International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2024: 7.101

Species Distribution Modelling (SDM) of *Panthera tigris tigris* and Prediction of Suitability of Habitats based on its Presence Locations and Environmental Variables

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Abstract: ***Over the past century tiger numbers have fallen dramatically, with a decreasing population trend. None of the Tiger Conservation Landscapes within the Bengal tiger range is large enough to support an effective population size of 250 individuals. Habitat losses and the extremely largescale incidences of poaching are serious threats to the species survival. The most significant immediate threat to the existence of wild tiger populations is the illegal trade in poached skins and body parts between India, Nepal and China. There are well-organized gangs of professional poachers, who move from place to place and set up camp in vulnerable areas. Other factors contributing to their loss are urbanization and revenge killing. Farmers blame tigers for killing catt le and shoot them. Their skins and body parts may however become a part of the illegal trade. The illicit demand for bones and body parts from wild tigers for use in Traditional Chinese medicine is the reason for the unrelenting poaching pressure on tigers on the Indian subcontinent. The study aims to predict and model the distribution of the species Panthera Tigris Tigris by combining various climatic, human influence, and environmental factors so as to predict alternate ecological niche for the already dwindling tiger habitats in India. The specific area for the study has been considers Uttaranchal state. The data were collected from Worldclim and Indian Biodiversity portal. The models used in the study were Google Earth Engine, GIS and MAXENT. The total data points were 313, and 50 data points were considered for training and balance for testing. Regularized training gain is 1.066, training AUC is 0.888, unregularized training gain is 1.272. Unregularized test gain is 1.064. Test AUC is 0.866, standard deviation is 0.032. Percent contribution and Permutation importance are 95.8 and 72.2 for one set of variable and 4.2 and 27.8 for other set of variable respectively. The best area for prediction is emerged as Deharadun, Haridwar, Paudi Garwal and Nainital. Which indicates that prediction is robust and derived results are trustworthy.***

Keywords: GIS, Biodiversity, Morphology, Tiger Conservation Landscapes, Tiger Conservation Units (TCUs), Maxent etc.

1. Introduction

In the Indian subcontinent, tigers inhabit tropical moist evergreen forests, tropical dry forests, tropical and subtropical moist deciduous forests, mangroves, subtropical and temperate upland forests, and alluvial grasslands. Latt er tiger habitat once covered a huge swath of grassland and riverine and moist semi-deciduous forests along the major river system of the Gangetic and Brahmaputra plains. Today, the best examples of this habitat type are limited to a few blocks at the base of the outer foothills of the Himalayas including the Tiger Conservation Units like Rajaji-Corbett, Bardia-Banke, and the transboundary Chitwan-Parsa- Valmiki, Dudhwa-Kailali and Sukla Phanta-Kishanpur where the Tiger densities are high. The Sundarbans contains one of the largest populations of the tiger subspecies, the royal Bengal tiger (*Panthera tigris tigris*). However, 1.5 million people use the same forest for their livelihoods (Kar and Jacobson, 2012).

Good tiger habitats in subtropical and temperate upland forests include the *Tiger Conservation Units* (TCUs) Manas-Namdapha. TCUs in tropical dry forest include Hazaribagh National Park, Nagarjunsagar-Srisailam Tiger Reserve, Kanha-Indravati corridor, Orissa dry forests, Panna National. Park, Melghat Tiger Reserve and Ratapani Tiger Reserve. The TCUs in tropical moist deciduous forest are probably some of the most productive habitats for tigers and their prey, and include Kaziranga-Meghalaya, Kanha-Pench, Simlipal and Indravati Tiger Reserves. The TCUs in tropical moist evergreen forests represent the less common tiger habitats, being largely limited to the upland areas and wett er parts of the Western Ghats, and include the Tiger Reserves of Periyar, Kalakad-Mundathurai, Bandipur and Parambikulam Wildlife Sanctuary. During the tiger census of 2008, the Shivaliks–Gangetic fl ood plain landscape having Rajaji and Corbett national parks, Dudhwa-Kheri- Pilibhit, Suhelwa Tigrer Reserve, Sohagi Barwa Sanctuary and Valmiki National Park had an estimated population of 259 to 335 individuals. In Central Indian landscapes of Kanha-Pench, Satpura-Melghat, Sanjay- Palamau, Navegaon-Indravati; Bandhavgarh, Tadoba, Simlipal and the national parks of Panna, Ranthambore–Kuno–Palpur–Madhav and Saranda; there are approximately 437 to 661 Tigers. In Eastern Ghats landscape having Srivenkateshwara National Park, Nagarjunasagar Tiger Reserve and the Gundla Brahmeshwara area, there are approx. 49 to 57 individuals. In Western Ghats landscape there are is estimated population of 336 to 487 Tigers. (Uttarakhand Biodiversity Board).

Morphology: The Bengal Tiger's coat is yellow to light orange, with stripes ranging from dark brown to black; the belly and the interior parts of the limbs are white, and the tail is orange with black rings. Male Bengal tigers have an average total length of 270 to 310 cm including the tail, while females measure 240 to 265 cm on average. The tail is typically 85 to 110 cm long, and on average, tigers are 90 to 110 cm in height at the shoulders. The average weight of males is 221.2 kg, while that of females is 139.7 kg.

Behaviour: The Bengal tiger is a carnivore. It eats boars, wild oxen, monkeys, and other animals. The Bengal tiger can catch big animals, but prefers killing either young or old animals because they don't run as fast. The Bengal tiger is a nocturnal and greatly feared predator. It eats wild oxen and other animals, which eat plants, which are part of the food web. So, it helps balance the web. The basic social unit of the tiger is the elemental one of mother and off spring. Adult animals congregate only on an *ad hoc* and transitory basis when special conditions permit, such as plentiful supply of food. Otherwise they lead solitary lives, hunting individually for the dispersed forest and tall grassland animals, upon which they prey. They establish and maintain home ranges. Resident adults of either sex tend to confine their movements to a definite area of habitat within which they satisfy their needs, and in the case of tigresses, those of their growing cubs. Besides providing the requirements of an adequate food supply, sufficient water and shelter, and a modicum of peace and seclusion, this location must make it possible for the resident to maintain contact with other tigers, especially those of the opposite sex. Those sharing the same ground are well aware of each other's movements and activities.

The home ranges occupied by adult male residents tend to be mutually exclusive, even though one of these residents may tolerate a transient or sub-adult male at least for a time. A male tiger keeps a large territory in order to include the home ranges of several females within its bounds, so that he may maintain mating rights with them. Spacing among females is less complete. Typically there is partial overlap with neighbouring female residents. They tend to have core areas, which are more exclusive, at least for most of the time. Home ranges of both males and females are not stable.

The shift or alteration of a home range by one animal is correlated with a shift of another. The tiger in India has no defi nite mating and birth seasons. Most young are born in December and April. Young have also been found in March, May, October and November. In the 1960s, certain aspects of tiger behaviour at Kanha National Park indicated that the peak of sexual activity was from November to about February, with some mating probably occurring throughout the year. Males reach maturity at 4–5 years of age, and females at 3–4 years. A tigress comes into heat at intervals of about 3–9 weeks, and is receptive for 3–6 days. Aft er a gestation period of 104–106 days, 1–4 cubs are born in a shelter situated in tall grass, thick bush or in caves. Newborn cubs weigh 780 to 1,600 g (1.7 to 3.5 lb) and they have a thick wooly fur that is shed aft er 3.5–5 months. Their eyes and ears are closed. Their milk teeth start to erupt at about 2–3 weeks aft er birth, and are slowly replaced by permanent dentition from 8.5–9.5 weeks of age onwards. They suckle for 3–6 months, and begin to eat small amounts of solid food at about 2 months of age. At this time, they follow their mother on her hunting expeditions and begin to take part in hunting at 5–6 months of age. At the age of 2–3 years, they slowly start to separate from the family group and become transient — looking out for an area, where they can establish their own territory. Young males move further away from their mother's territory than young females. Once the family group has split, the mother comes into heat again.

Threats: Over the past century tiger numbers have fallen dramatically, with a decreasing population trend. None of the *Tiger Conservation Landscapes* within the Bengal tiger range is large enough to support an eff ective population size of 250 individuals. Habitat losses and the extremely largescale incidences of poaching are serious threats to the species' survival. The most signifi cant immediate threat to the existence of wild tiger populations is the illegal trade in poached skins and body parts between India, Nepal and China. There are well-organized gangs of professional poachers, who move from place to place and set up camp in vulnerable areas. Other factors contributing to their loss are urbanization and revenge killing. Farmers blame tigers for killing catt le and shoot them. Their skins and body parts may however become a part of the illegal trade. The illicit demand for bones and body parts from wild tigers for use in Traditional Chinese medicine is the reason for the unrelenting poaching pressure on tigers on the Indian subcontinent.

Measures taken for conservation: An area of special interest lies in the Terai Arc Landscape in the Himalayan foothills of northern India and southern Nepal, where 11 protected areas comprising dry forest foothills and tall-grass savannas harbor tigers in a 49,000 square kilometres (19,000 sq mi) landscape. In Nepal a community-based tourism model has been developed with a strong emphasis on sharing benefit with local people and on the regeneration of degraded forests. The approach has been successful in reducing poaching, restoring habitats, and creating a local constituency for conservation. In 1972, Project Tiger was launched aiming at ensuring a viable population of tigers in the country and preserving areas of biological importance as a natural heritage for the people.

2. Literature Review

A study describes that the alarming loss of tiger (*Panthera tigris*) populations is due to degrading habitat called for an international commitment to double the wild tiger population by 2022 ("Tx2" goal). Multi-decadal remote sensing-based maps were used to assess the rate of deforestation from 1975 to 2016. The time-series analysis revealed that there is a low to moderate level of deforestation reported in PTCLs (Priority Tiger Conservation Landscapes) from 1975 to 2016. The use of the Mann Kendall trend test was also made to assess trend in deforestation.(Minu Merin Sabu et al).

Deforestation is a threat to habitat quality and biodiversity. In intact forests, even small levels of deforestation can have profound consequences for vertebrate biodiversity. To assess the impact of forest conversion and forest loss on biodiversity and habitat quality, forest loss in a tiger conservation landscape in Malaysia is analysed using Sentinel-2 imagery and the InVEST habitat quality model. Forest losses are identified from satellites using the random forest classification and validated with PlanetScope imagery at 3–5 m resolution for a test area. (Valentin Louis et al)

Tropical forests have been experiencing remarkable rates of transformation over the past century as they are getting degraded or decimated to a great extent by anthropogenic activities. An attempt was made at investigating the long-term forest cover transformation in Palamau Tiger Reserve (PTR), Jharkhand, India, using Landsat TM, ETM$^+$, and OLI satellite images during 1975–2015. The forest cover was delineated utilizing various keys of visual interpretation techniques. (Binita Kumari et al).

A study has utilized satellite imagery and data was digitally processed and collateral data were generated from topographic maps in a GIS framework. Various layers of different variables such as landuse land cover, forest density, measures of proximity to disturbances and water resources and a digital terrain model were created based on ground truthing. These layers, GPS location of animal's presence and "binomial multiple logistic regression (BMLR)" techniques were integrated in a GIS environment for the HSI modelling.(Ekwal Imam et al).

One study has made use of high spatial resolution, hyperspectral, thermal infrared, small-satellite constellation, and LIDAR sensors; and the techniques refer to image classification, vegetation index (VI), inversion algorithm, data fusion, and the integration of remote sensing (RS) and geographic information system (GIS),(Kai Wang et al).

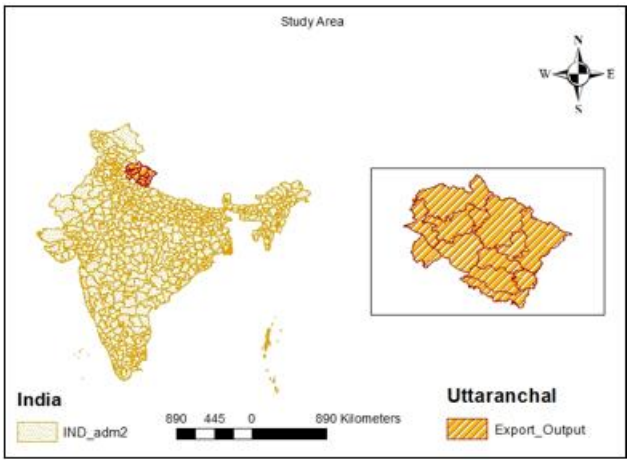
A study states, to assess the habitat suitability and potential corridors for Bengal tiger species (*Panthera tigris tigris*). Nine suitability conditioning factors (tree cover, prey richness, drainage density, vegetation types, elevation, slope, aspect, temperature, and rainfall) and seven threatening factors (forest fragmentation, land use land cover, distance from roads, railway tracks, settlement, range offices, and forest fire points) were selected for emphasizing species-environment association in VTR. The spatial layers of all the factors and presence location data of tigers were integrated into the MaxEnt model to prepare a habitat suitability map. The model was validated utilizing the receiver operating characteristic (ROC) curve (0.822),(Roshani et al).

The study aims to predict and model the distribution of the species Panthera Tigris Tigris by combining various climatic, human influence, and environmental factors so as to predict alternate ecological niche for the already dwindling tiger habitats in India. 19 Bioclimatic variables, Elevation level, 17 Land Cover classes, Population Density, and Human Footprint data were taken. MAXENT, SVM, Random Forest, and Artificial Neural Networks were used for modeling. Sampling bias on the species was removed through spatial thinning. These variables were tested for Pearson correlation and those having coefficient greater than 0.70 were removed. Kappa statistic and AUC were used to study the results of the methodology implemented (Bajaj et al).

3. Methodology

Study Area:

Uttarakhand also known as Uttaranchal is a state in northern India. The state is bordered by Himachal Pradesh to the northwest, Tibet to the north, Nepal to the east, Uttar Pradesh to the south and southeast, with a small part touching Haryana in the west. Uttarakhand has a total area of 53,483 km2 (20,650 sq mi), equal to 1.6% of the total area of India. Dehradun serves as the state capital, with Nainital being the judicial capital. The state is divided into two divisions, Garhwal and Kumaon, with a total of 13 districts. The forest cover in the state is 45.4% of the state's geographical area. The cultivable area is 16% of the total geographical area. The two major rivers of the state, the Ganges and its tributary Yamuna, originate from the Gangotri and Yamunotri glaciers respectively. Ranked 6th among the Top 10 Greenest States in India with Best AQI.



Data and Methodology:

Google earth Engine platform, GIS and MAXENT have been utilized in modeling the distribution of the species Panthera Tigris Tigris by combining various climatic conditions, human influence, Vegetation Index, Land Use Land Cover so as to predict alternate ecological niche for the already dwindling tiger habitats in study area.

Landsat 8 Collection 2 Tier 1 calibrated top-of-atmosphere (TOA) reflectance considered for assessing the status of vegetation, Chander et al. (2009)

Sentinel-2 10m Land Use/Land Cover was used in study for Land use land cover (LULC) ,which are an increasingly important tool for decision-makers in many industry sectors and developing nations around the world. The information provided by these maps helps inform policy and land management decisions by better understanding and quantifying the impacts of earth processes and human activity.

WorldClim Bioclimatic variables were taken from WorldClim version 2. They are the average for the years 1970-2000. WorldClim is a database of high spatial resolution global weather and climate data. These data can be used for mapping and spatial modeling. The data are provided for use in research and related activities.

Population data were taken from https://www.worldpop.org/blog/beta-test-our-new-global-population-data-2015-to-2030/.

After processing the considered variables in Google Earth Engine and GIS with SVM, used in MAXTENT to understand the impact of variables in distribution modelling and prediction of species.

Paper ID: SR25530145547 DOI: https://dx.doi.org/10.21275/SR25530145547

4. Results and Discussions

The present situation of Panthera Tigris in study area i.e. Uttarakhand state is depicted in the fig.1.0

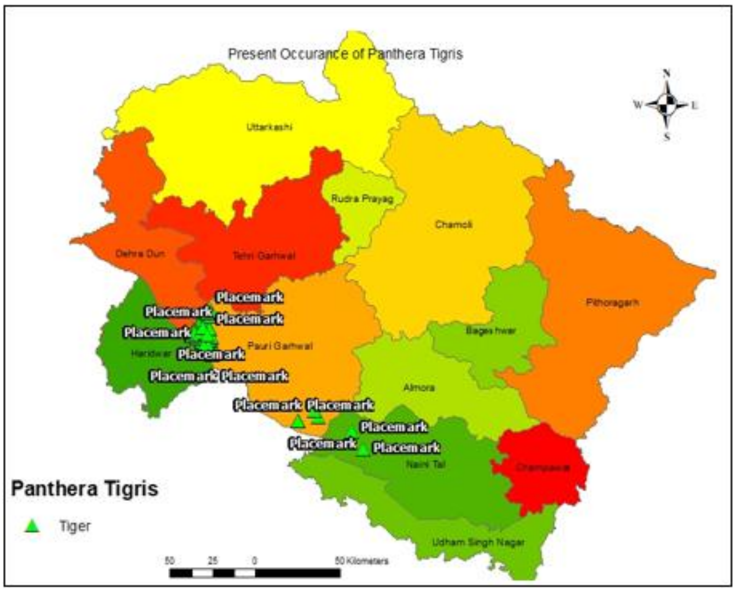


Figure 1

1) **Variable:** Biodiversity Climate Change

Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is calculated both on the training presence records, and (if test data are used) on the test records. The omission rate should be close to the predicted omission, because of the definition of the cumulative threshold.

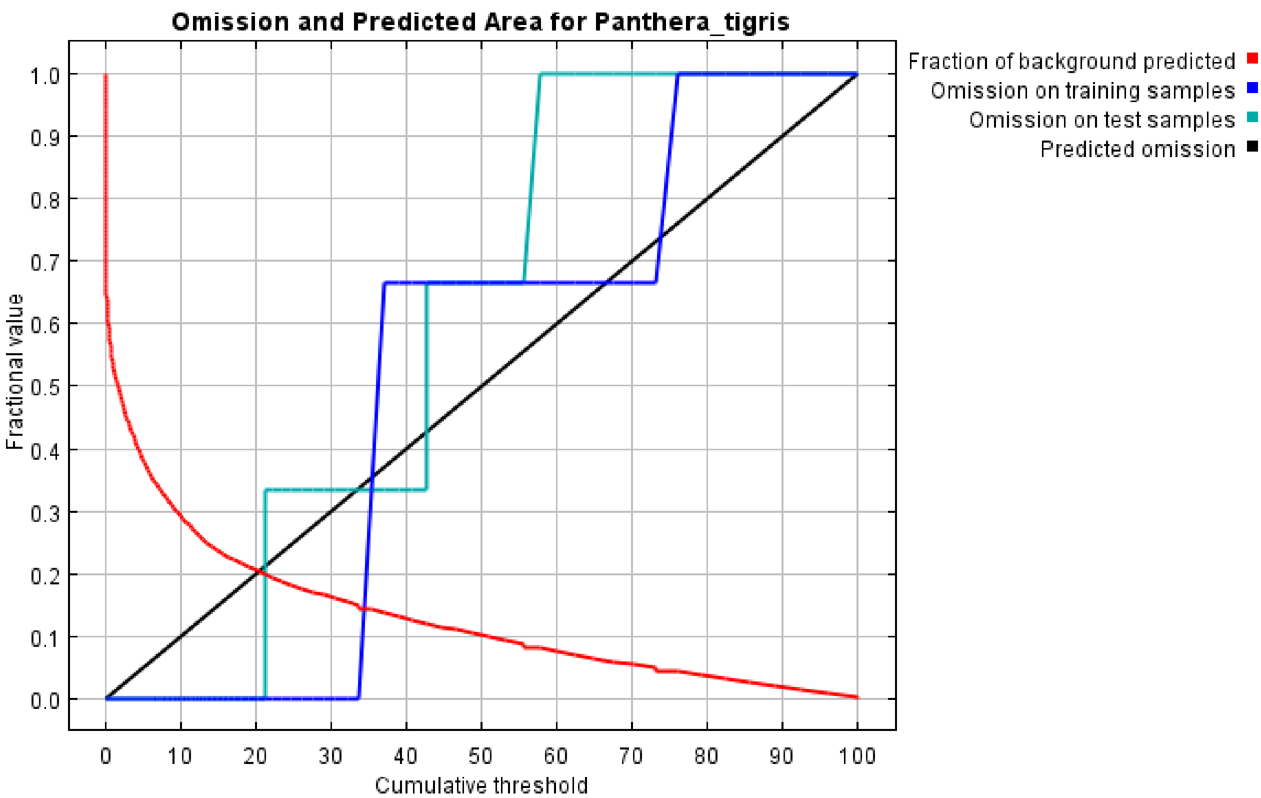


Figure 2

The next picture is the receiver operating characteristic (ROC) curve for the same data. To note that the specificity is defined using predicted area, rather than true commission (Phillips et al), This implies that the maximum achievable AUC is less than 1. If test data is drawn from the Maxent distribution itself, then the maximum possible test AUC would be 0.865 rather than 1; in practice the test AUC may exceed this bound.

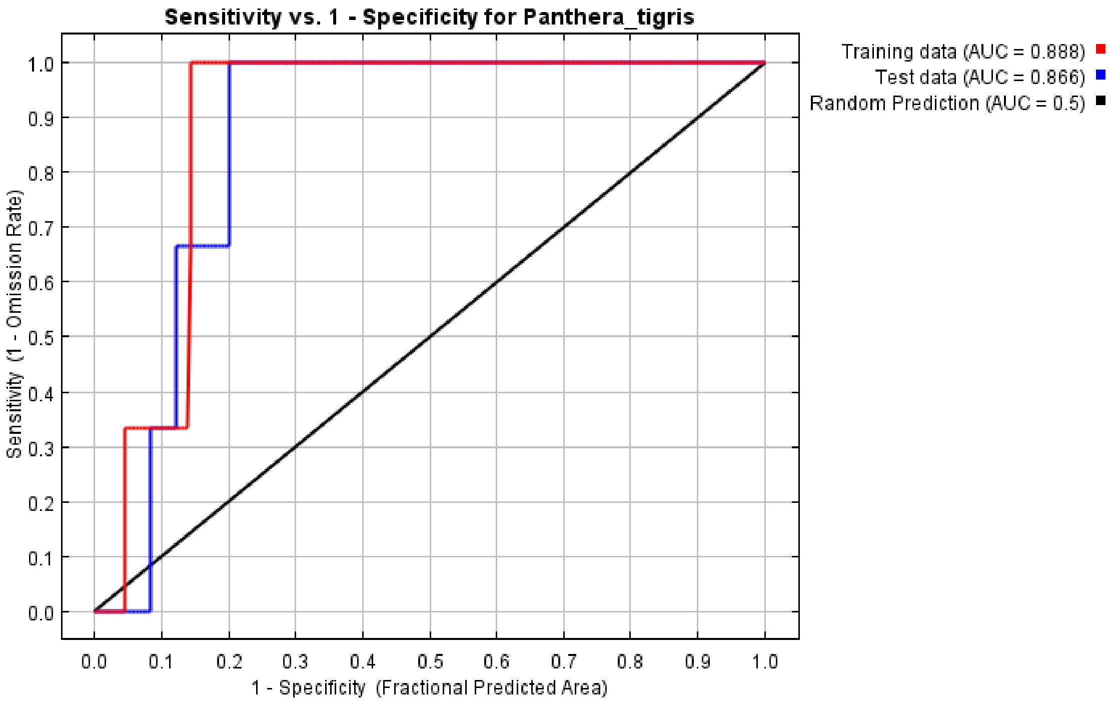


Figure 3

Some common thresholds and corresponding omission rates are as follows. These are 1-sided p-values for the null hypothesis that test points are predicted no better than by a random prediction with the same fractional predicted area. The "Balance" threshold minimizes 6 * training omission rate + .04 * cumulative threshold + 1.6 * fractional predicted area.

Cumulative threshold	Cloglog threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
1	0.057	Fixed cumulative value 1	0.528	0	0	1.47E-01
5	0.134	Fixed cumulative value 5	0.378	0	0	5.39E-02
10	0.219	Fixed cumulative value 10	0.289	0	0	2.41E-02
33.727	0.639	Minimum training presence	0.144	0	0.333	5.66E-02
33.727	0.639	10 percentile training presence	0.144	0	0.333	5.66E-02
33.727	0.639	Equal training sensitivity and specificity	0.144	0	0.333	5.66E-02
33.727	0.639	Maximum training sensitivity plus specificity	0.144	0	0.333	5.66E-02
21.144	0.464	Equal test sensitivity and specificity	0.2	0	0.333	1.04E-01
21.144	0.464	Maximum test sensitivity plus specificity	0.2	0	0	8.00E-03
4.952	0.116	Balance training omission, predicted area and threshold value	0.383	0	0	5.63E-02
7.024	0.165	Equate entropy of thresholded and original distributions	0.339	0	0	3.89E-02

Pictures of the model

This is a representation of the Maxent model for Panthera Tigris. Warmer colours show areas with better predicted conditions. White dots show the presence locations used for training, while violet dots show test locations.

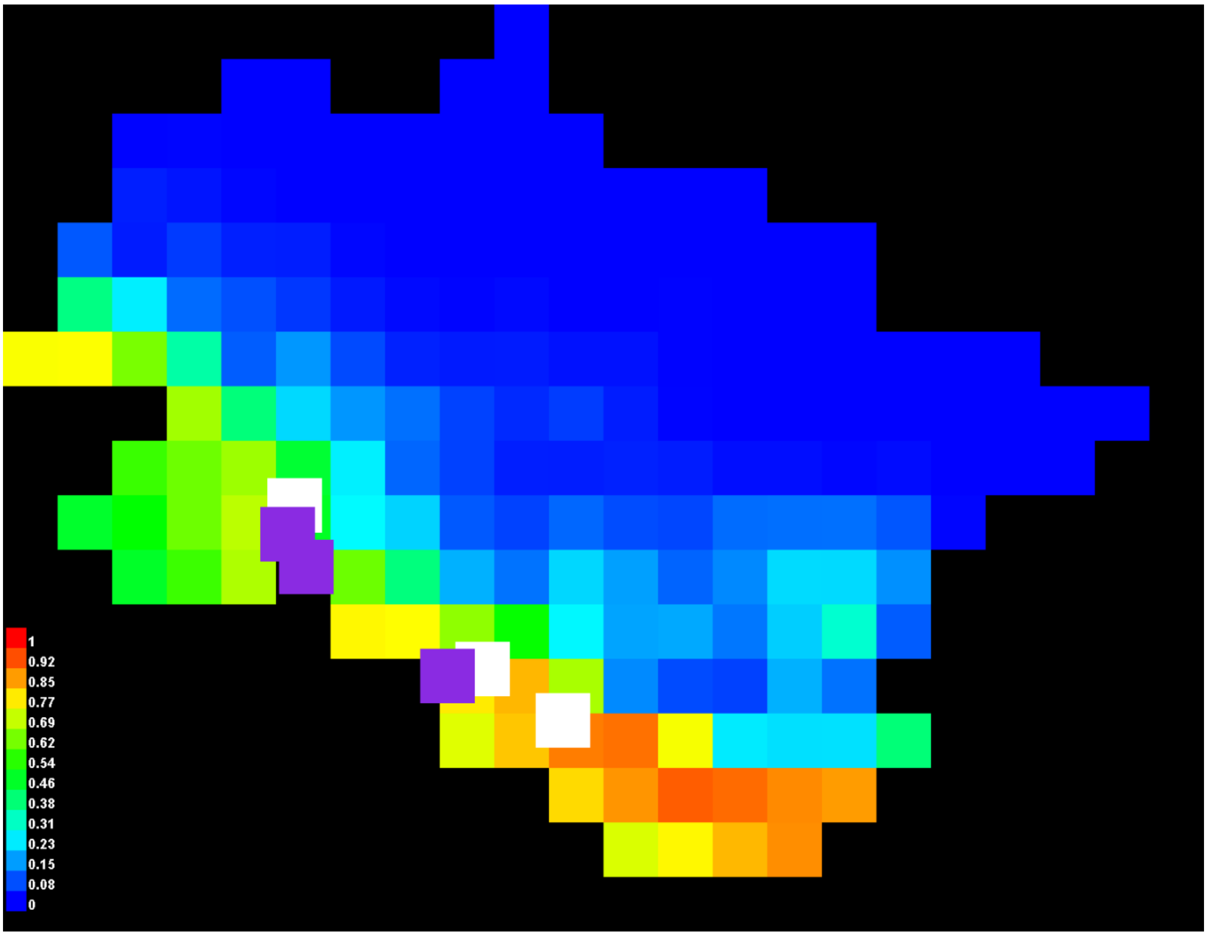


Figure 4

Response Curves

These curves show how each environmental variable affects the Maxent prediction. The curves show how the predicted probability of presence changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. May be noted that the curves can be hard to interpret if we have strongly correlated variables, as the model may depend on the correlations in ways that are not evident in the curves. In other words, the curves show the marginal effect of changing exactly one variable, whereas the model may take advantage of sets of variables changing together.

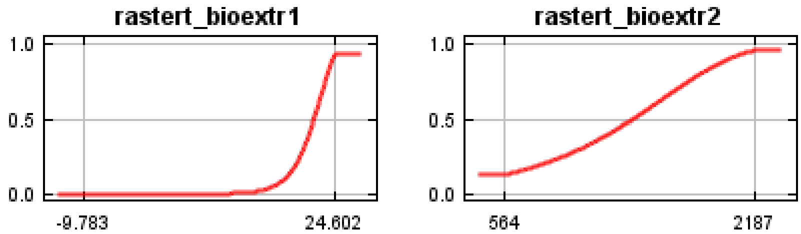


Figure 5

In contrast to the above marginal response curves, each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.

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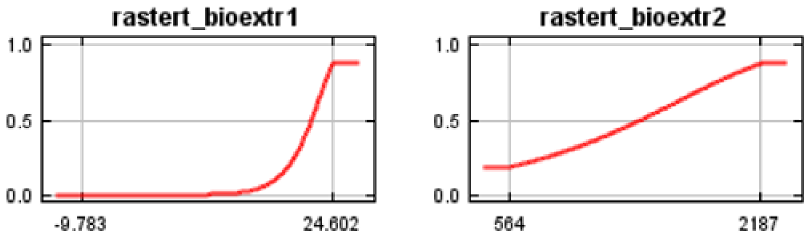

Figure 6

Analysis of variable contributions

The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from it if the change to the absolute value of lambda is negative. For the second estimate, for each environmental variable in turn, the values of that variable on training presence and background data are randomly permuted. The model is reevaluated on the permuted data, and the resulting drop in training AUC is shown in the table, normalized to percentages. As with the variable jackknife, variable contributions should be interpreted with caution when the predictor variables are correlated.

Variable	Percent contribution	Permutation importance
rastert_bioextr1	95.8	72.2
rastert_bioextr2	4.2	27.8

Regularized training gain is 1.066, training AUC is 0.888, unregularized training gain is 1.272.
Unregularized test gain is 1.064.
Test AUC is 0.866, standard deviation is 0.032 (calculated as in DeLong, DeLong & Clarke-Pearson 1988, equation 2).
Algorithm converged after 80 iterations (0 seconds).

(2) Variable: Vegetation Changes

Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is calculated both on the training presence records, and (if test data are used) on the test records. The omission rate should be close to the predicted omission, because of the definition of the cumulative threshold.

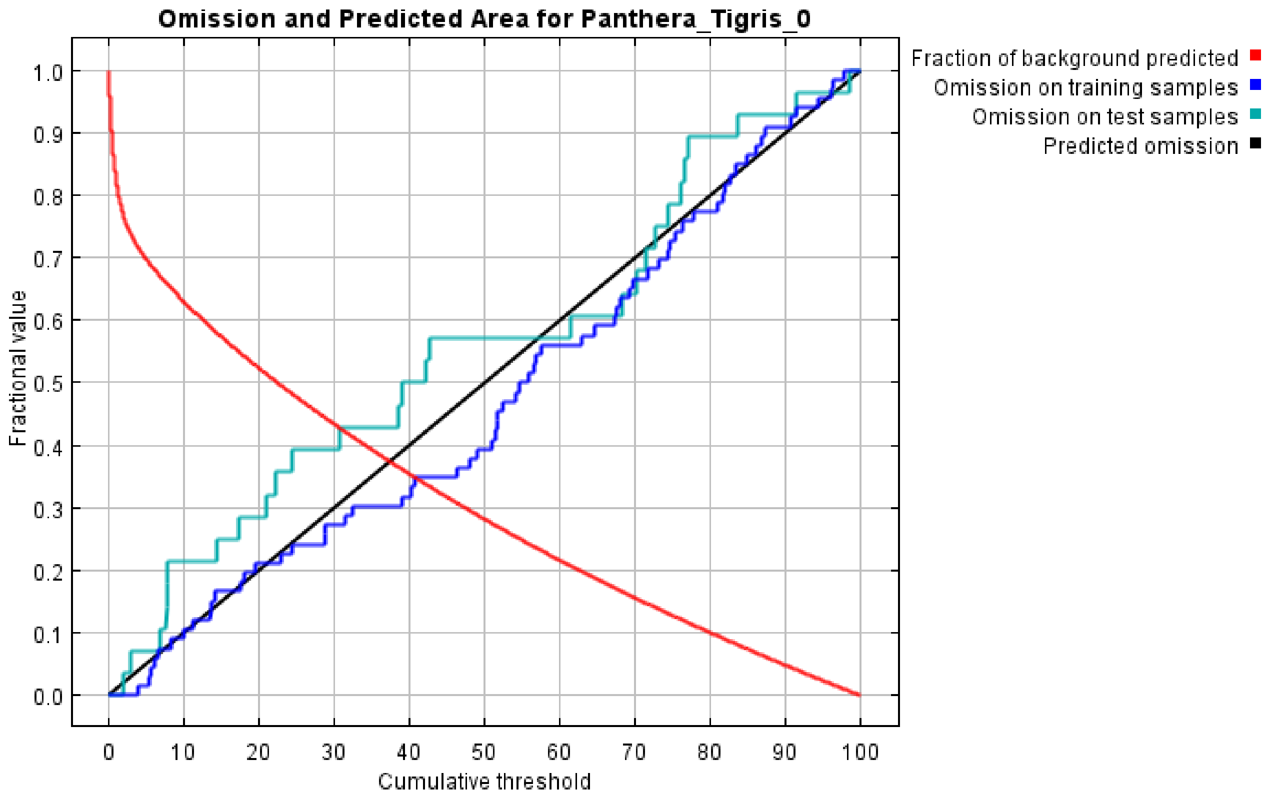

Figure 7

The next picture is the receiver operating characteristic (ROC) curve for the same data. Note that the specificity is defined using predicted area, rather than true commission (Phillips et al). This implies that the maximum achievable AUC is less than 1. If test data is drawn from the Maxent distribution itself, then the maximum possible test AUC would be 0.686 rather than 1; in practice the test AUC may exceed this bound.

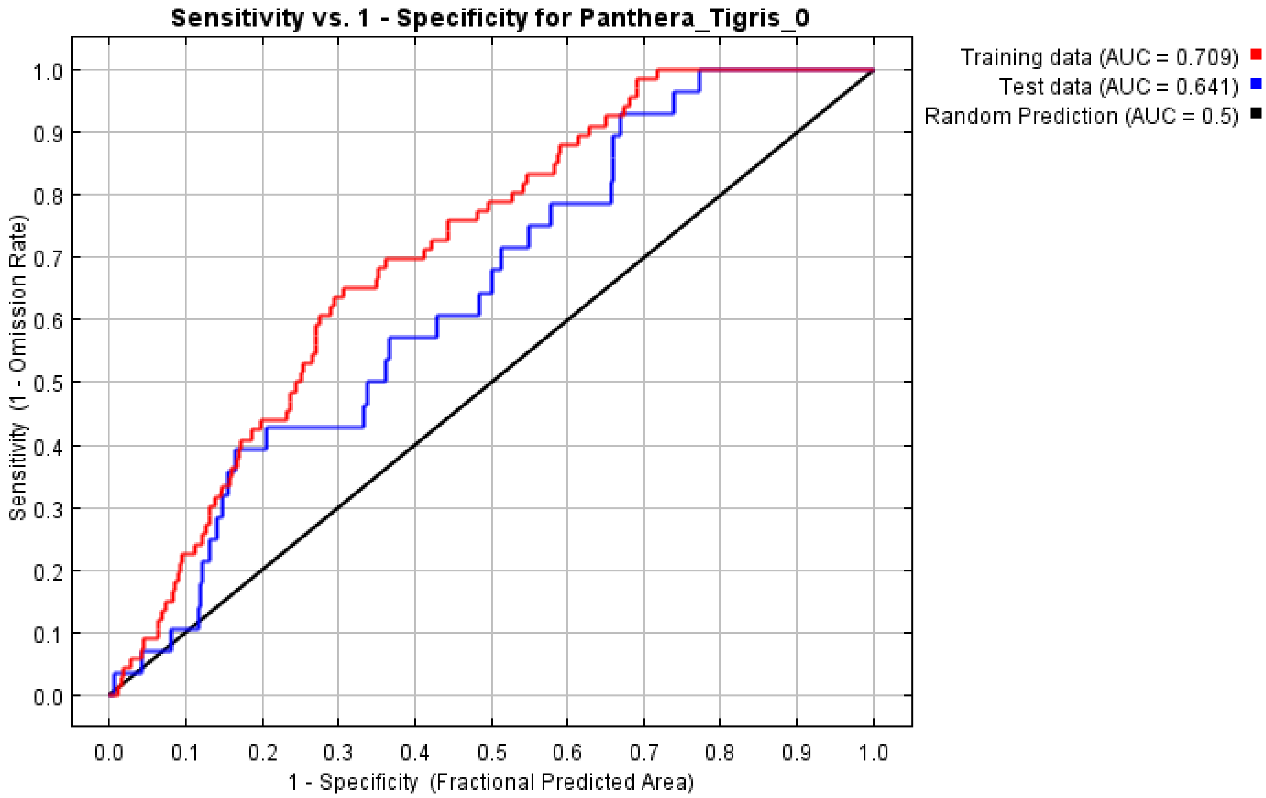

Figure 8

Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that test points are predicted no better than by a random prediction with the same fractional predicted area. The "Balance" threshold minimizes 6 * training omission rate + .04 * cumulative threshold + 1.6 * fractional predicted area.

Cumulative threshold	Cloglog threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
1	0.083	Fixed cumulative value 1	0.824	0	0	7.16E-03
5	0.381	Fixed cumulative value 5	0.697	0.015	0.071	3.89E-03
10	0.468	Fixed cumulative value 10	0.63	0.091	0.214	4.39E-02
3.858	0.333	Minimum training presence	0.717	0	0.071	6.55E-03
10.037	0.468	10 percentile training presence	0.63	0.091	0.214	4.35E-02
40.764	0.64	Equal training sensitivity and specificity	0.348	0.348	0.5	4.62E-02
46.33	0.659	Maximum training sensitivity plus specificity	0.308	0.348	0.571	8.30E-02
30.697	0.601	Equal test sensitivity and specificity	0.428	0.273	0.429	6.25E-02
6.87	0.426	Maximum test sensitivity plus specificity	0.67	0.076	0.071	1.82E-03
2.83	0.259	Balance training omission, predicted area and threshold value	0.74	0	0.036	3.38E-03
1.979	0.178	Equate entropy of thresholded and original distributions	0.766	0	0.036	6.64E-03

Pictures of the model

This is a representation of the Maxent model for Panthera_Tigris_0. Warmer colors show areas with better predicted conditions. White dots show the presence locations used for training, while violet dots show test locations.

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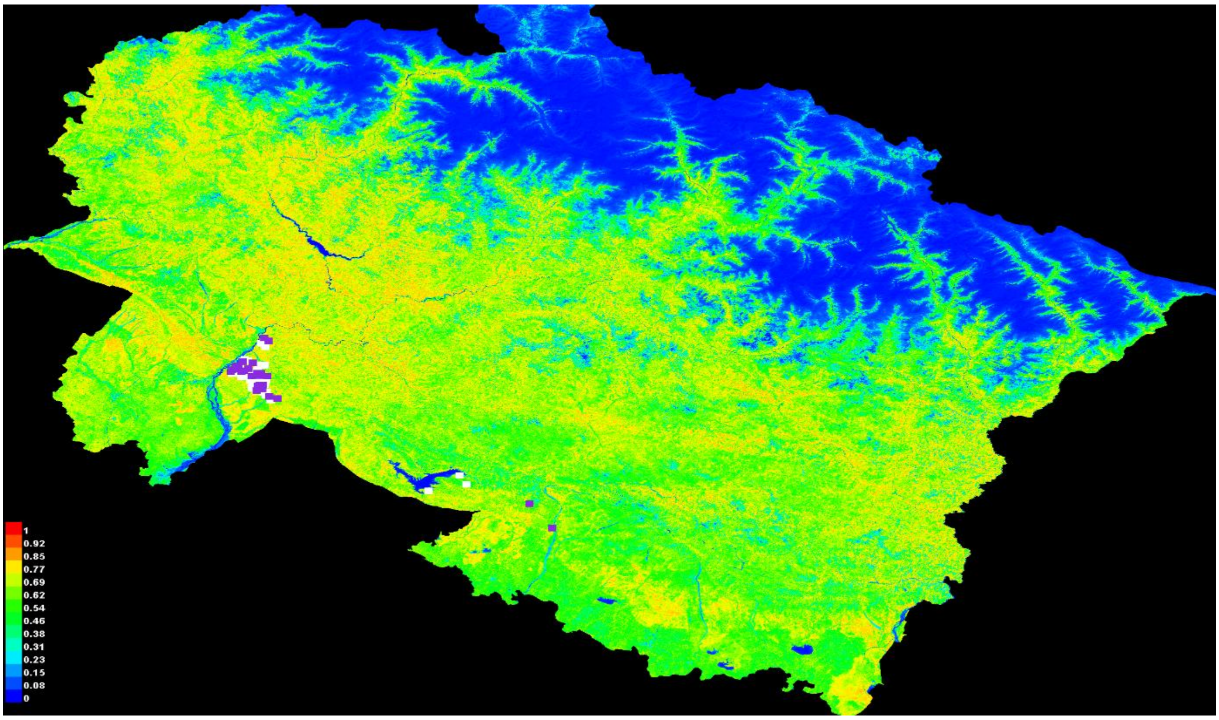

Figure 9

Response Curves:

These curves show how each environmental variable affects the Maxent prediction. The curves show how the predicted probability of presence changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. To note that the curves can be hard to interpret if we have strongly correlated variables, as the model may depend on the correlations in ways that are not evident in the curves. In other words, the curves show the marginal effect of changing exactly one variable, whereas the model may take advantage of sets of variables changing together.

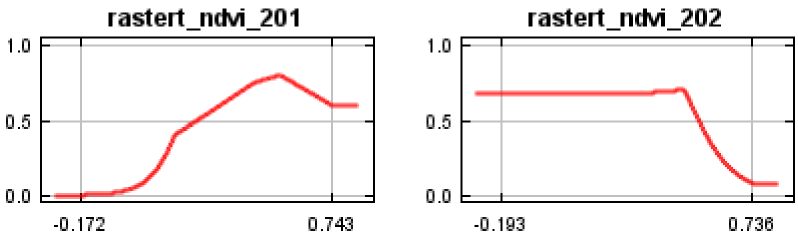

Figure 10

In contrast to the above marginal response curves, each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.

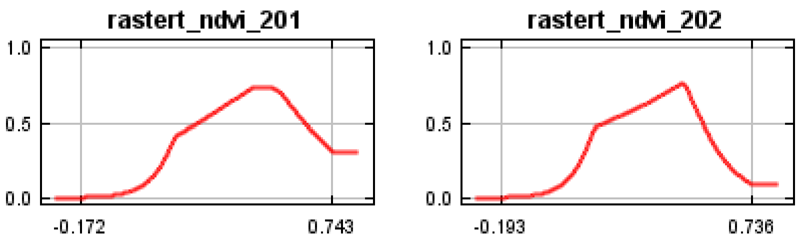

Figure 11

Analysis of variable contributions:

The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from it if the change to the absolute value of lambda is negative. For the second estimate, for each environmental variable in turn, the values of that variable on training presence and background data are randomly permuted. The model is reevaluated on the permuted data, and the resulting drop in training AUC is shown in the table, normalized to percentages. As with the variable jackknife, variable contributions should be interpreted with caution when the predictor variables are correlated.

Variable	Percent contribution	Permutation importance
rastert_ndvi_201	90.5	80.6
rastert_ndvi_202	9.5	19.4

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is rastert_ndvi_201, which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted is rastert_ndvi_201, which therefore appears to have the most information that isn't present in the other variables.

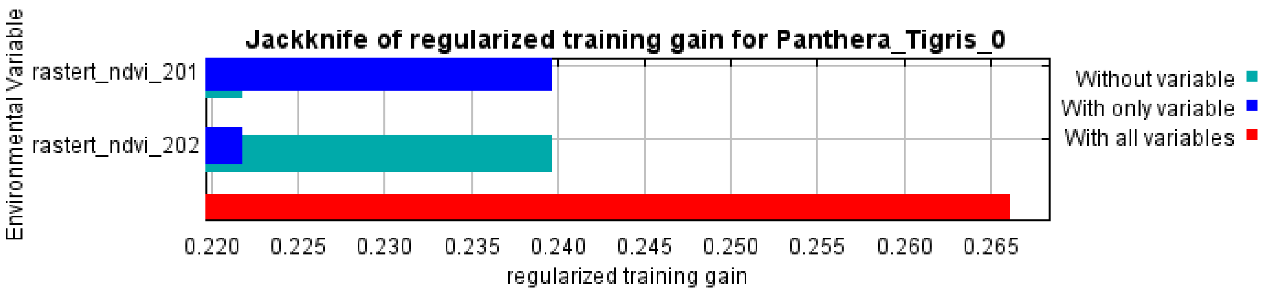

Figure 12

The next picture shows the same jackknife test, using test gain instead of training gain. Note that conclusions about which variables are most important can change, now that we're looking at test data.

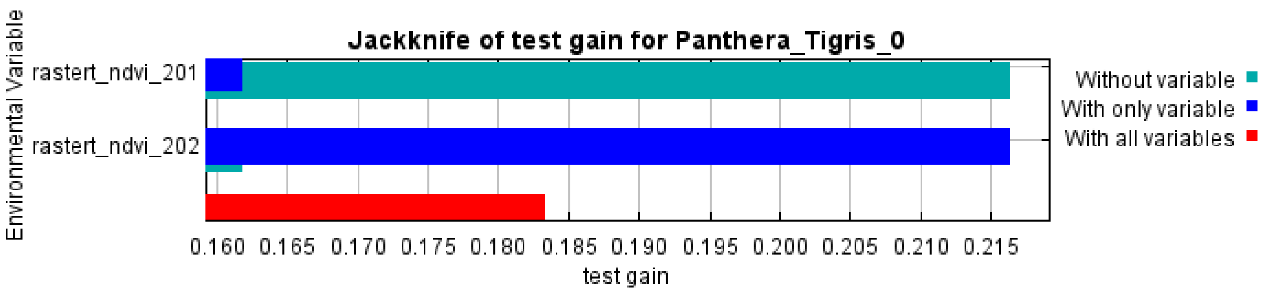

Figure 13

Lastly, we have the same jackknife test, using AUC on test data.

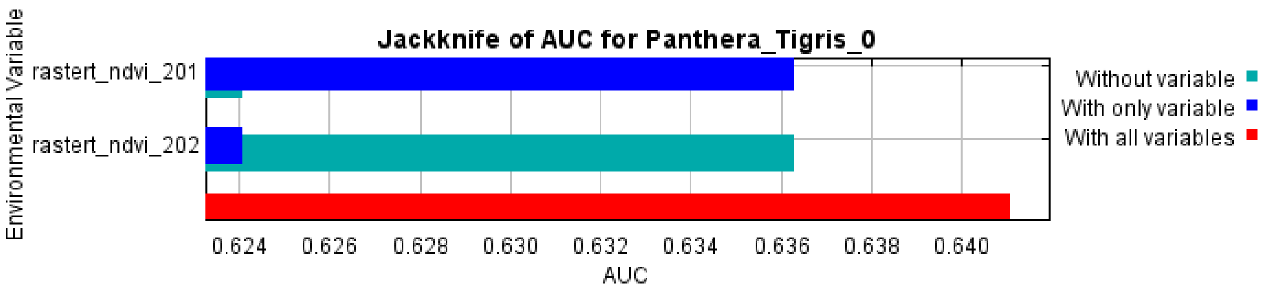

Figure 14

Raw data outputs and control parameters:
Regularized training gain is 0.266, training AUC is 0.709, unregularized training gain is 0.337.

Unregularized test gain is 0.183.

1) Test AUC is 0.641, standard deviation is 0.045 (calculated as in DeLong, DeLong & Clarke-Pearson 1988, equation
2) Algorithm converged after 280 iterations (2 seconds).
3) Variable: Land Use Land Cover Changes:

Analysis of omission/commission
The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is is calculated both on the training presence records, and (if test data are used) on the test records. The omission rate should be close to the predicted omission, because of the definition of the cumulative threshold.

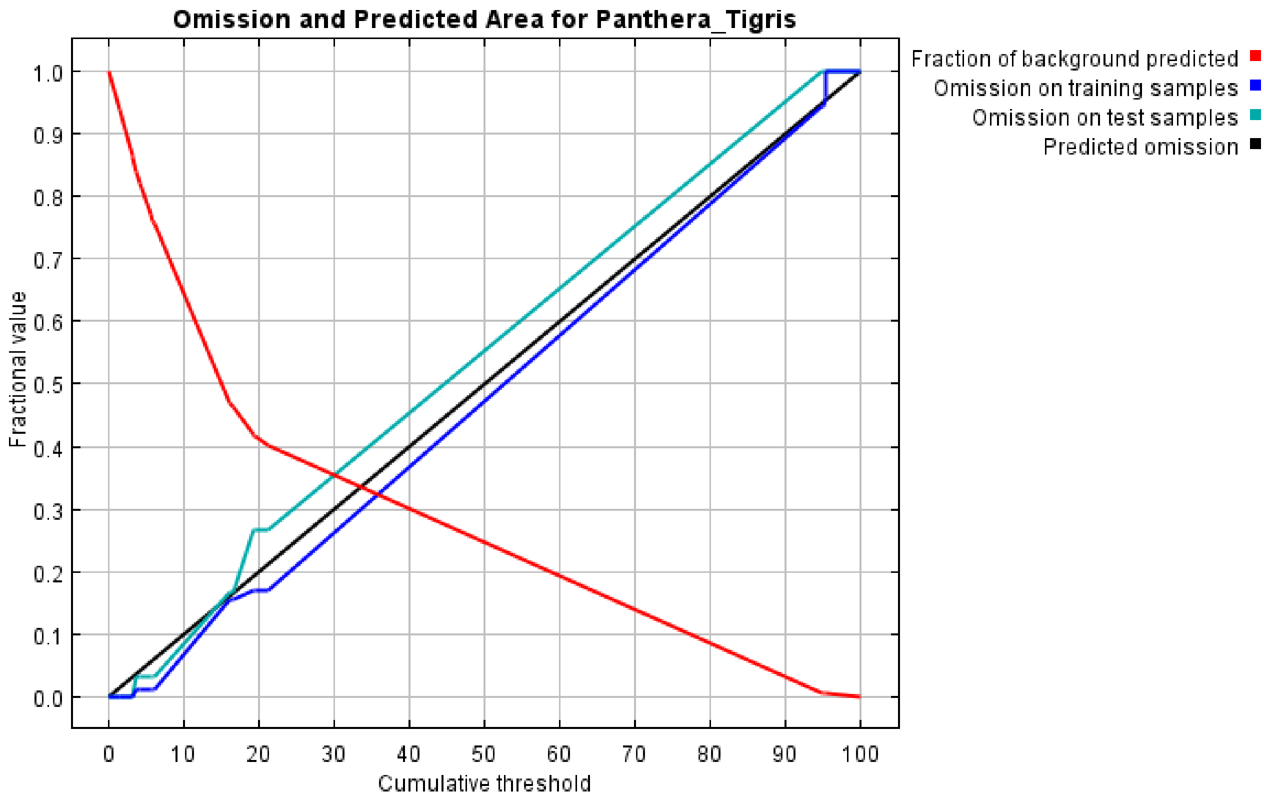

Figure 15

The next picture is the receiver operating characteristic (ROC) curve for the same data. Note that the specificity is defined using predicted area, rather than true commission (Phillips et al). This implies that the maximum achievable AUC is less than 1. If test data is drawn from the Maxent distribution itself, then the maximum possible test AUC would be 0.713 rather than 1; in practice the test AUC may exceed this bound.

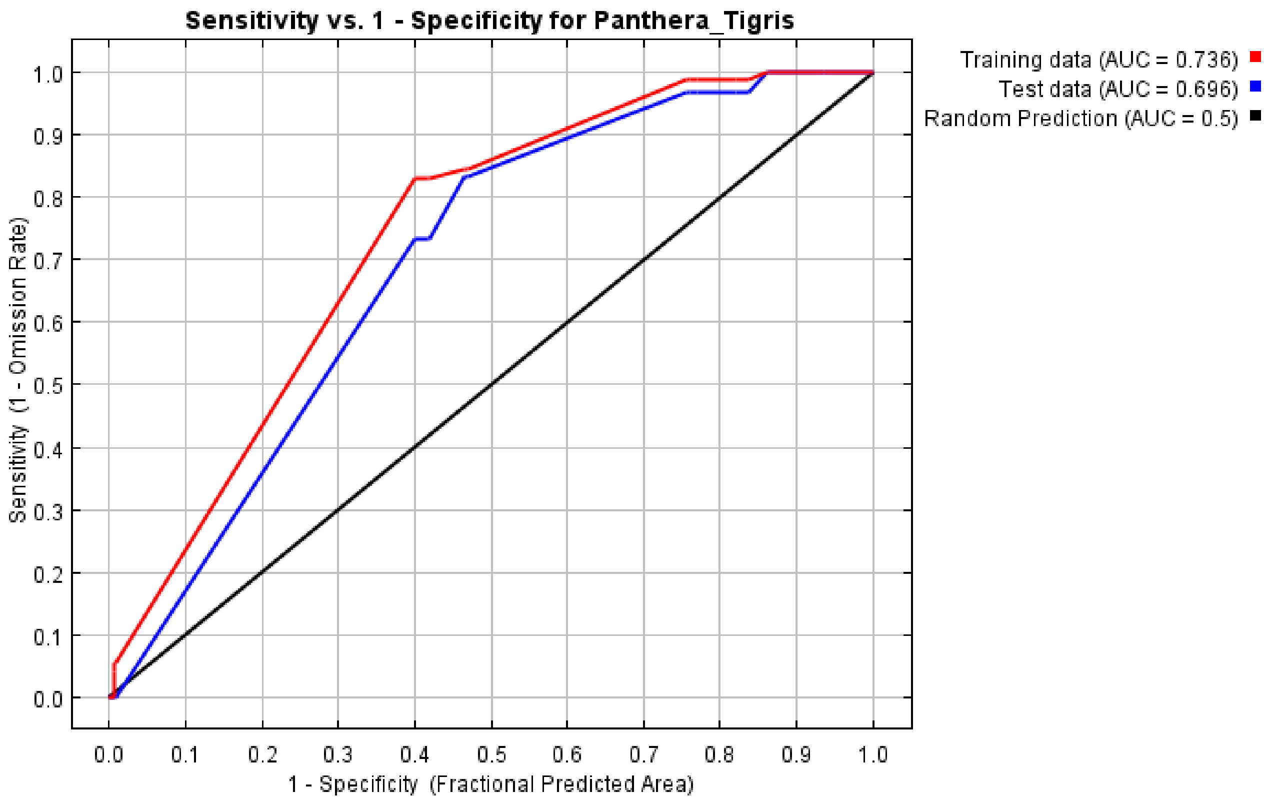

Figure 16

Some common thresholds and corresponding omission rates are as follows. These are 1-sided p-values for the null hypothesis that test points are predicted no better than by a random prediction with the same fractional predicted area. The "Balance" threshold minimizes 6 * training omission rate + .04 * cumulative threshold + 1.6 * fractional predicted area.

Cumulative threshold	Cloglog threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
1	0.15	Fixed cumulative value 1	0.937	0	0	7.74E-02
5	0.187	Fixed cumulative value 5	0.77	0.014	0.033	5.28E-03
10	0.319	Fixed cumulative value 10	0.469	0.157	0.167	3.22E-05
3.136	0.16	Minimum training presence	0.862	0	0	1.41E-02
6.088	0.218	10 percentile training presence	0.756	0.014	0.033	3.59E-03
21.145	0.73	Equal training sensitivity and specificity	0.401	0.171	0.267	1.02E-04
21.145	0.73	Maximum training sensitivity plus specificity	0.401	0.171	0.267	1.02E-04
21.145	0.73	Equal test sensitivity and specificity	0.401	0.171	0.267	1.02E-04
16.485	0.347	Maximum test sensitivity plus specificity	0.464	0.157	0.167	2.50E-05
3.136	0.16	Balance training omission, predicted area and threshold value	0.862	0	0	1.41E-02
16.204	0.319	Equate entropy of thresholded and original distributions	0.469	0.157	0.167	3.22E-05

Pictures of the model

This is a representation of the Maxent model for Panthera_Tigris. Warmer colors show areas with better predicted conditions. White dots show the presence locations used for training, while violet dots show test locations.

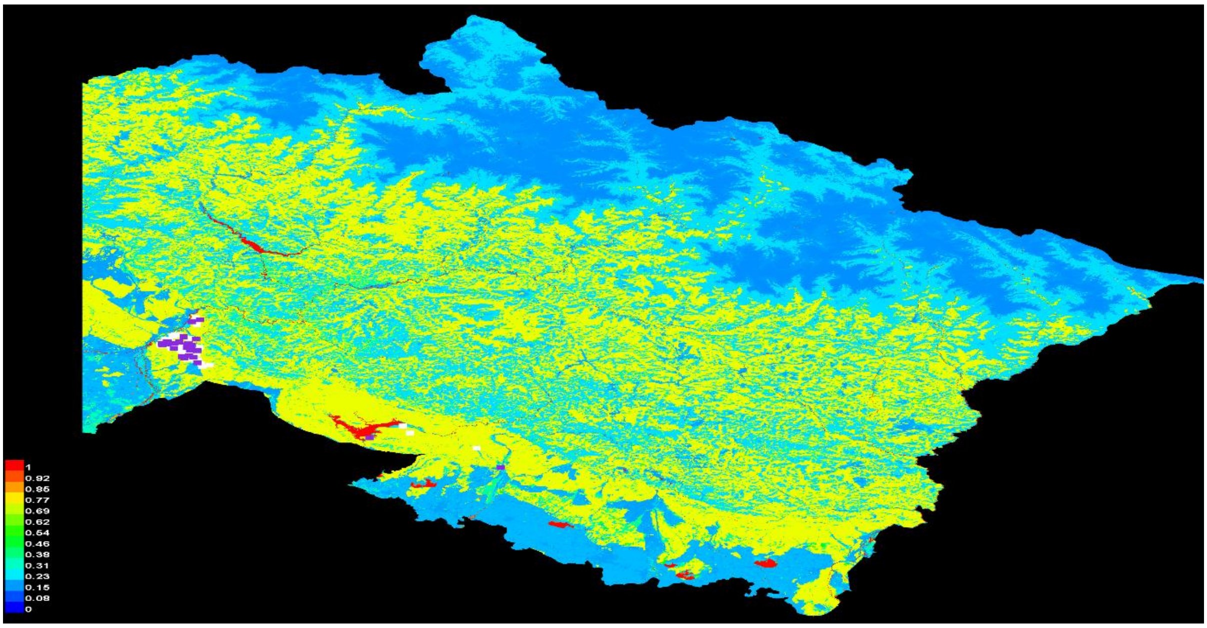

Figure 17

Response curves

These curves show how each environmental variable affects the Maxent prediction. The curves show how the predicted probability of presence changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. To note that the curves can be hard to interpret if you have strongly correlated variables, as the model may depend on the correlations in ways that are not evident in the curves. In other words, the curves show the marginal effect of changing exactly one variable, whereas the model may take advantage of sets of variables changing together.

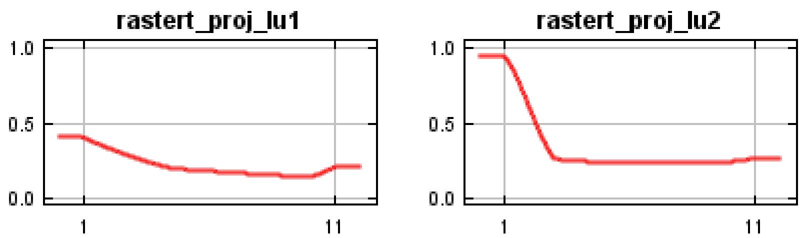

Figure 18

In contrast to the above marginal response curves, each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.

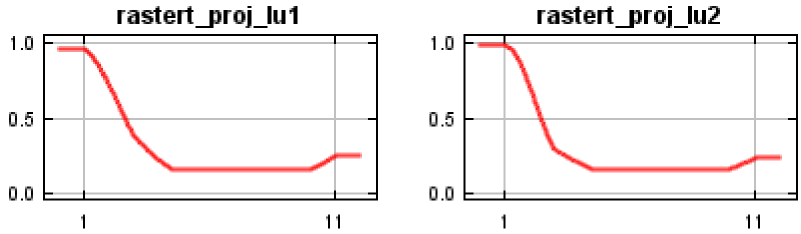

Figure 19

Analysis of variable contributions

The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from it if the change to the absolute value of lambda is negative. For the second estimate, for each environmental variable in turn, the values of that variable on training presence and background data are randomly permuted. The model is reevaluated on the permuted data, and the resulting drop in training AUC is shown in the table, normalized to percentages. As with the variable jackknife, variable contributions should be interpreted with caution when the predictor variables are correlated.

Variable	Percent contribution	Permutation importance
rastert_proj_lu2	82.1	93.7
rastert_proj_lu1	17.9	6.3

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is rastert_proj_lu2, which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted is rastert_proj_lu2, which therefore appears to have the most information that isn't present in the other variables.

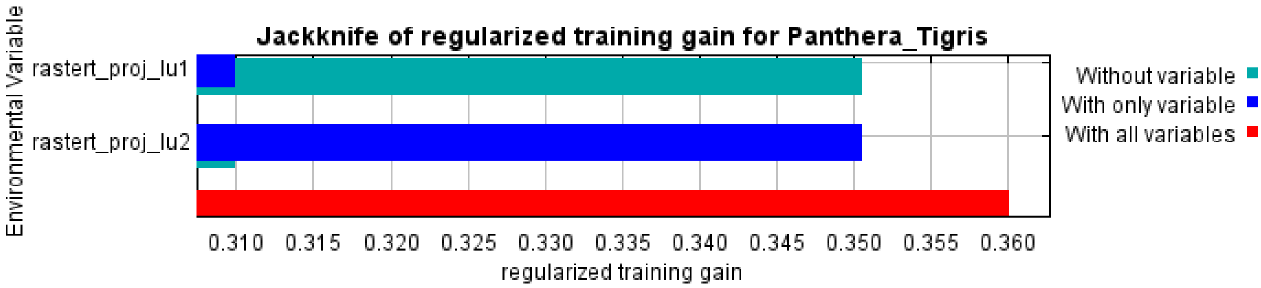

Figure 20

The next picture shows the same jackknife test, using test gain instead of training gain. Note that conclusions about which variables are most important can change, now that we're looking at test data.

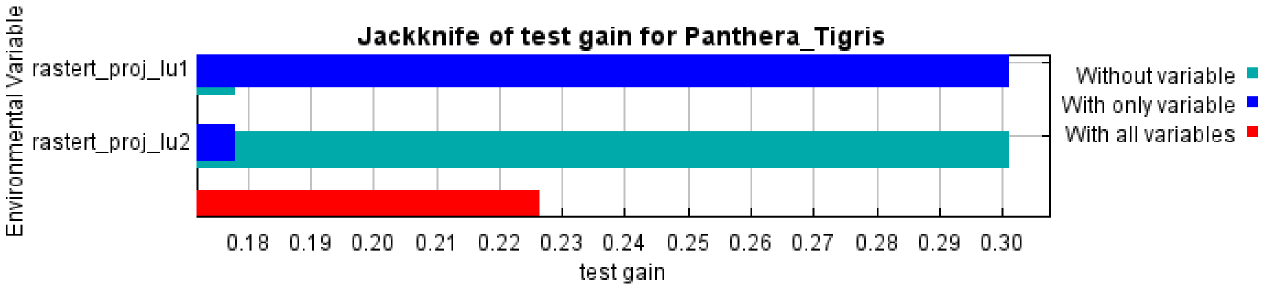

Figure 21

Lastly, we have the same jackknife test, using AUC on test data.

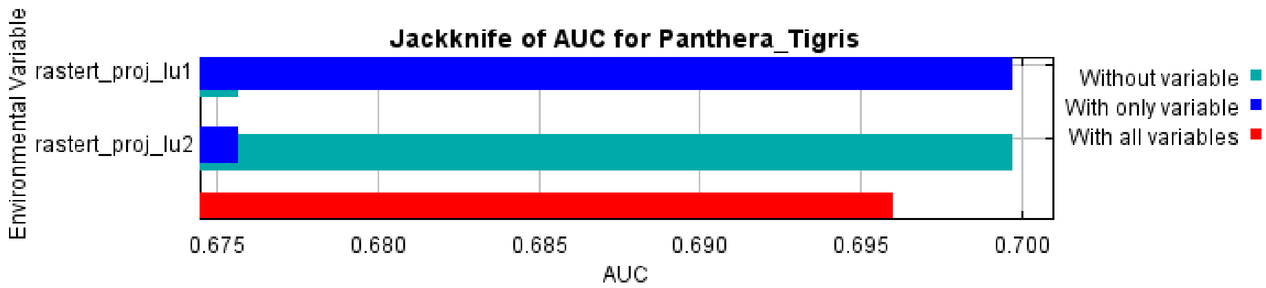

Figure 22

Raw data outputs and control parameters:
Regularized training gain is 0.360, training AUC is 0.736, unregularized training gain is 0.421. Unregularized test gain is 0.226. Test AUC is 0.696, standard deviation is 0.033 (calculated as in DeLong, DeLong & Clarke-Pearson 1988, equation 2). Algorithm converged after 240 iterations (1 seconds).

(4)Variable : Population Changes:
Analysis of omission/commission
The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is is calculated both on the training presence records, and (if test data are used) on the test records. The omission rate should be close to the predicted omission, because of the definition of the cumulative threshold.

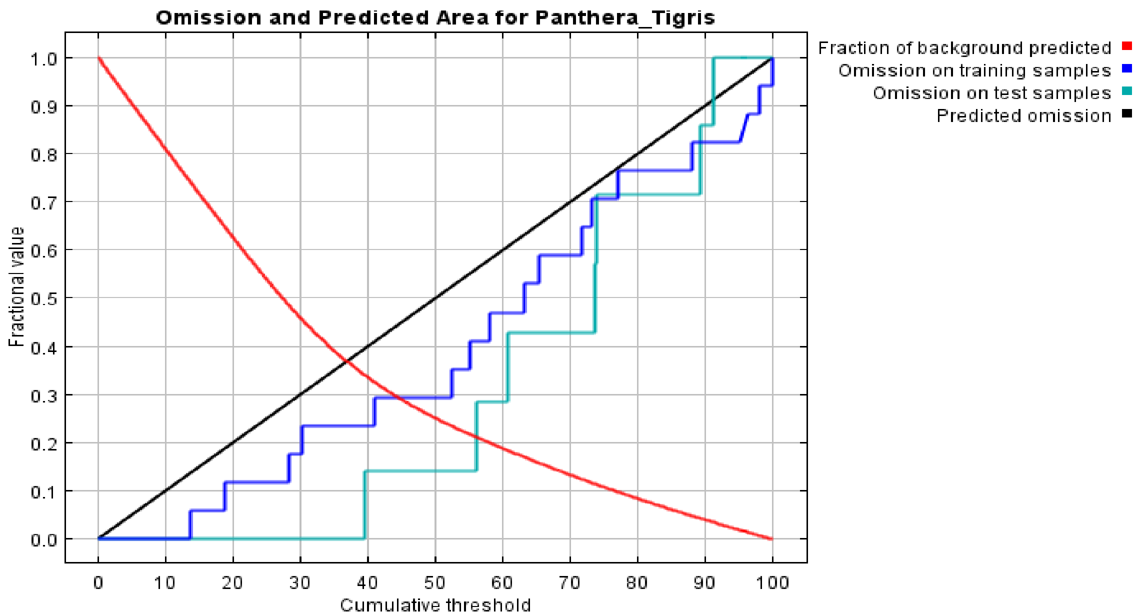

Figure 23

The next picture is the receiver operating characteristic (ROC) curve for the same data. Note that the specificity is defined using predicted area, rather than true commission (Phillips et al,). This implies that the maximum achievable AUC is less than 1. If test data is drawn from the Maxent distribution itself, then the maximum possible test AUC would be 0.659 rather than 1; in practice the test AUC may exceed this bound.

Paper ID: SR25530145547 DOI: https://dx.doi.org/10.21275/SR25530145547

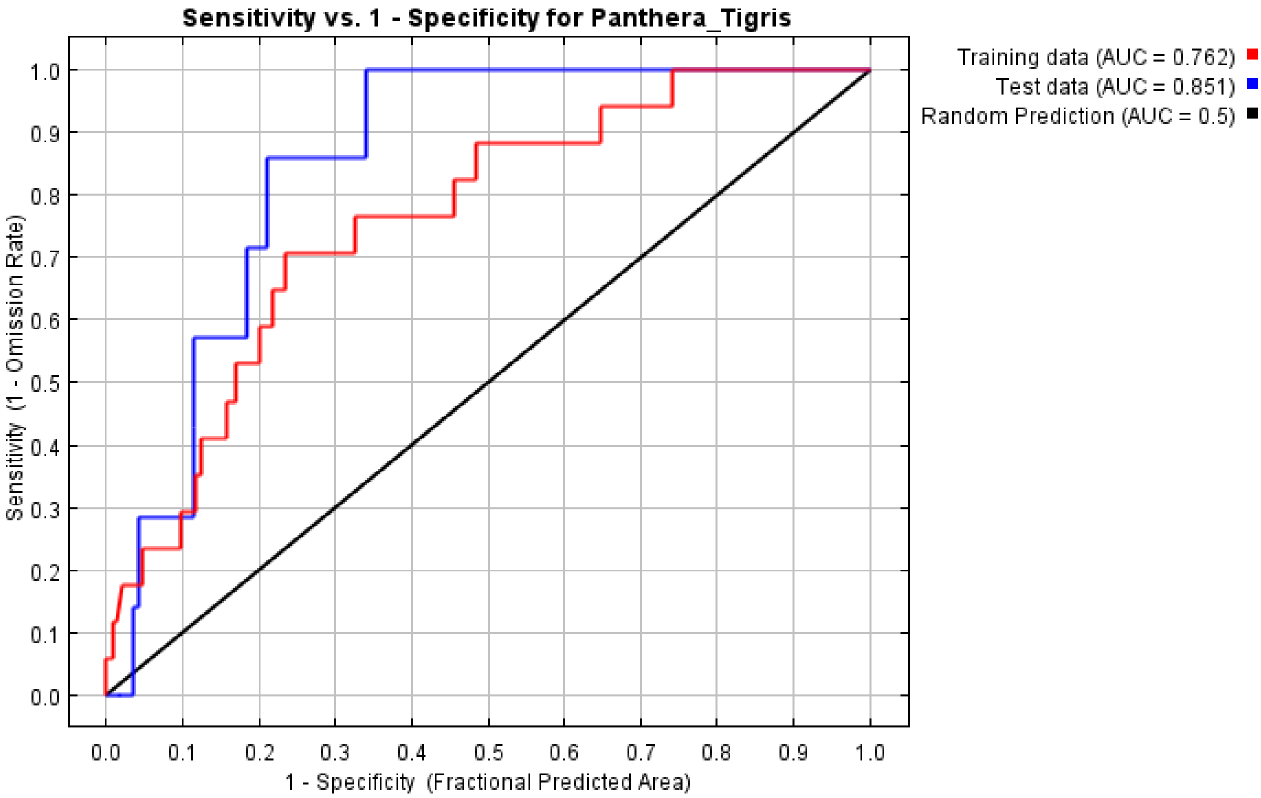

Figure 24

Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that test points are predicted no better than by a random prediction with the same fractional predicted area. The "Balance" threshold minimizes 6 * training omission rate + .04 * cumulative threshold + 1.6 * fractional predicted area.

Cumulative threshold	Cloglog threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
1	0.357	Fixed cumulative value 1	0.979	0	0	8.62E-01
5	0.359	Fixed cumulative value 5	0.903	0	0	4.90E-01
10	0.363	Fixed cumulative value 10	0.809	0	0	2.27E-01
13.593	0.366	Minimum training presence	0.742	0	0	1.24E-01
18.741	0.373	10 percentile training presence	0.648	0.059	0	4.80E-02
44.444	0.629	Equal training sensitivity and specificity	0.294	0.294	0.143	3.39E-03
52.428	0.723	Maximum training sensitivity plus specificity	0.235	0.294	0.143	9.34E-04
56.165	0.753	Equal test sensitivity and specificity	0.211	0.412	0.143	5.12E-04
39.503	0.556	Maximum test sensitivity plus specificity	0.341	0.235	0	5.32E-04
0.005	0.323	Balance training omission, predicted area and threshold value	1	0	0	1.00E+00
8.228	0.361	Equate entropy of thresholded and original distributions	0.842	0	0	3.00E-01

Pictures of the model

This is a representation of the Maxent model for Panthera_Tigris. Warmer colors show areas with better predicted conditions. White dots show the presence locations used for training, while violet dots show test locations. Click on the image for a full-size version.

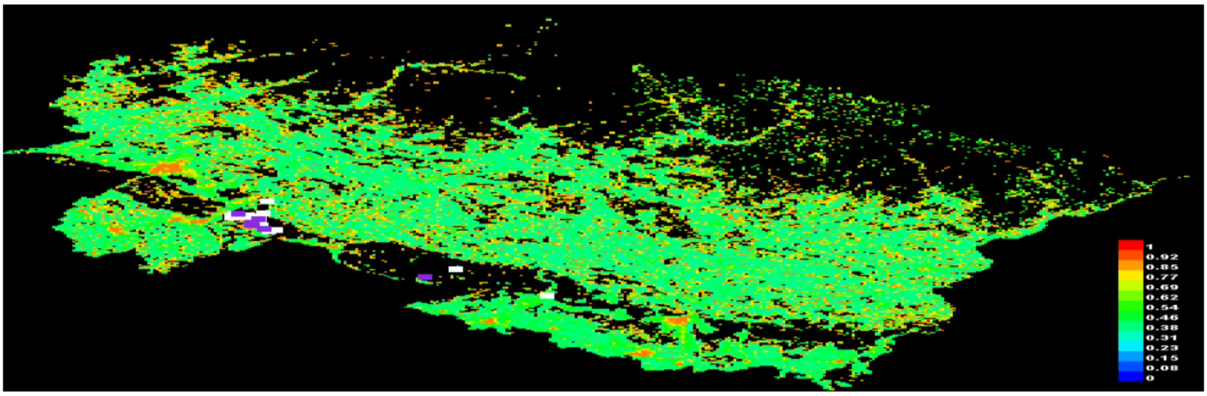

Figure 25

Response Curves

These curves show how each environmental variable affects the Maxent prediction. The curves show how the predicted probability of presence changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. To note that the curves can be hard to interpret if you have strongly correlated variables, as the model may depend on the correlations in ways that are not evident in the curves. In other words, the curves show the marginal effect of changing exactly one variable, whereas the model may take advantage of sets of variables changing together.

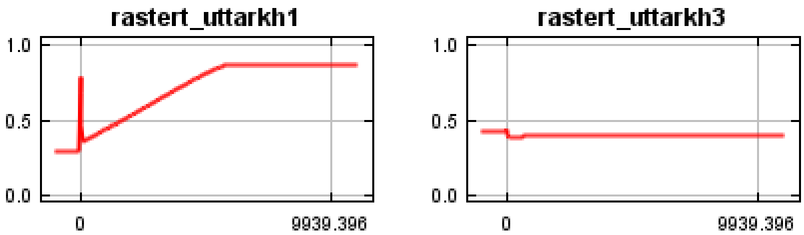

Figure 26

In contrast to the above marginal response curves, each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.

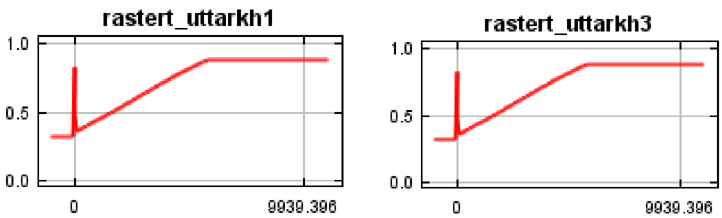

Figure 27

Analysis of variable contributions

The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from it if the change to the absolute value of lambda is negative. For the second estimate, for each environmental variable in turn, the values of that variable on training presence and background data are randomly permuted. The model is reevaluated on the permuted data, and the resulting drop in training AUC is shown in the table, normalized to percentages. As with the variable jackknife, variable contributions should be interpreted with caution when the predictor variables are correlated.

Variable	Percent contribution	Permutation importance
rastert_uttarkh1	99.9	84.9
rastert_uttarkh3	0.1	15.1

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is rastert_uttarkh1, which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted is rastert_uttarkh1, which therefore appears to have the most information that isn't present in the other variables.

International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2024: 7.101

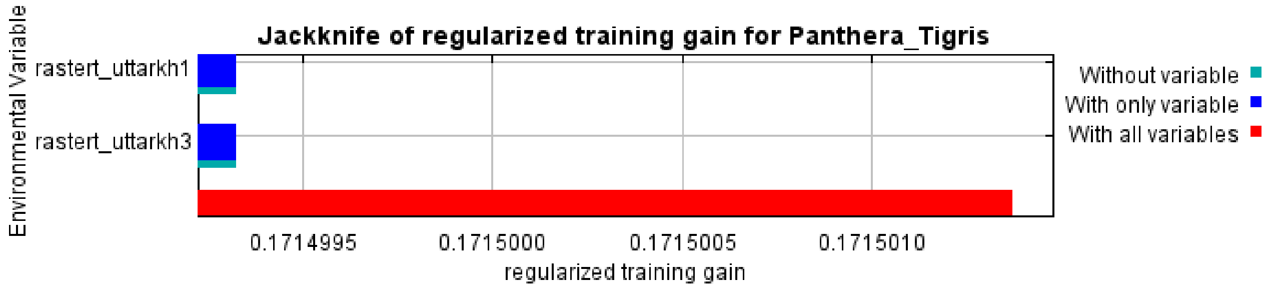

Figure 28

The next picture shows the same jackknife test, using test gain instead of training gain. Note that conclusions about which variables are most important can change, now that we're looking at test data.

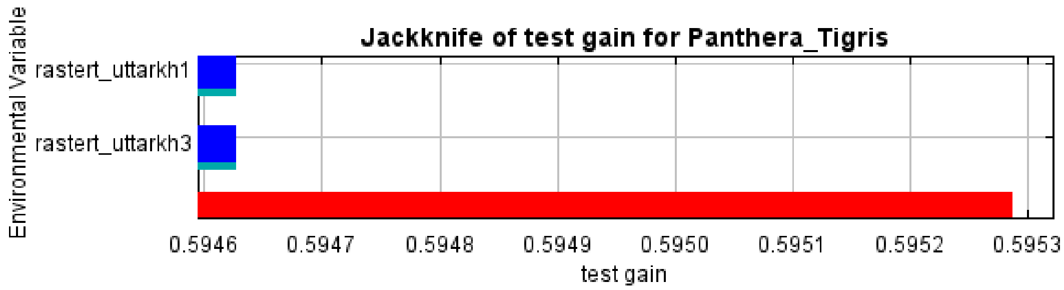

Figure 29

Lastly, we have the same jackknife test, using AUC on test data

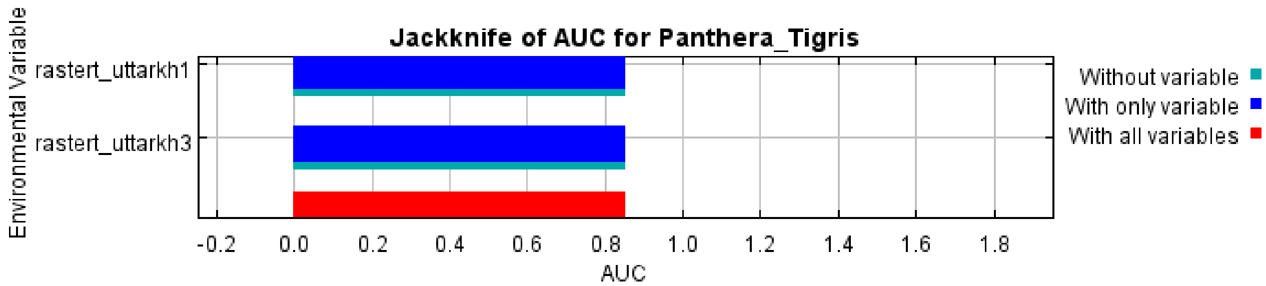

Figure 30

Raw data outputs and control parameters: Regularized training gain is 0.172, training AUC is 0.762, unregularized training gain is 0.373.
Unregularized test gain is 0.595.
Test AUC is 0.851, standard deviation is 0.037 (calculated as in DeLong, DeLong & Clarke-Pearson 1988, equation 2).

Conclusion

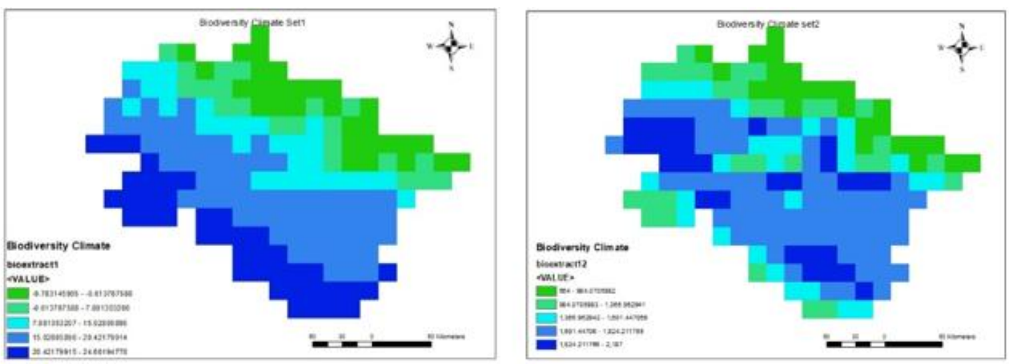

Figure 31

The study reveals that under the influence of biodiversity climate change, the value of test AUC is 0.866, standard deviation is 0.032 indicates that predicted area emerged as Deharadun, Haridwar, Paudi Garhwal, Udham Singh Nagar and Nainital are most inhabitant region for Panthera Tigris. The dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between the selected variable and other variables lies with first set of biodiversity climate variable i.e. rastert_bioextr1.

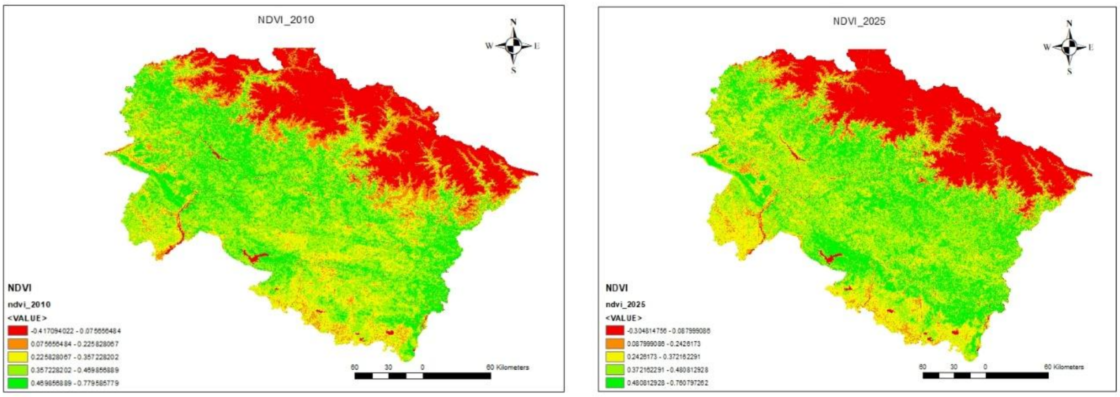

Figure 32

Under the influence of vegetation change, the value of test AUC is 0.641, standard deviation is 0.045 still indicates that predicted area emerged as Deharadun, Haridwar, Paudi Garhwal, Udham Singh Nagar and Nainital are most inhabitant region for Panthera Tigris. The dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between the selected variable and other variables lies with first set of NDVI variable i.e. rastert_ndvi_201(vegetation index in year 2010).

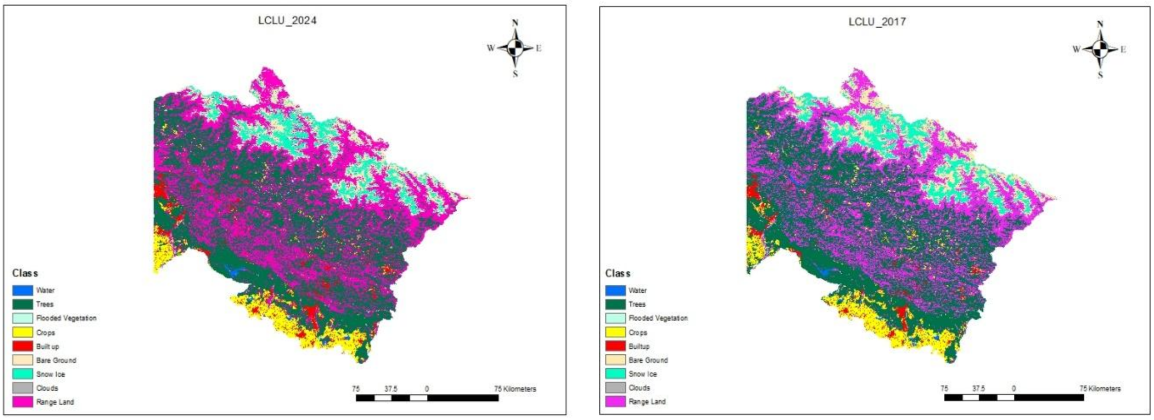

Figure 33

Under the influence of Land Use Land Cover change, the value of test AUC is 0.696, standard deviation is 0.033 again indicates that predicted area emerged as Deharadun, Haridwar, Paudi Garhwal, Udham Singh Nagar and Nainital are most inhabitant region for Panthera Tigris. The dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between the selected variable and other variables lies with first set of LULC variable i.e. rastert_proj_lu2 (Land Use Land Cover in year 2024).

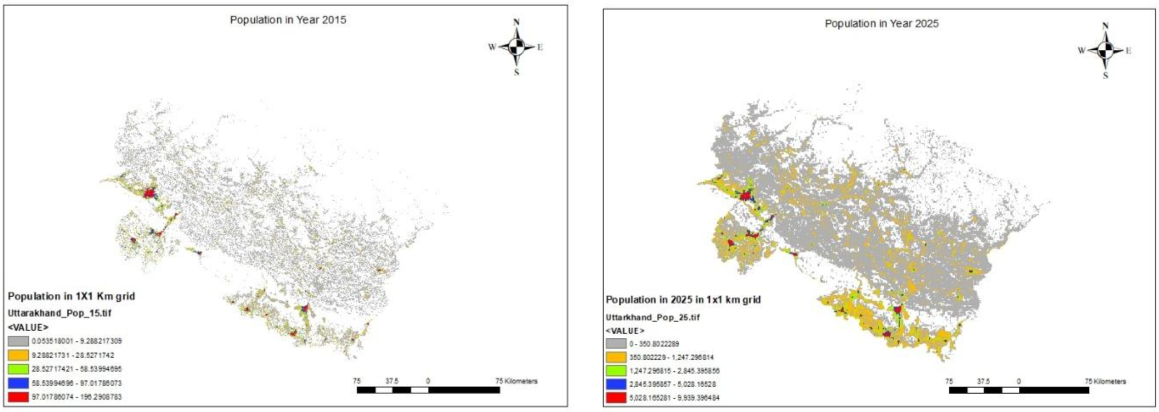

Figure 34

Under the influence of Population change, the value of test AUC is 0.851, standard deviation is 0.037 again indicates that predicted area emerged as Deharadun, Haridwar, Paudi Garhwal , Udham Singh Nagar , Almora and Nainital are most inhabitant region for Panthera Tigris. The dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between the selected variable and other variables lies with first set of population variable i.e. rastert_uttarkh1 (Population in year 2010).

Eventually, it is established that biodiversity climate change and population change effects significantly for inhabitation of Panthera Tigris and the region of Deharadun, Haridwar, Paudi Garhwal ,Tehri Garhwal, Champawat, Chamoli, Bageshwar and Nainital are found to be more suitable for prediction as well. The reason is quite obvious that population/settlement has increased in lower areas over a period of time.

Future Research Direction

Although methodology adopted in the study work completely serves the purpose/objective of study, nevertheless suggested areas in the study may be physically mapped by the concerned forest department of state.

Further, state Govt. should start strong initiatives to develop the protected areas, a community-based tourism model should have been developed with a strong emphasis on sharing benefits with local people and on the regeneration of degraded forests. The approach may result successful results in reducing poaching, restoring habitats, and creating a local constituency for conservation.

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