Feral Topographies: Modelling Wildlife-Environment Interactions through 3D Topography and Machine Learning

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1 Abstract

The ability to understand and predict the complex interactions between wildlife species and their environments is crucial for effective conservation and wildlife management. This study aims to investigate these interactions by integrating topographic and land feature data with wildlife movement (GPS) data, and utilizing machine learning techniques to analyze patterns and predict how topographical or environmental changes may affect wildlife behavior. Our approach is multifaceted and attempts to find modal solutions for this complex problem. We utilize convolutional neural networks, Conditional Generative Adversarial Networks and Agent-Based Modeling, to find the embedded multidimensional relationships between 3D topographical information, land feature data and GPS tracking of animal movement.

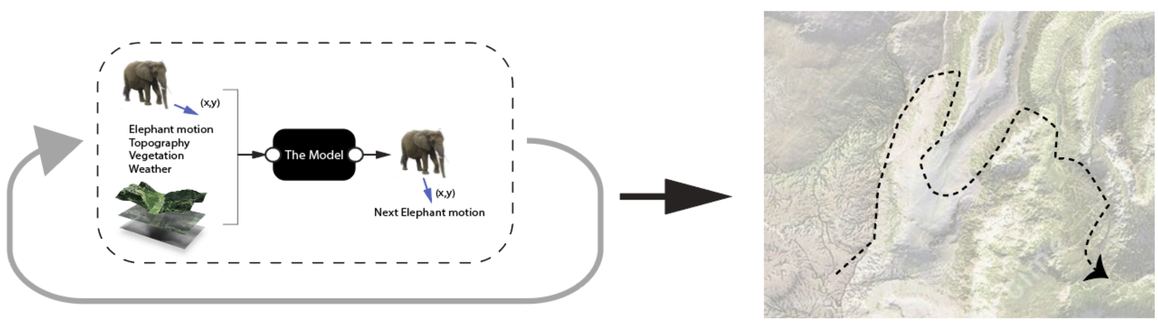


Figure 1: A conceptual framework for Elephant Movement Prediction

2 Introduction

The impacts of human land use changes and climate change are among the many factors that disrupt wildlife behavior and the ecosystems that they critically rely on for survival. These pressures underscore the critical need for more sophisticated, targeted interventions to ensure the preservation of non-human species. Central to the development of these interventions is a comprehensive understanding of the complex interplay between wildlife and their habitats, which in turn can elucidate the potential ramifications of these disturbances and help inform on effective conservation strategies.

Analyzing animal movements is an important step toward understanding the complexity and fragility of ecosystems and ecologies. Animal movements offer potential windows into habitat selection, population dynamics, and group behavior. According to Rew et al. 2019, the development of global positioning systems (GPS) and advanced research and global observation satellites (ARGOS) have accelerated animal movements studies and created new opportunities to model these behaviors.

Moving beyond the traditional approach of fine-tuning a singular computational model to address a wildlife behavioral research problem, we adopt a more holistic strategy. Our methodology focuses on the investigation and implementation of multiple models and the interconnections between them to uncover an array of predictions that inform one another. The intention is to foster an understanding of whether the integration of these models can lead to a more robust and insightful understanding of wildlife behavior and their interactions with the environment. We explore how different machine learning models, each with its unique attributes, can contribute to a comprehensive analytical framework that can identify patterns that may not be apparent when using a singular model. Our goal is to provide a broader, multi-faceted perspective on wildlife behavior, potentially leading to more effective conservation strategies.

3 Literature Review/Background

Many efforts have been made to model animal movements using both traditional statistical methods and machine learning. Patterson et al, using maximum likelihood and Monte Carlo (MC) methods, and a hidden Markov model (HMM), proposed a classification method for two animal behavior states: transient and resident. Using hidden Markov processes, MoveHMM showed that probability-based prediction is possible by using features such as animal step length and turning angle.

Deep learning has been used to fill the observation gap that frequently occurred while tracking wild animals with low frequency gps technology. Hirakawa et al. 2018 used inverse reinforcement learning to predict missing trajectories by estimating the gap as a reward function. Browning et al. 2018 predict diving behavior of seabirds by utilizing combined GPS and time depth record (TDR) from 108 individuals. The authors trained deep learning models for predicting the behavior of European shags, common guillemots, and razorbills, and achieved 94% and 80% prediction accuracy of non-diving and diving behavior.

According to Tuia et al. 2022, inexpensive and accessible sensors are and will continue to accelerate data acquisition in animal ecology. There are immense opportunities for large-scale ecological understanding, but these tools are limited by current processing approaches which inefficiently distill data into information for ecologists, local communities and conservation efforts to use effectively. Tuia et al. argue that animal ecologists can capitalize on large datasets generated by modern sensors by combining machine learning approaches with domain knowledge and by incorporating machine learning into ecological workflows could improve inputs for ecological models and lead to integrated hybrid modeling tools.

Parvizpalangpour, Venayagamoorthy, and Duffy 2011 describe methods to assess the impact of large nutritional values and destructive foraging of Elephants in South African wildlife reserves using particle swarm optimization (PSO), PSO initialized backpropagation and PSO initialized backpropagation through time algorithms to adapt a recurrent neural network's weights for migration prediction.

(Rew et al. 2019) proposed a novel approach for predicting animal movements using a predictive recurrent neural network (RNN). Their model compensates for missing geolocation records using random forest regression. They interpolate the missing records by using a random forest based on animal movement features and environmental features such as terrain and weather. The authors then grouped geolocations by various units and created a sequence of movement density images, which represent movement trends of animals; a movement prediction model is then built by training PredRNN++ using these sequence data.

Berti et al. 2022 developed ‘enerscape’, software that integrates a general locomotory model for terrestrial animals with GIS tools in order to map energy costs of movement in a given environment, resulting in energy landscapes that reflect how energy expenditures may shape habitat use. *enerscape* only requires topographic data (elevation) and the body mass of the studied animal. Other work in the field of machine learning and behavioral wildlife ecology is concerned with automatically identifying, counting, and describing wild animals in camera-trap images with deep learning (Norouzzadeh et al. 2018) and deep learning for pose tracking (Pereira et al. 2022).

Predictive analysis of wildlife behavior is a crucial tool for long term conservation efforts, currently there are no effective working models to predict where wildlife will move to next given a topographical or land feature change. The ability to predict future movements of a species would provide a useful tool for land management by assessing the future impact of a species by location and proposed land augmentation.

4 Methodology

Our research focussed on a selected species and specific geographical area. Data collection involved the acquisition of 3D topographical data, wildlife GPS data, and integrating these datasets for analysis. We attempted to employ multimodal machine learning techniques to model species movement patterns in response to topographical and environmental features.

Dataset:

This research required the creation of a comprehensive dataset that combines Global Positional System (GPS) data, Digital Elevation Model (DEM) data, and land features suitable for machine learning analysis. The combination of these different sources of data offers a rich and varied dataset that facilitates a deeper understanding of the complex connections between wildlife species and their environments.

The GPS data utilized in this study is sourced from research led by Frank van Langevelde from the Wildlife Ecology and Conservation Group at Wageningen University. Published in the Journal of Animal Ecology in 2011, the study “The spatial scaling of habitat selection by African elephants” offers valuable insights into the spatial scales at which African elephants select their habitats. This research focuses on 13 elephants with GPS collars located in Kruger National Park, South Africa, spanning from November 12, 2005, to September 21, 2008 and covering 160,000 square kilometers. This dataset contains location, temperature, low frequency time steps (30 minute intervals) and observational data of elephant behavior such as foraging, drinking, walking and group interaction. Kruger National Park, one of Africa’s largest game reserves, is known for its high biodiversity. It offers a complex and diverse landscape, from savannah grasslands to dense forests and river systems, making it a compelling area of study for understanding wildlife interactions with varied topography and land features. Leveraging the data from this well-established study, our research further builds upon these insights by employing advanced machine learning techniques to predict how topographical changes may impact wildlife behavior. The data is made available through Movebank, an online database of animal tracking data hosted by the Max Planck Institute of Animal Behavior. Movebank facilitates the archiving, analysis, and sharing of animal movement data among researchers and conservationists.

Figure 2: GPS elephant data, DEM and Land Features of Kruger National Park

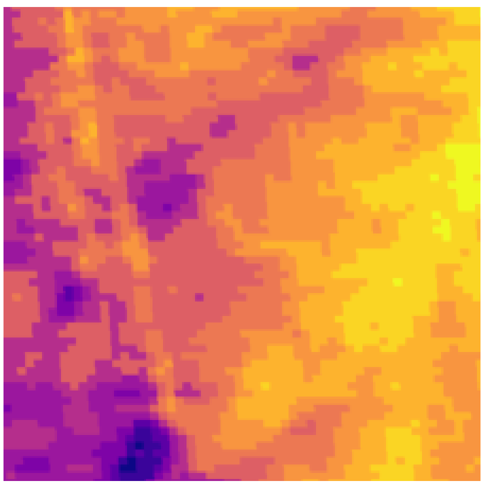
In tandem with the GPS data, our dataset also employs the land features obtained from the National Land Cover Database (NLCD) and Digital Elevation Models (DEM) from the Shuttle Radar Topography Mission at 30m resolution. The NLCD data offers a standardized, nationwide land cover inventory which, in combination with the DEMs, offers a detailed understanding of the terrain.

To render the data more manageable for the machine learning model, the NLCD data was processed into three general categories: water, ground, and vegetation. This simplification was aimed at preventing the model from being overwhelmed with excessive detail that could potentially obscure broader patterns, thereby enabling the model to between learn and predict elephants' behavior in response to fundamental environmental features. The compilation of this dataset from diverse resources provides an important foundation for analyzing the interactions between wildlife and their habitats. Furthermore, the systematic approach used to creat this dataset creation for application in machine learning holds significant potential for future research, particularly those exploring the interface between wildlife behavior and environmental factors.

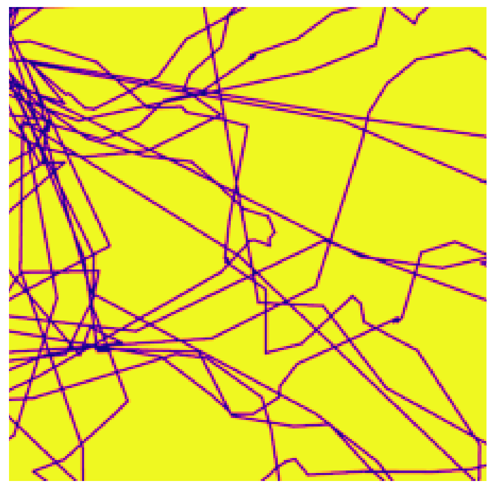
Models:

Test 01: Convolutional Neural Network

We attempted to train a convolutional neural network with the intention of using an inverse design method similar to those used for metasurface design. We conceptualized a model that formulated the path functionality as an objective function and performed an optimization task that could be subject to constraints. In the case of the predictive path finding, the constraints were DEMs and land features. Our intention was to define a desired target DEM and have the trained network predict paths. This method was unsuccessful due to the large variation in data between constraints.



DEM



Path

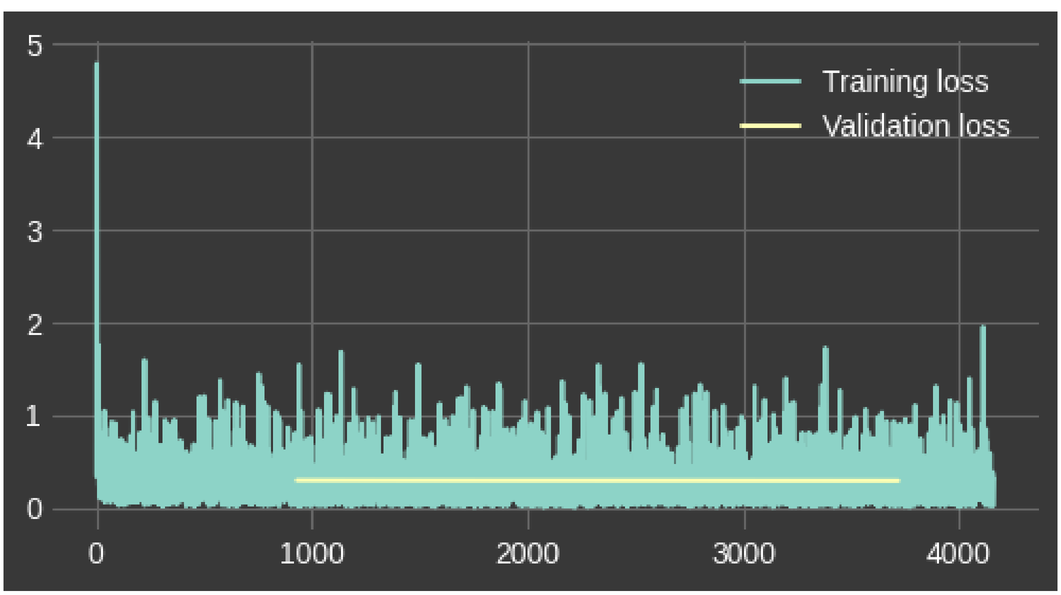


Figure 3: Result and Training/Validation Loss of CNN

Test 02: Pix2Pix Conditional Generative Adversarial Network

We also considered the prediction of paths from a DEM as an image-to-image translation problem. For this problem, we used conditional adversarial networks as a general-purpose solution for image-to-image translation. These networks not only learn the mapping from input image to output image, but also learn a loss function to train this mapping. Isola et al. 2018 demonstrate that this approach is effective at synthesizing photos from label maps, reconstructing objects from edge maps, and colorizing images, among other tasks. This solution however requires the translation of GPS vector data (that includes directionality and time) to static raster based images. The same technique could also be inverted and used to predict DEMs from path configurations.

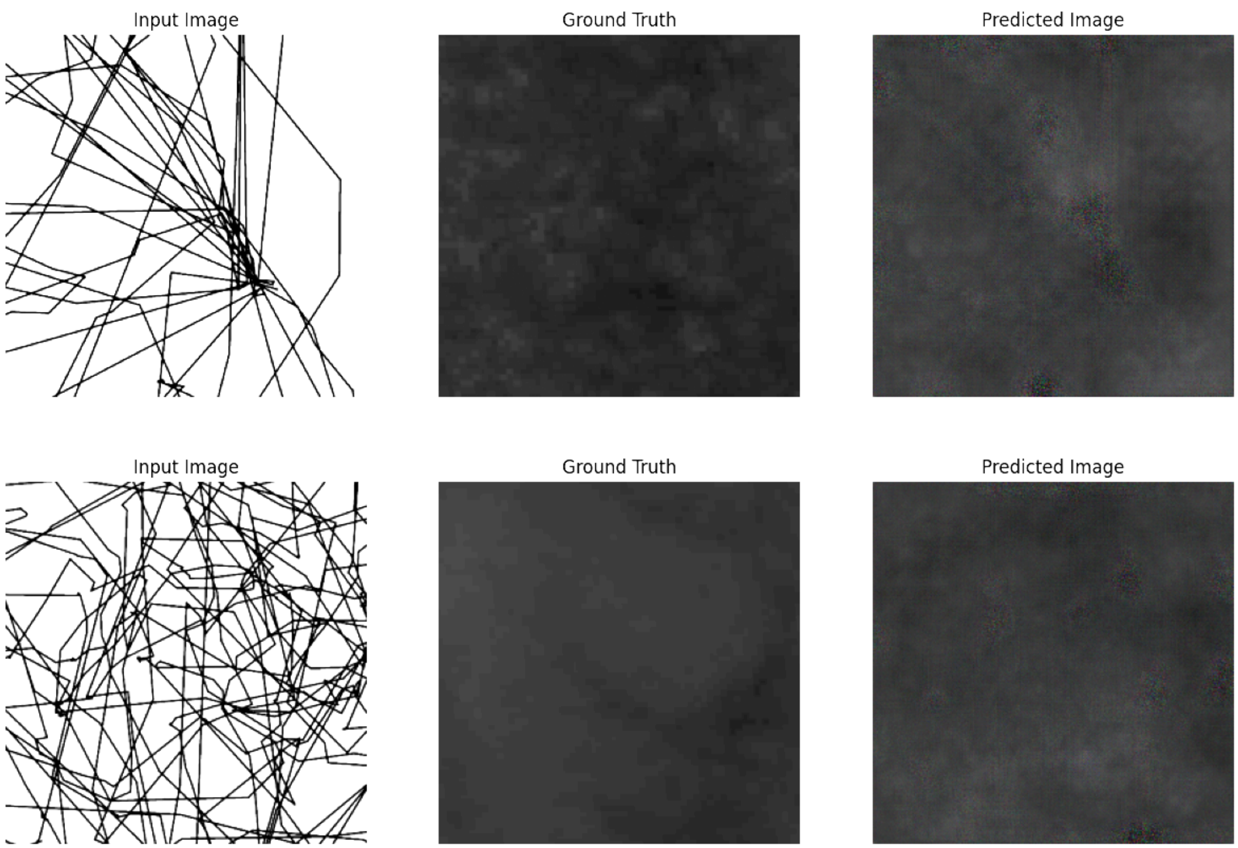


Figure 4: Result of GAN network tests - inconclusive

Test 03: Agent Based Model

We also developed an agent-based model (ABM) to visualize and simulate how an elephant behaves in a specific environment. To achieve this, the model utilizes the GPS portion of the dataset. The geolocation of the elephant's position is then associated to a position within the land features dataset. A bounding box is created to track the elephant's motion and extract relevant data in the surrounding area.

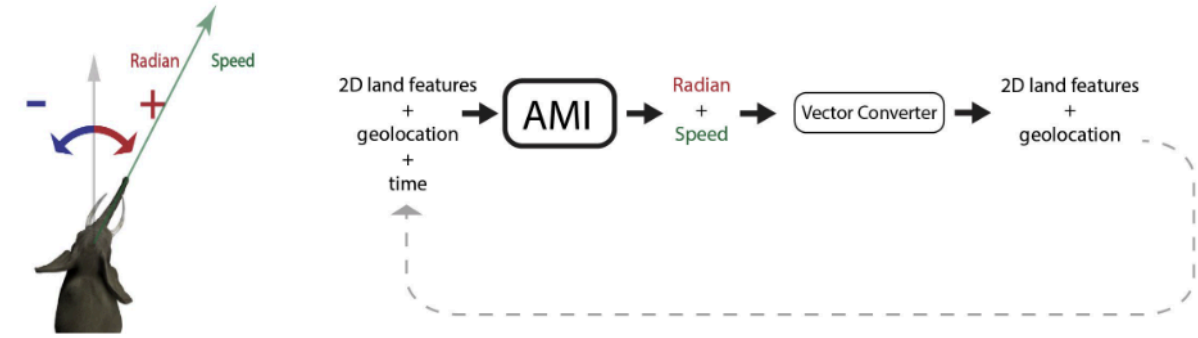


Figure 5: The mechanism of the agent based elephant model

This process allows for the generation of a series of data that includes geolocations, corresponding vectors representing the elephant's behavior, and data representing the environment at each geolocation. By combining the elephant's trajectory with the corresponding environmental data, a comprehensive understanding of how the elephant interacts with its surroundings can be obtained.

The agent-based model described includes a CNN-based neural network that aims to predict the next motion of an agent, specifically an elephant. The model takes into consideration the environmental surrounds of the agent, including topographical information, land features, and existing movement data of the elephant; these data are then represented as 2D arrays. To process the input data, the model combines the terrain, land features, and elephant's footprint into a three-channel representation. This combined data is then fed into a CNN encoder, which is responsible for extracting relevant features from the input data. The CNN encoder applies convolutional and pooling layers to capture patterns and condense information. The output of the encoder is a condensed and abstract representation of the input data. The features obtained from the CNN encoder are then flattened and the previous directional data (represented as a 2D vector) and the timestep information are concatenated with the flattened features. This concatenation combines the visual features learned by the CNN encoder with the historical motion information and temporal context. The concatenated data is then passed through a series of hidden layers, including fully connected layers with activation functions *Tanh* and *LeakyRelu*, to produce a two-dimensional output. The output data represents the rotation angle and speed that the agent, in this case the elephant, should take for its next step. The architecture of the model is described in figure 8.

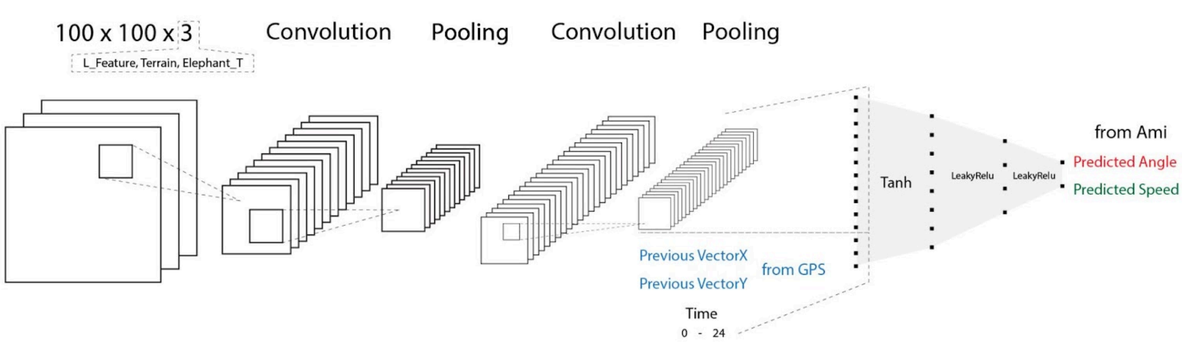


Figure 6: Architecture of the CNN based model for simulating elephant walking

The initial version of the model used a vector representation for motion, but the results were not satisfactory. Therefore, the model was adjusted to utilize the angle and speed representation, which was found to provide more realistic predictions.

Test 04: Simulator

Finally, a dedicated simulator was developed utilizing the ABM. This simulator incorporates the DEM, land features, and the elephant footprint map which serves as the backdrop for the simulation. To simulate the walking path of an elephant, the simulator allows the user to specify the initial location (geolocation) of the elephant, its initial motion (2D vector), and the time parameters. Based on these inputs, the model predicts a new motion for the elephant's next move, which includes both a turning angle and speed.

Once the elephant agent is given its starting position, the system tracks the elephant's position and crops a new environmental bounding box for the subsequent iteration. This ensures that the model takes into account the updated surroundings as the elephant progresses along its path. With each iteration, a series of points emerge, gradually forming a coherent path that represents the simulated movement of the elephant.

The simulator and agent-based model work in succession to integrate topographical, land feature and GPS data to predict elephant movement. Users can set the initial location, initial motion, and time parameters for the elephant. The model then predicts the next step distance, direction, turning angle and speed of the elephant. As the simulation progresses, the system tracks the elephant's movement, updates the environment accordingly, and generates a series of points that ultimately form a path, capturing the simulated walking trajectory of the elephant.

Figure 9 showcases different conditions simulated by the agent-based model. In the image on the right-hand side, a time cycle is introduced, with a period of 30 minutes between each point. the time updates throughout the simulation, allowing the elephant agent to experience varying conditions from daytime to nighttime. This dynamic time setting provides insights into how the elephant's behavior may differ at different times of the day.

The subsequent two images depict surreal conditions where time is fixed. In the middle image, the time is constantly set at noon, while in the right-hand image, the time is continuously set at midnight. These fixed-time scenarios enable the observation of the accumulating points (path) to gain a deeper understanding of how elephant behavior may differ between daytime and nighttime settings. Building on the research by Frank van Langevelde, the resulting paths in these different temporal contexts may provide researchers with valuable insights into how elephants navigate and interact with their environment at distinct times of the day. These simulated conditions provide a unique perspective on the behavioral patterns of elephants, shedding light on potential variations influenced by time factors.

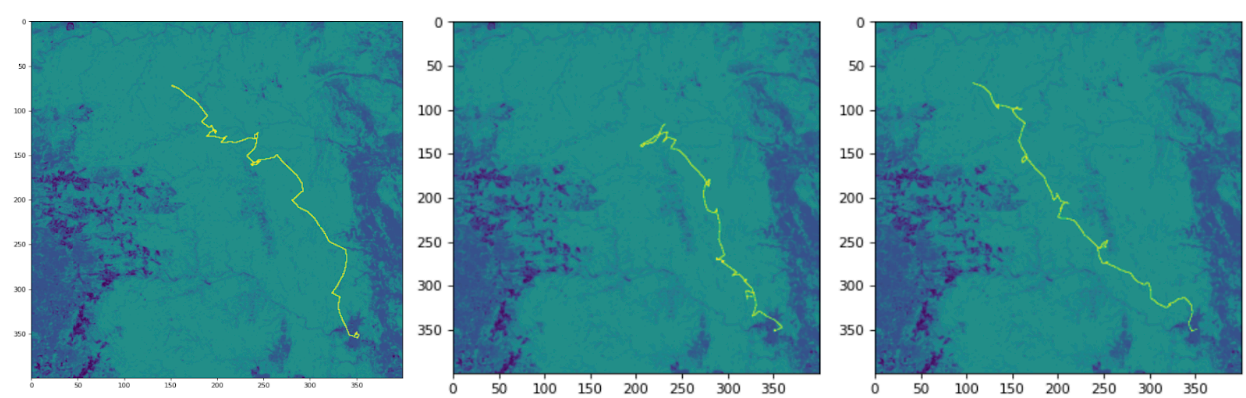


Figure 7: Temporal Influence on Elephant Walking Patterns.

Evaluation:

The success of our research is measured by the model's accuracy in predicting species movement patterns, its understanding of crucial environmental factors influencing wildlife behavior, and the ability to derive effective conservation strategies based on these insights.

To evaluate our model's performance, we implement the hold-out validation method, which is an effective technique to ensure the robustness of the model and prevent overfitting. We partition our dataset into a training set (80%) and validation set (20%). The model is trained on the training set, learning the underlying patterns and relationships within the data. The validation set, which the model has not seen during training, is then used to evaluate the model's performance. This process allows us to assess how well the model can generalize its learned patterns to new data.Throughout the training process, performance metrics are monitored such as accuracy, precision, and the F1 score. We examine the learned weights within the model to scrutinize the model's capability to identify and prioritize key environmental factors affecting wildlife behavior. Ultimately, predicted paths could also be compared with real data; elephants carve pathways into the landscape and these pathways are visible by satellite. Simulated paths could be compared with existing pathways in areas without GPS data.

5 Results

Expected Results:

Upon successful training, we expect our model to identify key environmental and topographical variables to show a clear indication that these factors influence the movement patterns of wildlife species, in this case, elephants in Kruger National Park, South Africa. Our models, specifically designed to handle complex datasets, are expected to generate accurate predictions showcasing how wildlife are forced to adapt to varying environmental conditions. These predictions include movement feedback against shifts in vegetation patterns, alterations in water availability, changes in the terrain, and/or anthropogenic modifications such as urban development or agriculture. Such predictive abilities could shed light on issues of habitat suitability, human-wildlife conflict, migration patterns, or changes in the feeding and mating behavior of the species.

We anticipate that our machine learning models will be able to accurately predict species movement paths based on topographical and environmental variables through a multimodal approach. The first model will not only consider existing movement data but will also synthesize this with the varying environmental and land features to make sophisticated predictions about potential paths. This approach will allow us to anticipate potential shifts in species movement resulting from changes in the landscape, such as alterations in water availability or vegetation patterns and output a predicted path.

Additionally, we expect our model to generate realistic DEMs based on input GPS paths. By leveraging the data derived from these paths, the model can help us visualize and understand the likely topographic profiles that elephants prefer to navigate. This model output can provide unique insights into how specific terrain features may influence the movements and behaviors of the elephants.

Actual Results:

Initial attempts to train a CNN and cWGAN on DEMs and land features resulted in poor outputs with the model unable to identify relevant features. We hypothesized that the lack of substantial variation within the land feature classifications could be a potential cause for this performance.

Given the close correlation between land features and topography, our focus pivoted to primarily working on generating DEMs and focusing on the connections between paths and elevation. This shift proved promising through the implementation of the pix2pix framework which provided a significant boost to the quality of our results. The agent-based model effectively produced credible predicted paths, factoring in varying times of the day and a predefined starting point. The resulting predictions were predominantly consistent with typical elephant behaviors. We gauged the model's effectiveness by monitoring the training and test loss (see figure 9). In general, the model demonstrated a satisfactory trend, despite some observed inconsistencies.

However, it is important to clarify that due to certain constraints, the model's accuracy within the simulated environment hasn't been quantitatively appraised yet. At this phase, we have managed to establish a training pipeline for the agent-based model, which can simulate an elephant's movement. To enhance the practicality of the tests, we simplified the scenario. This was necessitated by the absence of key data to create a fully realistic environment. We currently lack comprehensive data that captures the movement of an elephant group in unison. Moreover, data on other species, such as predators which significantly influence elephant behavior, is missing. This absence of vital information means that the simulation cannot yet mimic reality accurately. Hence, we have had to rely on the graph of training and test loss to determine if the model is learning correctly from the dataset.

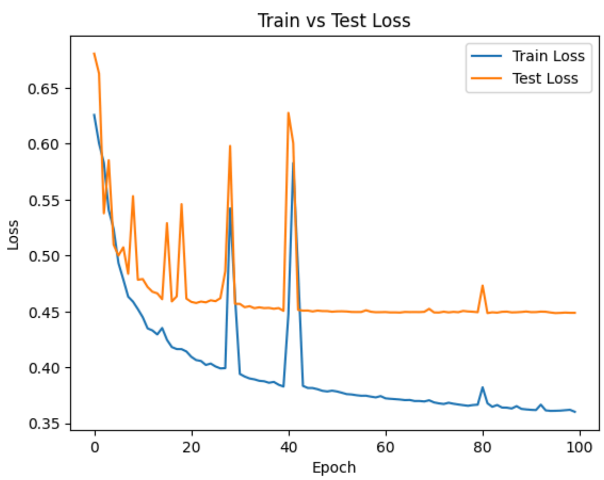


Figure 9: Train/Test Loss of Agent-Based Model

Looking ahead, we are devising ways to refine the model. Firstly, we plan to employ transformers in the training process, enhancing the model's capability to handle time-sequential data more efficiently. Secondly, we aim to collect more comprehensive elephant data to improve path predictions that may be influenced by elephant social behaviors. We will also explore ways to collect data on other influential species. Lastly, we've observed patterns in the data suggesting that decision-making frequency or triggers in elephants may require further investigation. We hope to delve deeper into this in future studies.

6 Future Research

Predictive RNNs

Predictive Recurrent Neural Networks (RNNs) have shown to be incredibly effective in handling time series and sequential data, making them a promising tool for our purposes. Rew et. al's work with swarm and particle dynamics simulations sets an insightful precedent that we can adapt and build upon. Their method of combining animal geolocation records with additional contextual data, such as weather and terrain, offers a dynamic and sophisticated approach to understanding animal movement. This strategy could be similarly applied to take advantage of the temporal nature of GPS data and combine it with rich contextual data from land features and DEMs to create a comprehensive picture of the animal's interactions with its environment over time.

Similar to Rew et. al, we would utilize our dataset with an appropriate interpolation technique to refine the movement pattern, treating the collected data as independent feature values. This technique would enable us to capture and consider the nuances in the animal's interactions with its environment. The relocation records are split and movement density sequences are generated to represent the valid range of elephant movement. These sequences would provide a temporal dimension to our data, capturing changes in the elephant movement patterns and land feature interactions over time. We would then train a predictive RNN on these movement density sequences to build our prediction model. The RNN, with its ability to capture temporal dependencies and patterns in sequential data, is particularly well suited to predicting future movement patterns based on past behavior and environmental context.

Agent-based Model

The existing agent-based model for elephants has shown potential for improvement, and we have outlined several plans to enhance its capabilities in the future. Our refinement strategies are as follows:

Incorporating transformers: To enhance the model's performance with time-sequential data, we plan to integrate transformer architectures during the training process. Transformers have proven effective in capturing long-range dependencies and contextual information, which can greatly benefit the analysis of temporal patterns in elephant behavior.

Gathering extensive elephant data: To improve path predictions, we aim to gather a more comprehensive dataset on elephants. This expanded dataset will include a broader range of variables, particularly focusing on factors related to elephant social behaviors. By incorporating these social dynamics, we can develop more accurate predictions of elephant movement and behavior patterns.

Data collection on other influential species: Recognizing the potential impact of other species on elephant behavior, we intend to explore methods for collecting data on these influential species. By understanding their interactions and relationships with elephants, we can refine the model to better reflect the complex dynamics of the ecosystem.

Investigating decision-making frequency and triggers: Our analysis has revealed certain patterns in the data that suggest a need for further investigation into decision-making among elephants. Specifically, we have observed recurring behaviors that indicate the presence of decision points or triggers. In future studies, we aspire to delve deeper into this aspect, exploring the factors that influence decision-making frequency and identifying the specific triggers that prompt certain behaviors.

Interface and visualization of the Agent-based Model

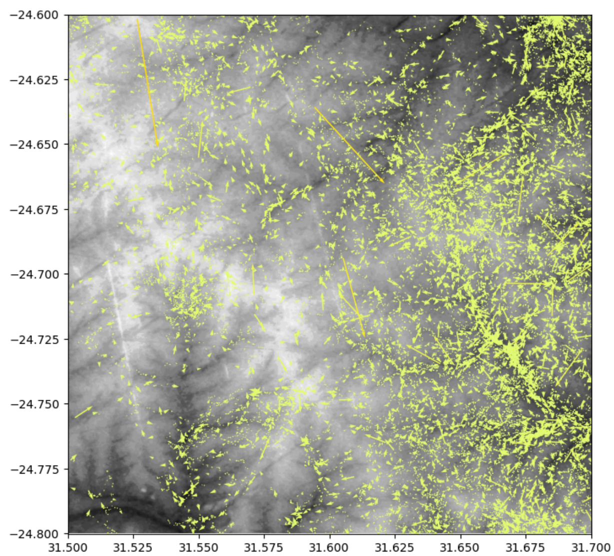
In addition to developing the agent-based model itself, we are also focusing on creating an intuitive interface and visualization system that enables users to effectively interact with and visualize the outputs of the model.

One aspect of this involves designing a user-friendly platform that enhances the user's experience. For example, we plan to implement a map interface that allows users to easily add agents representing elephants to specific locations of their choice. This feature will enable users to simulate and observe the behavior and interactions of elephants in different environments.

Furthermore, we aim to incorporate interactive elements such as sliders into the interface. These sliders will allow users to adjust various parameters, including time and initial motion vectors. By providing this level of control, users will be able to customize the simulation according to their specific interests and study the effects of different settings on the model's behavior.

Vector Field

One promising avenue for further exploration lies in the utilization of vector fields for representing animal movement patterns. A vector field provides a visual and mathematical depiction of the velocity of animals at each point in their environment. This can allow for a richer understanding of how wildlife species interact with their environment and navigate based on various factors.



By transforming our elephant GPS data into a vector field, we create a spatially continuous and detailed dataset that reflects the dynamic nature of animal movement. Each vector in this field would represent an instance of an elephant's direction and speed at a specific location. The magnitude and direction of the vectors provide information about the elephants' behavior and its relation to environmental features, capturing subtle details that might otherwise be overlooked.

Given the temporal and spatial characteristics of our data, RNNs, specifically Long Short-Term Memory (LSTM) networks, could be suited for training on such a vector field dataset.

Figure 10: Vector Field Analysis

The key advantage of LSTMs is their ability to learn long-term dependencies due to their unique memory cell structure, which can maintain information in memory for long periods. Transformer-based models have also shown remarkable performance on sequence prediction tasks. However, these models are complex to implement and require more computational resources. In the context of our work, the LSTM would take as input a sequence of vectors representing an elephant's past movements and would output a predicted next vector, indicating the expected direction and speed of the elephant's next movement. By training the LSTM on a vector field, we could develop a model capable of predicting future movements based on their past behaviors and the environmental features of their habitat.

7 Conclusion and Contributions

This project takes on a multidisciplinary approach through machine learning tools and ecological research, offering unique solutions to complex wildlife behavioral problems, specifically that of the African elephant. The focus is not on modeling an elephant's vision system, but rather on understanding the connection between the animal's movement and its environment. This approach not only contributes to our knowledge of mammal memory systems but also enriches broader ecological research by advancing machine learning applications within this domain.

Our predictive models, which stem from an understanding of the relationship between land features, topography, and wildlife behavior, allow us to monitor species movements in real-time and anticipate potential impacts of landscape changes. The real-time predictive capabilities of our models could be instrumental for land management and land-use planning, offering foresight into the effects of various landscape modifications. As GPS tracking technology improves, our model could reveal unseen information about landscape use. Beyond academic research, the work serves as a dynamic conservation tool, capable of guiding strategies aimed at mitigating potential harm to wildlife, contributing significantly to conservation efforts and habitat management strategies.

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