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PREDICTIVE ANALYTICS FOR REDUCING HUMAN-ANIMAL CONFLICT

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Forest-adjoining areas are prone to human–animal conflict. In such areas, there is an urgent need to develop methods that prevent animal intrusion in human habitats while also ensuring that wild animals are not harmed. We have applied data science to track animal (in this case, the Indian panther) movement in forests and animal intrusion in villages adjoining the forest environment. The Indian panther (*Panthera pardus fusca*) is a panther subspecies distributed across the Indian subcontinent. We find that analytics on pugmark data can be effectively applied to simulate movement of the animal and thus undertake preventive measures.

Keywords: Environment management, forestry management, data sciences, data analytics, human–animal conflict

1. Introduction

With the advent of new technologies and evolved societies, human beings have been gradually distanced from the natural environment. Although the human race has coexisted with animals for millennia, as the human population drastically increases and resources become scarce, the ground for human–animal conflict becomes even more fertile. It is critical that animals and, in particular, wildlife are protected and allowed to thrive to ensure integrated environmental management. In India, where a significant section of the population resides in areas prone to

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human–animal conflict, there is a pressing need to devise unique methods to prevent animal intrusion in human communities while at the same time ensuring that animals are not harmed in any way. Before embarking upon the possibilities of a solution, we would like to discuss the current context of animal intrusion in India. The Indian panther (*Panthera pardus fusca*) is listed as "Vulnerable" on the IUCN Red List of Threatened Species since its population has declined due to loss of habitat, fragmentation of environments, and persecution from human-conflict situations (Stein et al., 2016).

2. Current Context

Research in this field primarily focuses on human–animal conflict (HAC). The significant number of deaths per year caused by tiger intrusion is a source of concern for the people settled in these areas close to forest environments and the government alike. The violence that ensues after animal intrusion into human habitat also seems to be a two- way process. In the Sundarbans, 30 humans and three tigers lose their lives on average every year (Chaki, 2014). These data are alarming not only because of the loss of human life, but also because of the already waning tiger population. Although the Bangladesh government formulated a compensation policy in 2010, the needs of the locals were not met by such efforts. This has resulted in a vicious cycle where residents in surrounding areas of the Sundarbans have developed a negative attitude toward the wildlife, often blaming it for their hardships. The reason for HAC in the Sundarbans is also related to the loss of habitat. The tigers leave their territory in search of food and water. Once they wander close to the human habitat, the chances of conflict increase manifold, often resulting in the unfortunate deaths of humans, tigers, or both.

The source of local communities' negative attitudes toward wildlife can be traced back to the losses of life, property, and crops that they face. The lack of sensitization toward wildlife and awareness about the need for conservation also contribute to this attitude. Bhardwaj (2017) of the Wildlife Institute of India suggests that strict administrative action is needed to address this problem. The government offices in India need to understand the gravity of the situation and launch awareness programs in order to ensure that people inhabiting areas close to forests are made aware of environmental and wildlife issues. Education and awareness can cause a much-needed change in the attitude of humans toward animals. However, these programs need to be complemented with policies that ensure sufficient resources for wild animals, since the major cause of wild animals leaving their own territory is a lack of resources. This finding is echoed by Singh (2015) whose study concludes that the two primary reasons for human–animal conflict are lack of resources and habitat fragmentation. He also agrees with existing literature by identifying awareness creation and sensitization as possible solutions in the mitigation of human–animal conflict.

3. Research Agenda

Bhattarai and Fischer (2014) conducted personal interviews with stakeholders about their perception of HAC. The results of their work are different from the general perception of human attitudes about HTC. Even though loss of life and property affect people deeply,

the attitude toward tiger conservation was found to be generally positive. The benefits of ecotourism were one of the reasons identified for this positive attitude. A correlation was also found between level of education and positive attitude toward conservation, once again highlighting the need to educate and sensitize the populace in order to ensure harmony between humans and animals. The urgent need to convince the population about wildlife and its impact on the environment is also reiterated by Aiyadurai et al. (2010), who suggest that communication about wildlife should be given the highest priority to ensure peaceful coexistence between humans and animals. Inskip et al. (2013) argue for the inclusion of actions to reduce risk perceptions in order to effectively manage human–wildlife conflict. Their research establishes a correlation between human violence toward animals and humans' risk perception of wild animals. The study uses participatory risk mapping and personal interviews to work out people's perception of human–animal conflict. The researchers conclude that in-depth research to enhance understanding of wildlife, along with consideration of the socio-environmental context of these risks, can help identify and effectively change risk perception, thereby reducing human animal conflict.

A study conducted by Arunashantha (2015) to identify the impact of animal intrusion in Sinharaja rain forests points out that animal attacks have increased due to human intrusion in the buffer zone of the forest. This human movement has also impacted the socio-environmental health of the rural community living around Sinharaja. The study recommends that forest departments maintain a stricter buffer zone and formulate a systematic institutional plan to mark and protect these zones. The causes of animal intrusion have been identified through years of research and study. Lack of resources coupled with administrative inefficiencies and lack of awareness may be identified as the root causes of human–animal conflict. However, there is a need to formulate better and more foolproof methods to protect the rural communities who are at a risk of animal intrusion while at the same time protecting the environment.

4. Literature Review

Advancements in technology have, over the years, significantly enhanced the capability to track and monitor wildlife. Such technology includes wildlife-borne devices, which permit the gathering of precise time series of location of an individual (McConnell et al., 2010; Tomkiewicz et al., 2010); biotelemetry apparatus, which provide physiological data (Cooke et al., 2004; Payne et al., 2011); remote- sensing technologies; and geographic information systems to attain complete geographic data (Gao, 2002). Having said that, fresh challenges have also emerged in relation to the management, analysis, and collection of georeferenced animal location data (Cagnacci et al., 2010; Urbano et al., 2010). While GPS, along with supplementary relocation technologies, has made possible the acquisition of great quantities of animal location data from different aquatic and terrestrial areas (Tomkiewicz et al., 2010), model development for examination of such data has not developed at the desired pace. Although considerable attempts have been made to formulate survey approaches to estimate abundance of large carnivores, it continues to be a pressing challenge in wildlife conservation and management (McDonald, 2004; Long

et al., 2007). The problem is intensified in the case of large carnivores due to their low-density existence and secretive nature. Direct sighting surveys are also rendered unfeasible due to the aforementioned reasons.

Human–wildlife conflict, which can be understood as the struggle between humans and wild animals for habitat and natural resources (Aryal et al., 2012; Thirgood et al., 2000; Graham et al., 2005), poses a great challenge to ecological development and environmental sustainability. Carnivores, in particular, are difficult to integrate into sustainable management, largely due to actual and perceived acts of attacking livestock (e.g., Suryawanshi et al., 2013). Nevertheless, as argued by Solow (1993), ecological sustainability (inclusive of biodiversity values and ecological services) warrants the conservation of such elements in the long run. Studies have shown that in rangelands shared by both wildlife and livestock, such as the Himalayas, depredation of livestock turns out to be the main cause of scuffles between humans and wildlife (Oli et al., 1994; Jackson et al., 1996; Mishra, 1997; Hussain, 2003; Namgail et al., 2007). For example, snow panthers (*Panthera uncia*) have long been viewed as a major danger to trans-Himalayan communities (Aryal et al., 2012). Oli et al. (1994) reveal that within a particular district in Nepal, livestock lost to snow panther attacks equals around 25% of the average per capita income in a two-year period.

McPhee et al. (2012) derive an occupancy-abundance relationship by simulating the intersection of routes of the wolf (*Canis lupus*) and survey grid cells for a wolf-packet density. They also occupancy surveys as a potential method for estimating the presence of carnivores where other assessments were unviable. McClintock et al. (2012) synthesize prevailing and new approaches to frame a gnarl sequence of mechanistic models based on biased and correlated random walks that have permitted dissimilar behavioral conditions to direct (migration), explore (e.g., dispersal), confine the area (e.g., foraging), and other kinds of mobility. While prior studies on grey seals focused on correlated movements, they found significant evidence that bias toward haul-out or foraging locations better explained the seal movement than simple or correlated random walks. Posterior model probabilities also gave evidence that seals have been transferred from direct, limited, and exploratory movements related to harnessing, feeding, and other behaviors.

It is clear that effective measures need to be devised to predict the movement of animals and their intrusions on human-inhabited areas so that human–wildlife conflict is minimized; this might require multidisciplinary and integrated research endeavors. As operational research involves the application of advanced analytical methods and utilizes techniques from mathematical modeling, mathematical optimization, and statistical analysis, it might provide effective solutions to such ecological problems. As probable solutions for determining densities, managers have resorted to estimates of indirect measures of relative abundance (e.g., harvest statistics and catch-per-unit effort) and radio-telemetry studies (Rausch, 1967; Roughton and Sweeny, 1982; Fuller and Snow, 1988; Burch et al., 2005). In relatively recent times, transect intercept probability sampling and sampling unit probability estimator (SUPE), which contemplate the probability of locating network routes in snow (Becker, 1991; Van sickle and Lindzey, 1991; Becker et al., 1998; Patterson et al., 2004), have been employed due to their efficiency and suitability with respect to very large areas

of study (greater than or equal to 10,000 km2), nonreliance on collared animals, and ability to present confidence intervals (Becker et al., 1998). The aforementioned approaches, however, are rendered unfeasible where heavy forest cover prevents following of track networks by aircraft. Studies have also observed occupancy-abundance relationships (Tosh et al., 2004; He and Gaston, 2007), which are considered basic ecological patterns (Andrewartha and Birch, 1954). These relationships have been recognized across various taxonomic categories, such as amphibians, birds, plants, mammals, and fish (Winters and Wheeler, 1985; Gibbons et al., 1993; Boecken and Shachak, 1998; Mossman et al., 1998; Tosh et al.,2004).

Although occupancy-based studies have been conducted in the past to determine abundance of life forms (Nachman, 1981; He and Gaston, 2003; Royle and Nichols, 2003), such studies have seldom been conducted with respect to large carnivores given their low abundance, which makes it challenging to monitor them even in the presence of suitable study conditions. Nonetheless, sign-based occupancy estimates (as compared to direct observation) could prove to be suitable study approaches (Stanley and Royle, 2005; Thorn et al., 2011) where carnivore signs are easily noticeable (e.g., tracks in snow) (Magoun et al., 2007). A method that considers animal signs may not produce the same results as one that involves individual observation due to the fact that an animal may leave behind more than one sign per survey unit in the period of sampling, which may result in an animal being double counted. In such situations, models incorporating occupancy-abundance measures (e.g., He and Gaston, 2000; 2007; Figueiredo and Grelle, 2009) may not be applicable unless the sampling areas have sufficiently wide spaces in between to eliminate the chances of double counting. This may also not be feasible in cases where species having greater variability in home range size (Stanley and Royle, 2005). Further, such occupancy modeling requires data on the average number of sampling units overlapped by every home range; such information may not be available in the absence of concurrent radio-telemetry studies (Thorn et al., 2011). However, if standardization of sampling is achieved, empirically established associations between abundance and occupancy of survey units with an animal sign might offer a method to determine abundance. Empirical establishment of the occupancy-abundance association involving large carnivores is challenging as it warrants occupancy surveys across several regions with recognized animal density. It is noteworthy that if movement models are able to generate accurate tracks of an animal (Jonsen and Taylor, 2000; Zheng et al., 2009), they might offer a base for drawing occupancy-abundance relations capable of being validated over the course of time for employment animal surveys.

5. Methodology

The present study attempts to derive animal (panther) movement paths through analytics-based techniques. Data on the pugmarks are used to develop a stochastic differential equation (SDE) and estimate the travel paths. Animal movement paths are then simulated using a habitat-biased movement model using pugmark data. This could allow the prediction of animal movements and their intrusions in human-inhabited areas. Thus, this study could

help government departments take preventive measures when travel paths may lead to human populations.

The approach working with SDEs is to model the mobility of animals assuming no *a priori* information of the dissemination of resources or animal preferences. We develop SDEs to define the incremental phase of an animal at time (t), positioned at coordinates $r(t) = (x, y, t)$. This model has been framed and arranged according to the terms of drift (direction) and diffusion (random) in two-dimensional (x, y) space where the two dimensions are latitude and longitude.

Proposition 1

A univariate SDE is defined by:

$$dY(t) = \overline{x}(Y,t,\theta)dt + \rho(Y,t,\theta)dB(t) \tag{1}$$

where $Y(t)$ is a random variable, $\{B(t), t \geq 0\}$ is a random process, and θ is a set of parameters, some known and some unknown. The parameter $\overline{x}(Y,t,\theta) = E\{dY(T) \mid Y(s), S \prec t\}\}\, dt$ is interpreted as the instantaneous velocity of the individual (drift coefficient), and $\rho(Y, t, q) = se\ \{dY(t) \mid Y(s), s \prec t\} \mid dt$ is interpreted as the speed or the diffusion coefficient.

Most mobility models comprise different types of differential equations.

For example, the deterministic partial differential equation

$$\frac{\partial u(x,t)}{\partial t} = \frac{\partial}{\partial x}(\delta_i u(x,t)) + \frac{\partial^2}{\partial x^2}(\delta_2 u(x,t)) \tag{2}$$

was adopted to describe the steady-state probability density, $u(x, t)$, of beetles (Banks et al., 1985), coyotes (Moorcroft et al., 1999), and other free-ranging animal populations (White et al., 1996; Turchin, 1998).

The simplest model for the SDE in equation (1) is a pure diffusion model where $\overline{x}(Y, t, \theta) = 0$ and $B(t)$ is a Brownian process (i.e., the movements of each individual is a random walk independent of others).

Another special case is the mean-reverting Ornstein–Uhlenbeck (O–U) process where

$$\overline{x}(Y,t,\theta) = \alpha[Y(t) - a] \quad \text{and} \quad \rho^2(Y,t,\theta)dt = \rho^2 \tag{3}$$

In order to evaluate the ranges of animals, the O–U process was selected, where a is the mid-point of the home range (Dunn and Gipson, 1977; Dunn and Brisbin, 1985).

The intricate behavior of an animal's mobility can be studied by modeling the drift and diffusion coefficients as functions of exploratory variables. In this study, we model the drift term as the function of angle of the head amid the tracks of the animals and an emanating point to indicate the availability of food.

Proposition 2

In cases where the SDE in equation (1) may be approximated by the difference equation

$$Y(t_i) - Y(t_{i-1}) = \overline{x}(y,\theta)(t_i - t_{i-1}) + \rho(y,\theta)\varepsilon_i \tag{4}$$

where (ε_i, $I = 1, \ldots n$) are independent random noise, the parameters in θ may then be estimated using nonlinear regression techniques. In this study, we use regression techniques

to estimate effects of a heterogeneous environment on the movements of the animal. Given the SDE with $\{B(t),\ t \geq 0\}$ a Brownian process and θ the parameter of interest the log likelihood ratio function, an observed path can be calculated (Pearson and Blakeman, 1906). The observed path is given by:

$$L(\theta) = \int_0^T \frac{\overline{x}(y(s);\theta}{\rho^2(y(s))} dy(s) - \frac{1}{2}\int_0^T \frac{\overline{x}^2(y(s);\theta}{\rho^2(y(s))} \tag{5}$$

The maximum likelihood estimate (MLE) of θ can be estimated by explaining the derivates of the log likelihood ratio with respect to θ to zero and solving for θ. For example, to obtain the MLE for a in the O–U process with

$\overline{x}(y(t),\theta) = ay(t)$ and $\rho(y(t)) = \rho$, we solve the equation

$$\frac{\partial}{\partial_a} L(a) = \frac{1}{\rho^2}\int_0^T y(s)dy(s) - \frac{\hat{a}}{\rho^2}\int_0^T y^2(s)ds = 0$$

to obtain

$$\hat{a} = \frac{y(T) - y(0)}{\int_0^T y^2(s)ds} \tag{6}$$

This technique was adopted in wildlife biology, where the authors have evaluated the speed and other factors that defined the relocation tracks of elephant seals (Brillinger and Stewart, 1998). We apply a similar technique in this study to estimate the movement for panthers in the reserved forests.

$$dx(t) = [\alpha_x\{r(t),\ t\}]dt + D\{(t),\ t\}.\ [d\theta_x\ (t)] \tag{7}$$

$$dy(t) = [\alpha_y\ \{r(t),\ t\}]dt + D\{(t),\ t\}.\ [d\theta_y\ (t)] \tag{8}$$

where $dx\ (t)$ and $dy\ (t)$ are the incremental step sizes along the x- and y- axes

vector = (contains the drift parameters);

D (the diffusion matrix) is a function of both time and position; and ψx and ψy are random processes for which expected values = 0

If the drivers of the diffusion terms in (x, y) space are independent Brownian processes and the drift terms are uninterrupted over time, a diffusion process with continuous sampling tracks was obtained. The drift and diffusion parameter set and the direction and speed of the movement were regulated by the random processes.

6. Discussion of Results

Regularly monitoring animal movement helps researchers answer questions about the response of animal movement to intensive timber management, cattle grazing, vehicle traffic in the forest, etc. To test the model and understand its findings, we have analyzed pugmark data for a single animal (panther) observed over a six-month period. The animal has remained endogenous to a particular territorial range of forest. Usually, it is impractical to track an animal for long periods as the animal might move into an adjoining territory or may come into conflict with humans or other wildlife. So we identified an animal (through

discussions with the forest department officers) that was young and could hunt efficiently. The data were collected over a six-month time frame, which we extracted from forest departmental files of a specific district in North India. The forest sanctuary zone for which the data are collected is shown in Figure 1. It is situated next to a large national park known globally for high tiger and panther populations. It is also frequently visited by tourists across the world, so there are sanctuary zones kept around the national park. Figure 2 shows the animal's movement as evidenced from data. A first-cut analysis through visual inspection shows that the movement was not random since there is a gradual drift observed in certain time periods. There seems to be a dispersion effect too, but the animal does tend to move in a particular direction for specific periods of time thus indicating a drift effect.

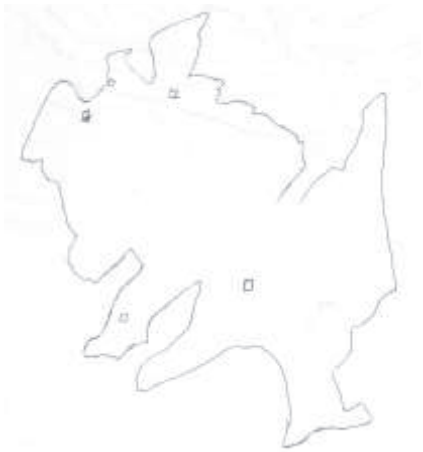

Figure 1: Forest sanctuary zone

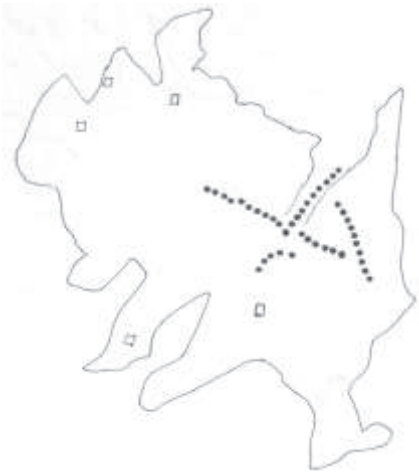

Figure 2: Panther movement inside the sanctuary zone as evidenced by Pugmark data

Pugmark data were captured and specific coordinates (latitudes and longitudes) were found in the data that could identify location of the species at any point in time. We tried to understand the distribution of these latitudes and longitudes, respectively, so as to use

statistical methods to simulate the pugmark movement. We attempted to identify the shape of distribution and fit our data into various distributions. The chi-squared test was used to check the goodness of fit. While analyzing the distribution, certain outliers were captured, which distorted the distribution. These outliers could be because of data capture error and hence were removed from the data set. For latitudes, triangular distribution fitted the data well with the chi-squared value of 17.17 (Figure 3).

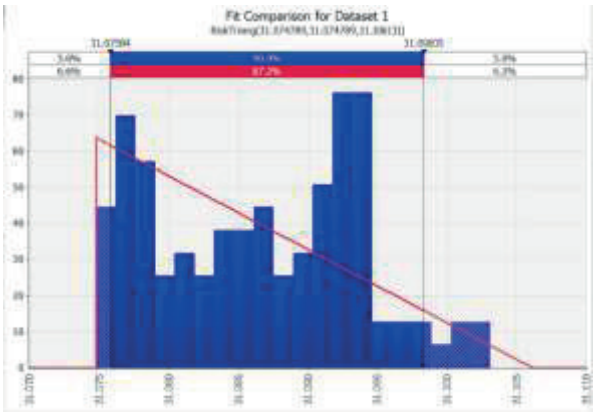

Figure 3: Data distribution along latitude

Triangular distribution fitted the longitude data the best as well, with the chi-squared value of -8763 (Figure 4).

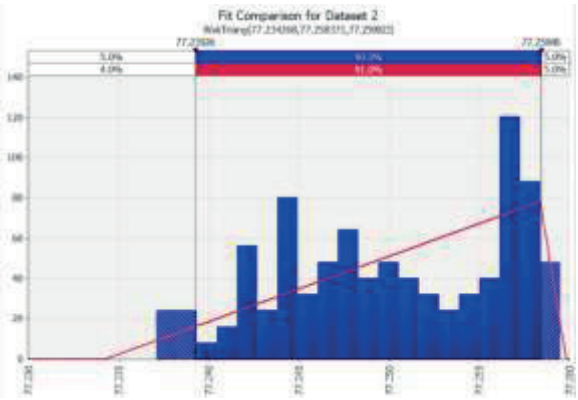

Figure 4: Data distribution along longitude

The animal's movement was next predicted based on two components: random movement (dispersion) and historical tendency or pattern (drift). Dispersion explains the random element of the animal's movement based on coefficient of variance. For the dispersion component, we used the historical movement and variance to predict the animal movement over the next 3-4 time periods. Usually, it was found that pug-mark data was collected in an interval of 2 days. Therefore, the prediction is done over the 6-8 days of interval. This was sufficiently spaced out to let the administrators undertake appropriate steps to prevent human-animal conflict. We adopted coefficient of variance to capture the effect of dispersion.

As it is a random walk, the factor that defines the proportion of movement is calculated by uniform distribution. This is done because the animal can move in any direction with equal probability. Therefore, two factors help calculate dispersion: coefficient of variance and proportion factor through uniform distribution. According to the goodness of fit test, we concluded that both latitude and longitude follow triangular distribution (Figure 3 and 4 respectively). Coefficient of variance computed for latitude and longitude are:

Coefficient of variance (latitude): 0.00000000130757
Coefficient of variance (longitude): 0.000000000510996

Next, the quantification of the number of steps in a 'run' was done. We define a 'run' as the number of steps that the animal usually takes when there is a drift in his movement pattern. It could be possible, that the animal is moving towards a particular objective or an area and, in so doing, it is drifting. We wanted to quantify the extent of this drift. This was done by looking at the runs (consistent movement in one direction). It was found that the runs/trends consisting of four steps in a single direction repeated most often. Hence, each run was found to be consisting of four steps. The number of runs across the latitudes and longitudes can be found in Table 1.

Table 1. Number of panther runs across the studied latitudes and longitudes

Total run	Latitude	Longitude
Positive direction	8	9
Negative direction	12	8

Drift was calculated based on the average distance moved during the runs.
Average movement in runs (latitude): 0.000000023774
Average movement in runs (longitude): 0.0000000198381

A 'run' can be in any direction i.e. it may have meandering tendency too as the animal behaviour is such that it may meander. Based on the run analysis, the number per run was found to be four; and so, resetting was done after four steps every time. Resetting the drift is important, which is done through simulation using uniform distribution. While simulating the drift of the animal movement, uniform distribution with values −1 and 1 was used to predict if the drift would be in the positive direction (1) or negative direction (−1).

Six replications of simulation were carried out to compute the dispersion component, and we tried to simulate the next steps of the animal (Figure 5). Since animal has the tendency to move in a certain direction (captured through the drift component); the drift component captures past pattern into animal movement. To calculate drift, we considered any tendency of the animal to move in certain directions or any historical patterns of movement for the animal. It was evaluated by analyzing the runs that could be seen in the data. Next, we quantified the number of runs. A run would be the number of steps that the animal usually takes when there is a drift in his/her movement pattern. It could be possible that the animal is moving toward a particular objective or area, and, in so doing, it is drifting. We wanted to quantify the extent of this drift. This was done by computing the number of steps in each run (consistent movement in one direction). In the next phase, to test out the model, we developed six replications of the simulated animal movement.

Parameters like variances, averages, coefficient of variance, and statistical distribution of the latitudes/longitudes were captured through the training data while the validity of model was checked by the test data.

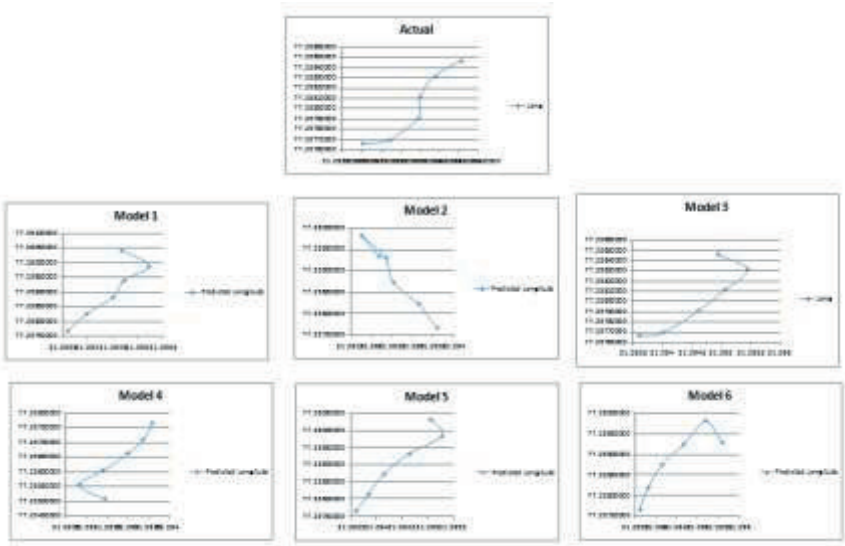

Figure 5: Simulation of animal movement.

For validation, we took four scenarios and compared the predicted movement with the actual movement. To capture the accuracy, mean absolute percentage error (MAPE) was calculated. MAPE was found to be a good indicator to assess the predictive accuracy as it evaluates the percentage error of absolute values. The lower the MAPE, the better the predictive capability of the model. All four of the scenarios and the predictive movement of the animal are presented in figures 5-9.

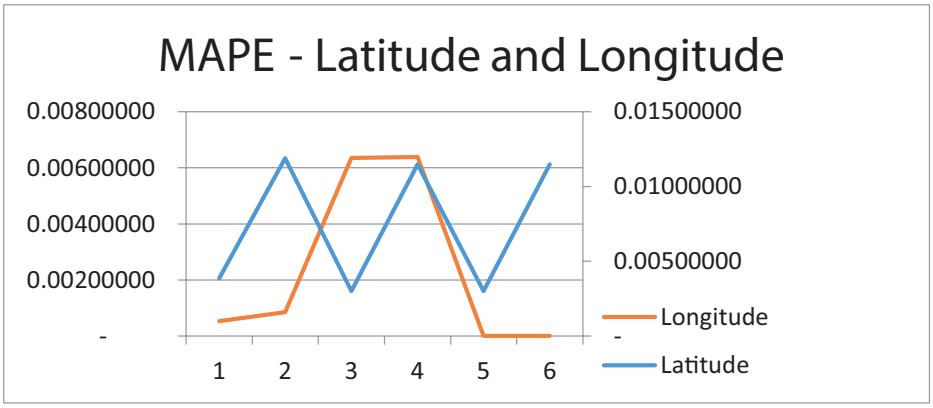

Figure 6: Scenario 1

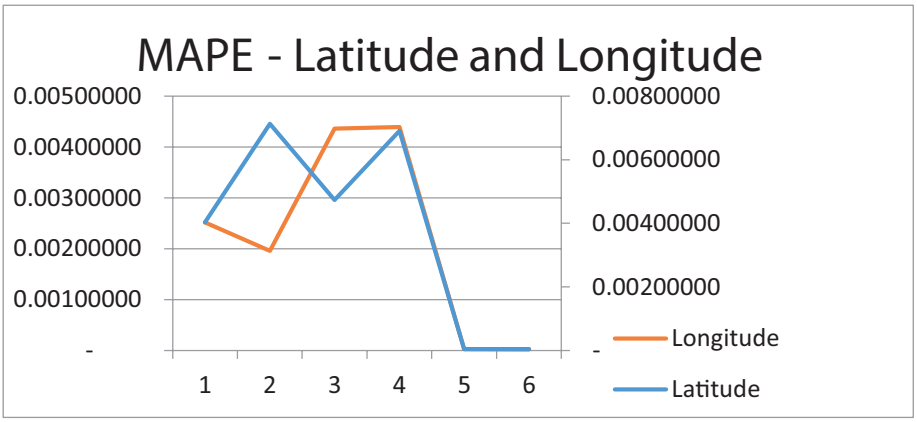

Figure 7: Scenario 2

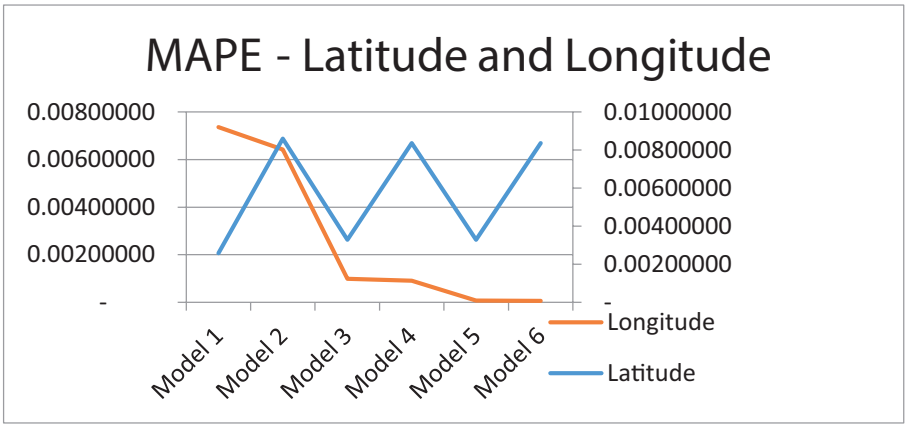

Figure 8: Scenario 3

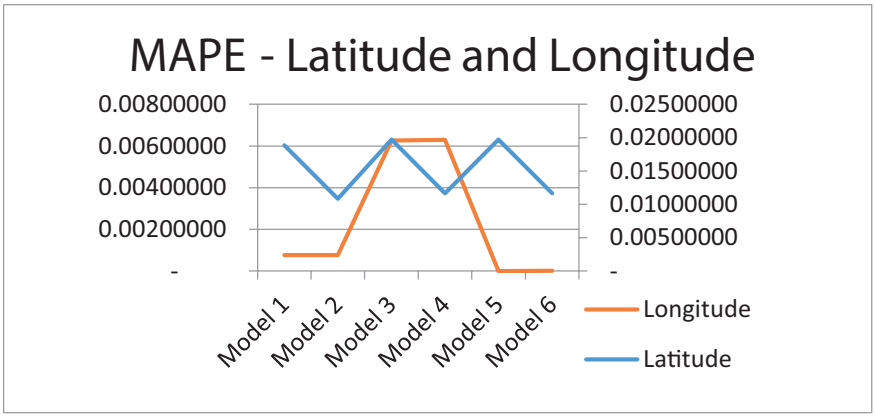

Figure 9: Scenario 4

We observed that replications 5 and 6 are able to predict animal movement better in all of the scenarios, with the accuracy of 99.9999%. Also, when calculating the standard deviation (SD) of all the steps, we found that the latitude SD was more than the longitude SD. This is

due to the fact that the animal moved more along the latitude than the longitude. This was captured when we calculated the SD of latitude and longitude, which were 0.007358027 and 0.006277487, respectively. According to a stochastic differential equation, high displacement along each step reduces the predictability, which is the case with latitude where we see more variance than longitude. Although this model has been applied to panther movement, the same model can be extended and modified to study movements of other animals. We have observed that the strength of this model lies in its flexibility and practical approach. It could also be worth applying in various stochastic data in ecological studies of marine animals and migratory birds.

7. Conclusion

It is possible to use data analytics and monitor the movement of a specific animal or species. Such monitoring can help in conservation. A pre-emptive monitoring can curtail movements of species toward human habitats. The identification of movement pattern of animals allows environmental administrators to have further visibility into what is causing these conditions and to take preventive steps accordingly. Stochastic Differential Equations have been found to be a good tool to model animal movements. In this case, the data was time–series and bivariate. We developed modelling equation which could shadow the movement of animal. Numerical tests of the stochastic model were also carried out. We simulated the animal movement on the data set and evaluated the simulation with actual movement. Model's ability to shadow the movement was found to be reasonably satisfactory. The fact that the model detects changes in direction of animal movement much earlier means preventive steps can be taken to stop animals from straying into human-inhabited territory. Even small drifts can be picked up quickly by observation of the previous few steps, and measures can be put into place to prevent animal intrusion into human habitation while keeping wildlife in sanctuary zones of forests. This body of work also illustrates the wider environmental benefits that data analytics can have on environmental systems where human–animal conflict can be reduced. Conservation is critical to the environment, and such data-driven approaches indirectly facilitate protection and conservation of natural resources and ecosystems. Specifically, in this study, we illustrate the application of data analytics in better understanding of panther (*panther pardus fusca*) movement. This understanding can help administrators to take preventive steps to curtail its straying in human habitations, thus avoiding potential conflict and saving precious human and animal life.

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