, McCarthy M & Zerger A (2003) Eliciting and integrating expert knowledge for wildlife habitat modelling. Ecological Modelling, 165: 251–264.

SUPPLEMENTARY MATERIAL

Table SM1. Sensitivity analysis of species distribution models of Bornean carnivores showing the three most important bioclimatic layers (Variable) with the highest contribution (% cont.) to explaining the distribution of records as well as AUC_{PO} . Only model results calculated from all listed environmental layers are shown, i.e. sensitivity analysis was not conducted for scenarios with 'non-correlated' environmental layers only. **Bold**: model runs (Balance models M_1) used to assess current distributions in the habitat suitability index (HSI) throughout Borneo (except for Sabah projections which derive from the spatially filtered models M_2). For Bornean ferret badger *Melogale everetti* and Sunda stink-badger *Mydaus javanensis* only the projections of the Spatial Filtering M_2 model were used because of the range restriction of these species). See table subtext for detailed description of variables.

Model		F	Reduction Saba	h (balanced) I	\mathbf{M}_1	
Bias File Used		Yes			No	
Species	AUC _{PO}	Variable ¹	% Cont.	AUC _{PO}	Variable	% cont.
Martes flavigula	0.67	bio_02 bio_22 bio_25	37.8 17.4 12.9	0.671	bio_02 bio_22 bio_25	33.1 16.7 13
Mustela nudipes	0.763	bio_07 bio_17 bio_04	17.6 12.8 12.2	0.755	bio_04 bio_07 bio_19	15.8 15.1 12.6
Melogale everetti	0.995	bio_09 bio_12 bio_17	28.7 23.5 8.2	0.995	bio_09 bio_12 bio_17	24.8 24.1 9.2
Mydaus javanensis	0.746	bio_02 bio_27 bio_25	46.7 34.3 6.1	0.751	bio_02 bio_27 bio_25	44.8 34.4 6.7
Prionodon linsang	0.65	bio_18 bio_26 bio_14	20.6 17.2 9.3	0.648	bio_18 bio_26 bio_14	18.8 15.8 8.9
Viverra tangalunga	0.661	bio_22 bio_08 bio_02	30.7 9.4 8.5	0.662	bio_22 bio_02 bio_08	29.7 9.1 8
Paradoxurus hermaphroditus	0.64	bio_13 bio_21 bio_15	14.2 12.8 11.4	0.642	bio_21 bio_13 bio_12	13.3 12.9 12.1
Paguma larvata	0.69	bio_15 bio_22 bio_07	27.7 20.8 8.5	0.686	bio_15 bio_22 bio_13	29.2 19 12.5
Arctictis binturong	0.701	bio_07 bio_15 bio_22	38.8 17.5 12.9	0.707	bio_07 bio_15 bio_22	34.8 17.8 11.1
Arctogalidia trivirgata	0.645	bio_02 bio_14 bio_13	21.1 19.5 13.1	0.637	bio_14 bio_13 bio_02	17.3 16.4 15.2
Hemigalus derbyanus	0.642	bio_07 bio_14 bio_13	16.3 15 13.6	0.643	bio_13 bio_07 bio_14	16.1 13.9 13.3
Diplogale hosei	0.957	bio_05 bio_15 bio_27	46.6 26.5 8.1	0.856	bio_22 bio_09 bio_12	18 13.9 13.7
Cynogale bennettii	0.495	bio_22 bio_19 bio_09	19 14 13.9	0.494	bio_22 bio_09 bio_12	18 13.9 13.7

Model		R	Reduction Sabal	h (balanced) N	M_1	
Bias File Used		Yes			No	
Species	AUC _{PO}	Variable ¹	% Cont.	AUC _{PO}	Variable	% cont.
Herpestes brachyurus	0.668	bio_15	24.3	0.666	bio_15	21.1
		bio_07	16.2		bio_07	20.6
		bio_27	12.8		bio_27	11.4
Herpestes semitorquatus	0.709	bio_22	30.7	0.71	bio_22	29
		bio_27	16.7		bio_27	19.3
		bio_07	10.8		bio_07	8.5
Neofelis diardi	0.569	bio_07	25.3	0.569	bio_07	23.6
		bio_26	21.3		bio_26	20.5
		bio_22	9.3		bio_22	8.8
Pardofelis marmorata	0.589	bio_27	15.4	0.575	bio_27	16.2
		bio_26	14.9		bio_26	14.2
		bio_02	14.7		bio_02	13.8
Catopuma badia	0.687	bio_22	31.3	0.686	bio_22	30
		bio_07	21		bio_07	21.8
		bio_25	10.6		bio_25	10.5
Prionailurus planiceps	0.713	bio_13	15.8	0.716	bio_13	18.3
		bio_25	15.2		bio_25	15.2
		bio_06	14		bio_09	12.7
Prionailurus bengalensis	0.645	bio_22	23.6	0.641	bio_13	22.3
		bio_13	17.2		bio_22	19.9
		bio_02	15.7		bio_02	16

Sensitivity analysis - Alternative 1: no reduction of clumped data through spatial filtering

Model			No Rec	luction		
Bias File Used		Yes			No	
Species	AUC _{PO}	Variable	% Cont.	AUC _{PO}	Variable	% cont.
Martes flavigula	0.787	bio_02	40.3	0.791	bio_02	27.9
		bio_04	11.5		bio_04	11.7
		bio_08	7.2		bio_16	8.7
Mustela nudipes	0.825	bio_12	17.2	0.837	bio_12	17.1
		bio_02	16		bio_04	12.2
		bio_04	12.2		bio_02	11
Melogale everetti	0.996	bio_09	22	0.997	bio_12	20.4
		bio_12	17.6		bio_09	16.8
		bio_08	13.4		bio_08	13.6
Mydaus javanensis	0.946	bio_02	37.3	0.945	bio_02	29.3
		bio_18	20.2		bio_18	17.4
		bio_04	16.8		bio_04	16.2
Prionodon linsang	0.786	bio_22	27.4	0.788	bio_22	23.9
		bio_18	23		bio_18	18.3
		bio_04	9.1		bio_04	11
Viverra tangalunga	0.86	bio_02	36.1	0.862	bio_02	24.4
		bio_08	12.1		bio_08	10.5
		bio_18	11.3		bio_18	9.7
Paradoxurus hermaphroditus	0.839	bio_02	36.1	0.846	bio_02	29.3
		bio_18	17.2		bio_18	14.9
		bio_04	15.8		bio_04	12.9

Kramer-Schadt et al.: Methods for BCS distribution modelling

Model			No Rec	luction		
Bias File Used		Yes			No	
Species	AUC _{PO}	Variable	% Cont.	AUC _{PO}	Variable	% cont.
Paguma larvata	0.792	bio_22 bio_16 bio_08	31 20.9 7.2	0.794	bio_22 bio_16 bio_08	25.5 19.6 6.9
Arctictis binturong	0.823	bio_02 bio_22 bio_16	22.1 17.3 10.6	0.809	bio_22 bio_02 bio_16	14 13.7 12.5
Arctogalidia trivirgata	0.749	bio_02 bio_04 bio_16	34.3 18.1 13.6	0.75	bio_02 bio_16 bio_04	26.2 11.8 11.1
Hemigalus derbyanus	0.844	bio_02 bio_04 bio_07	24.3 13.4 11.9	0.838	bio_02 bio_04 bio_16	19.4 12.9 12.8
Diplogale hosei	0.948	bio_05 bio_09 bio_15	53.1 17 9.5	0.951	bio_05 bio_09 bio_15	44.3 17.8 12.5
Cynogale bennettii	0.792	bio_04 bio_02 bio_18	28.7 21.8 13.3	0.779	bio_04 bio_02 bio_18	24 19.1 11.7
Herpestes brachyurus	0.844	bio_02 bio_18 bio_17	28.8 17.8 11.3	0.836	bio_02 bio_18 bio_17	20.8 15.4 13.1
Herpestes semitorquatus	0.862	bio_02 bio_04 bio_22	21.1 15.8 15.5	0.857	bio_02 bio_04 bio_22	19.1 14.2 12.8
Neofelis diardi	0.808	bio_02 bio_12 bio_17	30.8 11.7 9.1	0.821	bio_02 bio_17 bio_12	22.1 11.5 10.3
Pardofelis marmorata	0.844	bio_02 bio_18 bio_22	28 22.3 11.6	0.84	bio_02 bio_18 bio_22	22.9 20.6 10.5
Catopuma badia	0.811	bio_22 bio_12 bio_15	27.8 10.7 8.3	0.8	bio_22 bio_12 bio_15	21.1 11.2 10.2
Prionailurus planiceps	0.787	bio_04 bio_06 bio_02	28.3 16.6 8.4	0.796	bio_04 bio_06 bio_03	26.4 12.7 9.4
Prionailurus bengalensis	0.817	bio_02 bio_04 bio_16	35.6 15.9 13.8	0.833	bio_02 bio_04 bio_16	23.6 14.2 14.1

Sensitivity analysis 2 - Spatial data filtering within 2, 5 or 10 km, respectively

Model		F	Reduction Saba	h (balanced) N	\mathbf{M}_{1}	
Bias File Used		Yes			No	
Species	AUC _{PO}	Variable ¹	% Cont.	AUC _{PO}	Variable	% cont.
Martes flavigula	0.735	bio_02 bio_22 bio_04	44.5 10.8 8.7	0.73	bio_02 bio_22 bio_04	37 9.7 8.9
Mustela nudipes	0.806	bio_22 bio_02 bio_04	11.8 11.5 11.3	0.806	bio_04 bio_19 bio_12	12.6 9.9 9.7
Melogale everetti	0.995	bio_09 bio_12 bio_17	28.7 23.5 8.2	0.995	bio_09 bio_12 bio_17	24.8 24.1 9.2
Mydaus javanensis	0.912	bio_02 bio_04 bio_18	38.9 32 9.2	0.908	bio_02 bio_04 bio_18	34.3 31.2 8.8
Prionodon linsang	0.781	bio_22 bio_18 bio_04	26.7 22.9 10.8	0.782	bio_22 bio_18 bio_04	23.4 18.7 11.5
Viverra tangalunga	0.747	bio_02 bio_04 bio_08	25.4 11.5 8.6	0.746	bio_02 bio_04 bio_08	22.1 12.7 7.1
Paradoxurus hermaphroditus	0.691	bio_02 bio_04 bio_18	30.7 16 6.5	0.689	bio_02 bio_04 bio_18	27.7 16.1 6.7
Paguma larvata	0.768	bio_22 bio_16 bio_21	29.8 22.8 5.9	0.77	bio_22 bio_16 bio_05	25.6 22 8.9
Arctictis binturong	0.807	bio_22 bio_02 bio_15	22.6 20 13.6	0.797	bio_22 bio_02 bio_15	19.3 16.2 15.2
Arctogalidia trivirgata	0.729	bio_02 bio_04 bio_16	35.9 18.2 12.4	0.732	bio_02 bio_04 bio_16	29.5 13 9.8
Hemigalus derbyanus	0.751	bio_02 bio_04 bio_07	18.7 17.8 13.2	0.75	bio_02 bio_04 bio_07	18 16.1 10.7
Diplogale hosei	0.942	bio_05 bio_09 bio_15	59.6 9.9 8	0.943	bio_05 bio_09 bio_15	54.2 9.6 9.3
Cynogale bennettii	0.794	bio_04 bio_02 bio_22	30.3 20.6 14.1	0.783	bio_04 bio_02 bio_22	26 18.9 13
Herpestes brachyurus	0.742	bio_02 bio_15 bio_18	20.1 12 11.2	0.745	bio_02 bio_15 bio_18	17.6 12.9 10.2
Herpestes semitorquatus	0.863	bio_02 bio_04 bio_22	21.4 16.7 14.8	0.86	bio_02 bio_04 bio_22	19.7 15.9 12.3

Kramer-Schadt et al.: Methods for BCS distribution modelling

Model		R	Reduction Saba	h (balanced) M	M_1	
Bias File Used		Yes			No	
Species	AUC _{PO}	Variable ¹	% Cont.	AUC _{PO}	Variable	% cont.
Neofelis diardi	0.772	bio_02	37	0.711	bio_02	31.4
		bio_04	14.3		bio_04	13.5
		bio_18	7.1		bio_18	7.4
Pardofelis marmorata	0.838	bio 02	27.8	0.832	bio 02	23.4
		bio 18	23.3		bio 18	21.1
		bio_22	11		bio_22	10.1
Catopuma badia	0.775	bio_22	28.9	0.755	bio 22	23.8
•		bio_12	10		bio 19	10.9
		bio_19	9.6		bio_12	10.3
Prionailurus planiceps	0.789	bio 04	25.3	0.79	bio 04	23.3
		bio_06	14.9		bio 06	14.1
		bio_21	9.5		bio_03	10.3
Prionailurus bengalensis	0.701	bio 02	36.1	0.703	bio 02	31.4
_		bio_04	21.6		bio 04	20.6
		bio_18	7.5		bio_18	7.1

bio_1 = annual mean temperature; bio_2 = mean diurnal range (mean of monthly (max temp - min temp)); bio_3 = isothermality (bio_2 / bio_7) (* 100); bio_4 = temperature seasonality (standard deviation of annual temperature *100); bio_5 = max temperature of warmest month; bio_6 = min temperature of coldest month; bio_7 = temperature annual range (bio_5 - bio_6); bio_8 = mean temperature of wettest quarter; bio_9 = mean temperature of driest quarter; bio_10 = mean temperature of warmest quarter; bio_11 = mean temperature of coldest quarter; bio_12 = annual precipitation; bio_13 = precipitation of wettest month; bio_14 = precipitation of driest month; bio_15 = precipitation seasonality (coefficient of variation); bio_16 = precipitation of wettest quarter; bio_17 = precipitation of driest quarter; bio_18 = precipitation of warmest quarter; bio_19 = precipitation of coldest quarter. bio_21 = distance to nearest small river and water bodies; bio_22 = ruggedness index; bio_25 = Aspect; bio_26 = distance to medium sized rivers and water bodies; bio_27 = distance to main rivers and water bodies.

Table SM2. Spatial sensitivity analysis of species distribution models of Bornean carnivores with area calculation above fixed thresholds of 0.5 and 0.7 relative occurrence probability as produced by MaxEnt. Bias 'yes'/ 'no' refers to inclusion of a bias file or not. 'All' variables relates to using all environmental layers as spatial input in contrast to only 'non-correlated' ones*. 'No reduction' refers to scenarios using all species records as input, 'spatial filtering' is referring to scenarios selecting only one record within a defined radius (M_2 models) and 'balanced' are scenarios that additionally account for the geographical bias in the input data by reducing input records in the state of Sabah (M_1 models).

all	no reduction	4.65	1.54
all	no reduction	13.91	2.80
all	Spatial filtering	10.37	2.60
all	Spatial filtering	16.49	3.09
all	balanced	18.10	2.53
all	balanced	22.82	2.31
-correlated	no reduction	6.01	2.30
-correlated	no reduction	13.88	3.17
-correlated	Spatial filtering	12.48	3.40
-correlated	Spatial filtering	17.10	3.31
-correlated	balanced	25.51	1.77
-correlated	balanced	28.50	1.57
all	no reduction	6.38	1.44
all	no reduction	14.32	3.06
all	Spatial filtering	8.99	1.98
all	Spatial filtering	15.28	2.93
all	balanced	8.75	2.22
all	balanced	13.95	3.04
-correlated	no reduction	8.93	2.24
-correlated	no reduction	16.06	3.40
-correlated	Spatial filtering	10.66	2.28
-correlated	Spatial filtering	17.15	3.16
-correlated	balanced	9.92	2.34
-correlated	balanced	14.87	2.95
all	no reduction	0.20	0.07
all	no reduction	0.66	0.31
all	Spatial filtering	0.18	0.08
all	Spatial filtering	1.15	0.34
all	balanced	0.18	0.08
all	balanced	1.15	0.34
-correlated	no reduction	0.20	0.08
-correlated	no reduction	0.75	0.31
-correlated	Spatial filtering	0.18	0.07
-correlated	Spatial filtering	1.55	0.45
-correlated	balanced	0.18	0.07
-correlated	balanced	1.55	0.45
all	no reduction	1.51	0.48
all	no reduction	4.83	1.52
all	Spatial filtering	3.34	1.36
all	Spatial filtering	6.27	2.31
all	balanced	6.80	1.87
all	balanced	10.04	2.23
-correlated	no reduction	2.12	0.81
			2.22
			1.69
			2.79
			1.98
			2.22
1	n-correlated n-correlated n-correlated n-correlated n-correlated	n-correlated no reduction n-correlated Spatial filtering n-correlated Spatial filtering n-correlated balanced	n-correlated no reduction 6.15 n-correlated Spatial filtering 4.52 n-correlated Spatial filtering 6.94 n-correlated balanced 8.78

Kramer-Schadt et al.: Methods for BCS distribution modelling

Species	Bias	Variables	Model	%area>0.5	%area>0.'
Prionodon linsang	no	all	no reduction	9.11	2.69
	yes	all	no reduction	13.65	3.32
	no	all	Spatial filtering	9.59	2.77
	yes	all	Spatial filtering	13.80	3.31
	no	all	balanced	16.93	2.17
	yes	all	balanced	20.57	2.04
	no	non-correlated	no reduction	10.30	3.40
	yes	non-correlated	no reduction	14.07	3.65
	no	non-correlated	Spatial filtering	10.47	3.46
	yes	non-correlated	Spatial filtering	14.16	3.68
	no	non-correlated	balanced	21.62	1.75
	yes	non-correlated	balanced	24.65	1.48
Viverra tangalunga	no	all	no reduction	4.07	1.32
	yes	all	no reduction	14.71	2.72
	no	all	Spatial filtering	8.66	2.46
	yes	all	Spatial filtering	15.39	2.92
	no	all	balanced	20.63	2.64
	yes	all	balanced	23.55	2.27
	no	non-correlated	no reduction	5.25	1.70
	yes	non-correlated	no reduction	17.10	2.69
	no	non-correlated	Spatial filtering	10.31	2.87
	yes	non-correlated	Spatial filtering	17.02	3.01
	no	non-correlated	balanced	25.92	1.83
	yes	non-correlated	balanced	28.57	1.43
Paradoxurus hermaphroditus	no	all	no reduction	4.27	1.56
•	yes	all	no reduction	12.29	3.20
	no	all	Spatial filtering	9.22	2.93
	yes	all	Spatial filtering	13.68	3.32
	no	all	balanced	17.41	2.56
	yes	all	balanced	22.05	2.55
	no	non-correlated	no reduction	5.36	2.20
	yes	non-correlated	no reduction	13.78	3.31
	no	non-correlated	Spatial filtering	11.60	3.15
	yes	non-correlated	Spatial filtering	15.55	3.20
	no	non-correlated	balanced	20.42	2.58
	yes	non-correlated	balanced	24.36	2.02
Paguma larvata	no	all	no reduction	9.69	2.03
	yes	all	no reduction	14.92	3.34
	no	all	Spatial filtering	10.42	2.22
	yes	all	Spatial filtering	14.96	3.14
	no	all	balanced	11.84	3.08
	yes	all	balanced	15.88	3.17
	no	non-correlated	no reduction	13.20	2.71
	yes	non-correlated	no reduction	18.53	3.62
	no	non-correlated	Spatial filtering	14.08	3.21
	yes	non-correlated	Spatial filtering	18.65	3.58
	no	non-correlated	balanced	13.10	3.79
	yes	non-correlated	balanced	18.18	3.73

Species	Bias	Variables	Model	%area>0.5	%area>0.7
Arctictis binturong	no	all	no reduction	4.58	1.12
	yes	all	no reduction	13.16	2.71
	no	all	Spatial filtering	7.76	1.98
	yes	all	Spatial filtering	14.60	2.80
	no	all	balanced	12.19	2.99
	yes	all	balanced	16.01	3.36
	no	non-correlated	no reduction	6.32	1.58
	yes	non-correlated	no reduction	15.37	2.72
	no	non-correlated	Spatial filtering	10.33	2.59
	yes	non-correlated	Spatial filtering	15.10	2.90
	no	non-correlated	balanced	13.30	3.68
	yes	non-correlated	balanced	16.04	3.75
Arctogalidia trivirgata	no	all	no reduction	10.11	2.38
	yes	all	no reduction	17.24	3.36
	no	all	Spatial filtering	11.02	2.25
	yes	all	Spatial filtering	17.44	3.24
	no	all	balanced	13.38	1.80
	yes	all	balanced	20.30	2.27
	no	non-correlated	no reduction	11.97	2.69
	yes	non-correlated	no reduction	18.46	3.29
	no	non-correlated	Spatial filtering	12.86	2.68
	yes	non-correlated	Spatial filtering	18.91	3.22
	no	non-correlated	balanced	15.53	2.07
	yes	non-correlated	balanced	21.80	2.29
Hemigalus derbyanus	no	all	no reduction	5.01	1.55
	yes	all	no reduction	14.37	2.77
	no	all	Spatial filtering	8.96	2.66
	yes	all	Spatial filtering	14.80	3.02
	no	all	balanced	17.77	2.37
	yes	all	balanced	23.60	2.20
	no	non-correlated	no reduction	6.53	2.02
	yes	non-correlated	no reduction	14.50	2.84
	no	non-correlated	Spatial filtering	11.60	2.98
	yes	non-correlated	Spatial filtering	16.24	3.02
	no	non-correlated	balanced	20.01	2.88
	yes	non-correlated	balanced	25.18	2.44
Diplogale hosei	no	all	no reduction	2.50	0.51
7.00	yes	all	no reduction	4.38	0.94
	no	all	Spatial filtering	2.81	0.58
	yes	all	Spatial filtering	4.32	0.91
	no	all	balanced	1.87	0.46
	yes	all	balanced	3.48	0.40
	no	non-correlated	no reduction	3.08	0.61
	yes	non-correlated	no reduction	4.84	0.01
	-	non-correlated	Spatial filtering	3.42	0.71
	no	non-correlated	Spatial filtering	4.80	0.71
	yes	non-correlated	balanced	2.36	0.51
	no yes	non-correlated	balanced	3.92	0.31

Kramer-Schadt et al.: Methods for BCS distribution modelling

Species	Bias	Variables	Model	%area>0.5	%area>0.'
Cynogale bennettii	no	all	no reduction	2.49	1.21
	yes	all	no reduction	6.34	2.34
	no	all	Spatial filtering	2.58	1.24
	yes	all	Spatial filtering	5.90	2.27
	no	all	balanced	15.70	2.25
	yes	all	balanced	18.21	2.27
	no	non-correlated	no reduction	3.33	1.50
	yes	non-correlated	no reduction	6.39	2.65
	no	non-correlated	Spatial filtering	3.21	1.50
	yes	non-correlated	Spatial filtering	6.05	2.47
	no	non-correlated	balanced	22.77	1.67
	yes	non-correlated	balanced	24.89	1.61
Herpestes brachyurus	no	all	no reduction	3.50	1.19
	yes	all	no reduction	11.17	2.56
	no	all	Spatial filtering	11.91	2.69
	yes	all	Spatial filtering	16.60	2.82
	no	all	balanced	16.49	2.13
	yes	all	balanced	20.13	2.18
	no	non-correlated	no reduction	4.09	1.58
	yes	non-correlated	no reduction	13.03	2.72
	no	non-correlated	Spatial filtering	14.57	3.40
	yes	non-correlated	Spatial filtering	18.90	3.55
	no	non-correlated	balanced	18.97	2.12
	yes	non-correlated	balanced	21.92	2.26
Herpestes semitorquatus	no	all	no reduction	2.24	1.08
	yes	all	no reduction	7.67	2.10
	no	all	Spatial filtering	2.51	1.21
	yes	all	Spatial filtering	7.33	2.18
	no	all	balanced	11.54	1.85
	yes	all	balanced	14.05	2.00
	no	non-correlated	no reduction	2.97	1.24
	yes	non-correlated	no reduction	8.32	2.41
	no	non-correlated	Spatial filtering	3.44	1.45
	yes	non-correlated	Spatial filtering	7.73	2.45
	no	non-correlated	balanced	12.84	1.54
	yes	non-correlated	balanced	15.94	1.64
Neofelis diardi	no	all	no reduction	3.16	1.20
	yes	all	no reduction	12.28	2.59
	no	all	Spatial filtering	6.85	2.02
	yes	all	Spatial filtering	13.30	2.95
	no	all	balanced	19.92	2.39
	yes	all	balanced	24.41	2.09
	no	non-correlated	no reduction	4.80	1.67
	yes	non-correlated	no reduction	14.37	2.85
	no	non-correlated	Spatial filtering	8.75	2.43
	yes	non-correlated	Spatial filtering	15.35	2.97
	no	non-correlated	balanced	25.32	2.01
	yes	non-correlated	balanced	28.44	1.80

Species	Bias	Variables	Model	%area>0.5	%area>0.
Pardofelis marmorata	no	all	no reduction	3.92	1.52
	yes	all	no reduction	9.36	2.98
	no	all	Spatial filtering	4.15	1.64
	yes	all	Spatial filtering	8.87	2.92
	no	all	balanced	13.14	2.33
	yes	all	balanced	17.71	2.47
	no	non-correlated	no reduction	5.11	1.98
	yes	non-correlated	no reduction	10.09	3.03
	no	non-correlated	Spatial filtering	5.44	2.11
	yes	non-correlated	Spatial filtering	9.70	3.00
	no	non-correlated	balanced	14.24	2.46
	yes	non-correlated	balanced	19.01	2.48
Catopuma badia	no	all	no reduction	3.53	1.07
	yes	all	no reduction	9.87	2.14
	no	all	Spatial filtering	4.17	1.28
	yes	all	Spatial filtering	9.47	2.15
	no	all	balanced	15.74	1.81
	yes	all	balanced	17.93	1.84
	no	non-correlated	no reduction	5.71	1.73
	yes	non-correlated	no reduction	12.66	2.24
	no	non-correlated	Spatial filtering	7.49	1.94
	yes	non-correlated	Spatial filtering	12.63	2.34
	no	non-correlated	balanced	21.85	1.81
	yes	non-correlated	balanced	24.66	1.78
Prionailurus planiceps	no	all	no reduction	6.67	2.03
	yes	all	no reduction	13.24	3.25
	no	all	Spatial filtering	7.51	2.22
	yes	all	Spatial filtering	13.03	3.10
	no	all	balanced	10.70	2.26
	yes	all	balanced	15.44	2.63
	no	non-correlated	no reduction	10.37	2.94
	yes	non-correlated	no reduction	16.05	3.70
	no	non-correlated	Spatial filtering	11.61	3.15
	yes	non-correlated	Spatial filtering	15.95	3.59
	no	non-correlated	balanced	13.92	2.18
	yes	non-correlated	balanced	17.38	2.40
Prionailurus bengalensis	no	all	no reduction	5.09	1.63
	yes	all	no reduction	15.74	2.81
	no	all	Spatial filtering	9.65	2.70
	yes	all	Spatial filtering	15.62	3.01
	no	all	balanced	16.51	2.13
	yes	all	balanced	21.89	2.07
	no	non-correlated	no reduction	7.31	2.35
	yes	non-correlated	no reduction	16.14	3.51
	no	non-correlated	Spatial filtering	10.70	3.09
	yes	non-correlated	Spatial filtering	16.54	3.16
	no	non-correlated	balanced	20.82	1.77
	yes	non-correlated	balanced	25.86	1.77

 $[*]Non-correlated variables comprise: bio_1, 4, 7, 13, 14, 15, 22, 26 and 27 (for description see table subtext SM1; for correlation matrix: see Supplementary Material in Kramer-Schadt et al., 2013).$