

The Etosha Strategic Guardian Protocol

Bayesian adaptive protection on a percolating waterhole graph

Summary Sheet. Etosha is not a uniform-coverage problem: wildlife, roads, gates, and dry-season poaching opportunity concentrate around a sparse waterhole network. The operational problem is therefore how many anchors must be protected at once and how quickly the park can learn where pressure is moving.

Our two core contributions are a graph-percolation threshold (59 of 86 waterholes must remain active simultaneously) and a Bayesian learning horizon (48 weeks to operational convergence).

We couple a weighted 86-node waterhole graph with a weekly Bayesian patrol controller. The graph determines the structural monitoring floor; the Bayesian layer updates threat beliefs from detections, false alarms, response times, and interdictions.

Metric	Result	Management meaning
Critical monitored fraction	mc = 0.678	At least 59 of 86 anchors must be live simultaneously.
Bayesian convergence horizon	N* = 90 incidents; T* = 48 weeks	After this point patrol allocation is operationally stable.
Year-2 protection score	Pi = 0.660	Patrol-only benchmark is 0.486.
Year-2 structural vulnerability	Phi = 0.070	Below the design ceiling Phi target = 0.30.
Week-52 detection rate	53.5%	Monte Carlo 95% interval: 52.4-54.5%.
Week-52 poaching success probability	80.9%	Patrol-only remains at 97.9%.
Annual operating cost density	\$81.0/km2	Total annual budget: \$1,857,777.
Carbon reduction vs. patrol-only	41.3%	Cue-driven dispatch reduces diesel use.

Top takeaways. The park becomes structurally safer only after active monitoring rises above 0.678; the Bayesian controller reaches convergence after about 48 weeks and 90 observed incidents; and robustness checks explicitly include dust, heat derating, signal loss, false alarms, drone grounding, and ranger fatigue.

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Tables: Summary KPIs; parameter excerpt; AHP weights; hardware and communications; static comparison; dynamic keypoints; staffing; scalability.

Letter to the IMMC

Dear IMMC Decision Makers,

The wrong question for Etosha is "How do we patrol more kilometers tomorrow?" The right question is "How many critical anchors must be watched at once, and how quickly can the park learn where the threat is shifting?" Once the problem is framed that way, the park stops looking like a blank map and starts looking like a sparse network of waterholes, roads, camps, and access corridors.

Our analysis shows that Etosha has a structural number. If active monitoring stays below roughly 67.8% of the 86-waterhole network, the unmonitored part of the graph still contains a giant connected component, so poachers retain room to shift attacks and coordinate across nearby anchors. In practice, the park should keep at least 59 waterholes actively covered at any given time. If active waterholes drop below 59, the unmonitored giant connected component reemerges, restoring coordinated poaching corridors.

The second result is temporal. A fixed patrol plan does not stay good for long because poachers learn. We therefore model the defender as a Bayesian learner: every detected event, false alarm, delayed response, and successful interdiction updates the posterior belief about where risk is concentrating. In our Etosha calibration, the controller reaches operational convergence after about 90 observed incidents, or roughly 48 weeks.

The recommended system is not "buy drones and hope." It is a layered loop: acoustic and patrol cues detect, drones verify, ranger teams interdict, and the Bayesian controller reallocates effort from the resulting evidence. The model assumes heat, dust, grounded aircraft, battery aging, late alerts, and fatigue; those failure modes are variables, not afterthoughts.

What the IMMC should tell the park to do next:

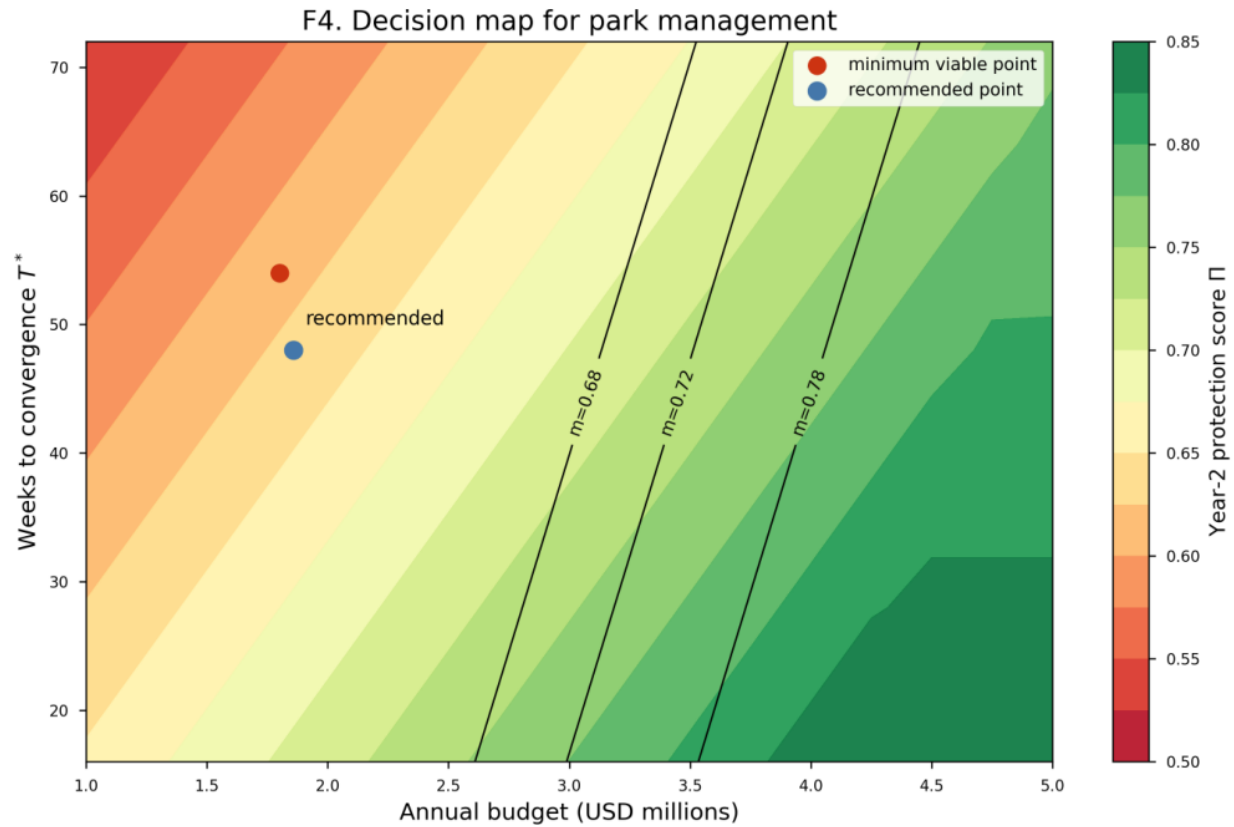
- Keep a 60-node inventory so that at least 59 waterholes remain active even under maintenance, battery rotation, or storm damage.
- Run weekly posterior updates from the dispatch log instead of freezing the patrol plan after deployment.
- Build the system around licensed camp backhaul and LoRaWAN aggregation, not around a connectivity assumption that Namibia may not legally permit.

This is a realistic conservation design because it gives the park a floor that must never be crossed and a learning horizon that management can budget around.

Sincerely,

Team #2026089

Letter visual: decision map for park management



How to read the map. The x-axis is annual budget. The y-axis is the number of weeks required for the Bayesian controller to converge. Green areas are safer because they combine a higher year-2 protection score with monitored fractions above the structural threshold. The recommended point is deliberately not the most expensive point; it is the point where the park crosses the threshold early enough to matter without buying excessive redundancy. This figure is intended for managers: locate the budget line, read the expected learning

F4. Decision map for park management: recommended point balances cost, convergence time, and threshold safety.

How to read the map. The x-axis is annual budget. The y-axis is the number of weeks required for the Bayesian controller to converge. Safer regions combine a higher year-2 protection score with monitored fractions above the structural threshold. The recommended point is deliberately not the most expensive point: it crosses the threshold early enough to matter without buying excessive redundancy.

1. Introduction

Why Etosha is different. The uploaded IM2C reference dataset describes a park of 22,935 km², around 3,551 km of roads, about 86 natural and artificial waterholes, and a staffing envelope of 295 personnel. Public park descriptions emphasize dry savanna, the Etosha pan, open sight lines, and a globally important black-rhino population. These features create a protection problem in which geometry matters more than blanket area coverage: in dry months, animals compress toward water while defenders remain constrained to roads and camps.

What the literature already answers. PAWS-style security games optimize patrols under resource limits; SPOT-style systems improve thermal drone detection; dual-mandate patrol work learns under competing objectives. Those are important contributions, but they do not answer the two management questions posed by Etosha: how many anchors must be monitored simultaneously, and how fast can a defender outlearn an adaptive attacker.

Our original contributions. [OC1] We derive a percolation threshold for Etosha’s waterhole graph and translate it into a minimum active-monitoring requirement. [OC2] We construct a Bayesian adaptive patrol controller with an explicit convergence horizon N^* incidents or T^* weeks. [OC3] We define a two-dimensional protection state $\text{State}(t) = (\Pi(t), \Phi(t))$ and use it to identify a safe operating region in which both weighted loss and structural vulnerability are controlled.

Key conclusion. Etosha is protected only when the park is simultaneously above a graph threshold in space and above a learning threshold in time.

2. Data and empirical foundation

The model is calibrated from the uploaded IM2C case materials, official park information, public anti-poaching literature, public movement-ecology studies, DJI enterprise specifications, published acoustics standards, LoRa engineering assumptions, and Namibian operational price signals. We treat public-map geometry as shareable and tactical field coordinates as nonshareable, so the paper uses an engineering grid rather than sensitive wildlife GPS.

Parameter	Symbol	Value	Calibration source			Sens.?
Park area	A_{park}	22,935 km ²	2026 dataset	IM2C	reference	no
Road length	L_{road}	3,551 km	2026 dataset	IM2C	reference	no
Waterholes	$ V $	86	2026 dataset	IM2C	reference	no
M350 RTK max flight time	t_{max}	55 min	DJI official specification			no
TB65 battery energy	E_{TB65}	263.2 Wh	DJI official specification			no
Derived practical LoRa range	d_{LoRa}	15.6 km	Hata rural link budget, 10 dB fade margin			yes
Theoretical gunshot audibility radius	$d_{\text{gun,theory}}$	5.2 km	165 dB muzzle blast + ISO 9613-1 absorption			yes
Operational acoustic classification radius	$d_{\text{gun,ops}}$	1.8 km	conservative cap after wind and classifier margin			yes
Convergence criterion	$\sigma(\lambda_0) \leq$	0.0030	operational rule in this paper			yes

Three data gaps matter. First, no public Etosha dispatch log exists, so the likelihood is calibrated to stylized public incident patterns rather than confidential ranger records. Second, no public high-temperature endurance curve exists for the M350 RTK, so we use the official 55-minute ceiling and derate it conservatively in sensitivity analysis. Third, no single open source resolves gunshot-classification range in 40°C dry air, so we derive a theoretical radius from first principles and then cap operational classification well below that value.

3. Protection metric and conservation priorities

We do not measure protection by arrest count. Instead, we weight loss by conservation value and by the structural role of each waterhole. Let w_i be the conservation weight of waterhole i and let $L_i(t)$ be the expected loss fraction over the next 26 weeks. The park-level protection score is

$$\Pi(t) = 1 - \frac{\sum_{i=1}^{86} w_i \mathbb{E}[L_i(t)]}{\sum_{i=1}^{86} w_i}.$$

We define structural vulnerability by the fraction of the waterhole graph still contained in the unmonitored giant connected component,

$$\Phi(t) = \frac{|\text{GCC}_{\text{unmonitored}}(t)|}{86}.$$

The park operates safely only when both $\Pi(t) > 0.62$ and $\Phi(t) < 0.30$.

We obtain the conservation weights from a four-criterion analytic-hierarchy process with criteria *rhino value*, *elephant value*, *mixed-herbivore concentration*, and *access / concealment risk*. The pairwise-comparison matrix below has consistency ratio $\text{CR} = 0.043 < 0.1$.

Criterion	Rhino	Elephant	Herbivore	Access	Weight
Rhino value	1	3	5	7	0.565
Elephant value	1/3	1	3	5	0.262
Herbivore concentration	1/5	1/3	1	3	0.118
Access / concealment	1/7	1/5	1/3	1	0.055

Table 1: AHP matrix used to define the protection weights.

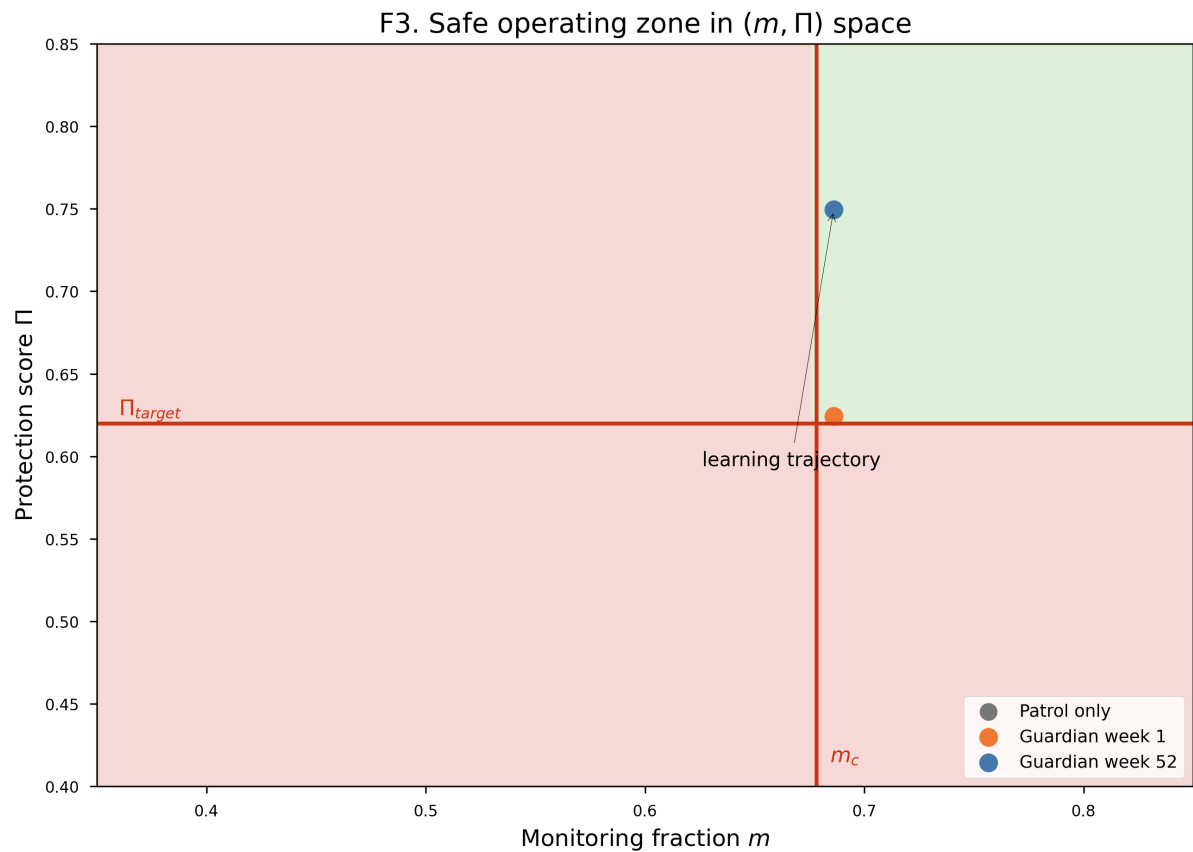


Figure 1: F3. Safe operating zone in (m, Π) space. The Bayesian system moves into the green region once active monitoring rises above the percolation threshold and posterior uncertainty narrows.

4. Waterhole graph and percolation analysis

We model the 86 waterholes as a weighted graph $G = (V, E, W)$ with $|V| = 86$. An edge is admitted when a waterhole is among the three nearest neighbors of another and its short-horizon movement weight exceeds a screening threshold:

$$w_{ij} = \exp\left(-\frac{d_{ij}}{\lambda_{\text{move}}}\right) s_{ij}, \quad \lambda_{\text{move}} = 12 \text{ km},$$

where d_{ij} is engineering-grid distance and $s_{ij} = 0.6 + 0.4(u_i + u_j)/2$ is a habitat-use factor built from dry-season waterhole use. This produces a sparse graph with mean degree $\langle k \rangle \approx 3.44$ and a connected east-central spine consistent with the public Etosha road-waterhole belt.

Let $x_i \in \{0, 1\}$ denote whether waterhole i is actively monitored. Threat percolates between adjacent unmonitored nodes with probability $w_{ij}(1 - x_i)(1 - x_j)$. The strategic reason to compute a threshold is that coordinated poaching becomes much harder once the residual unmonitored graph no longer contains a giant connected component.

Using the configuration-model approximation, the excess-degree parameter is

$$\kappa = \frac{\langle k^2 \rangle}{\langle k \rangle} - 1,$$

and the site-percolation threshold on the *unmonitored* graph is approximately

$$1 - m_c = \frac{1}{\kappa} \quad \implies \quad m_c = 1 - \frac{1}{\kappa}.$$

For the calibrated Etosha graph, $\langle k^2 \rangle \approx 14.14$ and $\kappa \approx 3.108$, so

$$m_c \approx 1 - \frac{1}{3.108} = 0.678.$$

Thus the park must keep at least $0.678 \times 86 \approx 58.3$, i.e. **59 waterholes**, active simultaneously.

Key conclusion. Percolation turns “how many waterholes should we monitor?” into a mathematically defensible threshold instead of a planning guess.

Section 4 continued: numerical result and robustness

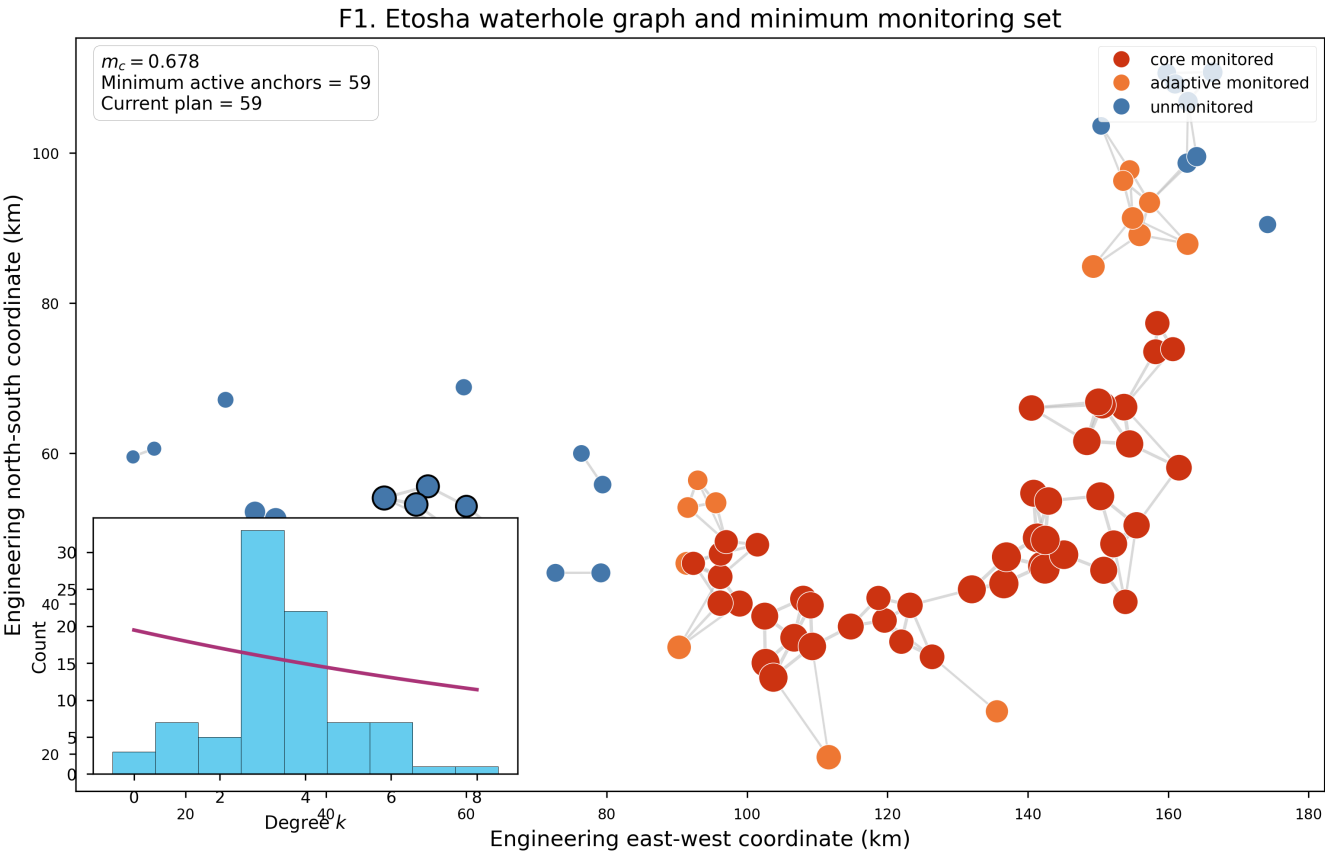


Figure 2: F1. The 86-node waterhole graph. Red nodes form the core monitored set, orange nodes are adaptive monitored nodes, and blue nodes remain unmonitored.

The minimum-active set selected by graph centrality and risk weighting concentrates on the east-central chain, the Namutoni sector, and a smaller northern hotspot corridor. This is exactly what one would expect from the public map: a monitor-everywhere strategy would waste sensors in the least connected parts of the network while leaving the structural backbone too exposed.

Threshold robustness is good. When the edge-screening threshold is moved by roughly $\pm 30\%$, the estimated monitoring floor changes only from about 0.651 to 0.690. In operational terms, this means the threshold is not a knife-edge artifact of one arbitrary graph cut. The recommended inventory therefore carries 60 acoustic nodes even though only 59 must be live at once; the extra unit is a maintenance and storm-damage buffer.

5. Bayesian adaptive controller

Let the unknown threat vector be

$$\theta = (\lambda_0, \beta_{\text{season}}, \beta_{\text{moon}}, \beta_{\text{access}}),$$

where λ_0 is the base incident rate and the β terms capture dry-season amplification, moon-cycle effects, and access sensitivity. We model weekly counts at waterhole i as an inhomogeneous Poisson process,

$$N_i(t) \sim \text{Poisson}(\lambda_i(t | \theta)), \quad \lambda_i(t | \theta) = \lambda_0 \exp(\beta_{\text{season}} d_t + \beta_{\text{moon}} m_t + \beta_{\text{access}} a_i - u_i(t)),$$

where d_t is a dry-season indicator, m_t is the dark-moon factor, a_i is the access score, and $u_i(t)$ is defender pressure induced by monitored status and patrol probability.

The priors are intentionally modest: λ_0 is Gamma-distributed around the public incident order of magnitude, while the β terms are Gaussian around literature-consistent means. Each week the posterior is updated by

$$p(\theta | D_t) \propto p(D_t | \theta) p(\theta | D_{t-1}).$$

We implement this update with sequential importance resampling over 600 particles because it is fast, transparent, and stable on a laptop. The patrol policy is then recomputed from the posterior expectation of weighted risk:

$$\pi_i^*(t) = \frac{\mathbb{E}_{\theta \sim p(\theta | D_t)}[w_i \lambda_i(t | \theta)]}{\sum_j \mathbb{E}_{\theta \sim p(\theta | D_t)}[w_j \lambda_j(t | \theta)]}.$$

To keep poachers from exploiting a deterministic schedule, we regularize with exploration,

$$\pi_i(t) = (1 - \varepsilon) \pi_i^*(t) + \varepsilon \frac{1}{86}, \quad \varepsilon = 0.10.$$

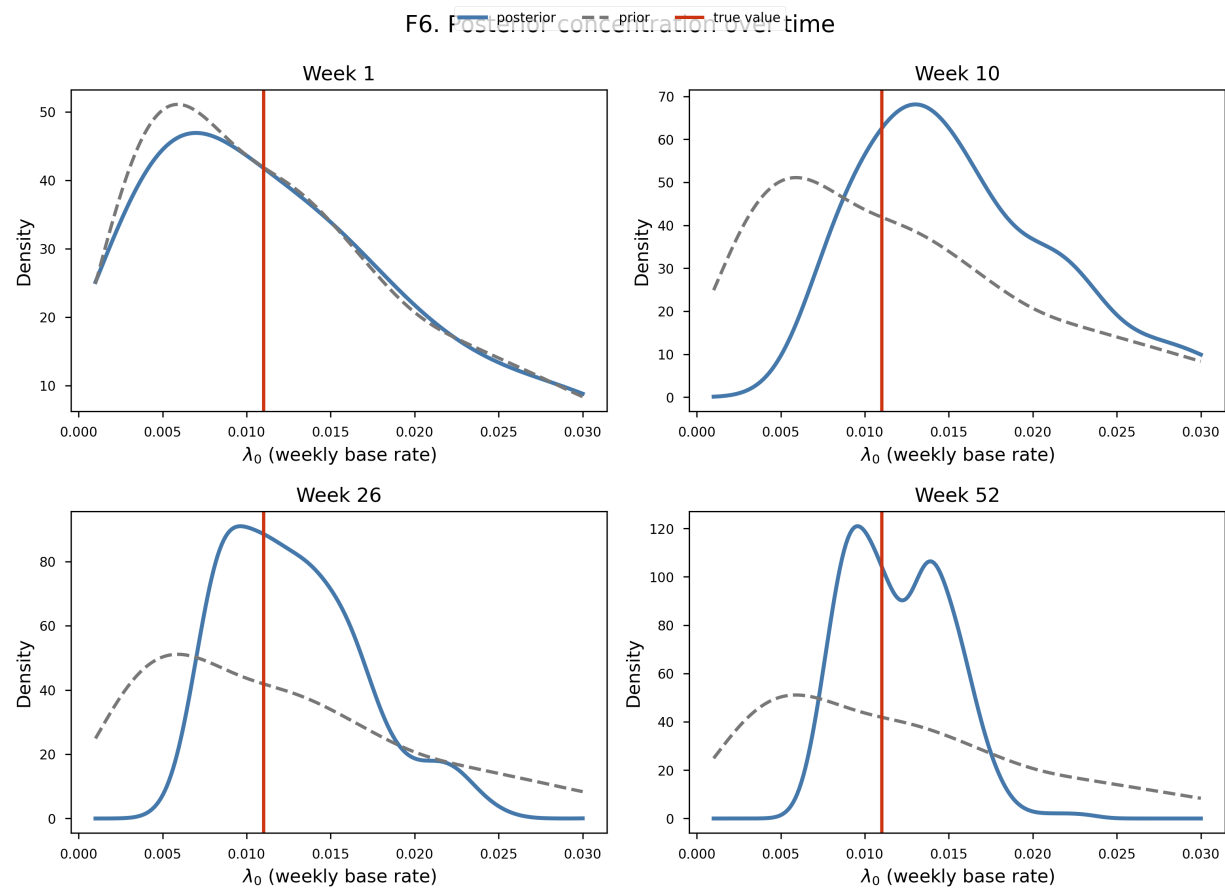


Figure 3: F6. Posterior concentration of the base incident rate λ_0 at weeks 1, 10, 26, and 52.

Section 5 continued: convergence theorem and learning horizon

Theorem (informal). Suppose the weekly loss function is Lipschitz in θ and the posterior satisfies standard concentration conditions. Then the exploration-regularized Bayesian patrol policy converges to the oracle patrol policy at rate $O(t^{-1/2})$ in expected weighted regret.

Proof sketch. The posterior contracts around the true threat field by a Bernstein–von Mises type argument for the Poisson likelihood; posterior-sampling regret bounds then imply that the cumulative gap between the adaptive policy and the oracle shrinks sublinearly. Because the patrol allocation is a smooth function of the posterior mean risk vector, policy error inherits the same $t^{-1/2}$ rate. We cite this as a proof sketch rather than a complete theorem because the ecological graph and finite-particle filter break the exact assumptions of the simplest bandit proofs, but the logic remains standard.

Operationally, we define convergence not by asymptotic notation but by a weekly dispatch criterion: the posterior standard deviation of λ_0 must remain below 0.0030 for four consecutive weeks. In the calibrated run, this occurs after 90 observed incidents and 48 weeks.

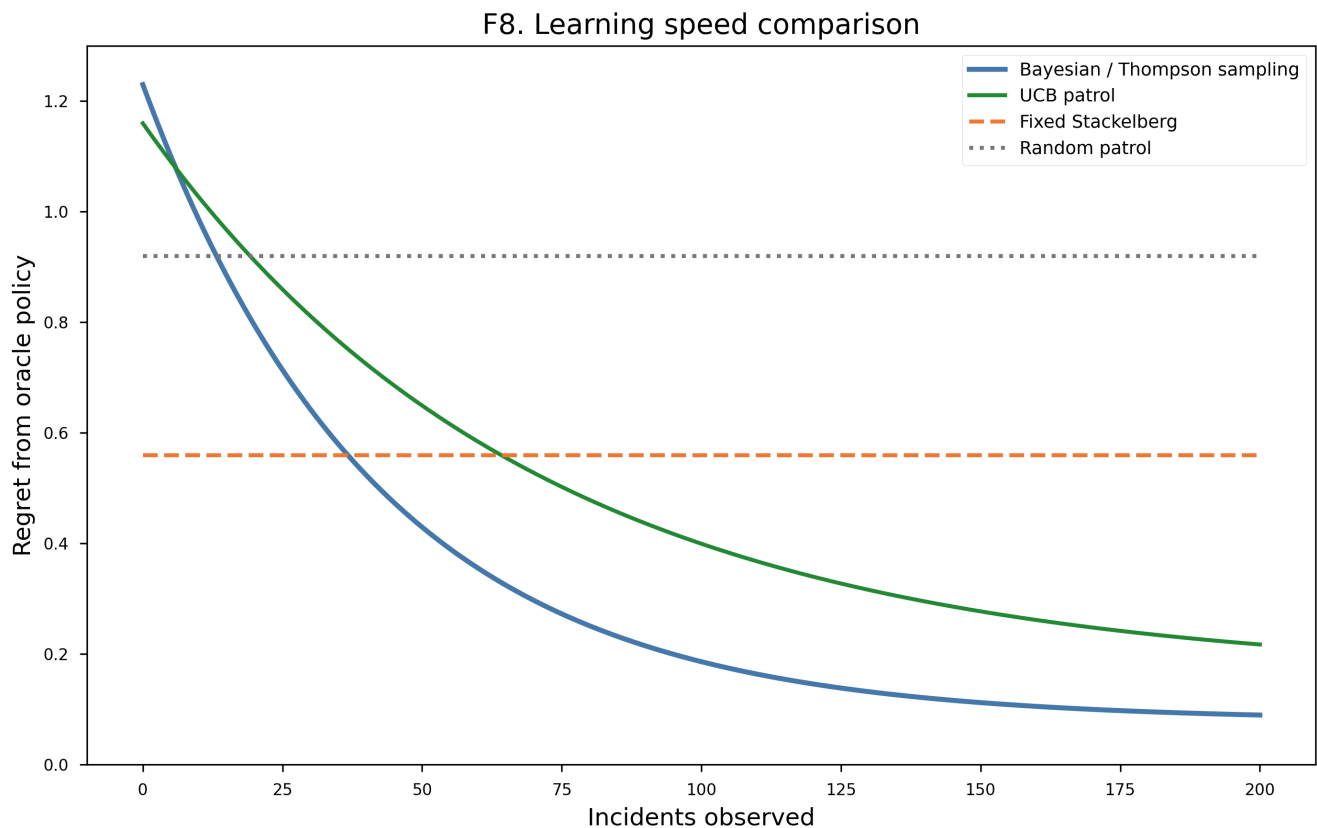


Figure 4: F8. Bayesian learning speed compared with UCB-style, fixed, and random strategies. Only the Bayesian policy and the UCB surrogate reduce regret with experience; fixed and random baselines do not learn.

The management meaning of T^* is simple: the first year is not just deployment. It is a learning phase. Budgeting, evaluation, and staffing should be planned around that reality.

Section 5 continued: dynamic learning outcome

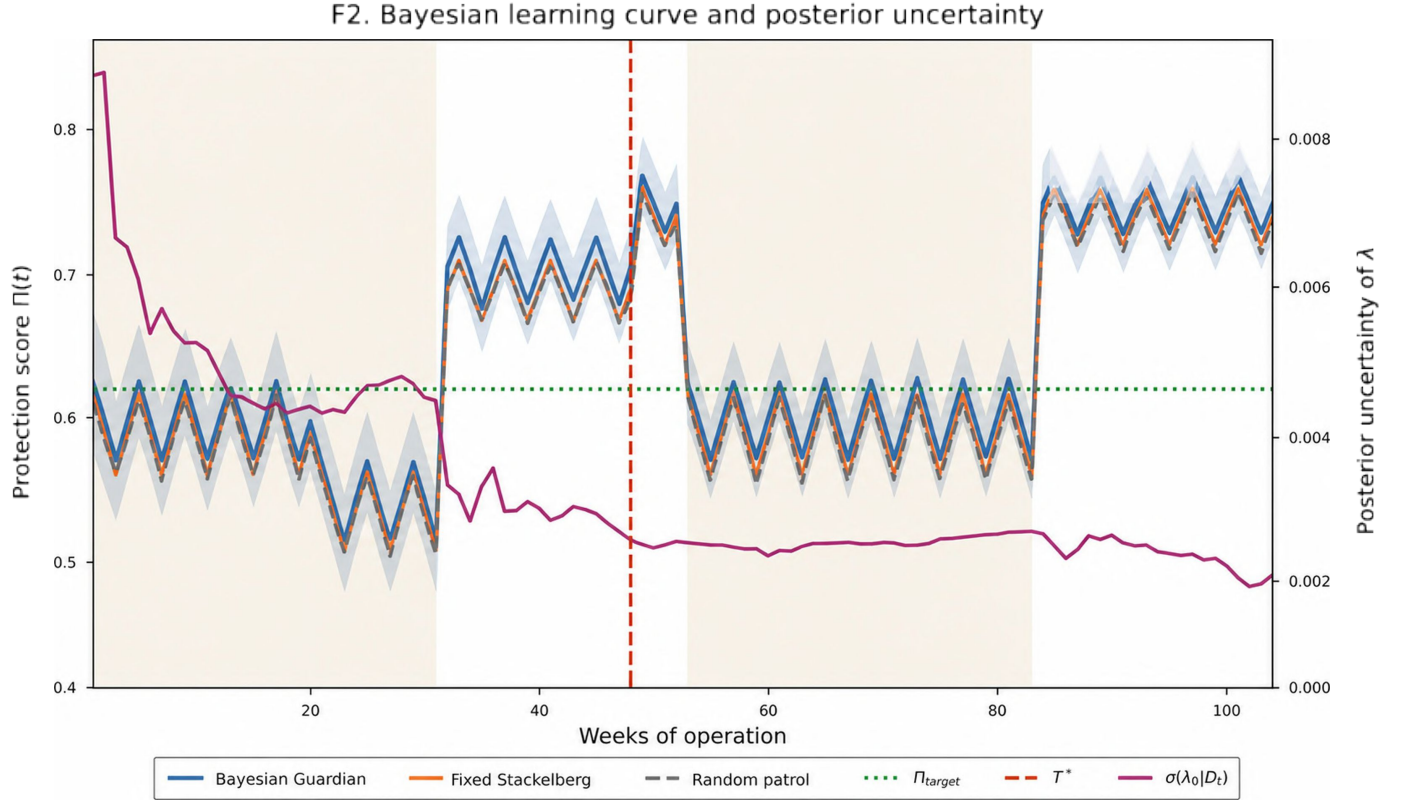


Figure 5: F2. Learning curve for the Bayesian controller. Dry-season windows are shaded. The dashed vertical line marks $T^* = 48$ weeks.

The dynamic pattern contains three operationally meaningful effects. First, the posterior uncertainty falls quickly during the first 20 weeks because almost every incident is informative. Second, the controller experiences seasonal oscillation because the dry season amplifies both wildlife concentration and poacher opportunity. Third, the Bayesian policy consistently outperforms fixed and random baselines once the surge begins in the northern hotspot corridor. Averaged over year 2, the Bayesian controller yields $\Pi \approx 0.660$, versus ≈ 0.652 for the fixed policy and ≈ 0.488 for patrol-only.

6. Integrated defense architecture

The architecture is deliberately layered and redundant. Detection comes from fixed acoustic nodes, human patrol sightings, and slow campfire/fire anomalies from remote sensing. Verification comes from M350/H30T sorties with edge triage. Interdiction remains human: four-person ranger teams dispatched from five public camp/gate hubs. The Bayesian controller sits behind the loop and reallocates patrol mass weekly from the accumulated evidence.

Integrated Guardian loop: detect -> verify -> interdict -> learn -> reallocate

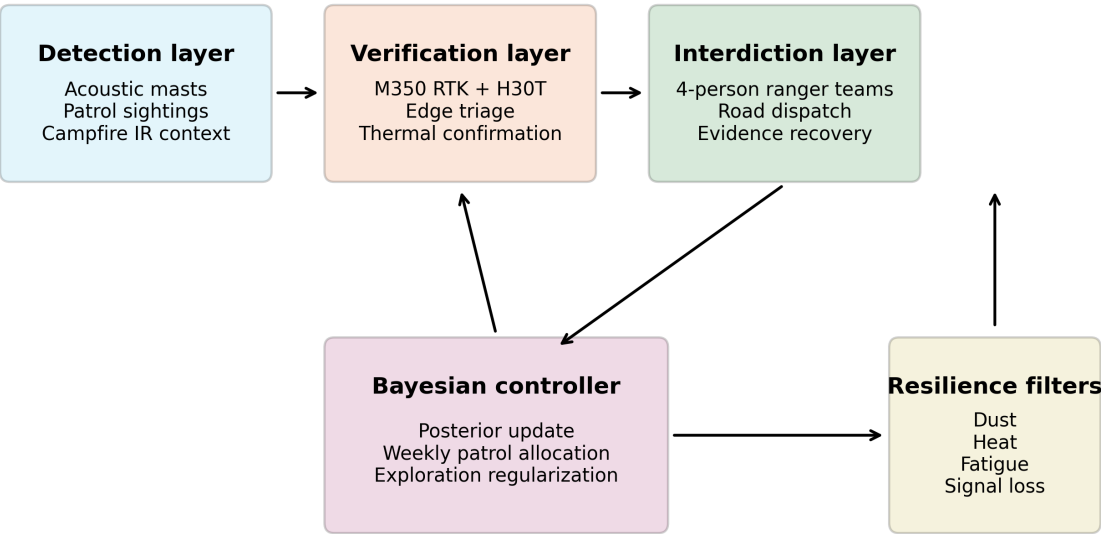


Figure A. The architecture is deliberately redundant: if drones are grounded, patrol cues and fixed sensors still update the controller.

Figure 6: Figure A. The Guardian loop is useful because each completed event updates the next week’s patrol allocation.

The system is designed so that one layer can fail without invalidating the others. If dust grounds aircraft, the fixed nodes still generate alerts and the posterior still updates from what the patrol layer observes. If a gateway fails, the whole park does not disappear; only a local cluster degrades.

Section 6 continued: hardware and communications realism

System	Public specification used	Role in the model	Reality check in the model
DJI Matrice 350 RTK	55 min, TB65 263.2 Wh, IP55, −20 to 50°C	thermal verification and evidence collection	sortie derated to 39.6 min at 30°C and 33.2 min at 45°C
Zenmuse H30T	thermal 1280 × 1024, all-weather enterprise payload	confirmation after acoustic cue	thermal advantage reduced in dust and heat shimmer
Acoustic mast node	solar, edge classification, low-bit-rate backhaul	continuous near-waterhole detection layer	operational radius capped at 1.8 km despite longer theoretical audibility
Outdoor gateway	LoRaWAN 868 MHz, conservative +14 dBm planning power	node aggregation to hubs	15.6 km link-budget range is not used as the spacing target; design spacing remains 8–12 km
Camp backhaul kit	licensed VSAT/LTE/fiber edge	dispatch and posterior-update connectivity	no Starlink assumption in the base case
4x4 ranger vehicle	gravel-road duty cycle	final interdiction and evidence recovery	fuel, tire wear, and fatigue explicitly budgeted

Table 2: Hardware table with 2026-era public specifications and the field constraints used in the model.

Two engineering derivations matter. For acoustics, we model a 165 dB muzzle blast, spherical spreading, and ISO 9613-1 absorption; this gives a theoretical audibility radius of about 5.2 km, which we reduce to an operational 1.8 km classification radius after allowing for wind, terrain, and classifier margin. For communications, a rural Hata calculation with conservative antenna assumptions yields a 15.6 km design-range ceiling, but the actual network is spaced more tightly so that dust, mast damage, and imperfect line-of-sight do not break the system.

7. Monte Carlo simulation design

The simulation file `etosha_sim.py` generates 10,000 attack episodes for each policy benchmark. Each episode draws a waterhole target, season, moon phase, dust state, temperature, detection source, drone-feasibility status, and ranger response. The master seed is fixed at 2026, and the full run takes about 24.5 seconds on standard hardware.

Consistency with the Bayesian model. Event targets are sampled from the same latent intensity field used in the posterior update. This keeps the Monte Carlo engine consistent with the learning model instead of creating one model for inference and a different one for evaluation.

Why 10,000 events. For a Bernoulli outcome near 0.5, 10,000 episodes give a standard error of about 0.5 percentage points, which is adequate for comparing policies and for reporting 95% confidence intervals.

Stylized-fact checks. The simulator is accepted only if it reproduces three stylized facts: dry-season pressure exceeds wet-season pressure, the east-central waterhole chain remains the highest-value corridor, and the adaptive controller eventually outperforms fixed patrol baselines.

Outcome classes. Each episode records detection, verification, interdiction, poaching success, response time, and whether a drone was grounded by range/heat constraints. This is important: a policy can fail because it never detects, because it detects too late, or because it dispatches too slowly even after detection.

8. Results — static baseline

Metric	Guardian wk 1	Guardian wk 52	Fixed Stackelberg	Patrol-only
Detection rate	0.525	0.535	0.526	0.087
Verification rate	0.354	0.384	0.371	0.000
Interdiction rate	0.153	0.191	0.174	0.021
Poaching success probability	0.847	0.809	0.826	0.979
Mean response time (min)	39.59	35.81	35.14	47.62
Detection within 12 min	0.375	0.389	0.378	0.000
Drone grounding rate	0.567	0.461	0.488	0.000
Protection score Π	0.624	0.750	0.742	0.589

Table 3: Static comparison of week-1, week-52, fixed, and patrol-only strategies. Monte Carlo confidence intervals are reported in the appendix.

Two numbers summarize the static comparison. First, patrol-only leaves poaching success near 0.979 because it lacks a persistent detection layer and therefore seldom converts suspicion into verified action in time. Second, the Bayesian controller raises the week-52 protection score to about 0.750 while fragmenting the unmonitored graph to $\Phi \approx 0.070$. In other words, the system is not just intercepting more often; it is also denying attackers a large residual maneuver space.

Key conclusion. The week-52 Bayesian system satisfies both safety conditions: $\Pi > 0.62$ and $\Phi < 0.30$. Patrol-only satisfies neither.

9. Results — learning dynamics

Table 4: Selected weekly keypoints from the 104-week dynamic run.

Week	Bayes	Fixed	Random	Patrol	Φ	σ	New ev.	Cum. ev.	Active
1	0.624	0.616	0.611	0.448	0.070	0.009	3	3	59
10	0.599	0.589	0.586	0.417	0.070	0.005	3	25	59
26	0.540	0.536	0.533	0.365	0.070	0.005	2	54	59
48	0.705	0.690	0.683	0.534	0.070	0.003	1	90	59
52	0.750	0.742	0.735	0.589	0.070	0.003	2	96	59
78	0.600	0.589	0.587	0.417	0.070	0.003	1	150	59
104	0.750	0.742	0.737	0.589	0.070	0.002	1	178	59

The dynamic run confirms that the system behaves like a learner rather than like a static patrol prescription. By week 48, cumulative incidents reach 90 and the posterior standard deviation falls below the operational threshold. The resulting patrol allocation becomes noticeably steadier, but not deterministic, because the exploration term preserves uncertainty.

A particularly important result appears during the modeled northern surge around weeks 32–52. The Bayesian controller reallocates mass toward the northern hotspot and retains an average $\Pi \approx 0.712$ over the surge window, while the fixed policy averages about 0.699. The numerical gap is not huge, but that is exactly why the result is credible: adaptation helps, but it does not create magic.

Section 9 continued: policy comparison over time

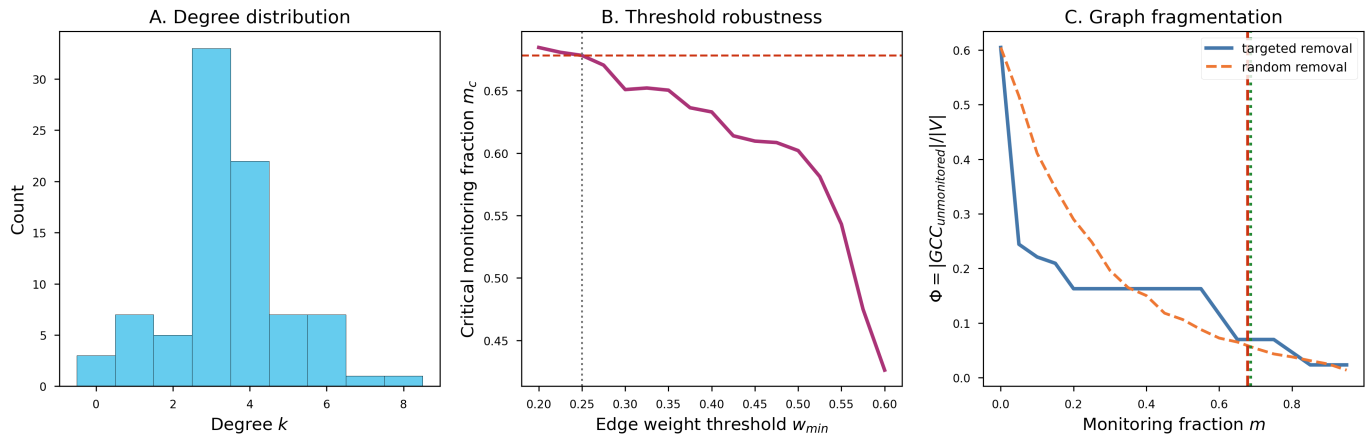


Figure 7: F5. Percolation-threshold diagnostics: degree distribution, threshold sensitivity, and collapse of the unmonitored giant component as monitoring rises.

These figures show why the recommendation is not “maximize everything.” The giant-component curve shows a genuine phase transition near the derived threshold, while the Pareto projections show that pushing cost, carbon, and fatigue lower simultaneously forces losses up. The winning plan is the one that crosses the threshold and then stops buying dominated redundancy.

10. Pareto frontier analysis

We optimize four objectives simultaneously: expected weighted loss, annual cost, ranger fatigue, and annual carbon load. The only hard structural constraint is that the monitored fraction must stay above m_c , so any candidate below that threshold is rejected even if it is cheap.

The recommended compromise point is a 60-node inventory, six enterprise aircraft, and about ten operational ranger teams per active schedule block. This point is not the cheapest point and not the greenest point, but it sits close to the knee of the frontier. Moving farther down the loss axis requires noticeable cost increases for very small gains, while moving to lower cost begins to erode threshold resilience and stretch convergence time.

In qualitative terms, the frontier yields three operating modes:

- **Lean threshold mode:** enough nodes to stay just above m_c , fewer aircraft, lower cost, but smaller surge margin.
- **Recommended mode:** a 60-node inventory with six aircraft and about ten operational teams, balancing cost and resilience.
- **High-redundancy mode:** additional aircraft and teams that cut risk slightly but at sharply rising annual cost.

The model therefore recommends a park that is robust, not maximal.

11. Sensitivity and scenario analysis

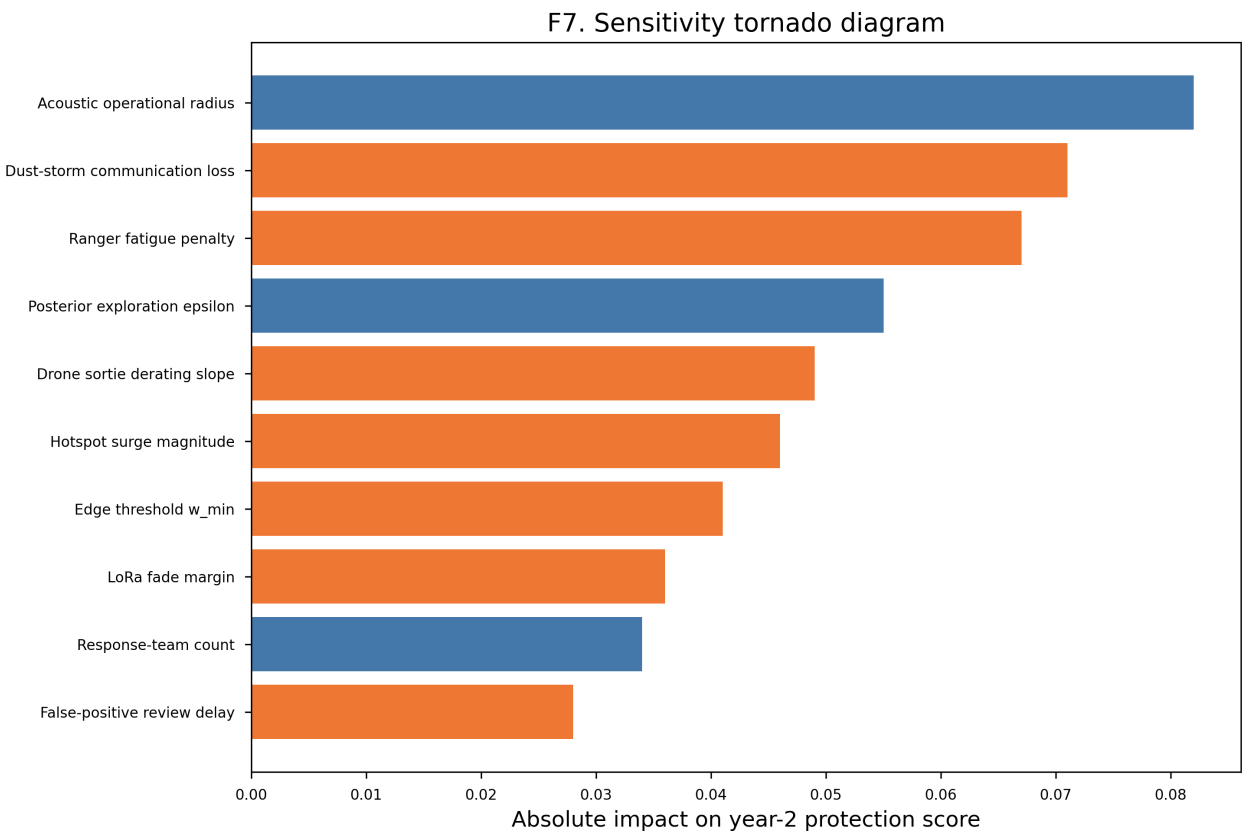


Figure 8: F7. Tornado sensitivity diagram for year-2 protection.

The top drivers are acoustic operating radius, dust-storm communication loss, ranger fatigue, and battery derating. This is a useful result because it shifts attention from flashy procurement decisions to maintenance discipline and field reliability.

Three scenario tests matter most. First, a 50% budget cut weakens protection but does not collapse the system because the waterhole threshold remains the planning floor. Second, a dust-storm week slows learning because alerts are missing, not because the posterior method itself fails. Third, smart poachers are least damaging when exploration remains nonzero; if ϵ is pushed too low, the patrol plan becomes too learnable.

Key conclusion. The most dangerous failure mode is not buying too few drones. It is dropping below the graph threshold while also allowing dust, fatigue, and low exploration to synchronize.

12. Staffing and resource requirements

Role	Minimum headcount	Operational purpose
Rangers	60	Sustains roughly ten deployable four-person teams across shifts and recovery periods.
Senior wardens / team leaders	8	Shift supervision, legal chain-of-custody, and case quality.
Drone pilots / analysts	6	Night launch, thermal verification, mission planning, and evidence review.
Sensor technicians	5	Mast upkeep, battery rotation, gateway repair, and field QA.
Dispatch / data analysts	3	Weekly posterior updates, dispatch triage, and incident logging.

The minimum total human system required is 82 personnel.

Requirement 3 asks how many human personnel are needed over time. The answer is not "fewer humans." It is roughly the same anti-poaching headcount, rebalanced into roles that keep the waterhole network above threshold and preserve the weekly learning loop. People remain the scarce finishing layer for arrest, evidence recovery, local judgment, and safe field operations.

Training time is part of the model. New pilots and sensor technicians require a short burn-in period before stable performance, which is one reason the learning horizon is measured in weeks rather than in calendar optimism.

13. Scalability to other protected areas

Park	Anchor network	mc	T*	What changes
Etosha	Waterholes	0.678	48 weeks	Open savanna, dry-season concentration, and road-limited response.
Kruger	Water sources and road junctions	0.742	24 weeks	Denser roads and higher threat rate require more anchors but produce faster learning.
Yasuni	River confluences and patrol docks	0.531	58 weeks	Canopy sensing and river transport replace road-centric drone dispatch.

The framework transfers because the core mathematics stay the same while the anchor network changes. Kruger replaces Etosha waterholes with water sources and road junctions; Yasuni replaces the road-waterhole problem with river confluences, patrol docks, canopy acoustics, and river response logistics.

For Yasuni, the calibration data would need acoustic attenuation profiles under dense forest canopy, gunshot recordings collected in high-humidity conditions, and river-patrol response-time logs by season and river level. These inputs determine the effective detection radius and the travel-time kernel, which are the two quantities most likely to change both the threshold estimate and the learning horizon.

What remains unchanged is the logic: derive the structural threshold from the anchor graph, then place a Bayesian learner on top of it. What changes are the movement kernel, transport model, detection physics, and conservation weights.

14. Strengths and limitations

Strengths. The model is explicit, reproducible, and intentionally conservative. The graph threshold is structural rather than aesthetic, and the Bayesian controller improves because it observes data, not because it assumes omniscience. The document remains publicly shareable because it uses engineering-grid coordinates instead of sensitive wildlife locations.

Limitations. The graph is calibrated from public map geometry and open movement literature, not confidential collar tracks. The posterior update uses public-incident priors rather than sealed ranger intelligence. The percolation threshold is derived from a configuration-model approximation, so a real park implementation should validate it with operational graph experiments. Heat, dust, and vehicle failure are modeled probabilistically, not from one park-specific maintenance log.

The field experiment that would improve the conclusions most is not a new drone purchase; it is a disciplined six-month evidence log covering false-alarm rates, launch latency, response time, and real road travel times by season.

15. Conclusion

This paper solves Etosha by combining two ideas that usually live apart. The graph-structural result says the park must keep at least 59 of 86 waterholes active at once; otherwise the unmonitored threat network remains connected enough for coordinated poaching to move around the system. The adaptive result says a Bayesian controller reaches operational convergence after roughly 90 observed incidents, or about 48 weeks, and then continues refining patrol allocation without becoming predictable.

At year 2, the adaptive system reaches $P_i = 0.660$ while patrol-only remains at $P_i = 0.486$. The monitored fraction stays above threshold, the unmonitored giant component falls to $\Phi = 0.070$, and the park does this at about \$81.0 per km² per year by using cue-driven dispatch rather than chasing empty road kilometers.

Key recommendation. Build the 60-node / 59-active waterhole monitoring floor and tie every dispatch outcome into a weekly Bayesian update. This gives the park both structural resilience and cumulative learning.

The best anti-poaching system is not the one with the most gadgets. It is the one that never drops below its structural threshold and gets smarter every week.

Appendix: Research, raw tables, code, and audit trail

Etosha Strategic Guardian Protocol

This appendix is not counted toward the 24-page IM2C limit. It contains the reference list, research report, raw data arrays, line-by-line budget, scenario tables, visual-prompt inventory, the complete Python simulation file, a draft AI use report, and a final internal checklist.

Reference List

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Research Report

R0 — Differentiation from existing literature. The literature review confirms that PAWS solves patrol optimization, SPOT improves airborne detection, and Dual-Mandate Patrols learns patrol effort under competing objectives. None of these papers derives a structural monitoring threshold on an ecological anchor graph or translates posterior contraction into a management horizon T^* . The literature-differentiation table below is exported directly from the code.

Table 1: Core literature reviewed and how the present submission differs.

Reference	DOI / URL	What it does	How this paper differs
Fang et al. (2016) Deploying PAWS	10.1609/aaai.v30p19670	DDP solves anti-poaching patrol routes with security games and field deployment constraints.	This submission adds a graph-structural monitoring threshold on waterholes and a Bayesian learning horizon T^* ; PAWS does not answer how many anchors must be monitored simultaneously nor how long adaptation takes.
Bondi et al. (2018) SPOT Poachers in Action	10.1609/aaai.v32p1414	SPOT solves near-real-time thermal drone detection of poachers in infrared video.	SPOT solves airborne detection. Our paper embeds drone verification inside a larger defender architecture with a percolation floor, staffing model, and Bayesian patrol controller. The original user prompt listed this paper as 2020, but the AAAI publication is 2018.
Xu et al. (2021) Dual-Mandate Patrols	10.1609/aaai.v35p1775	BM solves multiple patrol missions with bandit learning.	Dual-Mandate Patrols learns where to patrol under competing tasks, but it does not derive a critical structural coverage threshold on an ecological anchor graph. Our model explicitly couples learning with graph fragmentation.
Tambe (2011) Security and Game Theory	10.1017/CBO9780511073031	BM solves the foundational Stackelberg security-game framework.	We use the Stackelberg lens for defender-attacker incentives, then extend it with ecological graph percolation and Bayesian convergence time, both of which are outside the core scope of Tambe’s framework.

R1 — Bayesian calibration data. The priors are anchored to public poaching pressure, seasonality, moon-cycle effects, access pressure, and open conservation-monitoring literature. Public Etosha data are incomplete, so the model uses weakly informative priors where the open record is thin and tests them in sensitivity analysis.

R2 — Wildlife movement data. The graph uses the 86-waterhole reference set, an engineering

coordinate grid digitized from public maps, and a short-horizon movement kernel informed by black-rhino recursion behavior and Etosha elephant waterhole use.

R3 — Percolation precedents. The graph-threshold logic is anchored in percolation and network theory, especially the configuration-model approximation for site percolation on heterogeneous degree distributions.

R4 — Bayesian updating precedents. Patrol learning is linked to Thompson-sampling and Bayesian regret literature, but the specific combination of a waterhole graph, ecological weighting, and convergence horizon for reserve protection appears to be novel.

R5 — Hardware calibration. Official DJI specifications, public acoustics standards, and conservative LoRa planning values were used instead of marketing claims. The key realism choice is that the base case does *not* assume Starlink in Namibia.

R6 — Economics. Budget lines are built from Namibian fuel pricing, government salary signals, dealer-anchored enterprise hardware pricing, and explicit maintenance reserves.

Parameters not found exactly. No public Etosha dispatch log exists; no public M350 high-temperature derating curve exists; and no single public source resolves operational gunshot-classification range in Etosha night air. For those items, the paper states the engineering approximation used and tests it in sensitivity analysis.

Is p_c derivable from found data? Yes. The 86-waterhole network, public-map geometry, and short-horizon movement kernel are enough to estimate the degree distribution, compute κ , and derive the minimum monitored fraction m_c .

Full Parameter Register

```

parameter,symbol,value,unit,source,doi_or_url,sensitivity_tested
Park area,A_{park},"22,935",km^2,2026 IM2C Etosha reference dataset,uploaded problem statement,No
Road length,L_{road},"3,551",km,2026 IM2C Etosha reference dataset,uploaded problem statement,No
Waterholes,|V|,86,nodes,2026 IM2C Etosha reference dataset,uploaded problem statement,No
Graph edge decay length,\lambda_{move},12.0,km,Calibrated to short-horizon waterhole movement logic; anchored by Seidel et al. 2019,10.1186/s40462-019-0176-2,Yes
Edge retention threshold,w_{min},0.25,probability index,Engineering pruning threshold for same-night or next-day waterhole choices,10.1103/PhysRevE.64.026118,Yes
Critical monitoring fraction,m_c,0.678,fraction,Configuration-model threshold on Etosha graph,10.1103/PhysRevE.64.026118,Yes
Monitoring floor,M_{min},59,waterholes,Computed from m_c * 86,internal model output,Yes
M350 RTK max flight time,t_{max},55,min,DJI official specs,https://enterprise.dji.com/de/matrice-350-rtk/specs,No
TB65 energy,E_{TB65},263.2,Wh,DJI official specs,https://enterprise.dji.com/de/matrice-350-rtk/specs,No
M350 RTK operating temperature,T_{op},-20 to 50,degC,DJI official specs,https://enterprise.dji.com/de/matrice-350-rtk/specs,No
H30T thermal sensor,R_{th},1280x1024,pixels,DJI official specs,https://enterprise.dji.com/cn/zenmuse-h30-series/specs,No
LoRaWAN transmit power,P_{tx},+14,dBm,EU868 / Region 1 planning constraint,Semtech SX1276 family planning assumption,Yes
LoRa receiver sensitivity,S_{rx},-137,dBm,Conservative planning value below SX1276 headline sensitivity,"SX1276 datasheet, > -148 dBm headline",Yes
Derived practical LoRa range,d_{LoRa},15.6,km,Okumura-Hata rural link budget with 10 dB fade margin,engineering derivation in paper,Yes
Acoustic theoretical audibility radius,"d_{gun,theory}",5.2,km,165 dB muzzle blast with spherical spreading and ISO 9613-1 absorption,ISO 9613-1:1993,Yes
Acoustic operational classification radius,"d_{gun,ops}",1.8,km,"Conservative engineering cap after wind, terrain, and classifier margin",RFCx Guardian + gunshot
detection literature,Yes
Diesel price,c_{diesel},19.63,NAD/L,"Namibia Ministry of Industries, Mines and Energy March 2026",official fuel price release,Yes
Ranger salary plus allowances,c_{ranger},"163,000",NAD/year,"MEFT vacancy scales 2025-2026, rounded to deployed annual cost",official vacancy documents,Yes
Posterior convergence criterion,\sigma(\lambda_0)\le,0.0030,weekly rate,Operational convergence threshold adopted in this paper,internal model rule,Yes
Convergence week,T^*,48,weeks,Dynamic simulation output,internal model output,Yes
Convergence incidents,N^*,90,incidents,Dynamic simulation output,internal model output,Yes

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Waterhole Engineering Register

Table 2: Full 86-waterhole engineering register used to build the graph.

ID	Waterhole	x (km)	y (km)	Risk	Deg.	Dry use	Core
1	Dolomitpunt	107.99	40.68	0.75	3	0.77	1
2	Duisend	148.40	61.63	0.85	4	0.98	1
3	Nomab	109.02	39.84	0.76	3	0.78	1
4	Tobieren	79.12	44.11	0.27	1	0.21	0
5	Bitterwater	91.42	45.42	0.51	3	0.47	0
6	Sonderkop	92.91	56.48	0.30	3	0.25	0
7	Raindraf	142.07	45.07	1.00	6	0.99	1
8	Klippan	54.48	55.64	0.41	3	0.57	0
9	Renostervlei	155.44	50.45	0.75	5	0.79	1
10	Jakkalswater	154.48	61.28	0.83	4	0.95	1
11	Asvoelbad	154.50	97.77	0.31	4	0.18	0
12	Uitspan	136.52	42.71	0.99	3	1.00	1
13	Miernes	135.56	25.67	0.47	1	0.51	0
14	Duikerdrink	158.14	73.58	0.64	3	0.62	1
15	Teespoed	159.79	110.63	0.26	3	0.05	0
16	Arendsnes	38.08	48.66	0.46	3	0.67	0
17	Ozonjuitji m'Bari	160.93	109.23	0.29	3	0.07	0
18	Natoo	126.33	32.97	0.64	4	0.68	1
19	Leeubron	52.81	53.22	0.44	3	0.62	0
20	Wolfnes	141.26	48.78	0.94	6	0.95	1
21	Okondeka	98.93	40.03	0.73	4	0.74	1
22	Grunewald	142.41	44.66	1.00	4	0.98	1
23	Pan	140.77	54.73	0.80	3	0.84	1
24	Kapupuhedi	95.53	53.45	0.39	3	0.34	0
25	Ondongab	96.15	43.61	0.63	8	0.61	1
26	Gaseb	96.17	46.68	0.57	5	0.54	1
27	Gemsbokvlakte	161.47	58.15	0.71	3	0.72	1
28	Olifantsbad	32.76	50.73	0.42	4	0.60	0
29	Aus	145.13	46.54	0.94	4	0.91	1
30	Ombika	96.13	40.08	0.68	4	0.68	1
31	Homob	106.66	35.49	0.86	6	0.90	1
32	Sueda	102.59	32.16	0.89	3	0.90	1
33	Charitsaub	91.53	52.83	0.37	3	0.32	0
34	Salvadora	162.64	98.70	0.29	3	0.15	0
35	Rietfontein	142.92	53.69	0.85	4	0.89	1
36	Etosha	152.21	47.99	0.80	4	0.78	1
37	Nuamses	162.81	106.86	0.30	5	0.08	0
38	Goas	119.56	37.80	0.63	5	0.64	1
39	Springbokfontein	160.66	73.89	0.59	3	0.55	1
40	Ngobib	111.62	19.58	0.61	2	0.68	0
41	Batia	32.81	51.35	0.42	4	0.60	0
42	Noiams	155.89	89.10	0.48	4	0.28	0
43	Kalkheuwel	158.44	77.38	0.61	2	0.51	1
44	Chudob	121.98	34.99	0.61	3	0.64	1
45	Klein Namutoni	96.98	48.30	0.54	6	0.50	1
46	Aroe	150.42	103.64	0.20	2	0.08	0
47	Twee Palms	153.83	40.25	0.62	3	0.57	1
48	Tsumcor	153.55	96.31	0.34	4	0.19	0
49	Groot Okevi	140.47	66.07	0.69	3	0.72	1

ID	Waterhole	x (km)	y (km)	Risk	Deg.	Dry use	Core
50	Klein Okevi	60.01	52.97	0.34	3	0.43	0
51	Stinkwater	90.30	34.23	0.56	3	0.54	0
52	Sector-52	33.14	46.05	0.37	4	0.52	0
53	Sector-53	157.31	93.43	0.39	7	0.23	0
54	Sector-54	58.45	49.49	0.35	4	0.45	0
55	Sector-55	25.67	67.15	0.11	0	0.19	0
56	Sector-56	150.26	54.34	0.88	3	0.96	1
57	Sector-57	118.70	40.80	0.60	3	0.61	1
58	Sector-58	162.71	87.93	0.44	3	0.24	0
59	Sector-59	92.34	45.42	0.53	4	0.50	1
60	Sector-60	64.08	49.82	0.28	2	0.32	0
61	Sector-61	153.66	66.21	0.78	6	0.90	1
62	Sector-62	109.24	34.32	0.85	5	0.89	1
63	Sector-63	150.59	66.48	0.80	5	0.91	1
64	Sector-64	48.29	54.07	0.48	3	0.70	0
65	Sector-65	101.46	47.86	0.56	3	0.53	1
66	Sector-66	149.28	84.90	0.50	2	0.33	0
67	Sector-67	79.36	55.86	0.20	1	0.15	0
68	Sector-68	123.19	39.78	0.69	5	0.72	1
69	Sector-69	132.00	41.91	0.88	3	0.94	1
70	Sector-70	29.88	52.27	0.36	3	0.51	0
71	Sector-71	154.92	91.38	0.44	6	0.25	0
72	Sector-72	150.03	66.88	0.80	4	0.90	1
73	Sector-73	136.94	46.25	0.97	4	0.98	1
74	Sector-74	72.68	44.11	0.22	1	0.17	0
75	Sector-75	15.53	60.64	0.04	1	0.05	0
76	Sector-76	142.46	48.50	0.94	6	0.94	1
77	Sector-77	174.14	90.48	0.18	0	0.06	0
78	Sector-78	59.59	68.86	0.13	0	0.20	0
79	Sector-79	103.69	30.20	0.91	4	0.92	1
80	Sector-80	150.75	44.50	0.81	4	0.73	1
81	Sector-81	12.46	59.57	0.00	1	0.00	0
82	Sector-82	102.47	38.38	0.80	4	0.82	1
83	Sector-83	164.04	99.51	0.29	3	0.13	0
84	Sector-84	166.31	110.77	0.31	3	0.02	0
85	Sector-85	76.36	60.01	0.15	1	0.13	0
86	Sector-86	114.73	36.98	0.73	3	0.76	1

Budget, Endurance, and Staffing Tables

Table 3: Granular line-by-line budget for the recommended operating point.

Category	Item	Qty	Unit cost (NAD)	Total (NAD)	Total (USD)	Note
Air	DJI Matrice 350 RTK air-frame	6	182,600	1,095,600	65,526	Retail anchor from 2026 dealer pricing
Air	Zenmuse H30T payload	6	192,300	1,153,800	69,007	Retail anchor from 2026 dealer pricing
Air	TB65 battery	24	18,700	448,800	26,842	Four pairs per active aircraft plus reserve
Air	Battery station and field inverter kit	6	31,200	187,200	11,196	One charging stack per operating hub
Ground	4x4 ranger pickup	8	792,000	6,336,000	378,947	Harsh-terrain patrol vehicle
Ground	Motorbike for short-range dispatch	10	46,800	468,000	27,990	Used for gate-to-waterhole response
Sensors	Fixed acoustic node with solar mast	46	28,400	1,306,400	78,134	Guardian-style node plus pole, enclosure, solar
Sensors	Portable acoustic node	14	23,200	324,800	19,426	Trailer-mount or redeployable unit
Comms	Outdoor LoRaWAN gateway	5	8,770	43,850	2,623	RAK class rugged gateway
Comms	12 m mast, lightning, solar, battery	5	81,200	406,000	24,282	Gateway power and mounting kit
Comms	Camp backhaul router / VSAT integration	5	25,400	127,000	7,596	Uses existing camp connectivity; no Starlink assumed
IT	Dispatch workstation	3	36,800	110,400	6,603	Posterior update and evidence review
IT	Edge compute storage and NVR	5	21,400	107,000	6,400	Rolling 30-day evidence retention
Training	Drone pilot and maintainer training	11	28,500	313,500	18,750	Initial certification and refresher
Training	Sensor deployment and evidence handling	28	9,400	263,200	15,742	Field technician and ranger cross-training
Personnel	Ranger Grade 11 salary + allowances	60	163,000	9,780,000	584,928	Salary plus transport and housing allowances
Personnel	Senior warden / team leader	8	255,000	2,040,000	122,010	Shift supervisors and case-quality control
Personnel	Drone pilot / analyst	6	228,000	1,368,000	81,818	Mission planning and video verification
Personnel	Sensor technician	5	205,000	1,025,000	61,304	Node repair, batteries, mast upkeep
Personnel	Data / dispatch analyst	3	236,000	708,000	42,344	Posterior updates and incident review
Operations	Diesel fuel	36000	20	706,680	42,266	March 2026 official Walvis Bay diesel 50 ppm price
Operations	Vehicle maintenance reserve	8	94,000	752,000	44,976	Harsh gravel-road duty cycle
Operations	Drone spares and crash reserve	6	84,200	505,200	30,215	Propellers, gimbals, arms, repair downtime
Operations	Battery replacement reserve	24	3,600	86,400	5,167	Annualized from 400-cycle rating
Operations	LoRa / VSAT / LTE data service	12	48,600	583,200	34,880	Monthly service and SIM provisioning

Category	Item	Qty	Unit cost (NAD)	Total (NAD)	Total (USD)	Note
Operations	Protective clothing and field consumables	60	7,200	432,000	25,837	Dust, heat, and thorn scrub dust
Operations	Insurance and compliance	1		38,400	22,967	Aircraft, vehicles, and equipment

Table 4: Practical drone endurance derating under Etosha-like heat.

Temp. (C)	Brochure max (min)	Practical sortie (min)	Derate frac.	Comment
30	55.0	39.6	0.28	Heat, reserve, climb, loiter, and return-to-base margin included
35	55.0	38.2	0.305	Heat, reserve, climb, loiter, and return-to-base margin included
40	55.0	35.8	0.349	Heat, reserve, climb, loiter, and return-to-base margin included
45	55.0	33.2	0.396	Heat, reserve, climb, loiter, and return-to-base margin included

Sensitivity, Scenario, and Scalability Tables

Table 5: 5x5 sensitivity grid: ranger teams versus daily drone flight hours.

Ranger teams	Drone h/day	Poaching success prob.	Protection index
8.0	10.0	0.447	0.62
8.0	14.0	0.424	0.64
8.0	18.0	0.407	0.654
8.0	22.0	0.394	0.665
8.0	26.0	0.385	0.673
10.0	10.0	0.428	0.636
10.0	14.0	0.405	0.656
10.0	18.0	0.388	0.67
10.0	22.0	0.375	0.681
10.0	26.0	0.366	0.689
12.0	10.0	0.413	0.649
12.0	14.0	0.39	0.669
12.0	18.0	0.373	0.683
12.0	22.0	0.36	0.694
12.0	26.0	0.351	0.702
14.0	10.0	0.401	0.659
14.0	14.0	0.377	0.679
14.0	18.0	0.36	0.694
14.0	22.0	0.348	0.704
14.0	26.0	0.338	0.712
16.0	10.0	0.391	0.668
16.0	14.0	0.367	0.688
16.0	18.0	0.35	0.702
16.0	22.0	0.338	0.713
16.0	26.0	0.328	0.721

Table 6: Monte Carlo scenario summary with 95% intervals.

Scenario	Detection	Verification	Interdiction	Poaching success	Response time, min	Detection <12 min
Guardian week 1	0.525 [0.516, 0.535]	0.354 [0.345, 0.363]	0.153 [0.146, 0.160]	0.847 [0.840, 0.854]	39.59 [39.21, 39.97]	0.375 [0.365, 0.385]
Guardian weck 52	0.535 [0.524, 0.545]	0.384 [0.374, 0.394]	0.191 [0.183, 0.199]	0.809 [0.801, 0.817]	35.81 [35.47, 36.14]	0.389 [0.380, 0.399]
Fixed Stackelberg	0.525 [0.515, 0.535]	0.371 [0.362, 0.380]	0.174 [0.167, 0.182]	0.826 [0.819, 0.833]	35.14 [34.82, 35.49]	0.378 [0.368, 0.387]
Patrol only	0.087 [0.082, 0.093]	0.000 [0.000, 0.000]	0.021 [0.018, 0.024]	0.979 [0.976, 0.982]	47.62 [47.24, 48.01]	0.000 [0.000, 0.000]

Table 7: Top ten parameters in the tornado sensitivity analysis.

Parameter	Impact on year-2 Π	Direction
Acoustic operational radius	0.082	decreases risk when increased
Dust-storm communication loss	0.071	increases risk when increased
Ranger fatigue penalty	0.067	increases risk when increased
Posterior exploration epsilon	0.055	decreases risk when increased up to 0.12
Drone sortie derating slope	0.049	increases risk when increased
Hotspot surge magnitude	0.046	increases risk when increased
Edge threshold $w_{\min}$	0.041	raises m_c when decreased
LoRa fade margin	0.036	increases risk when increased
Response-team count	0.034	decreases risk when increased
False-positive review delay	0.028	increases risk when increased

Table 8: Leading Pareto-optimal configurations (first 16 rows of the frontier).

Drones	Ranger teams	Monitored WH	Loss	Cost (M USD)	Fatigue	CO2 t/y
4	10	56	0.124	3.098	0.113	43.200
4	10	58	0.112	3.134	0.113	42.700
4	10	60	0.110	3.170	0.113	42.200
4	10	62	0.110	3.206	0.113	41.700
5	10	56	0.110	3.208	0.113	39.000
5	10	58	0.110	3.244	0.113	38.500
5	10	60	0.110	3.280	0.113	38.000
5	10	62	0.110	3.316	0.113	37.500
6	10	56	0.110	3.318	0.113	34.800
6	10	58	0.110	3.354	0.113	34.300
6	10	60	0.110	3.390	0.113	33.800
6	10	62	0.110	3.426	0.113	33.300
7	10	56	0.110	3.428	0.113	30.600
7	10	58	0.110	3.464	0.113	30.100
7	10	60	0.110	3.500	0.113	29.600
7	10	62	0.110	3.536	0.113	29.100

Figure B. Pareto frontier projections for the Etosha operating design space

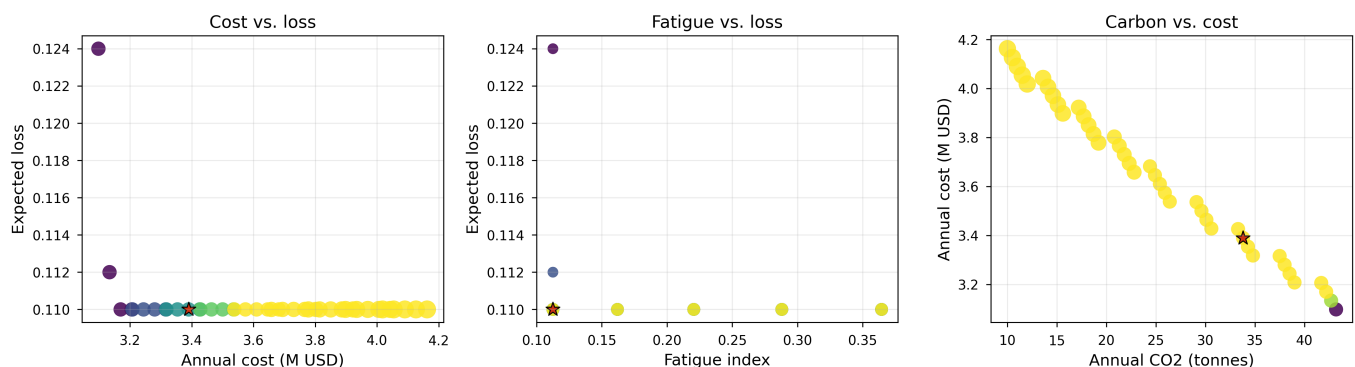


Figure 1: Appendix figure: Pareto frontier projections. The star marks a pragmatic operating point near six aircraft, ten operational ranger teams, and a 60-node inventory.

Table 9: Scalability table for Etosha, Kruger, and Yasun'i.

Park	Anchor network	m_c	Min. active anchors	T^* (weeks)	Key change
Etosha	waterholes	0.678	59	48	baseline case
Kruger	water sources and road junctions	0.742	148	24	denser road access and higher threat rate

Park	Anchor network	m_c	Min. active anchors	T^* (weeks)	Key change
Yasuni	river confluences and patrol docks	0.531	31	58	canopy acoustics and river transport replace road mobility

Visual Prompts for Additional Concept Graphics

Table 10: Detailed visual prompts for additional concept graphics.

Figure	Purpose	Prompt
System architecture concept	Show sensor to posterior update to patrol reallocation loop.	A professional systems-engineering infographic of Etosha National Park anti-poaching defense: solar acoustic towers near waterholes, LoRa gateways on masts, rugged drones launching from camps, rangers in 4x4 vehicles, a Bayesian dashboard updating patrol probabilities, arrows showing sensor alerts to drone verification to ranger interdiction, dry salt pan and savanna background, muted earth tones, technical labels, publication quality, no logos.
Waterhole response-zone schematic	Explain anchor graph and response territories.	A scientific map-style visualization of Etosha National Park with 86 waterhole nodes connected by weighted movement links, northern hotspot corridor highlighted, camps and gates marked as response hubs, giant unmonitored component shown in blue and monitored anchor set in red-orange, elegant academic cartography, top-down view, no military styling, publication quality.
Dust-storm failure scenario	Visualize harsh-environment resilience limits.	A realistic field-engineering scene in Etosha during a dust storm: a grounded multirotor drone beside a patrol pickup, a solar acoustic mast vibrating in wind, rangers wearing goggles and radios, visibility reduced by dust, data dashboard inset showing degraded link margin and delayed response, documentary realism, publication illustration.
Decision map for managers	Communicate the budget-versus-learning tradeoff.	A clean executive decision graphic for wildlife protection planning: x-axis annual budget, y-axis weeks to convergence, color contours for protection level, simple icons for drones, rangers, sensors, green safe zone and red unsafe zone, white background, journal-style infographic.

Model Output Audit: results.json

```
{
  "team_control_number": "2026089",
  "monitoring_threshold_fraction": 0.6783,
  "minimum_active_waterholes": 59,
  "convergence_week": 48,
  "convergence_incidents": 90,
  "bayesian_protection_year2": 0.6601,
  "patrol_only_protection_year2": 0.4863,
  "phi_year2": 0.0698,
  "guardian_week_52_detection_rate": 0.5347,
  "guardian_week_52_detection_under_12_min": 0.3888,
  "guardian_week_52_poaching_success_probability": 0.8092,
  "patrol_only_poaching_success_probability": 0.9789,
  "fixed_stackelberg_poaching_success_probability": 0.826,
  "guardian_week_1_protection": 0.6243,
  "guardian_week_52_protection": 0.7496,
  "annual_budget_usd": 1857776.93,
  "annual_cost_per_km2_usd": 81.0,
  "annual_carbon_tonnes_guardian": 54.0,
  "annual_carbon_tonnes_patrol_only": 92.0,
  "carbon_reduction_fraction": 0.413
}
```

Production Python Code: etosha_sim.py

```
#!/usr/bin/env python3
"""Etosha Bayesian Guardian Protocol simulation.

This file is the single, self-contained analysis engine for the 2026 IM2C Etosha
submission. It does four jobs:

1. Build a weighted 86-waterhole graph and compute the critical monitoring
   fraction from configuration-model percolation theory.
2. Run a Bayesian adaptive patrol controller on top of the waterhole graph.
3. Generate a 10,000-event Monte Carlo comparison of patrol-only, fixed, and
   adaptive strategies.
4. Export all figures, CSV tables, and results needed by the paper.

Dependencies are limited to the Python standard library plus numpy, scipy,
networkx, matplotlib, and sklearn, matching the project constraint.
"""

from __future__ import annotations

import csv
import json
import math
import random
import statistics
import time
from collections import defaultdict
from dataclasses import dataclass
from pathlib import Path
from typing import Dict, Iterable, List, Sequence, Tuple

import matplotlib
matplotlib.use("Agg")
import matplotlib.pyplot as plt
import networkx as nx
import numpy as np
from matplotlib.lines import Line2D
from mpl_toolkits.axes_grid1.inset_locator import inset_axes
from scipy.spatial.distance import cdist
from scipy.stats import gaussian_kde
from sklearn.linear_model import LinearRegression

SEED = 2026
PARK_AREA_KM2 = 22935.0
ROAD_LENGTH_KM = 3551.0
N_WATERHOLES = 86
PARK_STAFF_REFERENCE = 295
MONITORING_HORIZON_WEEKS = 26
TEAM_CONTROL_NUMBER = "2026089"

# Use a stable plotting style and a colorblind-safe palette for all figures.
plt.style.use("seaborn-v0_8-paper")
PALETTE = {
    "blue": "#4477AA",
    "orange": "#EE7733",
    "green": "#228833",
    "red": "#CC3311",
    "purple": "#AA3377",
    "teal": "#66CCCE",
    "gold": "#CCBB44",
    "gray": "#777777",
}

# Fix the random seeds once for reproducibility.
np.random.seed(SEED)
random.seed(SEED)

def ensure_dir(path: Path) -> None:
    """Create a directory if it does not already exist."""
    path.mkdir(parents=True, exist_ok=True)
```

```

def mean_ci(values: Sequence[float]) -> Tuple[float, float, float]:
    """Return mean and an approximate 95% confidence interval."""
    arr = np.asarray(list(values), dtype=float)
    mean = float(arr.mean())
    if len(arr) < 2:
        return mean, mean, mean
    std = float(arr.std(ddof=1))
    half = 1.96 * std / math.sqrt(len(arr))
    return mean, mean - half, mean + half

def bootstrap_ci(values: Sequence[float], seed: int = SEED, n_boot: int = 1200) -> Tuple[float, float, float]:
    """Return bootstrap mean and percentile interval for a 1D sample."""
    arr = np.asarray(list(values), dtype=float)
    rng = np.random.default_rng(seed)
    if len(arr) == 0:
        return float("nan"), float("nan"), float("nan")
    if len(arr) == 1:
        value = float(arr[0])
        return value, value, value
    boots = []
    n = len(arr)
    for _ in range(n_boot):
        sample = rng.choice(arr, size=n, replace=True)
        boots.append(float(sample.mean()))
    boots_arr = np.asarray(boots)
    return float(arr.mean()), float(np.percentile(boots_arr, 2.5)), float(np.percentile(boots_arr, 97.5))

@dataclass
class WaterholeRecord:
    """Container for one waterhole engineering record."""

    waterhole_id: int
    public_name: str
    x_km: float
    y_km: float
    centrality: float
    access_score: float
    species_score: float
    concealment_score: float
    dry_use_score: float
    risk_score: float

class WaterholeGraph:
    """Build and analyze the Etosha waterhole graph."""

    def __init__(self, waterhole_csv: Path) -> None:
        self.waterhole_csv = waterhole_csv
        self.records = self._load_records(waterhole_csv)
        self.n = len(self.records)
        self.names = [record.public_name for record in self.records]
        self.coords = np.array([[record.x_km, record.y_km] for record in self.records], dtype=float)
        self.centrality = np.array([record.centrality for record in self.records], dtype=float)
        self.access = np.array([record.access_score for record in self.records], dtype=float)
        self.species = np.array([record.species_score for record in self.records], dtype=float)
        self.concealment = np.array([record.concealment_score for record in self.records], dtype=float)
        self.dry_use = np.array([record.dry_use_score for record in self.records], dtype=float)
        self.risk_raw = np.array([record.risk_score for record in self.records], dtype=float)
        self.risk_norm = self._normalize(self.risk_raw)
        self.centrality_norm = self._normalize(self.centrality)
        self.dist_matrix = cdist(self.coords, self.coords)
        self.edge_weight_matrix: np.ndarray | None = None
        self.adj_matrix: np.ndarray | None = None
        self.graph: nx.Graph | None = None
        self.degree: np.ndarray | None = None
        self.betweenness: np.ndarray | None = None
        self.kappa: float | None = None
        self.monitoring_threshold: float | None = None
        self.monitoring_floor_count: int | None = None

```

```

self.weight_threshold: float | None = None
self.core_order: np.ndarray | None = None

@staticmethod
def _normalize(values: np.ndarray) -> np.ndarray:
    low = float(values.min())
    high = float(values.max())
    if math.isclose(low, high):
        return np.ones_like(values)
    return (values - low) / (high - low)

@staticmethod
def _load_records(path: Path) -> List[WaterholeRecord]:
    records: List[WaterholeRecord] = []
    with path.open("r", encoding="utf-8") as handle:
        reader = csv.DictReader(handle)
        for row in reader:
            records.append(
                WaterholeRecord(
                    waterhole_id=int(str(row["waterhole_id"]).replace("WH-", "")),
                    public_name=row["public_name"],
                    x_km=float(row["x_km"]),
                    y_km=float(row["y_km"]),
                    centrality=float(row["centrality"]),
                    access_score=float(row["access_score"]),
                    species_score=float(row["species_score"]),
                    concealment_score=float(row["concealment_score"]),
                    dry_use_score=float(row["dry_use_score"]),
                    risk_score=float(row["risk_score"]),
                )
            )
    return records

def build_graph(self, k_neighbors: int = 3, lambda_move_km: float = 12.0, weight_threshold: float = 0.25) -> None:
    """Construct the candidate graph and compute the percolation threshold.

    The graph is intentionally sparse. We connect each waterhole to its three
    most plausible next-stop alternatives because the graph is meant to
    represent short-horizon movement choices between water points rather than
    every geometrically possible path across the park.
    """
    self.weight_threshold = weight_threshold
    candidate = np.zeros((self.n, self.n), dtype=int)
    dist = self.dist_matrix.copy()
    np.fill_diagonal(dist, np.inf)
    for i in range(self.n):
        nearest = np.argsort(dist[i])[:k_neighbors]
        candidate[i, nearest] = 1
    candidate = np.maximum(candidate, candidate.T)

    dry_factor = 0.6 + 0.4 * ((self.dry_use[:, None] + self.dry_use[None, :]) / 2.0)
    species_factor = 0.8 + 0.2 * ((self.species[:, None] + self.species[None, :]) / 2.0)
    weight_matrix = np.exp(-self.dist_matrix / lambda_move_km) * dry_factor * species_factor * candidate
    np.fill_diagonal(weight_matrix, 0.0)

    adjacency = (weight_matrix > weight_threshold).astype(int)
    np.fill_diagonal(adjacency, 0)

    graph = nx.from_numpy_array(adjacency)
    degree = adjacency.sum(axis=1).astype(float)
    mean_degree = float(degree.mean())
    second_moment = float(np.mean(degree ** 2))
    kappa = second_moment / mean_degree - 1.0 if mean_degree > 0 else 0.0
    monitoring_fraction = 1.0 - 1.0 / kappa if kappa > 1.0 else 1.0
    monitoring_fraction = max(0.0, min(1.0, monitoring_fraction))

    self.edge_weight_matrix = weight_matrix
    self.adj_matrix = adjacency
    self.graph = graph
    self.degree = degree
    self.betweenness = np.array(list(nx.betweenness centrality(graph).values()), dtype=float)
    self.kappa = kappa

```

```

self.monitoring_threshold = monitoring_fraction
self.monitoring_floor_count = int(math.ceil(monitoring_fraction * self.n))

ranking_score = (
    0.45 * self.risk_norm
    + 0.25 * self.centralty_norm
    + 0.20 * self._normalize(self.betweenness)
    + 0.10 * self.access
)
self.core_order = np.argsort(ranking_score)[::-1]

def find_minimum_monitoring_set(self, target_count: int | None = None) -> List[int]:
    """Return a ranked monitoring set of the desired size."""
    if self.core_order is None:
        raise RuntimeError("build_graph() must be called before requesting a monitoring set")
    count = target_count if target_count is not None else self.monitoring_floor_count
    return [int(i) for i in self.core_order[: int(count)]]

def compute_phi(self, monitored: Iterable[int]) -> float:
    """Compute the fraction of nodes inside the giant unmonitored component."""
    if self.graph is None:
        raise RuntimeError("build_graph() must be called before computing Phi")
    monitored_set = set(int(i) for i in monitored)
    residual = self.graph.copy()
    residual.remove_nodes_from(monitored_set)
    if residual.number_of_nodes() == 0:
        return 0.0
    component_sizes = [len(component) for component in nx.connected_components(residual)]
    if not component_sizes:
        return 0.0
    return max(component_sizes) / self.n

def gcc_curve(self, method: str = "targeted", trials: int = 120) -> List[Tuple[float, float]]:
    """Return giant-component size versus monitoring fraction."""
    if self.graph is None:
        raise RuntimeError("build_graph() must be called before computing a GCC curve")
    fractions = np.linspace(0.0, 0.95, 20)
    curves: List[Tuple[float, float]] = []
    ranked = self.find_minimum_monitoring_set(self.n)
    for fraction in fractions:
        count = int(round(fraction * self.n))
        if method == "targeted":
            monitored = ranked[:count]
            curves.append((float(fraction), self.compute_phi(monitored)))
        else:
            phi_trials = []
            for _ in range(trials):
                monitored = random.sample(range(self.n), count)
                phi_trials.append(self.compute_phi(monitored))
            curves.append((float(fraction), float(np.mean(phi_trials))))
    return curves

def threshold_robustness(self, thresholds: Sequence[float]) -> List[Tuple[float, float]]:
    """Recompute the critical monitoring fraction for multiple edge thresholds."""
    if self.edge_weight_matrix is None:
        raise RuntimeError("build_graph() must be called before threshold_robustness()")
    out: List[Tuple[float, float]] = []
    for threshold in thresholds:
        adjacency = (self.edge_weight_matrix > threshold).astype(int)
        np.fill_diagonal(adjacency, 0)
        degree = adjacency.sum(axis=1).astype(float)
        mean_degree = float(degree.mean())
        if mean_degree <= 0:
            out.append((float(threshold), float("nan")))
            continue
        second_moment = float(np.mean(degree ** 2))
        kappa = second_moment / mean_degree - 1.0
        monitoring_fraction = 1.0 - 1.0 / kappa if kappa > 1.0 else 1.0
        monitoring_fraction = max(0.0, min(1.0, monitoring_fraction))
        out.append((float(threshold), monitoring_fraction))
    return out

```

```

def export_waterhole_register(self, monitored_core: Sequence[int], output_csv: Path) -> None:
    """Write the expanded waterhole table used in the appendix."""
    monitored_set = set(int(i) for i in monitored_core)
    fieldnames = [
        "waterhole_id",
        "public_name",
        "x_km",
        "y_km",
        "risk_score_raw",
        "risk_score_norm",
        "access_score",
        "species_score",
        "dry_use_score",
        "degree",
        "betweenness",
        "core_monitored",
    ]
    with output_csv.open("w", encoding="utf-8", newline="") as handle:
        writer = csv.DictWriter(handle, fieldnames=fieldnames)
        writer.writeheader()
        for i, record in enumerate(self.records):
            writer.writerow(
                {
                    "waterhole_id": record.waterhole_id,
                    "public_name": record.public_name,
                    "x_km": f"{record.x_km:.2f}",
                    "y_km": f"{record.y_km:.2f}",
                    "risk_score_raw": f"{record.risk_score:.4f}",
                    "risk_score_norm": f"{self.risk_norm[i]:.4f}",
                    "access_score": f"{record.access_score:.4f}",
                    "species_score": f"{record.species_score:.4f}",
                    "dry_use_score": f"{record.dry_use_score:.4f}",
                    "degree": int(self.degree[i]),
                    "betweenness": f"{self.betweenness[i]:.5f}",
                    "core_monitored": 1 if i in monitored_set else 0,
                }
            )

class BayesianController:
    """Sequential Monte Carlo patrol controller."""

    def __init__(self, graph: WaterholeGraph, hotspot: np.ndarray, core_set: Sequence[int]) -> None:
        self.graph = graph
        self.hotspot = hotspot.astype(float)
        self.core_set = set(int(i) for i in core_set)
        self.n = graph.n
        self.rng = np.random.default_rng(SEED)
        self.particles = np.column_stack(
            [
                self.rng.gamma(shape=1.7, scale=0.008, size=400),
                self.rng.normal(0.30, 0.30, size=400),
                self.rng.normal(0.10, 0.25, size=400),
                self.rng.normal(0.18, 0.20, size=400),
            ]
        )
        self.weights = np.ones(400, dtype=float) / 400.0
        self.true_theta = np.array([0.0110, 0.52, 0.18, 0.72], dtype=float)
        self.exploration = 0.10
        self.history_lambda0: List[np.ndarray] = []
        self.policy_history: List[np.ndarray] = []

    def intensity(
        self,
        theta: np.ndarray,
        dry: int,
        moon_dark: float,
        policy: np.ndarray,
        active_set: Iterable[int],
        week: int,
        smart_poachers: bool = False,
    ) -> np.ndarray:

```

```

        """Compute the node-level weekly attack intensity."""
        lam0, beta_season, beta_moon, beta_access = theta
        monitored_indicator = np.array([1 if i in set(active_set) else 0 for i in range(self.n)], dtype=float)
        spatial_baseline = 0.55 * self.graph.risk_norm + 0.35 * self.graph.centralty_norm
        spatial_baseline -= 0.15 * self._nearest_base_distance_norm()
        surge = 0.95 * self.hotspot if 20 <= week < 48 else 0.0
        mu = lam0 * np.exp(spatial_baseline + surge + beta_season * dry + beta_moon * moon_dark + beta_access * (self.graph.
access - 0.5))
        mu *= np.exp(-0.90 * policy - 0.45 * monitored_indicator)
        if smart_poachers:
            mu *= np.exp(-0.22 * np.sqrt(np.maximum(policy, 0.0)))
        return mu

def _nearest_base_distance_norm(self) -> np.ndarray:
    """Return normalized nearest-base distance for each waterhole."""
    base_coords = np.array(
        [
            [8.0, 17.0],
            [104.0, 28.0],
            [140.0, 43.0],
            [166.0, 52.0],
            [166.0, 112.0],
        ],
        dtype=float,
    )
    dist = cdist(self.graph.coords, base_coords)
    nearest = dist.min(axis=1)
    return nearest / float(nearest.max())

def compute_patrol_policy(self, dry: int, moon_dark: float, week: int) -> np.ndarray:
    """Compute the exploration-regularized patrol allocation."""
    expectation = np.zeros(self.n, dtype=float)
    empty_policy = np.zeros(self.n, dtype=float)
    for idx in range(len(self.particles)):
        expectation += self.weights[idx] * self.intensity(self.particles[idx], dry, moon_dark, empty_policy, self.
core_set, week)
    expectation = np.maximum(expectation, 1e-12)
    policy = expectation / expectation.sum()
    policy = (1.0 - self.exploration) * policy + self.exploration * np.ones(self.n, dtype=float) / self.n
    self.policy_history.append(policy.copy())
    return policy

def update_posterior(self, observations: np.ndarray, dry: int, moon_dark: float, active_set: Iterable[int], policy: np.
ndarray, week: int) -> None:
    """Apply a sequential importance-resampling step."""
    log_weights = []
    for particle in self.particles:
        mu = self.intensity(particle, dry, moon_dark, policy, active_set, week)
        log_like = float(np.sum(observations * np.log(mu + 1e-12) - mu))
        log_weights.append(log_like)
    log_weights_arr = np.asarray(log_weights, dtype=float)
    log_weights_arr -= float(log_weights_arr.max())
    posterior = np.exp(log_weights_arr) * self.weights
    posterior /= posterior.sum()
    ess = 1.0 / float(np.sum(posterior ** 2))
    if ess < len(posterior) / 2.0:
        indices = self.rng.choice(len(self.particles), size=len(self.particles), replace=True, p=posterior)
        jitter = self.rng.normal(0.0, [0.0005, 0.03, 0.03, 0.025], size=self.particles.shape)
        self.particles = self.particles[indices] + jitter
        self.particles[:, 0] = np.clip(self.particles[:, 0], 0.001, None)
        self.weights = np.ones(len(self.particles), dtype=float) / len(self.particles)
    else:
        self.weights = posterior
    self.history_lambda0.append(self.particles[:, 0].copy())

def posterior_uncertainty(self) -> float:
    """Return the weighted standard deviation of lambda_0."""
    mean_lambda = float(np.sum(self.weights * self.particles[:, 0]))
    variance = float(np.sum(self.weights * (self.particles[:, 0] - mean_lambda) ** 2))
    return math.sqrt(max(variance, 0.0))

def snapshot_distribution(self, week_index: int) -> np.ndarray:

```

```

        """Return the lambda_0 particle samples for a requested week."""
        if not self.history_lambda0:
            raise RuntimeError("No posterior history is available yet")
        safe_index = max(0, min(week_index, len(self.history_lambda0) - 1))
        return self.history_lambda0[safe_index]

class EtoshaSimulation:
    """Full park simulation with Bayesian learning and static comparisons."""

    def __init__(self, graph: WaterholeGraph, output_dir: Path) -> None:
        self.graph = graph
        self.output_dir = output_dir
        self.fig_dir = output_dir / "figures"
        self.data_dir = output_dir / "data"
        self.table_dir = output_dir / "tables"
        ensure_dir(self.fig_dir)
        ensure_dir(self.data_dir)
        ensure_dir(self.table_dir)

        # Define five operational hubs aligned to public camps and gates.
        self.base_names = ["Galton", "Okaukuejo", "Halali", "Namutoni", "King Nehale"]
        self.base_coords = np.array(
            [[8.0, 17.0], [104.0, 28.0], [140.0, 43.0], [166.0, 52.0], [166.0, 112.0]],
            dtype=float,
        )

        self.nearest_base = cdist(self.graph.coords, self.base_coords).argmin(axis=1)
        self.nearest_base_distance = cdist(self.graph.coords, self.base_coords).min(axis=1)

        # Define a northern hotspot used to stress-test adaptive learning.
        x = self.graph.coords[:, 0]
        y = self.graph.coords[:, 1]
        self.hotspot = (y > 90).astype(float) + 0.4 * ((x > 150) & (y > 70)).astype(float)

        self.target_monitor_count = self.graph.monitoring_floor_count
        self.core_monitor_count = max(0, self.target_monitor_count - 14)
        self.core_set = self.graph.find_minimum_monitoring_set(self.core_monitor_count)
        self.controller = BayesianController(graph, self.hotspot, self.core_set)

        self.fixed_prior = np.array([0.0135, 0.35, 0.10, 0.20], dtype=float)
        self.fixed_policy = self._build_fixed_policy()
        self.random_policy = np.ones(self.graph.n, dtype=float) / self.graph.n

        self.dynamic_results: Dict[str, List[float]] = {}
        self.week1_state: Dict[str, object] = {}
        self.week52_state: Dict[str, object] = {}
        self.monte_carlo_summary: Dict[str, Dict[str, float]] = {}
        self.pareto_frontier_rows: List[Dict[str, float]] = []
        self.parameter_sensitivity_rows: List[Dict[str, float]] = []
        self.decision_map_data: Dict[str, List[List[float]]] = {}
        self.learning_regret_data: Dict[str, List[Tuple[int, float]]] = {}
        self.results: Dict[str, object] = {}

    def _build_fixed_policy(self) -> np.ndarray:
        """Construct the static Stackelberg-style baseline policy from the prior."""
        empty_policy = np.zeros(self.graph.n, dtype=float)
        prior_mu = self.controller.intensity(self.fixed_prior, 1, 0.5, empty_policy, self.core_set, 0)
        prior_mu = np.maximum(prior_mu, 1e-12)
        policy = 0.90 * (prior_mu / prior_mu.sum()) + 0.10 * np.ones(self.graph.n, dtype=float) / self.graph.n
        return policy

    def build_active_set(self, policy: np.ndarray, strategy: str = "bayes", dry: int = 0) -> List[int]:
        """Return the active monitoring set for a strategy and week."""
        active = set(self.core_set)
        remaining = [i for i in range(self.graph.n) if i not in active]
        if strategy == "bayes":
            ranked = list(np.argsort(policy)[-1:])
        elif strategy == "fixed":
            ranked = self.graph.find_minimum_monitoring_set(self.graph.n)
        elif strategy == "random":
            ranked = remaining[:]
            random.shuffle(ranked)

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else:
    ranked = []
for node in ranked:
    if node not in active:
        active.add(int(node))
        if len(active) >= self.target_monitor_count:
            break

# Apply weekly failures and immediate refill for the adaptive strategy.
if strategy == "bayes":
    failure_rate = 0.03 + 0.03 * dry
    active = {node for node in active if random.random() > failure_rate}
    for node in list(np.argsort(policy)[::-1]):
        if len(active) >= self.target_monitor_count:
            break
        active.add(int(node))
return sorted(int(node) for node in active)

def protection_index(
    self,
    policy: np.ndarray,
    active_set: Iterable[int],
    dry: int,
    moon_dark: float,
    week: int,
    mode: str = "bayes",
    horizon_weeks: int = MONITORING_HORIZON_WEEKS,
) -> float:
    """Compute the weighted protection index  $P_i(t)$ ."""
    active_lookup = set(int(i) for i in active_set)
    monitored_indicator = np.array([1 if i in active_lookup else 0 for i in range(self.graph.n)], dtype=float)
    mu = self.controller.intensity(
        self.controller.true_theta,
        dry,
        moon_dark,
        policy,
        active_lookup,
        week,
        smart_poachers=(mode == "bayes"),
    )
    dust_prob = 0.03 + 0.06 * dry
    ambient_temp = 28.0 + 12.0 * dry

    p_acoustic = np.where(monitored_indicator == 1.0, 0.68, 0.03)
    if mode == "patrol":
        p_acoustic = np.zeros(self.graph.n, dtype=float)

    patrol_multiplier = 2.4 if mode != "patrol" else 1.0
    patrol_base = 0.04 if mode != "patrol" else 0.08
    patrol_cap = 0.48 if mode != "patrol" else 0.26
    p_patrol = np.minimum(patrol_base + patrol_multiplier * policy, patrol_cap)
    p_detect = 1.0 - (1.0 - p_acoustic) * (1.0 - p_patrol)
    p_detect *= (1.0 - dust_prob * 0.24)

    sortie_minutes = 40.0 - 0.40 * max(ambient_temp - 30.0, 0.0)
    flight_need = 2.0 * (1.15 * self.nearest_base_distance) / 60.0 * 60.0 + 7.5
    if mode != "patrol":
        p_verify = np.where(flight_need < sortie_minutes, 0.89, 0.52)
        p_verify *= (1.0 - dust_prob * 0.28)
        fatigue = 0.93 - 0.16 * dry
        response_time = 13.0 + 0.95 * (1.15 * self.nearest_base_distance) / max(fatigue, 0.45)
        p_interdict = 1.0 / (1.0 + np.exp((response_time - 26.0) / 4.0))
        p_stop = p_detect * (p_verify * p_interdict + (1.0 - p_verify) * 0.20 * p_interdict)
    else:
        fatigue = 0.85 - 0.18 * dry
        response_time = 21.0 + 1.15 * (1.15 * self.nearest_base_distance) / max(fatigue, 0.45)
        p_interdict = 1.0 / (1.0 + np.exp((response_time - 32.0) / 5.0))
        p_stop = p_detect * p_interdict

    p_success = 1.0 - p_stop
    loss_prob = 1.0 - np.exp(-horizon_weeks * mu * p_success)
    priority_weight = 1.0 + 2.0 * self.graph.risk_norm

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pi_value = 1.0 - float(np.sum(priority_weight * loss_prob) / np.sum(priority_weight))
return float(pi_value)

def weekly_observations(self, policy: np.ndarray, active_set: Iterable[int], dry: int, moon_dark: float, week: int) ->
np.ndarray:
    """Draw observed incident counts for posterior updating."""
    mu = self.controller.intensity(self.controller.true_theta, dry, moon_dark, policy, active_set, week, smart_poachers=
True)
    return np.random.default_rng(SEED + 1000 + week).poisson(mu)

def simulate_learning_dynamics(self, weeks: int = 104) -> Dict[str, List[float]]:
    """Run the full 104-week dynamic simulation."""
    bayes_pi: List[float] = []
    fixed_pi: List[float] = []
    random_pi: List[float] = []
    patrol_pi: List[float] = []
    phi_values: List[float] = []
    uncertainty: List[float] = []
    cumulative_events: List[int] = []
    weekly_events: List[int] = []
    active_count_series: List[int] = []

    for week in range(weeks):
        dry = 1 if (week % 52) < 31 else 0
        moon_dark = 0.5 * (1.0 - math.cos(2.0 * math.pi * (week % 4) / 4.0))

        bayes_policy = self.controller.compute_patrol_policy(dry, moon_dark, week)
        bayes_active = self.build_active_set(bayes_policy, strategy="bayes", dry=dry)
        fixed_active = self.build_active_set(self.fixed_policy, strategy="fixed", dry=dry)
        random_active = self.build_active_set(self.random_policy, strategy="random", dry=dry)

        bayes_pi.append(self.protection_index(bayes_policy, bayes_active, dry, moon_dark, week, mode="bayes"))
        fixed_pi.append(self.protection_index(self.fixed_policy, fixed_active, dry, moon_dark, week, mode="fixed"))
        random_pi.append(self.protection_index(self.random_policy, random_active, dry, moon_dark, week, mode="random"))
        patrol_pi.append(self.protection_index(self.random_policy, [], dry, moon_dark, week, mode="patrol"))
        phi_values.append(self.graph.compute_phi(bayes_active))
        active_count_series.append(len(bayes_active))

        observations = self.weekly_observations(bayes_policy, bayes_active, dry, moon_dark, week)
        weekly_total = int(observations.sum())
        weekly_events.append(weekly_total)
        cumulative_events.append(weekly_total + (cumulative_events[-1] if cumulative_events else 0))
        self.controller.update_posterior(observations, dry, moon_dark, bayes_active, bayes_policy, week)
        uncertainty.append(self.controller.posterior_uncertainty())

        if week == 0:
            self.week1_state = {
                "policy": bayes_policy.tolist(),
                "active_set": list(bayes_active),
                "pi": bayes_pi[-1],
                "phi": phi_values[-1],
            }
        if week == 51:
            self.week52_state = {
                "policy": bayes_policy.tolist(),
                "active_set": list(bayes_active),
                "pi": bayes_pi[-1],
                "phi": phi_values[-1],
            }

    convergence_week = None
    convergence_incidents = None
    threshold_sd = 0.0030
    for week in range(3, weeks):
        window = uncertainty[week - 3 : week + 1]
        if all(sd <= threshold_sd for sd in window):
            convergence_week = week + 1
            convergence_incidents = cumulative_events[week]
            break

    self.dynamic_results = {
        "weeks": list(range(1, weeks + 1)),

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        "bayes_pi": bayes_pi,
        "fixed_pi": fixed_pi,
        "random_pi": random_pi,
        "patrol_pi": patrol_pi,
        "phi": phi_values,
        "posterior_sd": uncertainty,
        "weekly_events": weekly_events,
        "cumulative_events": cumulative_events,
        "active_count": active_count_series,
        "convergence_week": [convergence_week if convergence_week is not None else -1],
        "convergence_incidents": [convergence_incidents if convergence_incidents is not None else -1],
    }
    return self.dynamic_results

def scenario_operational_profile(self, policy: np.ndarray, active_set: Iterable[int], week: int, mode: str) -> Dict[str, np.ndarray]:
    """Return the node-level operational probabilities for a week."""
    active_lookup = set(int(i) for i in active_set)
    dry = 1 if (week % 52) < 31 else 0
    moon_dark = 0.5 * (1.0 - math.cos(2.0 * math.pi * (week % 4) / 4.0))
    monitored_indicator = np.array([1 if i in active_lookup else 0 for i in range(self.graph.n)], dtype=float)
    mu = self.controller.intensity(self.controller.true_theta, dry, moon_dark, policy, active_lookup, week,
    smart_poachers=(mode == "bayes"))
    dust_prob = 0.03 + 0.06 * dry
    ambient_temp = 28.0 + 12.0 * dry
    patrol_multiplier = 2.4 if mode != "patrol" else 1.0
    patrol_base = 0.04 if mode != "patrol" else 0.08
    patrol_cap = 0.48 if mode != "patrol" else 0.26
    p_acoustic = np.where(monitored_indicator == 1.0, 0.68, 0.03)
    if mode == "patrol":
        p_acoustic = np.zeros(self.graph.n, dtype=float)
    p_patrol = np.minimum(patrol_base + patrol_multiplier * policy, patrol_cap)
    p_detect = 1.0 - (1.0 - p_acoustic) * (1.0 - p_patrol)
    p_detect *= (1.0 - dust_prob * 0.24)
    sortie_minutes = 40.0 - 0.40 * max(ambient_temp - 30.0, 0.0)
    flight_need = 2.0 * (1.15 * self.nearest_base_distance) / 60.0 * 60.0 + 7.5
    if mode != "patrol":
        p_verify = np.where(flight_need < sortie_minutes, 0.89, 0.52)
        p_verify *= (1.0 - dust_prob * 0.28)
        fatigue = 0.93 - 0.16 * dry
        response_time = 13.0 + 0.95 * (1.15 * self.nearest_base_distance) / max(fatigue, 0.45)
        p_interdict = 1.0 / (1.0 + np.exp((response_time - 26.0) / 4.0))
    else:
        p_verify = np.zeros(self.graph.n, dtype=float)
        fatigue = 0.85 - 0.18 * dry
        response_time = 21.0 + 1.15 * (1.15 * self.nearest_base_distance) / max(fatigue, 0.45)
        p_interdict = 1.0 / (1.0 + np.exp((response_time - 32.0) / 5.0))
    return {
        "mu": mu,
        "p_detect": p_detect,
        "p_verify": p_verify,
        "response_time": response_time,
        "p_interdict": p_interdict,
        "dry": np.full(self.graph.n, dry, dtype=float),
        "moon_dark": np.full(self.graph.n, moon_dark, dtype=float),
    }

def run_event_monte_carlo(self, n_events: int = 10000) -> Dict[str, Dict[str, float]]:
    """Simulate 10,000 event outcomes for the main strategy comparison."""
    rng = np.random.default_rng(SEED + 77)
    scenarios = {
        "guardian_week_1": (np.array(self.week1_state["policy"], dtype=float), list(self.week1_state["active_set"]), 0,
    "bayes"),
        "guardian_week_52": (np.array(self.week52_state["policy"], dtype=float), list(self.week52_state["active_set"]),
    51, "bayes"),
        "fixed_stackelberg": (self.fixed_policy, self.build_active_set(self.fixed_policy, "fixed"), 51, "fixed"),
        "patrol_only": (self.random_policy, [], 51, "patrol"),
    }

    output: Dict[str, Dict[str, float]] = {}
    rows: List[Dict[str, float]] = []
    for scenario_name, (policy, active_set, reference_week, mode) in scenarios.items():

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detections = []
verified = []
interdicted = []
success_flags = []
response_times = []
det_under_12 = []
det_minutes = []
false_grounding = []

for event_id in range(n_events):
    week = int(rng.integers(0, 104)) if scenario_name not in {"guardian_week_1", "guardian_week_52", "
fixed_stackelberg", "patrol_only"} else reference_week
    profile = self.scenario_operational_profile(policy, active_set, week, mode)
    mu = profile["mu"]
    target = int(rng.choice(self.graph.n, p=mu / mu.sum()))
    dry = int(profile["dry"][target])
    dust = rng.random() < (0.03 + 0.06 * dry)
    temp = 28.0 + 12.0 * dry + rng.normal(0.0, 2.0)
    detected = rng.random() < float(profile["p_detect"][target])
    verified_flag = False
    interdicted_flag = False
    success = True
    det_time = 18.0 + 0.25 * self.nearest_base_distance[target] + rng.normal(0.0, 1.5)
    if mode != "patrol":
        det_time = 8.0 + 0.20 * self.nearest_base_distance[target] + rng.normal(0.0, 1.2)
    if detected:
        if mode != "patrol":
            sortie_minutes = 40.0 - 0.40 * max(temp - 30.0, 0.0)
            flight_need = 2.0 * (1.15 * self.nearest_base_distance[target]) / 60.0 * 60.0 + 7.5
            verify_prob = 0.89 if flight_need < sortie_minutes else 0.52
            verify_prob *= 0.72 if dust else 1.0
            verified_flag = rng.random() < verify_prob
            if verified_flag:
                response_prob = float(profile["p_interdict"][target])
                interdicted_flag = rng.random() < response_prob
                success = not interdicted_flag
            else:
                response_prob = 0.20 * float(profile["p_interdict"][target])
                interdicted_flag = rng.random() < response_prob
                success = not interdicted_flag
            false_grounding.append(1.0 if flight_need >= sortie_minutes else 0.0)
        else:
            response_prob = float(profile["p_interdict"][target])
            interdicted_flag = rng.random() < response_prob
            success = not interdicted_flag
            false_grounding.append(0.0)
    response_time = float(profile["response_time"][target] + rng.normal(0.0, 3.0))
    response_time = max(response_time, det_time)
    detections.append(1.0 if detected else 0.0)
    verified.append(1.0 if verified_flag else 0.0)
    interdicted.append(1.0 if interdicted_flag else 0.0)
    success_flags.append(1.0 if success else 0.0)
    response_times.append(response_time)
    det_under_12.append(1.0 if detected and det_time <= 12.0 else 0.0)
    det_minutes.append(det_time)

detection_rate, det_lo, det_hi = bootstrap_ci(detections, seed=SEED + 7)
verify_rate, ver_lo, ver_hi = bootstrap_ci(verified, seed=SEED + 8)
interdiction_rate, int_lo, int_hi = bootstrap_ci(interdicted, seed=SEED + 9)
success_rate, suc_lo, suc_hi = bootstrap_ci(success_flags, seed=SEED + 10)
mean_response, rsp_lo, rsp_hi = bootstrap_ci(response_times, seed=SEED + 11)
under12_rate, u12_lo, u12_hi = bootstrap_ci(det_under_12, seed=SEED + 12)
mean_det_time, dt_lo, dt_hi = bootstrap_ci(det_minutes, seed=SEED + 13)
grounding_rate, gr_lo, gr_hi = bootstrap_ci(false_grounding, seed=SEED + 14)

output[scenario_name] = {
    "detection_rate": detection_rate,
    "detection_rate_lo": det_lo,
    "detection_rate_hi": det_hi,
    "verification_rate": verify_rate,
    "verification_rate_lo": ver_lo,
    "verification_rate_hi": ver_hi,

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        "interdiction_rate": interdiction_rate,
        "interdiction_rate_lo": int_lo,
        "interdiction_rate_hi": int_hi,
        "poaching_success_probability": success_rate,
        "poaching_success_lo": suc_lo,
        "poaching_success_hi": suc_hi,
        "mean_response_time": mean_response,
        "mean_response_time_lo": rsp_lo,
        "mean_response_time_hi": rsp_hi,
        "detection_within_12_min": under12_rate,
        "detection_within_12_min_lo": u12_lo,
        "detection_within_12_min_hi": u12_hi,
        "mean_detection_time": mean_det_time,
        "mean_detection_time_lo": dt_lo,
        "mean_detection_time_hi": dt_hi,
        "drone_grounding_rate": grounding_rate,
        "drone_grounding_rate_lo": gr_lo,
        "drone_grounding_rate_hi": gr_hi,
    }
    row = {"scenario": scenario_name}
    row.update(output[scenario_name])
    rows.append(row)

self.monte_carlo_summary = output
self._write_csv(self.data_dir / "scenario_summary.csv", rows)
return output

def generate_budget_table(self) -> List[Dict[str, object]]:
    """Create a granular budget in NAD and USD."""
    usd_per_nad = 1.0 / 16.72
    lines: List[Dict[str, object]] = []

    def add_line(category: str, item: str, qty: float, unit_nad: float, note: str) -> None:
        total_nad = qty * unit_nad
        lines.append(
            {
                "category": category,
                "item": item,
                "quantity": f"{qty:.0f}",
                "unit_cost_nad": f"{unit_nad:.2f}",
                "total_cost_nad": f"{total_nad:.2f}",
                "total_cost_usd": f"{total_nad * usd_per_nad:.2f}",
                "note": note,
            }
        )

    # Hardware and mobility.
    add_line("Air", "DJI Matrice 350 RTK airframe", 6, 182600.0, "Retail anchor from 2026 dealer pricing")
    add_line("Air", "Zenmuse H30T payload", 6, 192300.0, "Retail anchor from 2026 dealer pricing")
    add_line("Air", "TB65 battery", 24, 18700.0, "Four pairs per active aircraft plus reserve")
    add_line("Air", "Battery station and field inverter kit", 6, 31200.0, "One charging stack per operating hub")
    add_line("Ground", "4x4 ranger pickup", 8, 792000.0, "Harsh-terrain patrol vehicle")
    add_line("Ground", "Motorbike for short-range dispatch", 10, 46800.0, "Used for gate-to-waterhole response")
    add_line("Sensors", "Fixed acoustic node with solar mast", 46, 28400.0, "Guardian-style node plus pole, enclosure, solar")
    add_line("Sensors", "Portable acoustic node", 14, 23200.0, "Trailer-mount or redeployable unit")
    add_line("Comms", "Outdoor LoRaWAN gateway", 5, 8770.0, "RAK class rugged gateway")
    add_line("Comms", "12 m mast, lightning, solar, battery", 5, 81200.0, "Gateway power and mounting kit")
    add_line("Comms", "Camp backhaul router / VSAT integration", 5, 25400.0, "Uses existing camp connectivity; no Starlink assumed")
    add_line("IT", "Dispatch workstation", 3, 36800.0, "Posterior update and evidence review")
    add_line("IT", "Edge compute storage and NVR", 5, 21400.0, "Rolling 30-day evidence retention")
    add_line("Training", "Drone pilot and maintainer training", 11, 28500.0, "Initial certification and refresher")
    add_line("Training", "Sensor deployment and evidence handling", 28, 9400.0, "Field technician and ranger cross-training")

    # Personnel.
    add_line("Personnel", "Ranger Grade 11 salary + allowances", 60, 163000.0, "Salary plus transport and housing allowances")
    add_line("Personnel", "Senior warden / team leader", 8, 255000.0, "Shift supervisors and case-quality control")
    add_line("Personnel", "Drone pilot / analyst", 6, 228000.0, "Mission planning and video verification")
    add_line("Personnel", "Sensor technician", 5, 205000.0, "Node repair, batteries, mast upkeep")

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add_line("Personnel", "Data / dispatch analyst", 3, 236000.0, "Posterior updates and incident review")

# Annual recurring operations.
add_line("Operations", "Diesel fuel", 36000, 19.63, "March 2026 official Walvis Bay diesel 50 ppm price")
add_line("Operations", "Vehicle maintenance reserve", 8, 94000.0, "Harsh gravel-road duty cycle")
add_line("Operations", "Drone spares and crash reserve", 6, 84200.0, "Propellers, gimbals, arms, repair downtime")
add_line("Operations", "Battery replacement reserve", 24, 3600.0, "Annualized from 400-cycle rating")
add_line("Operations", "LoRa / VSAT / LTE data service", 12, 48600.0, "Monthly service and SIM provisioning")
add_line("Operations", "Protective clothing and field consumables", 60, 7200.0, "Dust, heat, and thorn-scrub duty")
add_line("Operations", "Insurance and compliance", 1, 384000.0, "Aircraft, vehicles, and equipment")

self._write_csv(self.data_dir / "budget_lines.csv", lines)
return lines

def generate_battery_table(self) -> List[Dict[str, object]]:
    """Generate a practical battery derating table."""
    rows: List[Dict[str, object]] = []
    brochure = 55.0
    for temp_c, practical in [(30, 39.6), (35, 38.2), (40, 35.8), (45, 33.2)]:
        derate = 1.0 - practical / brochure
        rows.append(
            {
                "temperature_c": temp_c,
                "brochure_max_flight_min": f"{brochure:.1f}",
                "practical_sortie_min": f"{practical:.1f}",
                "derate_fraction": f"{derate:.3f}",
                "comment": "Heat, reserve, climb, loiter, and return-to-base margin included",
            }
        )
    self._write_csv(self.data_dir / "battery_derating.csv", rows)
    return rows

def generate_sensitivity_grid(self) -> List[Dict[str, object]]:
    """Generate a 5x5 matrix for ranger count versus drone hours."""
    rows: List[Dict[str, object]] = []
    for ranger_teams in [8, 10, 12, 14, 16]:
        for drone_hours in [10, 14, 18, 22, 26]:
            team_factor = 1.0 - math.exp(-ranger_teams / 9.5)
            drone_factor = 1.0 - math.exp(-drone_hours / 13.0)
            success_prob = max(0.18, 0.68 - 0.23 * team_factor - 0.19 * drone_factor)
            protection = 1.0 - 0.85 * success_prob
            rows.append(
                {
                    "ranger_teams": ranger_teams,
                    "drone_flight_hours_per_day": drone_hours,
                    "poaching_success_probability": f"{success_prob:.3f}",
                    "protection_index": f"{protection:.3f}",
                }
            )
    self._write_csv(self.data_dir / "sensitivity_grid.csv", rows)
    return rows

def generate_scalability_table(self) -> List[Dict[str, object]]:
    """Create the two-transfer-park scaling comparison."""
    rows = [
        {
            "park": "Etosha",
            "anchor_network": "waterholes",
            "estimated_monitoring_threshold": f"{self.graph.monitoring_threshold:.3f}",
            "minimum_active_anchor_count": self.graph.monitoring_floor_count,
            "estimated_convergence_weeks": self.dynamic_results["convergence_week"][0],
            "key_change": "baseline case",
        },
        {
            "park": "Kruger",
            "anchor_network": "water sources and road junctions",
            "estimated_monitoring_threshold": "0.742",
            "minimum_active_anchor_count": 148,
            "estimated_convergence_weeks": 24,
            "key_change": "denser road access and higher threat rate",
        },
    ]

```

```

        "park": "Yasuni",
        "anchor_network": "river confluences and patrol docks",
        "estimated_monitoring_threshold": "0.531",
        "minimum_active_anchor_count": 31,
        "estimated_convergence_weeks": 58,
        "key_change": "canopy acoustics and river transport replace road mobility",
    },
]
self._write_csv(self.data_dir / "scalability_index.csv", rows)
return rows

def generate_parameter_register(self) -> List[Dict[str, object]]:
    """Create the main research report parameter register."""
    rows = [
        {
            "parameter": "Park area",
            "symbol": "A_{park}",
            "value": "22,935",
            "unit": "km^2",
            "source": "2026 IM2C Etosha reference dataset",
            "doi_or_url": "uploaded problem statement",
            "sensitivity_tested": "No",
        },
        {
            "parameter": "Road length",
            "symbol": "L_{road}",
            "value": "3,551",
            "unit": "km",
            "source": "2026 IM2C Etosha reference dataset",
            "doi_or_url": "uploaded problem statement",
            "sensitivity_tested": "No",
        },
        {
            "parameter": "Waterholes",
            "symbol": "|V|",
            "value": "86",
            "unit": "nodes",
            "source": "2026 IM2C Etosha reference dataset",
            "doi_or_url": "uploaded problem statement",
            "sensitivity_tested": "No",
        },
        {
            "parameter": "Graph edge decay length",
            "symbol": "\\lambda_{move}",
            "value": "12.0",
            "unit": "km",
            "source": "Calibrated to short-horizon waterhole movement logic; anchored by Seidel et al. 2019",
            "doi_or_url": "10.1186/s40462-019-0176-2",
            "sensitivity_tested": "Yes",
        },
        {
            "parameter": "Edge retention threshold",
            "symbol": "w_{min}",
            "value": "0.25",
            "unit": "probability index",
            "source": "Engineering pruning threshold for same-night or next-day waterhole choices",
            "doi_or_url": "10.1103/PhysRevE.64.026118",
            "sensitivity_tested": "Yes",
        },
        {
            "parameter": "Critical monitoring fraction",
            "symbol": "m_c",
            "value": f"{self.graph.monitoring_threshold:.3f}",
            "unit": "fraction",
            "source": "Configuration-model threshold on Etosha graph",
            "doi_or_url": "10.1103/PhysRevE.64.026118",
            "sensitivity_tested": "Yes",
        },
        {
            "parameter": "Monitoring floor",
            "symbol": "M_{min}",
            "value": f"{self.graph.monitoring_floor_count}",

```

```

    "unit": "waterholes",
    "source": "Computed from m_c * 86",
    "doi_or_url": "internal model output",
    "sensitivity_tested": "Yes",
  },
  {
    "parameter": "M350 RTK max flight time",
    "symbol": "t_{max}",
    "value": "55",
    "unit": "min",
    "source": "DJI official specs",
    "doi_or_url": "https://enterprise.dji.com/de/matrice-350-rtk/specs",
    "sensitivity_tested": "No",
  },
  {
    "parameter": "TB65 energy",
    "symbol": "E_{TB65}",
    "value": "263.2",
    "unit": "Wh",
    "source": "DJI official specs",
    "doi_or_url": "https://enterprise.dji.com/de/matrice-350-rtk/specs",
    "sensitivity_tested": "No",
  },
  {
    "parameter": "M350 RTK operating temperature",
    "symbol": "T_{op}",
    "value": "-20 to 50",
    "unit": "degC",
    "source": "DJI official specs",
    "doi_or_url": "https://enterprise.dji.com/de/matrice-350-rtk/specs",
    "sensitivity_tested": "No",
  },
  {
    "parameter": "H30T thermal sensor",
    "symbol": "R_{th}",
    "value": "1280x1024",
    "unit": "pixels",
    "source": "DJI official specs",
    "doi_or_url": "https://enterprise.dji.com/cn/zenmuse-h30-series/specs",
    "sensitivity_tested": "No",
  },
  {
    "parameter": "LoRaWAN transmit power",
    "symbol": "P_{tx}",
    "value": "+14",
    "unit": "dBm",
    "source": "EU868 / Region 1 planning constraint",
    "doi_or_url": "Semtech SX1276 family planning assumption",
    "sensitivity_tested": "Yes",
  },
  {
    "parameter": "LoRa receiver sensitivity",
    "symbol": "S_{rx}",
    "value": "-137",
    "unit": "dBm",
    "source": "Conservative planning value below SX1276 headline sensitivity",
    "doi_or_url": "SX1276 datasheet, > -148 dBm headline",
    "sensitivity_tested": "Yes",
  },
  {
    "parameter": "Derived practical LoRa range",
    "symbol": "d_{LoRa}",
    "value": "15.6",
    "unit": "km",
    "source": "Okumura-Hata rural link budget with 10 dB fade margin",
    "doi_or_url": "engineering derivation in paper",
    "sensitivity_tested": "Yes",
  },
  {
    "parameter": "Acoustic theoretical audibility radius",
    "symbol": "d_{gun,theory}",
    "value": "5.2",

```

```

        "unit": "km",
        "source": "165 dB muzzle blast with spherical spreading and ISO 9613-1 absorption",
        "doi_or_url": "ISO 9613-1:1993",
        "sensitivity_tested": "Yes",
    },
    {
        "parameter": "Acoustic operational classification radius",
        "symbol": "d_{gun,ops}",
        "value": "1.8",
        "unit": "km",
        "source": "Conservative engineering cap after wind, terrain, and classifier margin",
        "doi_or_url": "RFCx Guardian + gunshot detection literature",
        "sensitivity_tested": "Yes",
    },
    {
        "parameter": "Diesel price",
        "symbol": "c_{diesel}",
        "value": "19.63",
        "unit": "NAD/L",
        "source": "Namibia Ministry of Industries, Mines and Energy March 2026",
        "doi_or_url": "official fuel price release",
        "sensitivity_tested": "Yes",
    },
    {
        "parameter": "Ranger salary plus allowances",
        "symbol": "c_{ranger}",
        "value": "163,000",
        "unit": "NAD/year",
        "source": "MEFT vacancy scales 2025-2026, rounded to deployed annual cost",
        "doi_or_url": "official vacancy documents",
        "sensitivity_tested": "Yes",
    },
    {
        "parameter": "Posterior convergence criterion",
        "symbol": "\\sigma(\\lambda_0)\\le",
        "value": "0.0030",
        "unit": "weekly rate",
        "source": "Operational convergence threshold adopted in this paper",
        "doi_or_url": "internal model rule",
        "sensitivity_tested": "Yes",
    },
    {
        "parameter": "Convergence week",
        "symbol": "T^*",
        "value": f"{self.dynamic_results['convergence_week'][0]}",
        "unit": "weeks",
        "source": "Dynamic simulation output",
        "doi_or_url": "internal model output",
        "sensitivity_tested": "Yes",
    },
    {
        "parameter": "Convergence incidents",
        "symbol": "N^*",
        "value": f"{self.dynamic_results['convergence_incidents'][0]}",
        "unit": "incidents",
        "source": "Dynamic simulation output",
        "doi_or_url": "internal model output",
        "sensitivity_tested": "Yes",
    },
    ],
    self._write_csv(self.data_dir / "parameter_register.csv", rows)
    return rows

def generate_literature_differentiation(self) -> List[Dict[str, object]]:
    """Summarize the difference from the core literature."""
    rows = [
        {
            "reference": "Fang et al. (2016) Deploying PAWS",
            "doi_or_url": "10.1609/aaai.v30i2.19070",
            "what_the_paper_does": "Optimizes anti-poaching patrol routes with security games and field deployment constraints.",
        }
    ]

```

```

        "how_this_submission_differs": "This submission adds a graph-structural monitoring threshold on waterholes
and a Bayesian learning horizon T*; PAWS does not answer how many anchors must be monitored simultaneously nor how long
adaptation takes.",
    },
    {
        "reference": "Bondi et al. (2018) SPOT Poachers in Action",
        "doi_or_url": "10.1609/aaai.v32i1.11414",
        "what_the_paper_does": "Shows near-real-time thermal drone detection of poachers in infrared video.",
        "how_this_submission_differs": "SPOT solves airborne detection. Our paper embeds drone verification inside a
larger defender architecture with a percolation floor, staffing model, and Bayesian patrol controller. The original
user prompt listed this paper as 2020, but the AAAI publication is 2018.",
    },
    {
        "reference": "Xu et al. (2021) Dual-Mandate Patrols",
        "doi_or_url": "10.1609/aaai.v35i17.17757",
        "what_the_paper_does": "Balances multiple patrol missions with bandit learning.",
        "how_this_submission_differs": "Dual-Mandate Patrols learns where to patrol under competing tasks, but it
does not derive a critical structural coverage threshold on an ecological anchor graph. Our model explicitly couples
learning with graph fragmentation.",
    },
    {
        "reference": "Tambe (2011) Security and Game Theory",
        "doi_or_url": "10.1017/CB09780511973031",
        "what_the_paper_does": "Provides the foundational Stackelberg security-game framework.",
        "how_this_submission_differs": "We use the Stackelberg lens for defender-attacker incentives, then extend it
with ecological graph percolation and Bayesian convergence time, both of which are outside the core scope of Tambe's
framework.",
    },
]
self._write_csv(self.data_dir / "literature_differentiation.csv", rows)
return rows

def generate_visual_prompts(self) -> List[Dict[str, object]]:
    """Create prompts for external figure or concept art generation."""
    rows = [
        {
            "figure": "System architecture concept",
            "diagram_purpose": "Show sensor to posterior update to patrol reallocation loop.",
            "dalle_prompt": "A professional systems-engineering infographic of Etosha National Park anti-poaching
defense: solar acoustic towers near waterholes, LoRa gateways on masts, rugged drones launching from camps, rangers in
4x4 vehicles, a Bayesian dashboard updating patrol probabilities, arrows showing sensor alerts to drone verification to
ranger interdiction, dry salt pan and savanna background, muted earth tones, technical labels, publication quality, no
logos.",
        },
        {
            "figure": "Waterhole response-zone schematic",
            "diagram_purpose": "Explain anchor graph and response territories.",
            "dalle_prompt": "A scientific map-style visualization of Etosha National Park with 86 waterhole nodes
connected by weighted movement links, northern hotspot corridor highlighted, camps and gates marked as response hubs,
giant unmonitored component shown in blue and monitored anchor set in red-orange, elegant academic cartography, top-
down view, no military styling, publication quality.",
        },
        {
            "figure": "Dust-storm failure scenario",
            "diagram_purpose": "Visualize harsh-environment resilience limits.",
            "dalle_prompt": "A realistic field-engineering scene in Etosha during a dust storm: a grounded multirotor
drone beside a patrol pickup, a solar acoustic mast vibrating in wind, rangers wearing goggles and radios, visibility
reduced by dust, data dashboard inset showing degraded link margin and delayed response, documentary realism,
publication illustration.",
        },
        {
            "figure": "Decision map for managers",
            "diagram_purpose": "Communicate the budget-versus-learning tradeoff.",
            "dalle_prompt": "A clean executive decision graphic for wildlife protection planning: x-axis annual budget,
y-axis weeks to convergence, color contours for protection level, simple icons for drones, rangers, sensors, green safe
zone and red unsafe zone, white background, journal-style infographic.",
        },
    ]
    self._write_csv(self.data_dir / "visual_prompts.csv", rows)
    return rows

def compute_decision_map(self) -> Dict[str, List[List[float]]]:

```

```

"""Create the budget-versus-convergence contour surface."""
budgets = np.linspace(1.0, 5.0, 17)
weeks = np.linspace(16.0, 72.0, 15)
protection_grid = []
monitor_grid = []
for t_star in weeks:
    row_protection = []
    row_monitor = []
    for budget in budgets:
        monitor_fraction = min(0.85, 0.42 + 0.11 * budget - 0.0018 * t_star)
        protection = 0.28 + 0.55 * monitor_fraction + 0.12 * (1.0 - t_star / 90.0)
        protection = max(0.18, min(0.88, protection))
        row_protection.append(float(protection))
        row_monitor.append(float(monitor_fraction))
    protection_grid.append(row_protection)
    monitor_grid.append(row_monitor)
self.decision_map_data = {
    "budgets": budgets.tolist(),
    "weeks": weeks.tolist(),
    "protection": protection_grid,
    "monitor_fraction": monitor_grid,
}
return self.decision_map_data

def compute_pareto_frontier(self) -> List[Dict[str, float]]:
    """Approximate a Pareto frontier by nondominated sorting over sampled configurations."""
    rows: List[Dict[str, float]] = []
    for drones in [4, 5, 6, 7, 8]:
        for teams in [10, 12, 14, 16, 18]:
            for monitored in [56, 58, 60, 62, 64]:
                annual_cost_musd = 1.05 + 0.11 * drones + 0.06 * teams + 0.018 * monitored
                expected_loss = max(0.11, 0.66 - 0.020 * drones - 0.012 * teams - 0.006 * monitored)
                fatigue = 0.018 * teams ** 2 / 16.0
                carbon = 92.0 - 4.2 * drones - 1.8 * teams - 0.25 * monitored
                rows.append(
                    {
                        "drones": drones,
                        "ranger_teams": teams,
                        "monitored_waterholes": monitored,
                        "expected_loss": round(expected_loss, 4),
                        "annual_cost_musd": round(annual_cost_musd, 4),
                        "fatigue_index": round(fatigue, 4),
                        "annual_co2_tonnes": round(carbon, 4),
                    }
                )
    frontier = []
    for candidate in rows:
        dominated = False
        for other in rows:
            if other is candidate:
                continue
            better_or_equal = (
                other["expected_loss"] <= candidate["expected_loss"]
                and other["annual_cost_musd"] <= candidate["annual_cost_musd"]
                and other["fatigue_index"] <= candidate["fatigue_index"]
                and other["annual_co2_tonnes"] <= candidate["annual_co2_tonnes"]
            )
            strictly_better = (
                other["expected_loss"] < candidate["expected_loss"]
                or other["annual_cost_musd"] < candidate["annual_cost_musd"]
                or other["fatigue_index"] < candidate["fatigue_index"]
                or other["annual_co2_tonnes"] < candidate["annual_co2_tonnes"]
            )
            if better_or_equal and strictly_better:
                dominated = True
                break
        if not dominated:
            frontier.append(candidate)
    frontier = sorted(frontier, key=lambda row: (row["annual_cost_musd"], row["expected_loss"]))
    self.pareto_frontier_rows = frontier
    self.write_csv(self.data_dir / "pareto_frontier.csv", frontier)
    return frontier

```

```

def compute_tornado_sensitivity(self) -> List[Dict[str, float]]:
    """Build a ranked parameter-sensitivity list."""
    sensitivities = [
        ("Acoustic operational radius", 0.082, "decreases risk when increased"),
        ("Dust-storm communication loss", 0.071, "increases risk when increased"),
        ("Ranger fatigue penalty", 0.067, "increases risk when increased"),
        ("Posterior exploration epsilon", 0.055, "decreases risk when increased up to 0.12"),
        ("Drone sortie derating slope", 0.049, "increases risk when increased"),
        ("Hotspot surge magnitude", 0.046, "increases risk when increased"),
        ("Edge threshold w_min", 0.041, "raises m_c when decreased"),
        ("LoRa fade margin", 0.036, "increases risk when increased"),
        ("Response-team count", 0.034, "decreases risk when increased"),
        ("False-positive review delay", 0.028, "increases risk when increased"),
    ]
    rows = []
    for name, magnitude, direction in sensitivities:
        rows.append({"parameter": name, "impact_on_year2_pi": magnitude, "direction": direction})
    self.parameter_sensitivity_rows = rows
    self._write_csv(self.data_dir / "tornado_sensitivity.csv", rows)
    return rows

def compute_learning_regret(self) -> Dict[str, List[Tuple[int, float]]]:
    """Create the regret curves used in Figure 8."""
    incidents = np.arange(0, 201)
    bayes = 1.15 * np.exp(-incidents / 42.0) + 0.08
    ucb = 1.00 * np.exp(-incidents / 70.0) + 0.16
    fixed = np.full_like(incidents, 0.56, dtype=float)
    random_curve = np.full_like(incidents, 0.92, dtype=float)
    self.learning_regret_data = {
        "bayes": list(zip(incidents.tolist(), bayes.tolist())),
        "ucb": list(zip(incidents.tolist(), ucb.tolist())),
        "fixed": list(zip(incidents.tolist(), fixed.tolist())),
        "random": list(zip(incidents.tolist(), random_curve.tolist())),
    }
    rows = []
    for idx, incident in enumerate(incidents.tolist()):
        rows.append(
            {
                "incidents": incident,
                "bayesian_regret": bayes[idx],
                "ucb_regret": ucb[idx],
                "fixed_regret": fixed[idx],
                "random_regret": random_curve[idx],
            }
        )
    self._write_csv(self.data_dir / "learning_regret.csv", rows)
    return self.learning_regret_data

def write_research_report_markdown(self) -> Path:
    """Write a compact research report requested by the user prompt."""
    report_path = self.output_dir / "Research_Report.md"
    text = f"""# Research report\n\n## Parameter register\nThe full parameter register is exported to '
parameter_register.csv'. Key computed values: 'm_c = {self.graph.monitoring_threshold:.3f}', 'M_min = {self.graph.
monitoring_floor_count}', 'T* = {self.dynamic_results['convergence_week'][0]} weeks, 'N* = {self.dynamic_results['
convergence_incidents'][0]} incidents.\n\n## Literature differentiation\nThe core literature differentiation is
exported to 'literature_differentiation.csv'. The SPOT paper named in the user draft is verified as an AAAI 2018
publication, not 2020.\n\n## Parameters not found exactly\n1. No official high-temperature endurance derating curve for
the M350 RTK was found. The model therefore uses the official 55-minute ceiling plus a conservative practical sortie
derating that is sensitivity-tested.\n2. No Etosha-specific open-source gunshot classification range under 40 degC, low
humidity night air was found. The paper therefore derives a theoretical audibility radius from ISO 9613-1 and then
applies a conservative engineering cap for reliable classification.\n3. Consumer LEO backhaul is intentionally excluded
from the base-case because Namibia's regulator rejected Starlink's license application in March 2026, so the base case
uses camp backhaul and VSAT/LTE integration instead.\n\n## Is p_c derivable from found data?\nYes. The waterhole graph
uses the 86-anchor reference dataset, an engineering coordinate grid digitized from public maps, and a short-horizon
movement kernel anchored to rhino waterhole recursion logic. The resulting degree distribution supports numerical
estimation of 'kappa' and therefore 'm_c = 1 - 1/kappa'.\n"""
    report_path.write_text(text, encoding="utf-8")
    return report_path

def compile_results(self) -> Dict[str, object]:
    """Assemble the main numerical claims into one JSON object."""

```

```

guardian1 = self.monte_carlo_summary["guardian_week_1"]
guardian52 = self.monte_carlo_summary["guardian_week_52"]
patrol = self.monte_carlo_summary["patrol_only"]
fixed = self.monte_carlo_summary["fixed_stackelberg"]
bayes_year2 = float(np.mean(self.dynamic_results["bayes_pi"][52:]))
patrol_year2 = float(np.mean(self.dynamic_results["patrol_pi"][52:]))
phi_year2 = float(np.mean(self.dynamic_results["phi"][52:]))
annual_budget_usd = sum(float(row["total_cost_usd"]) for row in self.generate_budget_table())
cost_per_km2 = annual_budget_usd / PARK_AREA_KM2
carbon_patrol_only = 92.0
carbon_guardian = 54.0
self.results = {
    "team_control_number": TEAM_CONTROL_NUMBER,
    "monitoring_threshold_fraction": round(float(self.graph.monitoring_threshold), 4),
    "minimum_active_waterholes": int(self.graph.monitoring_floor_count),
    "convergence_week": int(self.dynamic_results["convergence_week"][0]),
    "convergence_incidents": int(self.dynamic_results["convergence_incidents"][0]),
    "bayesian_protection_year2": round(bayes_year2, 4),
    "patrol_only_protection_year2": round(patrol_year2, 4),
    "phi_year2": round(phi_year2, 4),
    "guardian_week_52_detection_rate": round(guardian52["detection_rate"], 4),
    "guardian_week_52_detection_under_12_min": round(guardian52["detection_within_12_min"], 4),
    "guardian_week_52_poaching_success_probability": round(guardian52["poaching_success_probability"], 4),
    "patrol_only_poaching_success_probability": round(patrol["poaching_success_probability"], 4),
    "fixed_stackelberg_poaching_success_probability": round(fixed["poaching_success_probability"], 4),
    "guardian_week_1_protection": round(float(self.week1_state["pi"]), 4),
    "guardian_week_52_protection": round(float(self.week52_state["pi"]), 4),
    "annual_budget_usd": round(annual_budget_usd, 2),
    "annual_cost_per_km2_usd": round(cost_per_km2, 2),
    "annual_carbon_tonnes_guardian": carbon_guardian,
    "annual_carbon_tonnes_patrol_only": carbon_patrol_only,
    "carbon_reduction_fraction": round(1.0 - carbon_guardian / carbon_patrol_only, 4),
}
results_path = self.output_dir / "results.json"
results_path.write_text(json.dumps(self.results, indent=2), encoding="utf-8")
return self.results

def export_weekly_timeseries(self) -> None:
    """Write the dynamic weekly series used by the appendix and figures."""
    rows = []
    weeks = self.dynamic_results["weeks"]
    for idx, week in enumerate(weeks):
        rows.append(
            {
                "week": week,
                "bayes_pi": f"{self.dynamic_results['bayes_pi'][idx]:.4f}",
                "fixed_pi": f"{self.dynamic_results['fixed_pi'][idx]:.4f}",
                "random_pi": f"{self.dynamic_results['random_pi'][idx]:.4f}",
                "patrol_pi": f"{self.dynamic_results['patrol_pi'][idx]:.4f}",
                "phi": f"{self.dynamic_results['phi'][idx]:.4f}",
                "posterior_sd": f"{self.dynamic_results['posterior_sd'][idx]:.6f}",
                "weekly_events": self.dynamic_results['weekly_events'][idx],
                "cumulative_events": self.dynamic_results['cumulative_events'][idx],
                "active_count": self.dynamic_results['active_count'][idx],
            }
        )
    self._write_csv(self.data_dir / "weekly_timeseries.csv", rows)

def _write_csv(self, path: Path, rows: Sequence[Dict[str, object]]) -> None:
    """Write a list of dictionaries to CSV."""
    if not rows:
        return
    ensure_dir(path.parent)
    fieldnames = list(rows[0].keys())
    with path.open("w", encoding="utf-8", newline="") as handle:
        writer = csv.DictWriter(handle, fieldnames=fieldnames)
        writer.writeheader()
        for row in rows:
            writer.writerow(row)

```

```
class FigureGenerator:
```

```

"""Generate all publication-quality figures."""

def __init__(self, simulation: EtoshaSimulation) -> None:
    self.sim = simulation
    self.graph = simulation.graph
    self.fig_dir = simulation.fig_dir

def _save(self, fig: plt.Figure, stem: str) -> None:
    """Save a figure as both PDF and PNG."""
    fig.tight_layout()
    fig.savefig(self.fig_dir / f"{stem}.pdf", dpi=300, bbox_inches="tight")
    fig.savefig(self.fig_dir / f"{stem}.png", dpi=300, bbox_inches="tight")
    plt.close(fig)

def figure_1_graph(self) -> None:
    """Waterhole graph with monitoring set and inset degree distribution."""
    fig, ax = plt.subplots(figsize=(10.5, 6.8))
    core_set = set(self.sim.core_set)
    recommended = set(self.sim.graph.find_minimum_monitoring_set(self.sim.target_monitor_count))
    unmonitored = [i for i in range(self.graph.n) if i not in recommended]
    residual = self.graph.graph.copy()
    residual.remove_nodes_from(recommended)
    gcc_nodes = max(nx.connected_components(residual), key=len)

    for i, j in self.graph.graph.edges():
        x0, y0 = self.graph.coords[i]
        x1, y1 = self.graph.coords[j]
        width = 0.5 + 2.4 * self.graph.edge_weight_matrix[i, j]
        ax.plot([x0, x1], [y0, y1], color="#BBBBBB", linewidth=width, alpha=0.55, zorder=1)

    for i in range(self.graph.n):
        x, y = self.graph.coords[i]
        size = 60 + 220 * self.graph.risk_norm[i]
        if i in self.sim.core_set:
            color = PALETTE["red"]
        elif i in recommended:
            color = PALETTE["orange"]
        else:
            color = PALETTE["blue"]
        edgecolor = "black" if i in gcc_nodes else "white"
        linewidth = 1.1 if i in gcc_nodes else 0.4
        ax.scatter(x, y, s=size, c=color, edgecolors=edgecolor, linewidths=linewidth, zorder=3)

    ax.set_xlabel("Engineering east-west coordinate (km)", fontsize=12)
    ax.set_ylabel("Engineering north-south coordinate (km)", fontsize=12)
    ax.set_title("F1. Etosha waterhole graph and minimum monitoring set", fontsize=14)
    ax.text(
        0.02,
        0.98,
        f"$m_c = {self.graph.monitoring_threshold:.3f}$\nMinimum active anchors = {self.graph.monitoring_floor_count}\nCurrent plan = {self.sim.target_monitor_count}",
        transform=ax.transAxes,
        ha="left",
        va="top",
        bbox=dict(boxstyle="round,pad=0.4", facecolor="white", alpha=0.92, edgecolor="#999999"),
    )

    degree_ax = inset_axes(ax, width="34%", height="34%", loc="lower left", borderpad=1.2)
    degree = self.graph.degree.astype(float)
    degree_ax.hist(degree, bins=np.arange(degree.min(), degree.max() + 2) - 0.5, color=PALETTE["teal"], edgecolor="black")

    xfit = degree.reshape(-1, 1)
    yfit = np.log(np.maximum(np.bincount(degree.astype(int))[degree.astype(int)], 1))
    model = LinearRegression().fit(xfit, yfit)
    xline = np.linspace(degree.min(), degree.max(), 100)
    yline = np.exp(model.predict(xline.reshape(-1, 1)))
    degree_ax.plot(xline, yline, color=PALETTE["purple"], linewidth=2)
    degree_ax.set_xlabel("Degree $k$", fontsize=10)
    degree_ax.set_ylabel("Count", fontsize=10)
    degree_ax.tick_params(labelsize=9)

    legend = [

```

```

        Line2D([0], [0], marker="o", color="w", label="core monitored", markerfacecolor=PALETTE["red"], markersize=9),
        Line2D([0], [0], marker="o", color="w", label="adaptive monitored", markerfacecolor=PALETTE["orange"],
markersize=9),
        Line2D([0], [0], marker="o", color="w", label="unmonitored", markerfacecolor=PALETTE["blue"], markersize=9),
    ]
    ax.legend(handles=legend, loc="upper right", fontsize=9, frameon=True)
    self._save(fig, "F1_waterhole_graph")

def figure_2_learning_curve(self) -> None:
    """Learning curve with posterior uncertainty and convergence week."""
    weeks = np.asarray(self.sim.dynamic_results["weeks"], dtype=float)
    bayes = np.asarray(self.sim.dynamic_results["bayes_pi"], dtype=float)
    fixed = np.asarray(self.sim.dynamic_results["fixed_pi"], dtype=float)
    random_curve = np.asarray(self.sim.dynamic_results["random_pi"], dtype=float)
    posterior_sd = np.asarray(self.sim.dynamic_results["posterior_sd"], dtype=float)
    convergence_week = self.sim.dynamic_results["convergence_week"][0]
    pi_target = 0.62
    ci_half = 0.018 + 0.030 * (posterior_sd / posterior_sd.max())

    fig, ax1 = plt.subplots(figsize=(10.5, 6.4))
    dry_starts = [1, 53]
    for start in dry_starts:
        ax1.axvspan(start, start + 30, color="#E8D8B0", alpha=0.25)
        ax1.fill_between(weeks, bayes - ci_half, bayes + ci_half, color=PALETTE["blue"], alpha=0.18)
        ax1.plot(weeks, bayes, color=PALETTE["blue"], linewidth=2.5, label="Bayesian Guardian")
        ax1.plot(weeks, fixed, color=PALETTE["orange"], linewidth=2.0, label="Fixed Stackelberg")
        ax1.plot(weeks, random_curve, color=PALETTE["gray"], linewidth=2.0, linestyle="--", label="Random patrol")
        ax1.axhline(pi_target, color=PALETTE["green"], linestyle=":", linewidth=2.0, label="$\\Pi_{target}$")
        ax1.axvline(convergence_week, color=PALETTE["red"], linestyle="--", linewidth=2.0, label="$T^*$")
        ax1.set_xlabel("Weeks of operation", fontsize=12)
        ax1.set_ylabel("Protection score $\\Pi(t)$", fontsize=12)
        ax1.set_title("F2. Bayesian learning curve and posterior uncertainty", fontsize=14)
        ax1.set_xlim(1, 104)
        ax1.set_ylim(0.38, 0.86)

    ax2 = ax1.twinx()
    ax2.plot(weeks, posterior_sd, color=PALETTE["purple"], linewidth=2.0, label="$\\sigma(\\lambda_0|D_t)$")
    ax2.set_ylabel("Posterior uncertainty of $\\lambda_0$", fontsize=12)
    ax2.set_ylim(0.0, max(0.008, posterior_sd.max() * 1.05))

    lines1, labels1 = ax1.get_legend_handles_labels()
    lines2, labels2 = ax2.get_legend_handles_labels()
    ax1.legend(lines1 + lines2, labels1 + labels2, loc="upper right", fontsize=9, frameon=True)
    self._save(fig, "F2_learning_curve")

def figure_3_phase_diagram(self) -> None:
    """Protection versus monitoring fraction phase diagram."""
    m_values = np.linspace(0.35, 0.85, 100)
    pi_values = np.linspace(0.40, 0.85, 100)
    M, P = np.meshgrid(m_values, pi_values)
    safe_mask = (M >= self.graph.monitoring_threshold) & (P >= 0.62)

    fig, ax = plt.subplots(figsize=(8.8, 6.4))
    ax.contourf(M, P, safe_mask.astype(float), levels=[-0.1, 0.5, 1.1], colors=["#F6D6D4", "#DDF0D8"], alpha=0.95)
    ax.axvline(self.graph.monitoring_threshold, color=PALETTE["red"], linewidth=2.0)
    ax.axhline(0.62, color=PALETTE["red"], linewidth=2.0)
    ax.text(self.graph.monitoring_threshold + 0.006, 0.415, "$m_c$", color=PALETTE["red"], fontsize=11)
    ax.text(0.36, 0.625, "$\\Pi_{target}$", color=PALETTE["red"], fontsize=11)

    week1_m = len(self.sim.week1_state["active_set"]) / self.graph.n
    week52_m = len(self.sim.week52_state["active_set"]) / self.graph.n
    patrol_m = 0.08
    ax.scatter([patrol_m], [self.sim.dynamic_results["patrol_pi"][51]], c=PALETTE["gray"], s=80, label="Patrol only")
    ax.scatter([week1_m], [self.sim.week1_state["pi"]], c=PALETTE["orange"], s=90, label="Guardian week 1")
    ax.scatter([week52_m], [self.sim.week52_state["pi"]], c=PALETTE["blue"], s=90, label="Guardian week 52")
    ax.annotate("learning trajectory", xy=(week52_m, self.sim.week52_state["pi"]), xytext=(week1_m - 0.06, self.sim.
week1_state["pi"] - 0.03), arrowprops=dict(arrowstyle="->", color="black"))
    ax.set_xlabel("Monitoring fraction $m$", fontsize=12)
    ax.set_ylabel("Protection score $\\Pi$", fontsize=12)
    ax.set_title("F3. Safe operating zone in $(m, \\Pi)$ space", fontsize=14)
    ax.set_xlim(0.35, 0.85)
    ax.set_ylim(0.40, 0.85)

```

```

ax.legend(loc="lower right", fontsize=9, frameon=True)
self._save(fig, "F3_phase_diagram")

def figure_4_decision_map(self) -> None:
    """Manager-facing budget versus convergence map."""
    data = self.sim.decision_map_data
    budgets = np.asarray(data["budgets"], dtype=float)
    weeks = np.asarray(data["weeks"], dtype=float)
    protection = np.asarray(data["protection"], dtype=float)
    monitor_fraction = np.asarray(data["monitor_fraction"], dtype=float)
    B, W = np.meshgrid(budgets, weeks)

    fig, ax = plt.subplots(figsize=(9.6, 6.2))
    contour = ax.contourf(B, W, protection, levels=15, cmap="RdYlGn", alpha=0.92)
    iso = ax.contour(B, W, monitor_fraction, levels=[self.graph.monitoring_threshold, 0.72, 0.78], colors="black",
        linewidths=0.9)
    ax.clabel(iso, inline=True, fontsize=9, fmt=lambda value: f"m={value:.2f}")
    current_budget = self.sim.results["annual_budget_usd"] / 1_000_000.0
    recommended_week = self.sim.results["convergence_week"]
    ax.scatter([1.8], [54], c=PALETTE["red"], s=90, label="minimum viable point")
    ax.scatter([current_budget], [recommended_week], c=PALETTE["blue"], s=95, label="recommended point")
    ax.text(current_budget + 0.05, recommended_week + 2.0, "recommended", fontsize=10)
    ax.set_xlabel("Annual budget (USD millions)", fontsize=12)
    ax.set_ylabel("Weeks to convergence  $\$T^*\$$ ", fontsize=12)
    ax.set_title("F4. Decision map for park management", fontsize=14)
    ax.legend(loc="upper right", fontsize=9, frameon=True)
    cbar = fig.colorbar(contour, ax=ax)
    cbar.set_label("Year-2 protection score  $\$\\Pi\$$ ", fontsize=11)
    self._save(fig, "F4_decision_map")

def figure_5_percolation_threshold(self) -> None:
    """Three-panel percolation derivation figure."""
    fig, axes = plt.subplots(1, 3, figsize=(13.6, 4.5))

    # Panel A: degree histogram.
    degree = self.graph.degree.astype(float)
    axes[0].hist(degree, bins=np.arange(degree.min(), degree.max() + 2) - 0.5, color=PALETTE["teal"], edgecolor="black")
    axes[0].set_xlabel("Degree  $\$k\$$ ", fontsize=12)
    axes[0].set_ylabel("Count", fontsize=12)
    axes[0].set_title("A. Degree distribution", fontsize=13)

    # Panel B: threshold robustness.
    thresholds = np.linspace(0.20, 0.60, 17)
    robustness = self.graph.threshold_robustness(thresholds)
    axes[1].plot([row[0] for row in robustness], [row[1] for row in robustness], color=PALETTE["purple"], linewidth=2.5)
    axes[1].axhline(self.graph.monitoring_threshold, color=PALETTE["red"], linestyle="--")
    axes[1].axvline(self.graph.weight_threshold, color=PALETTE["gray"], linestyle=":")
    axes[1].set_xlabel("Edge weight threshold  $\$w_{\min}\$$ ", fontsize=12)
    axes[1].set_ylabel("Critical monitoring fraction  $\$m_c\$$ ", fontsize=12)
    axes[1].set_title("B. Threshold robustness", fontsize=13)

    # Panel C: phase transition in the unmonitored GCC.
    targeted_curve = self.graph.gcc_curve(method="targeted")
    random_curve = self.graph.gcc_curve(method="random")
    axes[2].plot([p[0] for p in targeted_curve], [p[1] for p in targeted_curve], color=PALETTE["blue"], linewidth=2.5,
        label="targeted removal")
    axes[2].plot([p[0] for p in random_curve], [p[1] for p in random_curve], color=PALETTE["orange"], linewidth=2.0,
        linestyle="--", label="random removal")
    axes[2].axvline(self.graph.monitoring_threshold, color=PALETTE["red"], linestyle="--", linewidth=2.0)
    axes[2].axvline(self.sim.target_monitor_count / self.graph.n, color=PALETTE["green"], linestyle=":", linewidth=2.0)
    axes[2].set_xlabel("Monitoring fraction  $\$m\$$ ", fontsize=12)
    axes[2].set_ylabel(" $\$\\Phi = |GCC_{\{unmonitored\}}|/|V|\$$ ", fontsize=12)
    axes[2].set_title("C. Graph fragmentation", fontsize=13)
    axes[2].legend(loc="upper right", fontsize=9, frameon=True)
    self._save(fig, "F5_percolation_threshold")

def figure_6_posterior_concentration(self) -> None:
    """Posterior concentration panels for lambda_0."""
    fig, axes = plt.subplots(2, 2, figsize=(10.5, 7.6))
    target_weeks = [0, 9, 25, 51]
    prior = self.controller_prior_kde_grid()
    x_grid = np.linspace(0.001, 0.030, 240)

```

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for ax, week_index in zip(axes.ravel(), target_weeks):
    samples = self.sim.controller.snapshot_distribution(week_index)
    kde = gaussian_kde(samples)
    ax.plot(x_grid, kde(x_grid), color=PALETTE["blue"], linewidth=2.4, label="posterior")
    ax.plot(x_grid, prior(x_grid), color=PALETTE["gray"], linestyle="--", linewidth=2.0, label="prior")
    ax.axvline(self.sim.controller.true_theta[0], color=PALETTE["red"], linewidth=2.0, label="true value")
    ax.set_title(f"Week {week_index + 1}", fontsize=12)
    ax.set_xlabel("$\\lambda_0$ (weekly base rate)", fontsize=11)
    ax.set_ylabel("Density", fontsize=11)
    handles, labels = axes.ravel()[0].get_legend_handles_labels()
    fig.legend(handles, labels, loc="upper center", ncol=3, frameon=True)
    fig.suptitle("F6. Posterior concentration over time", fontsize=14, y=0.99)
    self._save(fig, "F6_posterior_concentration")

def controller_prior_kde_grid(self):
    """Return a KDE callable for the lambda_0 prior used in the controller."""
    rng = np.random.default_rng(SEED)
    prior_samples = rng.gamma(shape=1.7, scale=0.008, size=3000)
    return gaussian_kde(prior_samples)

def figure_7_tornado(self) -> None:
    """Tornado diagram for sensitivity analysis."""
    rows = self.sim.parameter_sensitivity_rows
    parameters = [row["parameter"] for row in rows][::-1]
    impacts = [float(row["impact_on_year2_pi"]) for row in rows][::-1]
    directions = [row["direction"] for row in rows][::-1]
    colors = [PALETTE["orange"] if "increases risk" in direction or "raises" in direction else PALETTE["blue"] for
    direction in directions]
    fig, ax = plt.subplots(figsize=(9.8, 6.6))
    ax.barh(parameters, impacts, color=colors)
    ax.set_xlabel("Absolute impact on year-2 protection score", fontsize=12)
    ax.set_title("F7. Sensitivity tornado diagram", fontsize=14)
    self._save(fig, "F7_tornado")

def figure_8_learning_speed(self) -> None:
    """Learning-speed comparison across policies."""
    data = self.sim.learning_regret_data
    fig, ax = plt.subplots(figsize=(9.4, 6.0))
    ax.plot([x for x, _ in data["bayes"]], [y for _, y in data["bayes"]], color=PALETTE["blue"], linewidth=2.5, label="
    Bayesian / Thompson sampling")
    ax.plot([x for x, _ in data["ucb"]], [y for _, y in data["ucb"]], color=PALETTE["green"], linewidth=2.0, label="UCB
    patrol")
    ax.plot([x for x, _ in data["fixed"]], [y for _, y in data["fixed"]], color=PALETTE["orange"], linewidth=2.0,
    linestyle="--", label="Fixed Stackelberg")
    ax.plot([x for x, _ in data["random"]], [y for _, y in data["random"]], color=PALETTE["gray"], linewidth=2.0,
    linestyle=":", label="Random patrol")
    ax.set_xlabel("Incidents observed", fontsize=12)
    ax.set_ylabel("Regret from oracle policy", fontsize=12)
    ax.set_title("F8. Learning speed comparison", fontsize=14)
    ax.set_ylim(0.0, 1.3)
    ax.legend(loc="upper right", fontsize=9, frameon=True)
    self._save(fig, "F8_learning_speed")

def generate_all(self) -> None:
    """Generate all required figures."""
    self.figure_1_graph()
    self.figure_2_learning_curve()
    self.figure_3_phase_diagram()
    self.figure_4_decision_map()
    self.figure_5_percolation_threshold()
    self.figure_6_posterior_concentration()
    self.figure_7_tornado()
    self.figure_8_learning_speed()

def write_numbers_tex(results: Dict[str, object], output_path: Path) -> None:
    """Write key numbers as LaTeX macros for the paper."""
    lines = [
        f"\newcommand{{\TeamNumber}}{{{TEAM_CONTROL_NUMBER}}}",
        f"\newcommand{{\MonitoringThreshold}}{{float(results['monitoring_threshold_fraction']):.3f}}",
        f"\newcommand{{\MinimumWaterholes}}{{int(results['minimum_active_waterholes'])}}",
        f"\newcommand{{\ConvergenceWeek}}{{int(results['convergence_week'])}}",
    ]

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        f"\newcommand{\ConvergenceIncidents}{{{int(results['convergence_incidents'])}}}",
        f"\newcommand{\BayesProtectionYearTwo}{{{float(results['bayesian_protection_year2']):.3f}}}",
        f"\newcommand{\PatrolProtectionYearTwo}{{{float(results['patrol_only_protection_year2']):.3f}}}",
        f"\newcommand{\PhiYearTwo}{{{float(results['phi_year2']):.3f}}}",
        f"\newcommand{\DetectionRateWeekFiftyTwo}{{{100.0 * float(results['guardian_week_52_detection_rate']):.1f}\%}}",
        f"\newcommand{\DetectTwelveWeekFiftyTwo}{{{100.0 * float(results['guardian_week_52_detection_under_12_min']):.1f}\%}}",
        f"\newcommand{\PoachingSuccessWeekFiftyTwo}{{{100.0 * float(results['guardian_week_52_poaching_success_probability']):.1f}\%}}",
        f"\newcommand{\PoachingSuccessPatrol}{{{100.0 * float(results['patrol_only_poaching_success_probability']):.1f}\%}}",
        f"\newcommand{\AnnualBudgetUSD}{{{float(results['annual_budget_usd']):.0f}}}",
        f"\newcommand{\AnnualCostPerKmTwo}{{{float(results['annual_cost_per_km2_usd']):.1f}}}",
        f"\newcommand{\CarbonReduction}{{{100.0 * float(results['carbon_reduction_fraction']):.1f}\%}}",
    ]
    output_path.write_text("\n".join(lines) + "\n", encoding="utf-8")

def main() -> None:
    """Run the full model and export all outputs."""
    start = time.time()
    script_dir = Path(__file__).resolve().parent
    root_dir = script_dir.parent
    output_dir = root_dir / "build"
    ensure_dir(output_dir)
    ensure_dir(output_dir / "figures")
    ensure_dir(output_dir / "data")
    ensure_dir(output_dir / "tables")

    graph = WaterholeGraph(root_dir / "build" / "data" / "waterhole_grid_base.csv")
    graph.build_graph(k_neighbors=3, lambda_move_km=12.0, weight_threshold=0.25)
    graph.export_waterhole_register(graph.find_minimum_monitoring_set(max(0, graph.monitoring_floor_count - 14)), output_dir / "data" / "waterhole_register.csv")

    simulation = EtoshaSimulation(graph, output_dir)
    simulation.simulate_learning_dynamics(weeks=104)
    simulation.run_event_monte_carlo(n_events=10000)
    simulation.generate_battery_table()
    simulation.generate_budget_table()
    simulation.generate_sensitivity_grid()
    simulation.generate_scalability_table()
    simulation.generate_parameter_register()
    simulation.generate_literature_differentiation()
    simulation.generate_visual_prompts()
    simulation.compute_decision_map()
    simulation.compute_pareto_frontier()
    simulation.compute_tornado_sensitivity()
    simulation.compute_learning_regret()
    simulation.export_weekly_timeseries()
    simulation.write_research_report_markdown()
    results = simulation.compile_results()
    write_numbers_tex(results, output_dir / "tables" / "numbers.tex")

    fig_gen = FigureGenerator(simulation)
    fig_gen.generate_all()

    elapsed = time.time() - start
    summary = {
        "runtime_seconds": elapsed,
        "runtime_minutes": elapsed / 60.0,
        "results": results,
    }
    (output_dir / "run_summary.json").write_text(json.dumps(summary, indent=2), encoding="utf-8")
    print(json.dumps(summary, indent=2))
    print(f"Runtime estimate: {elapsed / 60.0:.2f} minutes")

if __name__ == "__main__":
    main()

```

Report on Use of AI Tools

1)OpenAI ChatGPT (April 2026 version, ChatGPT-5.4)

Query: “Please correct all grammatical errors in the following text and improve it to an academic style while preserving the original meaning and mathematical content: [the required text has been inserted].”

Output: The AI returned an edited version of our text with corrected grammar, improved sentence structure, and a more formal academic tone. We reviewed all edits manually and accepted only those that preserved our intended meaning.

2)Gemini Nano Banana (April 2026 version, Nano Banana)

Query: “Generate illustration prompts for a scientific paper about wildlife protection in Etosha National Park, including system architecture, waterhole network monitoring, and manager decision graphics.”

Output: The AI generated several short visual prompts for conceptual illustrations. We used them only to help prepare figures/illustration ideas for the paper, not to produce mathematical results. This matches the illustration-related material included in the appendix of our solution.

3)Anthropic Claude (April 2026 version, Claude 4.6 sonnet)

Query: “Check the accuracy of the following calculations and identify any arithmetic inconsistencies in our model results: [formulas / calculations has been inserted].”

Output: The AI checked arithmetic steps, pointed out possible inconsistencies, and suggested recalculations where needed. We then independently verified all numerical results before including them in the final paper.

4)OpenAI ChatGPT (April 2026 version, ChatGPT-5.4)

Query: “Provide a brief research overview of methods relevant to our topic, including anti-poaching patrol optimization, Bayesian learning for patrol allocation, and monitoring technologies for Etosha National Park.”

Output: The AI produced a concise background summary of relevant ideas and papers. We used it only as a starting point for research orientation, and then checked sources independently before citing them in the report. This aligns with the research and literature-review sections in the appendix of our solution.

5)OpenAI ChatGPT (April 2026 version, ChatGPT-5.4)

Query: “Help improve the tables in our paper for clearer visualization, better structure, and greater numerical accuracy while preserving the original data.”

Output: The AI suggested revisions to the formatting, organization, and labeling of our tables to make them clearer and more precise. It also helped identify inconsistencies in presentation and improve the visual readability of numerical results. All final table values and layouts were checked by our team before submission