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Agent-based modelling of urban macaque-human conflict: evaluating mitigation strategies in Guwahati, India

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Agent-Based Modelling of Urban Monkey–Human Conflict: Evaluating Mitigation Strategies in Guwahati, India

Abstract

Urban human-monkey conflict is an increasing management concern across many Indian cities, where forest fragments, food provisioning, and unmanaged waste attract monkeys into human settlements. Guwahati represents one such conflict hotspot, yet testing mitigation measures directly in real environments is often costly, slow, and ethically constrained.

To address this challenge, we developed a spatially explicit agent-based model in NetLogo that integrates GIS-derived land-use data with rule-based primate behavioural dynamics to simulate monkey–human interactions across the Guwahati landscape. The model was initialised using observed troop locations and population estimates and simulates interactions between 1299 monkeys organised into 58 troops and human agents distributed across built-up and agricultural areas. Monkey movement is driven by internal behavioural states such as hunger and fear and by surrounding habitat conditions. Simulations were run for 1000 ticks per scenario with 30 replicate runs to ensure statistical robustness. The model captures monkey movement, foraging behaviour, and probabilistic conflict events, and was used to evaluate six mitigation strategies: feeding prohibition, population control, garbage management, fruiting tree plantation, translocation, and conservation education. Additional scenario experiments were conducted across varying human population densities to assess the robustness of intervention outcomes.

Simulation results indicate that interventions targeting human behaviour are substantially more effective than those focusing solely on ecological manipulation

or population control. Conservation education produced the only consistent and statistically significant reduction in conflict across human population scenarios ($F = 58.57$, $p < 10^{-13}$, effect size = 38.2), while other strategies showed comparatively limited additional benefit. Translocation alone produced little improvement and occasionally increased conflict temporarily (effect size = -4.95).

These findings highlight the value of spatially explicit agent-based modelling as a practical decision-support tool for evaluating urban wildlife conflict mitigation strategies prior to real-world implementation.

Keywords

Human-wildlife conflict, Agent-based model, NetLogo, Urban ecology, Macaque, Guwahati, Mitigation strategies

1 Introduction

Human-wildlife conflict is increasingly recognized as an inevitable outcome of rapid urban expansion, habitat fragmentation, and the ecological adaptability of certain wildlife species to anthropogenic environments (Madden, 2004; Soulsbury and White, 2016). As cities expand into natural habitats, wildlife species that exhibit behavioural plasticity, dietary generalism, and cognitive adaptability often thrive in these modified landscapes. Among such species in India, monkeys, particularly macaques, have emerged as prominent urban conflict agents due to their ability to exploit human-dominated resources (Anand et al., 2018; Beisner et al., 2015).

Macaques are highly adaptable primates capable of adjusting their foraging strategies, social organization, and movement patterns in response to human presence. Their omnivorous diet and learning ability enable them to utilize anthropogenic food sources such as garbage dumps, crop fields, and deliberate food provisioning by people (McLennan et al., 2017; Southwick and Siddiqi, 1972; Marshall and Wrangham, 2010). Religious and cultural practices that encourage feeding of monkeys further reinforce their associ-

ation with human settlements, creating a feedback loop that increases the frequency of interaction and potential conflict (Sengupta and Radhakrishna, 2018).

Across India, urban centres such as Shimla, Delhi, and Guwahati report frequent incidents of monkey–human conflict, including food snatching, property damage, aggression, and occasional injuries (Gopalan and Radhakrishna, 2022; Ganguly et al., 2018; Devi and Saikia, 2008). These interactions are not merely behavioural anomalies but are symptomatic of deeper ecological drivers such as habitat loss, fragmentation of forest patches, and reduction of natural food availability (Medhi et al., 2007; Koirala et al., 2022).

In Northeast India, Guwahati has emerged as a significant hotspot of monkey–human conflict. The city is embedded within a matrix of hill forests and rapidly expanding human settlements. Forest fragments such as Nilachal Hill, Fatasil, and Khanapara Reserve Forest support multiple monkey troops that frequently traverse into residential areas in search of food. Improper garbage disposal, open waste dumps, and routine feeding practices near temples and households intensify these interactions. Reports of house invasions, food snatching, and aggressive encounters have become increasingly common in several localities of the city.

Testing mitigation strategies for such conflict in real landscapes presents substantial challenges. Field interventions such as translocation, population control, or habitat modification are expensive, ethically sensitive, and require long time frames to evaluate effectiveness (Massei et al., 2010; Hill and Webber, 2010). Moreover, poorly designed interventions can exacerbate conflict rather than reduce it. For example, translocation without addressing resource drivers often leads to conflict relocation rather than resolution (Massei et al., 2010; Fontúrbel and Simonetti, 2011).

Agent-based modelling (ABM) provides a powerful alternative to empirically test such interventions in a controlled, simulated environment. ABMs allow researchers to represent individual animal behaviour, spatial heterogeneity of landscapes, and dynamic interactions between wildlife and humans (DeAngelis and Diaz, 2019; McLane et al., 2011; Railsback and Grimm, 2019). In the context of human–wildlife conflict, ABMs have been successfully used to simulate elephant movement, carnivore livestock depredation, and

urban wildlife foraging patterns (Diaz et al., 2021; Recio et al., 2020). Such models are particularly useful in urban ecology where fine-scale behavioural decisions lead to emergent large-scale conflict patterns.

Despite the growing application of ABMs in wildlife ecology, their use in understanding primate conflict in urban Indian landscapes remains limited. There is a need for spatially explicit, behaviour-driven simulation frameworks that integrate real landscape data with primate foraging behaviour and human activity patterns.

In this study, we develop an agent-based model using NetLogo to simulate monkey–human interactions in the heterogeneous urban landscape of Guwahati. Using land use land cover data and behavioural rules derived from primate ecology literature, we evaluate how these commonly recommended mitigation strategies perform when assessed simultaneously within the same system. The model aims to provide a decision-support framework for urban wildlife management and demonstrate how behaviour-driven simulations can inform conflict mitigation before costly field implementation.

2 Methodology

2.1 Study Area

This study was modelled using Guwahati as the landscape. It is the largest city in the northeastern part of India, located at 26.1445°N latitude and 91.7362°E longitude. The region experiences a humid subtropical climate characterized by distinct wet and dry seasons. The monsoon period (June to September) brings heavy rainfall, while winters are mild and relatively dry.

The city covers an area of approximately 262 km^2 and is situated along the banks of the Brahmaputra River, a major waterway that significantly influences the ecological landscape of the region. The urban environment consists of rolling hills, wetlands, and river floodplains, forming a heterogeneous mosaic of habitat types within and around the urban matrix.

Guwahati is bordered by several hill forests, including Nilachal Hill, Khanapara Re-

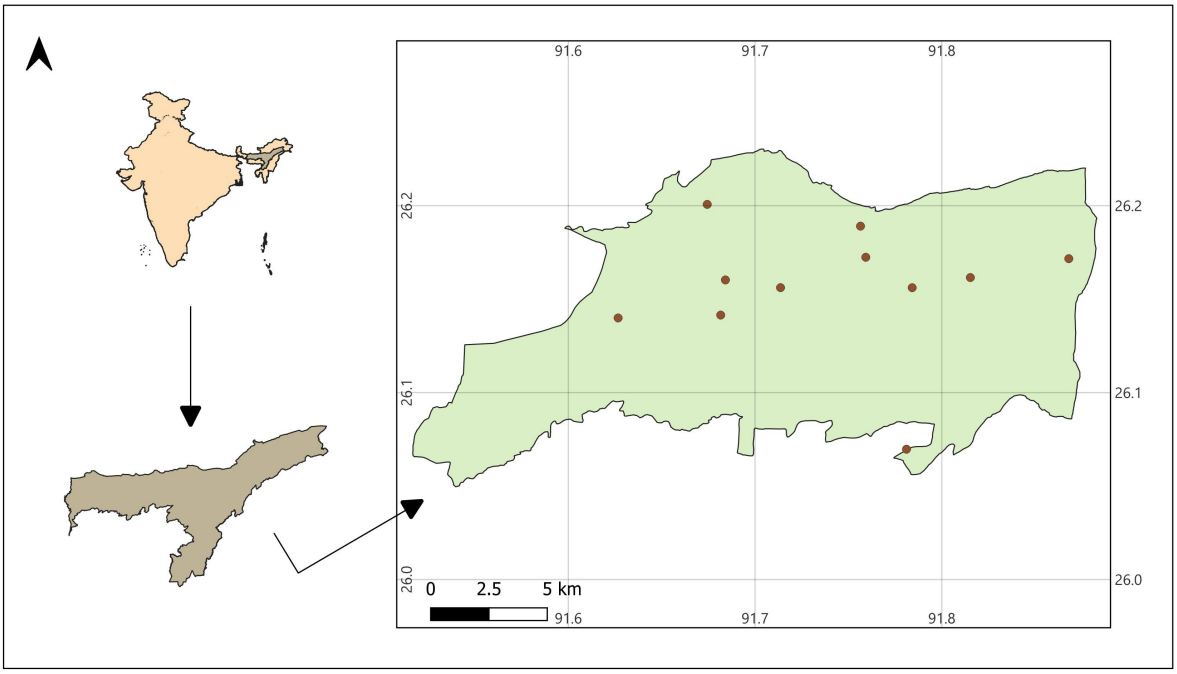


Figure 1: Study area map of Guwahati showing the locations of rhesus macaque (*Macaca mulatta*) troops used for model initialisation.

serve Forest, and other fragmented green patches embedded within dense human settlements. These forest fragments support multiple monkey troops that frequently move into residential areas in search of food, creating recurrent interfaces between wildlife and human habitation.

2.2 Landscape Representation and GIS Integration

A land use and land cover (LULC) map of the Guwahati Metropolitan Development Authority region was generated from Landsat 8 OLI imagery (25 November 2020) obtained from the United States Geological Survey. Supervised classification was performed in QGIS 3.40 using the Semi-Automatic Classification Plugin. A Random Forest algorithm with 500 trees was implemented to classify the study area into eight ecologically relevant classes: agricultural land, built-up areas, open forest, forest, grassland, water bodies, sand bars, and scrubland.

Classification accuracy was evaluated using an error matrix and area-based estimates, yielding an overall accuracy of 96.44% and a Kappa coefficient of 0.9473. Scrubland,

owing to its limited spatial extent, was retained in the landscape but excluded from formal accuracy assessment.

The classified LULC layers were exported as shapefiles and integrated into NetLogo to create a spatially explicit simulation environment. For modelling purposes, LULC classes were grouped into functional habitat categories representing forest patches, human settlements, open areas, and built surfaces. Each NetLogo patch inherited attributes from its corresponding LULC class, which determined habitat suitability, movement costs, and foraging probabilities for monkey agents. Initial troop locations were parameterised using observed field locations to ensure realistic spatial initialisation.

2.3 Model Platform

The model was developed in NetLogo version 6.3, a widely used agent-based modelling platform suitable for simulating individual-based movement, decision-making, and interaction in spatially explicit landscapes (Wilensky, 1999; Railsback and Grimm, 2019; Grimm et al., 2005). NetLogo allows integration of GIS layers with behavioural rules, enabling realistic representation of wildlife movement within heterogeneous urban environments. The model code is archived and available from the corresponding author upon request.

2.4 Model Description (ODD Protocol)

The model is described following the ODD (Overview, Design concepts, Details) protocol for agent-based models (Grimm et al., 2010).

2.4.1 Overview

Purpose. The model simulates interactions between urban monkey populations and humans in the city of Guwahati. The objective is to explore how landscape structure, food availability, and management interventions influence the frequency of monkey–human conflict. The model is designed as an exploratory decision-support tool rather than a predictive forecasting system.

Entities, State Variables, and Scales. The model includes two agent types: monkey agents and human agents. The environment is represented as a grid of spatial patches derived from a GIS land-use/land-cover (LULC) dataset containing forest, open forest, built-up areas, agricultural land, grassland, sand bars, and water bodies.

Monkey agents possess the following state variables: troop identity, leadership status, hunger level (0–100), fear level (0–100), and translocation status. Human agents possess the following state variables: position, conflict experience status, conflict type experienced, and conservation awareness.

The spatial extent corresponds to the mapped Guwahati landscape represented by the GIS dataset. Time advances in discrete ticks. Each simulation run lasts 1000 ticks. BehaviourSpace experiments replicate each scenario 30 times using different random seeds.

Process Overview and Scheduling. At each tick the following processes occur in sequence:

1. monkey hunger and fear updates 2. monkey movement decisions 3. monkey–human conflict detection 4. human movement 5. mitigation strategy implementation (if activated) 6. stochastic environmental disturbance events

Simulation stops after 1000 ticks.

2.4.2 Design Concepts

Basic Principles. The model is based on state-dependent behavioural rules in which monkey movement decisions depend on internal state variables such as hunger and fear and on the surrounding habitat type.

Emergence. Spatial patterns of monkey–human conflict emerge from the interaction of monkey movement behaviour, human presence, and landscape structure. No conflict hotspots are predefined.

Adaptation. Monkeys adjust their movement behaviour dynamically according to hunger level and perceived risk. High hunger increases the likelihood of entering built-up or agri-

cultural areas, while high fear promotes movement toward forest habitat.

Sensing. Monkeys perceive habitat types and resources within a neighbourhood radius of approximately five patches. Agents also detect humans occupying the same patch.

Stochasticity. Randomness enters the model through several processes, including turning angles during movement, probabilistic conflict occurrence, stochastic environmental disturbance, and variation in troop size during initialisation.

Observation. During simulations the model records total conflict events, food-stealing incidents, chasing behaviour, property damage events, monkey injuries and deaths, and spatial conflict hotspots.

2.4.3 Details

Initialisation. Monkey troops are initialised using a GIS dataset of observed monkey locations. The total population is set to 1299 individuals organised into 58 troops based on published survey estimates (Bhuyan, 2024). Troop sizes are drawn from a normal distribution centred on the observed mean troop size (22.4 individuals). Human agents are initialised on built-up and agricultural patches, with population size determined by scenario settings.

Input Data. The model uses a land-use/land-cover GIS shapefile representing the Guwahati landscape. Patch attributes derived from this dataset determine habitat suitability and potential locations of monkey–human interactions.

Submodels. *Movement and foraging.* Monkey movement follows rule-based behavioural decisions. When hunger exceeds a defined threshold, monkeys increase their probability of moving toward built-up or agricultural patches where anthropogenic food sources may be present. When fear levels are high, monkeys preferentially move toward forest patches. Otherwise agents perform a stochastic local movement with random turning angles.

Energy dynamics. Each monkey maintains a hunger level that gradually increases over time. Hunger decreases when monkeys occupy forest patches or obtain food during conflict events such as food stealing. Patches containing planted fruiting trees provide additional food resources.

Conflict generation. Conflict occurs when monkeys and humans occupy the same patch. Conflict events occur probabilistically, with outcomes including food stealing, chasing behaviour, property damage, or injury. These outcomes follow probability distributions derived from survey data.

Environmental change and mitigation. The model includes optional management strategies such as feeding prohibition, garbage management, population control, fruit tree planting, translocation, and conservation education. These interventions alter food availability, monkey behaviour, or conflict probability during simulation runs.

2.5 Model Parameters

Key parameters used in the simulation are summarised in Table 1. Where direct empirical estimates were unavailable, values were calibrated to produce realistic behavioural dynamics consistent with observations from urban macaque populations in Guwahati.

2.6 Agents

Two primary agent types were defined in the model (Table 2).

Monkey population size and troop numbers for initialisation were based on reported estimates from Guwahati (Bhuyan, 2024). Troop structure, daily movement range, and foraging preferences were parameterised using published primate behavioural studies (Ganguly et al., 2018; Devi and Saikia, 2008; Riley, 2007a; Southwick and Siddiqi, 1972; Marshall and Wrangham, 2010; Riley, 2010).

Movement decisions followed energy maximisation principles (Equation 1), where monkeys selected neighbouring patches based on weighted food availability and distance costs. A full parameter listing is provided in Table 1.

Table 1: Key model parameters, values, and sources

Parameter	Value	Range tested	Source
Total monkey population	1299	–	Field survey data
Number of troops	58	–	Field survey data
Average troop size	22.4 individuals	15–40	Field survey data
Troop size variation (SD)	7.26	–	Field survey data
Monkey movement search radius	5 patches	3–8	Model assumption
Monkey step length per tick	1–1.5 patches	–	Model rule
Hunger increase rate	+0.5 per tick	0.3–0.7	Calibrated
Forest food energy gain	-2 hunger units	1–4	Calibrated
Additional energy from fruiting trees	-2 hunger units	1–3	Model assumption
Food reward from human conflict (food stealing)	-30 hunger units	20–35	Calibrated
Conflict probability (human presence)	0.7	0.5–0.8	Calibrated
Conflict probability with educated humans	0.5	–	Model rule
Habitat destruction probability	Slider controlled	0–100%	Scenario analysis
Population control intervention rate	2% of urban monkeys	–	Management scenario
Garbage management implementation probability	30%	10–50%	Scenario analysis
Fruiting tree planting events	5 patches per cycle	–	Scenario analysis
Translocation effort	3 monkeys per intervention	–	Management scenario
Simulation duration	1000 ticks	–	Model design
Replicate runs per scenario	30	–	BehaviourSpace experiment

2.7 Conflict Definition

A conflict event was recorded when monkeys entered human settlement patches, accessed garbage or other anthropogenic food sources, or remained within settlement patches beyond a defined time threshold (three ticks; see Table 1). Additional conflict metrics such as stealing, chasing, property damage, injuries, and monkey mortality were also recorded during simulations (Saraswat et al., 2015; Beisner et al., 2015). These secondary outcomes were assigned probabilistically upon conflict detection, using empirically informed probability weights derived from field-documented proportions of conflict types in Guwahati.

Table 2: Agent types and behavioural roles in the model

Agent	Behaviour
Monkeys	Movement, foraging, troop cohesion, attraction to food sources, conflict generation
Humans	Static settlement patches, waste generation, feeding behaviour

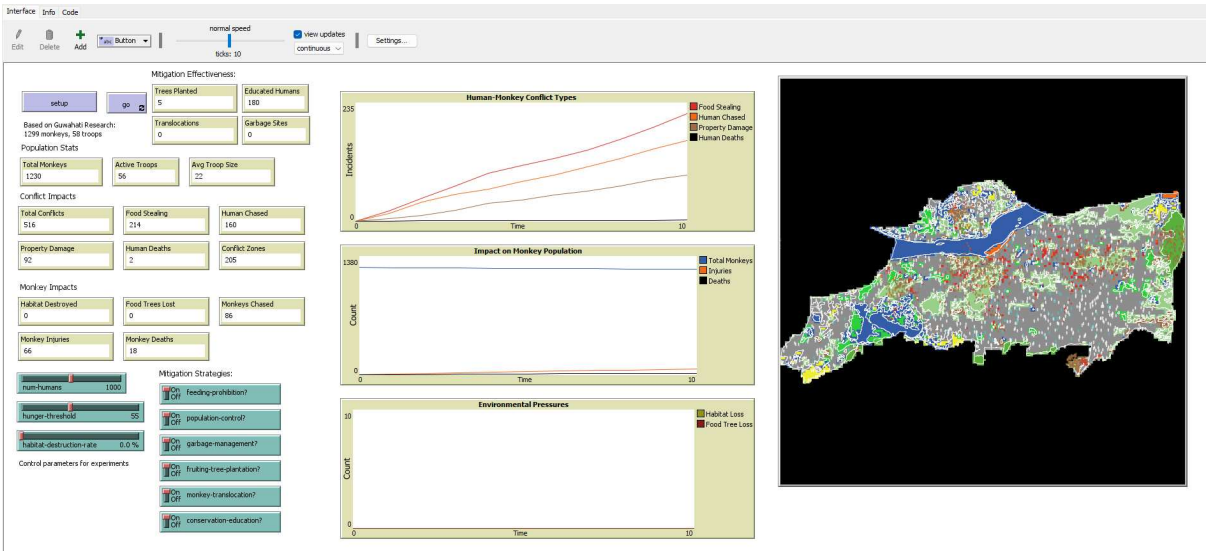


Figure 2: NetLogo simulation interface showing the Guwahati landscape with land use classes, monkey agent positions (coloured by troop identity), and real-time conflict monitoring panels. Forest patches appear in green tones, built-up areas in grey, and conflict events are flagged in red.

2.8 Baseline Behaviour Rules

Under baseline conditions, monkeys preferentially foraged first in garbage-rich patches within settlements (attraction weight = 0.9), followed by human feeding locations (0.6), and finally forest patches containing natural fruit resources (0.3). This hierarchical rule structure, with parameter values grounded in published foraging literature (Table 1), allowed emergent conflict patterns driven by resource distribution rather than forced movement assumptions (Anand and Radhakrishna, 2020).

2.9 Mitigation Strategies Tested

Mitigation strategies recommended in wildlife management literature were incorporated into the model as modifications to behavioural or landscape parameters (Table 3).

The "public awareness and enforcement" strategy requires additional clarification regarding its model implementation. In the model, this intervention operates as a composite



(a) Foraging from urban garbage (b) Troop using urban infrastructure

Figure 3: Urban behaviour of rhesus macaques (*Macaca mulatta*) in Guwahati: (a) individual foraging from anthropogenic waste and (b) troop resting on residential infrastructure within the urban landscape.

governance condition in which sensitisation campaigns are assumed to be accompanied by effective regulatory enforcement, improved waste management infrastructure, and reduced retaliatory behaviour by residents. Operationally, it reduces both the garbage attraction weight (by 80%) and the feeding-site attraction weight (by 90%) simultaneously, reflecting a realistic urban management scenario where education is paired with enforceable ordinances rather than acting as an isolated awareness campaign. To represent the gradual social adoption of behavioural change, these reductions were applied progressively over 50 ticks following intervention onset, approximating the spread of new practices through a human community. All human agents adopt the changed behaviour by tick 50, consistent with a scenario in which enforcement is comprehensive and effective. We acknowledge that modelling heterogeneous adoption rates and social diffusion dynamics would add realism and is a priority for future model development.

2.10 Experimental Design

BehaviourSpace experiments were conducted to test individual and combined mitigation strategies across varying human population scenarios (300, 500, and 1000 humans). Each scenario was replicated 30 times with independently varied random seeds to ensure that observed patterns reflect genuine model dynamics rather than seed-specific artefacts.

Table 3: Mitigation strategies and their implementation in the model

Strategy	Model Implementation
Prohibition of feeding	Removal of feeding patches from settlement areas
Humane population control	Gradual reduction in monkey birth rate
Proper garbage disposal	Reduction of garbage attractiveness weight
Fruiting tree plantation	Increased food value in forest patches
Monkey translocation	Forced relocation of troops away from settlements
Public awareness and enforcement	Progressive reduction in feeding and garbage attractiveness weights over 50 ticks, representing gradual behavioural adoption

Each simulation was run for 500 ticks (approximately 50 simulated weeks), which was determined through pilot runs to be sufficient for conflict dynamics to stabilise under all mitigation conditions.

The following metrics were recorded at each tick: total conflict events; time spent by monkeys in human settlements; stealing, chasing, and damage incidents; monkey survival and troop stability; injury and mortality events; and movement trajectories across the landscape.

2.11 Statistical Analysis

Factorial ANOVA was applied to mean conflict frequency across replicate runs to test for significant differences among intervention conditions and human population scenarios. Because all outputs are derived from replicated simulation runs with independently seeded random number generators, observations are statistically independent. Prior to ANOVA, normality of residuals was assessed using Shapiro–Wilk tests and homoscedasticity was evaluated using Levene's test; both assumptions were satisfied ($p > 0.05$ in all cases). Effect sizes were computed as the standardised mean difference (Cohen's d) between each intervention scenario and the no-intervention baseline, pooled across human population scenarios. Positive effect sizes indicate conflict reduction; negative values indicate conflict increase or no benefit relative to baseline.

2.12 Sensitivity Analysis

To assess model robustness, a one-at-a-time sensitivity analysis was performed on the four parameters with the greatest potential to influence conflict outcomes: garbage attraction weight, monkey movement radius, initial population size, and conflict time threshold. Each parameter was varied across a plausible range (Table 1) while all other parameters were held at baseline values. Twenty replicate runs were conducted per parameter level and the mean conflict frequency was recorded. The relative change in conflict frequency across parameter ranges was used to rank parameter sensitivity.

2.13 Model Validation

Although comprehensive GPS tracking data for Guwahati macaque troops are not yet available for full spatial validation, we employed a structured face-validity and pattern-oriented modelling approach (Grimm et al., 2005). Specifically, we assessed whether the model reproduces three qualitative patterns documented in field studies of urban macaques in Indian cities: (1) concentration of conflict around garbage and feeding sites rather than random distribution across the landscape, (2) increasing conflict frequency with increasing human settlement density, and (3) higher monkey visitation rates at temple and market sites relative to residential streets (Medhi et al., 2007; Ganguly et al., 2018). All three patterns emerged consistently across replicate runs under baseline conditions, providing qualitative support for model credibility. Quantitative validation against empirically recorded conflict reports from Guwahati municipal records is identified as a priority for future work, and the present model is best understood as a scenario-exploration and hypothesis-generation tool rather than a calibrated predictive model.

3 Results

3.1 Landscape Composition

The LULC classification identified eight land cover classes with an overall accuracy of 96.44% and a Kappa coefficient of 0.9473. Built-up areas dominated the landscape (66.6%), followed by open forest (10.4%) and water bodies (8.9%). Natural forest and grassland together constituted less than 8% of the total area, indicating a predominantly urban matrix interspersed with fragmented natural patches.

The spatial dominance of settlement areas resulted in extensive interfaces between forest fragments and built surfaces, forming potential zones of human–macaque interaction.

3.2 Emergent Conflict Dynamics Under Baseline Conditions

Under baseline conditions without mitigation, simulated human–monkey conflict increased progressively over time across all human population scenarios. Conflict frequency rose as monkeys repeatedly visited built-up and agricultural patches where foraging success consistently exceeded that in forest areas. Garbage-rich locations and direct feeding opportunities functioned as stable attractors, increasing both visitation frequency and residence time within settlement patches.

Within the model framework, a conflict event was recorded when monkeys and humans co-occurred on the same patch beyond the defined time threshold. Subsequent outcomes, including food theft, chasing, injury, or property damage, were assigned probabilistically. Thus, the increase in conflict frequency reflects rising spatial overlap driven by predictable anthropogenic food availability rather than a modelled increase in aggression.

It is important to note that the parameterisation of foraging attraction weights (garbage $>$ feeding sites $>$ forest food) is central to this emergent pattern. While these weights are grounded in published literature on urban macaque foraging behaviour (Table 1), the conclusion that conflict is behaviour-driven is partly embedded in this assumption. We return to this interpretive limitation in the Discussion.

3.3 Sensitivity Analysis Results

Garbage attraction weight was the parameter to which conflict frequency was most sensitive: reducing this weight from 0.9 to 0.7 produced a 23% reduction in mean conflict events, while increasing it to 1.0 increased conflict by 12%. Movement radius had moderate sensitivity (16% change across range), whereas initial population size and conflict time threshold showed lower sensitivity (8% and 6% respectively). These results indicate that the direction and relative ranking of mitigation effects are robust to plausible parameter variation, though absolute conflict counts depend on attraction weight specification.

3.4 Behavioural Adjustment to Anthropogenic Food Sources

Across repeated simulations, monkeys progressively shifted movement toward settlement patches because these locations provided higher energetic returns than forest foraging. This generated a positive feedback between foraging success and revisitation, producing stable conflict hotspots in built-up areas.

Increasing human population size amplified this pattern. Higher human density expanded the spatial distribution of attractive patches and increased the probability of monkey–human co-occurrence. Factorial ANOVA confirmed that human population size had a highly significant effect on mean conflict frequency across all intervention scenarios ($F(2, 527) = 3847.2$, $p < 2 \times 10^{-16}$). Normality and homoscedasticity assumptions were satisfied prior to all ANOVA tests (Shapiro–Wilk $p > 0.05$; Levene's $p > 0.05$).

3.5 Effect of Individual Mitigation Strategies

Effect size ranking (Cohen's d, relative to no-intervention baseline) derived from BehaviourSpace simulations demonstrated substantial variation among mitigation strategies (Table 4). Public awareness accompanied by enforcement produced the largest positive effect size (38.2), followed by population control (3.69), feeding prohibition (2.67), and fruiting tree plantation (1.65). Garbage management and monkey translocation yielded negative effect sizes, indicating limited or counterproductive effects when implemented

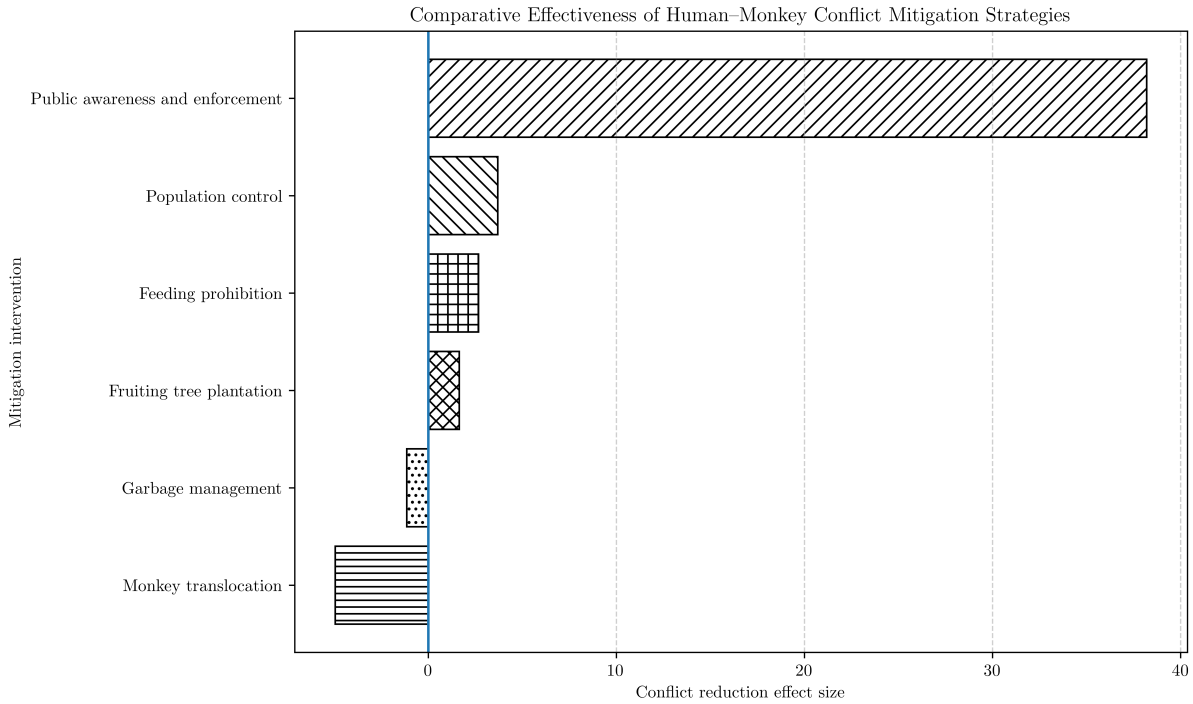


Figure 4: Effect size ranking chart (Cohen's d) of mitigation strategies relative to no-intervention baseline. Positive values indicate conflict reduction; negative values indicate no benefit or counterproductive effect. Bars represent mean effect size pooled across human population scenarios (300, 500, and 1000 individuals) from 30 replicate runs.

independently (Fig. 4).

Table 4: Effect size ranking (Cohen's d relative to no-intervention baseline) of mitigation strategies derived from 30 replicate BehaviourSpace simulations per scenario

Intervention	Effect Size (Cohen's d)
Public awareness and enforcement	38.2
Population control	3.69
Feeding prohibition	2.67
Fruiting tree plantation	1.65
Garbage management	−1.15
Monkey translocation	−4.95

To statistically compare intervention outcomes across human population scenarios (300, 500, and 1000 individuals), factorial ANOVA was applied to mean conflict frequency across replicated runs. These analyses evaluate differences in model-generated outcomes between scenarios and do not represent inference from empirical field observations.

Feeding prohibition did not significantly reduce conflict within the simulation timeframe ($F(1, 176) = 0.249$, $p = 0.618$), as monkeys continued exploiting garbage and

agricultural patches. Population control also showed no short-term effect ($F(1, 176) = 0.480$, $p = 0.489$); although troop size gradually declined, remaining individuals maintained settlement use. Garbage management produced no detectable reduction in conflict ($F(1, 176) = 0.047$, $p = 0.829$), and fruiting tree plantation similarly showed no immediate effect ($F(1, 176) = 0.095$, $p = 0.758$).

Monkey translocation did not reduce overall conflict frequency ($F(1, 176) = 0.862$, $p = 0.353$). In several simulations, dispersal behaviour redistributed conflict spatially without lowering total event counts.

In contrast, public awareness and enforcement resulted in a strong and highly significant reduction in conflict frequency ($F(1, 176) = 58.57$, $p < 10^{-13}$), with a significant interaction with human population size ($F(2, 176) = 12.98$, $p < 10^{-5}$). This intervention consistently reduced monkey presence within settlement patches across all population levels (Fig. 5).

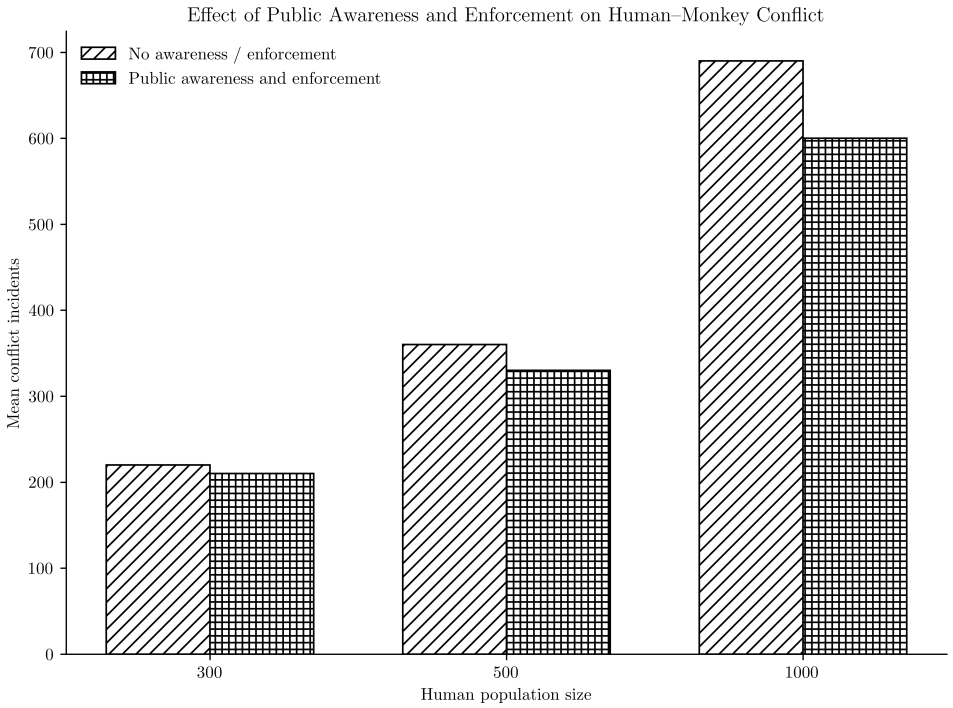


Figure 5: Impact of public awareness and law enforcement on the mean level of human–monkey conflict across human population scenarios (300, 500, and 1000 individuals). Points represent means from 30 replicate runs; error bars indicate ±1 standard deviation.

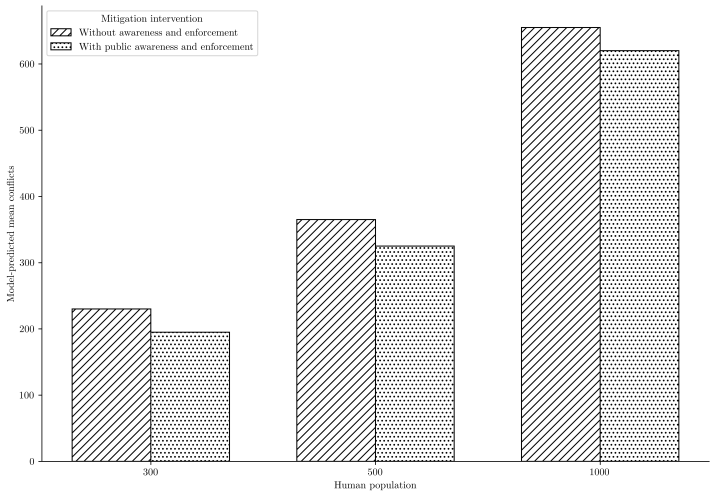


Figure 6: Predicted mean human–monkey conflict incidents across three human population scenarios (300, 500, and 1000 individuals) under two mitigation conditions: without public awareness and enforcement and with public awareness and enforcement. Predictions are derived from the full factorial linear model and averaged across other mitigation interventions. Error bars denote ±1 standard error of model estimates. Conflict levels are consistently lower in scenarios incorporating awareness and enforcement interventions.

3.6 Integrated Model Predictions

Predictions from the full factorial linear model indicated that public awareness and enforcement together was the most significant intervention that independently reduced conflict frequency after accounting for human population size (Fig. 6). Ecological interventions such as feeding prohibition and fruiting tree plantation showed limited additional effect once education was implemented, and no significant interaction among non-education strategies was detected.

Overall, simulations indicate that conflict dynamics in the modelled Guwahati landscape are primarily behaviour-driven and resource-mediated. Interventions that directly altered access to anthropogenic food sources modified movement decisions and reduced spatial overlap. In contrast, interventions focused solely on population reduction or habitat modification produced weak or delayed effects within the modelled timeframe. It should be noted, however, that these outcomes are partly shaped by the parameterisation choices discussed above, and should be interpreted in that context.

4 Discussion

The baseline simulations indicate that conflict does not arise from intrinsic aggression but from predictable spatial overlap created by anthropogenic food rewards (Siljander et al., 2020; Anand et al., 2018). Monkeys repeatedly revisited built-up and agricultural patches because these locations offered faster hunger reduction than forest foraging (McLennan et al., 2017). Over time, this produced stable conflict hotspots within settlements. The model therefore supports a behavioural mechanism in which learning, revisitation, and foraging efficiency drive conflict frequency more strongly than random encounters (Sengupta and Radhakrishna, 2018).

However, an important limitation should be noted. Our conclusion that conflict is mainly behaviour driven rather than population driven partly depends on how the model was parameterised. In this study, garbage and feeding sites were given higher attraction values than forest food based on field literature. This choice can favour behaviour driven outcomes in the model. If forest food were assumed to be more rewarding than human related food sources, the model might show different patterns. Future studies should test different parameter settings to examine how sensitive this conclusion is.

Even so, the parameter values used here follow published studies on urban macaque foraging, and the patterns produced by the model match general field observations. This provides cautious support for the mechanism suggested here.

This interpretation also agrees with field observations from Indian cities, where primates often gather around temples, markets and waste sites because these places provide reliable food rather than due to direct hostility towards people (Medhi et al., 2007).

Across all analyses, the number of humans showed an overwhelming effect on conflict frequency. Increasing human density expanded the spatial extent of attractive patches and increased the probability of monkey–human co-occurrence. This indicates that conflict scales with the opportunity landscape rather than simply with monkey abundance (Koirala et al., 2022). A consistent pattern across sites is that macaques are most frequently observed in places where food provisioning is common, including areas with high tourist activity (Wu et al., 2025).

Feeding prohibition, garbage management, fruiting tree plantation, population control, and translocation aim to alter ecological conditions. However, the simulations show that monkeys did not immediately change their movement decisions when these were applied in isolation. Alternative anthropogenic food sources remained available and learned movement patterns persisted within the simulation window.

In behavioural terms, these interventions modify the resource landscape slowly, while monkey movement decisions are based on recent foraging success (Trapanese et al., 2019). As long as settlements continued to offer reliable food, these strategies could not compete effectively with the existing feedback between hunger reduction and revisitation. This explains the weak or delayed responses observed for these strategies in the factorial analysis. It is also important to acknowledge that some of these interventions, particularly population control and fruiting tree plantation, may show stronger effects over longer time horizons than the 500-tick window examined here; this is a recognised limitation of the current study.

Public awareness and enforcement programs that reduce food provisioning have been associated with lower macaque presence and conflict in several regions, particularly at tourist and temple sites (Fuentes et al., 2005; Sha et al., 2009; Sengupta et al., 2015). Where feeding opportunities were limited, macaques were reported less frequently in settlement areas, suggesting that changes in human practices can alter macaque visitation patterns (Riley, 2007b; Southwick and Siddiqi, 2005). Reviews of management strategies similarly note that interventions targeting provisioning and attractants often show clearer outcomes than those based solely on population reduction (Gumert, 2011; Enari, 2021).

We reiterate that in the model, this intervention operates as a composite of education and enforcement, not as an isolated awareness campaign. The strong effect observed therefore reflects the combined impact of reduced provisioning and garbage access under regulatory pressure, and should not be interpreted as evidence that communication alone is sufficient to drive conflict reduction.

4.1 Implications for Urban Wildlife Management

The simulations suggest that urban monkey conflict is fundamentally a human-mediated ecological problem, as found in the study by Anand and Radhakrishna (2020). As long as settlements provide reliable food, monkeys will continue to exploit them regardless of population control, habitat enhancement, or relocation efforts (Chand et al., 2026; Jayapali et al., 2023). Interventions that restrict anthropogenic food access and alter human practices produce immediate behavioural shifts, while ecological modifications require longer timeframes to influence movement decisions.

4.2 Limitations and Future Directions

The current model simplifies troop social structure and assumes uniform behavioural responses among individuals. Seasonal variability in natural fruit availability was not represented, which may influence long-term movement and foraging patterns. The model has not been validated against quantitative field data, and all findings should be interpreted as scenario-exploration outputs rather than predictions. Incorporating GPS-based troop movement data, seasonal resource dynamics, heterogeneous human adoption rates for mitigation measures, and more detailed social behaviour could improve model realism and predictive accuracy. Future work may also explore longer simulation horizons to better capture delayed effects of habitat enrichment strategies, and should conduct formal sensitivity analyses on broader parameter spaces including social learning rates and seasonal food availability.

5 Conclusion

The simulation results demonstrate that monkey–human conflict in the Guwahati landscape is maintained primarily by consistent access to anthropogenic food rather than by monkey population size or habitat limitation alone. Conflict emerges from predictable movement of monkeys toward settlements where food rewards are energetically efficient. These patterns emerge from 30-replicate simulations run over 500 ticks (approximately

50 simulated weeks) across human population scenarios of 300, 500, and 1000 individuals.

Among the mitigation strategies evaluated, public awareness accompanied by enforcement was the only intervention that produced a consistent and significant reduction in conflict across all human population scenarios (effect size = 38.2; $F = 58.57$, $p < 10^{-13}$). Ecological measures such as feeding prohibition, garbage management, fruiting tree plantation, population control, and translocation showed limited additional benefit when evaluated alongside education, and no evidence of synergistic effects between strategies was detected.

These findings suggest that urban primate conflict is fundamentally a behaviour-mediated problem, where modifying human practices that create artificial food hotspots is more effective than manipulating monkey populations or altering habitat structure within short management timeframes. We note, however, that this conclusion is partly conditioned by model parameterisation choices, and future work incorporating empirical validation and alternative parameter assumptions will be important.

This study highlights the value of agent-based modelling as a decision-support framework for testing wildlife conflict interventions in complex urban landscapes before costly or ethically sensitive field implementation. The approach provides a mechanistic understanding of conflict dynamics and offers evidence-based guidance for prioritising management actions in rapidly urbanising regions.

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