

Protecting Wildlife at Scale

Optimizing Resource Allocation for Etosha National Park

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Context & Framing the Problem

Challenges:

- Etosha spans $\sim 23,000 \text{ km}^2$ with severe water scarcity.
- Only 295 staff members available.
- $\Rightarrow$ Uniform protection will *not* be possible

Our approach:

- Avoid uniform coverage of the park
- Protection is instead defined as the fraction of expected ecological loss prevented.

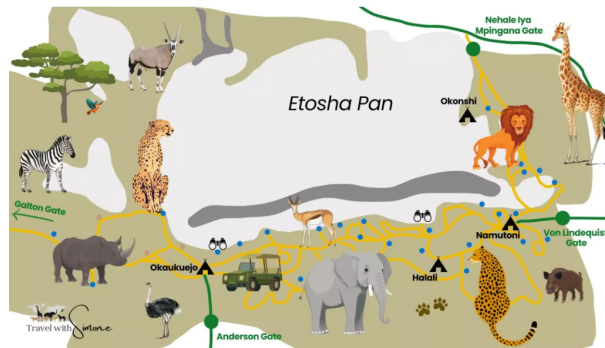


Illustration of Etosha National Park



Deployment Package

10
Patrol Routes

4
Drone Sorties

12
Sensor Sites

12
Base Staff

Active staff total
 $10 \times 6 + 4 \times 2 + 12 \times 0.25 + 12 = 83$

Active-staff formula:

$$N_{\text{active}} = 6B_{\text{patrol}} + 2B_{\text{drone}} + \left\lceil \frac{B_{\text{sensor}}}{4} \right\rceil + N_{\text{base}}$$

Each position requires roughly:

$\frac{24 \text{ hours a day}}{7 \text{ hours a shift}} \approx 3.5$ employees. With 83 active staff:

$$N_{\text{payroll}} \approx 3.5(83) \approx 291 < 295$$

Staffing limit is satisfied!



Grid-Graph Representation of the Park

To begin modelling, we divide Etosha's vast landscape into smaller, computationally manageable components.

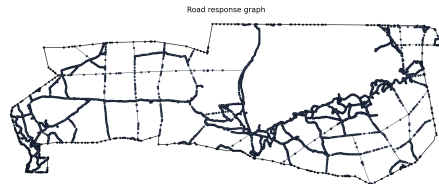
Grid

- Represents ecological value and threat
- Divides the park into 996 cells of 5×5 km
- Captures continuous spatial variation



Graph

- Represents response and mobility
- Nodes represent gates, camps, and road junctions
- Weighted edges represent roads and travel times



Mathematical Framework

Consider a given grid cell g :

Baseline Expected Loss (No Intervention)

$$L_g^0 = A_g C_g \lambda_g$$

Where A_g is cell area, C_g is ecological consequence, and λ_g is threat intensity.

Avoided Loss

$$L_g^{av} = L_g^0 R_g D_g$$

Where R_g, D_g are the response and detection success probabilities

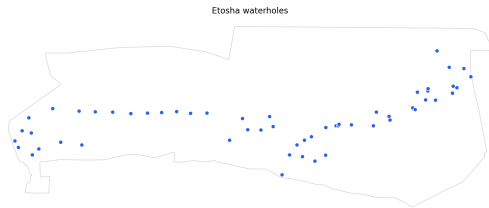
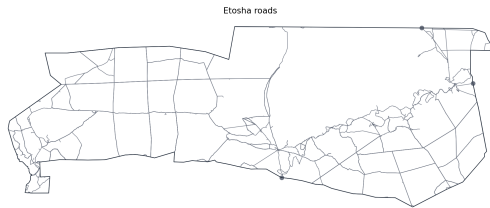
Protection Index: Objective to Maximize

$$PI = \frac{\sum_g L_g^{av}}{\sum_g L_g^0}$$

Higher $PI \implies$ greater proportion of baseline expected loss prevented.



Context Layers



Ecological Value (C_g)

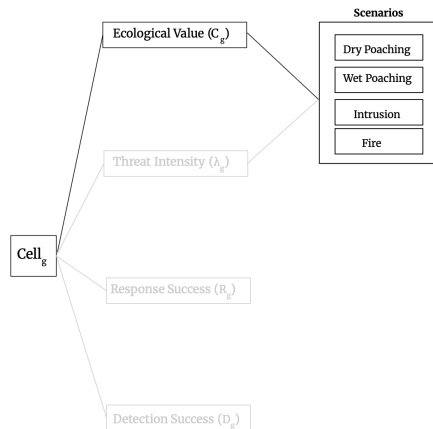
“How ecologically damaging would an event be there?”

Each cell is assigned four ecological value scores:

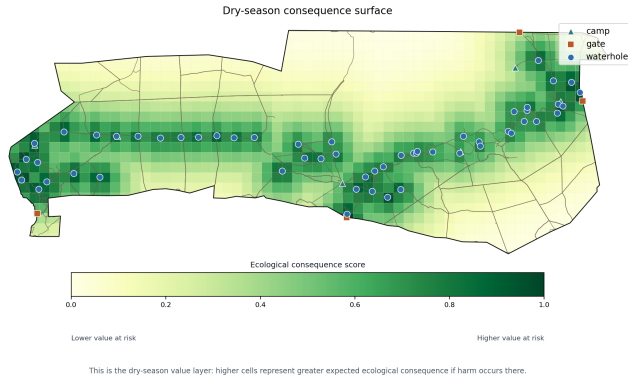
- Dry season poaching value ($C_{poach,dry}$)
- Wet season poaching value ($C_{poach,wet}$)
- Intrusion value ($C_{intrusion}$)
- Fire value (C_{fire})

These scores are based on:

- d_{water}
- d_{fence}
- d_{center}



Dry Season Ecological Value ($C_{poach,dry,g}$)



$$R_{dry} = e^{-d_{water}/12}$$

$$E_{dry} = e^{-d_{water}/18}$$

$$H_{dry} = e^{-d_{water}/22}$$

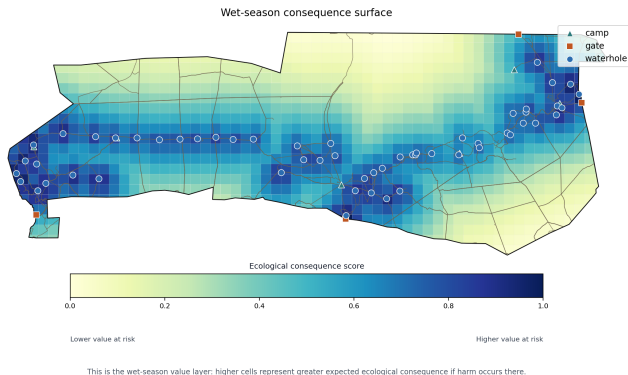
where:

- R_{dry} is the rhino-use proxy;
- E_{dry} is the elephant-use proxy;
- H_{dry} is the general-herbivore-use proxy.

$$C_{poach,dry,g} = \text{norm}(1.0R_{dry,g} + 0.6E_{dry,g} + 0.3H_{dry,g})$$



Wet Season Ecological Value ($C_{poach,wet,g}$)



$$R_{wet} = e^{-d_{water}/24}$$

$$E_{wet} = e^{-d_{water}/28}$$

$$H_{wet} = e^{-d_{water}/35}$$

where:

- R_{wet} is the rhino-use proxy;
- E_{wet} is the elephant-use proxy;
- H_{wet} is the general-herbivore-use proxy.

$$C_{poach,wet,g} = \text{norm}(1.0R_{wet,g} + 0.6E_{wet,g} + 0.25H_{wet,g})$$



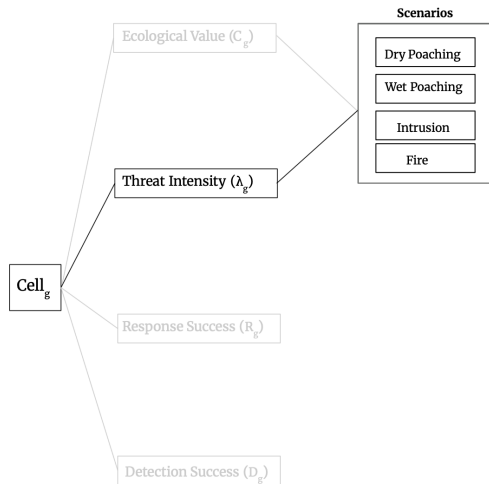
Threat Intensity (λ_g)

“How exposed is this cell to that event?”

Each cell is assigned four threat scores:

- $\lambda_{poach,dry}$
- $\lambda_{poach,wet}$
- $\lambda_{intrusion}$
- λ_{fire}

These scores are based on: d_{water} , d_{entry} , d_{road} , d_{fence} , d_{center} , slope, & elevation.



General Form

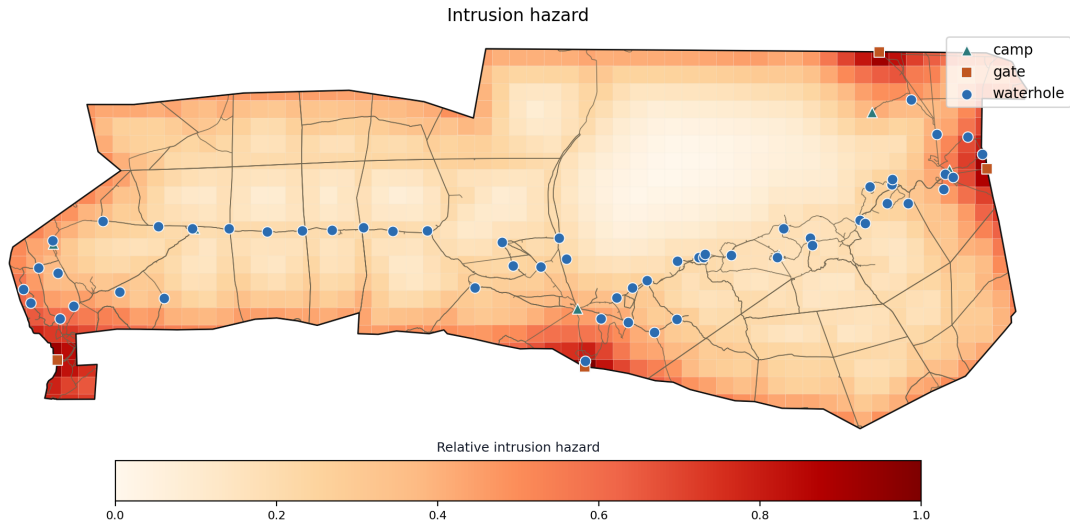
$$\lambda_{s,g} = \text{norm} \left[w_{s,0} R_{s,g} + \sum_{i=1}^{m_s} w_{s,i} \exp \left(-\frac{d_{i,g}}{\tau_{s,i}} \right) \right]$$

$s \in \{\text{dry-season poaching, wet-season poaching, intrusion}\}$

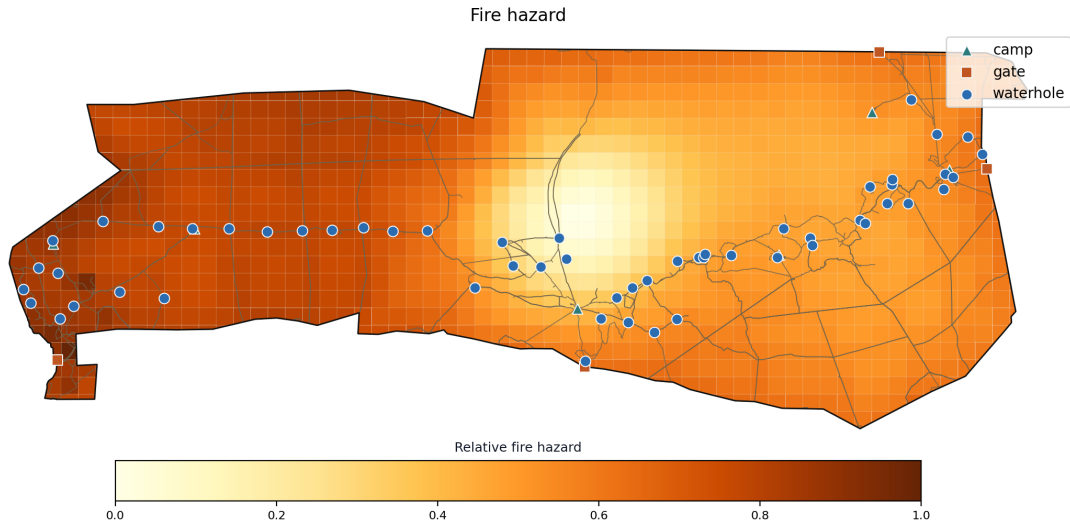
- $w_{s,i}$: weight assigned to feature i (sum to 1)
- $R_{s,g}$: rhino-use proxy (poaching)
- $d_{i,g}$: distance from cell g to feature i
- $\tau_{s,i}$: decay-distance parameter



Intrusion Threat Heatmap



Fire Threat Heatmap

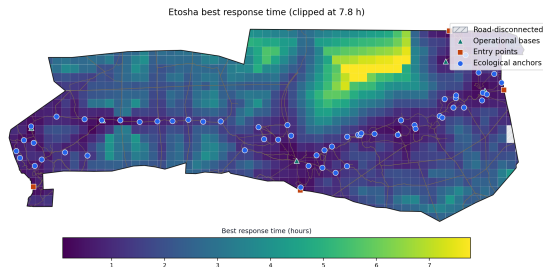


Can Rangers Respond in Time (R_g)?

Detection without intervention is merely observation.

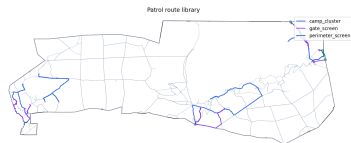
- **Terrain-Aware Mobility:** We calculate travel speed using road classes and slope penalties, transitioning to **Tobler's hiking function** for off-road approach.
- **Response Probability:** Best response time (τ_g) is converted to success probability via a logistic curve.

$$R_g = \frac{1}{1 + \exp(\kappa(\tau_g - \tau_0))}$$



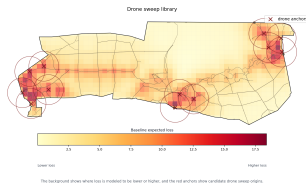
Detection: Three Complementary Assets

Detection: “How likely are we to detect harmful activity in cell g ?”



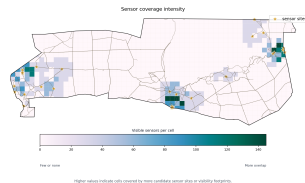
Patrol Routes ϕ_{rg}

$$\phi_{rg} = 1.5 \exp \left(-\frac{d_{rg}}{10} \right)$$



Drone Sorties ψ_{dg}

$$\psi_{dg} = 1.8 \max \left\{ 0, 1 - \frac{\|\mathbf{c}_g - \mathbf{a}_d\|_2}{16} \right\}$$



Sensor Sites χ_{sg}

$$\chi_{sg} = 0.95 \exp \left(-\frac{d_{sg}}{8} \right).$$

Influence Matrices

These functions produce three separate matrices. Each entry measures how strongly a candidate asset influences a particular cell (assuming the cell is in adequate proximity to that asset.)



Detection Surrogate: From Assets to Detection

$$\text{asset choices} \rightarrow M_g \rightarrow S_g \approx D_g$$

Monitoring score

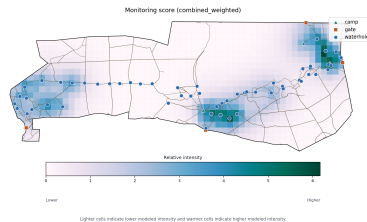
$$M_g = \sum_r \phi_{rg} y_r + \sum_d \psi_{dg} z_d + \sum_s \chi_{sg} x_s$$

- M_g : total monitoring intensity score of cell g
- D_g : true detection probability
- S_g : piecewise-linear surrogate for D_g

Why use a surrogate?

$$D_g^{\text{exact}} = 1 - \left(1 - P_g^{\text{patrol}}\right) \left(1 - P_g^{\text{drone}}\right) \left(1 - P_g^{\text{sensor}}\right)$$

- exact detection has overlap effects
- $D_g^{\text{exact}} \approx P_g^{\text{patrol}} + P_g^{\text{drone}} + P_g^{\text{sensor}}$. Higher order terms make the model nonlinear



Monitoring intensity M_g

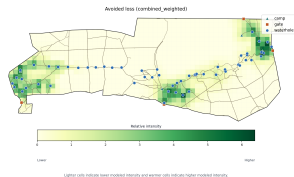
Surrogate mapping:

$$(m_j, s_j) : M_g = m_j \Rightarrow S_g = s_j$$

- increasing
- diminishing returns (ie concave)
- bounded



MILP: Turning the Surrogate into a Deployment



Avoided ecological loss

Resource constraints

$$\sum_r y_r \leq B_P$$

$$\sum_d z_d \leq B_D$$

$$\sum_s x_s \leq B_S$$

The deployment cannot exceed the available patrol, drone, or sensor capacity.

Decision variables

$$y_r, z_d, x_s \in \{0, 1\}$$

- y_r : choose patrol route r
- z_d : choose drone sortie d
- x_s : choose sensor site s

Surrogate interpolation

$$M_g = \sum_j m_j \lambda_{gj}, \quad S_g = \sum_j s_j \lambda_{gj}$$

$$\sum_j \lambda_{gj} = 1, \quad \lambda_{gj} \geq 0$$

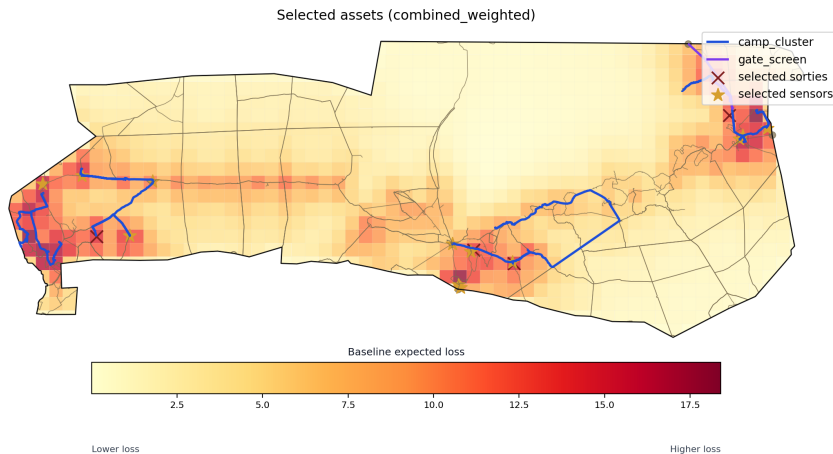
The weights λ_{gj} interpolate between calibrated anchor points, converting M_g into S_g .

Objective

$$\max \sum_{g \in G} L_g^0 R_g S_g$$



Results: Allocation Strategy



The shaded background shows pre-optimization loss, while the overlaid lines and markers show the assets selected by the optimizer.



Results: The Hotspot-First Strategy

Hotspots = top 10% of cells ranked by baseline loss (minimum avg. monitoring score threshold required)

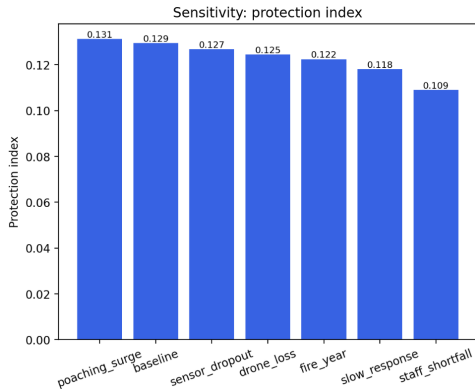
Table 1: Scenario-level Etosha results

Scenario	Protection index	Avoided loss	Hotspot PI
Dry poaching	0.148	506.0	0.244
Wet poaching	0.136	570.4	0.253
Combined weighted	0.129	534.4	0.250

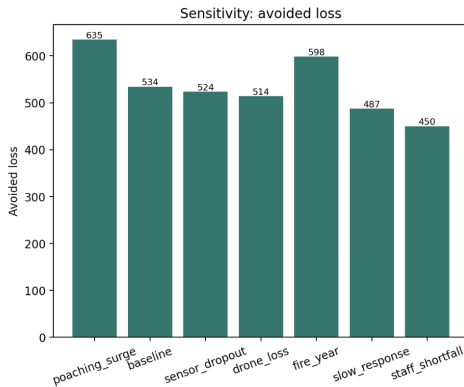
- ⇒ **12.9%** of expected loss is prevented across the whole park.
- ⇒ In the hotspots, **25%** of expected loss is prevented.
- ⇒ **Our strategy protects hotspots much more strongly than the park as a whole.**



Sensitivity Analysis



Greatest harm comes from `staff_shortfall`.
Model remains robust



Increased threats $\Leftrightarrow$ larger baseline loss $\Leftrightarrow$
larger avoided loss ($L_g^{av.} = L_g^0 R_g D_g$)



Our model uses open-source, real-world data:

- **OpenStreetMap:** Park boundaries, road networks, camps, and gates.
- **OpenTopography (DEM):** Elevation and slope data for mobility and line-of-sight.
- **NASA FIRMS & NASA POWER:** Wildfire history and weather data for the threat layer.



Yellowstone Generalization

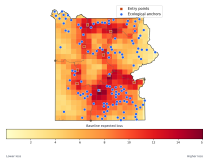
Unchanged: loss objective, grid-graph response, detection surrogate, and MILP.

Changes: Hydrology, seasons, threats, winter road closures.

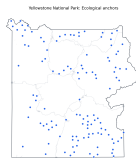


Road map

Yellowstone National Park baseline loss (Combined weighted)

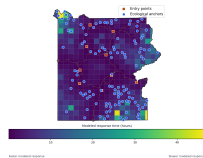


Combined baseline loss

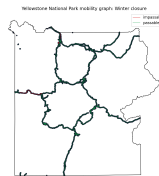


Visitor & ecological anchors

Yellowstone National Park response time (Summer open road)



Summer response time



Winter mobility graph

Rerun data

Cells	408
Access bases	9
Eco. anchors	120
Winter closures	19
Combined PI	0.141
Median response:	3.08 h → 3.49 h



Kaziranga Generalization

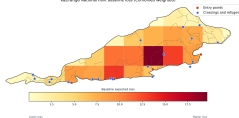
Unchanged: loss objective, grid-graph response, detection surrogate, and MILP.

Changes: crossings, refuges, flooding, road closures.



Road map

Kaziranga National Park baseline loss (Combined weighted)

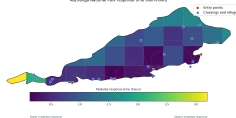


Combined baseline loss



Crossings and refuges

Kaziranga National Park response time (Non-flood)



Non-flood response time

Kaziranga National Park mobility graph: Flood-sensitive



Flood mobility graph

Recalibration

Ecology: 11 crossings and 8 refuges.

Mobility: flooding reduces road edges.

Threat: Poaching remains.

Rerun data

Cells	28
Access bases	4
Eco. anchors	19
Corridor segments	219
Combined PI	0.405
Median response: 0.88 h → 1.31 h	



Strengths

- Clearly defined protection
- Realistic Etosha data
- Detailed graphs & maps
- Incorporates ecological importance
- Robust & Generalizable

Limitations

- Efficiency-equity trade off
- Assumptions/proxies
- Surrogate
- Limited candidates
- Solely allocation-based



Conclusion

Main ideas

- Identify where ecological loss is greatest and where threats are most intense.
- Account for whether harmful activity can be detected and whether rangers can respond in time.
- Use a MILP to select the feasible combination of patrols, drones, and sensors that maximizes avoided loss.

Takeaways from our Model

- Supported by real open-source data, the hybrid grid-graph structure combines continuous value and threat with discrete mobility networks
- The model's separates the transferable parts (optimization) from park-specific ecology, threats, access, and seasonal conditions.
- The Yellowstone and Kaziranga generalizations successfully adapt to winter closures, flooding, etc.

