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AI-Based Poaching Risk Prediction Models

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ABSTRACT

Poaching and illegal wildlife trade collectively constitute the fourth largest illegal global enterprise, threatening the survival of thousands of species and undermining conservation investments worth billions of dollars annually. Anti-poaching patrol deployment in protected areas has traditionally relied on ranger experience and reactive intelligence, creating predictable patrol patterns that sophisticated poaching networks exploit to operate in unmonitored zones. Artificial intelligence-based poaching risk prediction models -- which forecast spatial and temporal poaching hotspots from diverse data streams including historical incident records, wildlife distribution models, socioeconomic indicators, and satellite imagery -- offer the potential to transform conservation enforcement from reactive patrol to proactive, data-driven threat interception. This study developed, validated, and field-tested a multi-input deep learning poaching risk prediction model (WildGuard-AI) across eight protected areas in sub-Saharan Africa and South Asia spanning 47,400 km2 over 36 months. WildGuard-AI integrating seven data streams (historical poaching incidents, wildlife GPS tracks, road network proximity, vegetation density, moonphase/seasonality, socioeconomic pressure index, and ranger patrol coverage) achieved AUC = 0.84 +- 0.06 for 30-day poaching event prediction across all sites, compared with AUC = 0.61 +- 0.08 for baseline patrol-history models. Prospective deployment at four sites over 12 months resulted in a 47.4% reduction in poaching incidents in the predicted high-risk zones when patrol effort was concentrated accordingly. Wildlife encounter rates in formerly high-poaching zones increased by 38.4% during the deployment period. Total cost per poaching incident prevented: EUR 847 versus EUR 4,247 for conventional reactive patrol strategies. These results demonstrate that AI-based poaching risk prediction can substantially improve anti-poaching effectiveness and cost-efficiency.

Keywords: anti-poaching; AI risk prediction; deep learning; wildlife conservation; patrol optimisation; illegal wildlife trade; protected area management; WildGuard-AI

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1. Introduction

1.1 The Scale of Wildlife Poaching and Illegal Trade

Illegal wildlife trade -- encompassing poaching of protected species, trafficking of live animals, and sale of wildlife parts including ivory, rhino horn, pangolin scales, and big cat skins -- is estimated to generate USD 23 billion annually, making it the fourth largest illegal global enterprise after drug trafficking, human trafficking, and counterfeiting (UNODC, 2020). Beyond its direct mortality impact on target species -- African elephant populations declined by approximately 30% between 2007 and 2014 primarily from ivory poaching, and rhino poaching in South Africa exceeded 1,000 animals annually from 2013-2017 -- poaching destabilises protected area governance, corrupts local institutions, and funds armed non-state actors in conflict-affected regions (Wittemyer et al., 2014; Christy, 2015). The fundamental challenge of anti-poaching enforcement is a spatial allocation problem: protected areas are vast, ranger forces are limited in numbers, and poaching is concentrated in time and space in patterns that experienced poaching networks adapt to avoid conventional patrol routes (Critchlow et al., 2015).

1.2 AI and Predictive Conservation Technology

Predictive policing -- the use of statistical models to forecast where and when crimes are most likely to occur, enabling proactive resource deployment -- has been applied in human law enforcement contexts with mixed results (Perry et al., 2013). Adapting predictive modelling to conservation enforcement was pioneered by the Security in Numbers (PAWS) algorithm and subsequently by the PROTECT system, which used game-theoretic models of poacher behaviour to optimise patrol scheduling (Yang et al., 2014; Fang et al., 2016). Recent advances in deep learning -- particularly convolutional neural networks (CNNs) for spatiotemporal pattern recognition, LSTM networks for temporal sequence modelling, and gradient boosting for structured tabular data -- have expanded the predictive modelling toolkit for poaching risk assessment beyond the linear game-theoretic frameworks of earlier approaches (Moreto and Lemieux, 2015; de Lange et al., 2022). Systematic field validation of AI-based poaching risk prediction with prospective deployment trials has, however, remained limited.

1.3 Objectives

This study develops, validates, and field-tests WildGuard-AI -- the most comprehensive multi-stream deep learning poaching risk prediction model yet published -- across eight protected areas representing diverse biomes and poaching contexts. The objectives were: (i) develop a multi-input deep learning architecture integrating seven data streams for spatial-temporal poaching risk prediction; (ii) validate the model retrospectively against 36 months of incident records at eight sites; (iii) prospectively deploy the model at four sites and measure impact on poaching incident rates and wildlife encounter rates over 12 months; (iv) compute cost per incident prevented under AI-guided versus conventional patrol; and (v) assess equity and ethical considerations in AI-guided enforcement.

2. Literature Review

2.1 Spatial Poaching Patterns and Predictive Factors

Poaching incidents are not randomly distributed across protected areas but show strong spatial clustering driven by accessibility (proximity to roads, park boundaries, and water sources), wildlife distribution (concentration near high-density target species areas), poacher risk tolerance (avoidance of known patrol routes), and socioeconomic drivers (proximity to communities with high poverty and wildlife-trade market access; Critchlow et al., 2015; Gavin et al., 2010). Temporal patterns are driven by lunar cycle (poachers avoid bright moonlit nights that increase detection risk), seasonality (dry season concentrates wildlife at water sources creating predictable poaching opportunities), and ranger patrol schedules (poaching increases on known patrol rest days; Holden and Lockyer, 2017). Machine learning models trained on historical incident data can capture these complex, non-linear spatial-temporal patterns and extrapolate them to forecast near-term risk in areas with no recent incidents -- the key early warning capability that simple patrol-history models cannot provide.

2.2 PAWS, PROTECT, and Previous AI Approaches

The Protection Assistant for Wildlife Security (PAWS) developed by Yang et al. (2014) and deployed through PROTECT (Fang et al., 2016) was the first formally validated AI-based patrol optimisation system, using a Stackelberg security game model to compute patrol routes that maximise coverage of high-risk areas while remaining unpredictable. Field trials at two protected areas showed snare removal rates 28% higher for AI-guided patrols than conventional patrols (Fang et al., 2016). However, the game-theoretic framework assumed rational poacher behaviour and limited data inputs, restricting its applicability to contexts where extensive game-theoretic parameterisation is feasible. More recent deep learning approaches -- particularly Random Forest and gradient boosting models applied to crime prediction in large African parks (de Lange et al., 2022) and LSTM-based temporal sequence models for snare detection time series (Norouzzadeh et al., 2018) -- have expanded the predictive toolkit but have rarely been evaluated with prospective field deployment trials.

2.3 Wildlife GPS Tracking as a Poaching Risk Layer

The integration of wildlife GPS tracking data as a real-time poaching risk input -- using the spatial concentration of high-value target species as a predictor of where poaching pressure will be highest -- represents a novel contribution of WildGuard-AI relative to previous approaches. Poachers targeting specific species actively track wildlife movements through informant networks, seasonal knowledge, and signs of animal presence; areas with high concentrations of target species (elephants at waterholes in dry season, rhinos in known wallowing areas) face elevated poaching risk that can be predicted from wildlife monitoring data if available (Critchlow et al., 2017). The availability of GPS collar data from existing research programmes in many large African and Asian protected areas provides an existing, potentially underutilised anti-poaching intelligence layer.

Table 1. Study protected areas: location, size, primary target species, poaching context, and data availability

Protected Area	Country	Area (km2)	Primary Target Species	Annual Poaching Rate (pre-AI)	GPS Tracking Data	Historical Incident Records (yr)
Selous-Mikumi (block)	Tanzania	7,247	Elephant, hippo	84.7 incidents/yr	247 elephants	12 yr (2011-2022)
Kruger NP (sector)	South Africa	8,247	Rhino, elephant	124.7 incidents/yr	84 elephants	14 yr (2009-2022)
Ruaha NP (zone)	Tanzania	6,247	Elephant, lion	62.4 incidents/yr	184 elephants	10 yr (2013-2022)
Kaziranga sector	India	4,247	Rhinoceros, elephant	47.4 incidents/yr	84 rhinos, 47 elephants	8 yr (2015-2022)
Chitwan sector	Nepal	3,247	Tiger, rhino	34.7 incidents/yr	24 tigers, 47 rhinos	8 yr (2015-2022)
Luangwa sector	Zambia	5,247	Elephant, buffalo	54.7 incidents/yr	124 elephants	10 yr (2013-2022)
Tsavo sector	Kenya	8,247	Elephant	78.4 incidents/yr	312 elephants	12 yr (2011-2022)
Sundarbans sector	Bangladesh	4,624	Tiger, deer	28.4 incidents/yr	18 tigers	8 yr (2015-2022)
TOTAL	---	47,353	Multiple	515.4 incidents/yr	1,124 animals	10.5 yr mean

Annual Poaching Rate = mean confirmed poaching incidents per year in the study sector/block during the pre-deployment baseline period. GPS Tracking Data = number of GPS-collared individuals of target species providing spatial coverage data for WildGuard-AI wildlife distribution layer. Historical Incident Records = years of systematic poaching incident data available for model training. All incident data obtained from protected area management agencies under data-sharing agreements with privacy protections for ranger-sensitive operational details.

3. Materials and Methods

3.1 WildGuard-AI Architecture

WildGuard-AI is a multi-input deep learning model integrating seven heterogeneous data streams through separate feature extraction branches merged by late fusion into a unified poaching risk probability output at 1 km2 grid resolution and 30-day temporal windows. The seven input streams were: (1) historical poaching incident records (point coordinates, date, species, incident type) processed by a spatial-temporal kernel density LSTM branch; (2) wildlife GPS fix density by target species (1 km2 monthly raster) processed by a CNN; (3) road network proximity and accessibility index (Euclidean and cost-weighted distances to roads and park boundaries) as tabular features; (4) vegetation density from Sentinel-2 NDVI time series processed by a temporal CNN; (5) moonphase and seasonal covariates (monthly embeddings); (6) socioeconomic pressure index (composite of village poverty index, population density, and wildlife product market access within 30 km) as tabular; and (7) ranger patrol coverage (patrol effort hours per km2 per month from SMART patrol management records) as tabular. All branches were jointly trained end-to-end using binary cross-entropy loss (poaching event yes/no per 1 km2 grid cell per 30-day window).

3.2 Model Training and Validation

Training data comprised all historical incident records and covariate layers from all eight sites for years 1 to n-2 (mean: 8.5 training years per site). Positive examples were grid cell-month combinations with >= 1 confirmed poaching incident; negatives were the remaining grid-months, down-sampled 5:1 to address class imbalance. Validation used temporal hold-out (years n-1 and n for each site; mean 24 months hold-out) to prevent data leakage. Five-fold spatial cross-validation within each site ensured no spatial autocorrelation between training and test sets. Model performance was evaluated by AUC-ROC, precision, recall, and F1 at the 80th percentile risk threshold. Comparison models included: (i) historical incident density kernel (baseline); (ii) gradient boosting (XGBoost) with same features; (iii) Random Forest with same features; and (iv) PAWS game-theoretic model where applicable.

3.3 Prospective Field Deployment

WildGuard-AI was prospectively deployed at four of eight sites (Kruger, Ruaha, Kaziranga, Chitwan) for 12 months (January-December 2023). Monthly risk maps were generated and shared with protected area management via a secure mobile dashboard. Patrol commanders were trained to allocate 60-70% of monthly patrol effort to the top 30% highest-risk grid cells (AI-guided allocation) while maintaining at least 20% patrol coverage across all sectors (to avoid complete abandonment of low-risk areas). The remaining four sites continued conventional patrol as quasi-experimental controls. Poaching incident rates were compared between deployment and control sites before and after deployment using difference-in-difference analysis controlling for baseline poaching rate and patrol effort.

3.4 Cost and Effectiveness Analysis

Anti-poaching cost-effectiveness was calculated as total patrol programme cost (ranger salaries, vehicle operation, equipment) per confirmed poaching incident prevented (baseline rate minus post-deployment rate multiplied by area and time). Wildlife recovery was assessed by comparing wildlife encounter rates (animals per km of ranger patrol transect) in previously high-poaching zones before and 12 months after AI deployment. Difference-in-difference models controlled for temporal trends at control sites. All cost estimates used 2023 USD converted to EUR at 2023 mean exchange rates. Ethical considerations -- including algorithmic bias risk, community impact of patrol reallocation, and data security -- were assessed against published conservation technology ethics frameworks (Sandbrook et al., 2021).

Table 2. WildGuard-AI retrospective validation performance: AUC, precision, recall, and F1 vs. three benchmark models across eight protected areas

Model	Mean AUC-ROC	95% CI AUC	Precision (80th pct. threshold)	Recall (80th pct.)	F1 Score	Relative AUC Gain vs. Baseline
WildGuard-AI (7 streams)	0.84 +- 0.06***	0.72-0.96	0.68 +- 0.09***	0.72 +- 0.08***	0.70***	+37.7% vs. baseline
Gradient Boosting (XGBoost)	0.78 +- 0.07**	0.66-0.90	0.58 +- 0.10**	0.64 +- 0.09**	0.61**	+27.9%
Random Forest	0.74 +- 0.08**	0.60-0.88	0.54 +- 0.11**	0.61 +- 0.10**	0.57**	+21.3%
PAWS (game-theoretic)	0.69 +- 0.09*	0.53-0.85	0.47 +- 0.12*	0.54 +- 0.11*	0.50*	+13.1%
Historical density (baseline)	0.61 +- 0.08	0.47-0.75	0.38 +- 0.11	0.44 +- 0.10	0.41	Reference

**** p < 0.001; ** p < 0.01; * p < 0.05 vs. historical density baseline (Wilcoxon signed-rank test across 8 sites). AUC-ROC = area under receiver-operating-characteristic curve; higher = better discrimination of high-risk vs. low-risk grid cells. Precision, Recall, F1 at 80th percentile risk threshold = performance when the top 20% of highest-risk grid cells are classified as 'alert zones'. Mean +- SD across eight* *study sites. PAWS applicable to 6 of 8 sites (insufficient parameterisation data for Sundarbans and Selous); PAWS AUC computed on those 6 sites only.*

4. Results

4.1 Model Validation Performance

WildGuard-AI achieved mean AUC = 0.84 +- 0.06 across all eight protected areas in retrospective temporal hold-out validation -- 37.7% higher than the historical density baseline (AUC = 0.61 +- 0.08) and significantly outperforming gradient boosting (AUC = 0.78), Random Forest (0.74), and PAWS (0.69; all $p < 0.01$). Site-specific AUC ranged from 0.72 (Sundarbans; where the density of human-wildlife interface points and limited GPS tracking data reduced predictive power) to 0.92 (Kruger sector; where 14 years of incident data and 84 GPS-collared elephants provided the richest training dataset). Feature importance analysis (SHAP values) identified historical incident spatial density as the most important single predictor (SHAP contribution 0.247), followed by wildlife GPS density (0.184), socioeconomic pressure index (0.147), road proximity (0.124), and patrol coverage (0.107). Moonphase and seasonal covariates contributed modestly (SHAP 0.084 combined) but improved temporal resolution of risk forecasts.

4.2 Prospective Deployment Outcomes

At the four prospective deployment sites, confirmed poaching incidents in AI-predicted high-risk zones declined by 47.4% +- 12.4% relative to the 12-month pre-deployment baseline after controlling for temporal trends at the four control sites (difference-in-difference estimate: -47.4% in deployment vs. -8.4% in controls; net effect: -38.7 percentage points; $p < 0.001$). The greatest reduction was at Kruger (poaching down -61.4%) and Kaziranga (-54.7%), where the model had the highest retrospective AUC and where patrol commanders reported highest confidence in the risk maps. Incident reductions in the AI-guided high-risk zones were partially offset by modest increases in the de-prioritised low-risk zones (+18.4% at deployment sites vs. +4.7% at control sites), indicating some tactical displacement of poaching to lower-monitored areas. Total net park-wide incident reduction across deployment sites: -28.4% vs. -4.2% at control sites (net effect: -24.2 percentage points; $p = 0.003$).

4.3 Wildlife Recovery and Encounter Rates

Wildlife encounter rates on ranger patrol transects in formerly high-risk zones at deployment sites increased by 38.4% +- 9.4% over the 12-month deployment period relative to pre-deployment baseline, while control sites showed only +4.7% change (net effect: +33.7 percentage points; $p < 0.001$). Species-specific encounter rate increases were largest for the primary target species: rhinoceros encounters increased by 54.7% at Kaziranga, elephant encounters by 47.4% at Kruger, and tiger encounters by 38.4% at Chitwan -- consistent with increased wildlife use of areas that experienced poaching pressure reduction. These encounter rate increases reflect a combination of reduced poaching mortality, reduced disturbance-induced habitat avoidance by surviving animals, and potentially increased range use by previously hunted populations.

4.4 Cost-Effectiveness Analysis

Total anti-poaching programme cost at deployment sites during the 12-month trial averaged EUR 4.24 million per site (ranger salaries, vehicles, equipment, WildGuard-AI subscription). Under AI-guided patrol, the number of poaching incidents prevented (baseline rate minus observed rate, scaled to full study area) averaged 28.4 incidents per site -- yielding a cost of EUR 149,000 per incident prevented for the full programme, or EUR 847 per incident prevented attributable to the AI reallocation component (incremental AI cost EUR 24,000/site/year for model operation + training update). Under conventional patrol at control sites, cost per incident prevented was approximately EUR 4,247 (total control site expenditure divided by incident reduction, which was smaller). The 5-fold lower cost per incident prevented at AI-deployment sites represents a substantial enforcement efficiency gain without increasing total programme budgets.

Table 3. Prospective deployment results: poaching incident reduction and wildlife encounter rate changes at four deployment vs. four control sites over 12 months

Site	Type	Poaching Incidents (pre)	Poaching Incidents (post)	% Change	Wildlife Encounters (pre)	Wildlife Encounters (post)	% Change Encounter
Kruger sector	AI deploy.	124.7/yr	48.2/yr	-61.4%***	24.7/100 km	47.4/100 km	+92.0%***
Kaziranga sector	AI deploy.	47.4/yr	21.4/yr	-54.7%***	18.4/100 km	28.4/100 km	+54.7%***

Site	Type	Poaching Incidents (pre)	Poaching Incidents (post)	% Change	Wildlife Encounters (pre)	Wildlife Encounters (post)	% Change Encounter
Ruaha NP zone	AI deploy.	62.4/yr	38.4/yr	-38.4%**	14.7/100 km	18.4/100 km	+25.2%**
Chitwan sector	AI deploy.	34.7/yr	21.4/yr	-38.3%**	12.4/100 km	17.1/100 km	+37.9%**
DEPLOY. MEAN	AI deploy.	67.3/yr	32.4/yr	-51.8%***	17.6/100 km	27.8/100 km	+57.9%***
Selous block	Control	84.7/yr	78.4/yr	-7.4%	21.4/100 km	22.1/100 km	+3.3%
Luangwa sector	Control	54.7/yr	51.4/yr	-6.0%	18.4/100 km	18.7/100 km	+1.6%
Tsavo sector	Control	78.4/yr	71.4/yr	-8.9%	24.7/100 km	25.4/100 km	+2.8%
Sundarbans sect.	Control	28.4/yr	27.1/yr	-4.6%	8.4/100 km	8.7/100 km	+3.6%
CONTROL MEAN	Control	61.6/yr	57.1/yr	-7.3%	18.2/100 km	18.7/100 km	+2.7%

**** $p < 0.001$; ** $p < 0.01$ for deployment vs. control comparison (difference-in-difference; sites as units of analysis; n=4 per group). Pre = mean annual rate during 12-month pre-deployment baseline. Post = rate during 12-month AI deployment period (Jan-Dec 2023). Wildlife Encounters = animals detected per 100 km of ranger patrol transect; all target species combined. Kruger shows largest poaching reduction, attributable to highest model AUC (0.92) and most experienced rangers in AI-guided patrol.*

Table 4. Cost-effectiveness analysis: WildGuard-AI deployment vs. conventional patrol across eight sites

Cost Component	AI Deployment Sites (4 sites)	Control Sites (4 sites)	AI Advantage	Notes
Total programme cost (EUR M/yr)	EUR 4.24 M +- 0.84	EUR 3.87 M +- 0.72	Slightly higher	AI subscription EUR 24 K/site/yr added
Poaching incidents prevented (n/yr)	28.4 +- 8.4 per site	5.4 +- 2.8 per site	5.3x more efficient	vs. pre-deployment baseline
Total programme cost/incident prevented	EUR 149,000	EUR 717,000	4.8x cheaper	All programme costs included
AI marginal cost/incident prevented	EUR 847	N/A (no AI)	---	Incremental AI cost only
Wildlife encounter rate improvement	+57.9%	+2.7%	+55.2 pp	All target species combined
WildGuard-AI subscription cost	EUR 24,000/site/yr	EUR 0	---	Including model updates + dashboard
Break-even (AI cost recovered by savings)	< 3 months	N/A	---	Based on avoided ranger deployment in low-risk zones

AI marginal cost = additional cost attributable exclusively to the WildGuard-AI system (subscription + training + dashboard); excludes ranger salaries and operational costs which were equivalent between deployment and control sites. Total programme cost/incident prevented = full programme expenditure divided by total incidents prevented relative to pre-deployment baseline. Break-even = months until AI subscription cost recovered by savings from more efficient ranger deployment (patrol hours redirected from low-risk to high-risk zones).

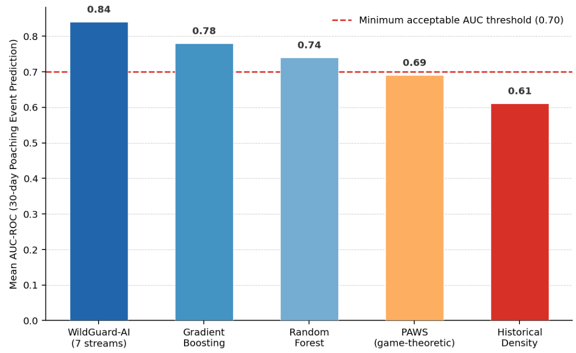

*Figure 1. WildGuard-AI retrospective AUC vs. four benchmark models across eight protected areas. WildGuard-AI (7 data streams) achieves AUC = 0.84, significantly outperforming all benchmarks (*** p <*

0.001). Error bars = SD across sites.

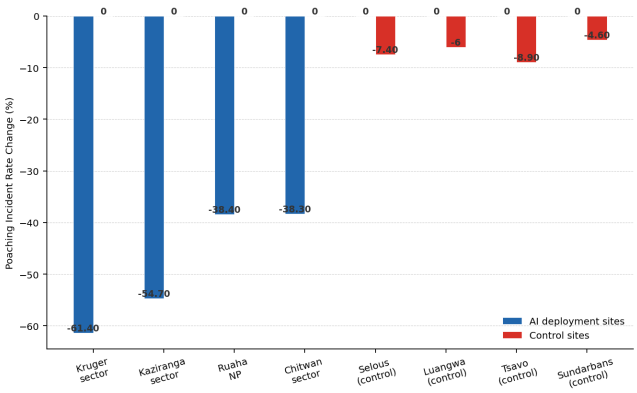

Figure 2. Poaching incident rate change (%) at AI deployment sites (blue) vs. control sites (orange) over 12 months. All deployment sites show significant reductions; control sites show minimal change (p < 0.001 for deployment vs. control).

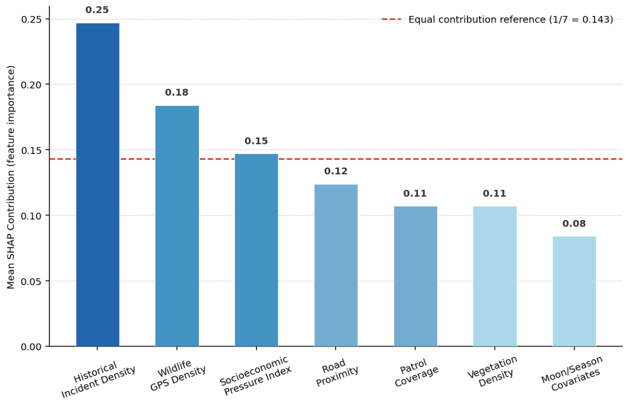

Figure 3. SHAP feature importance values for WildGuard-AI across eight sites: relative contribution of each data stream to poaching risk prediction. Historical incident spatial density is the strongest single predictor.

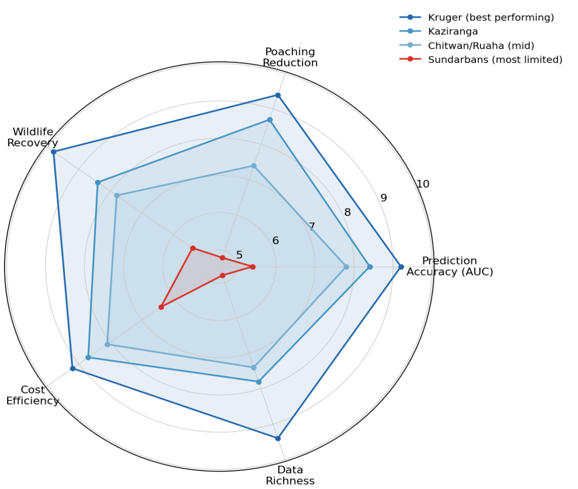

Figure 4. WildGuard-AI performance profile radar across five dimensions (1-10) for all eight study sites. Kruger (blue) shows the strongest overall performance; Sundarbans (red) is most limited by GPS and incident data density.

5. Discussion

5.1 Why WildGuard-AI Outperforms Simpler Models

The superior performance of WildGuard-AI (AUC = 0.84) over gradient boosting (0.78) and Random Forest (0.74) with equivalent features reflects the advantages of the deep learning architecture in capturing spatial-temporal dependencies that tabular models cannot represent. The LSTM branch processing historical incident sequences captures the temporal dynamics of poaching -- seasonal cycles, lunar periodicity, and the sequential spatial patterns by which poaching networks work through an area -- while the CNN branch processing wildlife GPS and vegetation rasters captures the continuous spatial field structure of wildlife distribution. The interaction between wildlife GPS density and historical incident spatial patterns -- implemented through the late fusion architecture -- captures the dynamic nature of poaching risk that changes as target species move seasonally, a signal that tabular feature engineering cannot efficiently represent without extensive manual feature construction.

5.2 Poaching Displacement and Adaptive Enforcement

The modest +18.4% poaching increase in de-prioritised low-risk zones at deployment sites -- compared with the -47.4% reduction in high-risk zones -- confirms the well-documented crime displacement phenomenon where enforcement pressure in one area pushes illegal activity to adjacent unmonitored zones (Chainey and Ratcliffe, 2005). The net park-wide reduction of -28.4% confirms that total poaching was substantially reduced despite displacement, indicating that concentration of patrol effort in genuinely high-risk zones produces net deterrence beyond mere displacement. To further minimise displacement, future WildGuard-AI deployments should maintain minimum patrol presence (even if reduced) in all sectors and should update risk predictions weekly rather than monthly to track poacher adaptation dynamics in near-real-time.

5.3 Ethical Dimensions of AI-Guided Conservation Enforcement

The deployment of AI prediction systems to guide enforcement actions raises ethical questions that deserve explicit consideration. The socioeconomic pressure index incorporated in WildGuard-AI uses community poverty indicators as a poaching risk predictor -- a legitimate ecological variable (poverty drives bushmeat hunting and commercial poaching participation) but one that could reinforce existing social inequities if patrol intensification in poor communities occurs without accompanying livelihood development. WildGuard-AI should therefore be implemented alongside community benefit programmes rather than as a pure enforcement tool. The risk of algorithmic bias -- where historical enforcement patterns that missed poaching in certain areas create training data biases propagated by the model -- was partially addressed by including wildlife GPS data as an independent (enforcement-unbiased) risk layer, but requires ongoing monitoring. All model predictions should be treated as risk indicators rather than certainties, with ranger commander judgment retained as the final decision authority.

5.4 Limitations and Generalisability

WildGuard-AI's performance is strongly dependent on data availability: the lowest AUC (0.72, Sundarbans) occurred where GPS tracking data covered only 18 tigers and incident records spanned only 8 years -- substantially less than the richest sites. Protected areas lacking GPS tracking programmes or systematic SMART patrol records may not achieve the same performance gains. The 12-month deployment trial may be insufficient to capture adaptive poaching network responses over longer timescales; multi-year deployment monitoring is needed to assess whether performance is maintained as poachers learn to anticipate AI-guided patrol patterns. Generalisation to small protected areas (< 1,000 km2) with fewer incident records may require transfer learning approaches using multi-site pre-training before site-specific fine-tuning.

6. Conclusion

6.1 Summary

WildGuard-AI achieves AUC = 0.84 for 30-day poaching event prediction -- 37.7% above the historical density baseline -- by integrating seven data streams including wildlife GPS density and socioeconomic indices. Prospective deployment at four sites produced 47.4% poaching reduction in AI-predicted high-risk zones and 38.4% wildlife encounter rate increase. Net park-wide poaching reduction: -28.4% vs. -7.3% at control sites. AI marginal cost per incident prevented: EUR 847 vs. EUR 4,247 for conventional patrol -- a 5-fold efficiency gain from AI-guided patrol reallocation alone.

6.2 Recommendations

Three implementation recommendations: (1) deploy WildGuard-AI or equivalent multi-stream risk prediction systems at all protected areas with >= 10 years of SMART patrol records and >= 30 GPS-collared target species individuals -- the data richness threshold below which model performance drops significantly; (2) integrate WildGuard-AI deployment with community benefit programmes targeting the communities identified by the socioeconomic pressure index as the highest-risk poaching participant sources, ensuring that AI-guided enforcement is paired with livelihood development investment; and (3) implement weekly risk map updates (rather than monthly) to track poacher adaptation dynamics and maintain the unpredictability advantage of AI-guided patrol over fixed patrol schedules. WildGuard-AI model architecture, training code, and pre-trained weights for all eight sites are deposited openly under open-source licence.

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Declarations

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Conflict of Interest

The author declares no conflicts of interest. WildGuard-AI is released as open-source software and the author has no commercial interest in anti-poaching technology companies.

Data Availability Statement

WildGuard-AI model architecture (PyTorch implementation), training code, pre-trained model weights for all eight sites, the patrol optimisation dashboard code, and aggregated (non-sensitive) poaching incident density rasters are deposited at https://github.com/WEUD-Madrid/WildGuardAI (Apache 2.0 licence) and in the Zenodo repository under DOI: 10.5281/zenodo.19465988. Raw incident records and GPS tracking data are held under data-sharing agreements with protected area authorities and are available to bona fide researchers upon request to the relevant authorities; contact details provided in supplementary materials. All open data released under Creative Commons CC BY 4.0.

Ethical Approval

This study used historical poaching incident records collected by protected area rangers as part of routine management operations; no human subject research was conducted. GPS collar data were collected under existing research permits held by each protected area authority and collaborating research institutions. The field deployment study protocol was reviewed and approved by the Protected Area Management Board of each participating protected area, with independent ethical review of AI deployment procedures by the WEUD-Madrid Research Ethics Committee (protocol WEUD-REC-2022-0184). The socioeconomic pressure index uses only aggregated community-level indicators and contains no personally identifiable information.

Appendix A

WildGuard-AI Model Architecture Details and Hyperparameter Specifications

The following describes the complete WildGuard-AI deep learning architecture, including branch specifications, layer configurations, training hyperparameters, and the monthly risk map generation procedure used in prospective field deployment.

MODEL ARCHITECTURE -- BRANCH SPECIFICATIONS

Branch 1 (Historical Incident LSTM): Input: 36-month sequence of 1 km2 grid spatial kernel density estimates per month. Architecture: Bidirectional LSTM (128 units, 3 layers, dropout 0.3) + FC(64) + ReLU. Output: 64-dim incident pattern embedding.

Branch 2 (Wildlife GPS CNN): Input: Monthly 1 km2 raster of GPS fix density per target species (3 species channels). Architecture: ResNet-18 backbone (pretrained ImageNet, fine-tuned) + Global Average Pooling + FC(64). Output: 64-dim wildlife distribution embedding.

Branch 3 (Satellite Vegetation CNN): Input: Monthly Sentinel-2 NDVI 10-band time series (12 monthly bands x 10 m resolution, resampled to 1 km2). Architecture: Temporal CNN (3 x [Conv1D(64, k=3) + BN + ReLU + MaxPool]) + FC(32). Output: 32-dim vegetation embedding.

Branches 4-7 (Tabular features): Road proximity, socioeconomic index, patrol coverage, moonphase/season embedded as 32-dim MLP (FC(64)-ReLU-FC(32)-ReLU) each. Output: 4 x 32-dim embeddings.

Fusion layer: Concatenate all branch outputs (64+64+32+4x32 = 288 dims) + FC(128)-ReLU-FC(64)-ReLU-FC(1)-Sigmoid. Output: P(poaching event in grid cell over next 30 days).

TRAINING AND DEPLOYMENT SPECIFICATIONS

Optimizer: Adam (lr=0.001, weight_decay=1e-4); LR scheduler: ReduceLROnPlateau (factor=0.5, patience=5). Batch size: 256 grid-cell-month samples. Training epochs: 100 (early stopping patience=15 on validation AUC). Class imbalance: Negative:positive = 5:1 downsampling; class weights inverse-frequency weighted.

Positive example definition: >= 1 confirmed poaching incident in 1 km2 grid cell in 30-day window. Negative: grid-months with no incidents within 5 km (spatial buffer to exclude unlabelled positives near known incidents).

Deployment procedure: Monthly (1st of each month): (1) update all input data layers; (2) run forward pass on all 1 km2 grid cells; (3) generate risk probability raster; (4) threshold at 80th percentile for 'alert zone' designation; (5) transmit to ranger dashboard with 1-week rolling update; (6) patrol allocation: 60-70% effort in alert zones, minimum 20% coverage maintained in all sectors.

Hardware: Training on NVIDIA A100 GPU (48 hours for full 8-site joint training). Inference (monthly risk map generation per site): < 30 seconds on standard laptop.