IM^{2}C 2026 ▪ TEAM #2026072

Protecting Wildlife at Scale

A Risk-Driven Resource Allocation Framework for Large Wildlife Reserves

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Presentation Roadmap

Allocation objective

Direct limited resources to the species, locations, and time periods where they reduce breach risk most effectively.

1. Problem Setting: Why Etosha Is Difficult

- Etosha National Park spans $22,935\,\mathrm{km}^2$ of open savanna, salt pans, and semi-arid scrubland.
- Boundary fence: approximately $850\,\mathrm{km}$.
- Total staff: 295.
- Persistent threats include organised black-rhino poaching, wildfire, and unauthorised entry.

Operational bottleneck

$$P_{\max} = \left\lfloor \frac{295}{3} \right\rfloor = 98$$

Under the three-shift assumption, the model treats 98 staff as the maximum active capacity per shift.

1. Problem Restatement and Modelling Scope

Four modelling tasks

1. Define quantitative protection metrics tied to conservation priorities.
2. Allocate limited resources strategically across the park.
3. Track protection over time and estimate staffing needs.
4. Develop a robust framework transferable to other reserves.

Spatial and operational scope

- $5\,\mathrm{km} \times 5\,\mathrm{km}$ grid
- Approximately 917 non-pan cells
- Etosha Pan excluded from optimisation
- Camps, roads, and fencing fixed
- Resource deployment is a decision variable
- Drone radius capped at $15\,\mathrm{km}$ from a camp charging base

Main modelling question

Given limited resources, where and when should they be deployed for the greatest protection effect?

1. Overall Model Architecture

Layer 1: Risk Map and Species Vulnerability
$R_s(j,t)$ from spatial threat factors, with $V_s(j,t) = P_s(j)R_s(j,t)$

Layer 2: Species-Specific Protection Index

$$\mathrm{PI}_s(j,t) = \frac{C_s(j,t)D_s(j,t)}{1+\tau(j)V_s(j,t)}$$

Layer 3: Resource Allocation
ILP + greedy deployment of patrols, drones, and hotspot sensors

Layer 4: Dynamic Simulation
Discrete-time Markov model: safe $\rightarrow$ detected threat $\rightarrow$ breach

Layer 5: Sensitivity and Scenario Analysis
OAT, staffing thresholds, drone sensitivity, and Sobol analysis

Layer 6: Adaptation Plan
Recalibration for Danum Valley and Manu National Park

2. Conservation Priority: Species Weights

Species group	ω_s	Reason for priority
Black rhinoceros	0.40	Critically endangered; primary poaching target
African elephant	0.25	Vulnerable; keystone ecosystem engineer
Lion / cheetah	0.20	Vulnerable; retaliatory killing risk
Plains herbivores	0.15	Ecosystem baseline and prey community

How the weights are used

$$\max \sum_{s\in\mathcal{S}} \sum_{j\in\mathcal{J}} \omega_s P_s(j)\mathrm{PI}_s(j)$$

A breach in rhino habitat is weighted more heavily than an equal breach in a lower-priority zone.

2. Defining Sufficient Protection

A cell j is sufficiently protected for its highest-priority species $s(j)$ if

$$\mathrm{PI}_{s(j)}(j,t) \geq \mathrm{PI}^*_{s(j)}.$$

Species / group	Protection target PI^*_s
Black rhinoceros	≥ 0.85
African elephant	≥ 0.70
Lion / cheetah	≥ 0.65
Plains herbivores	≥ 0.50

$$\mathrm{CoverageRate}(t) = \frac{|\{j \in \mathcal{J} : \mathrm{PI}_{s(j)}(j,t) \geq \mathrm{PI}^*_{s(j)}\}|}{|\mathcal{J}|}$$

3. Risk Map: Four Risk Factors

For each species s, spatial risk is a weighted sum of four interpretable factors:

$$R_s(j,t) = \sum_{k=1}^{4} w_{s,k} F_k(j,t), \qquad \sum_{k=1}^{4} w_{s,k} = 1, \qquad F_k \in [0,1].$$

1. F_1: waterhole aggregation
2. F_2: road and gate accessibility
3. F_3: predator proximity
4. F_4: fire risk

Species-specific risk

The same location can have different risk values for different species because the four risk factors are weighted differently.

3. Ecological Aggregation and Human Accessibility

F_1: Waterhole proximity

Permanent waterholes create predictable animal aggregation.

$$F_1(j,t) = \frac{S(t)}{Z_1} \sum_{k=1}^{86} \exp\left(-\frac{d_k(j)^2}{2\sigma_W^2}\right)$$

$$S(t) = \begin{cases} 1.4, & \text{dry season,} \\ 0.8, & \text{wet season.} \end{cases}$$

$\sigma_W = 10\,\mathrm{km}$

F_2: Road and gate accessibility

Poaching risk increases where roads and gates provide easier access.

$$F_2(j) = \frac{1}{Z_2}\left[\alpha e^{-\lambda_r d_{\mathrm{road}}(j)} + (1-\alpha) e^{-\lambda_g d_{\mathrm{gate}}(j)}\right]$$

$\alpha = 0.6, \qquad \lambda_r = 0.10\,\mathrm{km}^{-1}, \qquad \lambda_g = 0.08\,\mathrm{km}^{-1}$

Poaching-related spatial risk

Waterhole aggregation and easy access jointly raise poaching risk; the full score also includes predator proximity and fire risk.

3. Ecological Conflict and Seasonal Fire Risk

F_3: Predator proximity

$$F_3(j) = \frac{1}{Z_3} \sum_k \exp\left(-\frac{d_{p_k}(j)^2}{2\sigma_P^2}\right), \qquad \sigma_P = 8\,\mathrm{km}$$

- For prey species, predator-rich areas affect animal concentration.
- For apex predators, proximity to roads and settlements increases retaliatory-killing risk.
- Species groups therefore receive different AHP weights.

F_4: Fire risk

$$F_4(j,t) \propto f(T, RH, U)\, NDVI(j)\, S_{\mathrm{dry}}(t)$$

- Higher temperature increases fire danger.
- Lower humidity increases fire danger.
- Wind accelerates fire spread.
- NDVI represents available fuel load.

The full normalised fire-risk equation is retained in the backup slides.

3. AHP Weights for Risk Factors

AHP converts qualitative ecological importance into numerical weights.

Species group	Water	Road	Pred.	Fire	$\lambda_{\max}$	CR
Black rhinoceros	0.535	0.270	0.075	0.120	4.114	0.042
African elephant	0.492	0.306	0.125	0.078	4.048	0.018
Lion / cheetah	0.258	0.564	0.109	0.069	4.079	0.029
Plains herbivores	0.170	0.284	0.473	0.073	4.051	0.019

Consistency check

$$CR = \frac{\lambda_{\max} - n}{(n-1)RI_n}, \qquad CR < 0.10$$

All matrices satisfy the standard AHP consistency criterion.

3. From Habitat Probability to Species Vulnerability

Risk matters only where a priority species is likely to occur.

$$P_s(j) = \frac{1}{Z_s} \sum_m \phi_{s,m} h_m(j) \exp\left(-\frac{d_{s,\mathrm{feat}}(j)^2}{2\sigma_{H,s}^2}\right), \qquad V_s(j,t) = P_s(j) R_s(j,t)$$

Habitat probability

- Terrain preference
- Distance to preferred features
- Species-specific habitat scale

Vulnerability

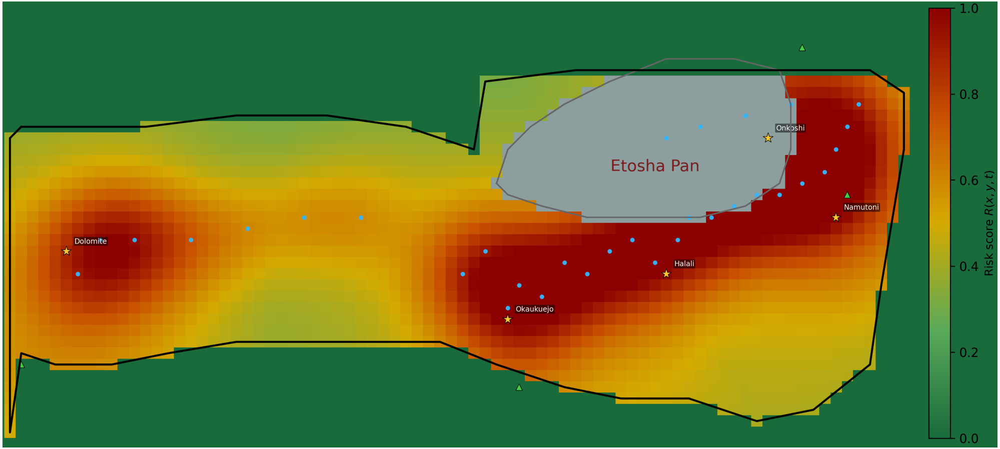
- High only when habitat and risk overlap
- Prevents allocation to irrelevant high-risk cells
- Combines species presence with local threat intensity

$$\bar{V}_s(t) = \frac{1}{|\mathcal{J}|} \sum_{j \in \mathcal{J}} V_s(j,t)$$

Binding conservation target

The species with the highest $\bar{V}_s(t)$ becomes the binding conservation target for that period.

3. Vulnerability Map Example: Rhino



Species vulnerability map $V_{\mathrm{rhino}}(j, t)$ under dry-season, night-time conditions. Blue dots indicate waterholes; yellow stars are main camps; green triangles are gates.

4. Protection Index: Conceptual Formula

Protection is not binary; it combines coverage, detection, and response speed.

$$\mathrm{PI}_s(j,t) = \frac{C_s(j,t)D_s(j,t)}{1+\tau(j)V_s(j,t)}$$

- $C_s(j,t)$: probability that a monitoring or deterrence resource covers the cell.
- $D_s(j,t)$: probability of correctly detecting a threat when coverage exists.
- $\tau(j)$: response-time penalty.
- $V_s(j,t)$: species-specific vulnerability.

Why coverage alone is insufficient

A well-monitored cell may still remain poorly protected when vulnerability is high or response is delayed.

4. Coverage by Multiple Protection Resources

Five monitoring and deterrence channels jointly determine whether a cell is covered:

$$C_s(j,t) = 1 - (1 - p_{ranger})(1 - p_{drone})(1 - p_{sat})(1 - p_{fence})(1 - p_{sensor})$$

Resource	Main contribution	Main limitation
Ranger	deterrence and interception	staffing and travel time
Drone	aerial and night monitoring	range and reliability
Satellite	wide-area observation	periodic coverage
Fence	entry prevention	breach-prone segments
Sensor	continuous hotspot monitoring	fixed installation

Resource redundancy

Combining independent monitoring channels reduces dependence on any single resource.

Coverage is useful only when a threat can be identified and responded to quickly.

$$D_s(j,t) = \frac{\sum_k \mu_{s,k} p_k(j,t) d_{s,k}(t)}{\sum_k \mu_{s,k} p_k(j,t) + \varepsilon}$$

$$\tau(j) = \min\left(3, \frac{T_{resp}(j)}{T_{ref}}\right), \qquad T_{ref} = 30 \text{ min}$$

- $D_s(j,t)$ combines resource coverage and detection performance.
- $\mu_{s,k}$ reflects the value of resource k for species s.
- $\tau(j)$ penalises remote cells with slow response times.

Detection–response bottleneck

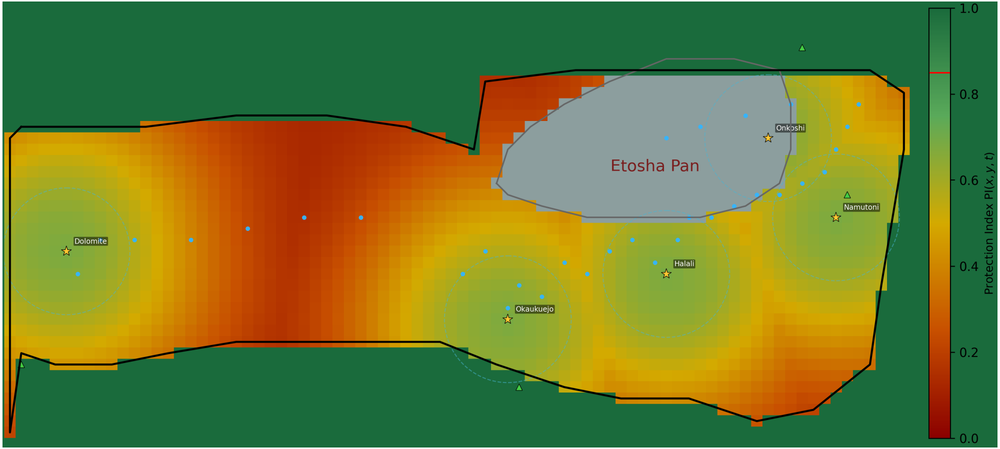
Nominal coverage does not guarantee protection when threats are missed or response is delayed.

Species	Ranger	Drone	Satellite	Static infra.	CR
Black rhino	0.284	0.172	0.074	0.471	0.019
Elephant	0.389	0.154	0.069	0.389	0.016
Lion / cheetah	0.277	0.161	0.466	0.096	0.012
Herbivores	0.227	0.227	0.423	0.123	0.004

Species-dependent resource value

Rhino protection depends most strongly on static infrastructure, whereas predator protection benefits more from wide-area satellite monitoring.

4. Baseline PI Map Example: Rhino



Baseline daytime

PI_{rhino} map under 98 rangers, 6 drones, and 30% satellite support. Camp-proximate zones are better protected; northern interior and eastern corridor remain weaker.

Variable	Type	Meaning
x_{ij}	binary	patrol unit i assigned to cell j
y_{dk}	binary	drone d assigned to base k
z_j	binary	fixed monitoring sensor installed in cell j

$$\max_{x,y,z} \sum_{s\in\mathcal{S}} \sum_{j\in\mathcal{J}} \omega_s P_s(j) \mathrm{PI}_s(j; x, y, z)$$

Allocation objective

The model maximises expected protection across all species and cells, weighted by habitat occupancy $P_s(j)$ and conservation priority ω_s.

5. Operational Constraints

Mobile resources

- At most 98 active rangers per shift
- Each patrol assigned to at most one cell
- Each drone assigned to one feasible base
- Patrol coverage limited by effective radius r_p

Protection and infrastructure

- Species-specific minimum PI in core habitat
- Patrol deployment constrained by road connectivity
- Fixed-sensor budget enforced
- Sensors installed only at eligible hotspot cells

$$\sum_i \sum_j x_{ij} \leq P_{\max} = 98, \qquad \sum_{j \in \mathcal{J}} z_j \leq M_{\text{sensor}}$$

$$\mathrm{PI}_s(j,t) \geq \mathrm{PI}_s^* \qquad \forall j \in \mathcal{R}_s, \qquad \mathcal{R}_s = \{j : P_s(j) \geq 0.5\}$$

Drone and sensor contributions are reduced using reliability coefficients $\eta_{\text{drone}} = 0.85$ and $\eta_{\text{sensor}} = 0.92$.

5. Greedy Resource Allocation

The complete ILP contains approximately $90{,}000$ binary variables and is computationally expensive to solve exactly.

$$j^* = \arg\max_{j \notin S} \sum_{s \in \mathcal{S}} \omega_s P_s(j) \Delta \mathrm{PI}_s(j)$$

1. Initialise the deployment set $S = \varnothing$.
2. Place drones at camp stations, prioritising camps with the highest weighted habitat value.
3. For each candidate cell, compute the marginal increase in the weighted protection objective.
4. Add the ranger deployment with the largest marginal gain and repeat until the ranger budget is exhausted.

Diminishing marginal gains

The objective is monotone submodular, so additional resources provide smaller marginal gains as protection accumulates in the same area. The greedy algorithm therefore achieves at least $(1 - 1/e) \approx 63\%$ of the optimal ILP value.

5. Staffing Thresholds by Species

Species	Minimum active rangers	Binding resource
Black rhinoceros	82	Fence + ranger joint coverage
African elephant	54	Perimeter corridor coverage
Lion / cheetah	38	Satellite + rapid-response coverage
Plains herbivores	29	Drone night coverage

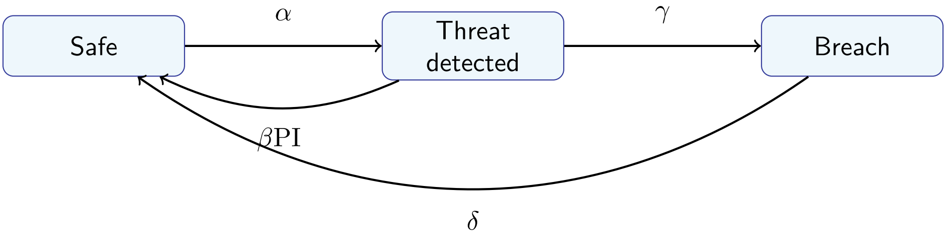
Binding constraint: rhino protection

The black-rhino constraint is the most resource-intensive: 82 is the minimum staffing level at which the optimiser can satisfy

$$\mathrm{PI}_{\mathrm{rhino}}(j,t) \geq 0.85 \qquad \forall j \in \mathcal{R}_{\mathrm{rhino}}.$$

Each species and grid cell occupies one of three states:

$$S_{s,j}(t) \in \{0 : \text{safe}, 1 : \text{threat detected}, 2 : \text{breach}\}$$



From static PI to dynamic outcomes

The state model converts PI into time-dependent probabilities of threat neutralisation and breach.

$$T_s(j,t) = \begin{pmatrix} 1-\alpha_{s,j}(t) & \alpha_{s,j}(t) & 0 \\ \beta \mathrm{PI}_s(j,t) & 1-\beta \mathrm{PI}_s(j,t)-\gamma_{s,j}(t) & \gamma_{s,j}(t) \\ \delta_s & 0 & 1-\delta_s \end{pmatrix}$$

- $\alpha_{s,j}(t)$: arrival probability of a new threat
- $\beta \mathrm{PI}_s(j,t)$: neutralisation probability
- $\gamma_{s,j}(t)$: escalation probability to breach
- δ_s: recovery probability

$$\alpha_{s,j}(t) = \min\bigl(0.9, V_s(j,t)a(t)\Delta t\bigr), \qquad \gamma_{s,j}(t) = \eta_s\bigl(1-\mathrm{PI}_s(j,t)\bigr)$$

How PI changes transitions

A larger PI shifts probability from breach escalation toward threat neutralisation.

Time	Threat multiplier $a(t)$	Patrol efficiency $e(t)$
06:00–12:00	0.6	1.00
12:00–18:00	0.5	1.00
18:00–24:00	1.4	0.60
00:00–06:00	1.8	0.40

$$\mathrm{CBR}_s(T) = \frac{1}{|\mathcal{J}|} \sum_{j \in \mathcal{J}} \mathbf{1}\left[\exists\, t \le 4T : S_{s,j}(t) = 2\right]$$

$$\mathrm{CBR}(T) = \sum_{s \in \mathcal{S}} \omega_s \mathrm{CBR}_s(T)$$

Highest-risk time window

From 00:00 to 06:00, threat intensity is highest while ranger efficiency is lowest.

6. Baseline Simulation Results

Species	90-day CBR	Avg. PI day 90	Target	Status
Black rhinoceros	11.3%	0.76	0.85	Average PI below benchmark
African elephant	7.8%	0.72	0.70	Met
Lion / cheetah	6.4%	0.68	0.65	Met
Plains herbivores	5.9%	0.54	0.50	Met
Weighted aggregate	8.2%	0.67	–	–

Caution

Average rhino PI below 0.85 does not contradict the optimisation feasibility threshold; the hard constraint is a cell-level criterion in the rhino core zone, while the simulation reports dynamic average PI.

6. Dynamic Simulation: Horizon and Key Outcomes

Simulation structure

- Baseline dynamic simulation: 180 days
- Four 6-hour time slots per day
- Baseline staffing: 98 active rangers
- Baseline drone fleet: 6 drones
- Satellite coverage: 30%

Reported protection outcomes

- Weighted 90-day CBR: 8.2%
- Rhino 90-day CBR: 11.3%
- Rhino average PI at day 90: 0.76
- 68% of breach events occur during 00:00–06:00

Role of the dynamic simulation

The Markov model tests how a static deployment performs over time as threat intensity and patrol efficiency change across the day.

The report uses the 180-day simulation to examine temporal behaviour, while the main baseline and scenario comparisons are reported using 90-day CBR metrics.

7. Sensitivity Analysis Overview

The model is evaluated using three complementary approaches:

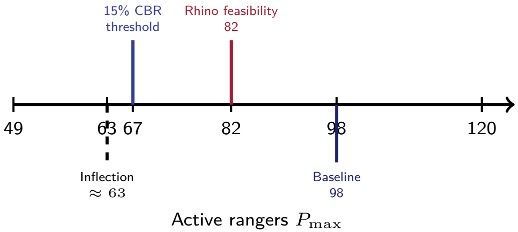
1. One-at-a-time (OAT) sensitivity analysis
2. Sobol variance-based global sensitivity analysis
3. Operational scenario testing

Parameter	Baseline	Range	ΔPI	ΔCBR
Patrol staffing $P_{\max}$	98	49–120	0.18	16 pp
Drone count N_d	6	0–15	0.09	7 pp
Detection efficiency β	0.60	0.30–0.90	0.12	9 pp
Threat rate η	0.15	0.05–0.30	0.10	14 pp
Patrol radius r_p	14 km	6–28 km	0.07	5 pp
Kernel radius σ	10 km	5–20 km	0.04	3 pp
Night multiplier β_n	0.50	0.2–0.8	0.06	8 pp

Key OAT finding

Patrol staffing $P_{\max}$ has the largest individual effect on both PI and CBR, followed by detection efficiency β and drone count N_d.

7. Ranger Staffing Thresholds



Critical staffing levels

- Inflection: ≈ 63
- 15% CBR threshold: ≈ 67
- Rhino feasibility: 82
- Baseline deployment: 98

Meaning of 82

82 is the minimum staffing level satisfying

$$\mathrm{PI}_{\mathrm{rhino}}(j,t) \geq 0.85, \qquad \forall j \in \mathcal{R}_{\mathrm{rhino}}.$$

82 is the cell-level rhino feasibility threshold; 98 is the recommended baseline operating level.

7. Drone and Global Sensitivity Results

Drone sensitivity

- Baseline fleet: $N_d = 6$
- Largest marginal gains occur for the first 4–6 drones.
- Additional gains diminish beyond this range.
- Complete drone removal increases 90-day CBR to 15.1%.

Emergency buffering

Under the $\eta \times 2.2$ poaching surge, adding 5 targeted drones to the baseline fleet reduces CBR to approximately 9.5%.

Parameter	Sobol index S_i
$P_{\max}$	0.38
β	0.21
N_d	0.17
η	0.13
r_p	0.06
σ	0.03
Other interactions	0.02

Sobol ranking

$P_{\max}$, β, and N_d together explain

$$0.38 + 0.21 + 0.17 = 0.76$$

or 76% of the variance in average PI.

7. Combined Sensitivity Summary

Analysis	Key result	Management implication
Ranger staffing	$P_{\max}$ is dominant	Maintain stable staffing
CBR threshold	15% at ≈ 67 rangers	Avoid severe personnel cuts
Rhino feasibility	Minimum 82 rangers	Protect core rhino habitat
Drone sensitivity	Largest gains at first 4–6	Modest fleet expansion is efficient
Sobol analysis	$P_{\max}, \beta, N_d$: 76%	Focus on controllable inputs

Overall sensitivity result

Stable staffing determines baseline protection, while drones provide the most flexible short-term buffer against sudden increases in threat pressure.

7. Scenario Analysis Results

Scenario	Avg. PI	CBR	Rhino PI	Assessment
Baseline	0.61	8.2%	0.76	Acceptable
50% personnel cut	0.47	23.8%	0.51	Critical
Poaching surge	0.53	31.4%	0.62	Critical
Drone removal	0.56	15.1%	0.69	Concerning

Largest scenario losses

Staffing reduction and threat surges produce the largest deterioration in protection, while drone loss primarily weakens night-time coverage.

7. Poaching Surge and Drone Buffer

Poaching-surge scenario

- Breach escalation rate η is multiplied by 2.2.
- CBR rises from 8.2% to 31.4%.
- Rhino PI falls from 0.76 to 0.62.

Targeted drone response

- Add 5 drones to the baseline fleet of 6.
- Total fleet increases to 11 drones.
- Drones are targeted to nocturnal hotspots.
- CBR is restored to approximately 9.5%.

Emergency deployment role

Targeted drone redeployment provides an effective short-term emergency buffer when rapid staff expansion is not possible.

Approximately 68% of breach events occur during the 00:00–06:00 period, making nocturnal deployment especially important.

8. Model Strengths

- Integrates threat intensity, biodiversity value, accessibility, and patrol effectiveness into a single prioritisation pipeline.
- Uses an explicit and auditable allocation stage, allowing decision-makers to trace why patrol resources are assigned to particular zones and time windows.
- Connects spatial resource allocation with a dynamic simulation of protection outcomes over time.
- Supports scenario testing under changing threat and operating conditions.

Ecology-to-deployment link

The framework translates ecological and threat information into explicit resource-allocation decisions that can be traced and evaluated.

8. Model Limitations

- Results depend on the quality of incident reports, habitat proxies, and detection-probability estimates.
- Uncertain or sparse detection data can bias calibrated protection scores.
- Operational constraints are simplified into tractable scheduling rules, so vehicle failures, sudden road closures, or staffing shocks can reduce realised performance.
- The staffing model assumes that the full ranger roster is stable and equally available across three shifts.
- Sick leave, training rotations, and the 6–12-month onboarding lag for new recruits are not modelled explicitly.
- The model may therefore overestimate near-term protection in scenarios requiring rapid personnel increases.

Practical implication

The framework should be used as a decision-support system and periodically recalibrated and validated with new monitoring and field data.

9. Transferability of the Framework

What stays the same

- Grid-based spatial modelling framework
- Risk and vulnerability mapping
- Protection Index structure
- Resource-allocation objective and constraints
- Greedy deployment algorithm
- Three-state Markov simulation
- OAT and Sobol sensitivity framework

What must be recalibrated

- Grid resolution and terrain representation, where necessary
- Ecological aggregation features
- Accessibility geometry
- Detection performance
- Species protection thresholds
- Local threat layers

Transfer condition

The decision architecture remains unchanged, while ecological proxies, movement constraints, detection parameters, and protection thresholds must be recalibrated for each park.

9. Adaptation Cases: Danum Valley and Manu

Danum Valley, Malaysia

- Area: $438\,\mathrm{km}^2$
- Terrain: primary lowland rainforest
- Main threats: illegal logging, wildlife trafficking, and encroachment
- Grid resolution reduced from 5 km to 1 km
- Vehicle patrol replaced by foot and river-boat patrol
- Drone and satellite detection reduced by dense canopy

Manu National Park, Peru

- Area: $17{,}162\,\mathrm{km}^2$
- Terrain: rainforest and Andean altitudinal gradient
- Main threats: illegal mining, bushmeat poaching, and drug-trafficking corridor use
- Road-based accessibility replaced by river networks and elevation bands
- Patrol geometry becomes river-based and anisotropic
- Drone and satellite performance recalibrated for cloud, humidity, and terrain

Danum requires finer spatial resolution and canopy-adjusted detection, while Manu requires river-based accessibility and elevation-sensitive risk layers

9. Cross-Park Comparison

Dimension	Etosha	Danum Valley	Manu
Area	22,935 km^2	438 km^2	17,162 km^2
Terrain	open savanna / salt pan	lowland rainforest	rainforest / Andean gradient
Primary mobility	vehicle patrol	foot / river boat	river boat
Key aggregator	waterhole	salt lick / river	river / oxbow lake
Primary threat	rhino poaching	illegal logging / trafficking	illegal mining / bushmeat
Satellite utility	moderate (30%)	low (15%)	low–moderate (20%)
Expected 90-day CBR	$\sim$8% (baseline)	$\sim$10% (est.)	~ 12–18% (est.)

Park-specific recalibration

Danum shifts the model toward finer grids and dense local monitoring, while Manu requires river-based patrol geometry and a distinct mining-threat layer.

10. Final Recommendations

1. Maintain at least 98 actively deployed rangers.
2. Add 4–6 drones and prioritise them for night deployment, especially in high-risk hotspot areas.
3. Adopt a dry-season surge strategy by shifting more patrol effort and drone coverage toward high-risk zones and night hours.

Recommended operating policy

Stable ranger staffing is the foundation of baseline protection, while drones provide the most effective flexible buffer when threat pressure rises suddenly.

The 82-ranger level is the minimum rhino-zone feasibility threshold, not the recommended normal operating level.

10. Closing Summary

Where?

Waterholes, gate and road corridors, and other zones where high ecological value and threat overlap.

When?

During the dry season and especially the 00:00–06:00 deep-night window.

How?

Maintain stable ranger staffing, expand drone coverage modestly, and concentrate protection rather than distributing resources evenly.

Management takeaway

The goal is not to monitor every place equally, but to protect the right places at the right times.

Thank you.

Species	Ranger d/n	Drone d/n	Satellite	Fence	Fixed sensor
Black rhino	.75/.60	.78/.88	.50	.92	.85
Elephant	.85/.70	.85/.80	.65	.80	.75
Lion / cheetah	.65/.45	.72/.82	.55	.60	.70
Herbivores	.70/.55	.80/.75	.70	.65	.72

Interpretation

Detection performance varies by species, resource type, and time of day. Night-time drones are particularly effective for rhino monitoring.

Backup B. Species Recovery Rates

Species	δ_s	Rationale
Black rhinoceros	0.05	mortality is irreversible; slow demographic recovery
African elephant	0.08	moderate recovery through herd dynamics
Lion / cheetah	0.10	retaliatory events are episodic
Plains herbivores	0.12	fastest reproductive recovery

Role in the dynamic model

The recovery parameter controls the transition

$$\text{Breach} \longrightarrow \text{Safe}.$$

Lower values represent more persistent ecological damage.

Backup C. Main Parameter Reference

Layer	Parameter	Baseline
Risk	σ_W	$10\,\mathrm{km}$
Risk	σ_P	$8\,\mathrm{km}$
Risk	λ_r, λ_g	$0.10,\ 0.08\,\mathrm{km}^{-1}$
Risk	S_{dry}	1.40
PI	r_p	$14\,\mathrm{km}$
PI	r_d	$15\,\mathrm{km}$
PI	ℓ_f	$5\,\mathrm{km}$
PI	p_{sat}	0.30
ILP	$P_{\max}$	98
Sim	$a(t)$	$0.6,\ 0.5,\ 1.4,\ 1.8$
Sim	$e(t)$	$1.0,\ 1.0,\ 0.6,\ 0.4$

Backup D. Full Fire-Risk Function

The complete fire-risk factor used in the spatial model is

$$F_4(j,t) = \frac{1}{Z_4}\left(1 - e^{-\kappa(T-T_0)}\right)\left(1 - \frac{RH}{100}\right)^{1.5}\left(\frac{U}{U_{ref}}\right)^{0.5} NDVI(j) S_{dry}(t).$$

- T: daily maximum temperature
- $T_0 = 25°\mathrm{C}$: reference temperature
- RH: relative humidity
- U: wind speed
- $U_{ref} = 30\,\mathrm{km/h}$
- $NDVI(j)$: vegetation fuel-load proxy

$$S_{dry}(t) = \begin{cases} 1.0, & \text{dry season,} \\ 0.1, & \text{wet season.} \end{cases}$$

Backup E. Robust Habitat Uncertainty

Habitat probability is uncertain because species distributions and field observations are imperfect.

$$P_s(j) \in \left[\hat{P}_s(j) - \delta_s^P, \hat{P}_s(j) + \delta_s^P\right].$$

The robust allocation considers the least favourable habitat distribution within this uncertainty range:

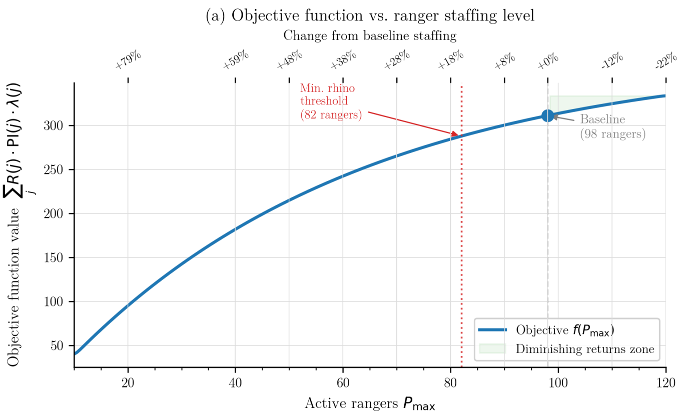
$$\max_{x,y,z} \min_{P_s(j)\in\mathcal{U}_s} \sum_{s\in\mathcal{S}} \sum_{j\in\mathcal{J}} \omega_s P_s(j) \mathrm{PI}_s(j; x, y, z).$$

- $\hat{P}_s(j)$: estimated habitat probability
- δ_s^P: habitat uncertainty margin
- $\mathcal{U}_s$: uncertainty set for species s

Purpose

The resource allocation should remain effective despite small errors in estimated species distributions.

Backup F. Staffing Objective Curve



The protection objective increases with active ranger count, but marginal improvements diminish as staffing approaches and exceeds the baseline level.

Backup G. Sobol Sensitivity Definition

The first-order Sobol index is

$$S_i = \frac{\mathrm{Var}_{X_i}\left[\mathbb{E}_{X_{\sim i}}(Y \mid X_i)\right]}{\mathrm{Var}(Y)}.$$

- X_i: parameter being evaluated
- $X_{\sim i}$: all parameters other than X_i
- Y: model output, such as PI or CBR

Interpretation

S_i is the proportion of total output variance explained by parameter X_i alone, excluding interaction effects.