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# AI-BASED SOLUTIONS FOR WILDLIFE SECURITY

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# Collaborations

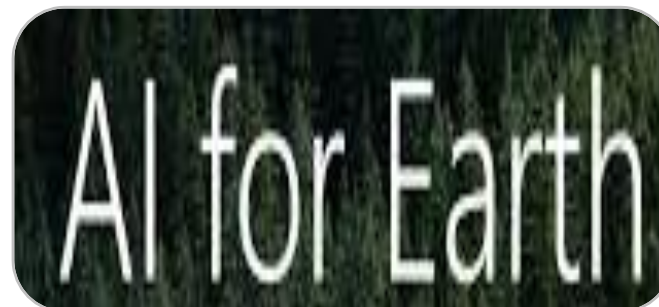


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School of Social Work

USC Viterbi  
School of Engineering

USC CENTER FOR ARTIFICIAL INTELLIGENCE IN SOCIETY

Carnegie Mellon University  
School of Computer Science



# Deployed AI-based Application: Protection Assistant for Wildlife Security (PAWS)



WCS



WWF



Panthera



Uganda



Indonesia



Malaysia

Field study in Indonesia





# Wildlife Protection

Wildlife



Snares for poaching



Rangers patrolling

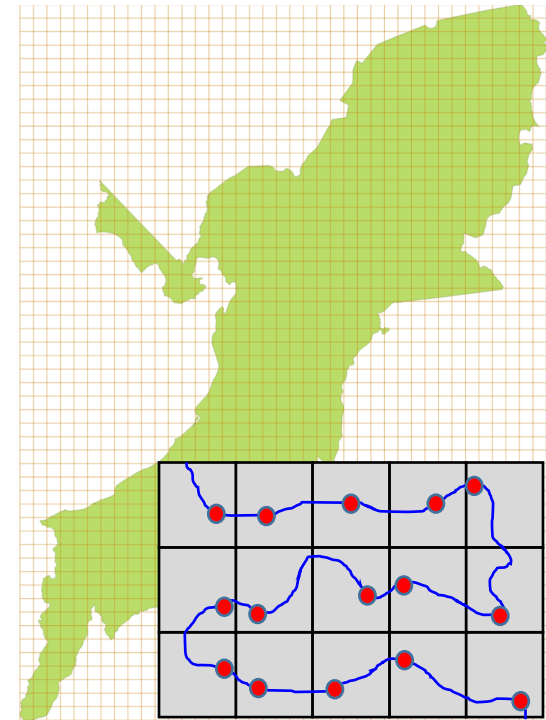




# Wildlife Protection: Security Game Model

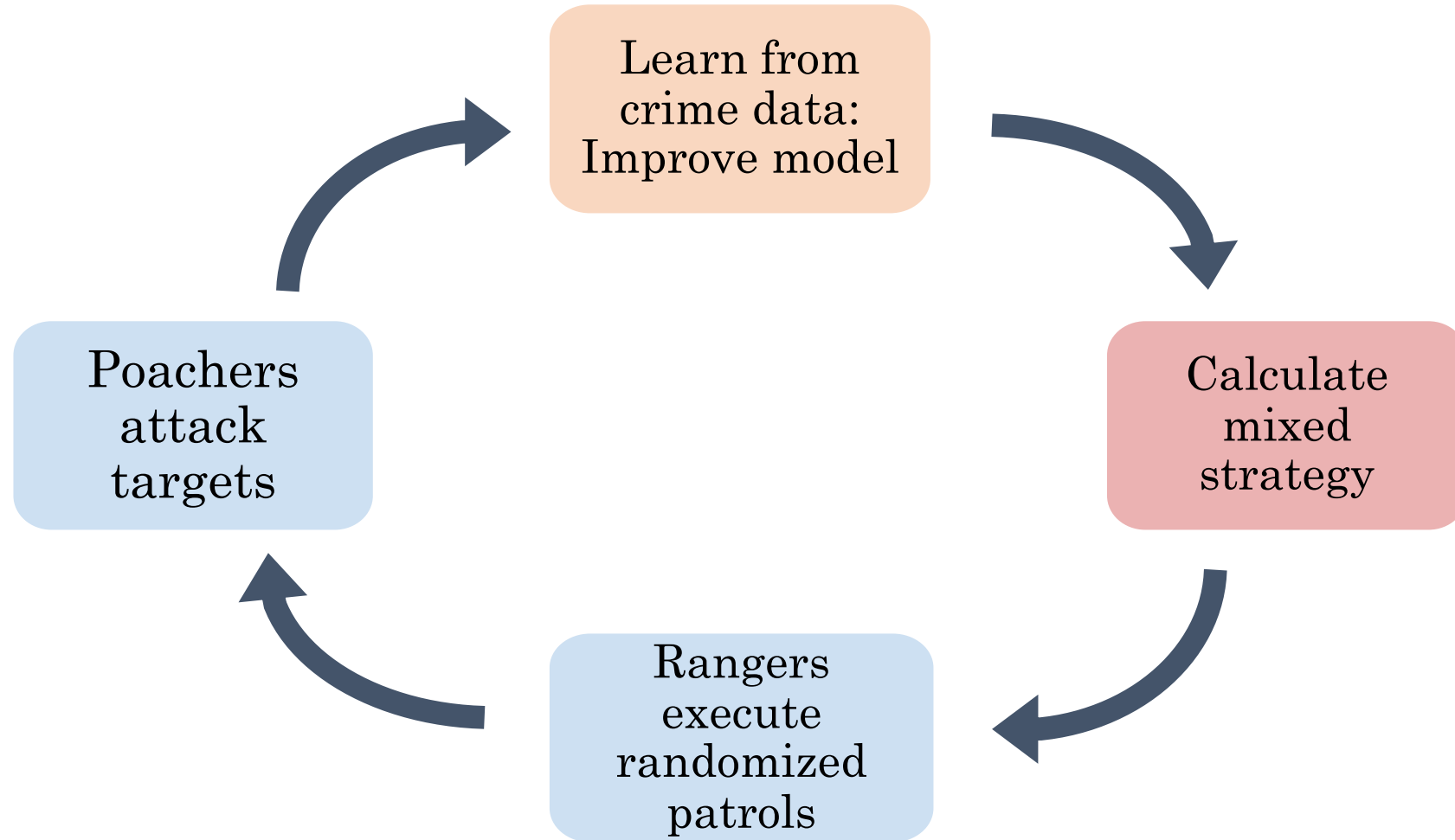
- Forest area
  - Divided into a grid, cell  $\sim$  target
  - Target values: e.g. animal density
- Rangers
  - Conduct patrols
- Poachers
  - Set trapping tools (e.g. snare)

Queen Elizabeth National Park  
(QENP)



# PAWS: Repeated Security Game Model

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# Poacher Behavioral Modeling and Learning: Research Question

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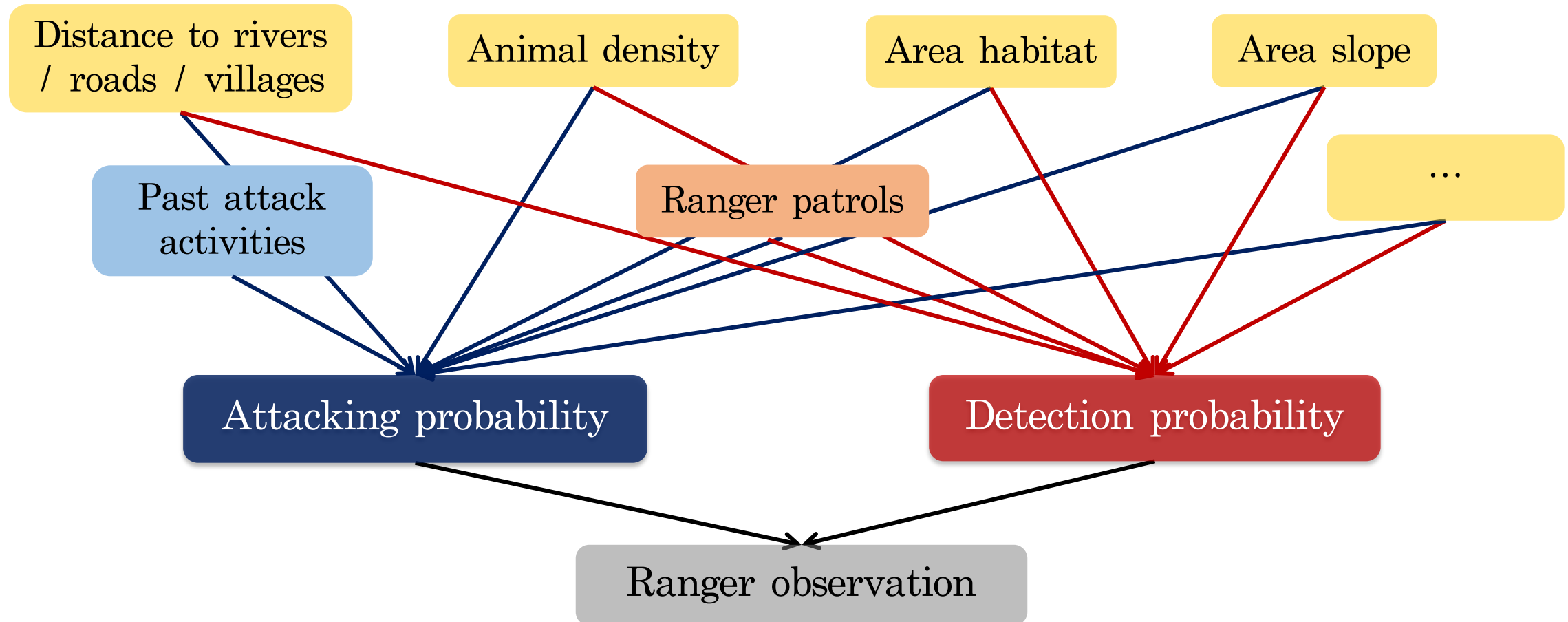
How to Model Human Poacher Behavior  
in Real World?

## CHALLENGE

- Take into account **domain features**
- Handle complex **temporal dependence** of behavior
- Cope with **imperfect observations** of poaching



# CAPTURE Model



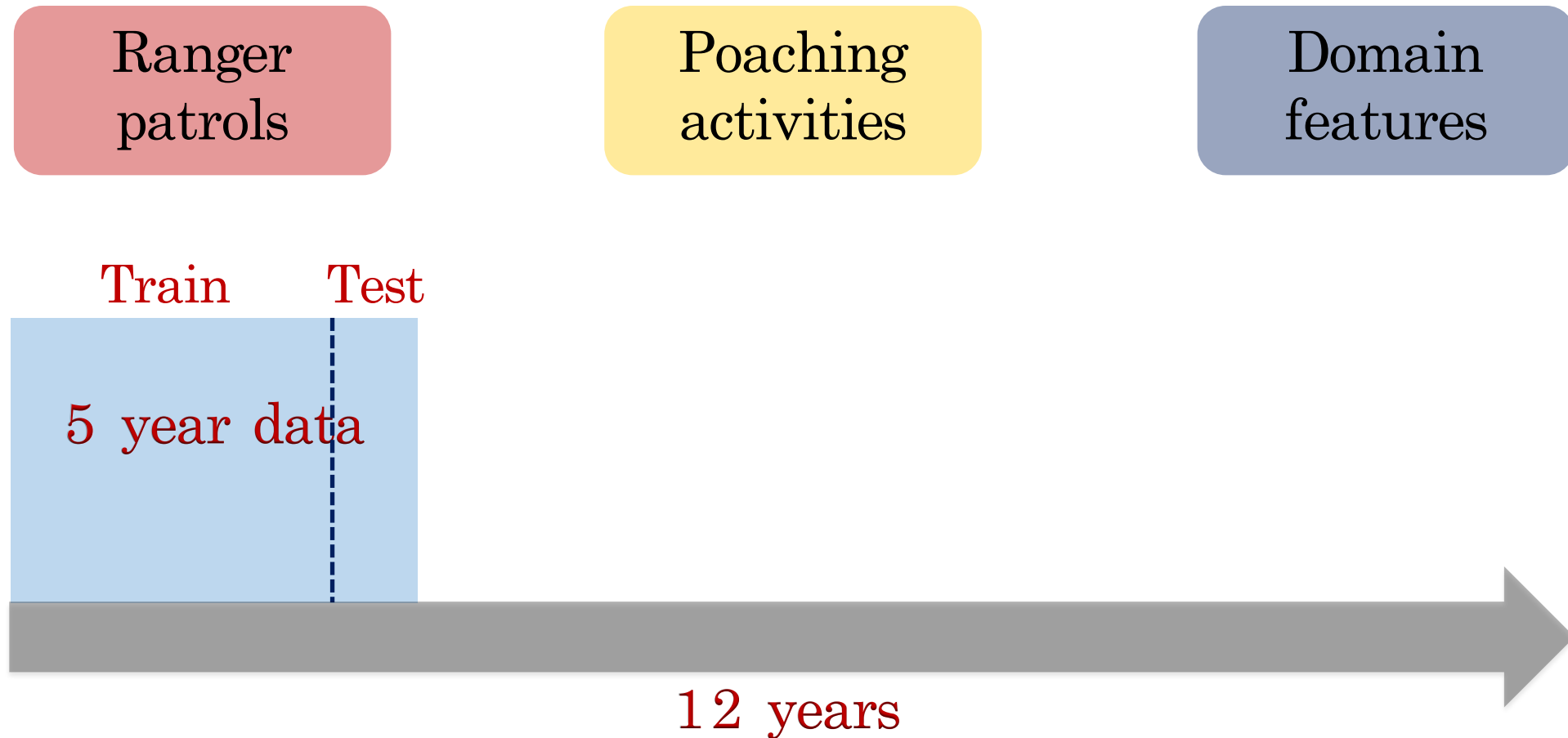
# Model Evaluation

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- Behavioral models
  - CAPTURE model
  - Machine learning models: Support Vector Machine (SVM), Logistic regression
- Real-world patrol/poaching data
  - Queen Elizabeth National Park (QENP):  $\sim 2500 \text{ km}^2$
  - 12-year patrols
  - $\sim 125000$  observations
  - 6 types of illegal activities

# Real-world Data of 12 Years

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# Model Comparison

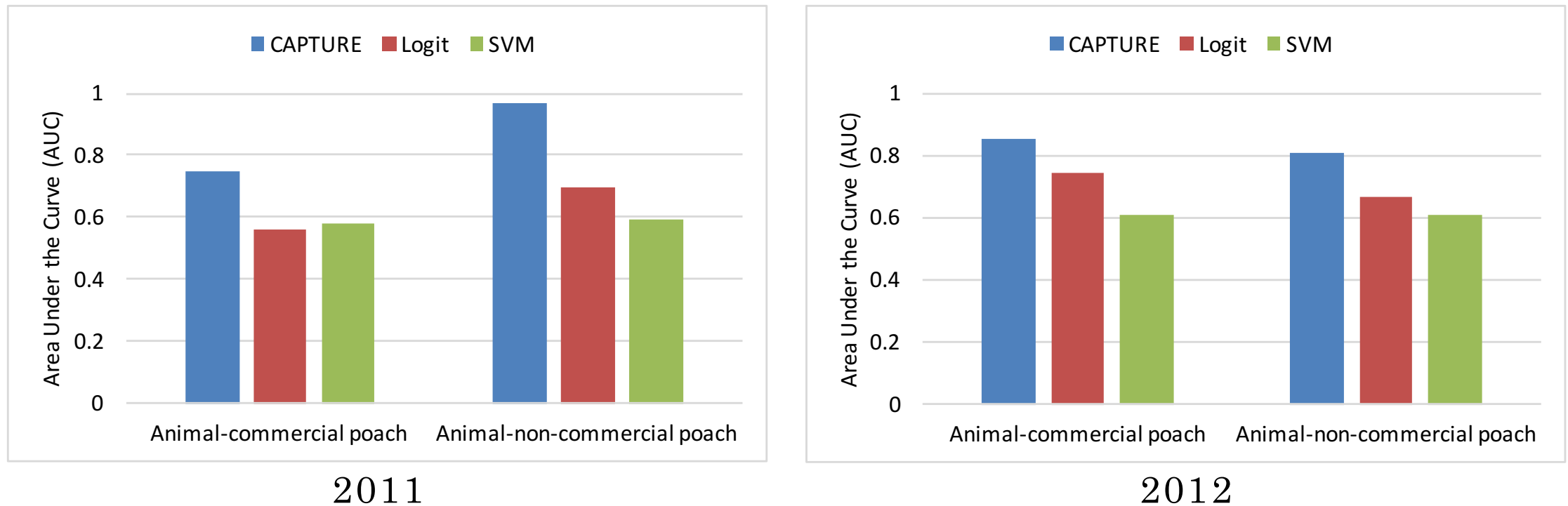
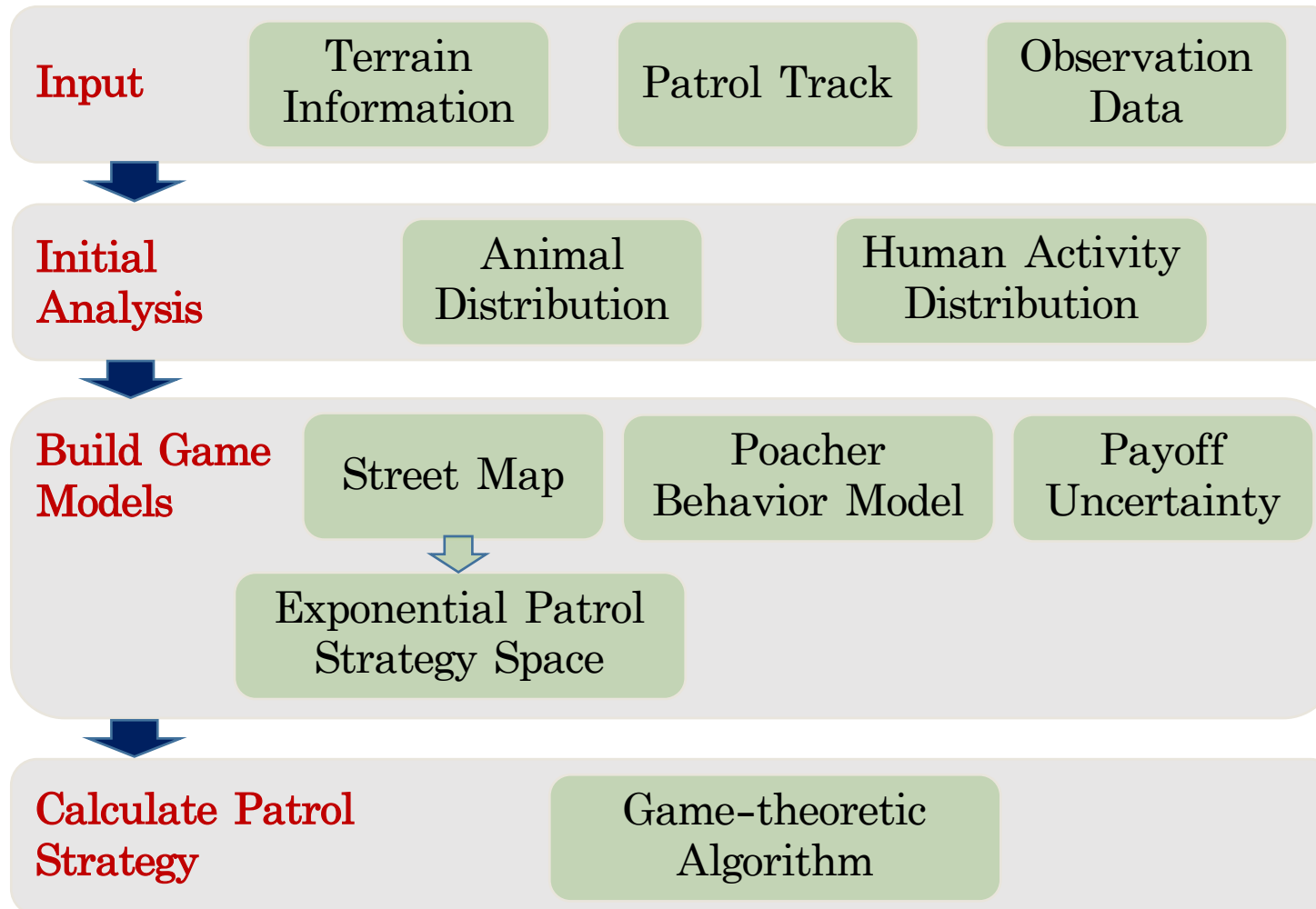


Figure 1: AUC for predicting poaching in dry season

# Patrol Planning Overview



# PAWS Tested in Malaysia: Build Street Map

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# PAWS Tested in Malaysia

- Challenges
  - Poacher behavior model
  - Animal density uncertainty
  - Ranger exponential action space
- Tested in Malaysia

Patrol Types	All PAWS Patrol	Explorative PAWS Patrol	Previous Patrol
Total Distance (km)	130.11	20.1	624.75
Avg# Human Signs per km	0.86	1.09	0.57
Avg# Animal Signs per km	0.41	0.44	0.18



Tiger sign (Nov 14)



Human sign (Jul 15)



Human sign (Aug 15)



Human sign (Aug 15)

# Latest Results (USC CAIS)

USC Center for  
Artificial Intelligence in Society

- Poacher behavior modeling:
  - Imperfect crime observation-aware ensemble model [2016]
- Patrol planning:
  - Integrating real-time “SPOT” information [2018]
  - Drone used to inform rangers [2019]

# PAWS Real-world Deployment in Uganda: Two Hot Spots Predicted

USC Center for  
Artificial Intelligence in Society

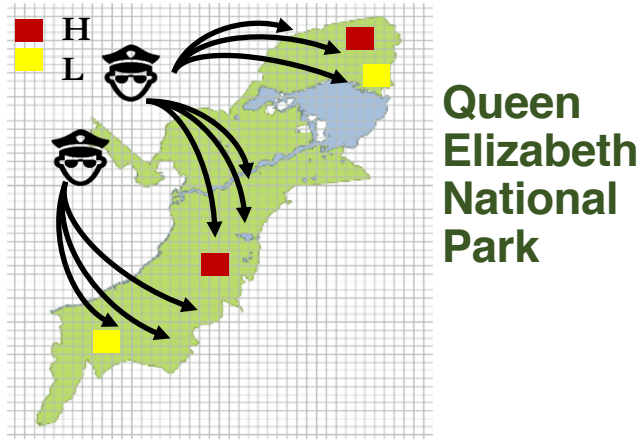


Historical Base Hit Rate	PAWS Hit Rate
Average: 0.73	3

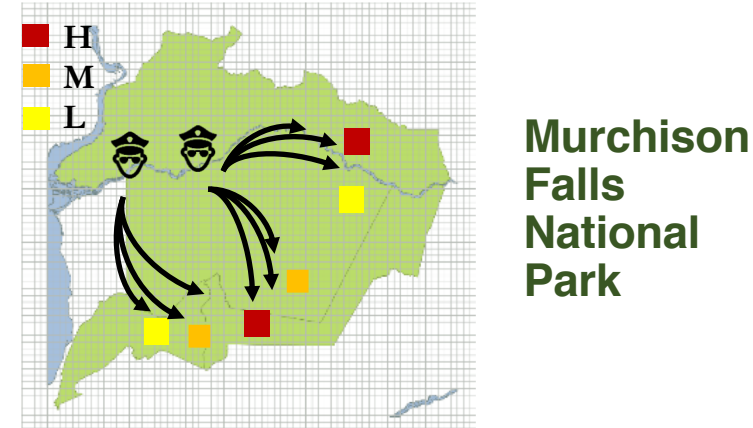
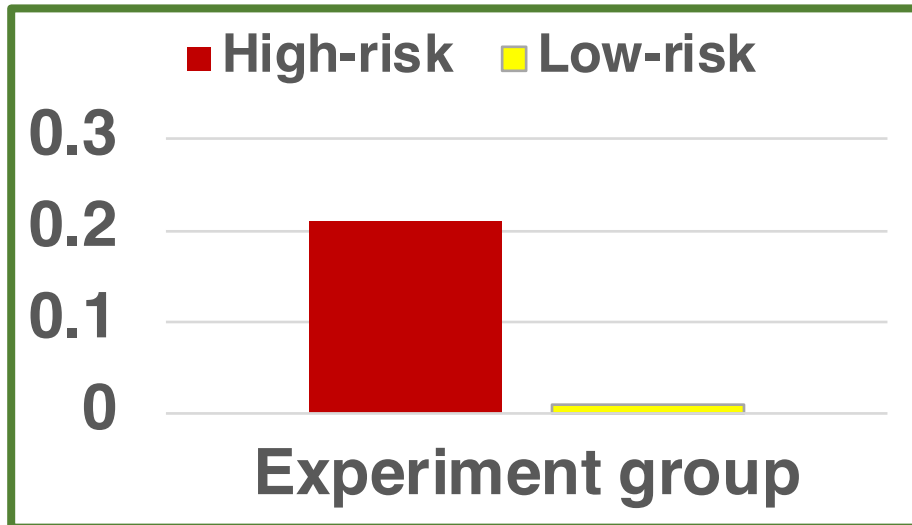




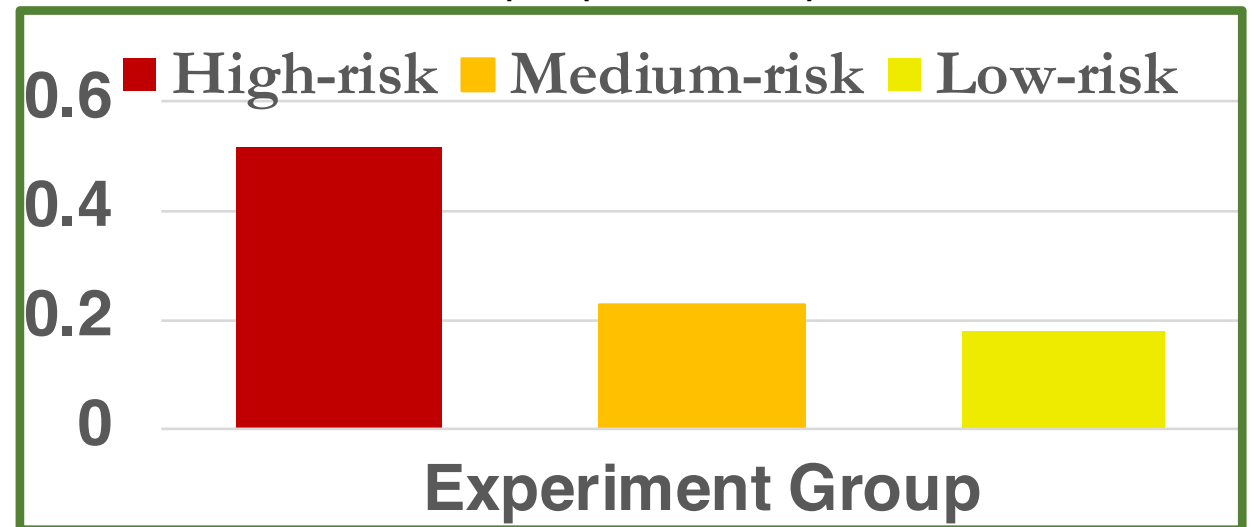
# PAWS Predicted High vs Low Risk Areas: 2 National Parks, 24 areas each, 6 months [2017]



Snares per patrolled sq. KM

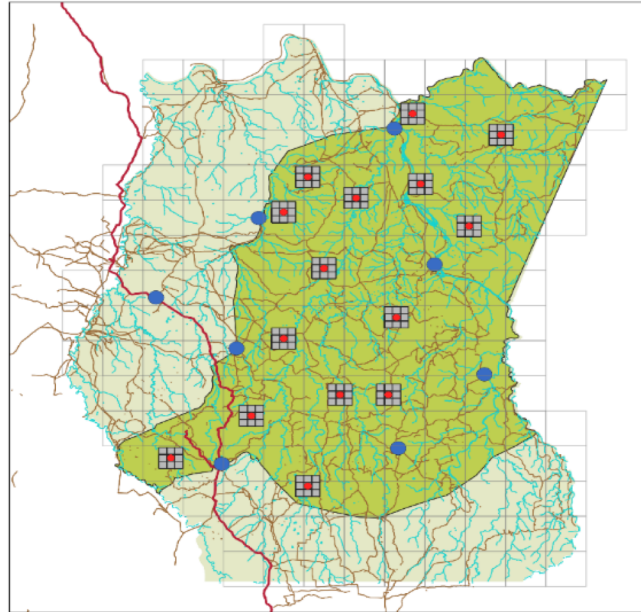


Snares per patrolled sq. KM



# PAWS Real-world Deployment in Cambodia: Srepok Wildlife Sanctuary [2018-2019]

USC Center for  
Artificial Intelligence in Society



Srepok Wildlife Sanctuary  
USC/PAWS  
Field test areas  
December 2018

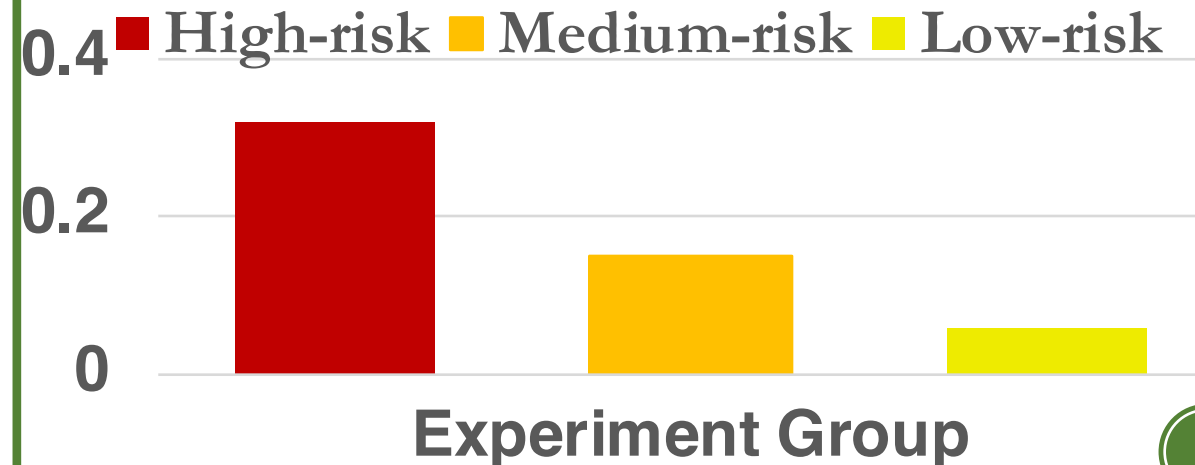
Field test areas  
Patrol blocks  
Patrol posts  
National Route 76  
Rivers  
Roads  
Core zone  
Boundary

■ *521 snares/month PAWS tests*

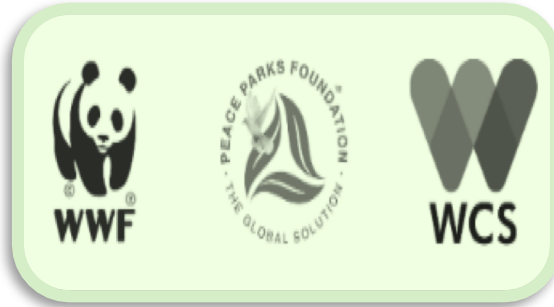
VS

■ *101 snares/month 2018*

Snares per patrolled sq. KM



# Green Security Games: Around the Globe with SMART Partnership [2019]



**Protect Wildlife  
600  
National Parks  
Around the Globe**

**Also: Protect Forests, Fisheries...**



# CONTACT

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