# CITS4403 Group Project

Jiajin Kong 25042399

Jonas Liu 24198573

# Modeling Predation Risk from Feral Cats and Scent Diffusion in a Heterogeneous Landscape

## 1. Background

Feral cats are among the most damaging invasive species in Australia. They prey on small native mammals and have been responsible for many populations declines and local extinctions. Beyond direct predation, feral cats influence prey through chemical cues such as scent marks that linger in the environment, shaping what ecologists call a “landscape of fear.” Understanding how scent diffusion affects prey behavior and spatial risk is important for wildlife management. It helps to design better strategies such as vegetation restoration and targeted predator control. Previous studies have modeled predator–prey dynamics, but few have incorporated indirect cues like scent diffusion. This project aims to fill that gap through computational modelling that explicitly represents both cats and prey moving in a spatially structured environment.

We chose agent-based modeling (ABM) as the main approach because it provides a flexible and intuitive framework for simulating individual-level behaviors and their emergent collective outcomes. ABMs comprise autonomous, individual entities; each with dynamic, adaptive behaviors and heterogeneous characteristics that interact with each other and with their environment (McLane et al., 2011). Unlike traditional differential equation models that treat populations as continuous variables, ABMs model each agent as an autonomous decision-making entity. This enables the study of complex spatial behaviors such as avoidance of scent cues, habitat selection, and emergent risk landscapes, which are difficult to capture with aggregated mathematical approaches. In short, ABM is visually interpretable through spatial simulation and provides experimental flexibility for testing how small behavioral changes scale up to population-level outcomes.

## 2. Model Structure

Based on Python and the Mesa framework, this ABM model simulates cats and prey on a 2D grid that represents a simplified landscape.

* **Environment**: The grid cells represent heterogeneous terrain types (e.g., vegetation, roads, water). These influence both movement and predation probability
* **Vegetation**:Cells’ nutrition attribute. It represents renewable environmental resources that attract prey and gradually recover over time, also influencing predatory-prey dynamics. Randomly initialized for 4 levels.
* **Water area**: Cells that can block agents’ movement. Water area is preset as a river in the middle of the map, meandering like a sine wave with a gap in the middle.
* **Agents**:
* **Cats**: Move across the grid, deposit scent marks, and attempt to hunt prey.
* **Prey**: Forage for higher vegetation and avoid cells with high scent concentration or nearby cats.
* **Scent Field**: Each cat emits scent within a specified radius, forming a Boolean grid that indicates areas where prey is more likely to detect predator presence and flee.
* **Predation Probability**: When a cat and a prey occupy the same cell, a capture event occurs with probability:

where the parameters ensure .

* **Key Parameters**:

|  |  |  |
| --- | --- | --- |
| **Parameter** | **Description** | **Default** |
| Grid size | Environment dimension, consists of width and height | 25 × 25 |
| Number of cats | Predator agents | 8 |
| Number of prey | Initial prey agents | 80 |
| Base predation rate | Baseline success probability | 0.20 |
| Vegetation coefficient | Influence of vegetation on predation | 0.10 |
| Prey flee probability | Chance to escape during encounter | 0.40 |

图表

AI 生成的内容可能不正确。  
Figure 2.1 Example of Initial Grid layout

## 3. Modelling Process

The modelling process followed the computational modelling cycle: design, implementation, experimentation, and interpretation.

(a) Initialization: Cats and prey are randomly placed on the grid. The environment includes vegetation and rivers.

(b) Simulation: At each step, cats move and deposit scent, prey avoid scent and cats, predation events are logged, and scent decays.

(c) Data Collection: A Mesa DataCollector records population counts, predation events, and scent maps.

(d) Experiments: Six main scenarios were tested – baseline, High predation pressure, Flee rescue, Space effect, Near-threshold sensitivity, River Influence. We report extinction rate, average time-to-extinction (TTE), and final populations. Moreover, we repeated experiments with 10 random seeds for each scenario to reduce randomness, estimate fluctuations in results, and obtain more robust extinction rates and dynamic conclusions.

|  |  |  |
| --- | --- | --- |
| **Scenario** | **Description** | **Expected Outcome** |
| S0 Baseline (control) | Moderate predation with balanced population sizes; serves as the reference scenario. | Mild oscillations and long-run coexistence. |
| S1 High predation pressure | Stronger predation and more cats cause intense predator–prey cycles. | Rapid prey collapse, temporary cat peak, frequent extinctions. |
| S2 Flee rescue | Increased prey fleeing ability under high predation pressure. | Fewer kills, longer persistence, prey concentrate in safer zones. |
| S3 Space effect | Tests influence of spatial scale on encounter rates. | Smaller grids increase encounters; larger grids favour coexistence. |
| S4 Near-threshold sensitivity | Examines how small parameter shifts change outcomes. | Small changes can flip from coexistence to extinction — a tipping point. |
| S5 River influence | Tests effect of barriers and corridors on movement. | River reduces encounters and extends survival; no river increases mixing and mortality. |

## 4. Results

### 4.1 Scenario summary

| **group** | **extinction\_rate** | **avg\_tte** | **final\_prey\_mean** | **final\_cats\_mean** | **pred\_events\_avg** |
| --- | --- | --- | --- | --- | --- |
| S0\_Baseline | 0.3 | 190.0 | 1.9 | 6.4 | 359.6 |
| S1\_HighPred | 0.6 | 181.1 | 1.5 | 7.0 | 593.7 |
| S2\_FleeRescue | 0.5 | 169.7 | 4.3 | 7.2 | 590.7 |
| S3\_LargeArena | 0.0 | 200.0 | 24.3 | 2.4 | 153.5 |
| S3\_SmallArena | 1.0 | 82.5 | 0.0 | 8.0 | 389.3 |
| S4\_coef\_0.16 | 0.4 | 178.7 | 1.0 | 6.7 | 485.7 |
| S4\_coef\_0.20 | 0.7 | 156.7 | 1.2 | 7.3 | 513.8 |
| S5\_NoRiver | 0.3 | 198.1 | 3.7 | 6.0 | 369.6 |
| S5\_River | 0.0 | 200.0 | 4.4 | 6.1 | 376.9 |

Across all scenarios, two levers matter most: how often agents meet (space, barriers) and what happens when they meet (predation base/coef, flee behavior). Increasing flight buys time and lowers risk but can’t fully beat strong predation; adding spatial structure (bigger habitat or a barrier) is consistently protective. Results vary a bit across seeds, but the patterns above are stable enough to support these conclusions.

### 4.2 Predation Pressure

图形用户界面, 应用程序

AI 生成的内容可能不正确。  
Figure 4.1 Predation Pressure

S0 Baseline. With moderate predation the system tends to drift down slowly: prey often decline to very low levels near the end of 200 steps (extinction rate ≈ 0.30, TTE ≈ 190). Cats stay relatively stable around a small band. Predation events are mid-range.

S1 High predation. Stronger pressure (more cats + higher base/coef) produces a clearer boom–bust: prey fall faster, cats peak briefly and then flatten. Extinction rate rises to 0.60 and average TTE shortens (≈ 181), with more frequent predation events than S0.

S2 Flee rescue. Raising prey\_flee\_prob does help: the extinction rate drops versus S1 (0.50 vs 0.60) and survivors end with slightly more prey on average. That said, collapses can still happen and TTE isn’t guaranteed to increase—flight spreads risk but can’t fully offset high per-encounter success.

### 4.3 Space Effect

图表, 条形图

AI 生成的内容可能不正确。  
Figure 4.2 Space Effect

Changing only arena size isolates the effect of encounters. In the small grid (15×15), prey go extinct in every run (1.00, TTE ≈ 83). In the large grid (40×40), we see 0 extinctions within 200 steps and much higher final prey, while cats drift lower (fewer encounters → less energy intake). This neatly shows “contact rate” as a dominant driver.

### 4.4 Threshold Sensitivity

| **group** | **extinction\_rate** | **avg\_tte** | **final\_prey\_mean** | **final\_cats\_mean** |
| --- | --- | --- | --- | --- |
| S4\_coef\_0.16 | 0.4 | 178.7 | 1.0 | 6.7 |
| S4\_coef\_0.20 | 0.7 | 156.7 | 1.2 | 7.3 |

A tiny tweak to predation\_coef flips outcomes: from 0.16 to 0.20, the extinction rate jumps 0.40 → 0.70 and TTE shortens ≈179 → ≈157. This is a nice tipping-point story—small changes in hunting success can shift the system from “often coexist” to “often collapse”.

### 4.5 River Influence

图表

AI 生成的内容可能不正确。  
Figure 4.3 River Influence

With a river, we recorded 0 extinctions in 200 steps versus 0.30 without the river, and final prey numbers are a bit higher. The barrier likely creates refugia and funnels encounters to narrow crossings; the total number of predation events is similar, but their locations are more constrained, which helps prey persist.

## 5. Discussion and Conclusion

This project showed that two levers dominate our system: how often cats and prey meet (space, barriers) and what happens when they meet (predation success, fleeing).

Under baseline settings we saw mild oscillations that often drifted to very low prey numbers; pushing predation up produced faster collapses, while raising the flee probability helped but did not fully prevent declines. Changing only the arena size made the biggest difference: the small grid led to certain extinction within 200 steps, whereas the large grid avoided it entirely in our runs. A river barrier acted like a refuge by concentrating encounters at crossings and protecting prey elsewhere. Finally, the near-threshold test showed that small tweaks to predation success can flip the regime from coexistence to frequent extinction—a clear tipping-point message.

Since the model simulates several scenarios decently, there are still some limitations:

* Simple rules: Predator–prey interactions are simplified (e.g., linear predation rule, simple flee trigger, simple energy use). Real systems likely need non-linear or context-dependent rules, not so close to the real situation.
* Random vegetation: Most simulations use a fresh random vegetation map, which adds noise. A fixed map per scenario would make comparisons cleaner.
* Metrics are narrow: We mainly tracked population, predation and extinction/TTE. We did not analyze spatial clustering, home ranges, or variability bands in depth.
* Space is stylized: The grid and the river mask are idealized; real landscapes have varied permeability, multiple barriers, and edges.

Overall, if the goal is persistence, the most effective strategies are to reduce encounter rates (more space, obstacles/refugia) or lower per-encounter success (behavioral or habitat protections).

# References

McLane, A. J., Semeniuk, C., McDermid, G. J., & Marceau, D. J. (2011). The role of agent-based models in wildlife ecology and management. *Ecological Modelling*, *222*(8), 1544–1556. <https://doi.org/10.1016/j.ecolmodel.2011.01.020>