Chapter 6

HABITAT SUITABILITY MODELING OF SMALL FELIDS, VIVERRIDS AND HERPESTIDS

6.1 Introduction

An understanding of the relationship between spatial distribution of animals and their habitat parameters plays an important role in conservation and management of lesser known species. Remote sensing and geographical information system (GIS) can be used as a tool for deriving information on the habitat preference of wildlife species. Research has become increasingly focused on the extrapolation of species distribution from incomplete data or a really small data set to obtain reliable distribution maps efficiently. By processing environmental information and presence/absence data, several statistical methods can provide estimates on the probability of occurrence of a given species (Guisan and Zimmermann 2000). Poorly known species are usually represented by low numbers. The ecological niche can be defined as the set of environmental conditions (abiotic factors) under which a species is able to maintain viable populations without immigration (Grinnell 1924). The quality of model predictions can be affected by the quality of the source data. Models can be weakened either by propagating errors inherent in the data-gathering processes or by not including all relevant ecological data. Niche-based modelling of potential distributions has been used recently to examine various ecological and evolutionary aspects, such as competition between phylogenetically related species (Mukherjee et al., 2010) or variation in species niche requirements through evolutionary time (Peterson and Holt 2003). At geographic scales habitat models provide a way to develop hypotheses about features that affect distribution (Manel et al., 2000). Distribution models should consider appropriate scale (spatial and temporal), predictive ability, and include an assessment of uncertainty. The challenge of developing habitat models at large scales, and using them to monitor habitat suitability, has been undertaken using various approaches. Identifying proper variables, but at an incorrect scale, may lead to weak or incorrect apparent relationships.
Predictive habitat modeling and mapping, based on species habitat relationships forms an analytical foundation for informed conservation planning, mapping patterns of biodiversity, detecting distributional changes from monitoring data and quantifying how variation in species performance is related to one or several controlling factors (Phillips et al., 2006). Predictive species mapping lays its foundation in the ecological niche-theory and predictor analysis from the spatial distribution of variables that correlate with or control the species occurrence. Available and published distribution maps on small carnivores in India in books and reports were created traditionally by compiling locality records in the species distribution range.

Predictive models provide an alternative way to build distribution or habitat suitability maps of species from field based intensive surveys and their correlations with the variables of interest or importance to the species. It is imperative to investigate how small carnivores respond or relate to variables within a Protected Area setting that hold acres of optimal habitat. Predictive species distribution models exist for selected small carnivore species around the world for eg:- jungle cat *Felis chaus*, leopard cat (*Prionailurus bengalensis*) (Mukherjee et al., 2010), fisher *Martes pennanti* (Zielinski et al., 2006), flat headed cat (*Prionailurus planiceps*) (Wilting et al., 2010), Andean cat (*Leopardus jacobita*) (Marino et al., 2011), Colombian Weasel (*Mustela felipei*) (Burneo et al., 2009), and European wild cat (*Felis silvestris*) (Monterroso et al., 2009). Jennings and Veron (2011) predicted the distribution of large-spotted civet (*Viverra megaspila*), Malay civet (*Viverra tangalunga*), large Indian civet (*Viverra zibetha*), small Indian civet (*Viverricula indica*), short-tailed mongoose (*Herpestes brachyurus*), Javan mongoose (*Herpestes javanicus*), collared mongoose (*Herpestes semitorquatus*), and crab-eating mongoose (*Herpestes urva*) within Southeast Asia using ecological niche modeling, determined their habitat/elevation niche preferences, examined interspecific differences in niche parameters, and investigated possible factors that affected their distribution and niche patterns.

Most determinant variables are environmental, bioclimatic, topographic and/or disturbance indices which are essential in documenting distribution across a wider landscape. Animals that are rare and secretive adapt to the environment for a variety of reasons some of which that are very hard to justify or interpret. The small carnivores are known to be either microhabitat specialists or generalists. Ecological
requirements of small carnivores provide substantial evidence that their distribution is determined by resources at the home-range scale. It is essential for managers to be able to distinguish between habitat suitability and actual population size. For most species, biological information is available to guide decisions regarding appropriate variables for inclusion in candidate models, which greatly facilitates development of a suite of candidate models. Ecological niche models, the Genetic Algorithm for Rule-set Prediction (GARP) and maximum entropy (MaxEnt) have been used to assess potential ranges and distributional connectivity of Asian and African viverrids (Papes and Gaubert 2007, Jennings and Veron 2011).

A predictive distribution model, or habitat suitability model, usually consists of a probability map depicting the likelihood of occurrence of a species. The categorization of habitat quality displayed in the spatial model can be used to prioritize areas requiring protection based on their value. This statement is made on the premise that the probability of species presence is positively correlated with the quality of the habitat. By providing baseline information about the spatial arrangement of potentially suitable habitat for a species, habitat suitability maps can be used to facilitate protection and restoration of critical habitat, and hence they have broad applicability in conservation biology and wildlife management (Manel et al., 2000). Several developments in ecological niche modelling (ENM) have provided new tools to estimate species ranges and identify suitable habitats (Gaubert et al., 2005a, Papes and Gaubert 2007, Thorn et al., 2009). The maximum entropy framework appears to be robust even if only few occurrence records are available (Pearson et al., 2007). The maximum entropy-based machine-learning method is used for making predictions when incomplete data are available. “MaxEnt estimates the probability distribution for a species occurrence that is most spread out given the constraints derived from the available data” (Phillips et al., 2006). These constraints are deduced from environmental conditions at species presence records and require that the expected value of an environmental variable or its function must be within a confidence interval derived from its empirical mean (Phillips et al., 2006). Maximum entropy modeling is an active area of research in statistics and machine learning, and progress in the field as a whole can be readily applied in this study.

The North-east and Western Ghats are rich biogeographic units and biodiversity "Hotspots" in the world (Myers et al., 2000). Status reports, synoptic work, behavioural observations on the small carnivores in the Western Ghats have
provided considerably useful knowledge on their habitat use (Prater 1971, Mudappa 2001). The diverse mammalian community in the north-eastern region is driven by contiguous rainforest habitats with South-east Asian forests along with wide altitudinal and habitat variation (Datta et al., 2008). Although small carnivore diversity is higher in the North-east than in the Western Ghats, the small carnivore assemblages in both hotspots are unique. The North-western and central India comprises semi-arid and dry tropical forests holding promising populations of sympatric species like jungle cat (*Felis chaus*), desert cat (*Felis silvestris ornate*), rusty spotted cat (*Prionailurus rubiginosus*), small Indian civet (*Viverricula indica*), common palm civet (*Paradoxurus hermaphrodites*), grey mongoose (*Herpestes edwardsii*) and ruddy mongoose (*Herpestes smithii*) (Gareja and Dharaiya 2011).

The study was aimed 1) to generate a habitat suitability model for predicting small carnivore distribution in Mudumalai Tiger Reserve using environmental variables and 2) to identify environmental variables associated with small carnivore occupancy.

6.2 Materials and methods

The fundamental limitation of presence-only data is that sample selection bias (whereby some areas in the landscape are sampled more intensively than others) has a much stronger effect on presence-only models than on presence-absence models (Phillips et al., 2009). For any modelling method – few samples provide limited information for determining relationships between the species and its environment (Pearson et al., 2007). The MaxEnt approach performs better with presence-only data than other methods such as bioclimatic envelope modeling or genetic algorithms (Elith et al., 2006).

6.2.1 Small carnivore species distribution data

Species distribution data was collected from camera trapping (methodology has been explained in chapter 3), direct sighting records, interviews with forest staff, local people (from villages and settlements, resort owners), and road kill incidents. All the records were pooled from 2009-2011 for every species separately. The small carnivores analysed were jungle cat (36 point localities), leopard cat (9), rusty-spotted cat (18), small Indian civet (51), common palm civet (22), brown palm civet (19), stripe-necked mongoose (55), ruddy mongoose (51) and grey mongoose (35).
created comma-separated value (.csv) file containing longitude and latitude coordinates of each species occurrence from an Excel spreadsheet. These were plotted in ArcGIS 9.3 and overlayed on 1 km$^2$ grid cells. Based on which the distribution maps were generated (Fig 36a, b, c).

Fig 36a. Spatially unique localities of small cats in Mudumalai Tiger Reserve (2009-2011).

6.2.2 Extraction of explanatory environmental predictors

I used the Geographic Information System (GIS) in ArcGIS 9.3 (Environmental Systems Research Institute [ESRI], Inc., Redlands, CA, USA) for data extraction. For species habitat suitability modeling the resolution, or pixel size of the raster data should relate to the home range of the species under investigation, yet this assumption could be violated for those that exceed more than grid size (eg: small cats and civets), however a fishnet of 1 km² was overlayed on the boundary and buffer layer of Mudumalai. Climatological variables, topographical variables, biological variables and anthropogenic variables were extracted using Zonal Statistic tool in the Spatial Analyst toolbox such that every 1 km² pixel is assigned the variable value.
A classified forest cover map from Forest Survey of India of categories; 1 = water bodies, 2 = non-forest, 3 = scrub, 4 = open forest, 5 = dense forest and 6 = very dense forest were obtained. The land use land cover map at 1:250000 scale was derived from DIVAGIS (version 7.1.7.2, http://www.diva-gis.org) where original data was resampled onto a 30 seconds grid (source-GLC2000). These were classified as categorical variables: 1 = tropical evergreen, 2 = subtropical evergreen, 8 = moist deciduous, 9 = dry deciduous, 16 = degraded forest.

I used the Shuttle Radar Topography Mission (SRTM) digital elevation data, aggregated from the native 90-m resolution to 1 km. In addition to mean elevation, the standard deviation based on the 90-m data was included as an indicator of surface ruggedness. Slope and aspect was calculated from elevation layer using Surface analysis tool from spatial analyst toolbox in Arcmap. The Slope layer had values measured in degrees (0 – 90) for each 1 km² pixel. The aspect degree was converted such that each pixel has a value assigned from -1 to 360 degrees.

Normalized difference vegetation index (NDVI) is a method of measuring and mapping the density of green vegetation. For its measurement scientists use satellite sensors that observe the distinct wavelengths of visible and near infrared sunlight which is absorbed and reflected by the plants, then the ratio of visible and near-infrared light reflected back up to the sensor is calculated. The ratio gives a number from minus one (−1) to plus one (+1). An NDVI value of zero means no green vegetation and close to +1 (0.8–0.9) indicates the highest possible density of green leaves. The ‘normalized difference vegetation index’ is calculated by the formula: 
\[ \text{NDVI} = \frac{(\text{IR} - \text{R})}{(\text{IR} + \text{R})} \]

where IR = infrared light and R = red light.

I obtained the 19 ‘bioclimatic’ variables based on the global climate data sets developed by Hijmans et al., (2005). These GIS data sets characterize global climates using average monthly weather station data and are available at 30 arc-seconds resolution (approximately 1 km²). I used the mean human influence index (HII) at 1 km², a measure of human influence on global surface, combining data of population density, land transformation, human access and presence of infrastructures. This information is a composite measure of multiple human activities that include urban extent, population density, roads, navigable rivers and agricultural land; (Last of the WILD DATA v. 2 2005). The HII values range from 0 (no human influence) to 64 (maximum human influence possible under the method). Actual evapo-transpiration (AET) is the effective quantity of water that is removed from the soil due to
evaporation and transpiration processes. AET is dependent on the available atmospheric energy, vegetation characteristics, quantity of water available in the soil and soil hydrological properties. I used global AET layers (the average 1950-2000 period) evapotranspiration (mm) at 30 arc-seconds (920 meters at equator). Surface water bodies (rivers and streams) were extracted for the country wide data from DIVAGIS (version 7.1.7.2, http://www.diva-gis.org) along with field data locations of potential water sources. I used the Euclidean distance tool to create a raster “distance to” (km) layer for the closest water source (d2w). This tool calculated a straight line distance to the nearest source variable of interest within the raster layer such that each pixel is assigned a value of distance to water and village.

Since most climatic and NDVI variables were highly correlated ($R^2 > 0.5$), to avoid the multicollinearity issue, I did not include other climatic and NDVI variables that were strongly correlated. I used only independent variables; bio3 = isothermality (mean diurnal temperature range/[maximum temperature of warmest month/minimum temperature of coldest month]), bio5 = max temperature of the warmest month, bio18 = precipitation of the warmest quarter, bio19 = precipitation of the coldest quarter, NDVI-March, NDVI-June and NDVI-July. Multicollinearity was also checked for all combinations of environmental variables.

### 6.2.3 Modelling approach

**MaxEnt**

MaxEnt is a machine learning algorithm that estimates the most uniform distribution (maximum entropy) across the study area given the constraint that the expected value of each environmental predictor variable under this estimated distribution matches its empirical average (Phillips et al., 2006). I used MaxEnt because it performs better than other presence-only modeling techniques (Elith et al., 2006), especially with low numbers of occurrence locations (Papes and Gaubert 2007). The reliability of the results of MaxEnt has been confirmed by its good capacity to predict novel presence localities for poorly known species (Pearson et al., 2007). This method has been used to develop habitat suitability models for a range of mammals (Monterroso et al., 2009, Wilting et al., 2010, Jennings and Veron 2011). The modelled probability is a ‘Gibbs’ distribution (i.e. exponential in a weighted sum of the features) and the model logistic outputs have a natural probabilistic
interpretation representing degrees of habitat suitability (0 = unsuitable to 0.99 = best habitat) (Pearson et al., 2007). Consequently, maximum entropy modeling consistently outperforms other methods of modeling spatial distribution (Elith et al., 2006, Phillips et al., 2006), except possibly those utilizing multiple repeated visitations to the same sampling points that correct for imperfect detection of individuals (i.e., occupancy modeling; MacKenzie et al., 2006). Like most maximum-likelihood estimation approaches, the MaxEnt algorithm a priori assumes a uniform distribution and performs a number of iterations in which the weights associated with the environmental variables, or functions thereof, are adjusted to maximize the average probability of the point localities (also known as the average sample likelihood), expressed as the training gain (Phillips 2006). These weights are then used to compute the MaxEnt distribution over the entire geographic space. Consequently, this distribution expresses the suitability of each grid cell as a function of the environmental variables for that grid cell. A high value of the function (in units of cumulative probability) for a particular grid cell indicates that the grid cell is predicted to have suitable conditions for the species in question (Phillips 2006). MaxEnt has several characteristics that make it highly suitable for the task of modelling species ranges (Phillips et al., 2006). These include a deterministic framework; the ability to run with presence-only point occurrences; a high performance with few point localities (Hernandez et al., 2006); better computing efficiency, enabling the use of large-scale high-resolution data layers; continuous output from least to most suitable conditions; and the ability to model complex responses through a number of distinct feature classes (e.g. functions of environmental variables).

**Data analyses and validation**

A set of ascii environmental layers and a .csv file of known locations of a species were used to produce probability maps that predict the potential distribution of a species.

The measure of fit implemented by MaxEnt is the area under the curve (AUC) of a receiver operating characteristic (ROC) plot (ranging from 0.5 = random to 1 = perfect discrimination). The selection and contribution of each variable depends on the other variables in the model, so highly correlated variables (bioclimatic layers and monthly NDVI) may greatly influence the final model. Only one of a pair of
correlated \((r > 0.50)\) variables was used in the model; the variable with the least biological importance was eliminated.

As a result, the final reduced data set used in this study converged to a total of 17 environmental layers which were projected to the UTM zone to match their coordinates, clipped to the extent of the boundary along with 2 km buffer, resampled to the cell size of 30 arc-seconds \((\sim 1 \text{ km}^2)\), and entered with the occurrence data into MaxEnt version 3.3.3 (http://www.cs.princeton.edu/~schapire/MaxEnt). I selected the jackknife option in the program through which the importance of individual environmental data layers can be estimated. It also provided response curves showing how the prediction depends on a particular environmental variable (Phillips 2006). For all model runs in this study, I used the MaxEnt default settings for regularization and in selecting the feature classes (functions of environmental variables). These include linear, quadratic, product, threshold and hinge features, depending on the number of point localities (Phillips 2006). Description for each of the feature type models can be found in Phillips et al. (2006) and Phillips and Dudik (2004). The Auto feature type allows the set of features used to depend on the number of presence records for the species being modeled using general empirically-derived rules. It should be noted that the model algorithm (MaxEnt) used in this study is largely robust to covariance among variables, and that data reduction was performed mainly to improve interpretation. I set the program to run 1000 iterations with a convergence threshold of 0.00001, a regularization multiplier of 1, a maximum of 10000 background points, the output grid format as “logistic,” algorithm parameters set to “auto features,” and all other parameters at their default settings (Phillips and Dudik 2008). I had the program randomly withhold 25% of the presence locations to test the performance of each model. The Linear Quadratic Hinge feature type was the best fit model for predicted distribution of jungle cat, common palm civet, brown palm civet, stripe-necked mongoose, ruddy mongoose and grey mongoose. Linear Quadratic feature type model was the best fit for rusty-spotted cat while the Linear feature type model fitted well for leopard cat and small Indian civet distribution.

6.2.4. Variable contribution and response curves

I considered MaxEnt’s heuristic estimates of the relative contribution of environmental variables to the models and the results of jackknife analyses for each
environmental layer (Phillips and Dudik 2008). For the variables with highest predictive value, I examined the response curves showing how each of these environmental variables affects the MaxEnt prediction (Phillips and Dudik 2008). The curves illustrate how the logistic prediction changes as each environmental variable is varied, while keeping all other environmental variables at their average sample value. The curves thus represent the marginal effect of changing exactly one variable. Each of the models was then re-run a second time, after selecting only those variables that contributed at least 2% to the initial model result. This methodology reduced the total numbers of variables used in the analysis.

6.3. Results

6.3.1 Jungle cat habitat modeling

Distribution models for jungle cat performed well based on the high (0.91) AUC value (Fig 37). Annual precipitation had the highest predictive power (46%) to the model output (Table 29). The jackknife test of variable importance showed the highest gain when the variable annual precipitation of the warmest quarter was used in isolation which therefore appears to have the most useful information by itself (Fig 37). This variable also decreased the gain when it was omitted showing that it had the most information that was not present in other variables (Fig 38). The variables annual precipitation of the warmest quarter, elevation, NDVI (March), forest type, aspect, NDVI (July) and distance to water together contributed 96% to jungle cat model. NDVI (March) was negatively related to predicted jungle cat presence where high probabilities were predicted at low NDVI areas (Fig 39a). Aspect and distance to water response curves showed bi-modal distribution (Fig 39b, c). The response curve for elevation showed that highest predicted suitability areas in areas of low to medium elevation (200 – 900 m). The land cover categories with the highest predicted probability of jungle cat as calculated in included deciduous and degraded areas in the south-eastern part of the reserve. The annual precipitation of the warmest quarter showed a skewed response curve with suitable conditions towards 210 mm of precipitation (Fig 39g). Predicted jungle cat presence showed a sigmoid curve starting from low values that accelerated and approached high NDVI (July) values (Fig 39h). The response curve showed jungle cat predicted probabilities decreasing abruptly from low to high topography wetness index. The MaxEnt model generated a map
(predicted probability of occurrence; Fig 40) of potential jungle cat distribution in Mudumalai showing that high probability areas (considered to be areas with > 0.6 probability of presence) accounted for a small portion (38 km²) of the reserve with the Linear Quadratic Hinge feature type models indicating the suitable habitat.

Fig 37. ROC curve of Sensitivity versus Specificity for the habitat model of jungle cat.

![ROC curve of Sensitivity versus Specificity for the habitat model of jungle cat.](image)

Fig 38. Jackknife analyses of individual predictor variables important in the development of the full model for jungle cat in relation to the overall model quality or the “regularized training gain.” Dark blue bars indicate the gain achieved when including only that variable and excluding the remaining variables; light blue bars show how much the gain is diminished without the given predictor variable.

![Jackknife analyses of individual predictor variables important in the development of the full model for jungle cat.](image)
Fig 39. Graphical representation of the relationship between (a) ndvi_march, (b) aspect, (c) distance to water source, (d) elevation, e) forest type, f) landcover type, g) annual precipitation of the warmest quarter, h) ndvi_july i) topography wetness index, and jungle cat probability of presence (2009-2011). Each of the curves represents a different MaxEnt model created using only the corresponding variable.
Fig 40. Predicted distribution for jungle cat in Mudumalai Tiger Reserve estimated by MaxEnt modeling (2009-2011). Potential areas are shown in grey shading with the white color indicating higher probabilities of occurrence.

6.3.2 Rusty-spotted cat habitat modeling

Distribution models for rusty-spotted cat performed well based on the high (0.88) AUC value (Fig 41). Land cover type had the highest predictive power (30.4%) to the model output (Table 29). The jackknife test of variable importance showed the highest gain when the variable annual precipitation at the warmest quarter type was used in isolation which therefore appears to have the most useful information by itself (Fig 42). This variable elevation decreased the gain when it was omitted showing that it had the most information that was not present in other variables. The variables landcover type, aspect, elevation, annual precipitation at the warmest quarter and wetness index contributed 95.6% to rusty-spotted cat model. Aspect, wetness index and annual precipitation of the warmest quarter were negatively related to predicted rusty-spotted cat presence (Fig 43a, e, f). The annual precipitation of the warmest
quarter decreased abruptly from low to high towards 300 mm or more (Fig 43d). The response curve for elevation showed a positive relationship with predicted rusty-spotted cat suitability where high probabilities occurred at higher elevations (> 1200 m) (Fig 43b). The land cover categories with the highest predicted probability for rusty-spotted cat as calculated includes only degraded areas in the south-eastern part of the reserve. The response curve for annual precipitation of the warmest quarter showed high predicted suitability in areas with low precipitation 150-220 mm (Fig 43d). The MaxEnt model generated a map (predicted probability of occurrence; Fig 44) of potential rusty-spotted cat distribution in Mudumalai showing that high probability areas (considered to be areas with > 0.6 probability of presence) accounted for a small portion (56 km²) of the reserve with the Linear Quadratic feature type models indicating the suitable habitat. The model output also predicted highly suitable areas in the buffer zone towards the south-eastern region of the reserve.

Fig 41. ROC curve of Sensitivity versus Specificity for the habitat model of rusty-spotted cat.
Fig 42. Jackknife analyses of individual predictor variables important in the development of the full model for rusty-spotted cat in relation to the overall model quality or the “regularized training gain.” Dark blue bars indicate the gain achieved when including only that variable and excluding the remaining variables; light blue bars show how much the gain is diminished without the given predictor variable.
Fig 43. Graphical representation of the relationship between (a) aspect, (b) elevation, (c) landcover type, (d) annual precipitation of the warmest quarter, (e) annual precipitation of the coldest quarter, (f) topography wetness index, and rusty-spotted cat probability of presence (2009-2011). Each of the curves represents a different MaxEnt model created using only the corresponding variable.
Fig 44. Predicted distribution for rusty-spotted cat in Mudumalai Tiger Reserve estimated by MaxEnt modeling (2009-2011). Potential areas are shown in grey shading with the white color indicating higher probabilities of occurrence.

6.3.3 Leopard cat habitat modeling

Distribution models for leopard cat performed well based on the high (0.89) AUC value (Fig 45). Land cover type had the highest predictive power (67.8%) to the model output (Table 29). The jackknife test of variable importance showed the highest gain when the variable landcover type was used in isolation which therefore appears to have the most useful information by itself (Fig 46). This variable decreased the gain when it was omitted showing that it had the most information that was not present in other variables. The variables landcover type, elevation, isothermality and actual evapotranspiration contributed 96.3% to leopard cat model. Actual evapotranspiration showed an S-shaped curve (Fig 47a) while elevation and
isothermality were positively related to predicted leopard cat presence (Fig 47 b, e). Predicted higher probabilities for leopard cat occurred at high elevations (> 1200 m) achieved stabilization beyond 1400 m and areas with high soil water content (evapotranspiration) and isothermality indicating affinity towards moist and warm localities. The land cover and forest type categories with the highest predicted probability for leopard cat as calculated includes sub-tropical evergreen and dense forests of the reserve (Fig 47c, d). The MaxEnt model generated a map (predicted probability of occurrence; Fig 48) of potential leopard cat distribution in Mudumalai showing that high probability areas (considered to be areas with > 0.6 probability of presence) accounted for a small portion (58 km²) of the reserve with the Linear feature type model indicating the suitable habitat.

Fig 45. ROC curve of Sensitivity versus Specificity for the habitat model of leopard cat.
Fig 46. Jackknife analyses of individual predictor variables important in the development of the full model for leopard cat in relation to the overall model quality or the “regularized training gain.” Dark blue bars indicate the gain achieved when including only that variable and excluding the remaining variables; light blue bars show how much the gain is diminished without the given predictor variable.

Fig 47. Graphical representation of the relationship between (a) actual evapotranspiration, (b) elevation, c) forest type, d) landcover type, e) isothermality, and leopard cat probability of presence (2009-2011). Each of the curves represents a different MaxEnt model created using only the corresponding variable.
c) 

\begin{figure}
\centering
\includegraphics[width=0.4\textwidth]{image1}
\caption{Bar chart showing the distribution of fen types.}
\end{figure}

d) 

\begin{figure}
\centering
\includegraphics[width=0.4\textwidth]{image2}
\caption{Bar chart showing the distribution of landcover types.}
\end{figure}

e) 

\begin{figure}
\centering
\includegraphics[width=0.4\textwidth]{image3}
\caption{Graph showing the relationship between soil pH and pH.}
\end{figure}
Fig 48. Predicted distribution for leopard cat in Mudumalai Tiger Reserve estimated by MaxEnt modeling (2009-2011). Potential areas are shown in grey shading with the white color indicating higher probabilities of occurrence.

6.3.4 Small Indian civet habitat modeling

Distribution models for small Indian civet performed well based on the high (0.87) AUC value (Fig 49). Elevation had the highest predictive power (31.7%) to the model output (Table 29). The jackknife test of variable importance showed the highest gain when the variable aspect was used in isolation which therefore appears to have the most useful information by itself (Fig 50). The variable annual precipitation at the coldest quarter decreased the gain when it was omitted showing that it had the most information that was not present in other variables. The variables elevation, aspect, forest type, annual precipitation at the coldest quarter, NDVI (March) and topography wetness index contributed 92.1% to small Indian civet model. NDVI (March) and wetness index response curve showed a bimodal peak with probability of small Indian civet distribution (Fig 51a). Medium aspect (100°) and elevation (400-
900 m) led to high probabilities (Fig 51b, c). Probabilities were skewed towards plain areas (1°, Fig 51g) and then stabilized from 5° onwards. High probabilities peaked at 100 mm of annual precipitation of the coldest quarter (Fig 51f). The MaxEnt model generated a map (predicted probability of occurrence; Fig 52) of potential small Indian civet distribution in Mudumalai showing that high probability areas (considered to be areas with > 0.6 probability of presence) accounted for a small portion (49 km²) of the reserve with the Linear feature type model indicating the suitable habitat.

Fig 49. ROC curve of Sensitivity versus Specificity for the habitat model of small Indian civet.
Fig 50. Jackknife analyses of individual predictor variables important in the development of the full model for small Indian civet in relation to the overall model quality or the “regularized training gain.” Dark blue bars indicate the gain achieved when including only that variable and excluding the remaining variables; light blue bars show how much the gain is diminished without the given predictor variable.
Fig 51. Graphical representation of the relationship between (a) NDVI_March, (b) aspect, (c) elevation, (d) forest type, (e) landcover type (f) annual precipitation of the coldest quarter (g) slope, (h) topography wetness index, and small Indian civet probability of presence (2009-2011). Each of the curves represents a different MaxEnt model created using only the corresponding variable.
Fig 52. Predicted distribution for small Indian civet in Mudumalai Tiger Reserve estimated by MaxEnt modeling (2009-2011). Potential areas are shown in grey shading with the white color indicating higher probabilities of occurrence.

6.3.5 Common palm civet habitat modeling

Distribution models for common palm civet performed well based on the high (0.91) AUC value (Fig 53). Annual precipitation of the warmest quarter had the highest predictive power (39%) to the model output (Table 29). The jackknife test of variable importance showed the highest gain when the variable annual precipitation of the warmest quarter was used in isolation which therefore appears to have the most useful information by itself (Fig 54). The variable elevation decreased the gain when it was omitted showing that it had the most information that was not present in other variables. The variables annual precipitation of the warmest quarter, elevation, actual evapotranspiration, landcover type and forest contributed 90.4% to common palm civet model. Annual precipitation of the warmest quarter was skewed towards 210.
Actual evapotranspiration peaked at 825 mm and elevation at 850 m (Fig 55a). Common palm civet probabilities were predicted highest in non-forest areas (Fig 55c) and dry deciduous habitats (Fig 55d). Predicted high probabilities were achieved from low to high NDVI (July) and then gradually dropped down towards highest NDVI values (Fig 55f) while NDVI (June) did not bring about any change in common palm civet probabilities (Fig 55g). Topography wetness index decreased abruptly from low values and remained constant towards 400 or more (Fig 55h). The MaxEnt model generated a map (predicted probability of occurrence; Fig 56) of potential common palm civet distribution in Mudumalai showing that high probability areas (considered to be areas with > 0.6 probability of presence) accounted for a small portion (23 km²) of the reserve with the Linear Quadratic Hinge feature type model indicating the suitable habitat.

Fig 53. ROC curve of Sensitivity versus Specificity for the habitat model of common palm civet.
Fig 54. Jackknife analyses of individual predictor variables important in the development of the full model for common palm civet in relation to the overall model quality or the “regularized training gain.” Dark blue bars indicate the gain achieved when including only that variable and excluding the remaining variables; light blue bars show how much the gain is diminished without the given predictor variable.
Fig 55. Graphical representation of the relationship between (a) precipitation of the warmest quarter, (b) AET, c) forest type, d) landcover type, e) elevation, f) NDVI_July, g) NDVI_June, h) topography wetness index and common palm civet probability of presence (2009-2011). Each of the curves represents a different MaxEnt model created using only the corresponding variable.
Fig 56. Predicted distribution for common palm civet in Mudumalai Tiger Reserve estimated by MaxEnt modeling (2009-2011). Potential areas are shown in grey shading with the white color indicating higher probabilities of occurrence.

6.3.6 Brown palm civet habitat modeling

Distribution models for brown palm civet performed well based on the high (0.95) AUC value (Fig 57). Annual precipitation of the warmest quarter had the highest predictive power (39.7%) to the model output (Table 29). The jackknife test of variable importance showed the highest gain when the variable NDVI (March) was used in isolation which therefore appears to have the most useful information by itself (Fig 58). The variable annual precipitation of the coldest quarter decreased the gain when it was omitted showing that it had the most information that was not present in other variables. The variables NDVI (March), annual precipitation of the coldest and warmest quarter and elevation contributed 93.8% to brown palm civet model. Predicted probabilities were skewed towards high NDVI (March) and actual evapotranspiration (0.78 and 980 mm respectively, Fig 59a, b) and moderate aspect (260°, Fig 59c). Probabilities showed an S-shaped curve from low values and gradually achieving stabilization at higher elevation (> 1400 m, Fig 59d) and a bell-
shaped curved with NDVI (June) (Fig 59 g). Annual precipitation of the warmest and coldest quarter showed skewed response curves towards low values (240 and 100 mm respectively, Fig 59e, f). The MaxEnt model generated a map (predicted probability of occurrence; Fig 60) of potential brown palm civet distribution in Mudumalai showing that high probability areas (considered to be areas with > 0.6 probability of presence) accounted for a small portion (34 km²) in the north-western part of the reserve with the Linear Quadratic Hinge feature type model indicating the suitable habitat.

Fig 57. ROC curve of Sensitivity versus Specificity for the habitat model of brown palm civet.
Fig 58. Jackknife analyses of individual predictor variables important in the development of the full model for brown palm civet in relation to the overall model quality or the “regularized training gain.” Dark blue bars indicate the gain achieved when including only that variable and excluding the remaining variables; light blue bars show how much the gain is diminished without the given predictor variable.

Fig 59. Graphical representation of the relationship between (a) NDVI (March), (b) actual evapotranspiration, c) aspect, d) elevation, e) annual precipitation of the warmest quarter, f) annual precipitation of the coldest quarter g) NDVI (June) and brown palm civet probability of presence (2009-2011). Each of the curves represents a different MaxEnt model created using only the corresponding variable.
Fig 60. Predicted distribution for brown palm civet in Mudumalai Tiger Reserve estimated by MaxEnt modeling (2009-2011). Potential areas are shown in grey shading with the white color indicating higher probabilities of occurrence.
6.3.7 Stripe-necked mongoose habitat modeling

Distribution models for stripe-necked mongoose performed well based on the high (0.83) AUC value (Fig 61). Elevation had the highest predictive power (41.7%) to the model output (Table 29). The jackknife test of variable importance showed the highest gain when elevation was used in isolation which therefore appears to have the most useful information by itself (Fig 62). This variable decreased the gain when it was omitted showing that it had the most information that was not present in other variables. The variables elevation, landcover type, annual precipitation of the coldest quarter, aspect, slope, actual evapotranspiration and forest type contributed to 94.6% for stripe-necked mongoose model. Predicted probabilities were skewed towards high actual evapotranspiration (Fig 63a). High probabilities occurred at medium aspect (Fig 63b), elevation (200-900 m, Fig 63c) and landcover types; subtropical evergreen and dry deciduous forests (Fig 63e). Probabilities were skewed towards low annual precipitation of the warmest and coldest quarter (Fig 63f, g). The response curve for slope showed a bi-modal curve (Fig 63h) and probabilities against topography wetness index dropped abruptly from 200 and gradually decreased towards high values (Fig 63i). The MaxEnt model generated a map (predicted probability of occurrence; Fig 64) of potential stripe-necked mongoose distribution in Mudumalai showing that high probability areas (considered to be areas with > 0.6 probability of presence) accounted for a substantial portion (57 km²) depicting a random probabilistic distribution in the reserve with the Linear Quadratic Hinge feature type model indicating suitable habitat.
Fig 61. ROC curve of Sensitivity versus Specificity for the habitat model of stripe-necked mongoose

![ROC curve image]

Training data (AUC = 0.927)
Test data (AUC = 0.734)
Random Prediction (AUC = 0.5)

Fig 62. Jackknife analyses of individual predictor variables important in the development of the full model for stripe-necked mongoose in relation to the overall model quality or the “regularized training gain.” Dark blue bars indicate the gain achieved when including only that variable and excluding the remaining variables; light blue bars show how much the gain is diminished without the given predictor variable.

![Jackknife analysis image]
Fig 63. Graphical representation of the relationship between (a) actual evapotranspiration, (b) aspect, (c) elevation, (d) forest type, (e) landcover type, (f) annual precipitation of the warmest quarter, (g) annual precipitation of the coldest quarter, (h) slope, (i) topography wetness index, and stripe-necked mongoose probability of presence (2009-2011). Each of the curves represents a different MaxEnt model created using only the corresponding variable.
Fig 64. Predicted distribution for stripe-necked mongoose in Mudumalai Tiger Reserve estimated by MaxEnt modeling (2009-2011). Potential areas are shown in grey shading with the white color indicating higher probabilities of occurrence.

6.3.8 Ruddy mongoose habitat modeling

Distribution models for ruddy mongoose performed well based on the high (0.91) AUC value (Fig 65). Elevation had the highest predictive power (21.6%) to the model output (Table 29). The jackknife test of variable importance showed the highest gain when annual precipitation of the warmest quarter was used in isolation which therefore appears to have the most useful information by itself (Fig 66). This variable aspect decreased the gain when it was omitted showing that it had the most information that was not present in other variables. The variables elevation, aspect, annual precipitation of the warmest quarter, NDVI (March), landcover type, forest type, annual precipitation of the coldest quarter and actual evapotranspiration contributed to 96% of ruddy mongoose model. The response curve for NDVI (March) and distance to water showed a bi-modal curve for predicted ruddy mongoose probabilities (Fig 67a, d). Actual evapotranspiration showed almost a bell-shaped
curve with probabilities occurring at moderate values (Fig 67b). Probabilities were skewed towards 40-60° of aspect (Fig 67c), 220 mm of annual precipitation of the warmest quarter (Fig 67h) and 100 mm of the coldest quarter (Fig 67i). Probabilities dropped abruptly at lowest topography wetness index (200, Fig 67j) The MaxEnt model generated a map (predicted probability of occurrence; Fig 68) of potential ruddy distribution in Mudumalai showing that high probability areas (considered to be areas with > 0.6 probability of presence) accounted for a substantial portion (40 km²) towards the eastern region in the reserve with the Linear Quadratic Hinge feature type model indicating suitable habitat.

Fig 65. ROC curve of Sensitivity versus Specificity for the habitat model of ruddy mongoose.
Fig 66. Jackknife analyses of individual predictor variables important in the development of the full model for ruddy mongoose in relation to the overall model quality or the “regularized training gain.” Dark blue bars indicate the gain achieved when including only that variable and excluding the remaining variables; light blue bars show how much the gain is diminished without the given predictor variable.
Fig 67. Graphical representation of the relationship between (a) NDVI (March), (b) actual evapotranspiration, (c) aspect, (d) distance to water (e) elevation, (f) forest type, (g) landcover type, (h) annual precipitation of the warmest quarter, (i) annual precipitation of the coldest quarter, topography wetness index and ruddy mongoose probability of presence (2009-2011). Each of the curves represents a different MaxEnt model created using only the corresponding variable.
Fig 68. Predicted distribution for ruddy mongoose in Mudumalai Tiger Reserve estimated by MaxEnt modeling (2009-2011). Potential areas are shown in grey shading with the white color indicating higher probabilities of occurrence.

6.3.9 Grey mongoose habitat modeling

Distribution models for grey mongoose performed well based on the high (0.92) AUC value (Fig 69). Annual precipitation of the warmest quarter and landcover categories had the highest predictive power (34.5% and 33.3%) to the model output.
(Table 29). The jackknife test of variable importance showed the highest gain when annual precipitation of the warmest quarter was used in isolation which therefore appears to have the most useful information by itself (Fig 70). This variable also decreased the gain when it was omitted showing that it had the most information that was not present in other variables. The annual precipitation of the warmest quarter, landcover type, elevation, actual evapotranspiration, NDVI (June) contributed to 94% for grey mongoose model. The response curve for actual evapotranspiration showed a bell-shaped curve (Fig 71a). Probabilities were skewed towards 900 m of elevation (Fig 71b). High probabilities were achieved for degraded landcover type (Fig 71c), they were skewed towards low annual precipitation of the warmest quarter (200 mm, Fig 71d) and high NDVI (June, 0.72, Fig 71f). Predicted probabilities showed an S-shaped curve from low to medium isothermal temperature (Fig 71e). Probabilities dropped abruptly from low topography wetness index and gradually stabilized at 400 or more (Fig 71g). The MaxEnt model generated a map (predicted probability of occurrence; Fig 72) of potential grey mongoose distribution in Mudumalai showing that high probability areas (considered to be areas with > 0.6 probability of presence) accounted for a small portion (38 km²) towards the south-eastern region in the reserve with the Linear Quadratic Hinge feature type model indicating suitable habitat.

Fig 69. ROC curve of Sensitivity versus Specificity for the habitat model of grey mongoose.
Fig 70. Jackknife analyses of individual predictor variables important in the development of the full model for grey mongoose in relation to the overall model quality or the “regularized training gain.” Dark blue bars indicate the gain achieved when including only that variable and excluding the remaining variables; light blue bars show how much the gain is diminished without the given predictor variable.

Fig 71. Graphical representation of the relationship between (a) actual evapotranspiration, (b) elevation, c) landcover type, d) annual precipitation of the warmest quarter e) isothermality f) ndvi (June) g) topography wetness index and grey mongoose probability of presence (2009-2011). Each of the curves represents a different MaxEnt model created using only the corresponding variable.
Fig 72. Predicted distribution for grey mongoose in Mudumalai Tiger Reserve estimated by MaxEnt modeling (2009-2011). Potential areas are shown in grey shading with the white color indicating higher probabilities of occurrence.
Table 29. Estimates of relative percent contribution (PC) and permutation importance normalized to percentages (PI) for variables used in MaxEnt modeling of small carnivore distribution in Mudumalai Tiger Reserve (2009-2011).

<table>
<thead>
<tr>
<th>Environmental variables</th>
<th>Jungle cat</th>
<th>Leopard cat</th>
<th>Rusty-spotted cat</th>
<th>Small Indian civet</th>
<th>Common palm civet</th>
<th>Brown palm civet</th>
<th>Stripe-necked mongoose</th>
<th>Ruddy mongoose</th>
<th>Grey mongoose</th>
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MaxEnt = maximum entropy, bio18 = annual precipitation of the warmest quarter (mm), bio19 = annual precipitation of the coldest quarter (mm), bio3 = isothermality, dem = elevation (m), ndvi_march = Normalized Differentiation Vegetation Index, forest = categorical forest types, aspect = degrees, ndvi_july = , ndvi_june = Normalized Differentiation Vegetation Index, d2w = distance of species presence to nearest water source (m), landcov = categorical land cover type, wetness_index = topography wetness index, aet = actual evapotranspiration, slope = degrees.
6.4. **Discussion**

Habitat suitability map provided baseline information about the spatial arrangement of potentially suitable habitat for lesser carnivores in Mudumalai. In the spatial model, areas predicted as highly suitable (i.e. probability of occurrence) are clearly delineated, surrounded by areas of lower habitat quality depending upon the species ecological requirements. The modeling results were congruent with our understanding of small carnivore natural history and specifically their habitat preferences. While models developed from coarse-grained landscape variables can predict species distribution effectively, but unfortunately, finer scaled habitat variables, such as food resources, food species, prey distribution, refuge habitat etc., are unlikely to be captured at a landscape level which are essential for small ranging and small sized carnivores that could turn out to be a limitation in this study. Interestingly each of the study species showed a unique distribution pattern; restricted, gradient or random thus indicating the importance of the landscape heterogeneity along with intermediate factors that shape up the distribution of sympatric small carnivore community. Identifying areas of high habitat suitability for lesser carnivores lays the foundation for planning future research and conservation initiatives.

**Jungle cat:** Its high probability of presence at low precipitation of the warmest quarter and medium elevation, supports the fact that the species prefer open habitats, scrub jungles and agro-ecosystems also supporting its negative relationship with NDVI (March) explaining the species preference towards low canopy areas. The negative relationship of jungle cat with NDVI was also recorded in Sariska Tiger Reserve, North-western India since the area has relatively dry open and scrub forest with sparse vegetation cover (Gupta 2011). High probabilities at sites close to and even away from water sources suggests that this species does not have any specificity towards water. Mudumalai has a high density of large predators (Ramesh 2010) hence it is possible that there could be other variables like capture rates of competing felids (large and small) that could play a major role in its distribution and this must be investigated in detail.

**Rusty spotted cat:** The negative association of rusty spotted cat with aspect, annual precipitation, of the coldest quarter and wetness index supports that the species preference towards cool and dry areas. Higher probabilities in degraded land explain
that the species is tolerant to anthropogenically driven altered habitats. These results support evidence from literature stating that it even occupies abandoned houses in south India and urban cities in the vicinity of forests and amidst agricultural areas (Nowell and Jackson 1996, Mukherjee 1998, Nekaris 2003) although such adaptation could have resulted from the over growing urbanization even in forested areas. Although there are several records of rusty-spotted cats from cultivated and settled areas, it is not known to what degree their populations are able to persist in such areas (Nowell and Jackson 1996) and a large-scale country wise survey would give a better picture.

**Leopard cat:** The suitability map from this study showed the species suitable habitat to lie mainly in the transition zone from deciduous to evergreen forests. This zone has sites which are relatively moist and dense as depicted from the response curves showing its likelihood towards high elevation, isothermality and evapotranspiration. This species share similar morphological characters with oriental species which may indicate an equal preference for relatively more closed habitats (Mukherjee et al., 2010). A large-scale country wide study based on molecular tools produced suitability maps of various climatic variables with leopard cat locations showing that the maximum temperature in the warmest month (Bio 5) explained leopard cat distribution the most (Mukherjee et al., 2010).

**Small Indian civet:** This species was likely to be distributed in sites with low and high NDVI and wetness index and medium aspect and elevation with no particular affinity towards forest type. The species seems likely to be found in sites with low precipitation of the coldest quarter and plain terrain. These findings support the fact that across southeast Asia it has been recorded at elevations up to 1500 m, but 88.4% of records were below 600 m with no particular preference for forest type (Jennings and Veron 2011). Small Indian civets occur with a similar frequency in evergreen forest/scrub (47.8%) and deciduous forest/scrub (43.4%) and even in degraded forest (8.7%) in Southeast Asia (Jennings and Veron 2011). Tropical forests in south India are relatively moist and humid than dry semi-arid forests in North-west India which explains why Gupta (2011) reported affinity of the species towards dense canopy cover and water sources.
**Common palm civet:** This species preferred areas with low precipitation of the warmest quarter and wetness index, medium elevation and evapotranspiration. This species is known to occur in forested areas, urban landscapes and low land areas across the country. Mudappa (2001) did not record the species in rainforests of the Western Ghats thus providing further evidence to our data.

**Brown palm civet:** Brown palm civet preferred areas with high evapotranspiration, aspect, elevation and moderate to high NDVI which characterize rainforests and evergreen forests that are preferred by the species even in its distributional range in the Western Ghats. The key food tree species of the brown palm civet in the reserve as recorded from this study are *Elaeocarpus variablis, Gnetulum ula, Bischovia javanica, Piper nigrum* which grow only in the evergreen forests and have also been reported in the species diet from the rainforests of south India (Mudappa et al., 2010).

**Stripe-necked mongoose:** This species although forest-dwelling, seems to be a generalist due to the availability of sufficient suitable habitat in the study area. Based on the habitat suitability map, the species is likely to be widely distributed across the reserve. The species is likely to be found in areas having low to high evapotranspiration, elevation, aspect and forest type except that it was skewed towards low precipitation and wetness index.

**Ruddy mongoose:** This species not only has a wide geographical distribution, but it also occurs in varied vegetation types from arid regions in the plains of northern and western India to high altitudes (> 2000 m) of southern India, as well as in human-dominated agricultural landscapes (Choudhury 1997). The response curves for this species is probably typical for mongooses supporting its generalist habits from the fact that predicted probabilities seem to be distributed across from low to high values of other environmental variable except for its likelihood towards low aspect, precipitation and wetness index.

**Grey mongoose:** The most suitable habitat for this species included areas with medium evapotranspiration, elevation, NDVI and low precipitation of the warmest quarter and wetness index. These results are congruent with available literature where the species is known to thrive in open forests, scrublands, and cultivated fields close to water sources (Choudhury et al., 2011).
The model can be tested by future field surveys across the Nilgiris Biosphere Reserve for small carnivore presence in (1) areas predicted to have a high probability and (2) areas predicted to have no probability where the model may be wrong. The niche modeling from the present study depicts sympatric spatial distribution pattern between jungle cat, grey mongoose and ruddy mongoose. Although small cats are larger than mongooses, differences in activity pattern might reduce interspecific competition between the two groups. The brown palm civet and common palm civet appear to be spatially separated probably to avoid competition. The common palm civet has never been recorded in the evergreen forests of Western Ghats and hence it can be hypothesized that both species exhibit allopatric distribution in the Western Ghats however co-occurrence analyses would explain this phenomenon in greater detail. Species like the brown palm civet are likely to face extinction as they inhabit a highly specialized habitat. A recent study by Jennings and Veron (2011) revealed the tendency for each civet and mongoose species in Southeast Asia to separate spatially from related species on geographical, habitat, and elevation gradients. Several factors could account for these distribution and niche patterns and explain how these species coexist within Southeast Asia, including interspecific competition, biogeography, and anthropogenic factors. To confirm any interspecific competition, field studies are needed to determine each species’ microhabitat usage, behavior and food habits. Further research is needed to determine the ecological sensitivity of small carnivores towards anthropogenic activities.

Overhunting, deforestation, and land conversion have caused range contractions in many mammal species in Southeast Asia, which could account for the absence of some species in fragile ecosystems. Ecological niche modeling highlighted areas with the highest probabilities of occurrence, thereby indicating key localities for long-term conservation of threatened species where further research activities should be prioritized. To confirm my results and further explore the mechanisms responsible for these distribution and niche patterns field studies are needed to gather more data on the distribution, abundance, and ecology of lesser carnivores in India. For instance, insufficient occurrence data exist to investigate spatial or temporal changes in ecological niches, and too little is known about the natural history and ecology of these small cats, civets and mongooses to determine how other biotic factors, such as predation and disease, or the presence of key resources (e.g., den sites, food distribution), also have played a role in determining their distribution patterns.