Stay Ahead of Poachers:

Illegal Wildlife Poaching Prediction and Patrol Planning Under Uncertainty with Field Test Evaluations

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Illegal wildlife poaching threatens ecosystems and drives endangered species toward extinction. Building on the Protection Assistant for Wildlife Security (PAWS) [1], we take an end-to-end approach to the data-to-deployment pipeline to help rangers in detect snares and combat poachers.

- We address challenges prevalent throughout machine learning, including **extreme class imbalance (up to 1:200) and uncertainty**.
- We use Gaussian processes to quantify predictive uncertainty, which we exploit to improve robustness of our prescribed patrols.
- We present the results of large-scale field tests conducted in Murchison Falls and Srepok Wildlife Sanctuary.

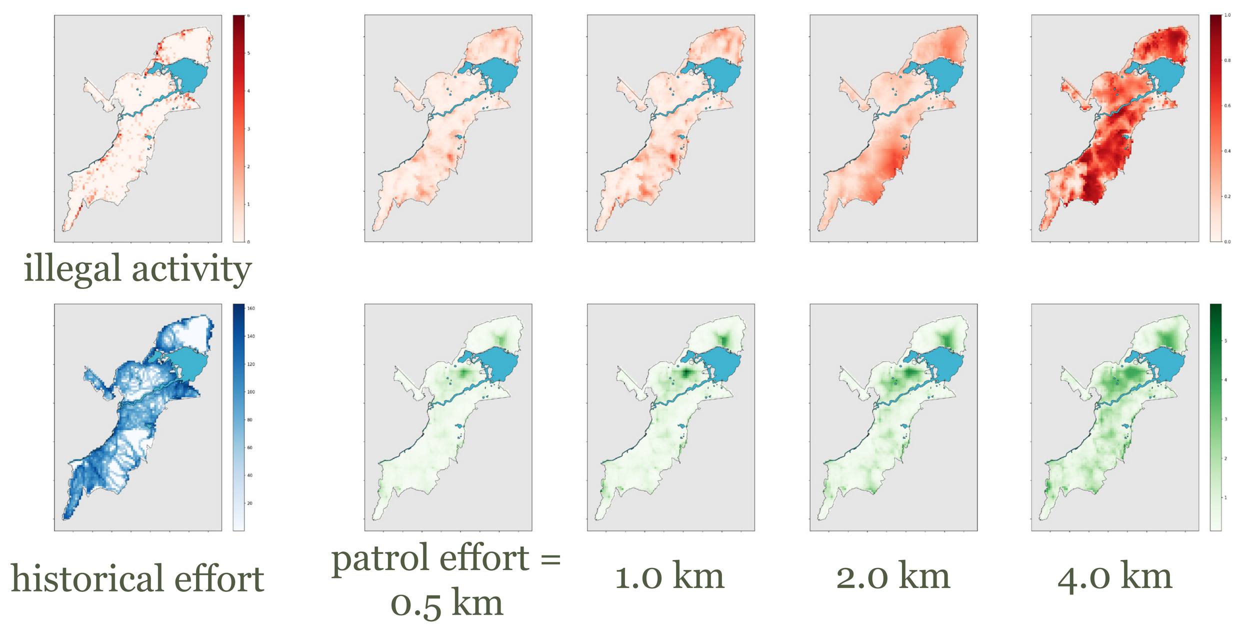
This paper is part of an effort to expand PAWS to 800 parks worldwide by integrating with SMART conservation software.

We evaluate our method on real-world historical poaching data from three national parks.

Stage 1: Predictive Modeling

machine learning model to identify poaching risk throughout a park

- We use Gaussian process (GP) classifiers as the weak learners in the iWare-E ensemble [2]. GPs compute a variance for each prediction, which we exploit as an uncertainty metric.
- Features include forest cover; slope; distance to rivers, roads, villages, and waterholes; animal density and NPP; and past patrol effort.
- iWare-E consistently improves the AUC across all models, raising the AUC by 0.100 on average. The GP model generally performs best, particularly on imbalanced datasets.



Prediction values and uncertainties for different levels of patrol effort in QENP in Uganda in the first quarter of 2017.

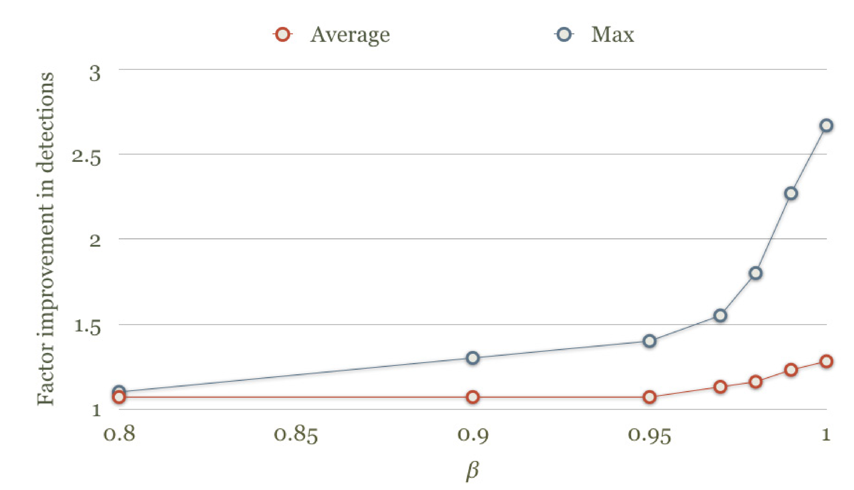
Stage 2: Patrol Planning

game-theoretic model to plan optimal patrol routes for rangers

- We make use of the variance values from GPs to plan more informed patrol routes.
- We introduce the parameter β where larger values correspond to greater risk-aversion.
- *Accounting for risk-averse patrols increases the detection of snares by 30% on average.*

We modify the defender utility by penalizing the probability of detection g_v by the uncertainty ν_v, scaled by β:

$$U_v(c_v) = g_v(c_v) - \beta g_v(c_v)\nu_v(c_v)$$

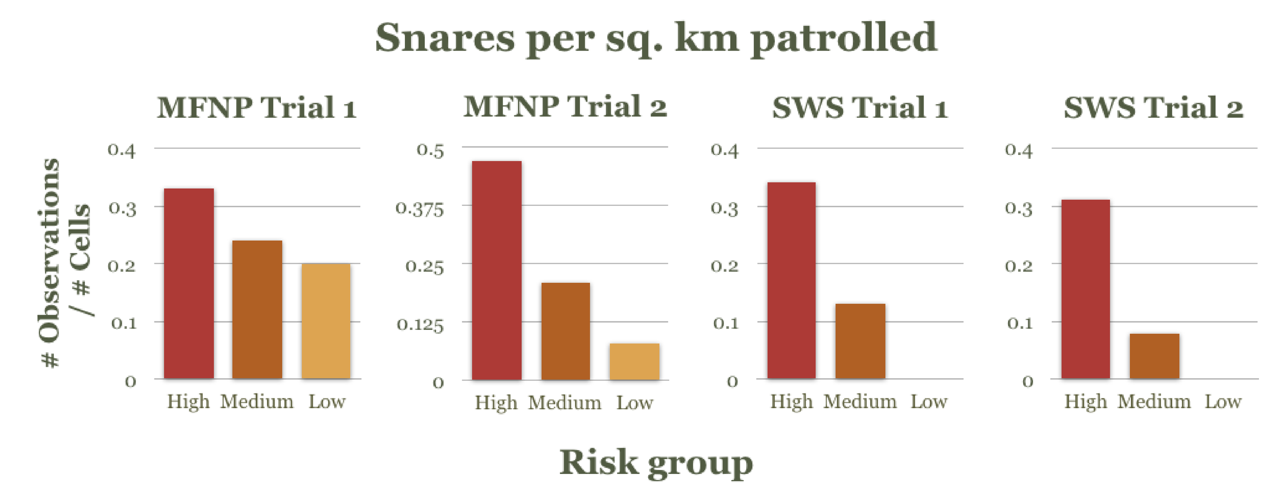


Improvement in detection of snares when accounting for uncertainty in patrol planning. Park shown is SWS.

Deployment: Field Tests

Rangers in Srepok Wildlife Sanctuary with snares and chainsaws confiscated during our field tests in December 2018.

- We give rangers areas identified by our predictive model as having high, medium, or low poaching threat.
- *In SWS, rangers found no poaching activity in low-risk areas, despite exerting a comparable amount of effort in those regions.*



[1] Yang, R., et al. (2014). Adaptive resource allocation for wildlife protection against illegal poachers. AAMAS-14.
[2] Gholami, S., et al. (2018). Adversary models account for imperfect crime data: Forecasting and planning against real-world poachers. AAMAS-18.