



AI for Wildlife Conservation



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AI & Multiagent Systems Research for Social Impact



**Wildlife
Conservation**



Public Health



**Public Safety
and Security**

Optimize Our Limited Intervention Resources

Lesson #1: Conservation & AI researchers both benefit from collaboration

Domain Impact & AI Innovation Go together: Incentives for collaboration



Green
security
games

Wildlife
Conservation

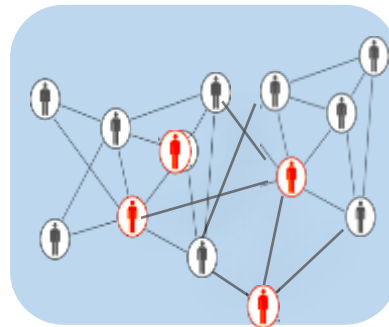
Multiagent
Systems
Research



Stackelberg
security
games



Public Safety
& Security



Social
Networks &
Bandits



Public Health

Lesson #2:

AI4SI only possible with interdisciplinary partnerships, with NGOs (non-profits)



Empower non-profits to use AI tools; avoid being gatekeepers to AI4SI technology

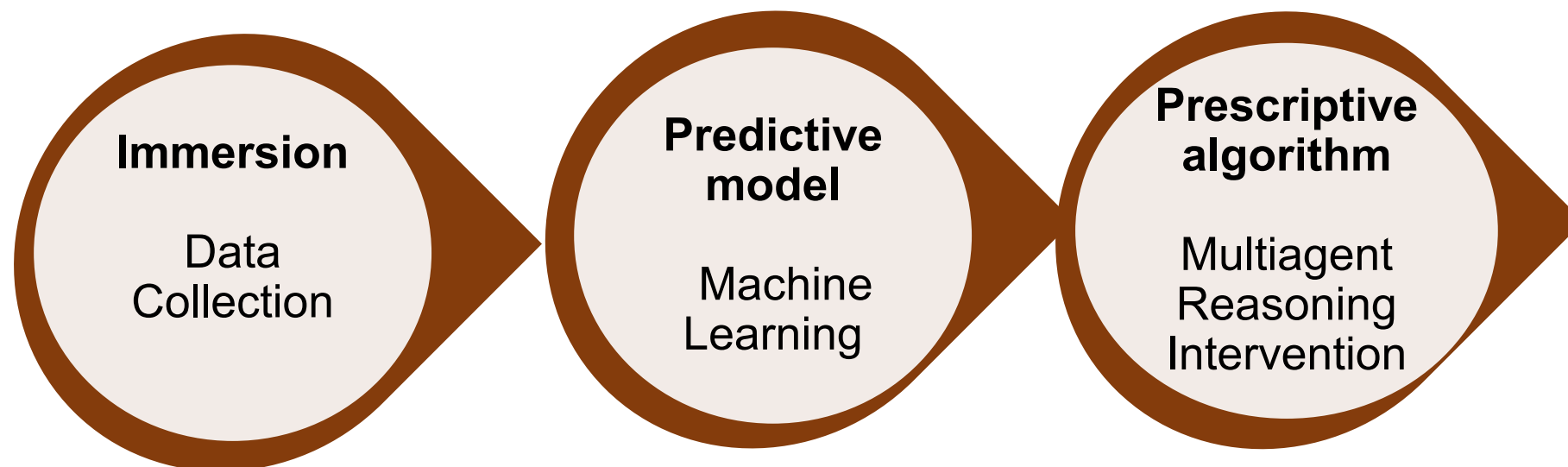


ASHOKA TRUST FOR RESEARCH IN
ECOLOGY & THE ENVIRONMENT



Lesson #3:

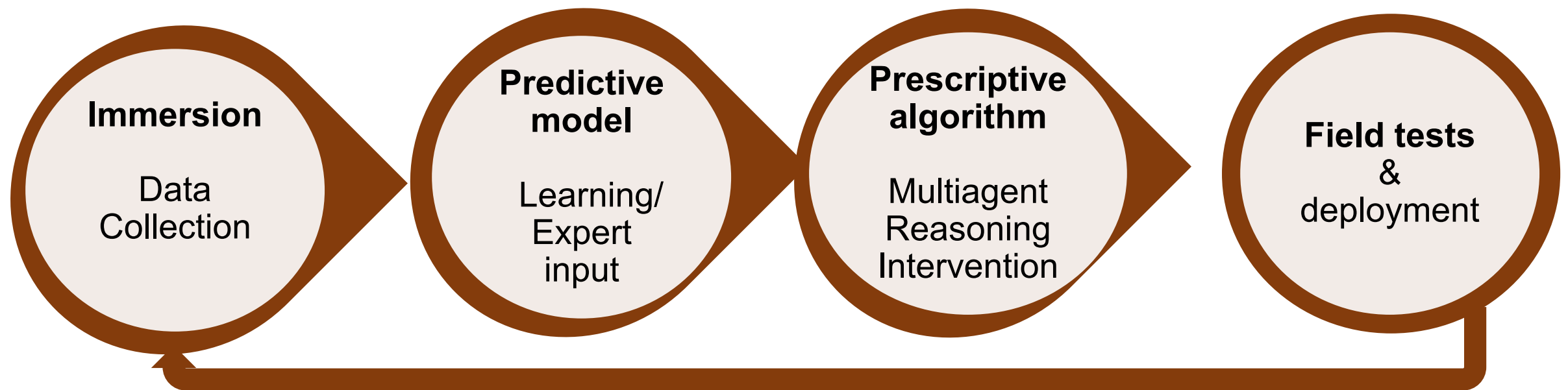
Data-to-deployment pipeline: Partner interactions throughout the pipeline



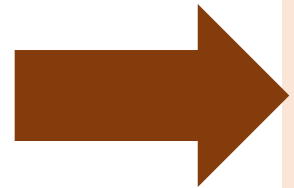
Lesson #3:

Data-to-deployment pipeline

Field test & deployment: Social impact is a key objective



Outline: AI for Wildlife Conservation



- *Background: How I got into this area*
- *Anti-poaching prediction and foot patrols*
- *Future directions: Data limitations, drones*
- *Google AI for Social Good workshops*
- *Future directions: Human-wildlife conflict*

- Cover papers from AAMAS, AAI, IJCAI, NeurIPS...
- PhD students & postdocs highlighted
- Collaboration with Andy Plumptre

AI researcher: theory/simulations in the lab...Until 2006...

11 July 2006: Mumbai



ARMOR Airport Security: LAX(2007)

Game Theory direct use for security resource optimization?

Erroll Southers



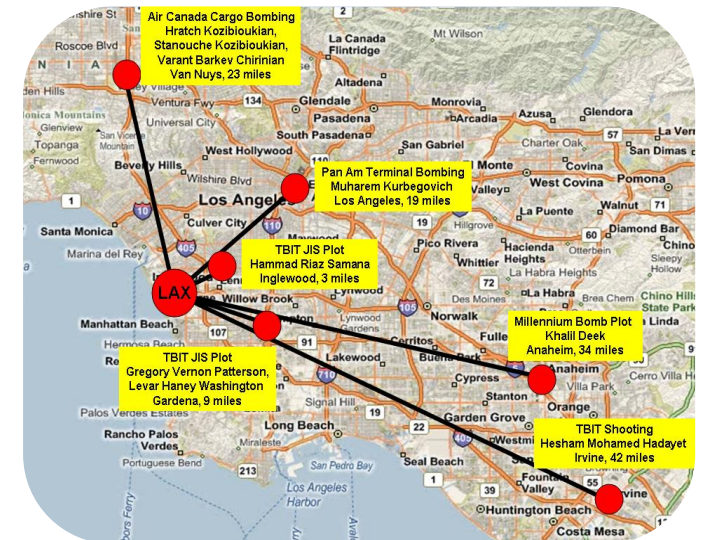
LAX Airport, Los Angeles



LAX Checkpoint

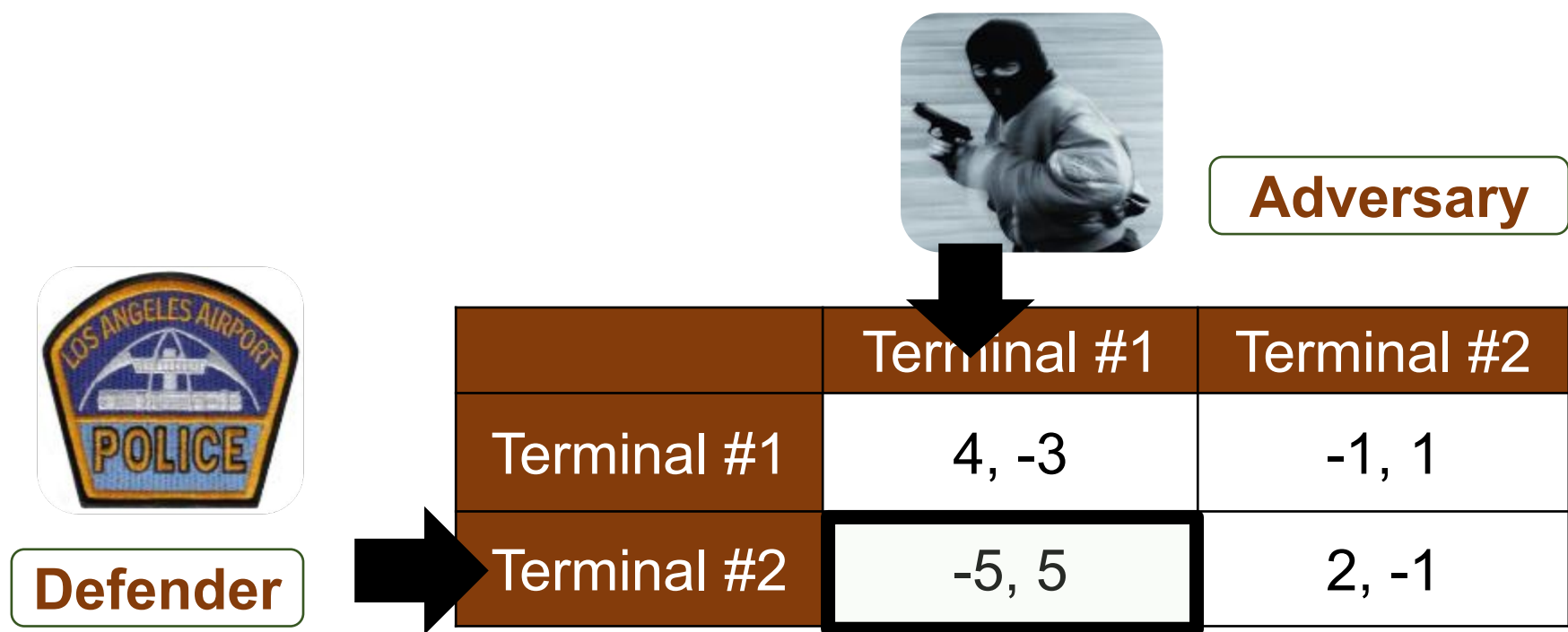


Surveillance



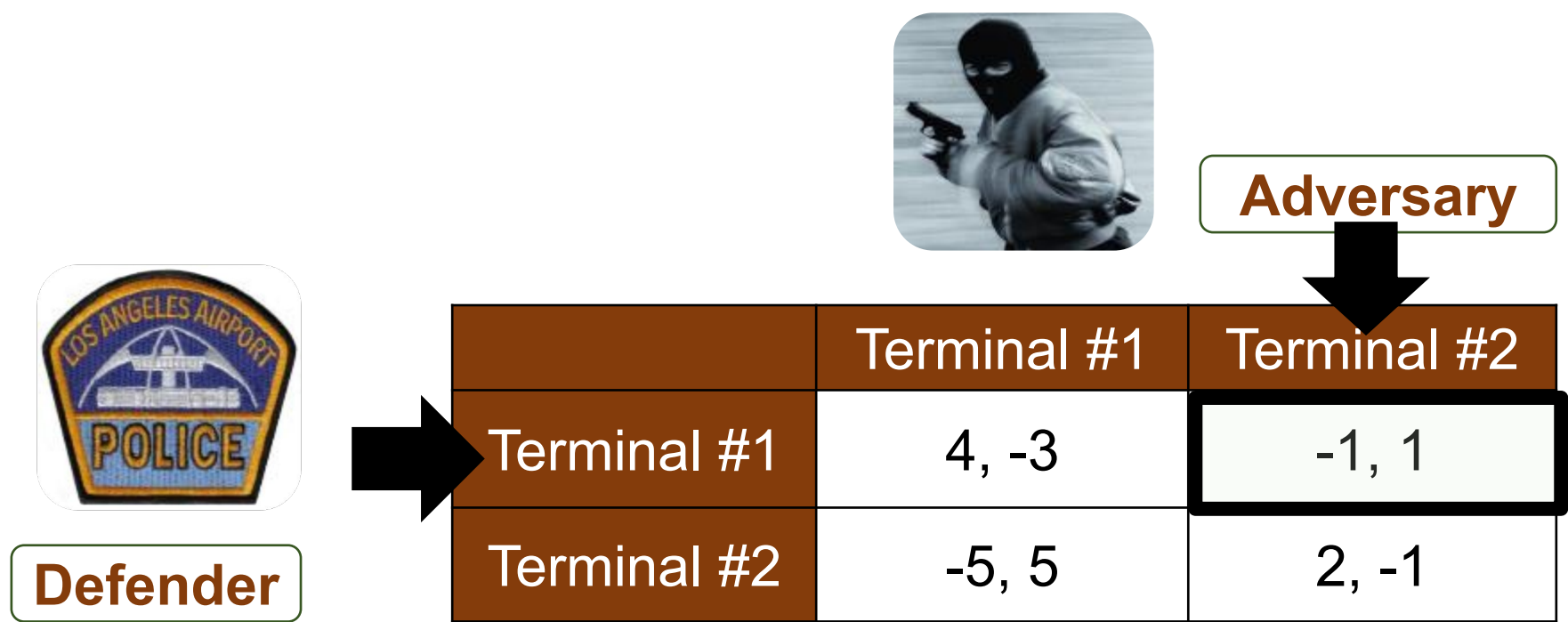
Game Theory for Security Resource Optimization

New Model: Stackelberg Security Games



Game Theory for Security Resource Optimization

New Model: Stackelberg Security Games




Game Theory for Security Resource Optimization

New Model: Stackelberg Security Games

Stackelberg: Defender commits to randomized strategy, adversary **strategic** response

Security game: Played on targets, payoffs based on calculated losses

Optimization: Not 100% security; increase cost/uncertainty to attackers

| | | | |
|---|----------|---|-------------|
| | |  | Adversary |
|  | Defender | | |
| | | Terminal #1 | Terminal #2 |
| | | Terminal #1 | Terminal #2 |
| | | 4, -3 | -1, 1 |
| | | -5, 5 | 2, -1 |

ARMOR at LAX

Basic Security Game Operation [2007]



Kiekintveld



Pita



| | Target #1 | Target #2 | Target #3 |
|-------------|-----------|-----------|-----------|
| Defender #1 | 2, -1 | -3, 4 | -3, 4 |
| Defender #2 | -3, 3 | 3, -2 | |
| Defender #3 | | | |



Mixed Integer Program



$\Pr(\text{Canine patrol, 8 AM @Terminals 2,5,6}) = 0.17$

Canine Team Schedule, July 28

| | Term 1 | Term 2 | Term 3 | Term 4 | Term 5 | Term 6 | Term 7 | Term 8 |
|------|--------|--------|--------|--------|--------|--------|--------|--------|
| 8 AM | | Team1 | | | Team3 | Team5 | | |
| 9 AM | | | Team1 | Team2 | | | | Team4 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... |

ARMOR: Optimizing Security Resource Allocation [2007]

First application: Computational game theory for operational security



January 2009

- January 3rd *Loaded 9/mm pistol*
- January 9th *16-handguns,
1000 rounds of ammo*
- January 10th *Two unloaded shotguns*
- January 12th *Loaded 22/cal rifle*
- January 17th *Loaded 9/mm pistol*
- January 22nd *Unloaded 9/mm pistol*

Deployed Security Games Systems... Getting out of the lab & into the field!



ARMOR

2007-



IRIS

2009-



PROTECT

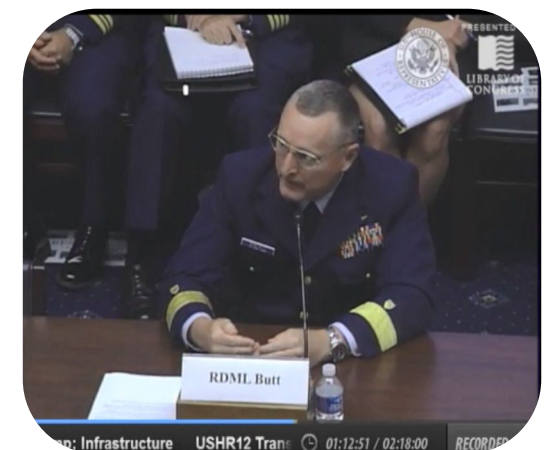
2011-



**Erroll Southers testimony
US Congress subcommittee**



**TSA testimony
US Congress subcommittee**



**Coast Guard testimony
US Congress subcommittee**

Estimated > \$100 Million savings in decade of deployment (Winterfeldt et al)

World Bank Global Tiger Initiative

How I got into AI for Wildlife Conservation



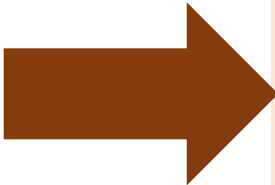


Visiting Uganda & Meeting Andy Plumptre

Date: 6/1/2021



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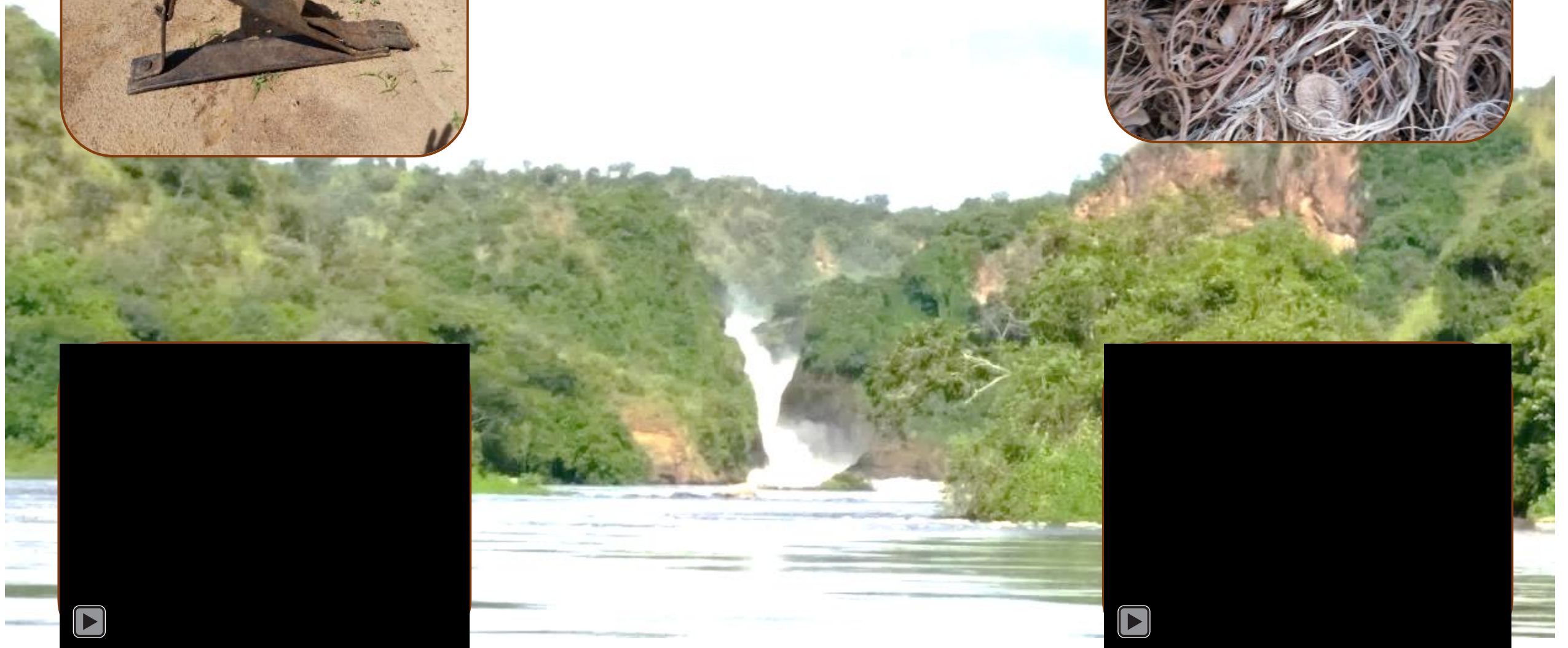
Poaching of Wildlife in Uganda

Limited Intervention (Ranger) Resources to Protect Forests

Snare or Trap



Wire snares

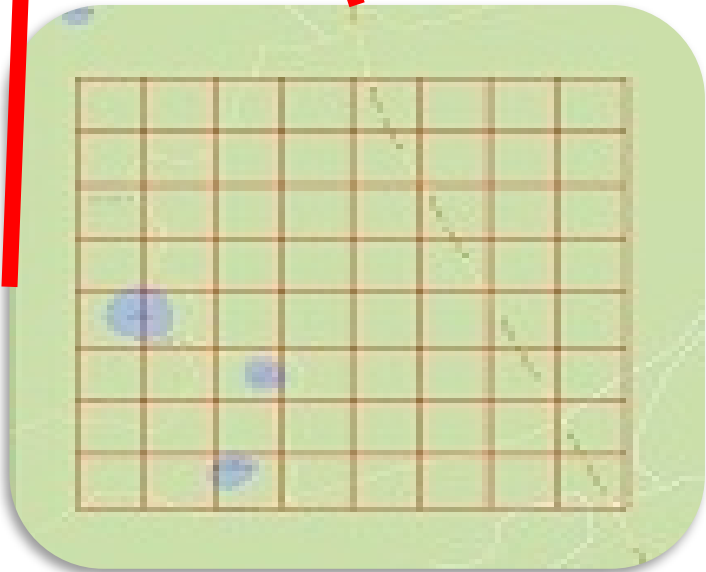
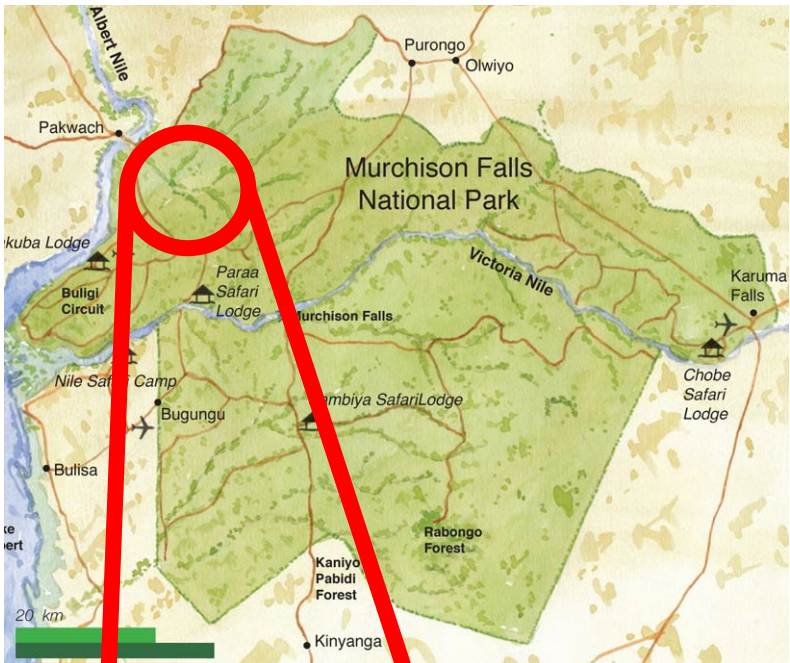


Stackelberg Security Games?

(IJCAI 2015)



Fang



➤ Stackelberg security games (SSG)



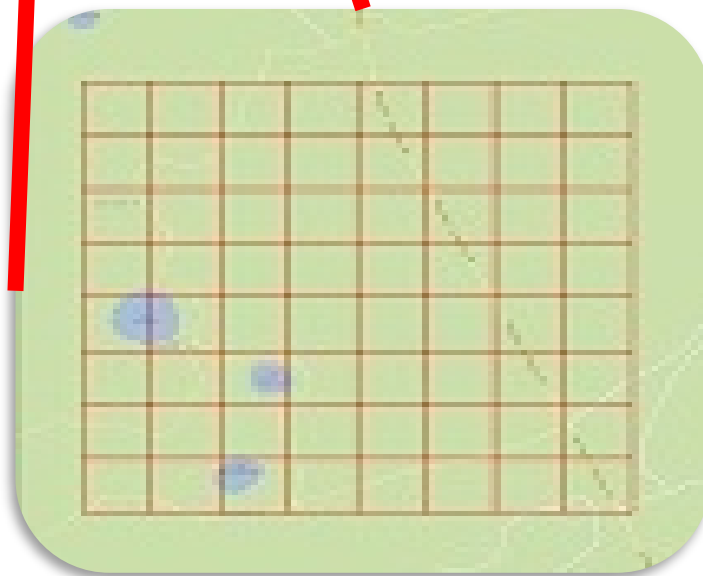
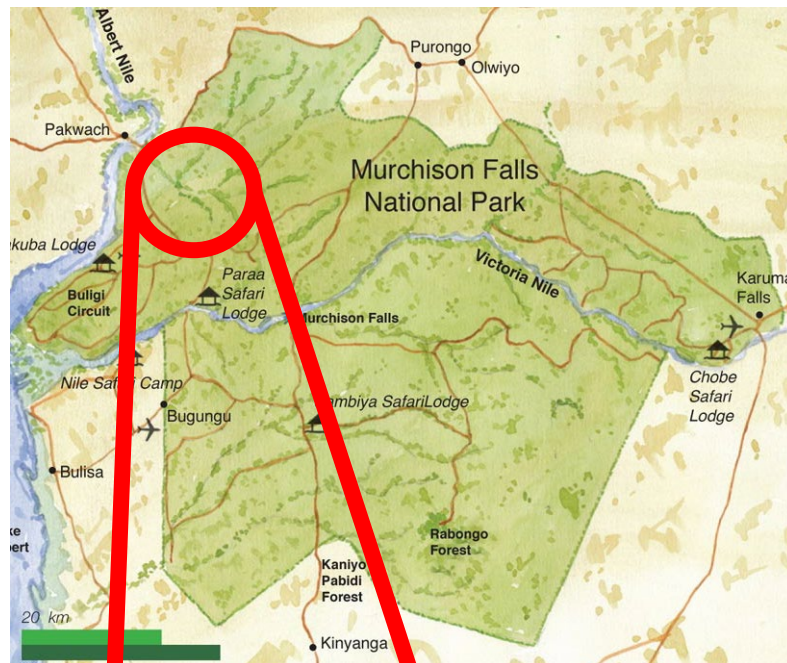
| | Area1 | Area2 |
|-------|-------|-------|
| Area1 | 4, -3 | -1, 1 |
| Area2 | -5, 5 | 2, -1 |

Green Security Games Combine Stackelberg Security Games and Machine Learning

(IJCAI 2015)



Fang



- *Not fully strategic adversaries*
- *Boundedly rational poachers, past poaching data*
- *Learn adversary response model at targets “i”*



| | Area1 | Area2 |
|-------|-------|-------|
| Area1 | 4, -3 | -1, 1 |
| Area2 | -5, 5 | 2, -1 |

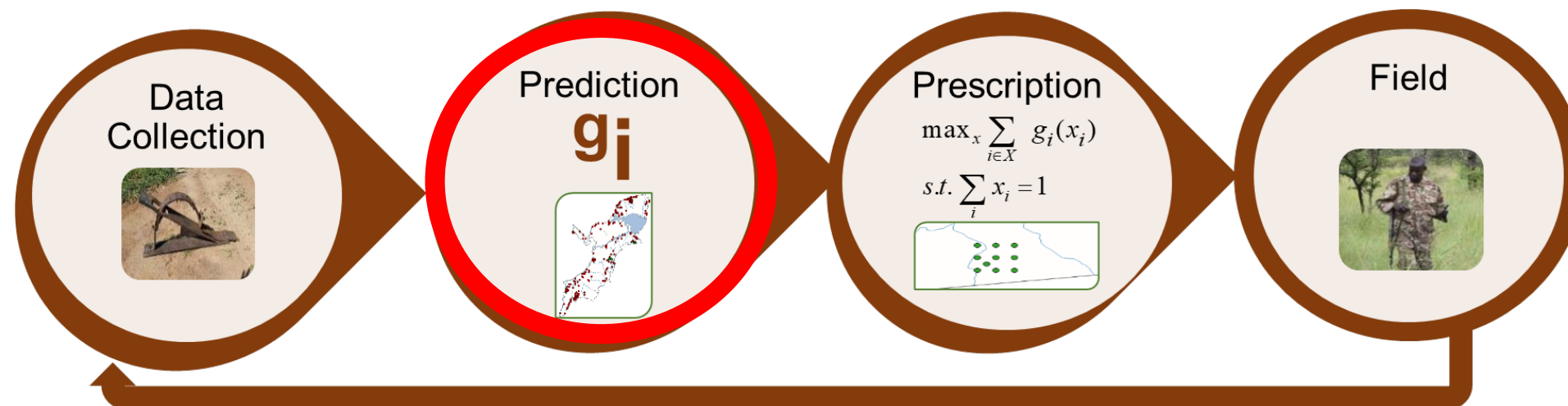
Learning Adversary Response Model: Uncertainty in Observations



Nguyen



Gholami

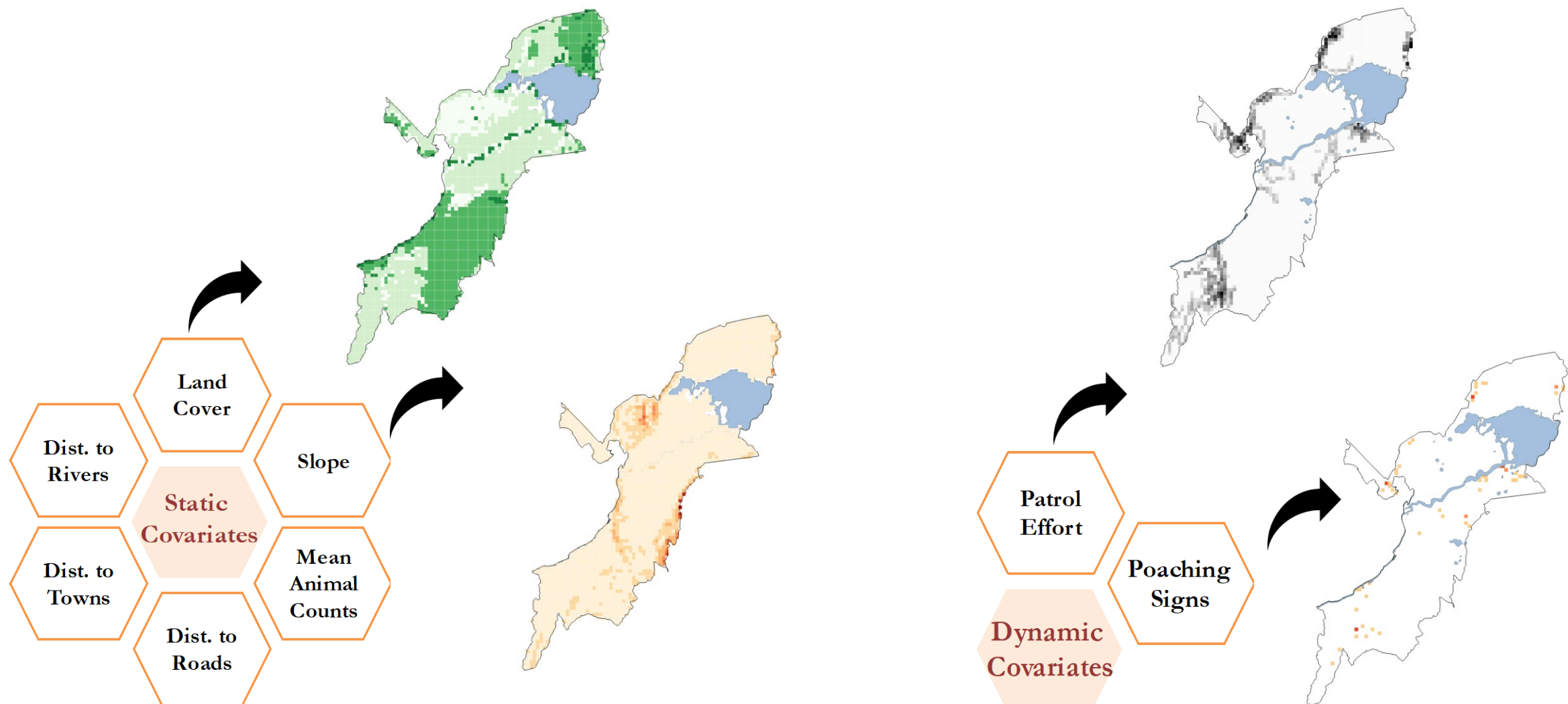


Datasets Predictive Covariates (Features)

14 years of Past Poaching Data from Uganda



Gholami



Spatiotemporal Data Processing



Gholami



- Discretize space into grid (e.g., 1km×1km)
- Discretize time into small time steps (e.g. 3 Month)

Predictive Covariates

Time Step 1: Jan-Mar 2011

| | Animal Density | Forest Cover | |
|--|---------------------|----------------------|----------------------|
| | 0.5, 0.6, ..., 0.1 | 0.25, 0.16, ..., 0.9 | 0.4, 0.6, ..., 0.2 |
| | 0.3, 0.8, ..., 0.15 | 0.55, 0.8, ..., 0.2 | 0.7, 0.6, ..., 0.7 |
| | 0.7, 0.3, ..., 0.55 | 0.8, 0.3, ..., 0.35 | 0.2, 0.35, ..., 0.95 |

\propto

Snare Detections

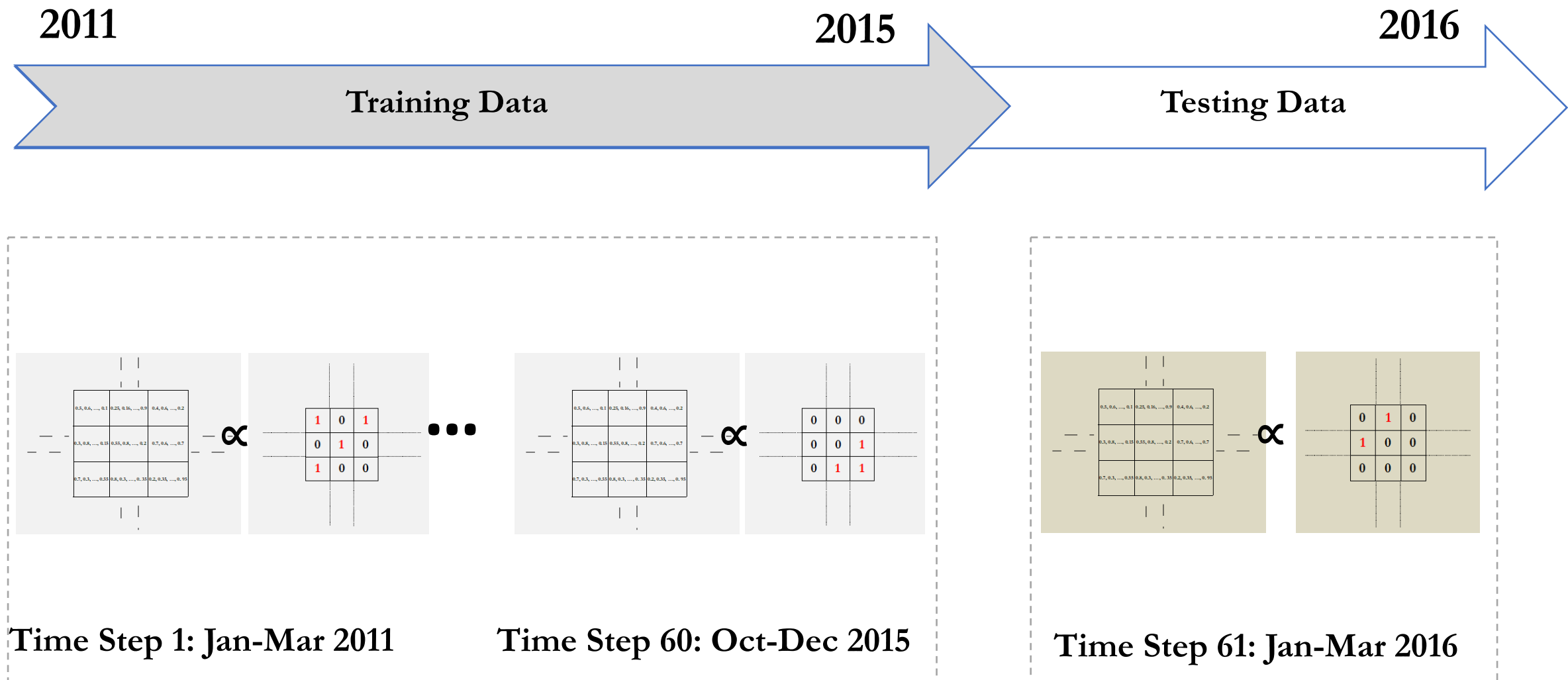
| | Snare detected | Snare not detected | |
|--|----------------|--------------------|---|
| | 1 | 0 | 1 |
| | 0 | 1 | 0 |
| | 1 | 0 | 0 |

Spatiotemporal Dataset Generation



Gholami

Data: Predictive Covariates + Snare Detections



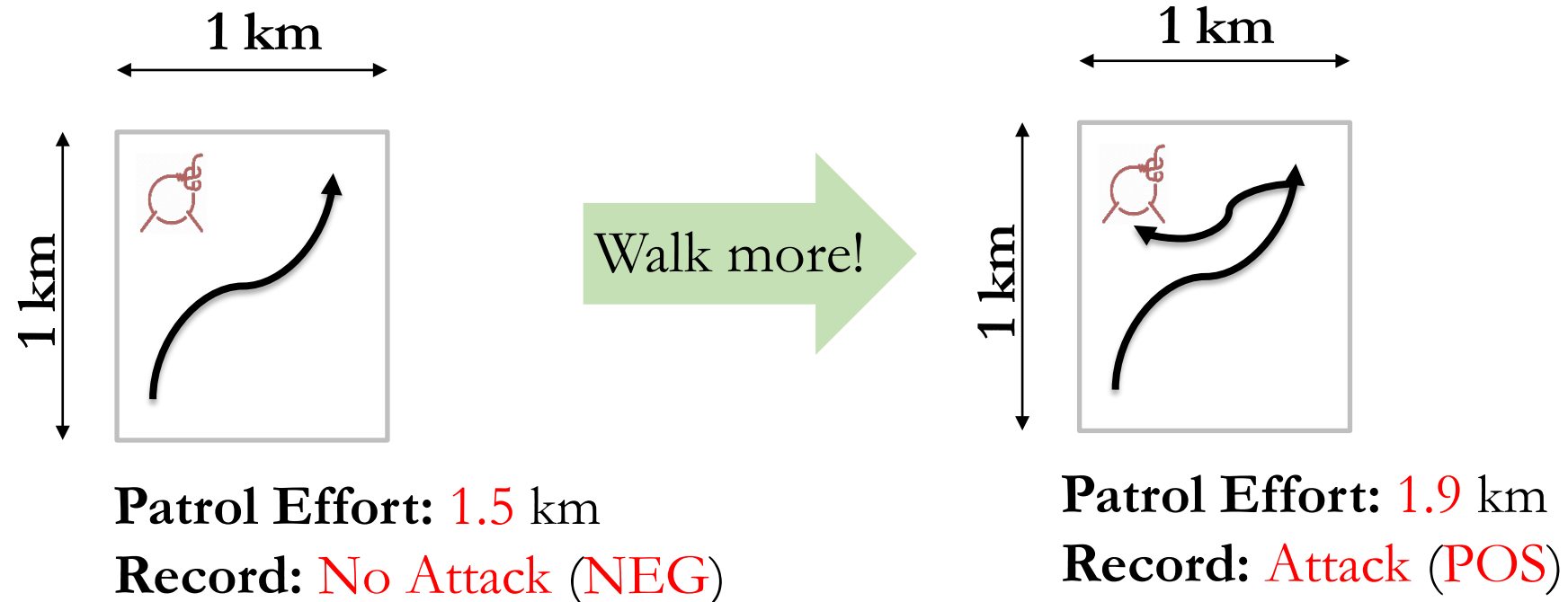
Positive and Unlabeled Data



Gholami

Assumptions:

- Negative attack records are **uncertain & uncertainty** is related to **patrol effort**

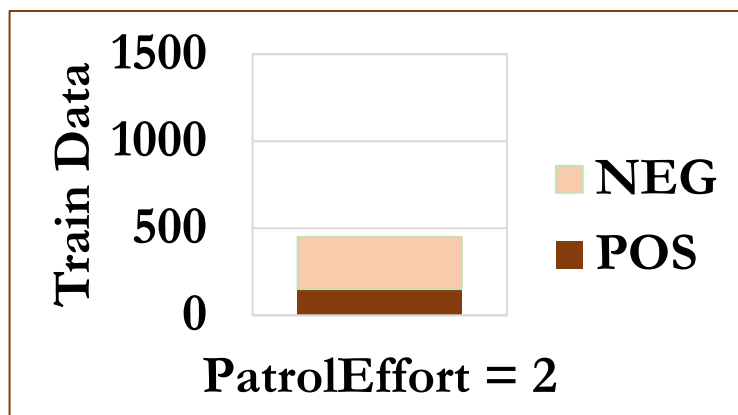
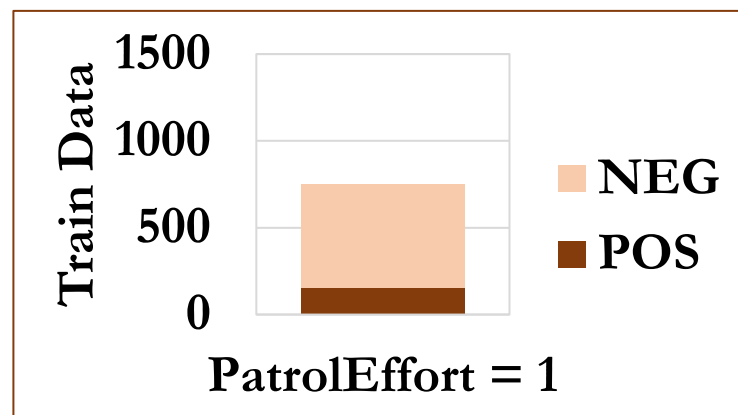
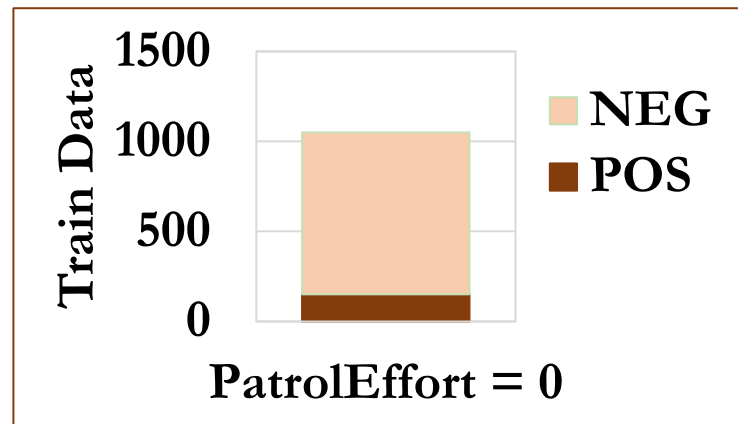


Adversary Response Modeling

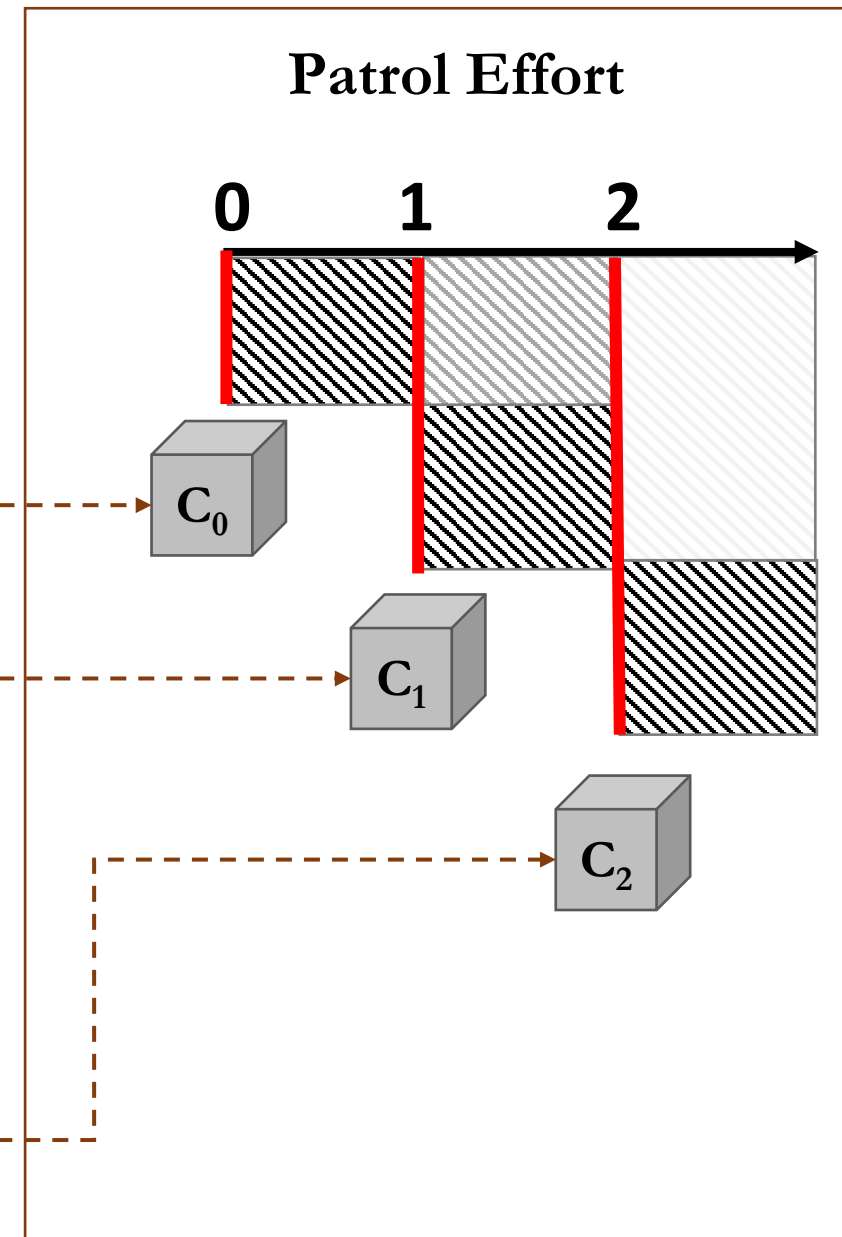
Imperfect Observation Ensemble Model



Training: Filtered Datasets



Predict: Ensemble of Classifiers



PAWS: Protection Assistant for Wildlife Security

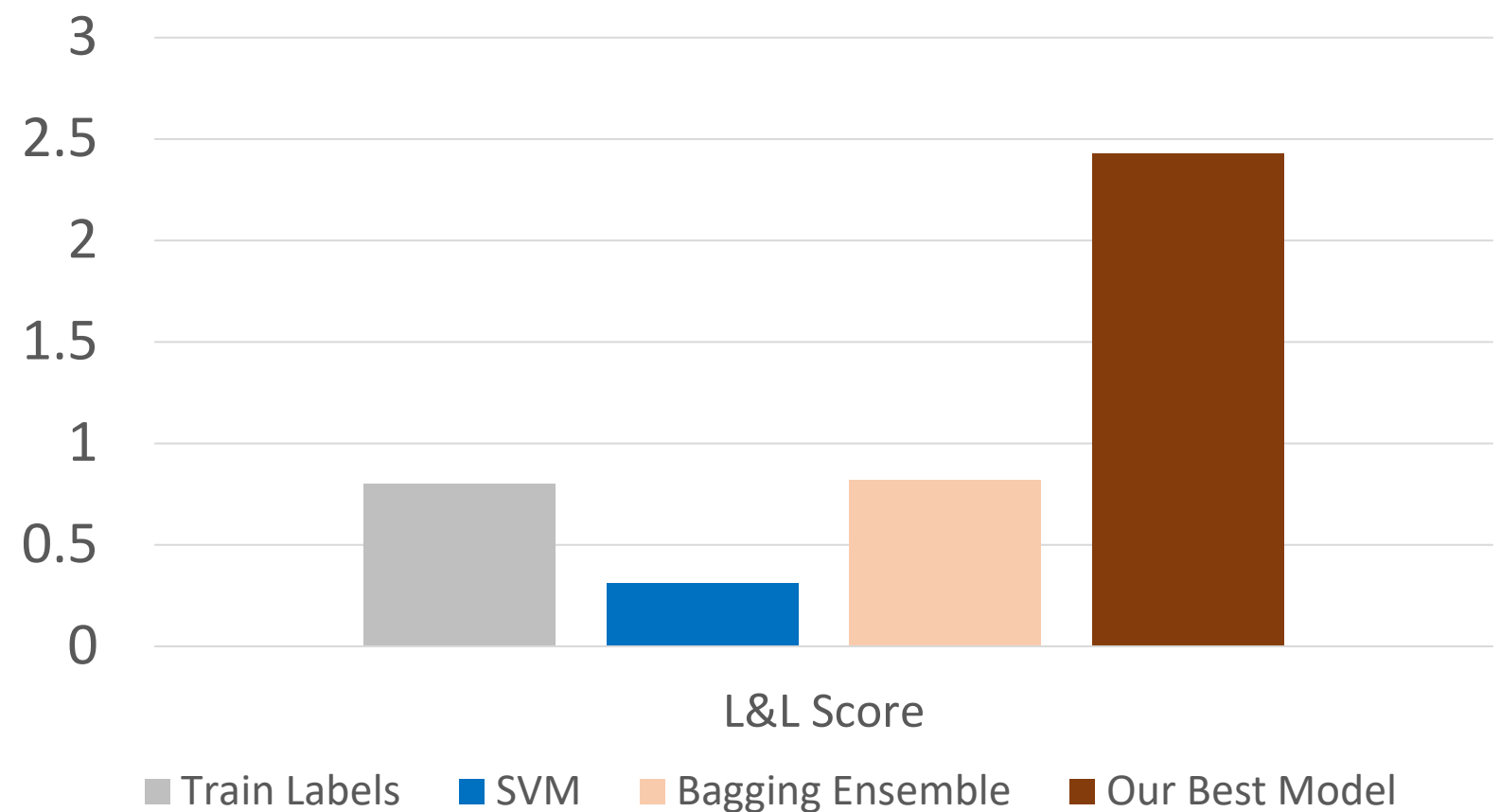
Queen Elizabeth National Park Predictions



Poacher Behavior Prediction



Results from 2016



PAWS: First Pilot in the Field

(AAMAS 2017)



Ford

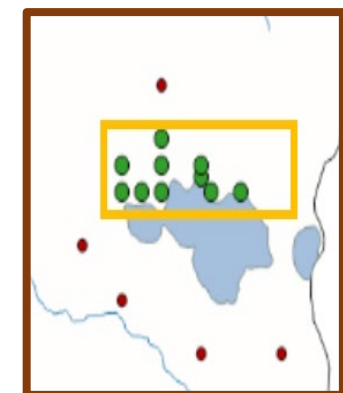
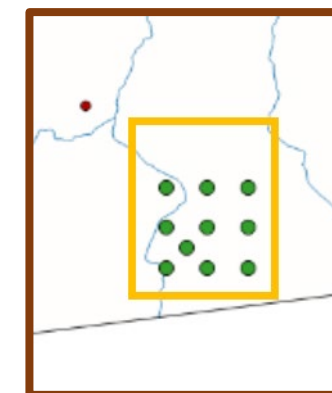
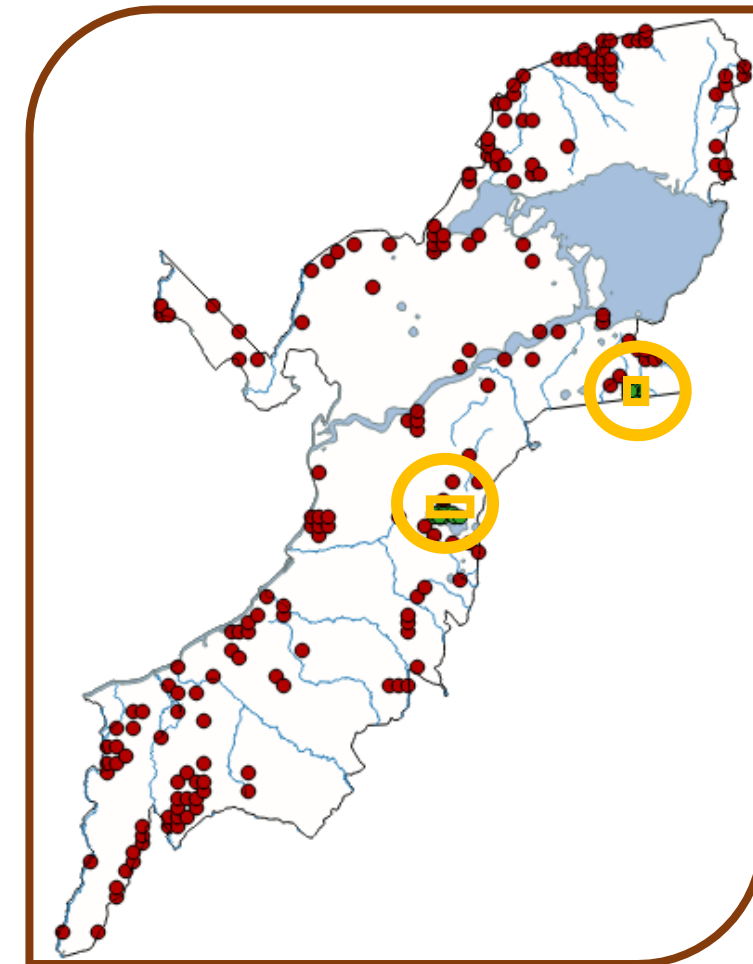


Gholami

- Two 9-sq.km areas, infrequent patrols



- Poached elephant
- 1 elephant snare roll
- 10 Antelope snares



PAWS Predicted High vs Low Risk Areas: 2 National Parks, 24 areas each, 6 months

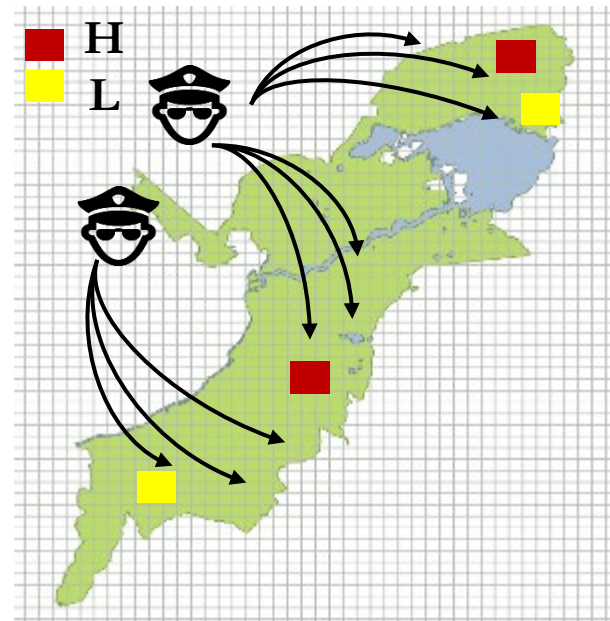
(ECML PKDD 2017, ICDE 2020)



Ford

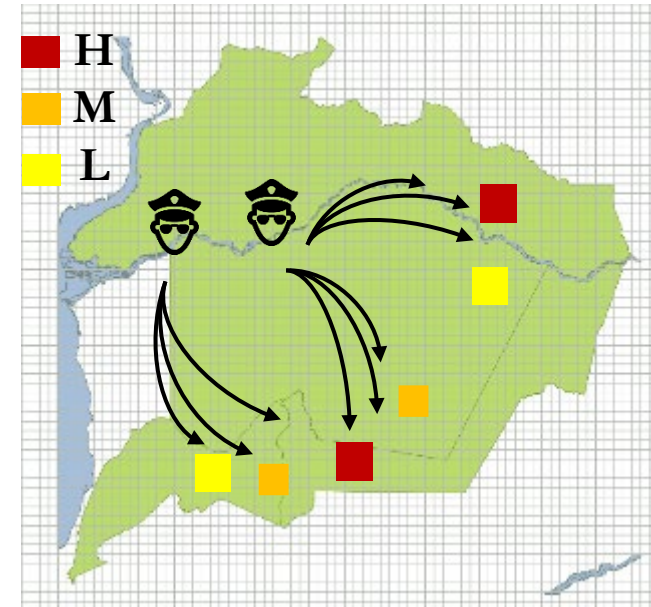
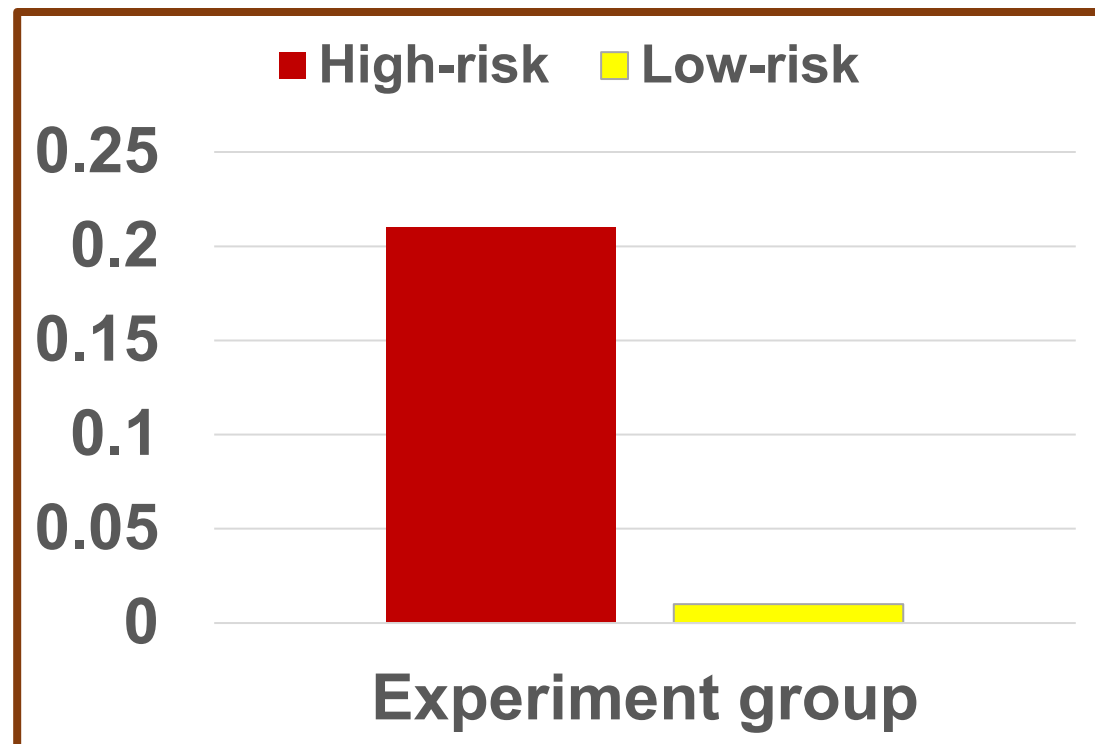


Gholami



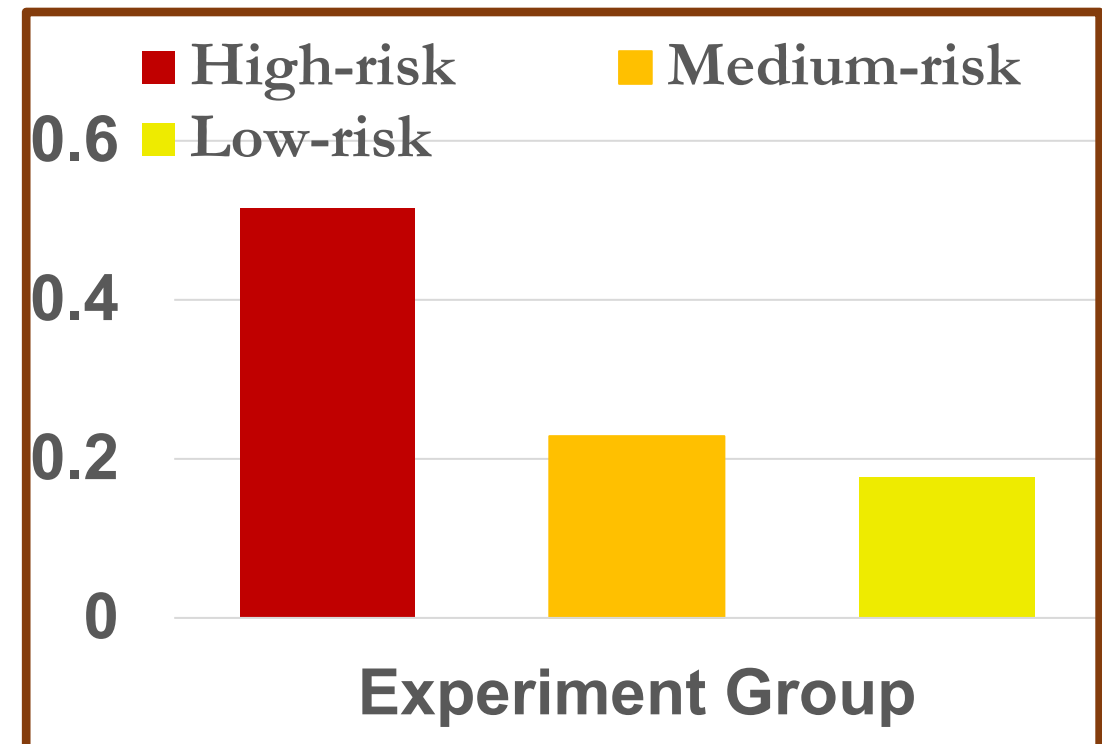
Queen Elizabeth National Park

Snares per patrolled sq. KM



Murchison Falls National Park

Snares per patrolled sq. KM



PAWS Real-world Deployment

Cambodia: Srepok Wildlife Sanctuary [2018-2019]

Srepok Wildlife Sanctuary has been identified as the most suitable site for **tiger reintroduction** in Southeast Asia.



PAWS Real-world Deployment Cambodia: Srepok Wildlife Sanctuary

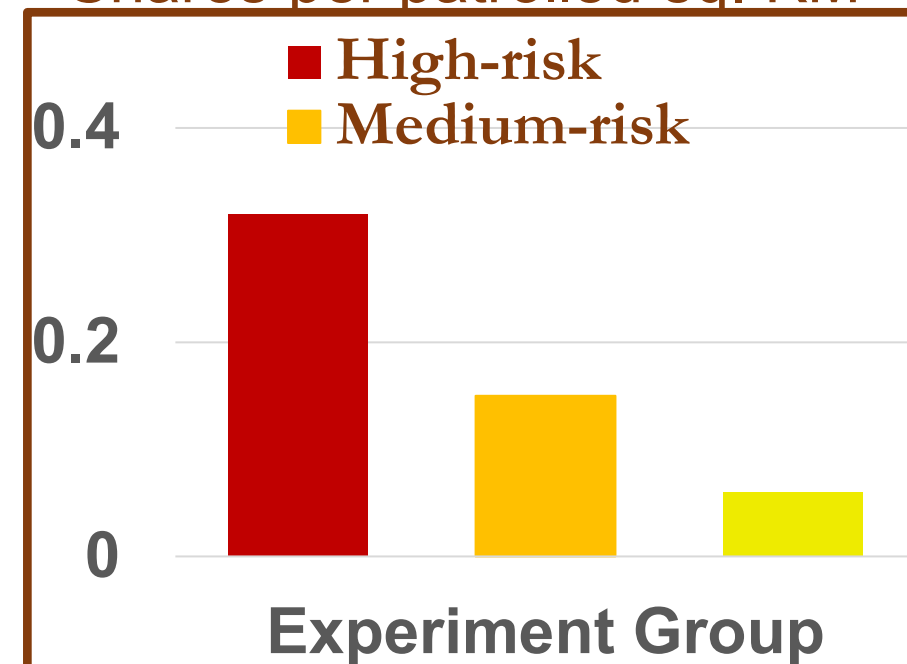
(ICDE 2020)



Xu



Snares per patrolled sq. KM



2019: 521 snares/month

VS

2018: 101 snares/month

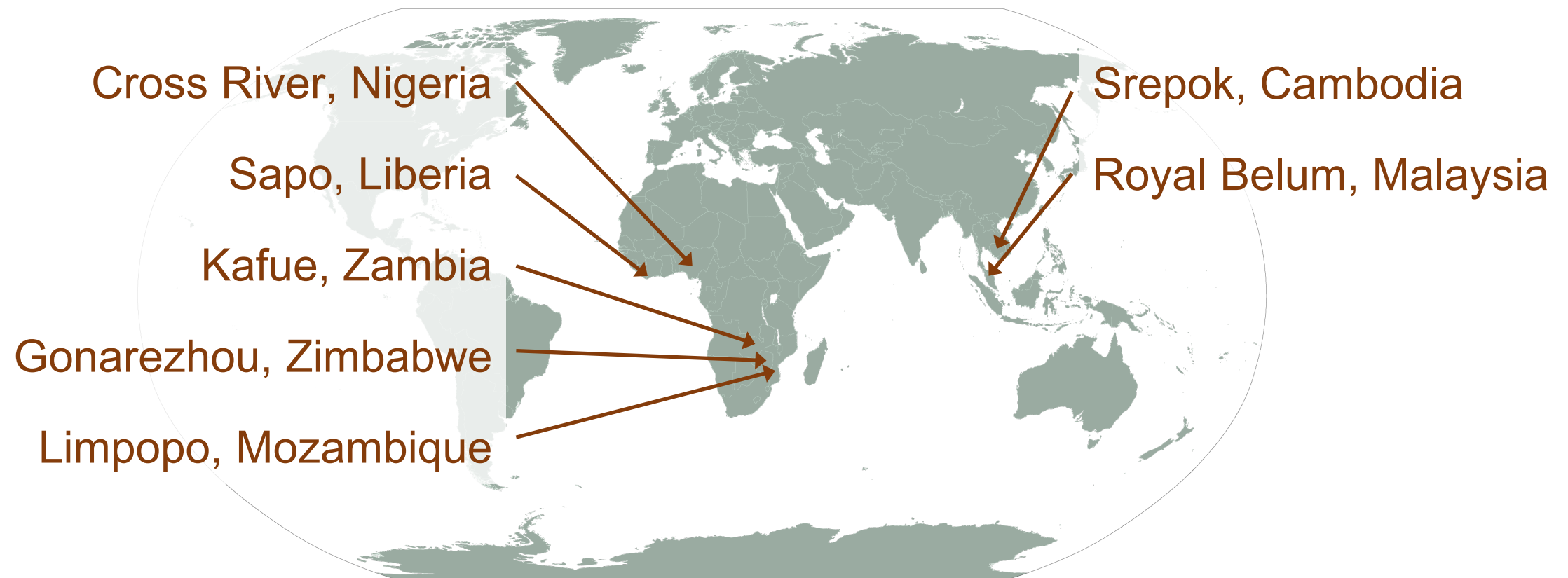
2021 PAWS

1,000 snares in March

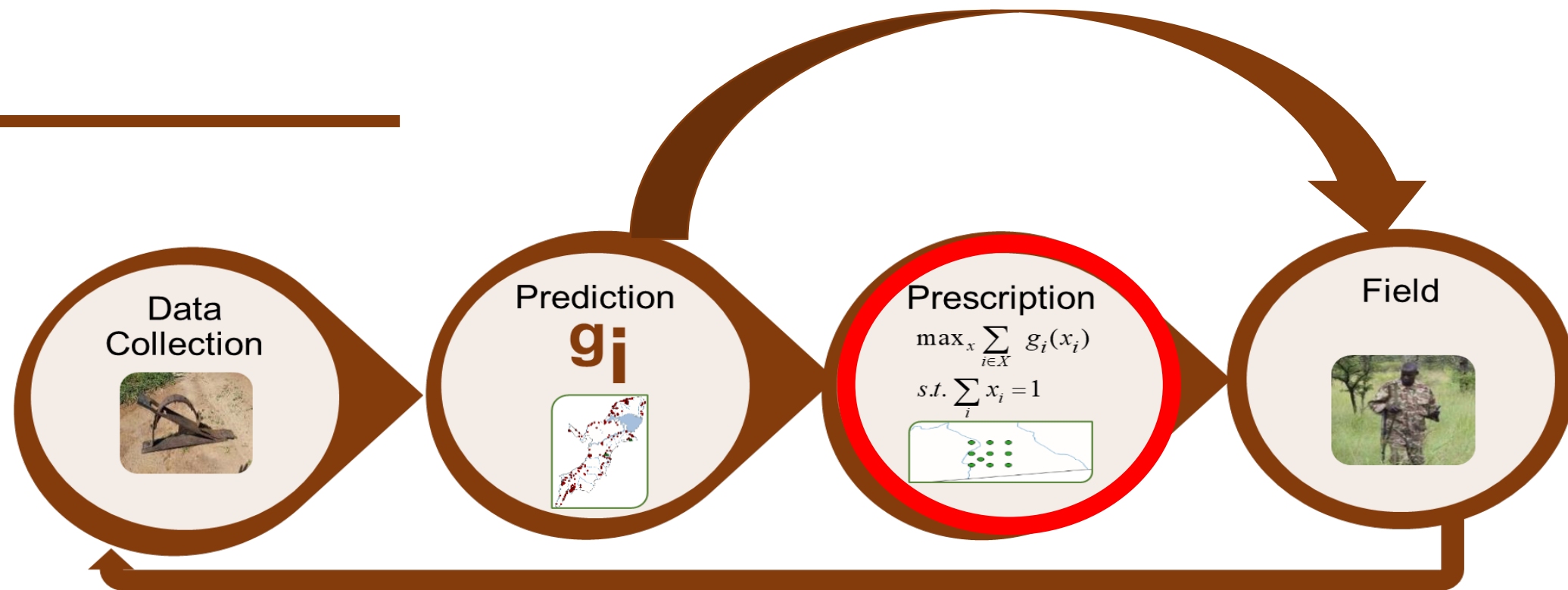
PAWS GOES GLOBAL with SMART platform!!



**Protect Wildlife
800 National Parks
Around the Globe**



Prescription Phase to Improve Recommendations



| | Area1 | Area2 |
|-------|-------|-------|
| Area1 | 4, -3 | -1, 1 |
| Area2 | -5, 5 | 2, -1 |

Is Adversary observing & Reacting to Patrols?

Evidence from the Field Justifies Stackelberg Assumption



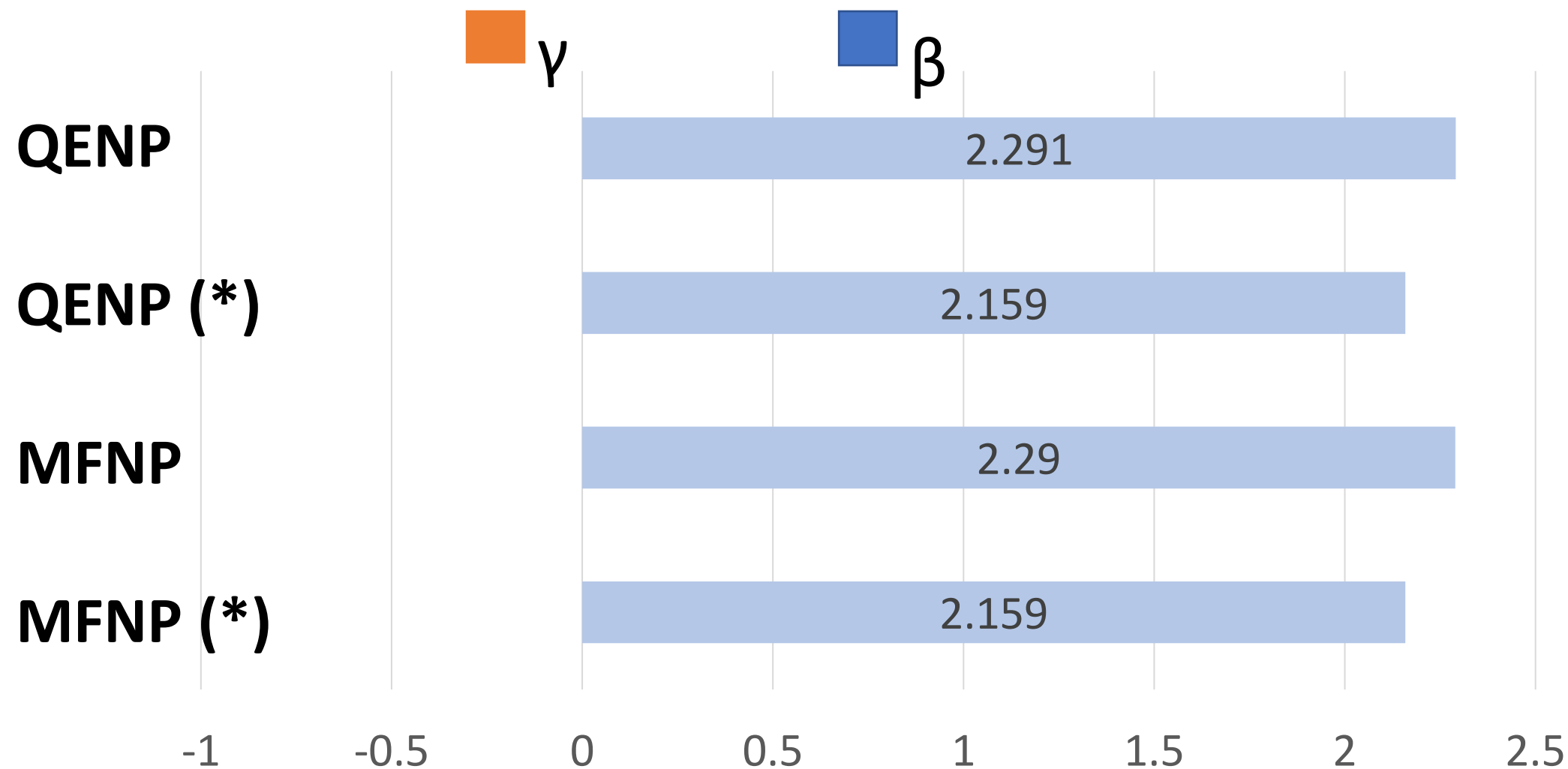
Xu



Perrault

- Logistic regression model

$$a_i + \gamma \cdot \text{past_effort} + \beta \cdot \text{current_effort}$$



Demonstrating Deterrence: Evidence from the Field Justifies Stackelberg Assumption (UAI 2021)



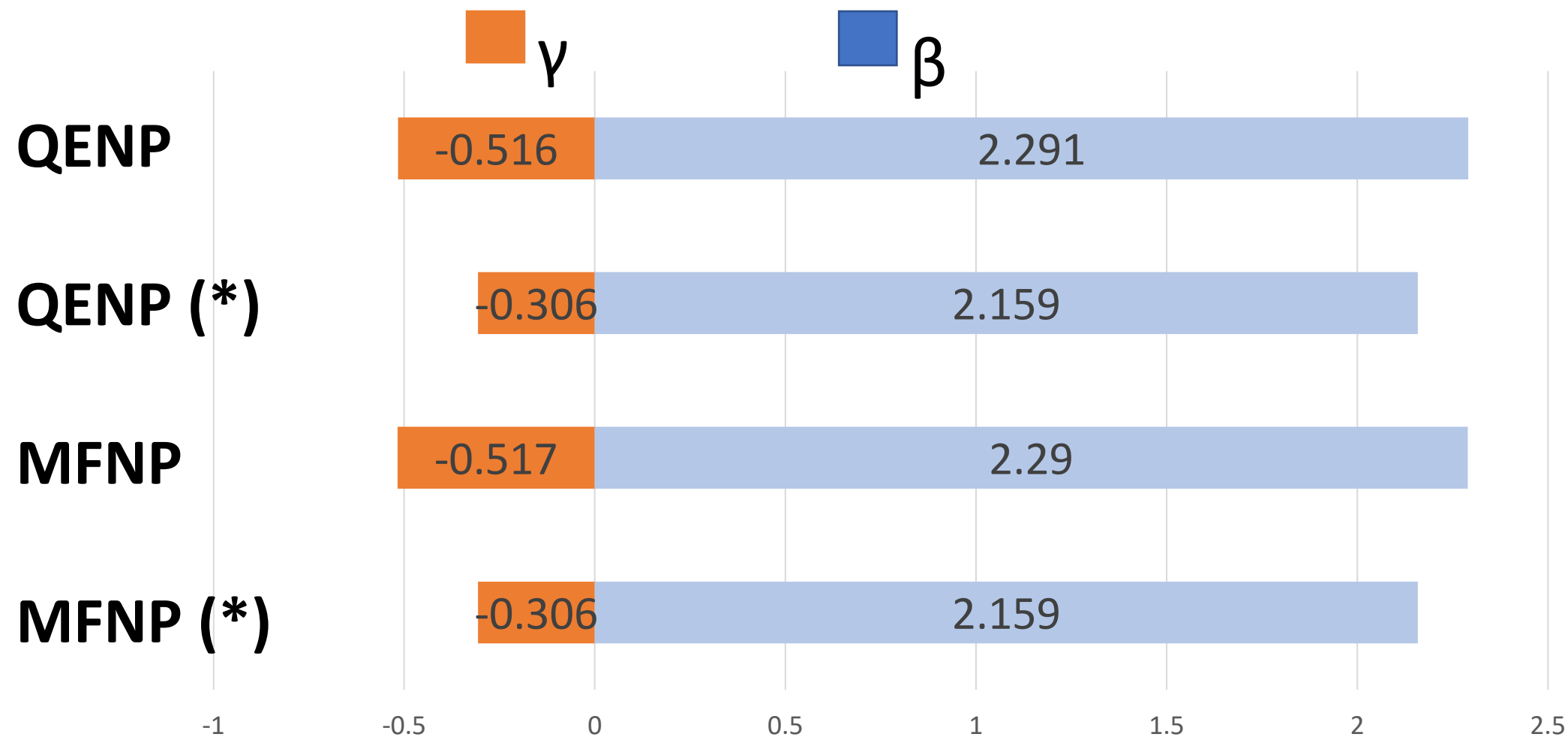
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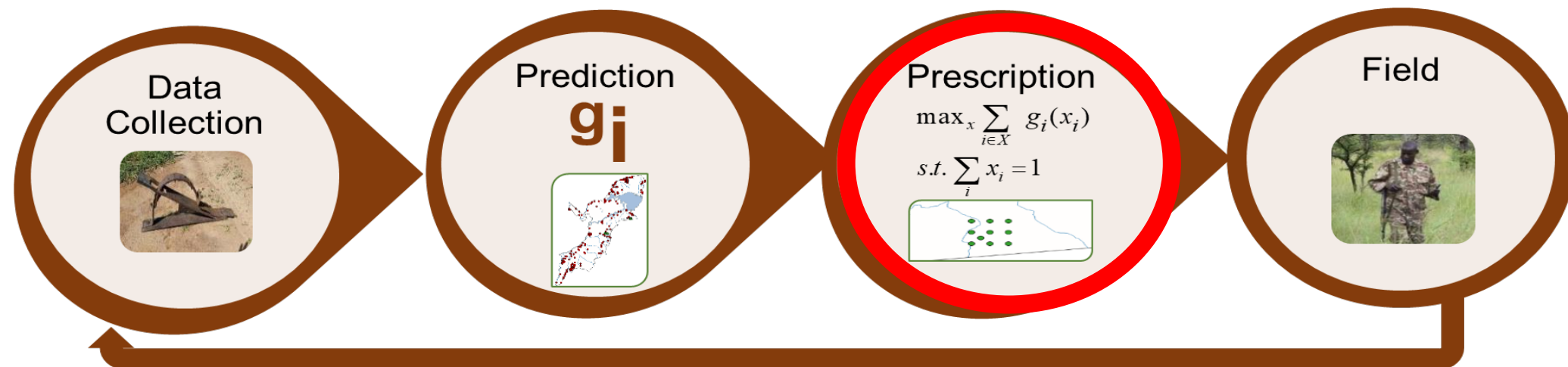
Perrault

- Is adversary observing & reacting to patrols? Logistic regression model

$$a_i + \gamma \cdot \text{past_effort} + \beta \cdot \text{current_effort}$$



New Challenges in Solving Games to Prescribe Patrols



| | Area1 | Area2 |
|-------|-------|-------|
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Patrol Routes in Complex Terrain: Solving Security Game with Learned Adversary Model

- Solving Stackelberg security game with learned adversary model
 - Difficulty of generating routes: many constraints on patrols



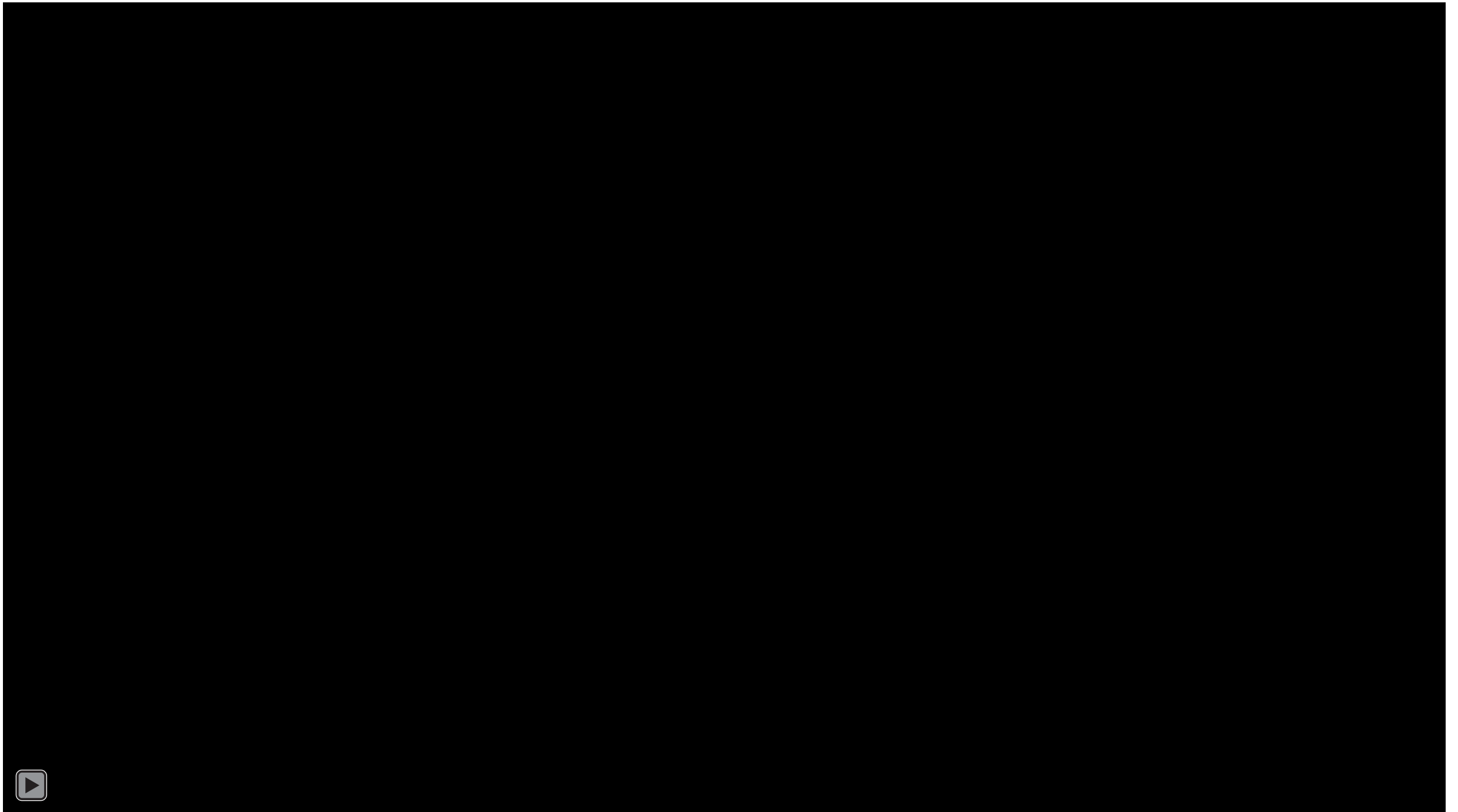
Malaysia:
Tamen Negara



Panthera



PAWS: Protection Assistant for Wildlife Security



Challenge: Uncertainty in Deterrence-Based Patrol Planning *(UAI 2021)*



Xu



Perrault

$$a_i + \gamma \cdot \text{past_effort} + \beta \cdot \text{current_effort}$$

Uncertainty in exact parameter value



Robust planning

evaluated in terms of **regret**: how well we could have done

Patrol in time T affects adversary behavior in time $T + 1$



Sequential decision making

MIRROR: Deterrence-Based Patrol Planning

Simulation Results (UAI 2021)

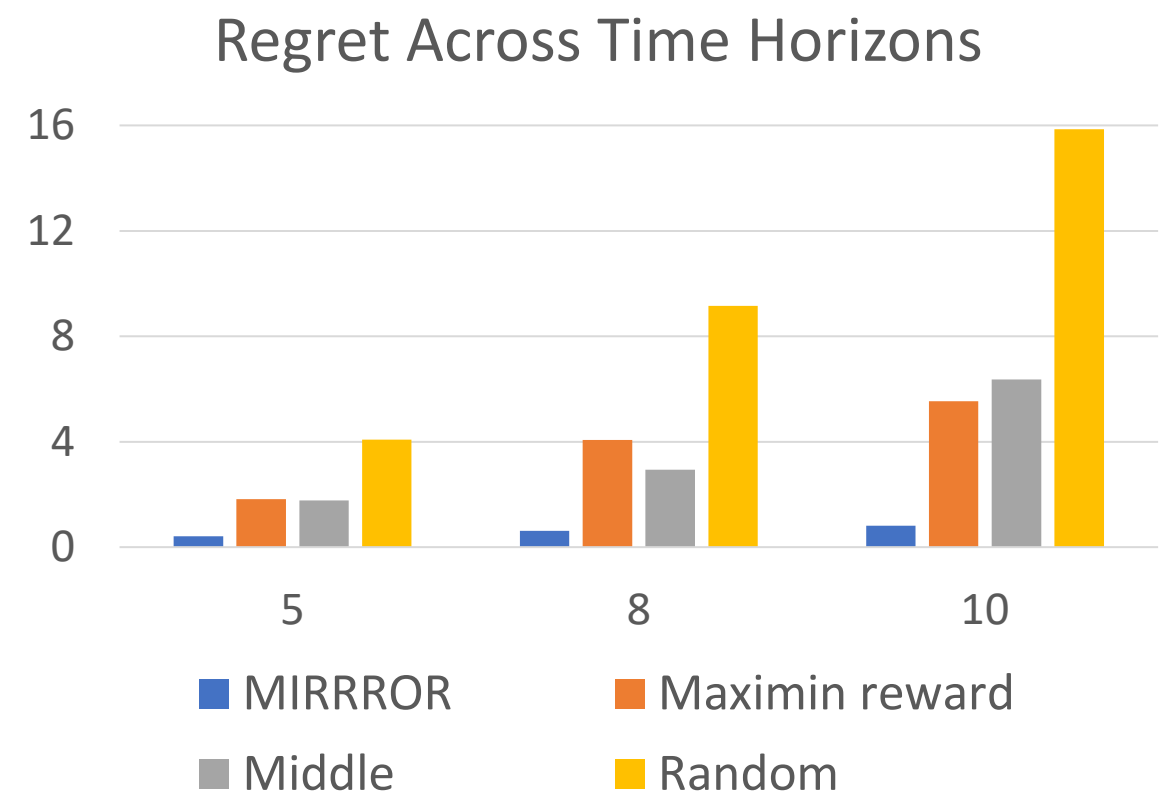
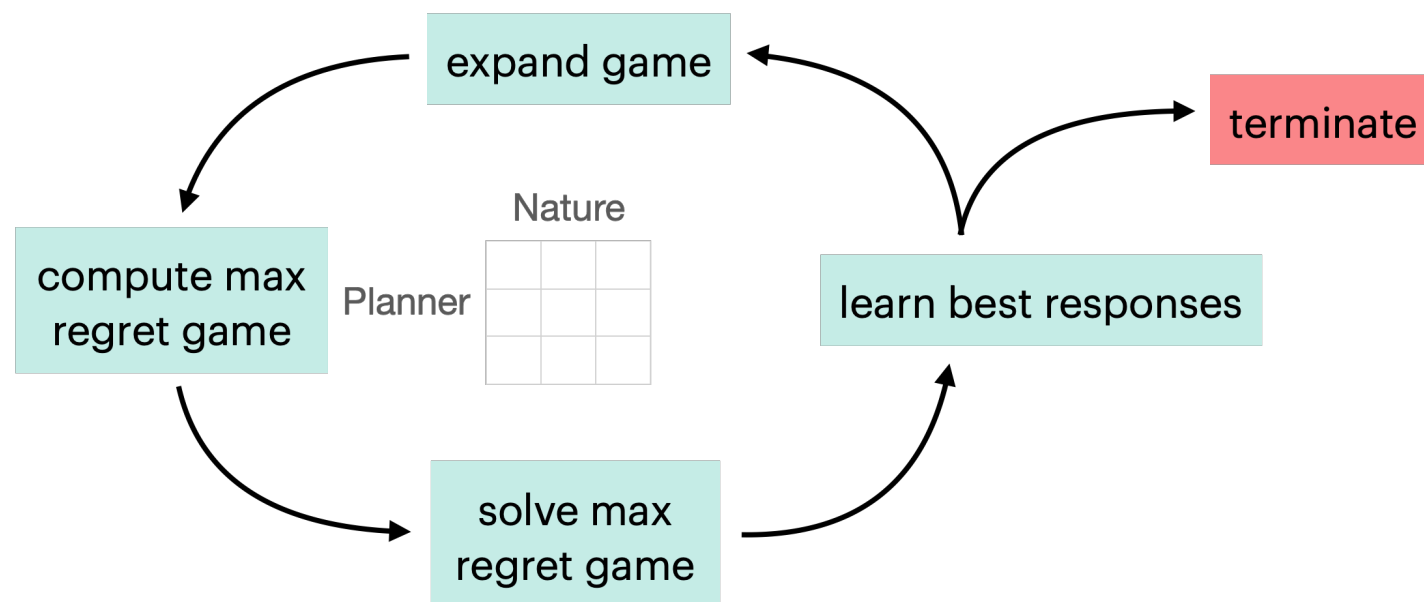


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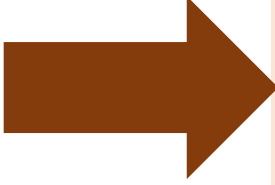


Perrault

- Game-theoretic interaction between planner and nature
- Iteratively solve for equilibrium then learn best response
- Final strategy is guaranteed to minimize max regret



Outline: AI for Wildlife Conservation

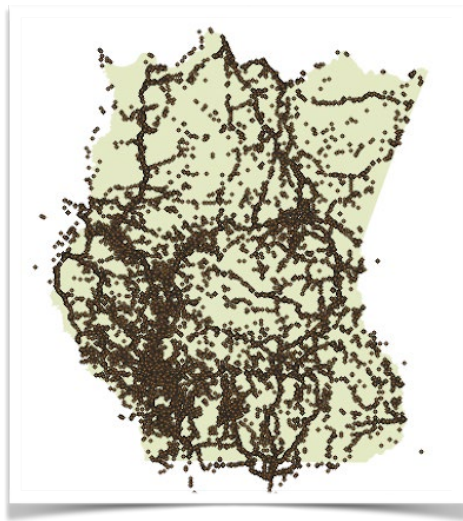
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Direction #2: Data Scarce Parks



Xu

Data-rich parks: build predictive models to plan patrols

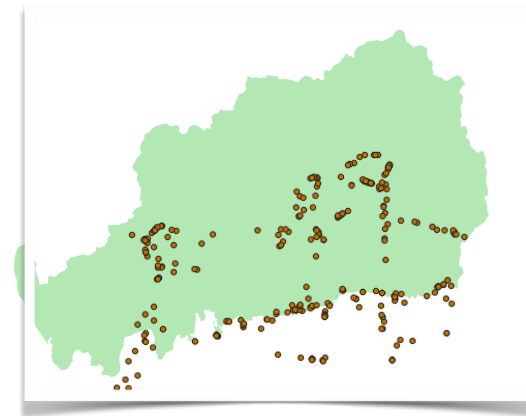


Srepok, Cambodia
43,269 patrol observations
2013 – 2018

Data-scarce parks: conduct patrols to detect illegal activity and collect data to improve the predictive model

exploitation

exploration



Royal Belum, Malaysia
824 patrol observations
June – August 2018

LIZARD: Multiarmed Bandit

Lipschitz Arms with Reward Decomposability

(AAAI 2021)



Xu

- Input: N Targets with features, T Time Horizon
- Stochastic adversary, who places snares at targets
- Patrolling algorithm: Specify patrol effort in each target up to budget B
- Reduce regret wrt OPT , optimal patrol effort, for capturing snares

Lizard exploits decomposability, smoothness, monotonicity

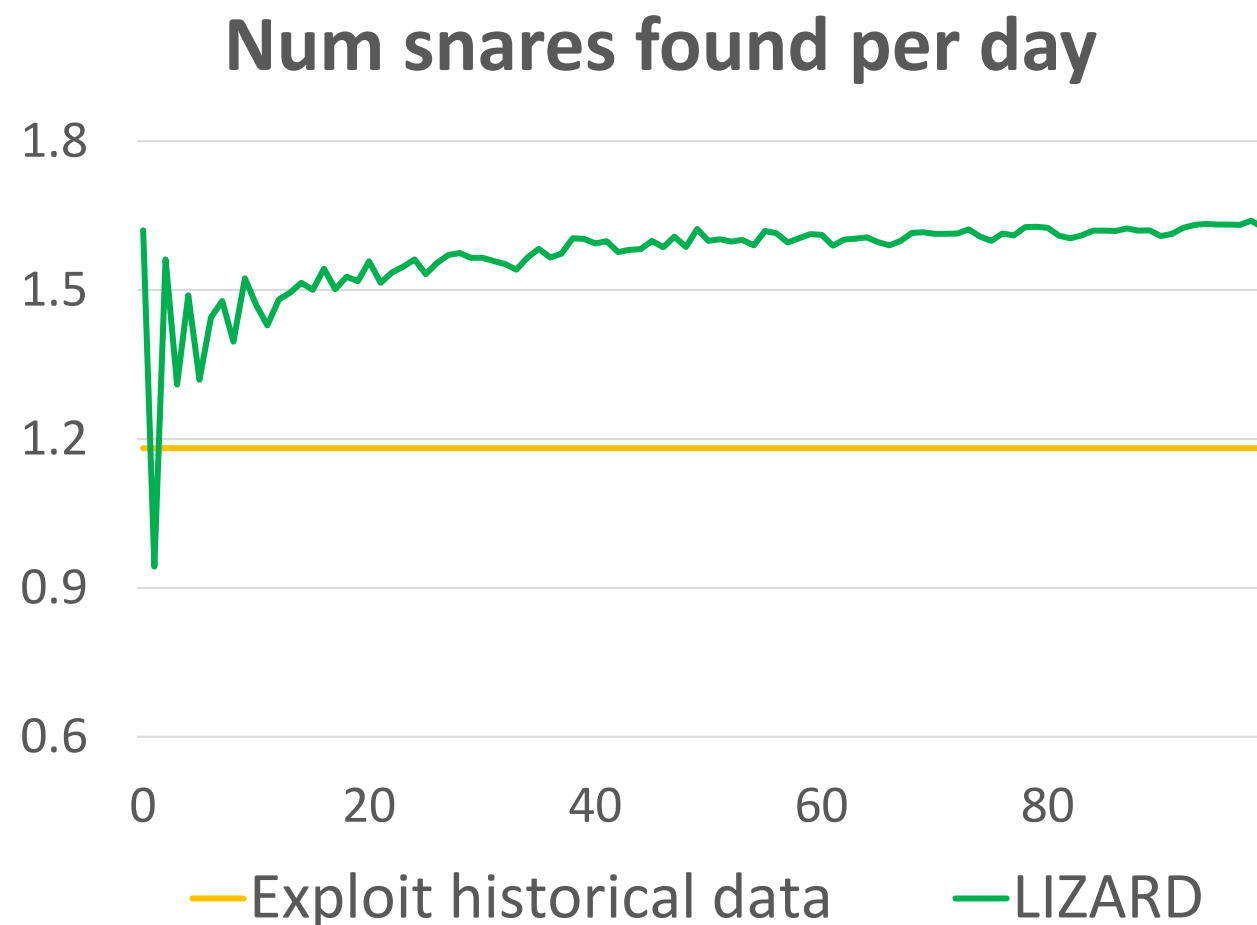


LIZARD: Multiarmed Bandit SIMULATION

(AAAI 2021)



Xu



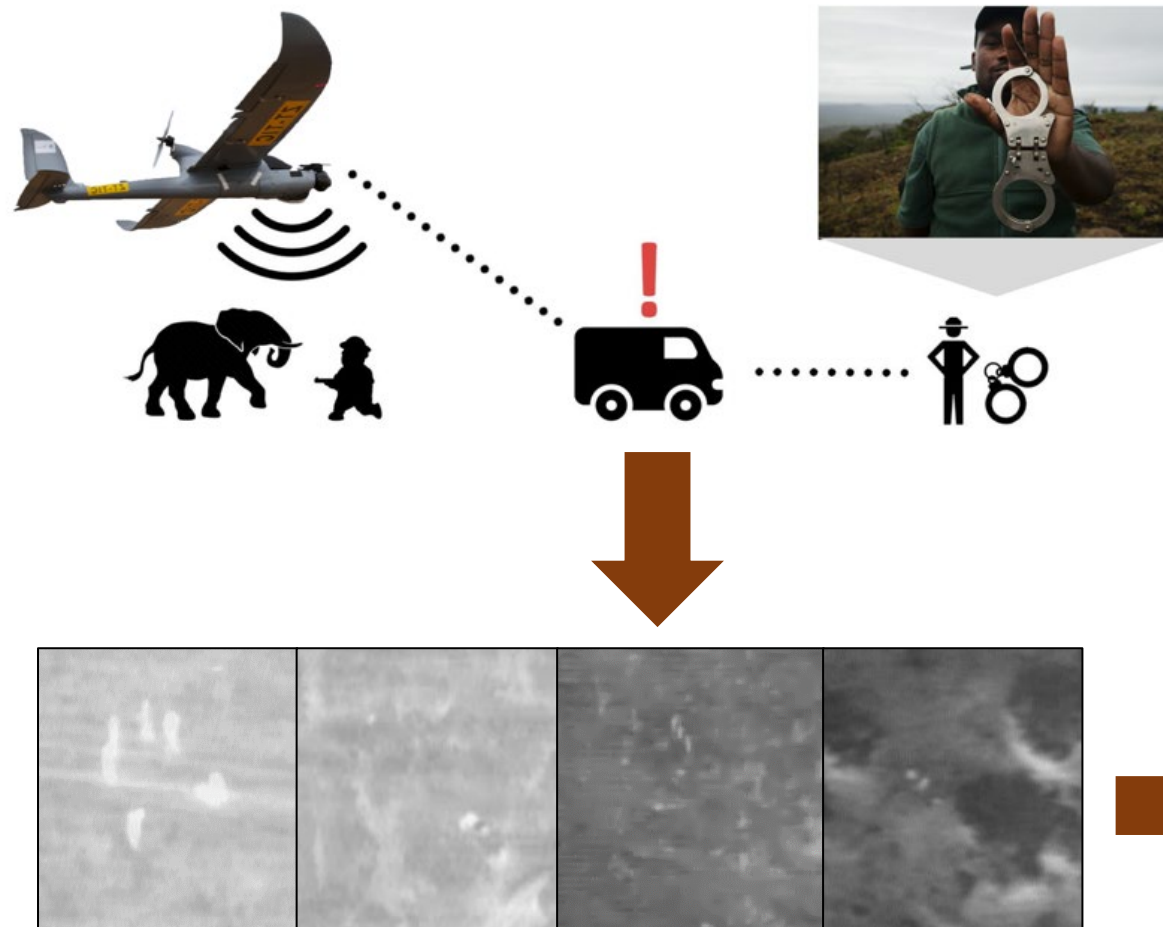
**Proactively exploring areas with high uncertainty
allows us to find more snares in the long run**

Green Security Games: Integrating Real-Time “SPOT” Information

(IAAI 2018)



Bondi



Goal: automatically find poachers

Drone Used to Inform Rangers

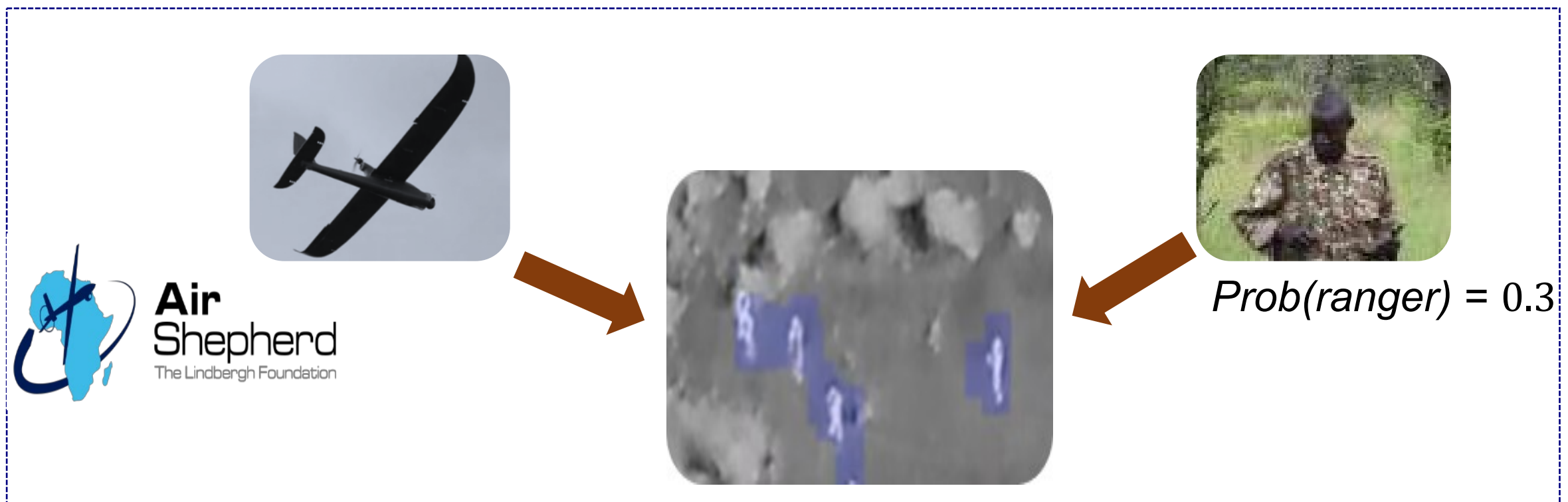


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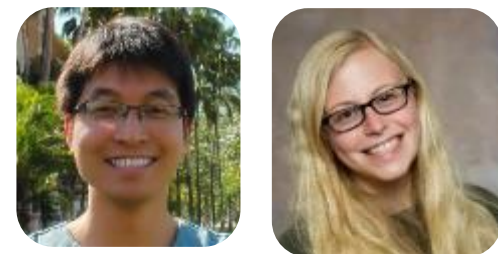


Bondi

- $Prob(ranger\ arrives) = 0.3$ [poacher may not be stopped]
- Deceptive signaling to indicate ranger is arriving



Drone Used to Inform Rangers



Xu

Bondi

- $Prob(\text{ranger arrives}) = 0.3$ [poacher may not be stopped]
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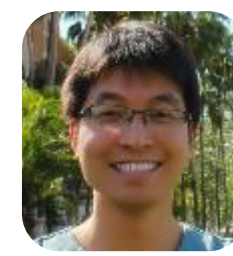
Bondi

- $Prob(ranger\ arrives) = 0.3$ [poacher may not be stopped]
- Deceptive signaling to indicate ranger is arriving
- Must be strategic in deceptive signaling



Exploiting Informational Advantage Defender Knows Pure & Mixed Strategy

(AAAI 2018, AAAI 2020, AAMAS 2021)



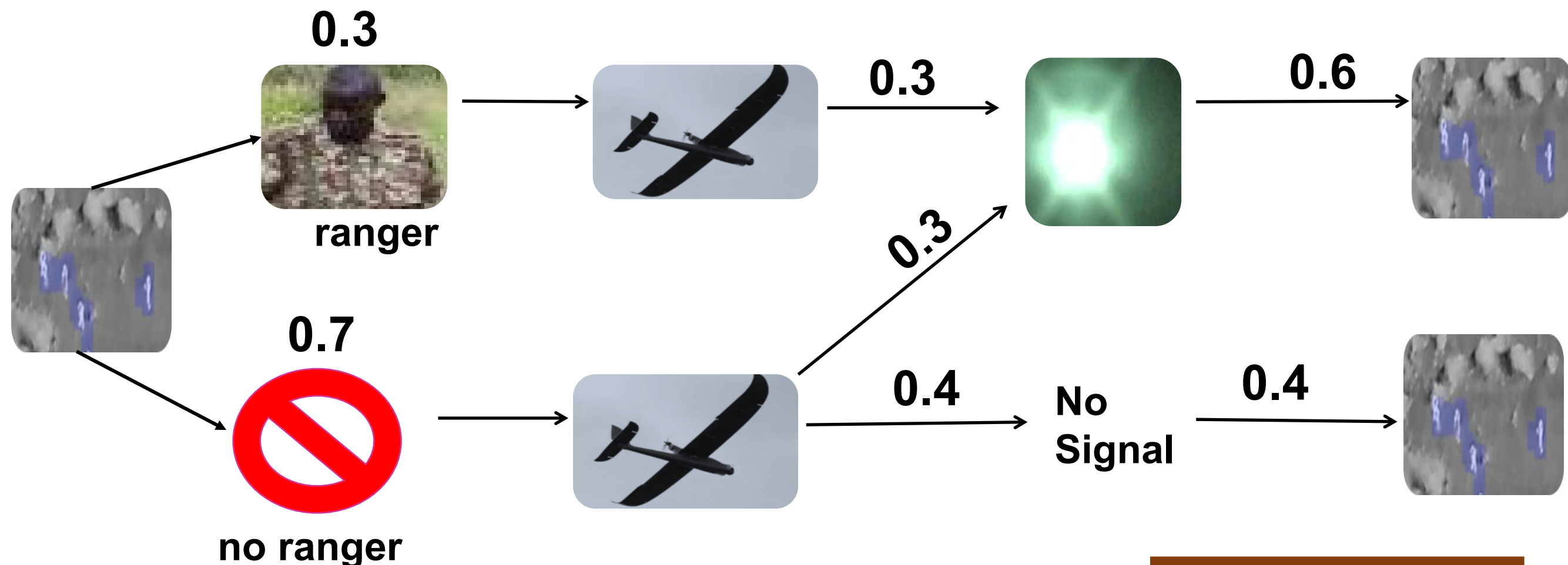
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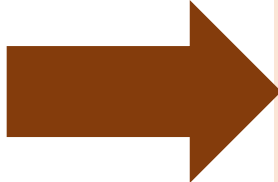
Bondi

Si-G Model: Stackelberg Security Games with Optimal Deceptive Signaling

- Poacher best interest to “believe signal” even if know 50% defender deception
- Recent work used RL for deception policy generation (AAMAS 2021)



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AI4SG Workshop - November 2019



- NGOs, Academics (AI, Policy, Sociology), Googlers
- 25+ Proposals submitted in 2 days
- Selected six projects as combination NGO+academics +Googlers

AI4SG Workshop - November 2019

Partners

Public Health:



Conservation:



ASHOKA TRUST FOR RESEARCH IN
ECOLOGY & THE ENVIRONMENT



Education:



Academic Partners:

IIT Madras, IIIT Delhi,

Singapore Management University, Nanyang Tech



Google Research India is based out of Bengaluru and will be part of and support Google's global network of researchers (Bloomberg)

Google funds six AI-based research projects in India

1 min read . Updated: 18 Feb 2020, 02:52 PM IST
ANS

- Google Research India will provide each team with funding and computational resources in addition to supporting the efforts
- Among the six projects are improving health information for high HIV/AIDS risk communities from team from IIT Delhi



from healthcare to wildlife conservation,
Google launches six AI research projects
in India

Poona M Published: | 18th February 2020 12:59 PM



Google Research

AI4SG Workshop – May 2021

Workshop on AI for Social Good

[Home](#) · [Organizers](#) · [Application Details](#) · [2019 Projects](#)

AI for Social Good Workshop, Google

**Deadline for proposal submission for workshop
attendees : March 1, 2021**

Google is excited to launch the second call for applications to join a collaborative NGO + academic AI for Social Good workshop.

- 180 academics
- 180 NGOs
- 30 winners!
- \$20K for NGO, \$10K for researcher

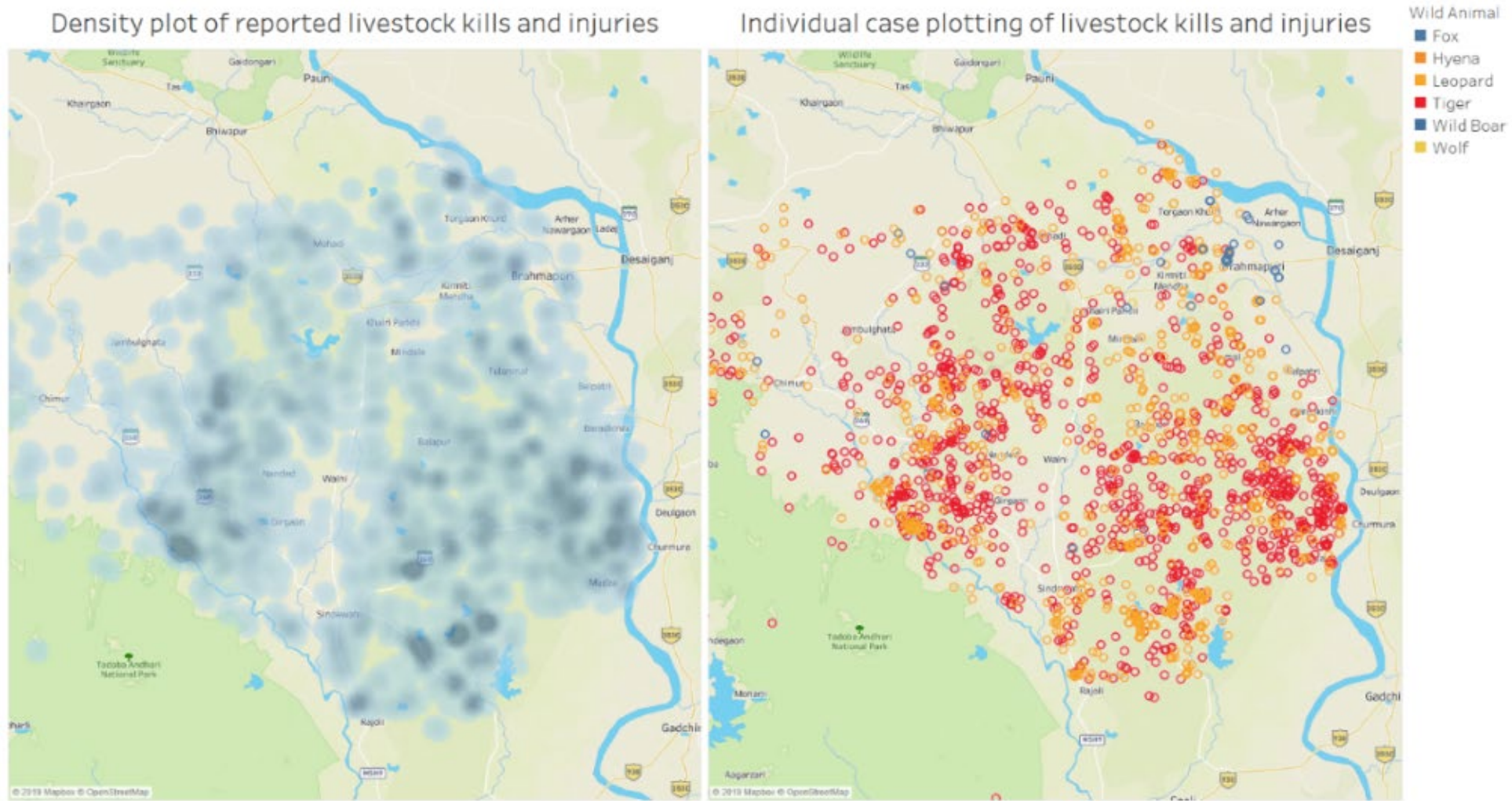
Google Research

Wildlife Conservation Trust



- Most forest areas in India are multi-use, instead of being Protected Areas.
- Wild animals & humans co-habit
- High density of carnivores and herbivores – scope for conflicts with humans with loss of crops, cattle and lives

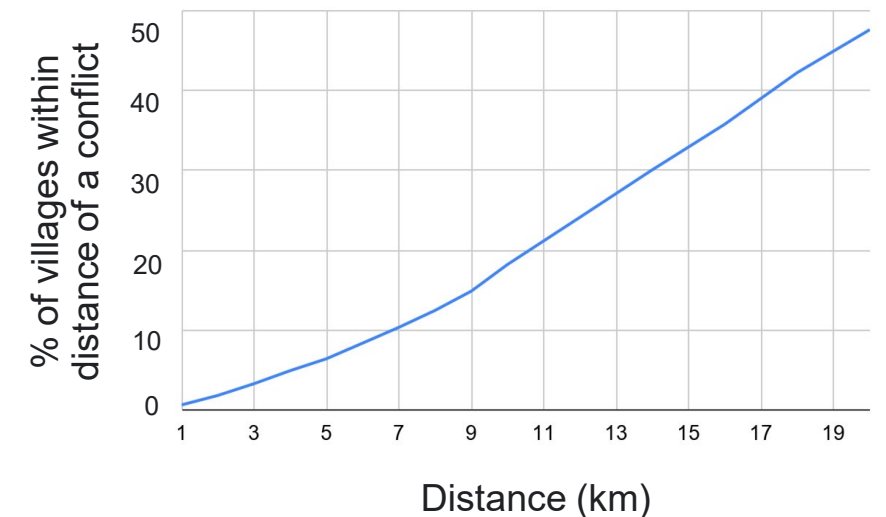
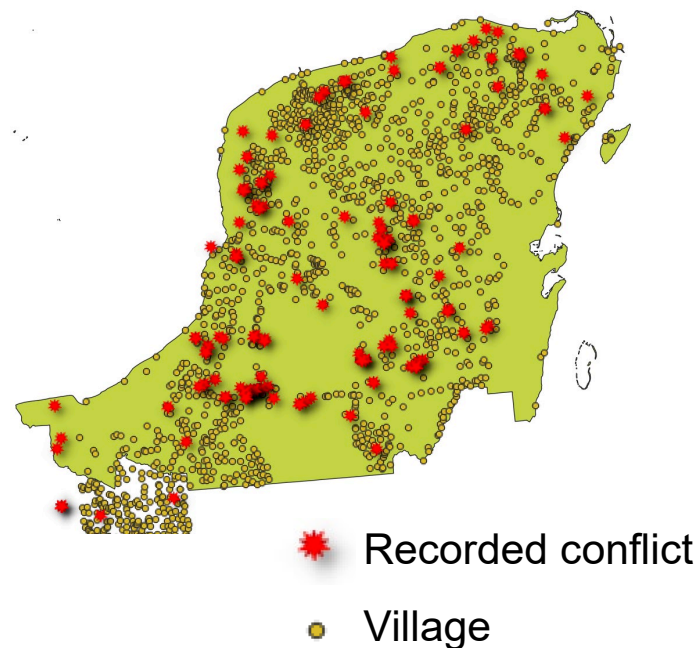
Conflict Map: Maharashtra



Given past data of conflicts, cultivated crops, village boundaries, animal movements can we predict conflict?

Human-Wildlife Conflict: Mexico

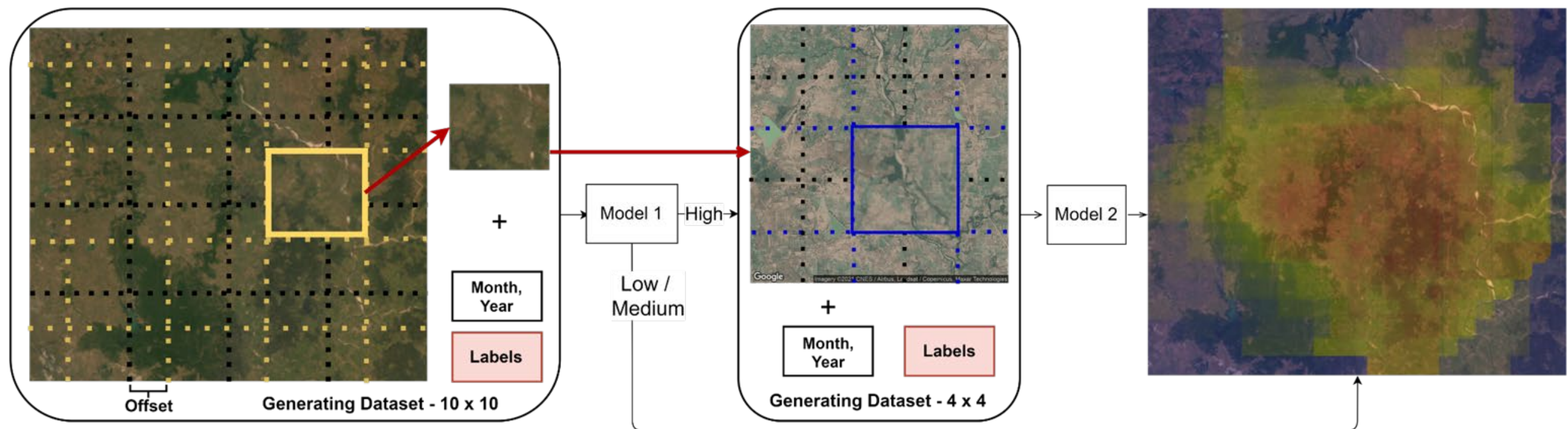
- *Problem:* Livestock depredation by coyotes, pumas, and jaguars
- *Data:* Insurance reports from 2017–2019
- *Mitigation strategies:* Build electric fences, train ranchers



Conflicts in the Maya Forest, Mexico

Hierarchical solution

- Limited data - use offsets to create more training samples
- Two step classification - macro (bigger) and micro (smaller)
- 80.4% accuracy - with 76% precision and 76% recall for conflict areas.



Future: AI for Social Impact (AI4SG or AI4SI)



Achieving social impact & AI innovation go hand in hand



Empower non-profits to use AI tools; avoid being gatekeepers to AI4SI tech



Data to deployment: Not just improving algorithms, new AI4SI evaluation



Important to step out of the lab and into the field



Embrace interdisciplinary research -- social work, conservation



Lack of data is the norm, a feature; part of the project strategy

Key Collaborators on Papers Referenced

(In the order papers referenced)



Invitation to collaborate!

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