

ABSTRACT

MODELING THE EFFECTS OF HABITAT FRAGMENTATION ON THE MOVEMENTS OF THE MONGOLIAN GAZELLE IN THE EASTERN MONGOLIAN STEPPE

Team PATH: Predicting Animal Travel Habits

C. Gibb, M. Kleyman, M. Koelbel, R. Natoli, K. Orlando, M. Rice, C. Weber, W. Weston-
Dawkes. 2015

Thesis directed by: Dr. Bill Fagan

The Mongolian gazelle, *Procapra gutturosa*, resides in the immense and dynamic ecosystem of the Eastern Mongolian Steppe. The Mongolian Steppe ecosystem dynamics, including vegetation availability, change rapidly and dramatically due to unpredictable precipitation patterns. The Mongolian gazelle has adapted to this unpredictable vegetation availability by making long range nomadic movements. However, predicting these movements is challenging and requires a complex model. An accurate model of gazelle movements is needed, as rampant habitat fragmentation due to human development projects - which inhibit gazelles

from obtaining essential resources - increasingly threaten this nomadic species. We created a novel model using an Individual-based Neural Network Genetic Algorithm (ING) to predict how habitat fragmentation affects animal movement, using the Mongolian Steppe as a model ecosystem. We used Global Positioning System (GPS) collar data from real gazelles to “train” our model to emulate characteristic patterns of Mongolian gazelle movement behavior. These patterns are: preferred vegetation resources (NDVI), displacement over certain time lags, and proximity to human areas. With this trained model, we then explored how potential scenarios of habitat fragmentation may affect gazelle movement. This model can be used to predict how fragmentation of the Mongolian Steppe may affect the Mongolian gazelle. In addition, this model is novel in that it can be applied to other ecological scenarios, since we designed it in modules that are easily interchanged.

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1. Introduction

The Eastern Mongolian Steppe, one of the world's last intact grassland ecosystems, is home to the Mongolian gazelle, *Procapra gutturosa*. The Mongolian gazelle is severely threatened by habitat fragmentation due to human development projects (Olson et al., 2010). These projects - land cover change, oil and mineral extraction efforts, fences along administrative boundaries, construction of transportation infrastructure, etc. - degrade and fragment the habitat of Mongolian gazelles, with potentially deleterious effects (Ito et al., 2005). In this project we have endeavored to predict the extent to which these anthropogenic landscape changes may impact Mongolian gazelle movement and the possible repercussions for the species.

The Mongolian gazelle is particularly vulnerable to habitat fragmentation because its habitat, the Mongolian Steppe, is an extremely unpredictable disequilibrium system (Stumpp, et al., 2005). In such a disequilibrium system, the spatial location, quality, and quantity of resources vary wildly from year to year, even from month to month. A barrier that separates the gazelles from a large portion of their habitat - a railroad or fence, for example - may prevent access during a period of time when that habitat contains a significant portion of the food resources in the entire landscape. Thus, due to the dynamic nature of the Mongolian Steppe, any large-scale fragmentation of gazelle habitat has the potential to limit the gazelles' range and thereby increase the gazelles' probability of starvation (Ito et al., 2005).

1.1 Significance

Protecting gazelle populations is important for both ecological and societal motives. Gazelles are

a crucial source of protein for predators in the Mongolian Steppe, such as the grey wolf, or *Canis lupus*, and they play an important role as grazing herbivores in the Mongolian Steppe ecosystem, the last remaining intact temperate grassland in the world (Olson et al., 2005). Furthermore, large grazing mammals, such as the Mongolian gazelle, can increase plant diversity in Asian temperate grasslands by consuming competitively overly dominant, lower-quality vegetation (Olf & Ritchie, 1998). Moreover, gazelles are large mobile herbivores and transport and disperse seeds and soil over very long ranges. Gazelles may also boost soil variation and enhance soil regeneration sites through their urine and fecal output over a vast, diverse range (Olf & Ritchie, 1998).

Ungulates in large, high-density herds sometimes contribute to erosion and have adverse effects on soil, which decreases plant diversity (Olf & Ritchie, 1998). However, due to the constantly changing size and structure of gazelle herds, negative impacts to the soil and vegetation are most likely short-lived (Olf & Ritchie, 1998). This negative effect would also likely be mitigated in the Mongolian Steppe due to the Mongolian gazelle's nomadic movement patterns and low population densities.

The trophic cascade is a well-known example that demonstrates the important ecological influence of herbivorous ungulates. A trophic cascade occurs when changes in the number of species from one trophic level influences the number of species at a different trophic level (Cain et al., 2014). This occurred in Yellowstone National Park with wolves and elk, their prey. Wolves were removed and then reintroduced into this ecosystem affecting not only the elk population they preyed on, but also indirectly influencing the primary production of plant species

within the ecosystem, such as willows and aspens (Fortin et. al., 2005). Species' interactions in the Mongolian Steppe differ from those found in Yellowstone National Park because weather patterns and resource availability have are more influential on gazelle population size and abundance than carnivorous natural predators. However, a cascade may still occur since gazelle populations can potentially influence healthy growth of different vegetation species. The resulting quantity, quality, and location of vegetation throughout the steppe can then influence the distribution of other species which depend on it for food and shelter. The quantity, quality, and location of vegetation also directly impacts Mongolian citizens who depend on it as a critical food source for their livestock.

Gazelles are also important from a cultural perspective. Mongolian pastoral herders frequently hunt and consume gazelle meat as an important source of protein in their traditional nomadic lifestyle. Approximately one-third of the Mongolian population is composed of these nomadic pastoral herders, and half of the population depends on the pastoral economy to make a living (Fernandez-Gimenez, 2000). Due to these important ecological, social and economic concerns, protecting Mongolian gazelles should be a critical priority.

1.2 Research Question

This project addresses the following research question: “How does landscape exploitation and fragmentation affect the movements of highly mobile animals in highly dynamic landscapes?”

To answer this question, we created a computer model that replicates animal movement patterns in response to vegetation and landscape obstacle inputs. We used movement data from radio collars on Mongolian gazelles to train this model specifically to gazelle movement behavior. We

also used satellite imagery to simulate vegetation patterns in the Mongolian Steppe. In addition, we gathered spatial datasets of population density and human development projects as causes of habitat fragmentation and degradation.

We hypothesized that habitat fragmentation in the Mongolian Steppe will negatively impact the movement patterns of the Mongolian gazelle by inhibiting access to scarce resources. With our model, we predicted how habitat fragmentation changes the animal movement patterns and survival rates of a nomadic species in a highly variable landscape.

Previous models have been able to predict the movement of migratory animals on specific migration paths (Zhang et al., 2009). However, the movement patterns of the Mongolian gazelles are nomadic and therefore do not follow a specific migratory path. Existing models have also attempted to predict non-route based movement on the position of the animals with respect to resources (Dalziel et al., 2008). However, they have not accounted for the effects of anthropogenic fragmentation on non-route based movements. Our model is designed to add these functionalities and is furthermore designed as a set of modules that can easily be interchanged so that our framework can be used to study completely different ecosystem scenarios. The unique functionality and flexibility of our model novel and contributes valuable knowledge to the field of conservation ecology.

We created an innovative broad-scale population-level modular model that combines an Individual Based Model (IBM), an Artificial Neural Network (ANN), and a Genetic Algorithm (GA) to predict how habitat fragmentation affects animal behavior. Ultimately, our goal is to allow scientists as well as conservational and governmental planning groups to use our model as

a tool when making decisions about the optimal locations for human development projects and land use conversion. Ideally, our model will allow them to make decisions that minimize impacts to the ecosystem. Additionally, due to the modular design of our model, we hope to enable other conservation ecologists to apply our model framework to their data to identify patterns in the movements of other animal species and make predictions about space use.

2. Literature Review

2.1 Fragmentation Due to Anthropogenic Pressures

Human exploitation of a landscape often results in habitat fragmentation; the construction of roads, railroads, and fences, for example, may section off part of an animal's habitat, making some regions inaccessible or undesirable to an individual or a herd. Along with overexploitation - often through poaching and unregulated hunting - and habitat loss, habitat fragmentation is one of the most devastating threats to migratory ungulates (Bolger et al., 2008). Several species of ungulates, including wildebeests, hartebeests, and Mongolian gazelles, have experienced catastrophic population declines and even local extinction due to the construction of barriers across their habitats (Bolger et al., 2008). This is largely because barriers prevent these animals from reaching an optimal resource patch, leaving them malnourished (Ito et al., 2005).

In addition, basic human development, such as small houses, can have a considerable impact on local populations of nomadic animals. For example, on the Mongolian Steppe, one research study found that in regions with houses, the density of gazelles was 76 to 98 percent lower compared to regions without houses (Olson et al., 2011). These data have been incorporated into a statistical model that indicates a strong negative relationship between household presence and gazelle distribution (Olson et al., 2011).

Mining sites present yet another significant concern for habitat fragmentation and degradation in the Mongolian Steppe. The Mongolian economy has shifted considerably in the last century. Historically, the Mongolian economy was primarily dependent on traditional herding and

agriculture practices (The World Factbook, 2014). Although these traditional economic contributors remain important components of the Mongolian economy and GDP, growth in Mongolia's mineral extraction sector coupled with Mongolia's vast mineral deposits have transformed the Mongolian economy (The World Factbook, 2014). Mongolia boasts significant deposits of copper, petroleum, gold, molybdenum, fluor spar, uranium, tin, and tungsten (The World Factbook, 2014). The vast amount of mineral resources have attracted a large number of foreign investors hoping to capitalize on the wealth of Mongolia's natural resources; unfortunately this is occurring at the cost of environmental fragmentation and degradation (The World Factbook, 2014). Fragmentation of landscapes leads to reduced habitat area, increased isolation (reduction of corridors and ecotones), and increased edge effects (Haddad et al., 2015).

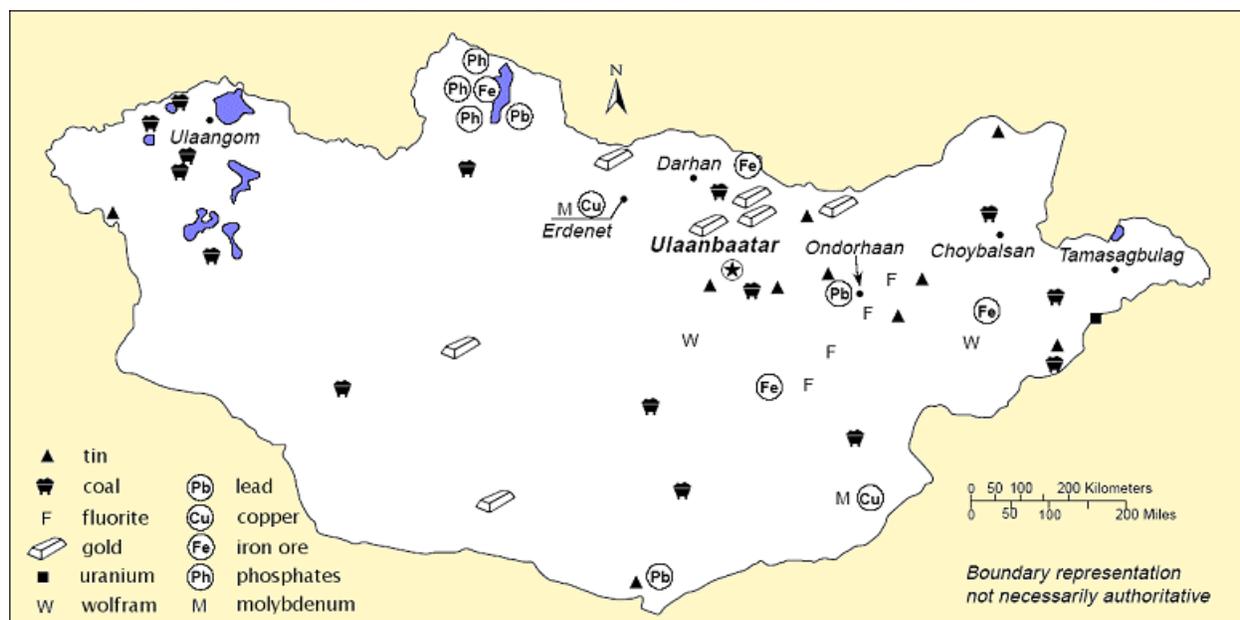


Figure 1. Map of Mongolia mineral deposit sites from 1985. This map shows the numerous types of minerals which can be exploited in Mongolia, as well as the vast spatial range that these mineral deposit sites cover. For both of these reasons, mining is a major anthropogenic activity which disrupts the Mongolian landscape (Reprinted from Worden, Savada & Lohninger, 2004).

2.2 Landscape Dynamics of the Mongolian Steppe

The Eastern Mongolian Steppe is one of the last intact temperate grasslands in the world (Leimgruber et al., 2001). Although the Mongolian Steppe extends from central and eastern Mongolia into northeast China and the North China Plain, our study area will only consider the parts of the Mongolian Steppe within Mongolian borders. This region is bordered by Russia to the north, China to the east, the Gobi desert to the south, and the Altai Mountain range foothills to the west. The Mongolian Steppe is characterized as a Palearctic semi-arid grassland ecosystem and is estimated to encompass 275,000 km² (Olson et al., 2010).



Figure 2. A map of Mongolia depicting the principal biomes in the region, including the Eastern steppe region on which this project focuses (Reprinted from Protect, 2015).

The Mongolian Steppe is very flat with gentle undulating hills, providing extensive sightlines.

Temperatures range from 30°C in the summer to -45°C in the winter (Land, 2003). Winters are

long and brutal, with average temperatures either close to or below freezing from October to April. The spring season is short, spanning only May and June. The remaining months comprise summer and fall, which together form the wet season of the Steppe. During this time, the region receives the majority of its annual precipitation (Land, 2003). The Mongolian Steppe is characterized by unpredictable precipitation patterns and is commonly plagued by periods of drought (Sternberg, Thomas, and Middleton, 2010).



Figure 3. Spring in the Mongolian Steppe (Drelling, 2014).



Figure 4. Winter in the Mongolian Steppe. Vegetation is extremely sparse during this season ("The Nomadic Herders of Mongolia", 2014).

Weather is variable in the Steppe, which accounts for significant changes in the density, quality, and location of vegetation (Liu et al., 2012). In fact, the Steppe is categorized as a disequilibrium system, meaning that due to variations in the spatial distribution of precipitation, the ecosystem undergoes rapid changes in vegetation in a period of less than a year. Intensifying this variability, one specific resource patch will only contain edible grasses for a few weeks (Stumpp, et al., 2005).

Despite this ecosystem's harsh and rapidly changing climate, a diverse array of species live in the Mongolian Steppe. This grassland is home to many large mammals other than the Mongolian gazelle, such as wolves, wild boars, marmots, raccoon dogs, red deer, Asiatic wild ass, argali sheep, Ussurian moose, and the recently re-introduced Przewalski's horse (Wildlife of

Mongolia).

2.3 Movement of the Mongolian Gazelle

Animal travel patterns are heavily correlated with the patterns of resource availability within their ecosystems (Mueller et al., 2007). Migration, which we define as movement that occurs along the same route annually, is typically found in areas with predictable seasonal variation in resources. If specific regions have predictable resources at given times each year, animals that migrate between these regions will have an advantage over non-migratory species (Mueller et al., 2011). In contrast, nomadic movements correspond to unpredictable resource availability; if a region has varying resources each year, animals generally travel to the closest patch of adequate resources, resulting in irregular nomadic movement patterns (Mueller et al., 2011). Since the availability of vegetation is unpredictable in the Eastern Mongolian Steppe due to the region's unpredictable precipitation patterns, it is more advantageous for Mongolian gazelles to be nomadic rather than migratory (Mueller et al., 2007).

Besides resource availability, anthropogenic barriers also impact the gazelles' movements. One study tracked two gazelles near the Trans-Mongolian Railway over a one-year period, and found that the gazelles moved roughly parallel to the railroad but never crossed it. Crossing this railroad is difficult for gazelles in part because it is lined by a fence on both sides. The gazelles stayed closer to the railroad during the winter, but only one gazelle ever crossed it. All other individuals remained on the relatively barren side even though there was more edible greenery on the other side of the barrier. All of these observations support the assertion that the railroad is an effectively insurmountable barrier to the Mongolian gazelle (Ito et al., 2005).

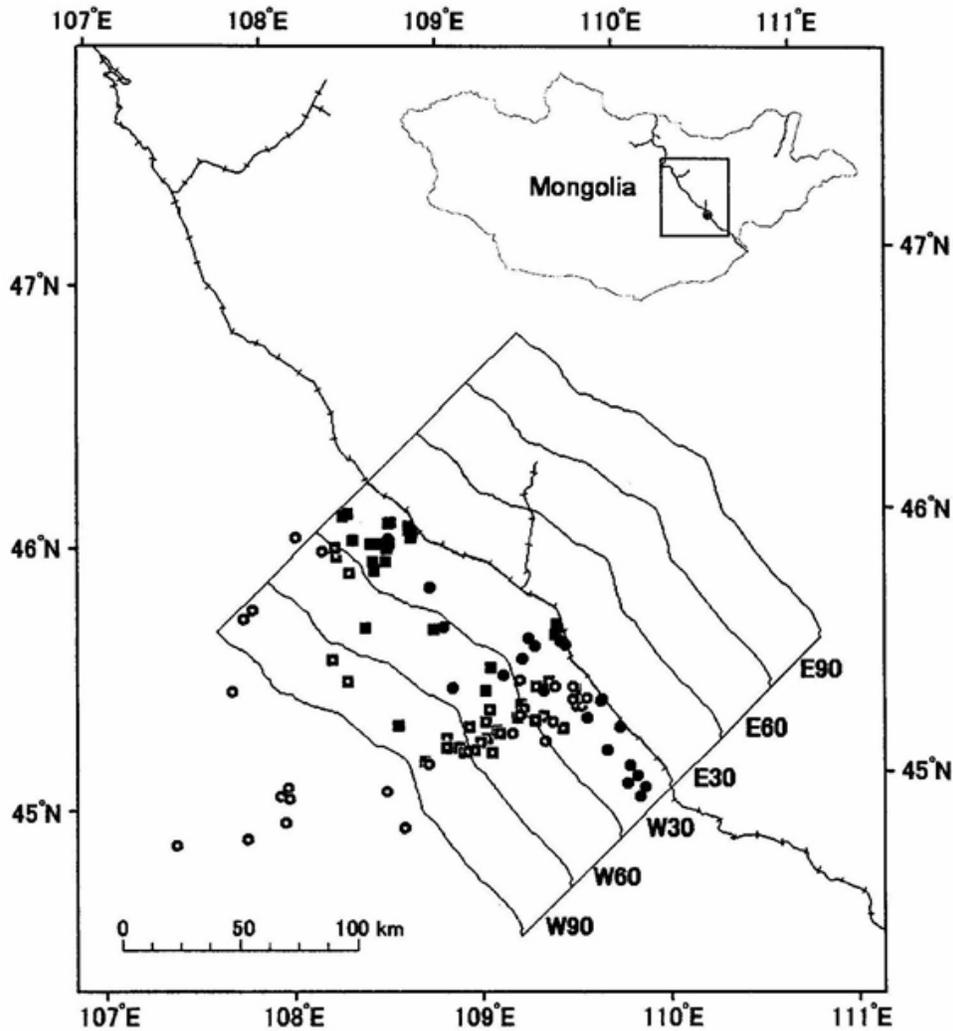


Figure 5. Gazelle locations near the Trans-Mongolia Railway (Ito et al. 2005). The diagonal, ticked line across the image represents the Trans-Mongolian Railway. The solid dots represent gazelle locations during the winter, while the open dots represent gazelle locations during the summer. The gazelles stayed in closer proximity to the railroad during winter, but did not cross it.

Furthermore, anthropogenic barriers can have a one-sided effect, impacting individuals on one side of a barrier more so than on the other side. A study by Ito et al. found that the Trans-Mongolian Railway had affected gazelles in this way (2008). The Trans-Mongolian Railway

stretches from the northwest to the southeast, dividing the Steppe into a northeast half and a southwest half. Thus, gazelles in the southwest section could not easily move to the northeast section. This fragmentation seemed to be especially problematic during the winter, presumably because during the colder months the northeast half of the Steppe has less harsh weather and more vegetation (Ito et al., 2008). As a result, gazelles that were already in the northeast region had higher survival rates compared to those that were confined to the southwest region (Ito et al., 2008). This study also recorded Mongolian gazelle carcasses along a 630 km. stretch of the railroad. The researchers found roughly two-thirds of the carcasses on the southwest side of the railroad, and about one-third of the carcasses on the northeast side (Ito et al., 2008). This suggests that the Trans-Mongolian railroad has a greater impact on gazelles moving from the southwest to the northeast, compared to gazelles moving in the opposite direction.

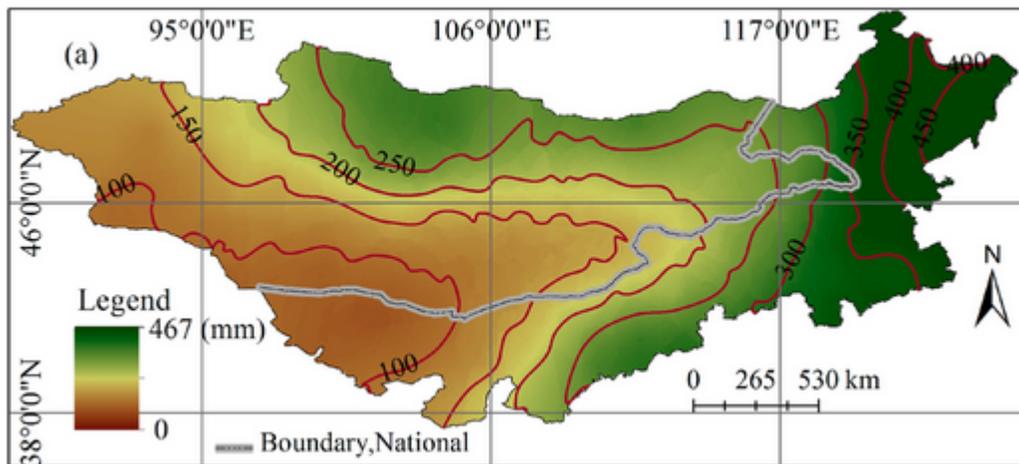


Figure 6. Map of average annual precipitation on the Mongolian Steppe from 1982 to 2010. The northeast part of the Steppe has more precipitation, suggesting it also has more desirable vegetation. During the winter, this could draw gazelles toward the northeast part rather than the southwest part of the Steppe, creating a one-sided barrier effect of the railroad (Bao et al., 2014).

The same study also found that the Trans-Mongolian railroad may not be a complete barrier to gazelle movement. The railroad is flanked by a fence on both sides, and slightly under one-third of the gazelle carcasses that were found were found inside the fence (Ito et al., 2008). This indicates that the railroad fences are not wholly impermeable obstacles to gazelle movement. This contradicts the findings of earlier studies that found that the Trans-Mongolian Railroad is an impermeable barrier to gazelle movement (Ito et al., 2005).

Herd dynamics influence gazelles' movements as well. In Gueron et al. (1996) researchers developed a mathematical model to determine how individuals move in response to various movement scenarios of the entire herd and surrounding individuals. The study formulated four zones around an individual determining their movement. When an individual's closest neighbor occupies the first zone, the stress zone, the individual becomes uncomfortable and moves away. The neutral zone is second, and when the nearest neighbor is in this zone, the individual is indifferent. Third is the attraction zone. When an individual's closest neighbor occurs in this zone, the individual moves towards the neighbor for protection. These three zones occur principally in front of an animal, and behind the animal is the rear zone. When the nearest neighbor occupies this zone, the individual becomes the leader of a herd formed by itself and its trailing neighbors. In this way, the movement and position of other animals within a group influence the movement patterns of an individual and the group as a whole (Gueron, et al. 1996).

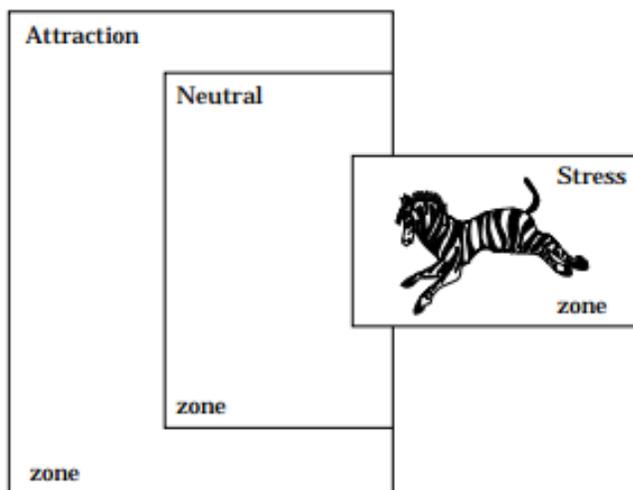


Figure 7. Rough illustration of zones that determine movement. The sequence of zones in front of the individual governs whether it is attracted to or repelled by its neighbor (Gueron, et al. 1996).

Livestock can also impact the movement patterns of gazelles. Mongolian gazelles and livestock - specifically goats and sheep - have similar grazing diets and thus are very likely to compete for the scarce food resources on the Steppe (Stumpp et al., 2005; Campos-Arceiz, Takatsuki, & Lhagvasuren, 2004). Consequently, gazelles tend to move away from areas with herds of livestock since these regions will likely have more competition for resources.



Figure 8. A herd of livestock in the Mongolian Steppe. Herds such as this one compete with gazelles for valuable resources, often driving gazelles away ("The Nomadic Herders of Mongolia", 2014).

2.4 Remote Sensing

Although gazelle movement depends on many different factors, vegetation is the chief predictor of gazelle location. In this study, we measure vegetation through remote sensing, specifically the Normalized Difference Vegetation Index (NDVI). Remote sensing is the process of remote data acquisition via satellites or aircraft. These satellites or aircraft detect energy that is reflected off of the Earth to collect data. For example, a satellite may obtain images of the amount of heat being reflected off of different areas of the Earth, or images of the visual section of the electromagnetic spectrum resulting in images of the Earth from space. These satellites then transmit these images and datasets back to Earth.

2.4.1 NDVI

The Normalized Difference Vegetation Index (NDVI) is a type of data derived from remote sensing. It is used to detect the presence or absence of vegetation based on the amounts of near-infrared and visible (red) radiance from a specific site. To determine NDVI, red and infrared bands are extracted from a remote sensing dataset, such as those from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) or Landsat instruments (Ramos, 2010). For this project, we use MODIS data because of the large spatial extent of our study area and the higher radiometric and temporal resolution compared to Landsat data.

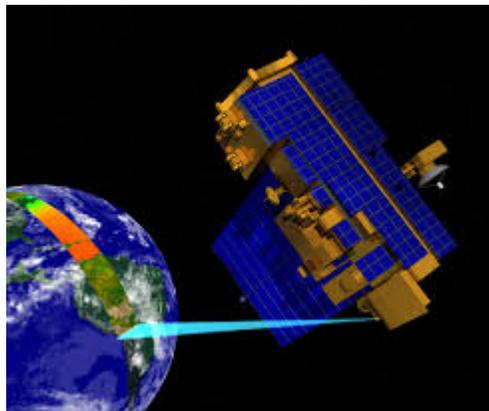


Figure 9. MODIS Terra Satellite collecting data from space ("Numerical Terradynamic Simulation Group"). The NDVI value of each pixel in a satellite image is calculated with the following equation: $NDVI = (Near-Infrared - Red) / (Near-Infrared + Red)$ (Ramos, 2010).

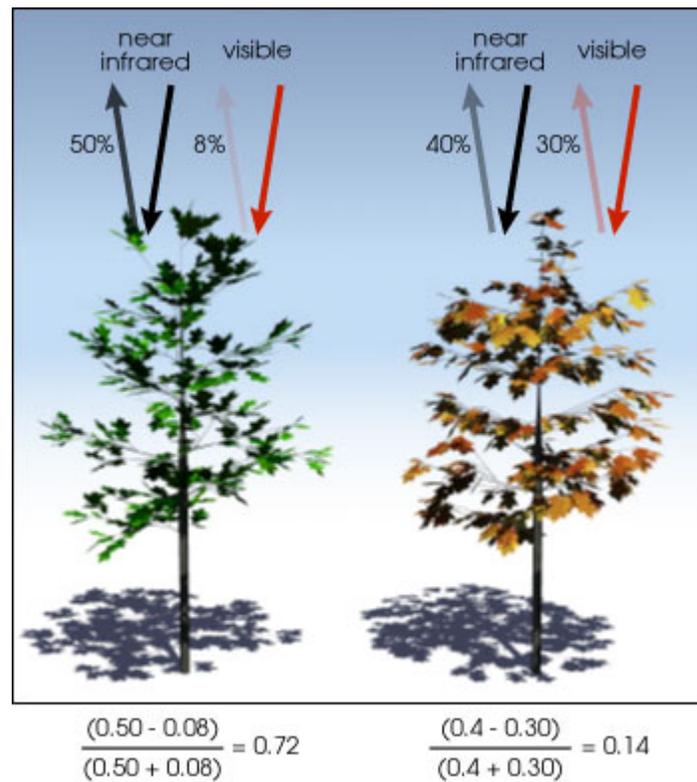


Figure 10. Calculation of NDVI of vegetation (Weier, 2000).

Values of NDVI range from -1 to 1. Values of NDVI near -1 correspond to areas of water. Values between -0.1 and 0.1 correspond to desolate areas of snow, sand, rock, or extremely sparse vegetation. Values between .2 and .4 correspond to grasslands. Values near 1 correspond to areas of verdant and highly productive vegetation, namely rainforests (Ramos, 2010). For normal application, NDVI typically ranges from -0.1 to 0.6, corresponding to a range between barren regions and very verdant regions.

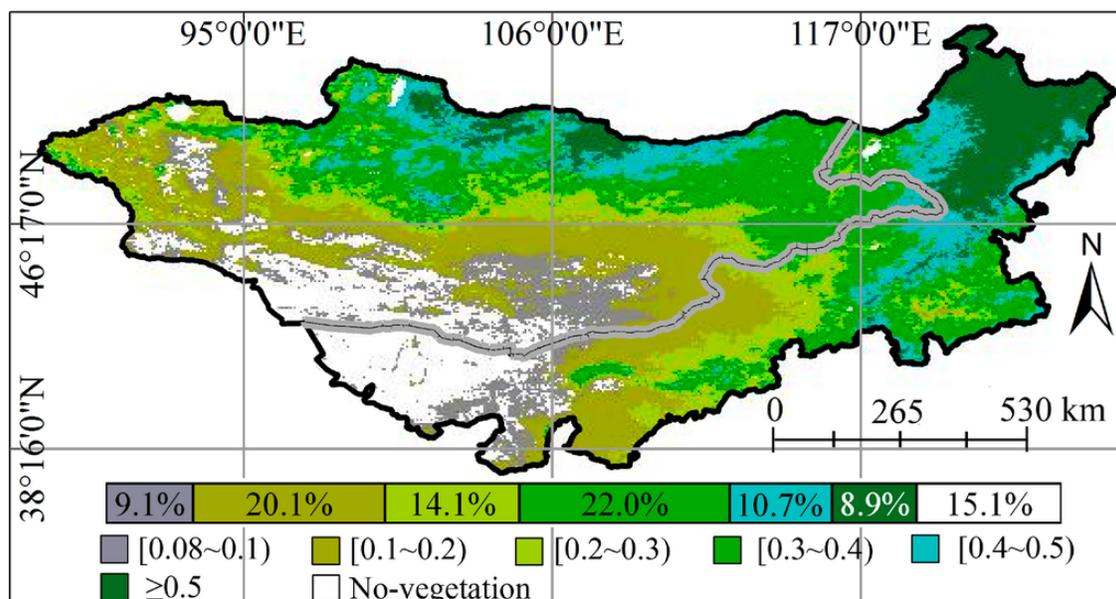


Figure 11. Map displaying the mean NDVI values of Mongolia from 1982 to 2010. Values were measured during the spring (Bao et al., 2014).

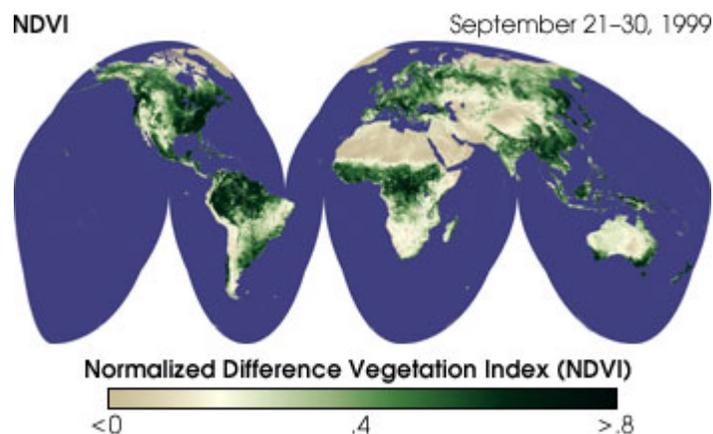


Figure 12. World map of NDVI values (Weier, 2000), highlighting the Mongolian Steppe as having intermediate NDVI values.

NDVI is particularly important when predicting gazelles' movements because vegetation, the main source of energy intake for gazelles, is a significant determinant of where and why gazelles move (Pettorelli et al., 2011). Additionally, the Mongolian Steppe is extremely dynamic,

meaning that vegetation can change from having a low NDVI to having a high NDVI in a matter of weeks (Stumpp, et al., 2005). Figure 13 below shows the deviation from the average NDVI in Mongolia over approximately 10 years. Darker colors represent a larger deviation, which makes it clear that NDVI in Mongolia changes drastically from year to year.

Departure from Average NDVI images. 1990-2001, Mongolia. NOAA/AVHRR

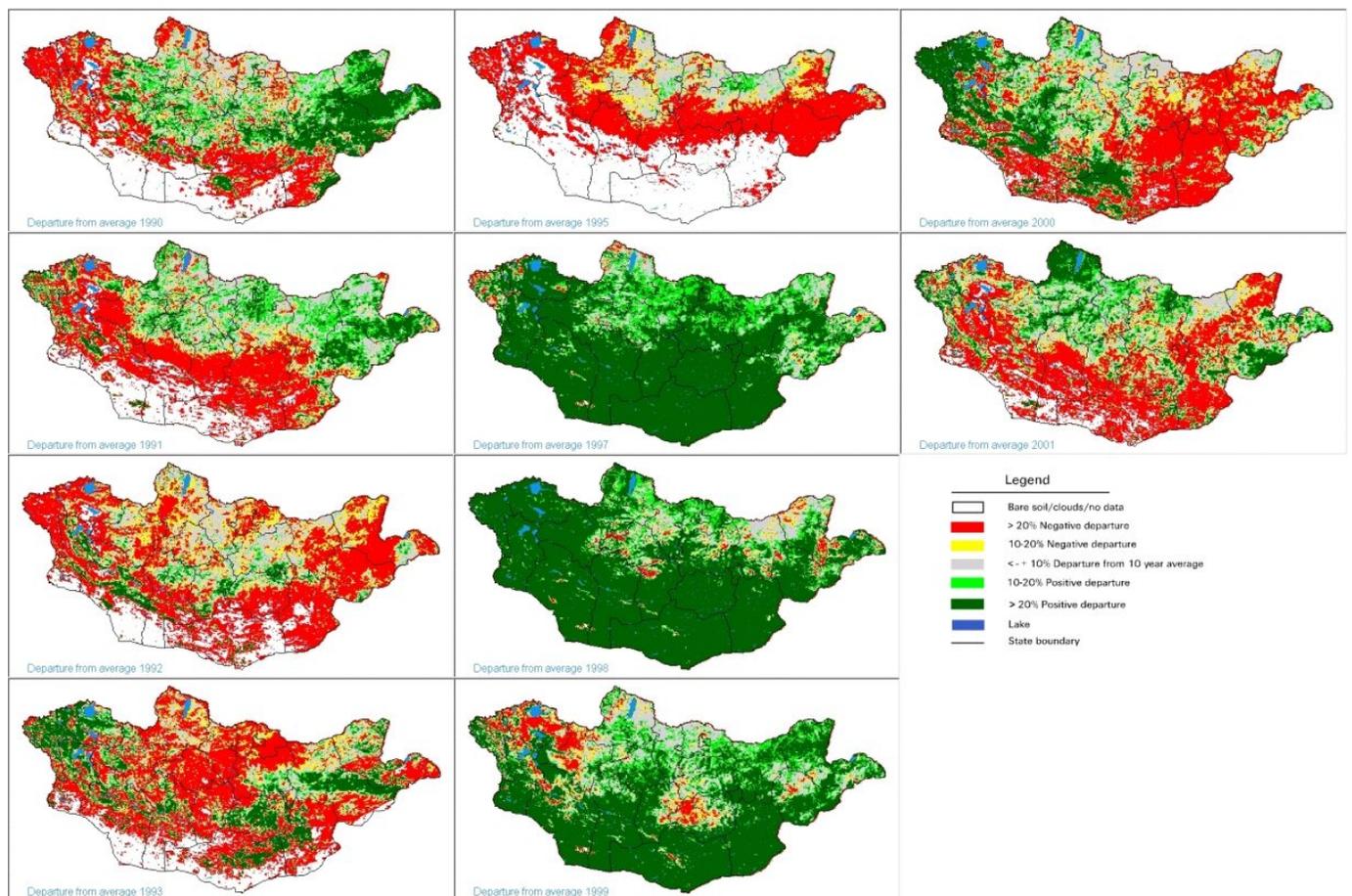


Figure 13. Maps of average annual anomalies in NDVI values in Mongolia. NDVI on the Steppe was measured during 10 years between 1990 and 2001. The average was computed, and each figure above shows the difference between the average NDVI and the recorded NDVI for each

year. Dark green and red correspond to a difference of greater than 20 percent, and gray corresponds to a difference of less than 10 percent (Naidansuren, 2002).

Given that low NDVI values denote barren areas with little or no vegetation, gazelles searching for resources do not prefer low NDVI areas. At the same time, relatively high NDVI values on the Mongolian Steppe correspond to areas with mature grasses. However, these grasses are often too tough to provide much nutrition, so gazelles do not prefer high NDVI areas. Intermediate NDVI values indicate areas that have recently received rain or snowmelt where young, tender grasses which are highly nutritious for the Mongolian gazelle are beginning to grow. Thus, NDVI values can be used as a predictor of the Mongolian gazelle's location (Mueller et al., 2007).

2.5 Movement Models

The simplest existing models of ungulate movement use information about the location of ungulates over time, population density, and data layered in a Geographic Information System (GIS). With this information, the models predict common movement routes of ungulates, along with the amount of traffic through those routes (Sawyer, 2009). This method for ecological modeling of animal movement is the Brownian Bridge Movement Model (BBMM). The BBMM constructs a probabilistic estimate of the migration routes of a sampled population, distinguishes between route segments, and prioritizes areas for conservation. These prioritized areas are established by weighing regions that are used as mating and resource-gathering sites against those that are used as movement corridors, based upon the proportion of the sampled population that uses them. Highly variable landscapes do not allow for consistent migration routes because

resource patches change so rapidly, therefore a BBMM is not very suitable for the purposes of this work (Olson et al., 2010).

An alternative common class of statistical models, known as a particle model, defines ungulates as particles and predicts their movements using a potential function. This prediction of movements is similar to a physicist's prediction of a particle's movement in a force field. In these models, each individual factor has a coefficient of attraction or repulsion which is based on its level of influence on ungulates' movements (Brillinger et al., 2001). In our model, an example of a factor is a patch of edible grass which attracts gazelles, or an area inhabited by humans which repels gazelles. The particle model depends largely on pre-determined rules as opposed to empirical data, and is rather too simplistic to accurately simulate the Mongolian Steppe ecosystem. For example, the simplicity of the particle model could result in inaccurate predictions, such as a Mongolian gazelle remaining stationary when a ger - a mobile dwelling of the nomadic Mongolian people sometimes referred to as a yurt - blocks its path to a food source, instead of simply moving around the obstacle as a real gazelle might.

Another predominant class of models is based on the property of emergence. Emergence describes the phenomena of simple behaviors compounding to create a complex and adaptable model which can accurately portray the behavior of a large group. One model in this class is an individual-based model (IBM). According to this model, the interactions between individuals are generated in response to environmental stimuli. These local interactions are important for predicting global behavior (Hamilton, 1971).

Swarm intelligence models are a subclass of IBMs, and have been widely used for modeling herd

populations. Swarm intelligence models base behavior on competition, social-cooperation, and self-adaptation. Each individual has its own programmed behavior that is highly dependent on other individuals in its surrounding area. Swarm intelligence models assume that animals in a social setting will try to be in a position of best fit and change the factors in the optimization equation according to that goal (Zhang, 2009). The optimization equation chooses the next movement of the animal in the model based on the likelihood that the movement will help the animal obtain resources. While Mongolian gazelles do often form herds, these herds are ephemeral and often change in numbers and composition. Mongolian gazelles have also been observed traveling alone (Olson et al., 2009). Because gazelle movements are not as intimately linked as the movements of other animals, modeling gazelles with a swarm model is not appropriate.

Artificial Neural Networks (ANNs) are a class of models in which individuals develop and evolve behaviors in response to environmental stimuli. A neural network consists of an interconnected group of artificial neurons, or nodes. Nodes are simple functions that convert input into output. The neural network has three classes of node layers: input layers, internal hidden layers, and output layers. The functions in the internal layers are not apparent to the programmer, so this layer is called, “hidden”. All neural networks possess one input layer, one output layer, and a variable number of hidden layers. Information is processed as it passes from the input layer, through the hidden layer, to the output layer. The input data are transformed into an output value by weighted interconnections between the each consecutive layer. In every node at each layer, except for the input layer, the cumulative weighted input from the previous layer is

fed into an activation function. If the cumulative input to the activation function at a node exceeds a certain threshold value, the node propagates those values to the next layer, similar to a neuron firing. If the threshold value is not met, then the node does not propagate the values.

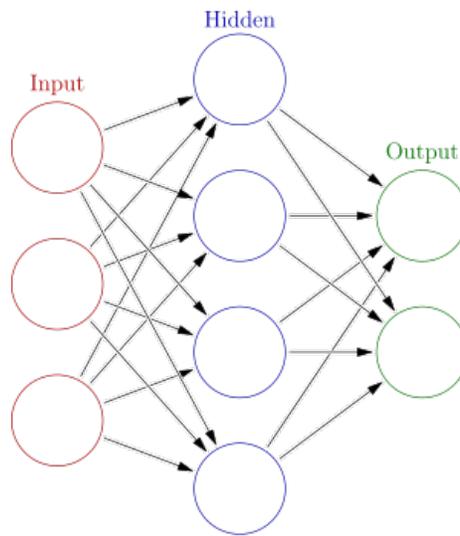


Figure 14. Sample artificial neural network illustrating interconnections among nodes arranged in different layers.

A neural network has a training phase during which it identifies which path through the nodes provides the optimal result. The neural network then uses empirical data to set the constants in the functions of each node according to this optimal path. Through this training phase, the ANN develops its own rules to model the empirical data it received. A validation phase follows where a second set of empirical data is tested on the generated rules (Mueller et al., 2011).

Genetic algorithms are another form of emergent algorithm that can utilize empirical data to

optimize a complex behavior. Genetic algorithms assign computer-generated genetic codes to individual agents in the model. The individuals that survive and are more successful will reproduce at a higher rate, so their genetic code will become more prevalent in the model. The code of unsuccessful individuals will be eliminated (Wood, 2007). A fitness function based on empirical data helps determine if an individual is successful, and those that do not satisfy this fitness function die off at a much higher rate. In this way, genetic codes that fit the empirical data will remain in the model while others will be filtered out.

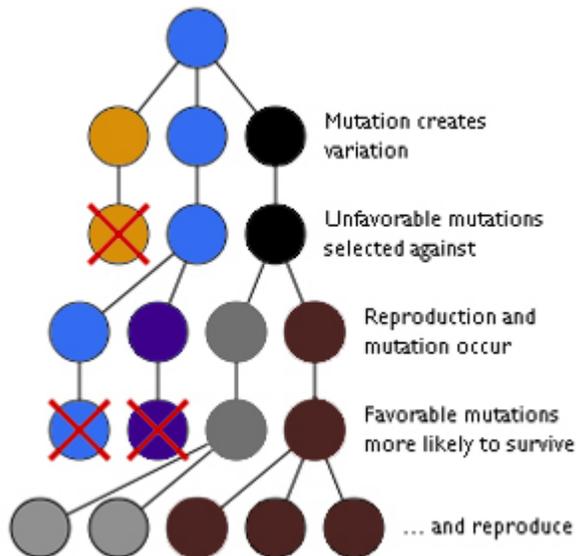


Figure 15. A graphical depiction of a genetic algorithm that illustrates its evolution-like properties (Venton, 2008).

We chose to utilize an individual-based neural network genetic algorithm (ING), a model that combines ANNs and genetic algorithms. INGs model populations as sets of individuals who each

have their own genetic codes but who share an artificial neural network (Mueller et al., 2011). The behaviors of individuals in our model depend on their own genetic codes which acts as weights in their neural networks, thus determining their individual behavior. INGs allow the model to adapt to the empirical data of the entire gazelle population using ANNs, as well as to individual gazelle data using genetic algorithms. By utilizing the best attributes of the two most suitable models we found, we created an optimally accurate and adaptable model for highly mobile animals in highly variable landscapes.

2.6 Software

We explored numerous options for platforms to use to develop our model, but we eventually narrowed these down to three main options: SWARM, NetLogo, and Repast. SWARM was developed in 1996 by the Santa Fe Institute, Repast in 2000 by the Center for Social Complexity at George Mason University, and NetLogo in 1999 by the Center for Connected Learning and Computer-Based Modeling at Northwestern University.

SWARM is implemented using Objective-C, Java, or both. It has some integrated GIS functionality, and runs on Windows, UNIX, Linux, and Mac OS X (Castle & Crooks, 2006). Though these features seemed ideal, the SWARM wiki and official documentation contained various outdated and broken links. In addition, SWARM was very difficult to install on a Windows system, to the point that many features were inaccessible to us. SWARM is also not well supported by the academic community due to other newer platforms for IBMs. SWARM does have some historical significance though, as it is considered a precursor to both NetLogo, a programmable modelling framework, and to Repast, an agent-based framework (Robertson,

2005).

NetLogo uses its own proprietary scripting as the implementation language and is available on Windows, UNIX, Linux, and Mac OS X. This language is intended to be used for various models and applications in biology, economics, physics, and other disciplines. NetLogo was a viable option because it is oriented around various agents, or individuals. These agents come in the form of “turtles”, agents that move around the world, “patches”, square pieces of “ground” over which turtles can move, “links”, agents that connect two turtles, and the “observer”, an agent that gives instructions to the other agents. In addition, NetLogo is a very high-level language that was designed to have a low learning curve, and it is well supported and maintained. Unfortunately, due to the simplicity of NetLogo, more complicated models may be outside of its capabilities. This eliminated it from our consideration since our project required complex parameters that NetLogo could not easily account for (Robertson, 2005). For instance, NetLogo lacked the capability to have a genetic algorithm optimize a neural network. Also, because it is such a high-level language, NetLogo can be very slow for larger models.

Repast is a family of agent-based platforms called the Repast Suite. Repast Suite is a collection of free, open source agent-based modeling and simulation platforms that have been under development for more than ten years. Repast Symphony can use both ReLogo and Java, while Repast for High Performance Computing uses C++. The entire suite is available on Windows, UNIX, Linux, and Mac OS X. Each individual platform had extensive documentation on the Repast website, and Repast in general has nearly universal academic community support. Repast is also very useful because it has extensive integrated GIS functionality, such as OpenMap, Java

Topology, and GeoTools. It can also be run within ArcGIS through an extension. Due to its versatility, capabilities, strong community, and extensive documentation and support, our team decided to use Repast to develop our model.

Repast Symphony models can be developed in several different programming languages: ReLogo (a dialect of the Logo programming language and similar to NetLogo), point-and-click flowcharts, Groovy, and Java. We used Java as our programming language because it is object-oriented, cross-platform, and, while high-level, runs significantly faster than the other options. Furthermore, Java is a popular programming language with extensive documentation and many existing libraries of functions that we can utilize. To aid in our programming, Repast Symphony also offers Graphical User Interface (GUI) features such as buttons to start, stop, pause, speed up, and slow down the simulation. We used this GUI to display the model while it runs.

In summary, from our literature review we learned that the Mongolian Steppe is a complex disequilibrium system where food and other resources for the Mongolian gazelle are spatially dynamic and temporally unpredictable. In order to survive in this environment, gazelles have adapted to lead a nomadic lifestyle and move towards resource patches. Because of this, habitat fragmentation is a major threat to this species. To be able to predict the effects of fragmentation on gazelles, we decided to create a model. We chose to build an ING model because it allowed us to train model gazelles to behave like real gazelles from GPS collar data by using a genetic algorithm to evolve weights for unique ANNs that determine each individual's movement. We decided to build this model using Repast Symphony since it is the best documented and most powerful of the available modeling platforms.

3. Methodology

3.1 Model

An Individual-based Neural network Genetic algorithm (ING) is the optimal framework to model an ecosystem as highly variable as the Mongolian Steppe and a species as highly mobile as the Mongolian gazelle (Mueller et al. 2011). In this section, we describe the various components of the model: individual-based models, an artificial neural network, and a genetic algorithms. Finally, we discuss how we trained and validated our model.

3.1.1 Individual-based Models

Individual-based (agent-based) models (IBMs) seek to understand both how individuals behave and how the interactions among many individuals lead to large-scale outcomes (Axelrod & Tesfatsion, 2006). IBMs calculate the behavior of each agent individually, which makes these models more closely resemble reality, but they also require more calculations and therefore more computing time. An individual-based model is particularly suitable for modeling the Mongolian gazelle because the herds tend to break up and recombine frequently due to decisions made by individual gazelles. It also allows us to test hypothetical landscape situations on trained model gazelles in a way that mathematical function based models do not.

3.1.2 Artificial Neural Networks

The artificial neural network (ANN) is responsible for generating the movement decisions for every gazelle at each time step of the model simulation. In our model, we will assume that

animal movement consists of three main types of mechanisms: memory, oriented, and non-oriented movement. Oriented mechanisms are movement patterns that emerge in response to stimuli that are within an animal's sensory range; these mechanisms are further divided into vegetation-oriented and obstacle-oriented movement. For example, a large vegetation patch may draw an animal towards it, so this is a vegetation-oriented movement. A railroad may repel an animal away from it, so this is an obstacle-oriented movement (Mueller et al., 2007; Ito et al., 2005). In memory-based movement, the movement largely depends on recent movement decisions. This enables longer range movements that gazelles sometimes exhibit. Non-oriented mechanisms are not toward or away from any specific stimuli; instead, they represent a gazelle's randomly determined decision to keep or change its current speed. This type of movement can happen when a gazelle is searching for a suitable grass patch but has not yet found one.

ANN Input Variables

During the simulation, the ANN takes in a gazelle's sensory and state variables, such as distances to anthropogenic obstacles, values of vegetation patches, and memory of past movements. We used the following elements as inputs to the neural network:

- Current Resource Uptake: the NDVI value at the location that a gazelle is currently occupying.
- Cumulative Resource Uptake for Past 8 Steps: Moving summation of NDVI values at locations that a gazelle has occupied.
- Maximum NDVI in Sight: Maximum NDVI value within a gazelle's vision range.
- Search Effort: Defined as the amount of deviation from travel in a straight line.

- Previous Step Angle: the absolute angle of an individual gazelles last movement step relative to the cardinal direction East.
- Previous Step Distance: the magnitude of displacement of an individual gazelle's last movement step.
- Absolute Displacement Over 14 Steps: the magnitude of continuous displacement of an individual gazelles current location and the location it occupied 14 steps previously
- Current X Location: the x location, in continuous space, of an individual gazelle.
- Current Y Location: the y location, in continuous space, of an individual gazelle
- Step Count: the total number of steps the individual has taken for a given generation

These inputs encapsulate information that model gazelles use to decide which movement mechanism to use during the time step of the model, which occurs after inputs are fed through the ANN. Inputs, such as the current x location, current y location, and step count, serve to encode absolute spatial and temporal reference information for model gazelles. These inputs are directly related to memory mechanism movement, so certain values in these parameters may particularly serve to initiate a memory based movement.

Following calculation of the inputs, the ANN applies the appropriate functions to each variable, and produces a movement decision. The ANN is organized into three layers: an input layer that takes in the sensory and state variables, a hidden layer that applies an emergent function to the variables and multiplies them by certain weights, and an output layer that returns five results, described below.

ANN Output Variables

The five results given by the output layer range between 0-1. The first two outputs correspond to the shape and scale of a Weibull distribution, and the second two outputs correspond to the peak position and scale of a Wrapped Cauchy distribution. These two distributions, which determine how far and in what direction the gazelles move, are explained below. The fifth output indicates what type of movement - vegetation-oriented, memory-based, obstacle-oriented, or non-oriented - the individual exhibits. .

The Weibull distribution describes the distribution of distance moved when movement is governed by simple diffusion, the movement from a more concentrated area towards a less concentrated area. However, the shape of the Weibull distribution is flexible, so this distribution can also describe the distance moved under other types of movement (Morales et al., 2004). For this reason, the Weibull distribution is very appropriate for our purposes. This distribution's shape parameter defines the shape of its spread, and the scale parameter defines the value with the greatest probability. For each movement step, we drew a randomly sampled value from the Weibull distribution to determine the distance that the gazelle moved in the simulation.

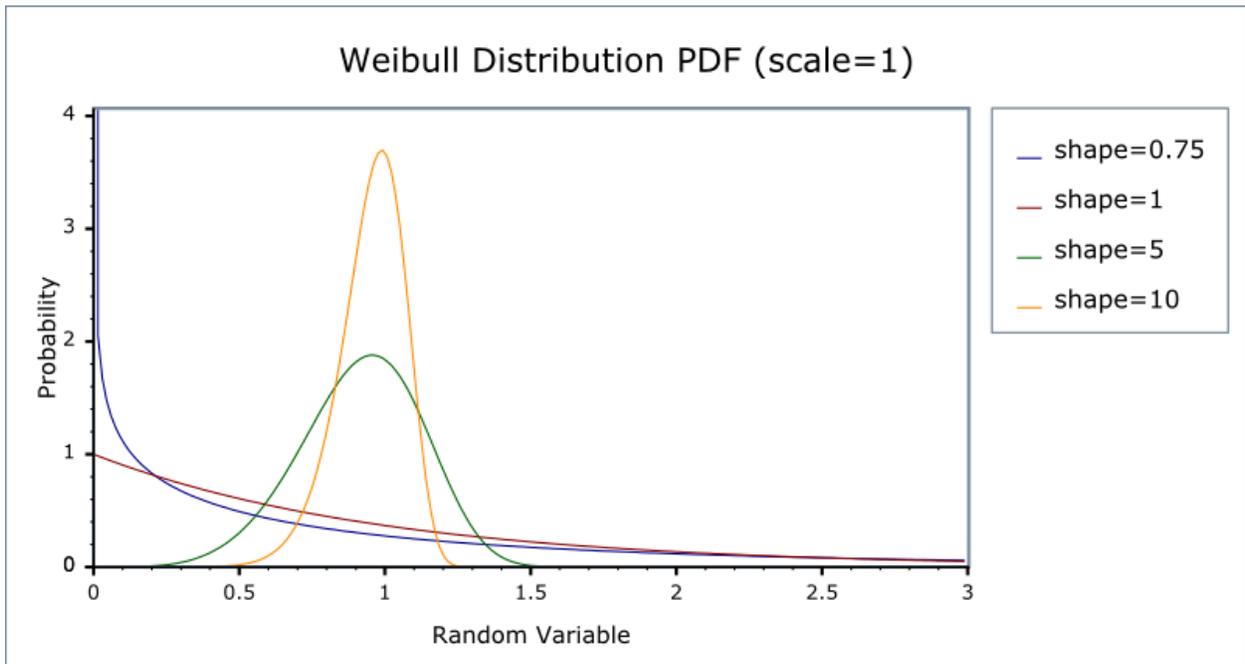


Figure 16. Weibull distribution curves with various shape parameters (Maddock et al., 2006).

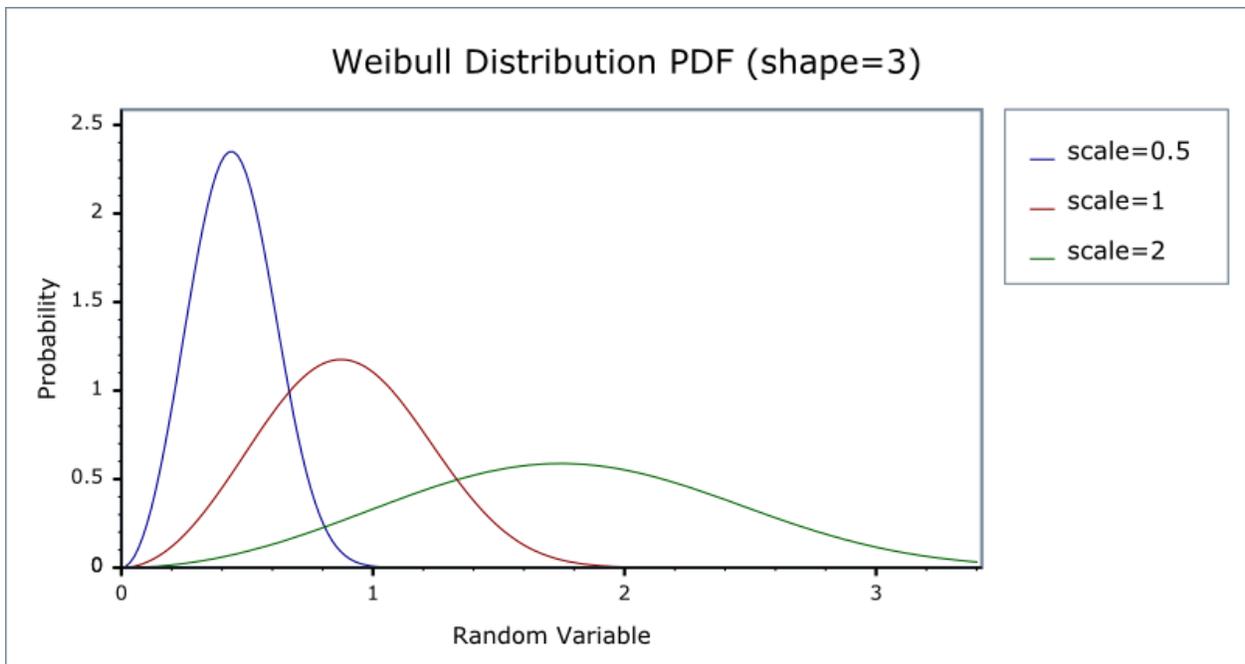


Figure 17. Weibull distribution curves with 3 scale parameters (Maddock et al., 2006).

We used the Wrapped Cauchy distribution, a probability density function over a range of 0 degrees to 360 degrees (Morales et al., 2004), to describe the distribution of turning angles for the simulated gazelles. The peak position parameter defines the angle with the greatest probability and the scale parameter defines the spread, thereby determining the probability of each angle. As the scale parameter increases, the probability spread over the range of angles becomes more evenly distributed. Similar to the Weibull distribution, we drew a randomly sampled value from the Wrapped Cauchy distribution to determine the turning angle for the gazelle during that step of the model.

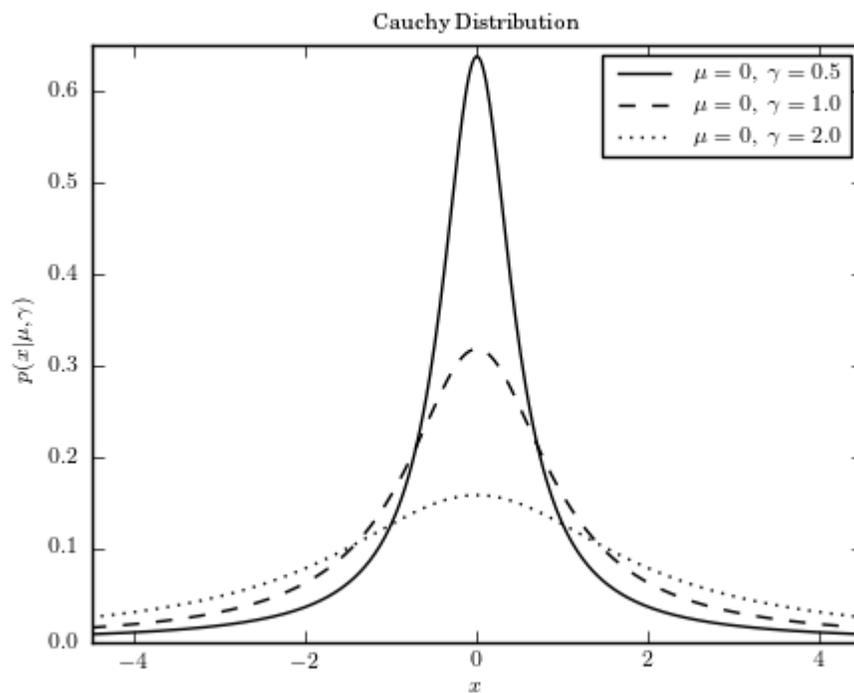


Figure 18. Wrapped Cauchy distributions with different scale parameters. All three distributions

have a peak position of 0 degrees, indicating that the next movement is most likely to be straight ahead (Cauchy Distribution).

ANN Movement Mechanism Selection

The fifth output of the neural network determines which of the four movement decision mechanisms - vegetation-oriented, obstacle-oriented, memory-based, and non-oriented - the individual will use for the current time step. The choice of a particular mechanism applies an offset to the movement angle, produced by sampling the wrapped Cauchy distribution, and thus changes the movement angle to be relative to different landscape features.

Movement decisions are made according to the following criteria. If the output of the neural network is less than .25, then the movement is non-oriented. If the output is between .25 and .5, then the movement is memory-based. If the output is between .5 and .75, then the movement is vegetation-oriented. If the output is greater than .75, then the movement is obstacle-oriented.

3.1.3 Genetic Algorithm

The genetic algorithm portion of the model is responsible for determining optimal neural net weights - contained within the genetic code - for making the model gazelles behave like real gazelles. A genetic algorithm operates by mimicking the evolutionary process of genetic codes found in nature. In nature, natural selection occurs when there is variation in a certain trait among a population, given that this specific trait affects fitness and is at least partially heritable. The genetic algorithm in our model simulates natural selection; an individual that survives longer must have a more successful genetic code, and this code will be more prominent in the next

generation of gazelles. The genetic code allows the model to account for variability in behavior of the individuals of the model. A genetic algorithm consists of four different sequential steps: fitness evaluation, selection, crossover, and mutation (Castro, 2006, p.37). The genetic algorithm is applied after every model year, which corresponds to a full year cycle of vegetation scenarios. The “genetic code” we have in our model corresponds to the weights on the interconnections between layers of the ANN. This combination of a genetic algorithm and an ANN makes our model more comprehensive and adaptable than most existing ecological models, such as Brownian Bridge Movement Models and particle models. Thus, our model can handle dynamic landscapes and highly mobile animals, which are prevalent in our study system.

Fitness Evaluation

Along with a genetic code, each of the gazelles in the model has a fitness value. This fitness value is based on the model gazelle’s goodness of fit to spatio-temporal patterns of the real gazelle data. Our model evaluates fitness based on three separate spatio-temporal patterns of gazelles:

- 1) Distribution of NDVI values at spaces that the gazelle occupied: This metric describes the variety of vegetation that a gazelle visited. If a model gazelle’s distribution differs significantly from that of real gazelles, it likely got insufficient nourishment.
- 2) Distribution of distance from anthropogenic features: This metric represents how close gazelles were willing to get to real anthropogenic features in the landscape. These features include roads, railways, human population centers, and mining sites.
- 3) Distribution of displacement squared at critical time lags: This metric, which is derived

from the variogram approach of Fleming et al. (2013), provides a quantitative way to assess whether our model gazelles match the qualitative shape of real gazelle movements by comparing displacements at different time scales. We chose to train based on two critical time scales: one day during which real gazelles demonstrated ballistic foraging movement patterns and two week when they began to exhibit diffusive searching movement patterns. The distribution of displacement squared at each time scale shows how gazelles will move under each of these patterns.

A model gazelle's fitness is evaluated by comparing the aforementioned distributions of the model gazelle to that of our real gazelle data set using the reciprocal of a Kolmogorov-Smirnov test. A Kolmogorov-Smirnov test measures the geometric distance between two cumulative distributions, and can be seen below.

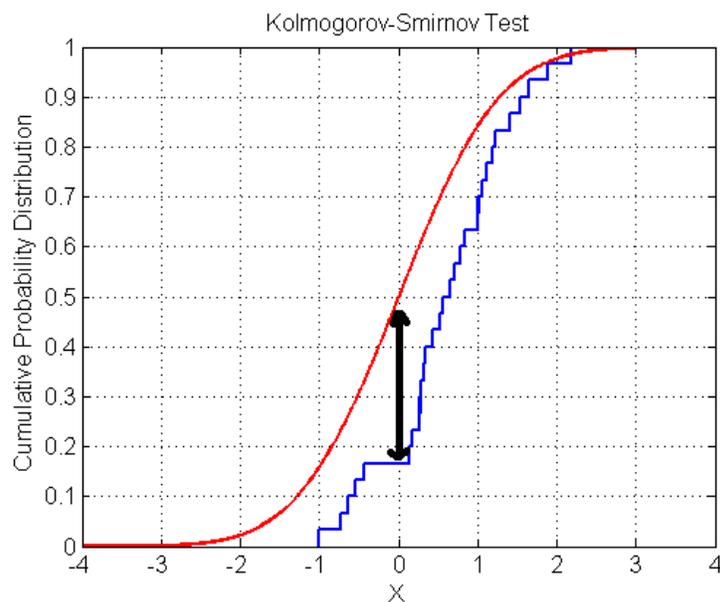


Figure 19. Example of a Kolmogorov Smirnov test.

As the distance decreases between the distributions of our model gazelles and our real gazelles, the fitness of the model gazelle increases. In order to make use of all three distributions, we created a multiparameter fitness based on a weighted sum of all of the fitnesses. We scaled each single parameter fitness with a weight that accounted for its importance in training (Castro, 2006, p.166). New constraints were scaled to have a greater importance than old constraints.

Selection

Our genetic algorithm uses a selection method based on elitism and tournament competition (Castro, 2006, p.66). The elitism part of the selection algorithm chooses the M best model gazelles to be copied over into the next generation pool. The rest of the next generation pool is selected using tournament selection where N random model gazelles are drawn from the previous generation without replacement and the one with the best fitness is selected to be in the next generation. This tournament selection process is repeated until next generation pool has been filled (Castro, 2006, p.63). M and N are user specified parameters.

Crossover

On unique aspect of genetic algorithms among optimization algorithms is the possibility of a crossover step. Crossover allows individuals to combine different optimization solutions, the genetic codes in our model, into a new optimization solution. This new optimization solution has dual benefits; it creates a faster fitness optimization rate and provides better exploration of the fitness landscape. Our genetic algorithm uses Uniform Pair crossover. Uniform Pair Crossover draws model pairs of gazelles from the new generation and applies the Uniform Crossover

Operation with probability P_1 . The Uniform Crossover Operation will switch $C \cdot G$ genes between the pair gazelles chosen, where C is the probability of crossover and G is the number of genes (Castro, 2006, p.50). P_1 and C are parameters that are selected at runtime of the model training.

Mutation

Our genetic algorithm uses two different mutation policies over the course of training. During early training, uniform range mutations are used. Early training is defined as time during which the fitness curve follows a “concave up” pattern. During this time, genes are mutated with a probability of P_2 by replacing the gene with a value selected from a uniform distribution between $-R$ and R . After the inflection point, where the fitness curve follows a “concave down” pattern, our genetic algorithm begins to use creeping mutations. Creeping mutations act by mutating with genes with probability P_2 and adding a value drawn from a Cauchy distribution with a location parameter of 0 and a scale parameter of S to the gene value (Castro, 2006, p.44). We chose to use two mutation strategies to account for exploration versus exploitation trade-offs in genetic algorithms. Initially, we focus on exploration of the fitness landscape, which can be achieved faster with uniform range mutations. Uniform range mutations are exceptional for finding crests in a fitness landscape, but they are not very suitable for finding the maxima in those crests (Castro, 2006, p.44). Finding the maxima of fitness crests is known as exploitation, and we found creeping mutations to be optimal for this task. The parameters P_2 , R , and S , are chosen by the user at runtime.

3.1.4 Data

We used three main sets of data for creating our theoretical model and applying it to the Mongolian Steppe: Global Positioning System (GPS) data from collared Mongolian gazelles, Normalized Difference Vegetation Index (NDVI) data, and human population and land use data. We obtained GPS collar data from researchers at the University of Maryland who are studying Mongolian gazelle movements, including our mentor, Dr. Bill Fagan. The movement data is packaged in comma separated values (csv) files and includes identification information, times, and longitude and latitude coordinates for each data collection point. The NDVI data, which reveals the amount and type of vegetation, comes from the Moderate Resolution Imaging Spectroradiometer (MODIS) instruments on the Aqua and Terra spacecrafts. We obtained NDVI data from NASA's Earth Observing System (EOS) Data and Information System (EOSDIS) website. These data are packaged in HDF-EOS file format, so we designed a file-conversion pipeline to convert these data into a tab-delimited text format to reduce the amount of memory used by our model. This step allowed us to use the NDVI data directly in our model program rather than having to interface with other software. We acquired human population density data from the LandScan database available from the Oak Ridge National Laboratories, and we obtained human land use data from an American Geosciences Institute's Global GIS Database: North Eurasia CD-ROM. We used these data to represent human impact on the landscape. These data also contain the locations of all towns and cities in Mongolia, as well as the locations of the transportation network, such as the Trans-Mongolian Railway and civilian roads.

NDVI

Vegetation in our model is visualized by displaying the NDVI data set in ArcMap, a GIS

program. We can compare different maps of NDVI data sets to see how the distribution of vegetation, and thus viable habitat for the Mongolian gazelles, changes over time (Mueller et al., 2007). The NDVI data sets which were available to our team for use in this project were 16-day NDVI values with cells of 8 km², compiled from MODIS remote sensing data.

3.1.5 Incorporating Anthropogenic Pressures

Based on the literature review, we chose to include transportation infrastructure and areas of human habitation in our model as the main anthropogenic pressures. Transportation infrastructure, especially railroads, has been shown to prevent gazelles from reaching resources. For example, in a study by Ito et al. from 2005, Mongolian gazelles wearing radio collars were shown to move roughly parallel to the Trans-Mongolian Railway, which is a fenced corridor bisecting the Eastern Mongolian Steppe. The gazelles were effectively prohibited from accessing any resources that might be located on the other side (Ito et al., 2005).

We chose to consider regions of human habitation because prior studies have shown that Mongolian gazelles generally avoid human settlements (Olson et al., 2011). Also, research has revealed that agricultural animals, such as goats and sheep, likely compete with the Mongolian gazelle for food, and thus influence gazelle movements (Olson et al., 2011).

Transportation infrastructure and human habitation have been established as significant barriers to gazelle movement. As such, these are crucial factors to consider when predicting gazelle movements. Our model incorporates these factors while training and allows users to test hypothetical fragmentation situations, offering an important tool for conservation efforts.

3.2 Implementation

We constructed our ING model such that individual model gazelles make movement decisions based on their ANNs. The ANN takes in environmental input variables and gives certain outputs based on calculations in the hidden layer which depend on weights. In our model, each individual model gazelle's ANN weights are contained in its genetic code. This code passed on to subsequent generations of model gazelles based on their fitness, which is determined based on how closely several distributions characterizing their movement patterns match the distributions of real gazelles observed in GPS collar data. The genetic algorithm mutates and crosses over the genetic codes that are passed down, exploring various behaviors, until a genetic code which can accurately reproduce real gazelle movement patterns is found.

After constructing our model, we used it to train model gazelles to behave like real gazelles, validated these trained model gazelles, and put them into hypothetical situations to see how fragmentation may affect Mongolian gazelles.

3.2.1 Validation

To determine if our model produced accurate and useful projections of gazelle movements, we chose three statistical measures to assess its validity: gazelle occurrence at different NDVI values, distance from anthropogenic features, and displacement squared at critical time lags. These are the same metrics we used to train the gazelles, however we here compared them to a validation data set from real gazelles GPS collar data, which we separated from the training data set from the real gazelles. For each measure, we used a corresponding statistical test to assess the

distribution of the measure for our model gazelles and for the real gazelles. We sought to minimize the difference between these two distributions. Ideally, the trained model gazelles' distributions will lie somewhere between the training and validation sets; if the trained distribution diverges from the validation set, that would indicate over-training.

Gazelle Occurrence at Different NDVI Values

We observed real gazelle visitation frequency at vegetation patches of different NDVI values in order to use vegetation quality as a predictor of gazelle movement. We recorded the NDVI values of spaces occupied by real and model gazelles at each time step and then created several histograms; one using real gazelle data from the training set, one using real gazelle data from the validation set, and several using model gazelle data at different points in training. The histograms graphed gazelle visitation frequency at each NDVI value. We generated cumulative distribution functions from these histograms, and compared them using a Kolmogorov-Smirnov test.

Distance from Anthropogenic Features

We recorded gazelle movement relative to anthropogenic features (such as human population centers) in the landscape from our USGS dataset. Our model's output describes how model gazelles change their movement patterns in response to these obstacles. At each time step, an individual's position is taken with reference to the nearest human population center, and the magnitude of the distance between those two points is recorded. We then created histograms which graphed the distance for each time step, created cumulative distribution functions, and compared using the Kolmogorov-Smirnov test, as above.

Displacement Squared at Critical Time Lags

We used displacement squared at critical time lags to validate the behavior of our model gazelles. Data collected from real gazelles shows three very distinct movement behaviors. Initially, in periods of low time lag, gazelles exhibit straight-line movement with short bursts of speed as they forage for food on a single grass patch. This movement is known as ballistic motion. When time lag is increased, there is an inflection point where the displacement begins to increase at a much higher rate. This reflects Brownian motion, or random non-oriented movement, as gazelles leave the current grass patch and search for new vegetation. Eventually, this rate of growth in displacement slows down to the point of stagnation, which reflects a maximum home range for these gazelles.

All three of these behaviors create a sigmoid shape when plotting displacement squared as a function of time lag for real gazelles; we hoped to reproduce the same sigmoid shape in our model gazelles' behaviors.

To validate this behavior in the model gazelles we used two distributions: the cumulative distributions of displacement over one day, where real gazelles exhibit ballistic movement, and over two weeks, where this transitions to long range movement. If our model gazelles can match these two distributions, then they are exhibiting both of these movement patterns (Mueller et al., 2011). As above, we compared the model gazelle's distributions with the real gazelle training and validation sets using Kolmogorov-Smirnov tests.

4. Results

4.1 NDVI Training

We first trained the model gazelles using NDVI based fitness only. Below, Figure 20 shows the a violin plot of the distribution of NDVI values visited by the untrained model gazelle population on a static landscape, plot A, in comparison with the training and validation NDVI distributions exhibited by GPS collar data from real gazelles. Notably, the untrained model gazelles display a similar bimodal distribution to the real gazelles; this suggests that the bimodal distribution is inherent to the landscape rather than being particularly indicative of gazelle vegetation preferences. We then trained model gazelles on a static landscape for approximately 700 generations. Plot B provides the distribution of NDVI values visited by the trained model gazelle population. As seen in the figure below, the NDVI distribution fits the training and validation sets well for most of its range; however, the first peak of the bimodal distribution is all but lost.

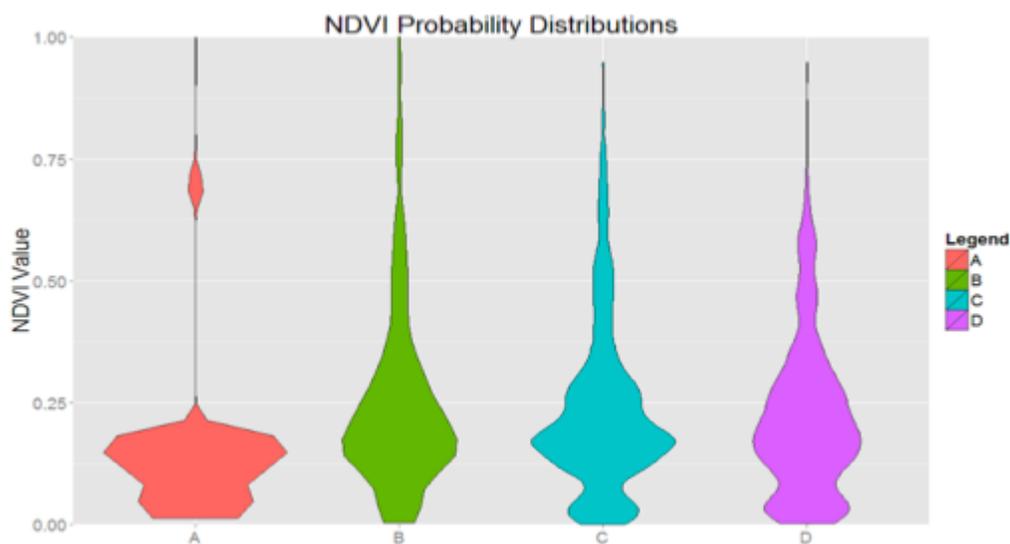


Figure 20. NDVI patch residency probability distribution for untrained model gazelles (A), trained model gazelles (B), the training set (C), and the validation data set (D).

In Figure 21 below, all of the cumulative distribution functions (CDFs) of the NDVI distribution data from the previous graphs are consolidated in a single graph for the sake of clarity. The trained model gazelles follow the CDFs of the real gazelles much more closely compared to the untrained gazelles. These results provide initial validation that an ING model can be used in a pattern-based modeling approach to generate artificial agents whose characteristic behavior matches that of real animals.

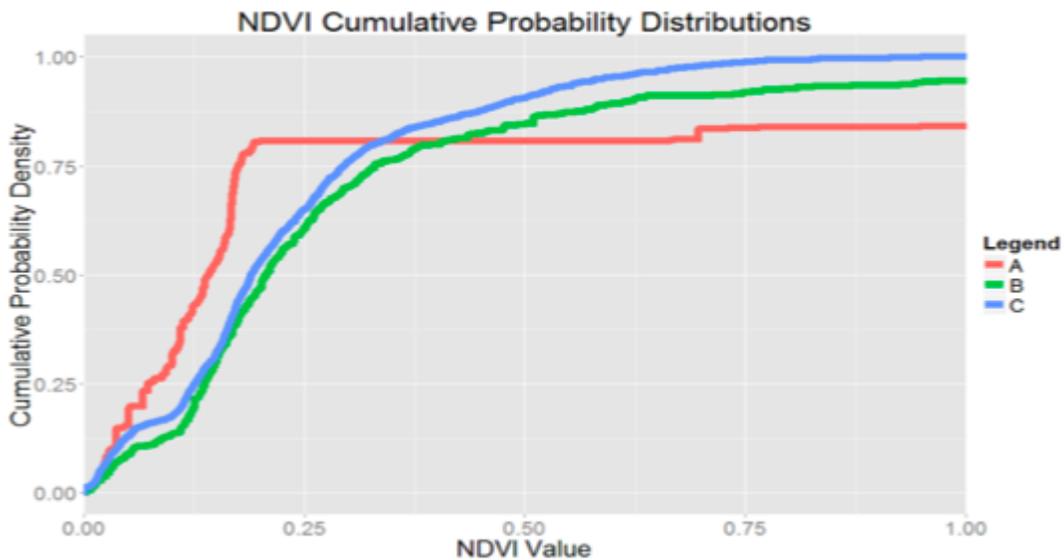


Figure 21. NDVI patch residency cumulative probability function for untrained model gazelles (A), trained model gazelles (B), and training data (C).

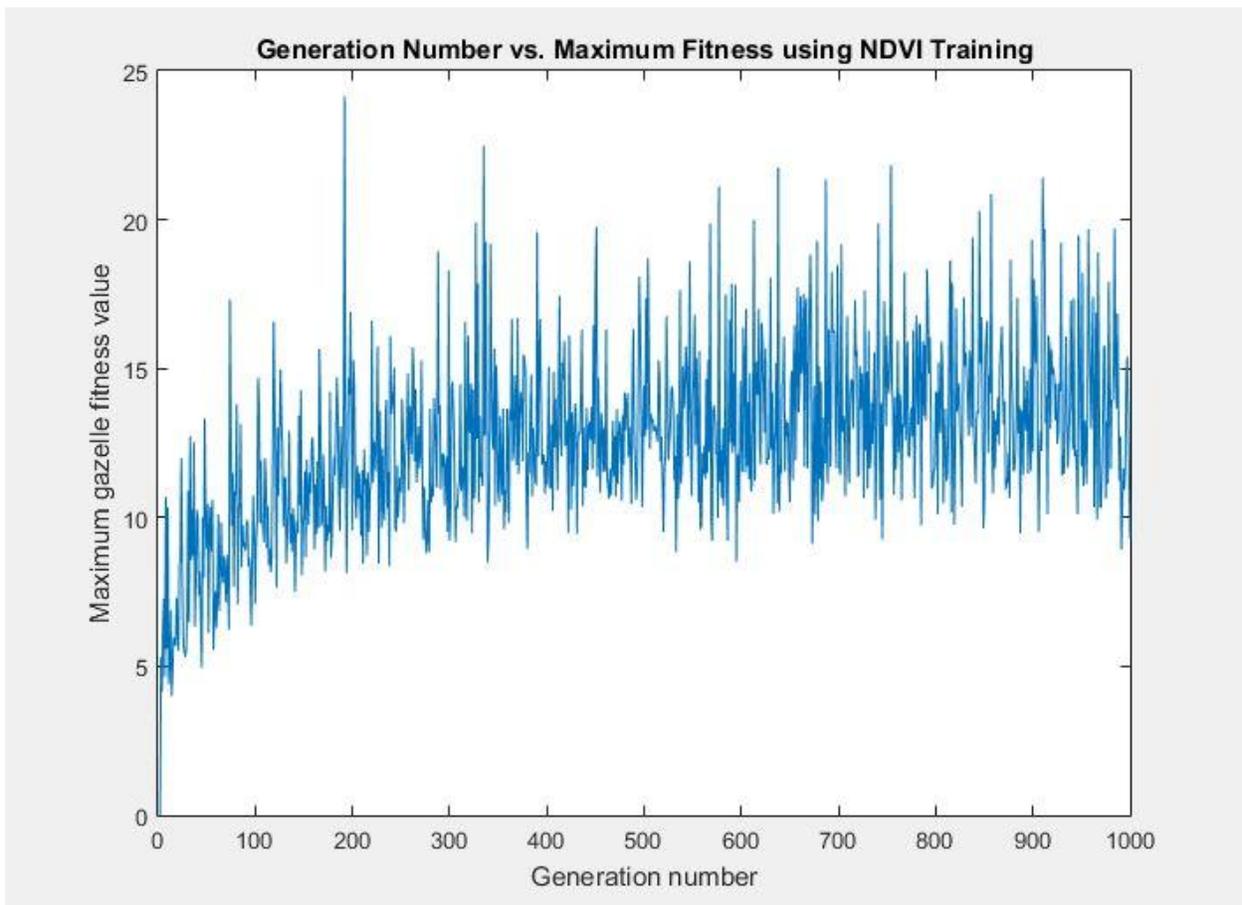


Figure 22. Fitness curve for NDVI training

When the genetic algorithm trained the model gazelles to match the real gazelles' NDVI distribution, the model gazelles' fitness increased over succeeding generations as shown in Figure 22 above. The maximum fitness for each generation is obtained by logging the calculated fitness of every gazelle on the landscape, and then selecting the maximum of these values from each given generation. The fitness increases sharply at first, and then the growth tapers. There is a relatively large variation between a given generation's maximum attained fitness and the fitness of generations immediately before or after.

4.2 Displacement Squared versus Time Lag Training

After training with NDVI based fitness, we trained the model gazelles based on their displacement distribution at a time lag of two weeks. We chose the time lag of two weeks because we found it to be the inflection point between ballistic motions and diffusive searching movement in our real gazelle data. We found that NDVI trained model gazelles had a much wider displacement squared distribution compared to real gazelles. This likely occurred because, our model gazelles were bound only by a top speed, not by energy constraints; they were able to constantly sprint at top speed between preferable patches of grass. To correct for this discrepancy, we trained the model gazelles again, this time using displacement squared versus time lag based fitness in addition to NDVI based fitness. This additional fitness constraint resulted in a distribution of model gazelle displacement that more closely matched the distribution of real gazelle displacement over the two week time lag.

Figure 23 compares the probability density functions of four different sets of gazelles: model gazelles trained on NDVI only, model gazelles trained on NDVI and displacement squared versus time lag training, the training set of real gazelles, and the validation set of real gazelles. As with the previous figure, all distributions have very similar shape, so adding semivariance-based training does not have a significant impact on a model gazelles NDVI-based fitness, although as is clear from Figure 23, this training improves semivariance-based fitness, so combining the two results shows a net increase in model gazelle fitness.

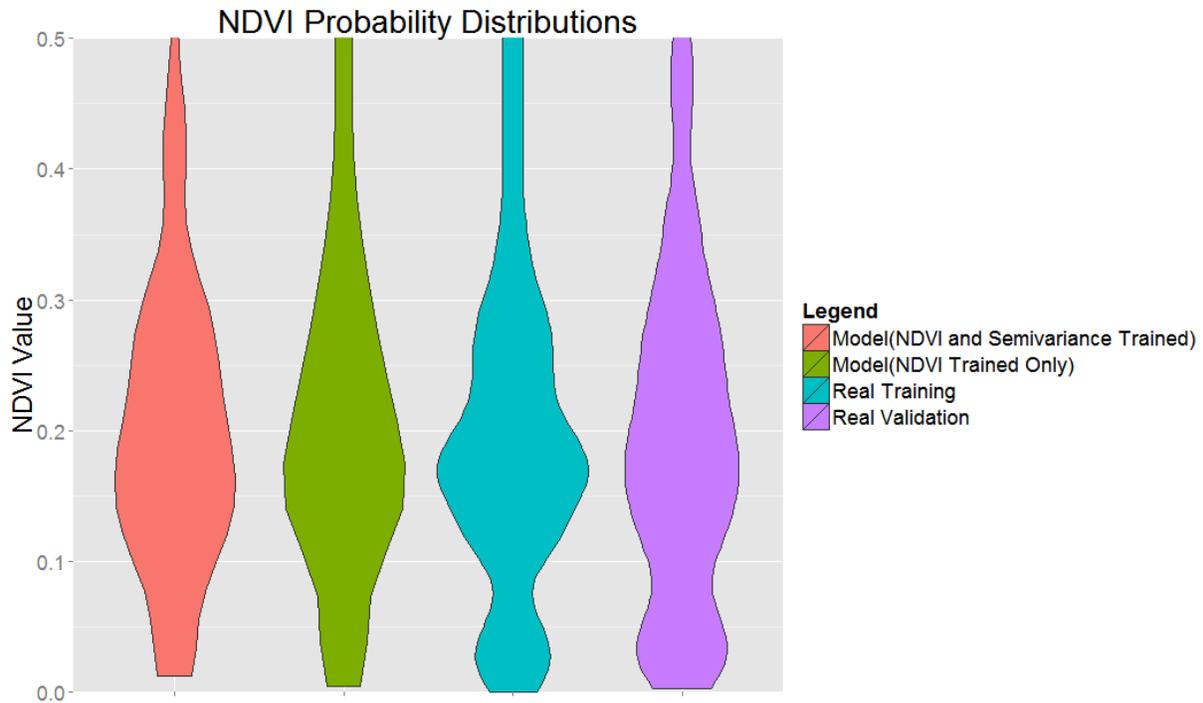


Figure 23. NDVI patch residency Probability Distribution Functions.

In Figure 24 below, we show approximations of the CDFs of the square of the displacement over a two week time lag. We show this for three different sets of gazelles: the real gazelles in the training set, the model gazelles that were trained only with NDVI based fitness, and the model gazelles that were trained with both NDVI based fitness and displacement squared versus time lag based fitness. We see that the final set is clearly the best “fit”, since it closely matches the data gathered from real gazelle training set.

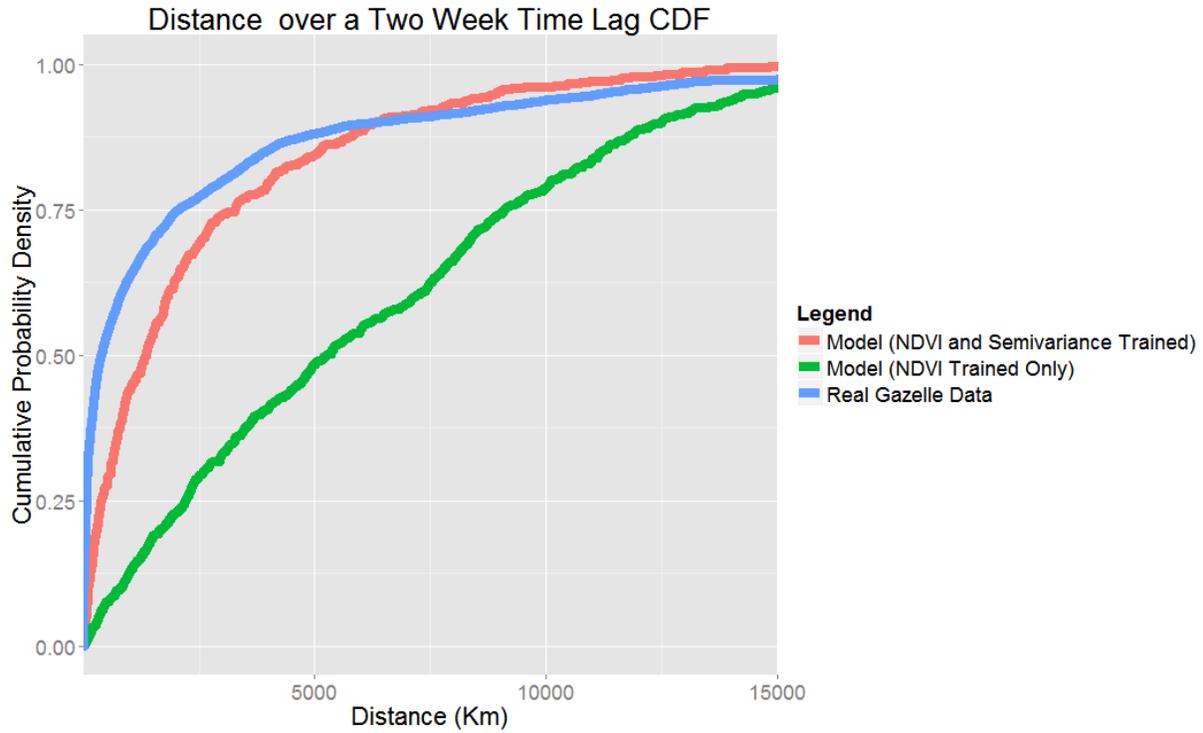


Figure 24. Empirical Distribution Functions of real and model trained gazelles.

Figure 25 below shows the cumulative distribution function of the NDVI preferences of various gazelles. All three distributions have very similar shapes, so we can conclude that while adding semivariance-based training does not cause the model gazelles to more closely conform with NDVI training data, it also does not cause significant deviation.

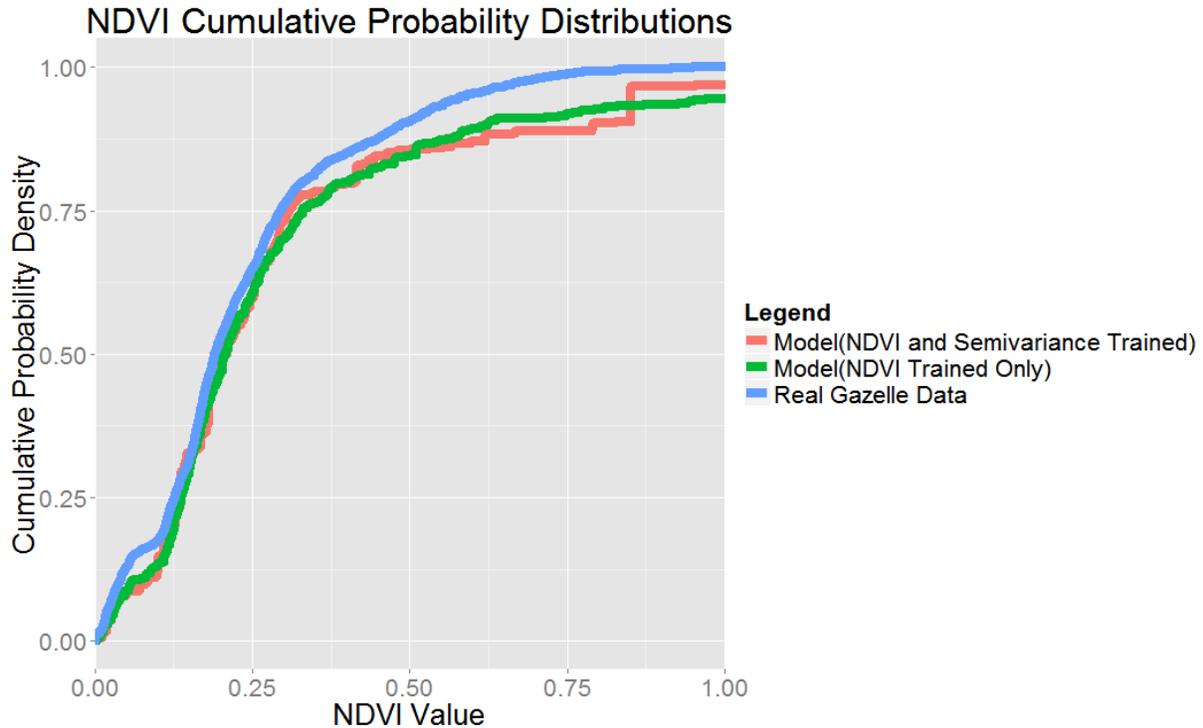


Figure 24. Empirical Distribution Functions of real and trained gazelles.

Figure 26 below was generated in the same way as Figure 22, with displacement squared over a given time lag as the input statistic for fitness training. This graph has a longer-term increase compared to the NDVI-based training, is slightly more oscillatory, and reaches roughly the same final maximum fitness. There is also significantly less variation between maximum fitness in a given generation and that of nearby generations.

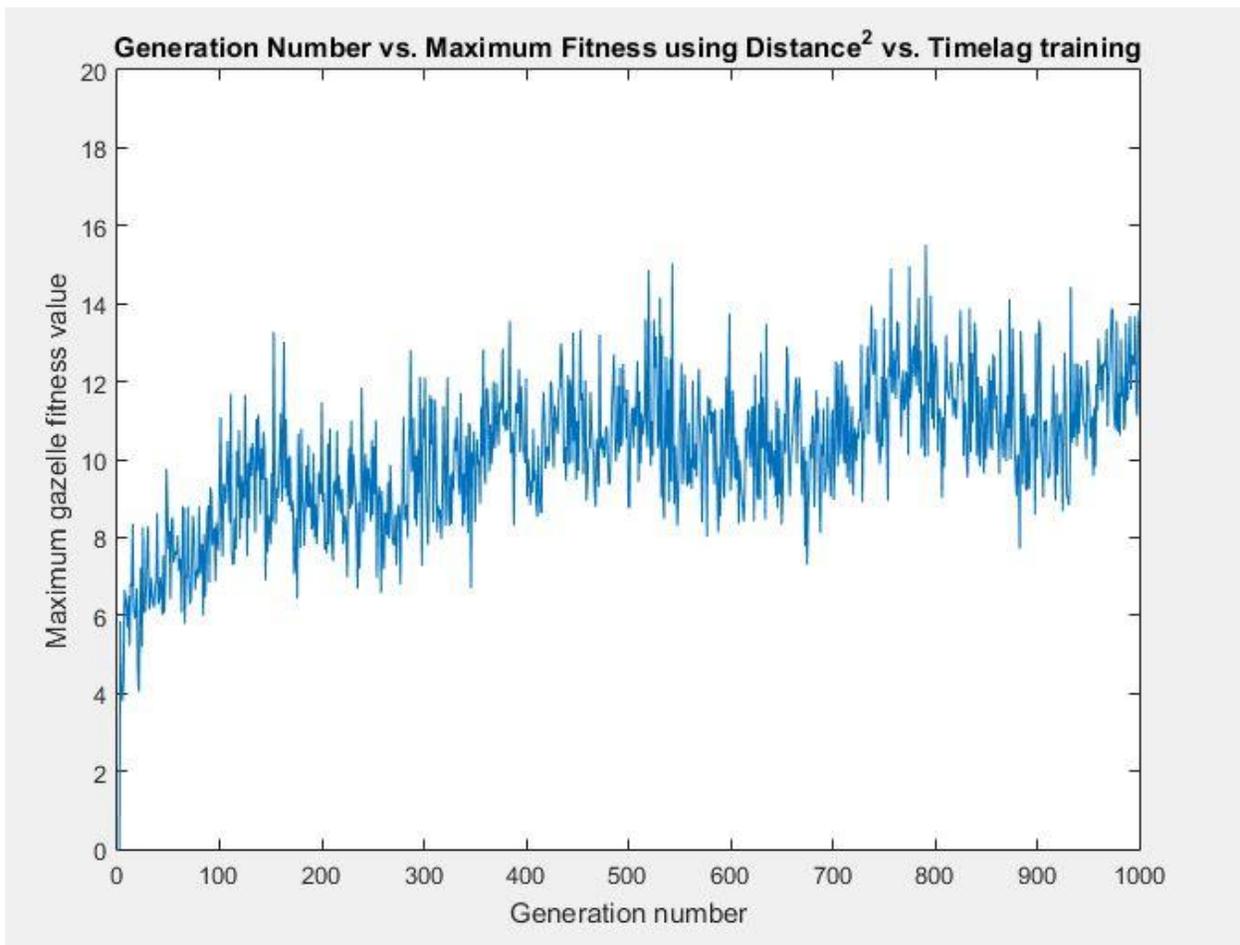


Figure 26. Fitness Curve for Distance² versus time lag Training

4.3 Anthropogenic Feature Training

As part of our initial training steps, we performed training on a gazelle's minimum distance anthropogenic features, or landscape obstacles, such as population centers and railroad tracks in the Eastern Mongolian Steppe. This phase of training provides a baseline fitness value for subsequent training runs that combine Obstacle training fitness measures with NDVI and Displacement Squared versus Time Lag fitness measures. We chose to use population centers such as cities and towns, along with railroad tracks, since these are indicators of human presence

and relatively impermeable fragmentation respectively.

Figure 27 below shows the probability density functions for four different sets of gazelles that were trained only on distance to anthropogenic features. Clearly, the untrained model gazelles have a very different shape than the trained model gazelles and the real gazelles. On the other hand, the trained model gazelles have a very similar shape to both sets of real gazelles; all three of those sets peak and then taper off at around the same distance on the y-axis. From this, we can conclude that training only on distance from anthropogenic features is effective at causing the model gazelle movement to conform to real gazelle movement.

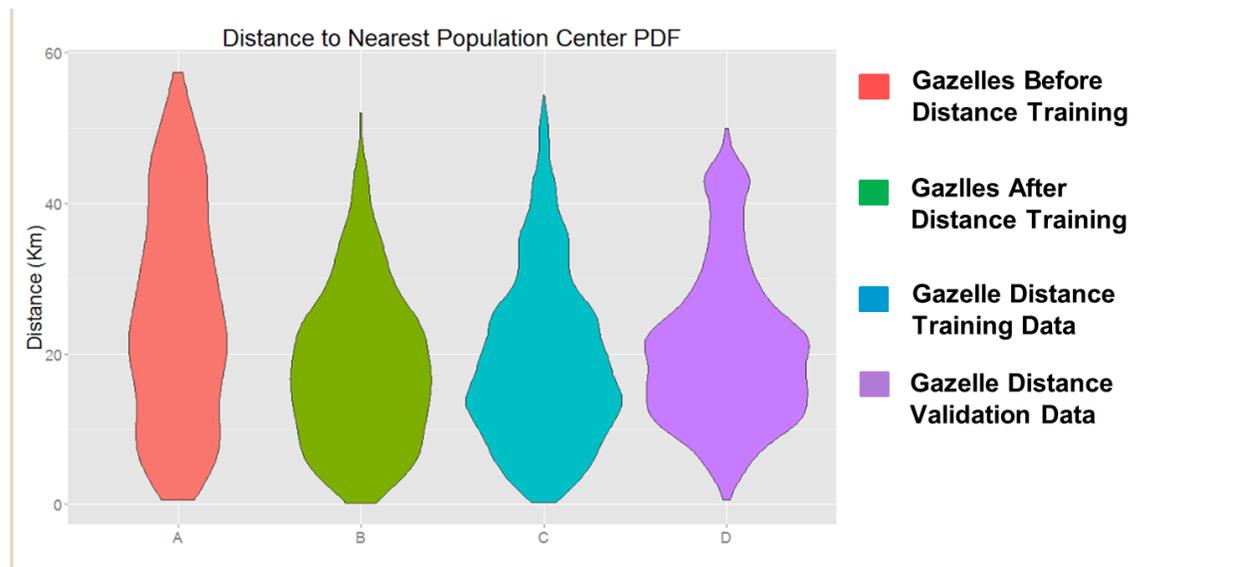


Figure 27. Obstacle Avoidance Probability Distribution Functions

Figure 28 below show the CDFs of three different sets of gazelles, all of which were trained only on distance from anthropogenic features: untrained model gazelles, trained model gazelles,

and the training set of real gazelles. It is easy to see that the untrained model gazelles diverge from the other two sets, while trained model gazelle curve follows the real gazelle curve very closely. This implies, like the figure above, that training only based off of distance from anthropogenic features can effectively make model gazelles exhibit similar movements to real gazelles.

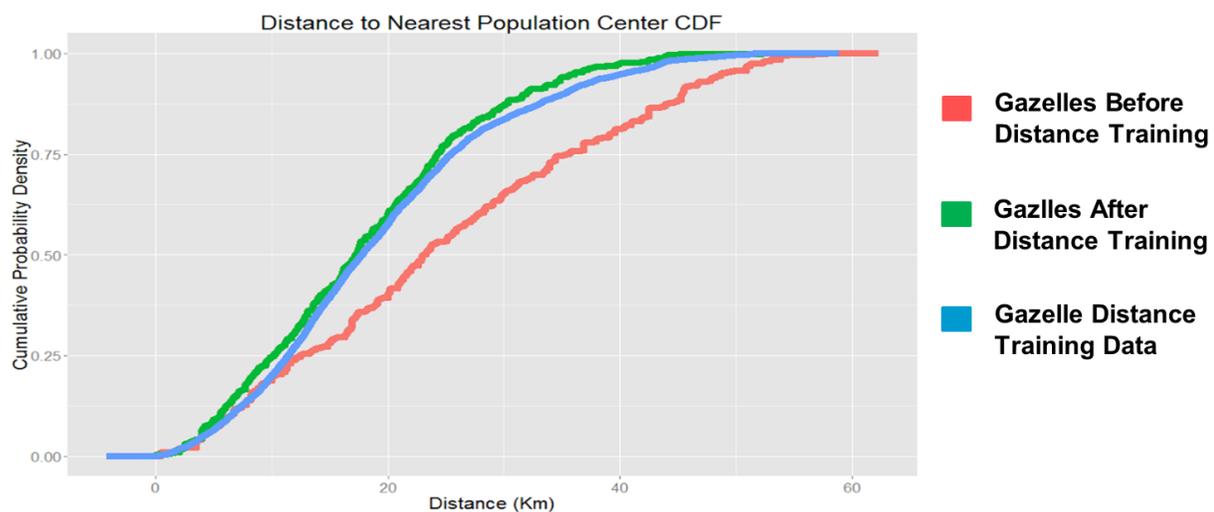


Figure 28. Empirical Distribution Functions of real and trained gazelles.

4.5 Combined NDVI and Anthropogenic Feature Training

Our next step in training was to combine the NDVI fitness metric with the anthropogenic feature fitness metric. Model gazelles trained with these two metrics have the same vegetation preferences and obstacle avoidance behavior as real gazelle individuals. Figure 29 compares the NDVI occupancy distributions of model gazelles trained only to NDVI, those trained to both

NDVI and obstacle avoidance, and real gazelles.

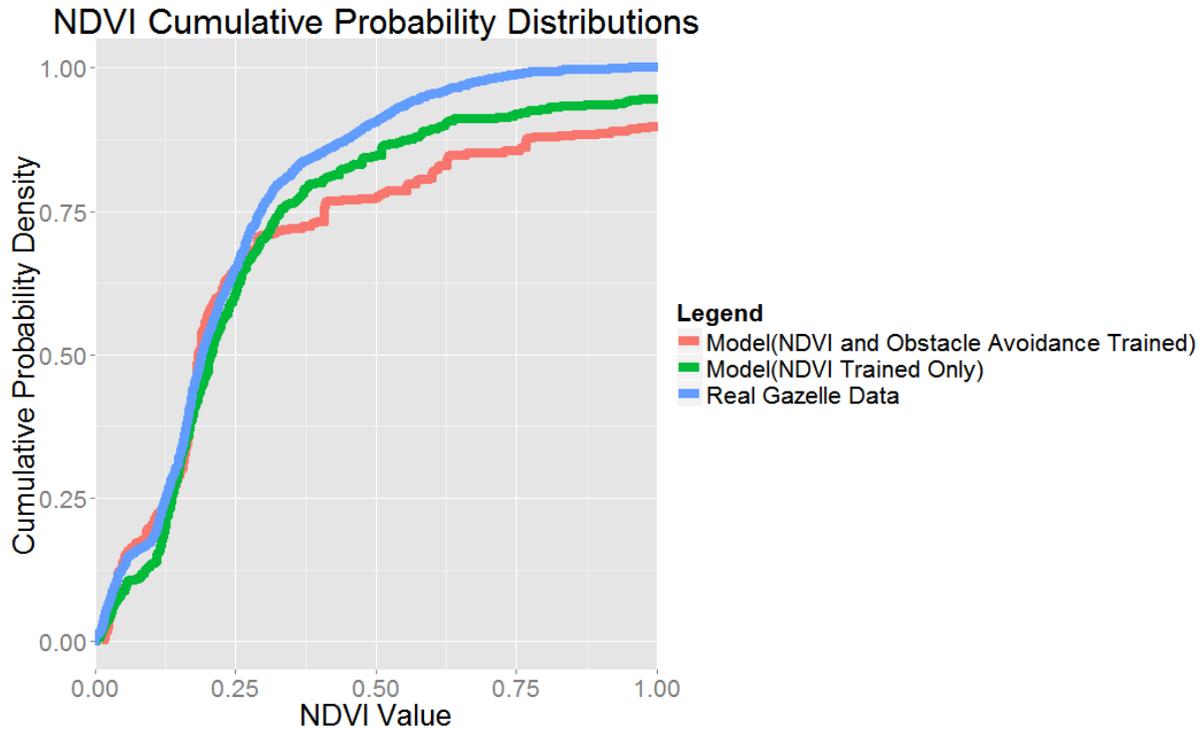


Figure 29. Empirical Distribution Functions of real and trained gazelles.

The obstacle avoidance trained model gazelles do not match the NDVI distribution of the real gazelles as do the model gazelles trained only to NDVI. This is to be expected; there is a trade off between the accuracy replicated NDVI behavior and obstacle avoidance behavior. Figure 30 shows the same distributions in violin plots; it seems that the first peak, observable in the real gazelles, of the bimodal distribution is more suppressed in the obstacle trained model gazelles.

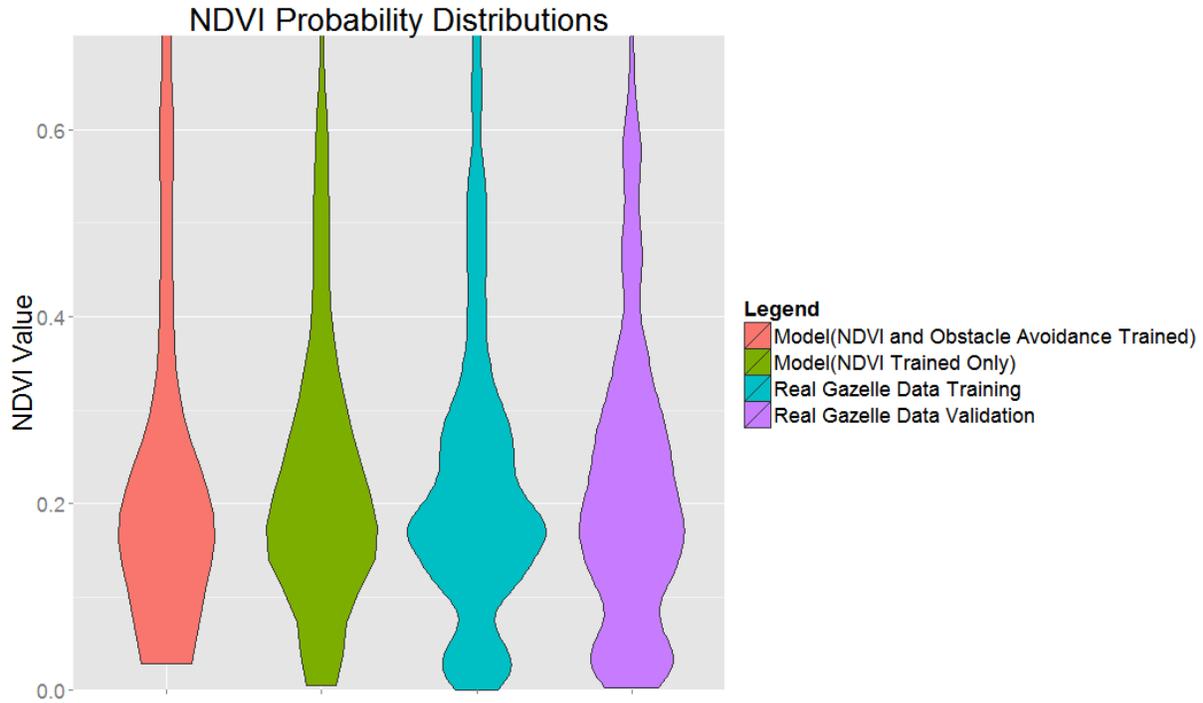


Figure 30. NDVI patch residency Probability Distribution Functions

Although adding obstacle avoidance sacrifices some of the features of the real gazelles' NDVI behavior, as seen in Figure 31, it allows model gazelles to closely mimic the obstacle avoidance behavior of real gazelles. The plots of distance to nearest obstacle of the trained model gazelles and real gazelles overlap, while the untrained model gazelle's distribution is significantly different.

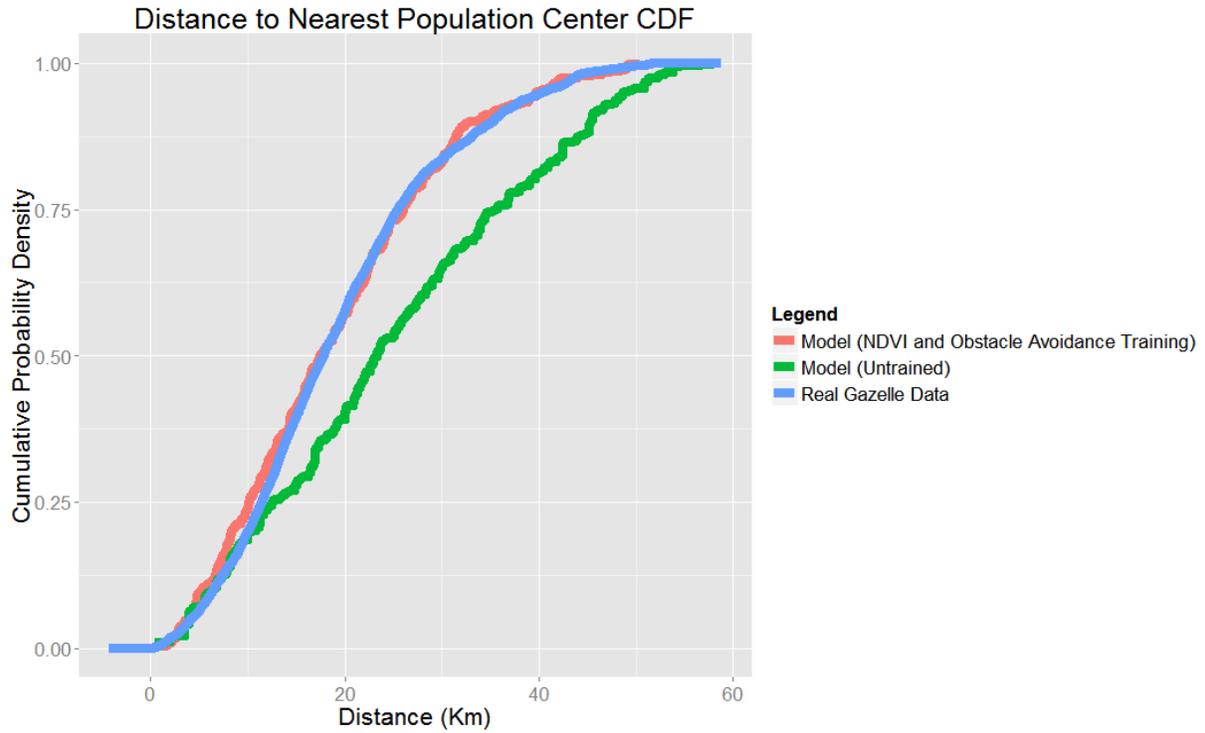


Figure 31. Empirical Distribution Functions of real and trained gazelles.

The success of this training can also be seen in the violin plots of Figure 32, which also shows significantly improved matching between trained model gazelle and real gazelle distributions.

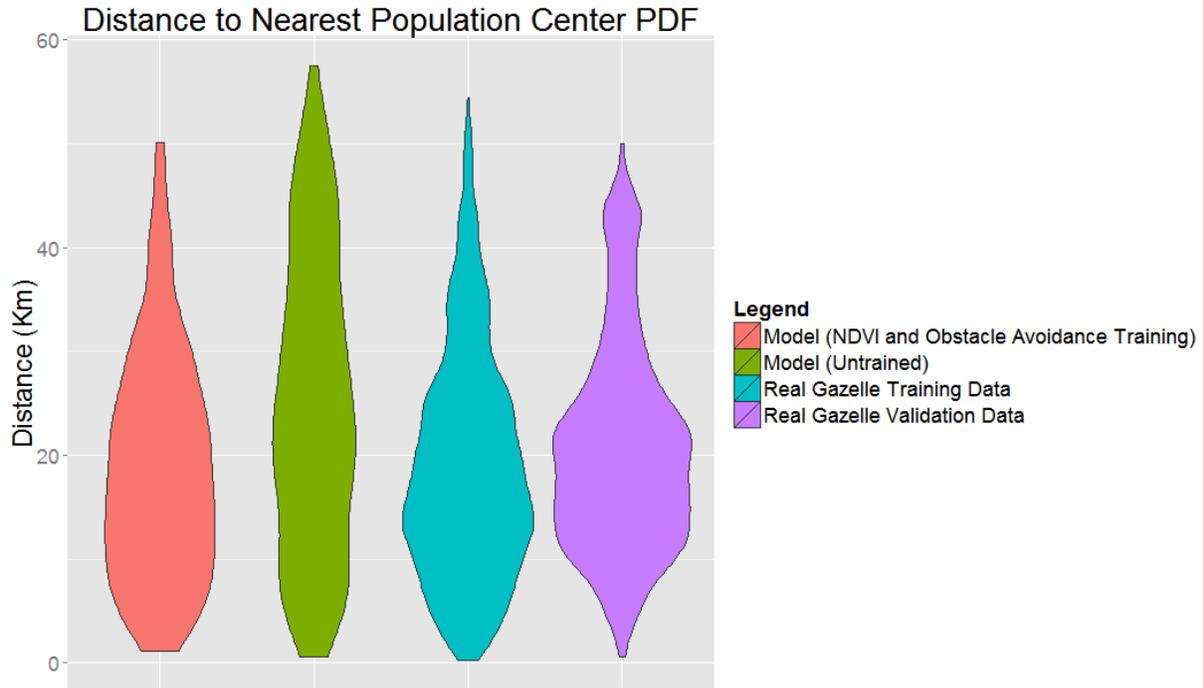


Figure 32. Obstacle avoidance Probability Distribution Functions

4.6 Scenario Testing: Additional Fragmentation by New Railroads and Implementation

A powerful and unique feature of our model is to test completely new and hypothetical landscapes for their effect on Mongolian gazelle movement and possible damage on the gazelle population. Damaging effects on the gazelle population can be shown by observing the NDVI Frequency Distributions for hypothetical landscapes. If the NDVI Frequency Distribution has a large deviation from the normal range, then gazelle population could be endangered by the hypothetical scenario, as it shows that the gazelles are unable to physically get to the vegetation

they need. We tested two hypothetical scenarios in our model. The first scenario extended to trans-Siberian railroad from Ulaanbaatar to Manzhouli, a city in China which is a feasible extensions of the Mongolian transportation network. This placed a very impenetrable divide in the habitat of the Mongolian Gazelle further fragmenting it. The second hypothetical scenario has the same extensions to the trans-Siberian railroad as the first, but also includes three breaks in the extensions, each approximately 50 meters wide, allowing gazelles to cross the railroad at specific locations. In Figure 33 we see the effects of both scenarios on the gazelle population.

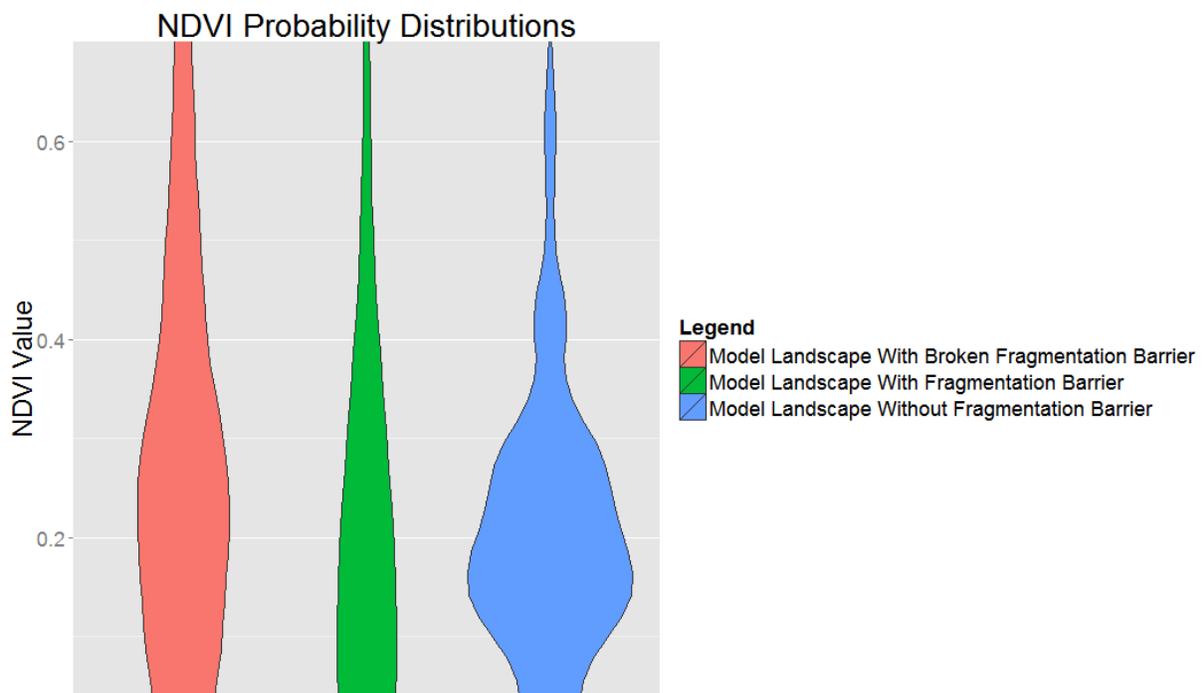


Figure 33. NDVI Frequency Rates in Hypothetical Scenario Testing

We can observe in Figure 33 that, before the hypothetical trans-Siberian railroad extension is placed in the landscape, model gazelles are able to get to the the grass patches with preferred

intermediate levels of NDVI. When the trans-Siberian railroad extension is added, the gazelles frequency of NDVI values in their preferred range drastically decreases, showing they are unable to travel to the vegetation that is most optimal for them. When breaks are introduced into the trans-Siberian railroad, we see a the NDVI value frequency distribution partially revert to its previous range. The reversion shows that these small breaks, which can represent crossing bridges or tunnels, help mitigate the effects of the fragmentation by the extensions the trans-Siberian railway. By knowing which new anthropogenic features can damage Mongolian gazelle populations, and what changes to those features can mitigate their detrimental effects, our model can be used to as tool for those who wish to make sure the Mongolian gazelle population does not become endangered due to anthropogenic fragmentation.

5. Discussion

The diverse and unpredictable climate of the Eastern Mongolian Steppe, specifically the fluctuations in precipitation, has a variety of influences on the Steppe's landscape and inhabitants. The unpredictable climate not only influences the behavior of the Mongolian gazelle and other wildlife species, but it has also historically influenced the lifestyle of the people who depend on the Steppe's resources. Approximately 50 percent of the Mongolian rural human population practices climate-dependent pastoralism as a method for providing sustenance for themselves and their families (Sternberg, Thomas, & Middleton, 2010). Not only could poorly designed large-scale human land use projects have detrimental effects towards gazelle populations, but they may also disrupt the lives of the Mongolian people whose livelihoods depend on the Steppe.

This magnifies the importance of investigating the potential impact of human infrastructure projects on the landscape and species of the Eastern Mongolian Steppe. Observational studies have provided significant insight into the degradation and loss of habitat that results from habitat fragmentation (McGarigal and Cushman, 2002); however, there is a clear need for a better understanding of the long-term pattern of fragmentation effects over time. Computer-based population models can be invaluable tools for investigating this system. These models can also target ecosystems and wildlife populations beyond the Mongolian gazelle in the Eastern Mongolian Steppe that are particularly vulnerable to the effects of habitat fragmentation. Within the scope of Pattern Oriented Modeling, which advocates ecological models satisfying larger spatio-temporal patterns, our model accurately reproduces Mongolian gazelle movement

through analysis of their vegetation preferences and spatial diffusion patterns. Our model treats landscape as an input and includes individual model gazelle agents that evaluate the landscape each time step so it can be used in a predictive fashion for new or theoretical landscapes.

Moreover, our model can be used as a framework for future ING models, especially those that are pattern oriented. We programmed the model in such a way that is generalizable to completely different landscapes and movement patterns if given robust training data. Each part of our model - the agent-based Repast framework, the genetic algorithm, the artificial neural network, and the pattern-oriented fitness evaluation - were created in such a way that they could be easily modified and/or swapped out for a different technique. For example, one could substitute a Markov-based Monte Carlo algorithm for our genetic algorithm without having to change any other part of the model. Of the few ING ecological models that have been created before our study, we found all had very rigid and inflexible use for further studies. By creating a general ING software package that fits well with the Repast framework, and using that package within our model, we have provided a powerful and flexible tool for future ecological researchers that can be used to create new movement models for different species.

5.1 Population Dispersion Index

Future analysis using our model could include the Population Dispersion Index (PDI). The PDI is a measure of the dispersion or clustering of a population (Mueller et. al., 2011). A positive value indicates dispersion, while a negative value indicates clustering. In PDI, a bivariate k-function is used to calculate the expected number of points in a pattern within a given distance of

another pattern. Relocation points of all other individuals are used to calculate the PDI score. This score is then plotted on the y-axis and spatial lag is plotted on the x-axis. Using PDI as either a distribution to train on or to validate based could allow the model to better capture the herd dynamics of the Mongolian gazelle or other species the model could be applied to. It would also be interesting to see whether the MCI naturally approached that of real gazelles through our training.

5.2 Movement Coordination Index

Additional analysis could investigate the ways that gazelles' movements influence each other, possibly resulting in herd-like behavior. To assess the extent to which individual model gazelles move similarly to one another, future work could examine the Movement Coordination Index (MCI). The MCI statistic is a measure of the variation in direction and magnitude of movement for a sample of the population. It is calculated by measuring the x and y direction vectors of individuals in a group, and dividing the variance of these vectors by their sum. The MCI will be closer to 1 when the movements of the sample individuals are more closely matched, and it will be closer to 0 when the movements are less closely matched.

MCI is a number dependent on movement patterns and it is different for each species. It is possible to analyze how MCI changes as a function of distance from a centroid of one animal to another. If the animals have the ability to gauge each other's distance and are communicating, then MCI would be expected to decrease as distance between the animals increases. For example, caribou are migratory rather than nomadic, so they are communicating and coordinating their movements over a much larger distance compared to gazelles. For caribou, we

expect a higher level of MCI which decreases more quickly as their distance increases.

Conversely, gazelles are nomadic. They travel in herds of varying sizes, and they move more independently from one another than caribou. For this reason, we expect a lower MCI for gazelles.

Since the MCI statistic would act as a function of distances, future work could conduct t-tests at different distances. Incorporating MCI would be important when utilizing the model for migratory or herding animals or if trying to learn more about herd dynamics among gazelles.

5.3 Future Research Directions

Further animal movement patterns that our model could be used to validate include calves' disinclination to return to their birth sites. Olson et al. found, after tracking many gazelles over a five-year period, that calves very rarely returned to their birth sites (2010). Our model could be used to determine whether a calf's distance from its birth site over time followed a similar pattern to the patterns measured by this study.

Our research answers important questions about gazelle movement and behavior in response to barriers across their habitat; however, it also raises many questions about gazelle population conservation and the movement of other species in response to habitat fragmentation. The model could be used by policy makers and biologists to predict the effect of development projects on gazelle populations in the Eastern Mongolian Steppe. Thus it can be used as a powerful tool for conservation.

Increasing the connectivity of the landscape is a potential solution to reducing the adverse impacts of habitat fragmentation on wildlife populations. With our model researchers can also

investigate the best method of assisting Mongolian gazelles in crossing the Trans-Mongolian Railroad, and assess whether this would impact the gazelles' survival. Different techniques that have been used to allow animals to avoid various obstacles could be added to hypothetical scenarios. Ecoducts or overpasses that cross over roadways, are commonly used in the Netherlands. These overpasses are very effective in allowing red deer, along with a variety of small mammals, to cross highways (Bohemen,, 1998). However, ecoducts are most helpful when they cross a roadway at ground level, because the animals need not ascend or descend unnaturally (Bohemen, 1998). This means that the highway or railroad must be below ground level, which may not be feasible in the Mongolian Steppe. Furthermore, our model does not include elevation since it was not relevant in the case of the gazelle; if elevation is important for a mitigation strategy of for another species the model is applied to, elevation should be added as a training and validation metric.



Figure 27. Ecoduct de Woeste Hoeve in the Netherlands. The ecoduct is at ground level, allowing the animals to cross it without climbing a man-made hill, resulting in more natural travel (Nichols, 2013).

A more appropriate solution may be to improve the fencing along the Trans-Mongolian Railway in order to make it more passable for gazelles. Slight modifications to the current wire fencing may allow gazelles to pass through without becoming entangled, and at the same time discourage crossing by humans and livestock (Olson et al., 2009). Future studies could apply our model to determine the most effective and efficient way to allow gazelles to pass through the wire fences that line the Trans-Mongolian Railway.



Figure 28. Mongolian gazelle calf caught in a barbed wire fence. Although this fence is on the Mongolia-Russia border, fences along the Trans-Mongolia Railway are similar and can also ensnare gazelles, barring their movement (Kirilyuk, 2010).

Our model can also be used to answer questions about how habitat fragmentation impacts ecosystems other than the Eastern Mongolian Steppe, questions which are becoming increasingly relevant in the field of ecology and wildlife conservation. A recent study demonstrated the impacts of habitat fragmentation across a diverse array of environments over the course of thirty five years (Haddad et al., 2015). This research demonstrates the significant role that habitat fragmentation plays in reducing biodiversity (Haddad et al., 2015). As the negative consequences of habitat fragmentation become more severe over time, there is an urgent need for more research on habitat fragmentation. With this research, scholars can begin to determine the extent to which damage and disruption to wildlife populations is the result of fragmentation versus other anthropogenic and biological factors such as climate change and disease. By having an accurate understanding of the role that habitat fragmentation plays in wildlife ecology, scientists

and policy-makers can better mitigate the negative impact of human land use on individual populations, reduce species extinction rates, and preserve the health and stability of ecosystems. Specific ecosystems are especially appropriate targets for this type of research. For example, the tropical rainforests of the Amazon have been subject to a drastic rise in deforestation and fragmentation over the past few decades (Laurance & Vasconcelos, 2009). In particular, the Trans-Amazonian Highway, powerlines, and other transportation projects, as well as cattle ranching, industrial agriculture, oil drilling and logging have all contributed to the rapid increase in forest fragmentation in the Amazon (Laurance & Vasconcelos, 2009). This fragmentation is especially harmful to tropical species because some species avoid even very narrow clearings, while others are more vulnerable to predation and hunting by humans near roads (Laurance, Goosem, & Laurance, 2009). Therefore, the tropical rainforests of the Amazon are another prime study area for future research on animal movement and habitat fragmentation.

In the Central Highlands of Victoria and the south-east forests of New South Wales, Australia, roadways through forests also severely disturb the ecosystems and public concern for wildlife is on the rise in these countries (Andrews, 1990). Consequently, these areas are convenient centers for further research on habitat fragmentation as it relates to animal movement and survival.

Climate change is also currently a prominent factor disrupting weather patterns and ecosystem dynamics in biomes across the globe, and is arguably the most significant current threat to biodiversity. Over the last 40 years, Mongolia has experienced an increase in temperature by 1.8 °C (Sternberg, Thomas, & Middleton, 2010). Because the steppe of Mongolia is such a dynamic landscape that already experiences unpredictable weather patterns, including seasons of drought, climate change could cause these patterns to increase and intensify, disrupting the balance of the

grassland ecosystem. Therefore, the Mongolian steppe would be a unique and informative area of study for investigating and modeling how changes in climate will impact animal populations and their movement strategies in fragmented habitats. Investigating whether species that inhabit these dynamic ecosystems such as the Mongolian steppe are better adapted to respond to climate change, or more vulnerable to it, would have important implications for the conservation of vulnerable, threatened, and endangered wildlife populations. One could easily replace the real world NDVI scenarios used in our study with hypothetical NDVI scenarios representing the Mongolian Steppe affected by climate change to observe potential effects on gazelles; however, there would be much uncertainty as to the validity of such scenarios.

Now more than ever, ecosystems around the world are changing. As the global population continues to grow, human-wildlife conflict will inevitably increase and is therefore a crucial area of study in order to understand how human modification of the natural world impacts wildlife populations. Human development projects have caused a shift from the stable, diverse, and harmonious structure of many ecosystems to a structure that is often unbalanced and unpredictable. Our research concludes that this disruption is evident through the habitat fragmentation impacts on Mongolian gazelle populations of the Eastern steppe. However, to gain a true understanding of the impact of habitat fragmentation on biodiversity and wildlife behavioral responses, it is essential to continue to investigate the long term effects of habitat fragmentation on all levels of an ecosystem.

Appendix A: Glossary

Anthropogenic: Originating in human activity

Artificial Neural Network (ANN): A mathematical model inspired by biological neural networks. A neural network consists of an interconnected group of artificial neurons, or nodes, which are simple functions that convert input into output. The neural network processes information as it passes from the input layer of nodes to the internal hidden layers, where the data is transformed by the weights of the interconnections between the layers. The neural network then sends the result to an output node. Put simply, an ANN is an input/output machine where the function that is used to manipulate data is changed based on the path that the information took through the internal nodes. A neural network has a learning phase in which it finds the path through the nodes that provides the optimal result. ANNs are capable of modeling complex relationships, and they are used to find patterns in data.

Code Libraries: Collections of already written code that provide useful functions to help perform a given task.

Collar Data: This is data that is retrieved from tracking collars that have been attached to gazelles, it includes latitude and longitude data along with a timestamp.

Comma Separated Values File (CSV): A file that stores tabular data in a plain text format with each piece of data typically delimited by a comma or tab.

Genetic Algorithm: A heuristic algorithm that mimics the process of natural evolution. This type of evolutionary algorithm generates solutions to optimization problems using techniques inspired by natural processes such as inheritance, mutation, and crossover of genetic information.

Genetic Code (of an individual in the model): These help the model differentiate between various individuals in the model based on various physical characteristics (e.g., weight, gender) and behaviors (e.g., tendency to diverge from the herd). This is a collection of characteristics which affect how each individual reacts to environmental stimuli.

Graphical User Interface (GUI): An interface that allows the human user to operate a computer using a point-and-click mouse to manipulate menus, icons, windows, and other graphical features. This simplifies human-computer interaction because the user has to simply move the mouse and click, as opposed to typing complicated commands.

Habitat Fragmentation: Discontinuities in an organism's preferred environment. This can be caused by either geological processes that slowly alter the physical environment, or by human activity such as deforestation and land conversion.

High-Level Language: A programming language in which a higher percentage of tasks are allotted to the computer than to the programmer. These typically have a shorter development time but tend to be slower and less powerful than low-level languages.

Individual-based model (IBM): A class of computational models that simulates a group as a set of individuals and aims to assess that state of the group.

Individual-based Neural Network Genetic Algorithm (ING): A type of model in which the individual employs an Artificial Neural Network (ANN) at each movement step to determine a behavioral decision. The ANN uses location and individual specifics as an input layer, and it converts those inputs into a single movement response. Individuals carry specific weights (i.e., their "genetic code" in the model) which are used to transform state variables and the interconnections in the ANN. A genetic algorithm evolutionarily trains those weights by

selecting individuals that made the best decisions with regards to a fitness measure (i.e., how successful they were at finding food) and “breeding” those individuals to produce offspring that will eventually make optimal foraging decisions.

Machine Learning: The process by which a machine (in our case a computer program) generates and/or improves modeling rules based on provided data.

Memory Mechanisms: Memory mechanisms rely on an animal’s recollection of past areas, an animal’s communication with other animals, and an animal’s genetic factors to determine animal movement.

Metapopulation: A group of spatially-separated subpopulations of one species that interact with one another.

Movement Mechanisms: Rules that nomadic animals follow when they make movement decisions. For the purpose of this project we will be using three main types of mechanisms to govern the travel patterns of ungulates: memory, oriented and non-oriented.

Movement Step (in the model): A defined time interval in the model, in which the state variables of the individual gazelles are updated. For our project, the movement step is one day.

Non-oriented Mechanisms: Non-oriented mechanisms determined by stimuli that are at an animal’s current location. These stimuli cause a change in speed of an animal’s movement.

Normalized Difference Vegetation Index (NDVI): A simple graphical indicator that indicates the productivity level, or the “greenness” of vegetation. NDVI values are garnered from remote sensing satellite data.

Oriented Mechanisms: Oriented mechanisms are determined by stimuli that are within an animal's sensory range but not at an animal's current location. These stimuli cause a change in

direction of the animal's movement. Oriented mechanisms can be vegetation-oriented or obstacle-oriented.

Stochastic System: A system in which the state is non-deterministic. This means that the subsequent state is determined by both the predictable actions of the system and a random element.

Training (a model): A program compares the results of simulations from the theoretical model to empirical data collected from the field. Using machine-learning techniques, the program then applies corrections to the algorithm such that later simulations generate output that more closely match the real-world data.

Ungulates: A group of mammals that use the tips of their toes, usually hooved, to support their whole body weight while moving. Examples include: X, Y, Z.

Appendix B: Parameter Configuration Files

NDVI Run File: ndvi_batch_params.xml

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Semivariance Configuration File: ndvi_batch_params.xml

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  <parameter name="prevStepDistNNI" type="constant" constant_type="boolean"
value="true" />
  <parameter name="nearestObjNNI" type="constant" constant_type="boolean"
value="true" />
  <parameter name="prev14StepDistNNI" type="constant" constant_type="boolean"
value="true" />
  <parameter name="AvgDistNearestObjPast8StepsNNI" type="constant"
constant_type="boolean" value="true" />

</sweep>

```

Combined NDVI and Distance Squared vs Time Lag:

```

<?xml version="1.0"?>
<sweep runs="1">
  <parameter name="ndviTrainingSetSize" type="constant" constant_type="number"
value="6374" />
  <parameter name="obstacleTrainingSetSize" type="constant"
constant_type="number" value="6374" />

```

```

    <parameter name="vegScenarioMode" type="constant" constant_type="number"
value="1" />
    <parameter name="scenarioStartIndex" type="constant" constant_type="number"
value="30" />
    <parameter name="scenarioEndIndex" type="constant" constant_type="number"
value="30" />
    <parameter name="gazelleCount" type="constant" constant_type="number"
value="100" />
    <parameter name="stepsPerDay" type="constant" constant_type="number" value="1"
/>
    <parameter name="daysPerScenario" type="constant" constant_type="number"
value="14" />
    <parameter name="NDVIFitnessCalc" type="constant" constant_type="boolean"
value="true" />
    <parameter name="SemivarianceFitnessCalc" type="constant"
constant_type="boolean" value="true" />
    <parameter name="DistanceFitnessCalc" type="constant" constant_type="boolean"
value="false" />
    <parameter name="stepCountNNI" type="constant" constant_type="boolean"
value="true" />
    <parameter name="currXLocNNI" type="constant" constant_type="boolean"
value="true" />
    <parameter name="currYLocNNI" type="constant" constant_type="boolean"
value="true" />
    <parameter name="searchEffortNNI" type="constant" constant_type="boolean"
value="true" />
    <parameter name="resourceUptakePrev8StepsNNI" type="constant"
constant_type="boolean" value="true" />
    <parameter name="currNDVINNI" type="constant" constant_type="boolean"
value="true" />
    <parameter name="maxNDVIInRangeNNI" type="constant"
constant_type="boolean" value="true" />
    <parameter name="prevStepAngNNI" type="constant" constant_type="boolean"
value="true" />
    <parameter name="prevStepDistNNI" type="constant" constant_type="boolean"
value="true" />
    <parameter name="nearestObjNNI" type="constant" constant_type="boolean"
value="true" />
    <parameter name="prev14StepDistNNI" type="constant" constant_type="boolean"
value="true" />
    <parameter name="AvgDistNearestObjPast8StepsNNI" type="constant"
constant_type="boolean" value="true" />

```

</sweep>

Combined NDVI and Anthropogenic Feature:

```
<?xml version="1.0"?>
<sweep runs="1">
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value="6374" />
  <parameter name="obstacleTrainingSetSize" type="constant"
constant_type="number" value="6374" />
  <parameter name="vegScenarioMode" type="constant" constant_type="number"
value="1" />
  <parameter name="scenarioStartIndex" type="constant" constant_type="number"
value="30" />
  <parameter name="scenarioEndIndex" type="constant" constant_type="number"
value="30" />
  <parameter name="gazelleCount" type="constant" constant_type="number"
value="100" />
  <parameter name="stepsPerDay" type="constant" constant_type="number" value="1"
/>
  <parameter name="daysPerScenario" type="constant" constant_type="number"
value="14" />
  <parameter name="NDVIFitnessCalc" type="constant" constant_type="boolean"
value="true" />
  <parameter name="SemivarianceFitnessCalc" type="constant"
constant_type="boolean" value="false" />
  <parameter name="DistanceFitnessCalc" type="constant" constant_type="boolean"
value="true" />
  <parameter name="stepCountNNI" type="constant" constant_type="boolean"
value="true" />
  <parameter name="currXLocNNI" type="constant" constant_type="boolean"
value="true" />
  <parameter name="currYLocNNI" type="constant" constant_type="boolean"
value="true" />
  <parameter name="searchEffortNNI" type="constant" constant_type="boolean"
value="true" />
  <parameter name="resourceUptakePrev8StepsNNI" type="constant"
constant_type="boolean" value="true" />
  <parameter name="currNDVINNI" type="constant" constant_type="boolean"
value="true" />
  <parameter name="maxNDVIIInRangeNNI" type="constant"
constant_type="boolean" value="true" />
```

```
<parameter name="prevStepAngNNI" type="constant" constant_type="boolean"
value="true" />
<parameter name="prevStepDistNNI" type="constant" constant_type="boolean"
value="true" />
<parameter name="nearestObjNNI" type="constant" constant_type="boolean"
value="true" />
<parameter name="prev14StepDistNNI" type="constant" constant_type="boolean"
value="true" />
<parameter name="AvgDistNearestObjPast8StepsNNI" type="constant"
constant_type="boolean" value="true" />

</sweep>
```

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