Saving Wildlife with Generative AI: Latent Composite Flow Matching for Poaching Prediction

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The Biodiversity Crisis

	Rhino	Tiger	Elephant
In 1990	**850,000**	**100,000**	**10 million**
Today	**4,880**	**3,890**	**415,000**
	99.5% decline	***96% decline***	***96% decline***

1 million species in danger of extinction

Slide Credit: Lily Xu

The biodiversity Crisis is also a Climate Crisis

Biodiversity Loss Fuels Climate Change

- Degraded ecosystems release carbon
- Fewer species = weaker ecosystems

Climate Change Accelerates Biodiversity Loss

- Warming, droughts, wildfires destroy habitats
- Oceans and poles under stress

Protecting biodiversity is protecting our climate.

Joint IPBES–IPCC Report (2021): Nature-based solutions can provide one-third of needed climate mitigation.

Poaching Threatens Biodiversity

- Poaching: the illegal hunt or capture of wild animals
- Threatens animal populations, biodiversity, ecosystem and climate



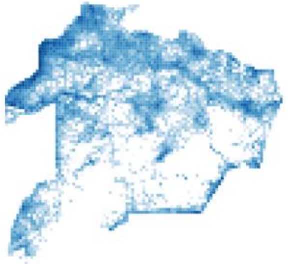




Ranger Patrols to Prevent Poaching

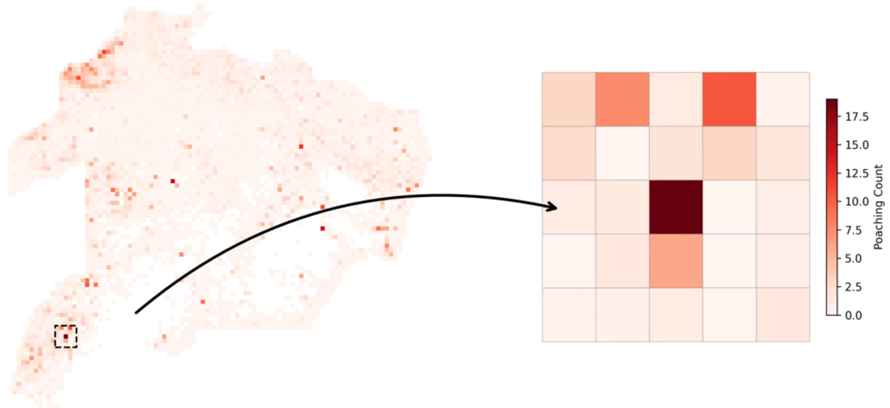
Machine Learning for Poaching Prediction

Historical patrol effort (km)

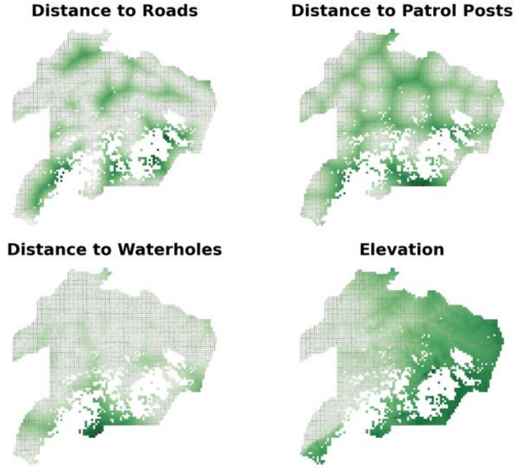


Prob of poaching in 1KM Grid Square)

ML Model



Additional features



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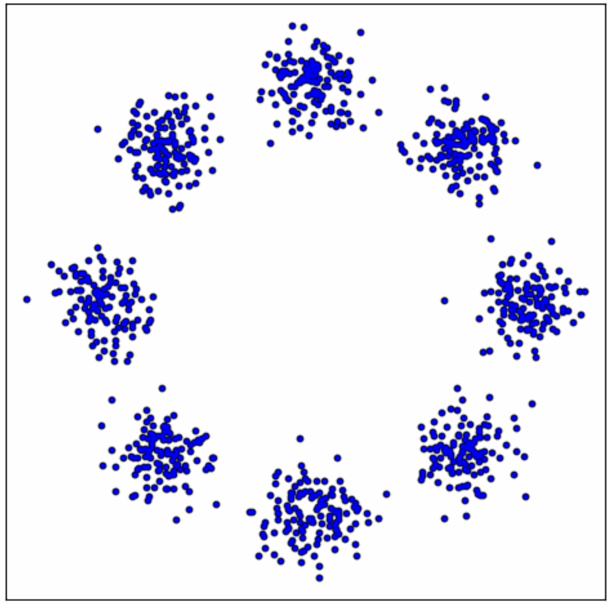
[Xu, 2021]: Linear model
[Xu, 2020]: Gaussian Process

- Limited expressiveness for capturing complex spatial patterns ❌

Background on Flow Matching

- Idea: learn a time-varying velocity field $v\left(\psi^{(s)}, s\right)$
- Start $\psi^{(0)} \sim p_0$, integrate $\psi^{(1)} = \psi^{(0)} + \int_0^1 v\left(\psi^{(s)}, s\right) ds$ to reach p_1
- p_0: flexible, not restricted to standard Gaussian as in diffusion models
- Conditional version:
    - feature conditioned velocity field $v\left(\psi^{(s)}, s, \mathbf{c}\right)$
    - historical patrol effort and terrain features
- Good at capturing complex patterns and provide predictive uncertainty



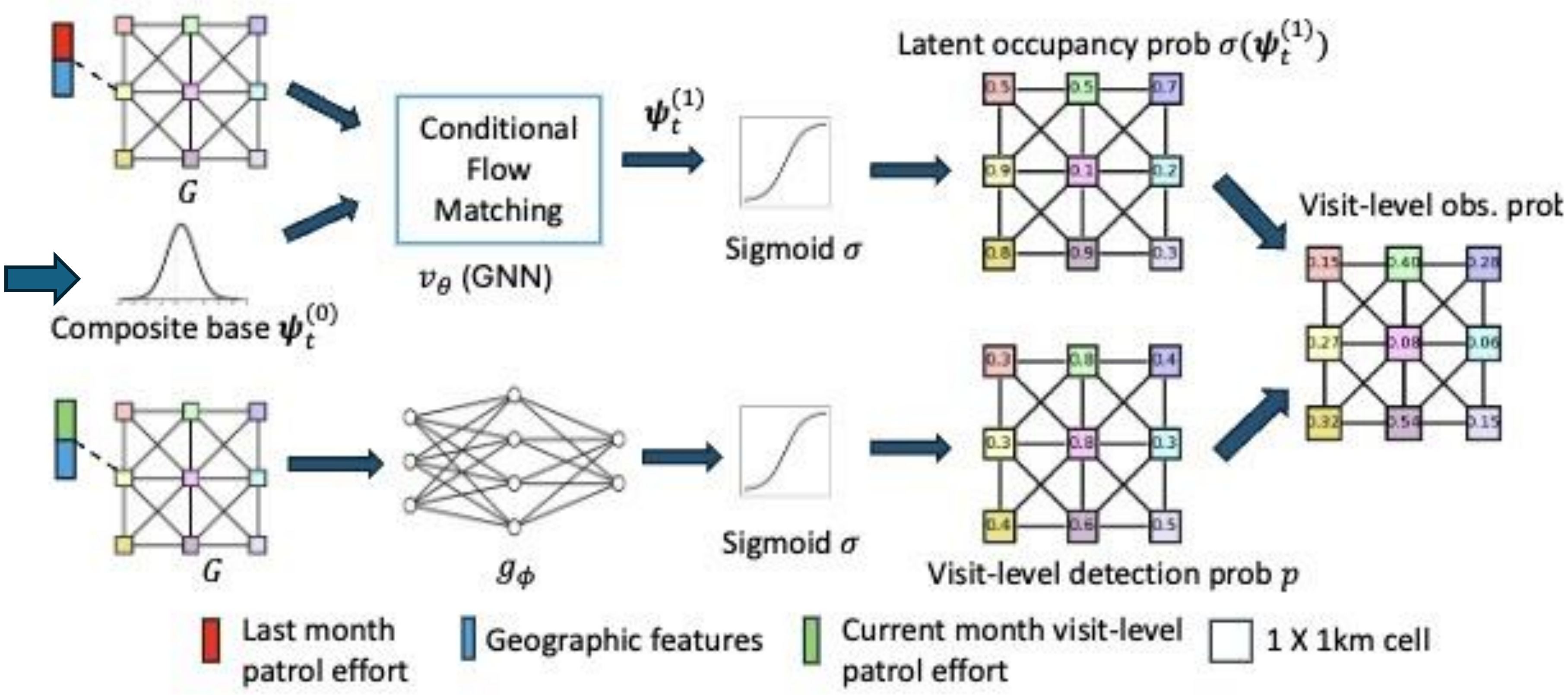
Challenges

Photo Credit: League

- Imperfect Detection
  - Snares/traps are well hidden
  - Detection varies by habitat, visibility, and patrol effort
- Small Data
  - Strong nonstationarity: staffing, land use, economic shifts
  - Only most recent (~3) years of data are usable
- Our solution: WildFlow!

Overview of *WildFlow*

Linear occupancy model



- Small Data: Composite base distribution from a linear occupancy model
- Imperfect Detection: Flow matching + occupancy model

Training Challenges

- Linear path flow matching training objective

$$\psi^{(s)} = (1-s)\psi^{(0)} + s\psi^{(1)}$$

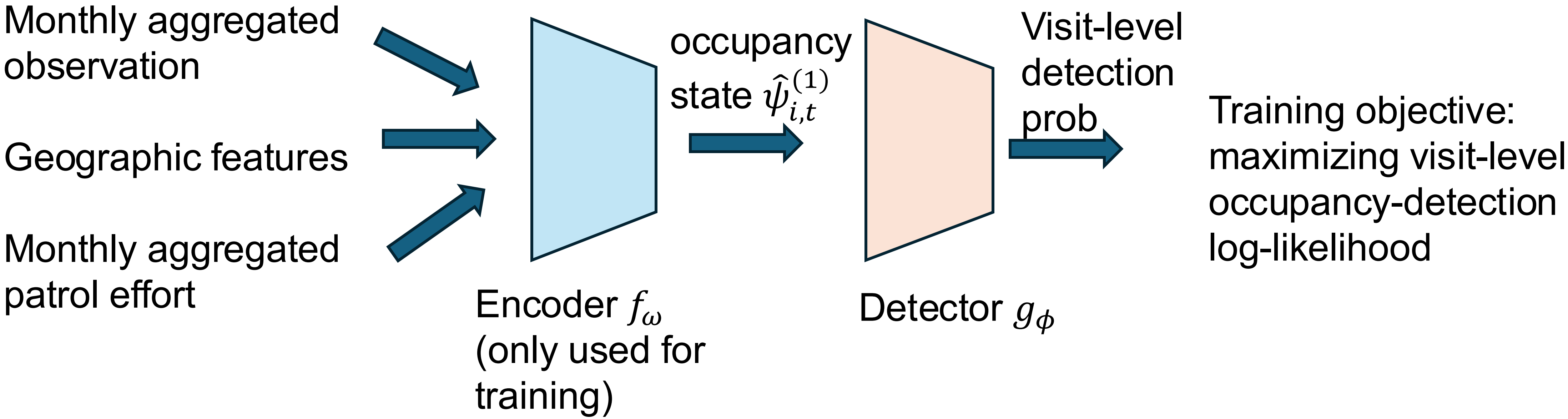
$$\mathcal{L}_{\mathrm{FM}}(\theta) = \mathbb{E}_{\substack{\mathbf{c}\sim p_{\mathrm{data}}(\mathbf{c}),\ \psi^{(1)}\sim p_{\mathrm{data}}(\cdot|\mathbf{c}),\\ \psi^{(0)}\sim p_0(\cdot|\mathbf{c}),\ s\sim\mathcal{U}(0,1)}} \left\| v_\theta(\psi^{(s)}, s; \mathbf{c}) - \left(\psi^{(1)} - \psi^{(0)}\right) \right\|_2^2,$$

Target velocity, linear path

- We need to have samples $\psi^{(1)}$ from the target distribution
- We do not have the true occupancy state for the training

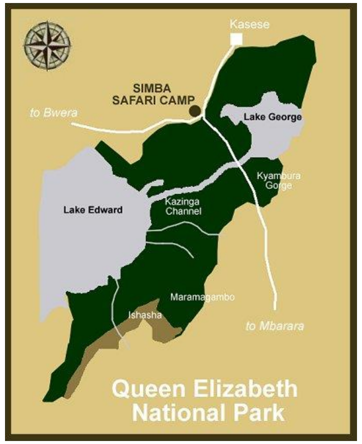
Two-stage Training Algorithm

- Stage I: Encoder-detector training



- Stage II: Training Latent Flow Matching
  - Use the surrogate occupancy state $\hat{\psi}_{i,t}^{(1)}$ from the encoder as the target

Experimental Setup



- Two National Parks:
  - Murchison Falls and Queen Elizabeth
- Training Dataset:
  - We use a moving window strategy, only use the previous 3 years data to predict the next year
- Evaluation
  - Prediction: probability of at least one detection in the month,
  - ground-truth, binary monthly label
  - Area under the precision-recall curve (AUPR)

Experimental Results

Park	Year	LogReg	GP	MLP	GNN	Transformer	Diffusion	Ours
MFNP	2017	0.305	0.278 ±0.001	0.288 ±0.017	0.336 ±0.004	0.314 ±0.016	0.313 ±0.021	**0.374** ±0.032
	2018	0.344	0.308 ±0.002	0.325 ±0.004	0.260 ±0.000	0.302 ±0.064	0.279 ±0.001	**0.377** ±0.011
	2019	0.406	0.359 ±0.002	0.388 ±0.007	**0.526** ±0.015	0.475 ±0.141	0.362 ±0.003	0.409 ±0.009
	2020	0.421	0.401 ±0.003	0.408 ±0.004	0.366 ±0.014	0.327 ±0.002	0.439 ±0.023	**0.473** ±0.006
	2021	0.360	0.364 ±0.011	0.335 ±0.010	**0.430** ±0.023	0.295 ±0.085	0.342 ±0.032	**0.423** ±0.004
	Avg	0.367	0.342	0.349	0.384	0.343	0.347	**0.411**
QENP	2014	0.119	0.107 ±0.003	0.103 ±0.003	**0.136** ±0.013	0.100 ±0.002	0.102 ±0.003	0.116 ±0.009
	2015	0.180	0.156 ±0.002	0.172 ±0.006	0.111 ±0.000	0.173 ±0.016	0.162 ±0.028	**0.201** ±0.017
	2016	0.258	0.220 ±0.005	0.227 ±0.004	0.238 ±0.009	0.220 ±0.019	0.201 ±0.034	**0.299** ±0.027
	Avg	0.186	0.161	0.167	0.162	0.164	0.155	**0.205**

Table 1: AUPR comparison on MFNP and QENP. All methods use a linear detection head for a fair comparison. Cells in green indicate a clear winner (best mean and the runner-up lies outside the winner's std), while yellow denotes a practical tie (within one std of the best). LogReg is trained with deterministic optimization and therefore has no variance.

Improve AUPR by **7**% and **10**% than the strongest baseline in MFNP and QENP

Ablation Study

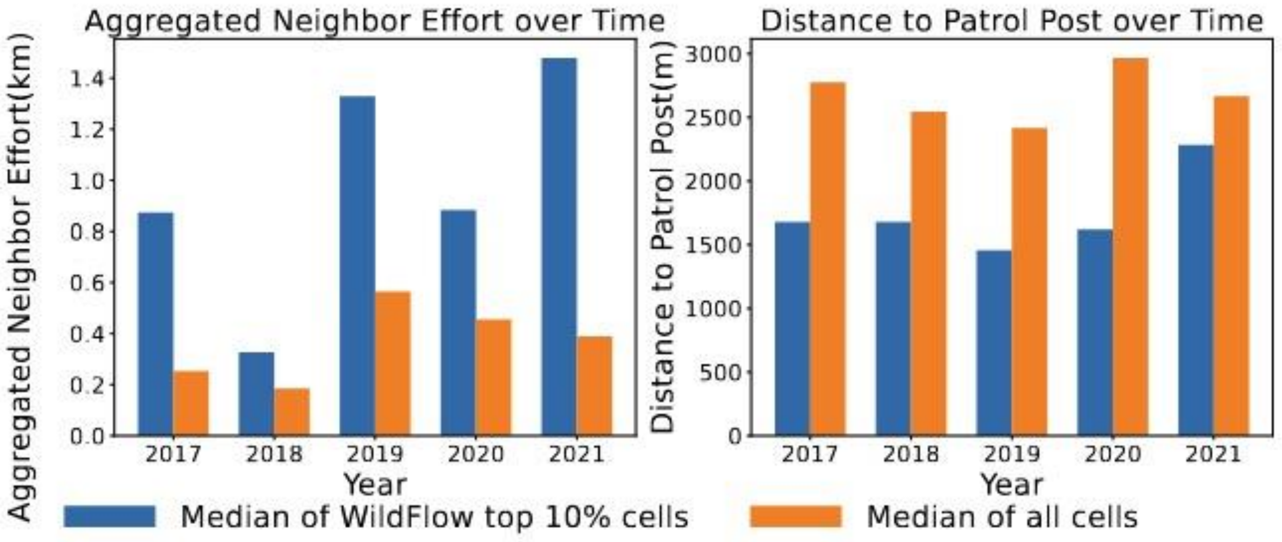
Year	w/o base	w/o det.	Ours
2017	0.341 ±0.008	0.278 ±0.011	**0.374** ±0.032
2018	0.368 ±0.019	0.265 ±0.006	**0.377** ±0.011
2019	0.382 ±0.006	0.301 ±0.006	**0.409** ±0.009
2020	0.429 ±0.007	0.350 ±0.005	**0.473** ±0.006
2021	0.338 ±0.040	0.290 ±0.009	**0.423** ±0.004

Table 2: Ablation on MFNP (AUPR).

Removing either the composite base or the detection head leads to a **consistent drop** in AUPR across all years

Case Study

Compare median features of all cells vs. top 10% where WildFlow outperforms logistic regression



- Largest gains occur near areas with high patrol effort, highlighting WildFlow's strength in modeling displacement-driven dynamics.
- Improved performance near patrol posts, likely due to more reliable detections.

Conclusion and Next Steps

- First generative AI framework for poaching prediction.
- Handle small data and imperfect detection
- Strong empirical performance in two national parks in Uganda
- We are actively looking for partners to conduct field test

GenAI is not only driving commercial success, it's also creating meaningful societal impact!