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Agent-Based Modeling of Human-Wildlife Conflict in Agricultural Landscapes

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Abstract

Objective: The study aims at comprehending and mitigating human-animal conflict in the Nilgiris district of Tamil Nadu, where crop damage occurs near forest edges by wildlife such as elephants, wild boars, sloth bears, Indian porcupines, bonnet macaques, and gaurs. Using an agent-based modeling approach, it assesses the potential effect of different mitigation strategies on the pattern of conflict and the amount of crops lost. Materials: The description of the research refers to the use of a spatially explicit agent-based analytic platform developed with NetLogo for the simulation of a 100 km² agro-forest landscape. The system has 500 farmer agents, interacting with multiple wildlife species whose behaviour is modelled on real-life data. The data sources include land use maps from the Forest Survey of India, reports of conflicts from the Tamil Nadu Forest Department, and maps of wildlife corridors. Three scenarios were tested with the simulation: baseline (no management intervention), deterrents (fences, watchtowers), and crop switching (low-risk crops). Result: Simulation results showed 420 crop-raiding events per season in the baseline scenario, reduced to 220 with

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deterrents, and further to 150 with crop switching. Crop loss occurred in 18% without mitigation, 10% with deterrents, and 6% with crop switching. Crop attractiveness played an important role; bananas and maize had more raids, while tea and lemongrass were less affected. Conflict hotspots were mostly near wildlife corridors, and smaller farms close to forests suffered the most. Sensitivity analysis confirmed that wildlife density, deterrent effectiveness, and crop type strongly influenced outcomes. Conclusion: Interaction with human-wildlife conflict can be treated with agent-based modelling. Within the strategies tested, crop switching helped best to reduce conflicts and crop losses. The study shows that mitigation methods should be tailored to each location and based on behaviour, supporting both conservation and farming.

Keywords:

Agent-based modeling, human-wildlife conflict, crop raiding, conflict mitigation, nilgiris, wildlife corridors, land-use planning.

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Introduction

In terms of agriculture, forests, and protected areas, people and wildlife must co-exist despite the many challenges that arise in this realm. Wildlife sometimes enters the farmlands in pursuit of food, resulting in crop depredation, loss of property, and economic hardship for farmers (Begum & Vijaya, 2024). These conflicts develop into negative perceptions against wildlife conservation and sometimes outright retaliation against wildlife. In many landscapes, especially biodiversity-rich human-occupied landscapes, such conflict has become the focal concern of both conservationists and local communities (Green et al., 2022).

The Nilgiris district of Tamil Nadu, historically a part of the Nilgiri Biosphere Reserve, is a hotbed of human-wildlife conflict (Puyravaud & Davidar, 2013). This region is a patchwork of forests, tea plantations, vegetable farms, and rural settlements. This mosaic landscape is also influenced by demographic shifts and migration patterns that affect land use and agricultural practices in rural communities (Menon & Deshpande, 2023). It is also connected to major wildlife corridors used by elephants, wild boars, gaur, Sloth bears, Indian porcupines, and bonnet macaques. Crops such as banana, maize, and jackfruit, which are cultivated at low altitudes of the mountains, are highly attractive to wildlife and often lead to crop-raiding (Naha et al., 2020). Conflict events are frequent in this region and are reported to increase during certain seasons, particularly in farms close to forest edges and known animal pathways (Digal & Singh, 2023).

In addition to the ongoing efforts, human-wildlife conflict management remains a tough task without having an integrated picture of how and why both wildlife and farmers make decisions and respond to each other over space and time. Classical methods concentrate either on reactive measures or on studies of one species, thus failing to perceive the complex interactions between human behaviour, wildlife movement, crop patterns, and landscape features. Computational modelling approaches are also applied in other domains to manage interactions among multiple agents in complex environments. For example, in wireless sensor networks, LEACH-based approaches using first-order models have been used to improve energy-efficient routing for mobile healthcare monitoring (Marhoon & Shaker, 2025). Such cross-disciplinary applications highlight the flexibility of modeling frameworks for addressing dynamic, multi-agent systems like human–wildlife interactions.

To cover this gap, ABM-style models are used to simulate wildlife farmer interactions within a realistic spatial canvas. Agent-based modeling is a powerful and flexible framework that describes individual agents, such as animals and farmers, their behaviour, memories, and rules for decision-making. Wildlife agents simply move through the landscape depending on food availability, risk, and habitat conditions. Farmer agents check the damage to crops and, considering their level of tolerance and available resources, may employ deterrent measures or even plant less attractive crops. Through simulation of behaviours on the individual level, ABM may shed light on how localised actions translate into broader patterns of conflict or coexistence (McLane et al., 2011).

This study applies agent-based models to the area of Nilgiris and describes the spatial and temporal dynamics of human-wildlife conflict, and examines the efficacy of two standard mitigation measures: physical deterrents and crop switching. Also included is a baseline model that does not apply any intervention for comparison. Doing so intends to provide evidence-based insights to support land-use planning, conflict management, and policy decisions that promote coexistence in areas of high conflict.

Literature Review

There have been many studies of human-wildlife conflicts in ecological and socio-environmental research, given the threatening nature of such incidents on rural livelihoods and biodiversity conservation. Various studies report that a conflict appears to arise when agricultural expansion occurs near forested areas and wildlife habitats, causing an overlap between human activities and animal movement routes (Alipoura et al., 2016; Karanth & Ranganathan, 2018; Shaffer et al., 2019). Environmental conditions such as water quality in agricultural landscapes can also influence crop productivity and attractiveness to wildlife, further intensifying conflict risk (Alipour et al., 2016). Typically, wildlife targets highly nutritious value crops such as banana, maize, and jackfruit, and hence it is easy for them to do so (Nyhus, 2016).

Several traditional approaches to conflict mitigation, such as electric fencing, compensation schemes, and relocation, have been implemented across regions, but many of these methods provide only short-term solutions and do not consider the behavioural dynamics of both farmers and wildlife (Shaffer et al., 2019). There is increasing recognition that long-term strategies must incorporate spatial patterns, seasonal variation, and local adaptation mechanisms in order to be effective.

Conflict management is effective when it happens among different stakeholders and the acts are coordinated. Historically, international NGOs have facilitated peace and security in areas of conflict by promoting dialogue, creating resources, and encouraging community-based resolutions (Ayaz, 2019; Ramakrishnan et al., 2015). Similar NGOs can play a parallel role in the human-wildlife conflict by raising awareness, supporting local communities, and implementing sustainable coexistence measures.

Recently, ABM has become a potent tool for investigating the intricate interplay in human-environment settings. ABMs simulate the decision-making process and interactions of individual agents who are heterogeneous in space (Grimm & Railsback, 2005). It is especially useful in understanding humankind-wildlife conflicts where wildlife agents (like elephants or wild boars) respond to landscape features and resource availability, while human agents (such as farmers) may change their behaviour based on perceived risk and past experiences (Crevier et al., 2021).

Tracey et al. (2014) argued the usefulness of ABM in studying the influence of landscape fragmentation on conflict behaviour and wildlife movement. (Musayev et al., 2022) implemented agent-based simulations to investigate agricultural choices under the shadow of environmental risks. In related settings, (Shahpari & Eversole 2023) employed ABM to analyse how farmers change land use under conflict pressures and policy shifts. These studies show how ABM integrates ecological data, land-use patterns, and social behaviour into one simulation environment.

Standardising documentation of ABM structure and logic via the ODD (Overview, Design concepts, and Details) protocol, as initiated by (Grimm et al., 2020), instils transparency and reproducibility in ABMs. This approach enables clear communication regarding the model's structure by researchers and facilitates replication by others. Furthermore, (Baskaran et al., 2024) highlight the need to focus on conflict hotspots and main causes of elephant-related crop damage in the Nilgiri Biosphere Reserve as an important context for spatial modeling (Nasrallehzadeh et al., 2023). Conducting sensitivity analysis is also pivotal in these modeling studies to ascertain how variations in input parameters affect the results. According to (Helton & Davis 2003), global sensitivity analysis utilising Random Latin Hypercube Sampling is suggested to investigate parameter uncertainty in complex systems.

Nevertheless, very few studies have been implemented to model human-wildlife conflicts at a landscape scale with ABM, particularly within an Indian setting of a biodiversity-rich zone like the Nilgiris. In spite of the availability of ecological data and incident reports, however, their use in conflict scenarios and mitigation strategy simulation remains an enormous gap. This study attempts to reduce that gap by using ABM to simulate farmer-wildlife interactions in a spatially explicit environment for conflict hotspot mapping, behavioural adaptation, and the assessment of deterrents and crop-switching strategy effectiveness.

Materials and Methods

Study Area

The study area lies in the Nilgiri District of Tamil Nadu, India, which is only a part of the Nilgiri Biosphere Reserve. The region is a matrix of forests, tea plantations, vegetable farms, and settlements. The tiger reserves of Mudumalai and Bandipur are linked through wildlife corridors. The area is prone to human-wildlife conflicts, mainly in crop-raiding by elephants, wild boars, and gaurs and livestock depredation by leopards. Crop-raiding and wildlife conflicts occur where agricultural activity extends to forest edges and where high-value crops such as banana, jackfruit, and vegetables are cultivated along forest peripheries. The area is located at an elevation of 900–2,600 m, has a subtropical climate, and receives rainfall ranging from 1,200 mm to 2,500 mm. The study area was chosen because of the high level of conflict intensity and the availability of secondary data through sources like the Forest Department and earlier studies (Baskaran et al., 2024).

Research Design

To represent agent-environment interaction in this study, we captured the complex nature of the human-wildlife conflict in which farmers and wildlife make decisions affecting each other. An ABM is an apt tool for the system under study, since individual behaviours generate landscape-level behaviour such as wildlife crop-raiding (Tracey et al., 2014). For clarity of documentation and to help with transparency and replicability, the model followed the ODD protocol (Overview, Design concepts, and Details; Grimm et al., 2020). It was developed and executed in NetLogo (version 6.1.1), which is a mainstream platform used in ecological and socio-environmental modelling because of its capability of visualising the interaction among agents in a spatial environment (Wilensky & Evanston, 1999). This framework was chosen since it provides the greatest flexibility in terms of including decision-making by wildlife and by farmers (Grimm &Railsback, 2005; Crevier et al., 2021).

Data Sources

The study used data from reliable sources to ensure accuracy. Land use and land cover maps came from the Forest Survey of India and the Bhuvan ISRO platform, both of which provide verified geospatial data for research. These maps were used to define agricultural areas and forest boundaries. Conflict incident records were sourced from official reports of the Tamil Nadu Forest Department for the period between 2018 and 2023. Authenticity regarding events was checked against local media and departmental publications. This included the collection of socio-economic data during farmer visits using a structured form with informed consent and from secondary reports on crop types and farming systems (Musayev et al., 2022). From the peer-reviewed literature and elephant corridor maps of the Wildlife Trust of India (WTI), accepted standards for conservation planning in the area were extracted for wildlife movement patterns. Each data source was duly acknowledged and cited for academic purposes with proper consideration to ethical issues and intellectual property rights. These datasets were used for agent attribute initialisation and spatial environment construction of the simulation.

Model Structure

The ABM was made up of three central components: agents, environment, and processes. There were two classes of agents. The wildlife agents consisted of elephants, wild boars, sloth bears, Indian porcupines, bonnet macaques, and gaurs. Each animal had traits such as energy, ability to move, and risk perception, and they moved depending on habitat quality, distance to crops, and deterrents (Crevier et al., 2021). The second class consisted of the farmers who were the units of representation for households with traits such as land size, crop type, and conflict tolerance. Farmers could react to crop damage either by using deterrents themselves or by planting crops less attractive to wildlife per their past experience (Shahpari & Eversole, 2023; Brady et al., 2012). The environment was made up of a grid consisting of 100×100-m cells that were categorised as forest, farmland, settlement, or road. The farmland cells had attractiveness values for crops, with banana being highly attractive to wildlife, moderately attractive to vegetables, and less attractive to tea.

The simulation was run in discrete daily time steps. Conservationist agents moved in between the cells of the landscape, each step, with an energy-gain vs risk trade-off (Crevier et al., 2021). Whenever a conservationist entered a crop cell, a conflict event would be registered by the farmer agent linked to that field. Upon such conflicts or damages, the farmer agent chose either to install deterrents, such as fencing or watchtowers, or to switch to less attractive crops whenever these conflicts surpassed the farmer-agent's threshold of tolerance (Brady et al., 2012).

Simulation Scenarios

The investigation was conducted in three different management scenarios to test their effects on decreasing conflict between humans and wildlife. Scenario one considered the assumed baseline, whereby the current landscape was modeled without any interventions. Scenario two dealt with deterrence: farmers undertaking measures such as fences or watchtowers to keep wildlife away from their fields. Scenario three dealt with switching crops so that farmers can replace high-risk crops that attract wildlife with less attractive ones. Each of these scenarios was simulated for one cropping season, assumed to last 120 days. To minimise randomness and hence ensure reliability of the results, each scenario was repeated 100 times (Tracey et al., 2014).

Model Calibration and Validation

Adjustment of the model parameters was undertaken to reproduce the real behaviour of wildlife and farmers. Wildlife agents would have movement patterns adjusted with knowledge from GPS data for elephants and wild boars, as reported by the Wildlife Trust of India, or even others (Marley et al., 2019). The decision-making rules for farmer agents were verified using information from field surveys and insights from earlier agent-based modeling studies in agricultural systems (Musayev et al., 2022). To check the accuracy of the model, the simulated outputs, including the spatial distribution of crop-raiding events, were compared with actual conflict records from the study area. This comparison helped to validate that the model produced results close to real-world patterns.

Output Metrics

Hereafter, several performance indicators were developed to evaluate the effectiveness of the model and managerial options. First is the number of conflict events generated in each scenario, and thus examines how frequently wildlife entered crop fields and caused damage (Crevier et al., 2021; Goswami et al., 2015). Second, the percentage of crop loss for different farm types indicates the economic effects of wildlife activities on small, medium, and large farms (Musayev et al., 2022; Shaffer et al., 2019). The third indicator analyses the overall reduction of conflicts by each management method as compared to the base situation, quite a common way of assessing in agent-based simulation studies (Tracey et al., 2014; Nyhus, 2016). These management methods involved the use of deterrent methods and the switching of crops. The success of such methods has been evaluated by the decrease in crop-raiding incidents and the losses due to them. Alongside the above indicators, the spatial configuration of wildlife movements and conflict sites was also examined to develop an understanding of how landscape changes and farmer behavioural changes have influenced wildlife access into agricultural areas. Similar methods have been used in earlier studies on human-wildlife interactions and land-use planning (Brady et al., 2012; Grimm et al., 2020). Spatial hotspot mapping techniques, such as kernel density estimation and weighted severity indices, have also been applied in other fields, for example, in identifying urban traffic black spots (Sing, 2024). These approaches demonstrate the versatility of spatial analysis tools for pinpointing high-risk zones, which is directly relevant for mapping conflict hotspots in the Nilgiris.

Sensitivity Analysis

Global sensitivity testing is used to determine how shifts in parameters alter model outcomes. In that step, you assured the accuracy of agent-based modeling, where slight changes in inputs could lead to altered outputs. The study involved testing the three main parameters: wildlife density, effectiveness of deterrents, and attractiveness of the different crops for wildlife. They varied wildlife densities to see how crop-raiding incidences would be affected by increasing population pressure: low, medium, or high. Meanwhile, the parameter of deterrent effectiveness was also manipulated to represent different levels of success of methods, for example, fencing and watchtowers. Similarly, crop attractiveness values were changed to study conflict patterns when more or fewer high-risk crops, such as bananas, were planted. Each parameter set ran through many simulations to bring out variability and look for the most sensitive ones. The sensitivity analysis then pointed out those parameters that strongly impact the frequency of conflict, crop loss, and management success, so that there was confidence in the results of the model (Tracey et al., 2014; Helton & Davis, 2003).

Results

Human-Wildlife Conflict Events

The NetLogo simulation showed clear differences in the number of crop-raiding events under three management scenarios. In the Baseline scenario, which reflected current practices without interventions, the model recorded an average of 420 conflict events per cropping season. The deterrent strategies, which included fencing and watchtowers, brought this number down to 220. Crop-switching yielded the greatest reduction in conflict events with 150, against the baseline, thus a reduction of 64% (Wilensky & Evanston, 1999).

Simulated conflicts grasped the most important wildlife species, such as elephant (Elephas maximus), wild boars (Sus scrofa), sloth bears (Melursus ursinus), Indian porcupines (Hystrix indica), bonnet macaques (Macaca radiata), and gaur (Bos gaurus). These animals accounted for nearly all of the crop damage, mainly on banana, maize, and sugarcane fields. Smaller crops were damaged by species such as porcupines and monkeys, especially those near the forest edge. Farms closer to forest patches and known corridors experienced very high numbers of conflict events. This is typical of the Nilgiris landscape, wherein a mosaic of forests and farmlands is interspersed with major wildlife corridors facilitating animal movement (Balasundaram et al., 2015).

Table 1. Summary of human-wildlife conflict events and crop loss across management scenarios

Scenario	Description	Avg. Conflict Events	Avg. Crop Loss (%)
Baseline	No mitigation strategies applied	420 ± 18	18%
Deterrent	Farmers use fences and watchtowers	220 ± 12	10%
Crop Switching	Farmers replace high-risk crops with low-risk crops	150 ± 10	6%

Across all simulation runs (n=100 per scenario), the number of human-wildlife conflict events showed measurable variation. In the Baseline scenario, the mean number of crop-raiding incidents was 420 ± 18 (SD). In comparison, as shown in Table 1, the Deterrent scenario recorded 220 ± 12 (SD), and the Crop Switching scenario averaged 150 ± 10 (SD) events per season. A 95% confidence interval showed that crop loss in the Baseline scenario ranged between 16.5% and 19.3%, while it ranged between 5.2% and 6.8% in the Crop Switching scenario. These results confirm the relative stability and robustness of the modelled outcomes across multiple runs (Figure 1) (Wilensky & Evanston, 1999; Grimm & Railsback, 2005).

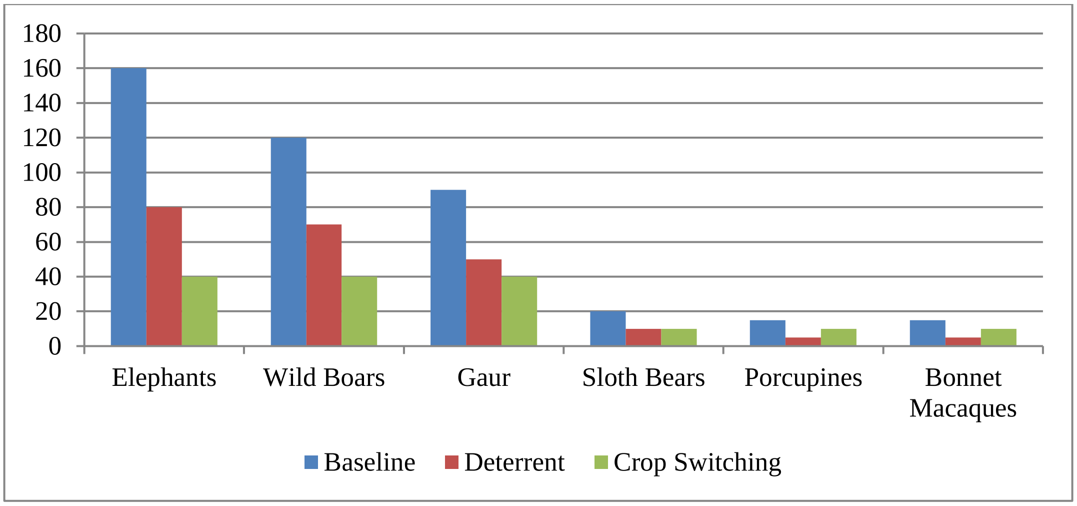

Figure 1. Comparison of crop-raiding incidents by species across management scenarios

This displays the number of simulated crop-raiding incidents all combined, which can be caused by different wildlife species under the three scenarios: baseline, deterrent, and crop-switching scenarios. The largest conflict contributors were those of elephants and wild boars, especially under baseline conditions, but crop switching reduced the number of incidents from all species.

Crop Loss and Plant Attractiveness

Crop damage differed greatly under the three human-wildlife management scenarios. Crop loss averaged 18% under the Baseline scenario, with no mitigation measures implemented. With fence and watchtower deterrents on, the crop loss was halved to 10%. Under the Crop Switching scenario, where farmers would switch risky crops for less attractive ones, crop loss was recorded as the lowest, at 6% (see Figure 2 for details).

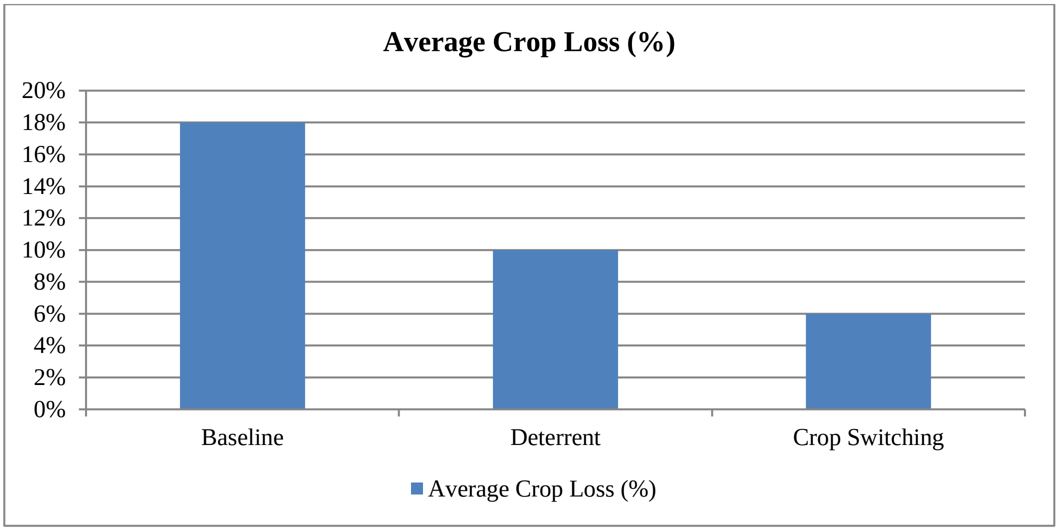

Figure 2. Average crop loss across management scenarios

The bar chart illustrates the average percentage of crop loss under the Baseline, Deterrent, and Crop Switching approaches. Crop loss is highest in the Baseline arrangement (18%) and lowest under the Crop Switching arrangement (6%), with the mitigation approach's relative effectiveness reflected accordingly.

A great extent of human-wildlife conflicts was witnessed due to wildlife's preference for crops in the Nilgiris. Whereas banana, jackfruit, and maize were hardly grown in the high altitudes, they were cultivated in smaller amounts in lower elevation farms near the forest edges. These were the most attractive crops for elephants, wild boar, and gaur, and the damage was very frequent. Traces, however, were observed to some extent of damage in carrot, beetroot, potato, tubers, and some fruit, caused mainly by Indian porcupine, bonnet macaques, and sloth bears. Tea, coffee, and lemongrass crops presented little wildlife attractiveness and hence were least affected (Hockings & McLennan, 2012). These low-risk crops that are widely grown in the Nilgiris are more suitable for farms located near forest boundaries and along wildlife corridors (see Table 2). The existence of a variety of wildlife species brings in a handful with different crop preferences and, thus, places importance on crop planning and mitigation strategies based on localised conditions (Karanth et al., 2012).

Table 2. Wildlife crop preference matrix in the nilgiris region

Crop Type	Elephants	Wild Boars	Gaur	Porcupines	Macaques	Sloth Bears
Banana	High	High	Medium	Low	Medium	Low
Maize	High	Medium	High	Low	Low	Medium
Jackfruit	High	Medium	Medium	Medium	Medium	Low
Vegetables	Medium	Medium	Medium	Medium	Medium	Medium
Tuber crops	Low	Medium	Low	High	High	Medium
Tea	Low	Low	Low	Low	Low	Low
Lemongrass	Low	Low	Low	Low	Low	Low

The table indicates the relative preference of common crops to some important wildlife species, based on simulation parameters and literature. Levels of preferences are indicated in colours: High (Red), Medium (Yellow), and Low (Green), and thus represent the likelihood of crop-raiding by a given species.

There are very clear differences in crop loss that depend on farm size and tolerance levels. Farms classified as smallholder (<1 hectare) generally suffered average losses much higher than their counterparts. For instance, more than 70% of them sustained crop damage exceeding 10% under the Baseline scenario. Medium- and large-sized farms suffered relatively lower losses, in part, due to better buffer zones and greater area between their crop plots and forest edges. Farmers with lower tolerance thresholds (≤ 0.1) were faster to implement deterrents or opted to change cropping practices to curb losses, which, in turn, led to further reduction with time. Adaptations thus influenced the proper utility of management interventions at both individual and landscape scales (Musayev et al., 2022; Nafiza Begum & Vijaya, 2024; Shahpari & Eversole, 2023).

Simulation and Environmental Setup

The NetLogo Agent-Based Model for a 100 km² area in the Nilgiris divided the land into 10,000 patches (each 100×100 m) and categorized them as Trees (50%), Crops (15%), Built areas (7%), Rangeland (27%), and Water bodies (1%) (Patel, 2025). This spatial arrangement has been obtained from the land use/land cover data and imitates a fairly realistic agro-forest mosaic typical of the region (refer to Figure 3). Wildlife agents consisted of elephants (Elephas maximus), wild boars (Sus scrofa), gaur (Bos gaurus), sloth bears (Melursus ursinus), Indian porcupines (Hystrix indica), and bonnet macaques (Macaca radiata). Each species was assigned a daily movement range of 1-6 km, an energy preference for different crop types, and variable tolerances for risk. The model further simulated 500 farmer agents, one tied to each a unique farm unit, where attributes including farm size, location, crop type, mitigation strategy, and tolerance threshold for conflict had been specified. Farmer actions were reactive in nature; the agents may have adopted deterrent measures (e.g., fences, watchtowers) or switched to less attractive crops after repeated incidents of crop damage. Three management scenarios, Baseline, Deterrent, and Crop Switching, were simulated over a cropping season of 120 days. Each scenario was run on 100 replications to eliminate the effect of randomness and to render the averages of the outcomes across the replications.

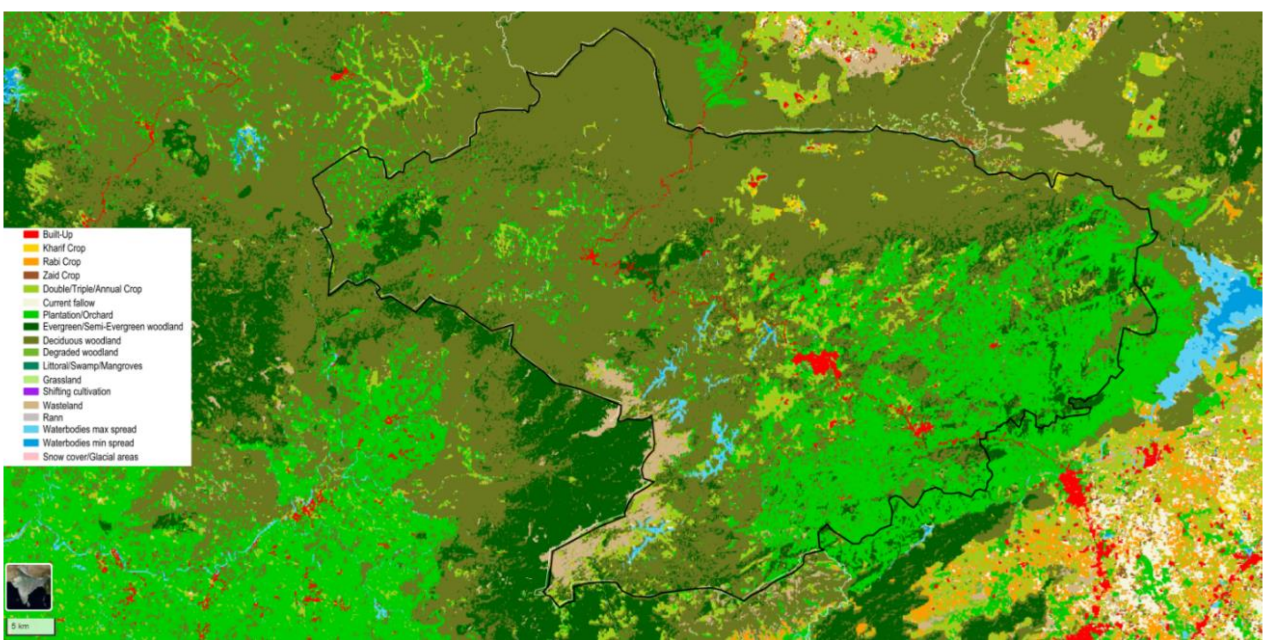

Figure 3. Land use and land cover (lulc) classification map of the nilgiris district (indian space research organisation, national remote sensing centre, n.d.)

A spatial map showing the distribution of the major land-cover types, such as forests, croplands, built-up areas, rangelands, and water bodies in the Nilgiris has been prepared. The classification supports the spatial setting used in the NetLogo simulation model for the analysis of human-wildlife conflict (Wilensky, 1999).

Spatial Patterns of Conflict

The simulation showed that crop raiding didn't happen everywhere in the study area but was mainly concentrated in a few hotspot locations. These hotspots were mainly located near the edges of forests, wildlife corridors, and fields with crops that are attractive to animals, such as banana and maize. Conflicts in the Nilgiris are mainly reported in the southern and eastern zones. These zones adjoin protected forest regions and elephant corridors like Sigur Plateau and Moyar Valley. The corridors have higher wildlife movements, particularly those of elephants. Farms and settlements along the corridors suffered intermittent damage. The crop raids mostly occurred in the early hours of the morning (from 5 to 8) and in the evening (from 6 to 9), which forms the usual time of activity of wild animals (Sukumar, 2006). Steep and hilly zones had more such conflicts. This is because that kind of terrain becomes difficult in the installation and monitoring of deterrents like fences or watch towers. In such places, even the smaller critters like porcupines and monkeys damaged the crops, particularly those growing tubers and fruits (Figure 4).

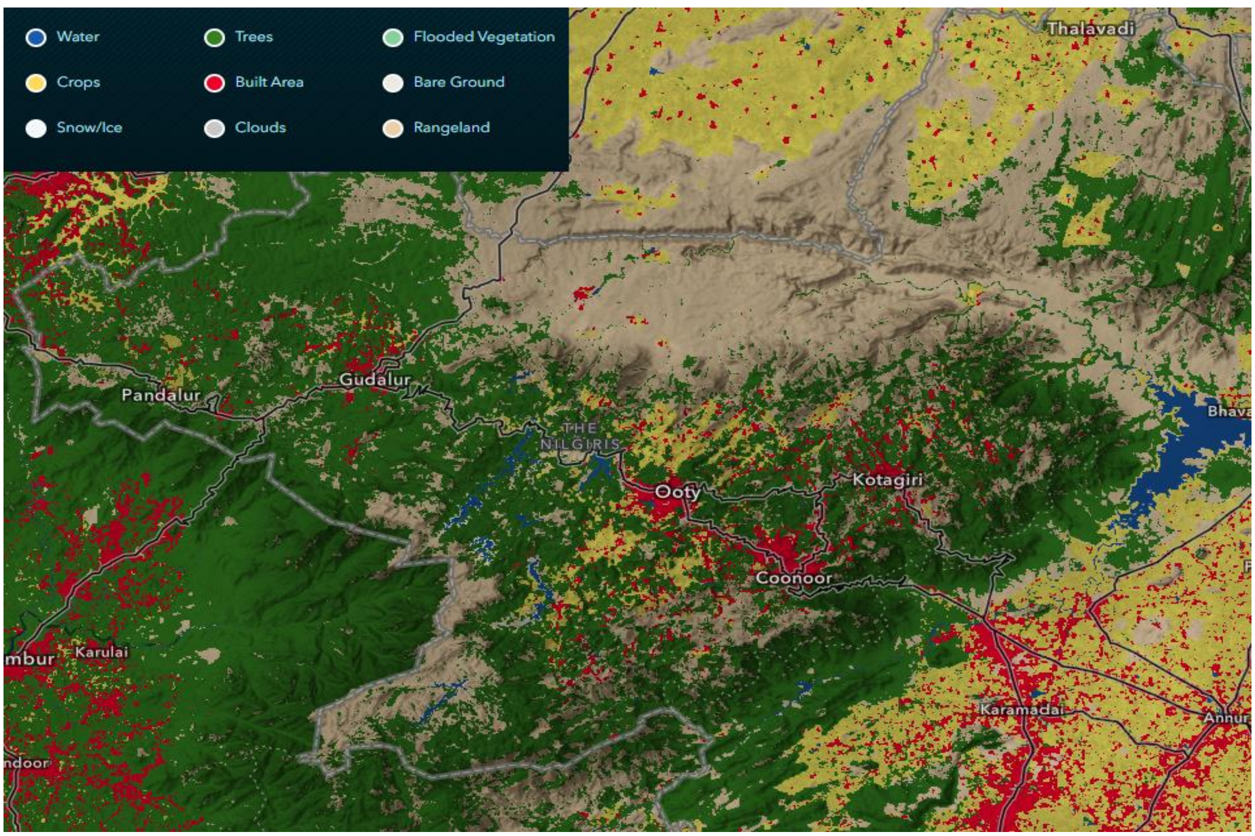

Figure 4. Spatial distribution of conflict hotspots and land cover in the nilgiris district (esri & impact observatory, 2024).

The map illustrates crop-raiding hotspots in relation to land cover types such as forests, croplands, and built-up areas. Frontier cases are less concentrated or are located solely in wildlife corridors near Ooty, Coonoor, Kotagiri, and the Sigur Plateau, and thus, the case encompasses a spatial conflict set between human and wildlife movement patterns.

Farmer Behaviour and Adaptive Responses

The simulation showed human behaviour when their crops have been damaged by a wild animal. Whereas most farmers experienced moderate crop loss without taking any action under the Baseline scenario, they just continued growing the same crops without protective apparatuses. Inhibiting actions began to be used by 70 per cent of the farmers in the Deterrent scenario, whose presence helped lower the incidences of crop raids from time to time. Farmers with higher levels of crop damage were more likely to use deterrents earlier in the simulation than those with lower levels of crop damage. In the Crop Switching scenario, many farmers stopped growing high-risk crops like banana and jackfruit. Instead, they chose less attractive crops such as tea, lemongrass, or finger millet. This change was seen mostly among small and medium-sized farms, especially those located near forest edges or wildlife corridors (Shahpari & Eversole, 2023; Musayev et al., 2022). For farmers who live far away from the forest or in low-conflict zones, the probability of installing deterrents and changing the crops was very low. This shows that the level of conflict in each location influenced how farmers responded to wildlife damage (see Figure 5).

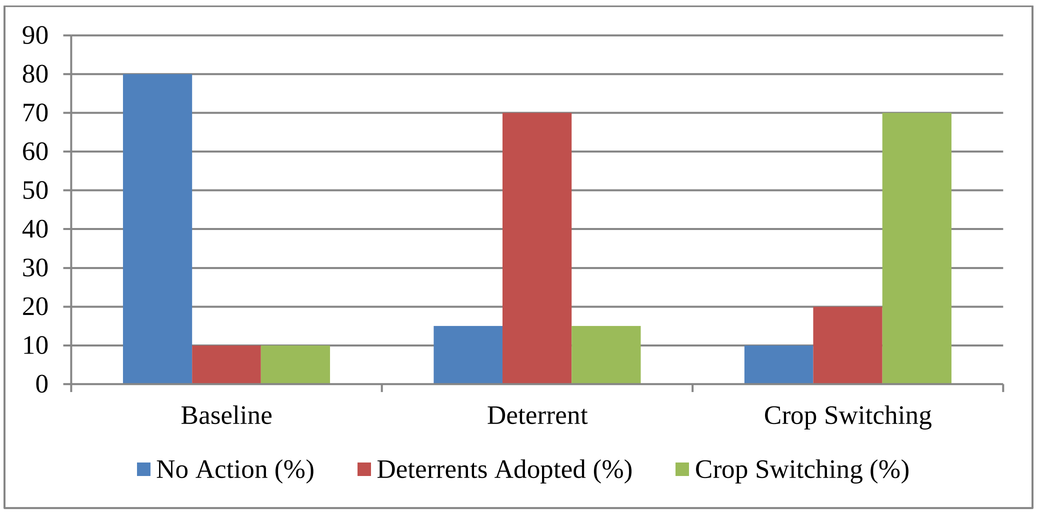

Figure 5. Farmer response patterns under different conflict management scenarios

The chart illustrates the percentage of farmers who took no action, adopted deterrents (e.g., fences, watchtowers), or switched to low-risk crops under three simulated conditions: Baseline, Deterrent, and Crop Switching. Results highlight adaptive behaviour based on conflict intensity and location.

Sensitivity Analysis Outcomes

A global sensitivity analysis was carried out to understand how key factors influenced the simulation results. Three main parameters were tested: wildlife density, effectiveness of deterrents, and crop attractiveness. The density of wildlife, especially elephants and wild boars, had the biggest impact on the number of conflict events. When elephant density was increased by 20%, the number of crop-raiding incidents rose by 35%. This shows that higher animal populations can lead to more frequent conflicts with farmers. The effectiveness of deterrent methods, such as fences and watchtowers, was also important. When these tools were only 50% effective, their impact on reducing conflict dropped sharply. This result indicates that the maintenance of a deterrent and its consistent use by farmers is of paramount importance. Then, the attractiveness of crops seems to have largely influenced wildlife movement. Farms that grew more of these high-risk crops, like banana, maize, or jackfruit, were more regularly damaged across a larger area. Therefore, replacing these crops with less attractive ones, like tea or lemongrass, will lessen the conflicts. The findings suggest that density of wildlife, quality of deterrents, and types of crops play a major role in the manifestation of conflicts; thus, managing them may help better channel efforts towards reducing human-wildlife conflict in high-risk areas.

Wildlife Movement and Seasonal Trends

Simulating wildlife movement along the landscape using this method showed that, under certain conditions, elephants exhibited long-distance movement with more than one land patch crossed in a day. Elephant movement was more pronounced in the dry season, when food and water became scarce in the forest. In contrast to that, wild boars and porcupines were generally active near forest edges, moving very short distances but always returning to the same crop fields, especially those attracting certain crops (Shaffer et al., 2019).

Seasonal changes had obvious effects on the movement of wild animals. During such dry months, activity would be much higher, and so there would be those incidents of crop raiding. These observations came true with field observations and prior studies of seasonal conflict in the Nilgiris, thus confirming that a shortage of food in forests increases the prospects of human-wildlife interaction (Baskaran et al., 2024; Fernando & Leimgruber, 2011).

Comparison with Observed Conflict Reports

The simulation results closely reflected real-world patterns documented by local authorities. The modeled average of 420 conflict events per cropping season under current conditions closely mirrors the 400–450 incidents annually reported by the Tamil Nadu Forest Department between 2018 and 2023. The simulation found hotspot zones, like the Sigur Plateau and the eastern farming areas, which match known high-conflict regions. This means the model closely reflects real-world situations and can be useful for planning different scenarios (Manickavasagam et al., 2024).

Discussion

This study used an agent-based modeling approach to simulate human-wildlife conflict in the Nilgiris district, focusing on interactions between farmers and wildlife under different management scenarios. The model was able to incorporate real land-use data, crop types, wildlife behaviour, and farmer responses to yield conflict patterns for a 100 km² landscape. It was found that wild animals were responsible for most crop damage and that elephants, wild boars, and gaurs were the species most responsible for these damages, especially near the forest edge and corridor areas. Crop attractiveness influenced the degree of conflict, with bananas, jackfruit, and maize being the most significant. Spatial analysis showed that conflict hotspots in the southern and eastern Nilgiris coincided with known wildlife corridors such as the Sigur Plateau.

The simulation study clearly showed that management actions can greatly reduce the conflict. Switching crops was most effective and managed to reduce conflict events and crop loss much more than deterrents. The sensitivity analysis also confirmed that wildlife densities, effectiveness of deterrents, and crop type have the strongest influence on the conflict outcomes. Moreover, farmers responded to the conflict in a dynamic manner, with those incurring high losses willing to adopt mitigation measures. Smallholder farms closer to the forest were those suffering the worst loss, but were equally highly responsive to conflict. The conflict interactively amplified through the seasonal movements of wildlife, particularly in the dry months, aligned with the observed trend in the region. The model outputs showed a good agreement with real conflict records obtained from the Tamil Nadu Forest Department, thus confirming the reliability and accuracy of the model. This legitimises the application of agent-based modeling as a formidable technique in understanding complex socio-ecological systems like human-wildlife conflict. It also draws attention to the need for spatial data, agent-behavioural overcrowding, and scenario-based approaches in mitigating the conflicts.

Conclusion

The research has proven that the use of agent-based models can simulate and analyse conflicts between man and wildlife in an extremely intricate agro-forest landscape such as that in Nilgiris. The model identified spatial hotspots, crop preferences, and the relative effectiveness of the control methods. From the various scenarios tested, changing crops was identified as the best way to reduce crop damage and the frequency of conflicts, with the deterrents following behind. This stresses the fact that area-specific strategies should be developed based on wildlife movement, crop selection, and farmer behaviour. These insights can help guide policies and conservation plans that support peaceful coexistence between people and wildlife, while still allowing farming to continue. In the future, the model can be improved by including more animal species, longer time periods, and economic factors. To manage lands in areas where human-wildlife conflict is common, this would make it even more useful.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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