SCHOOL OF
COMPUTER SCIENCE

Preserving the Pathways of Wildlife Conservation

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Introduction

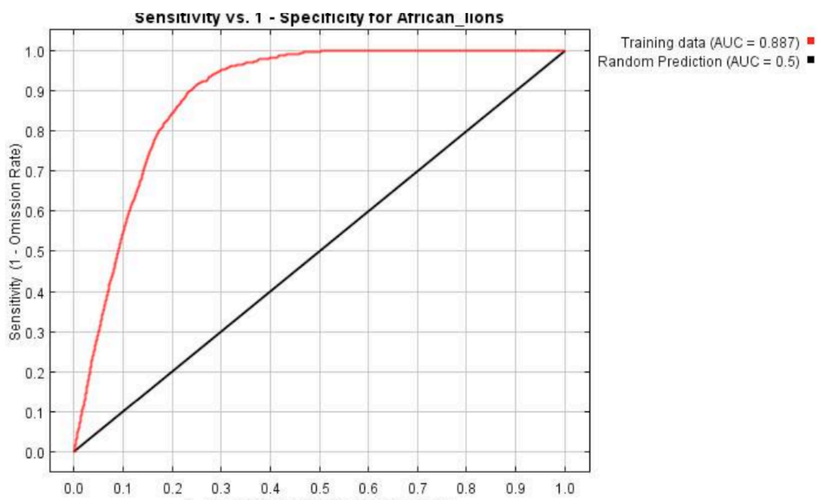
This project focuses on leveraging Machine Learning to predict the movement of large terrestrial species, specifically lions, to address challenges like habitat loss, human-wildlife conflict, and illegal poaching. By analysing historical data and ecological patterns, the model identifies potential corridors, ensuring sustainable conservation efforts and the preservation of natural habitats for these majestic creatures.

Problem Identification

- **Habitat Loss & Conflict:** Urbanization and human activities are fragmenting habitats, causing isolation and conflicts with wildlife.
- **Endangered Species Threat:** Lions face risks from poaching and reduced genetic diversity due to habitat fragmentation.
- **Need for Corridors:** Protecting ecological pathways is critical for safe wildlife movement and biodiversity preservation.

ROC and AUC of the Model

The ROC curve for the data uses specificity defined by predicted area instead of true commission . This limits the maximum achievable AUC to less than 1. If test data comes from the Maxent distribution, the maximum test AUC would be 0.870, though in practice, it can exceed this limit.



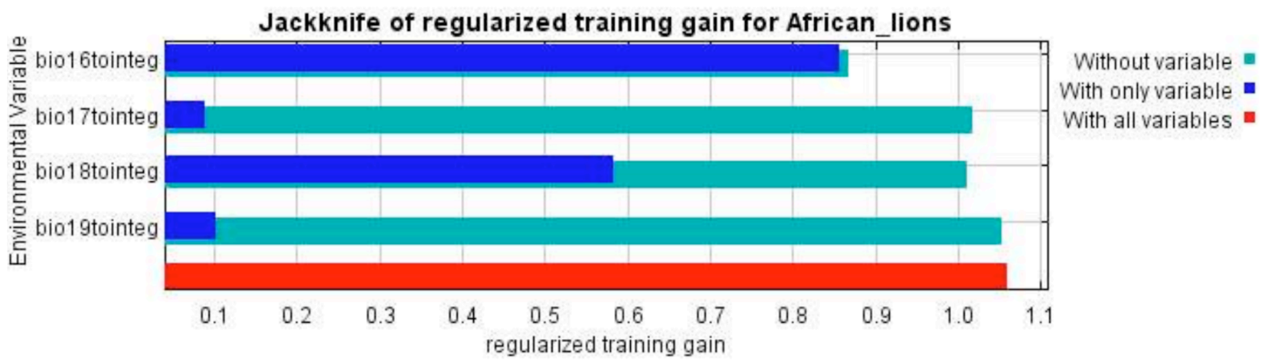
Analysis of Variable Contributions

1. Regularized Gain Contribution: This estimate calculates how much each environmental variable contributes to improving the model's predictive performance during training. At each iteration, the increase in regularized gain is assigned to the corresponding variable. If the absolute value of lambda decreases, the gain is subtracted instead. This method reflects the direct impact of each variable on model training.

2. Permutation Importance: This estimate evaluates the importance of each environmental variable by randomly permuting its values across the training presence and background data. The model is then re-evaluated, and the resulting decrease in training AUC is used to measure the variable's importance. The results are normalized to percentages, indicating the relative significance of each variable.

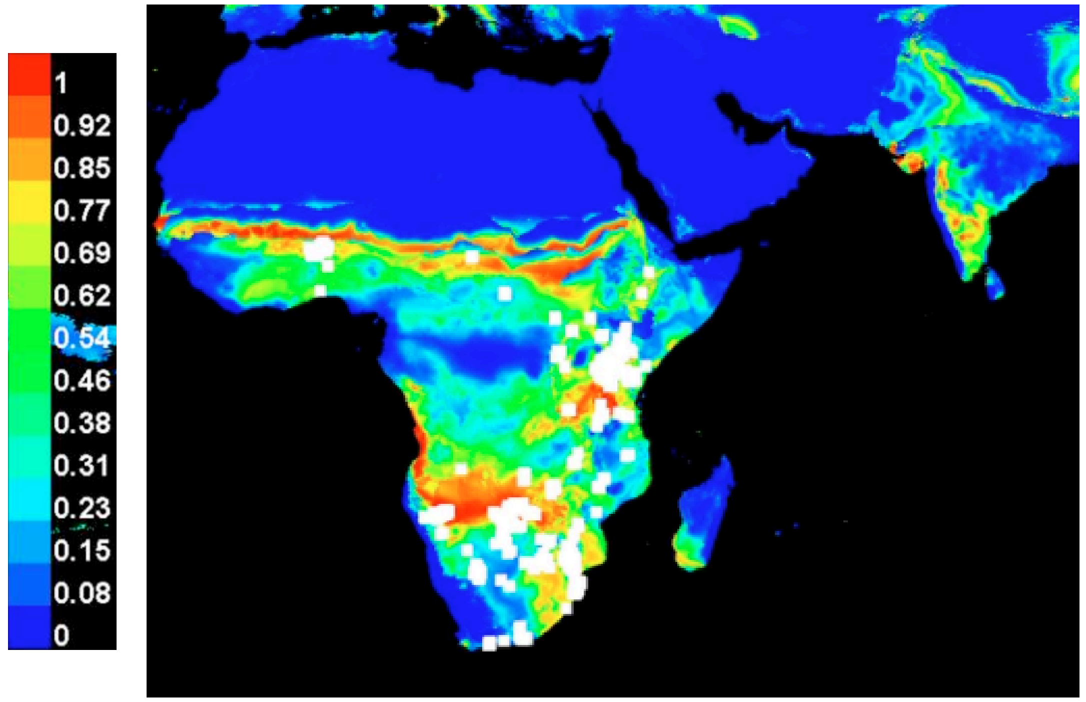
Variable	Percent contribution	Permutation importance
bio16tointeg	60.8	55.9
bio18tointeg	23.3	29.7
bio17tointeg	14.5	13.5
bio19tointeg	1.4	0.9

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio16tointeg, 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 bio16tointeg testing, which therefore appears to have the most information that isn't present in the other variables.



Picture Of the Model

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



Response Curves