

Exploring the potential of neural networks for Species Distribution Modeling

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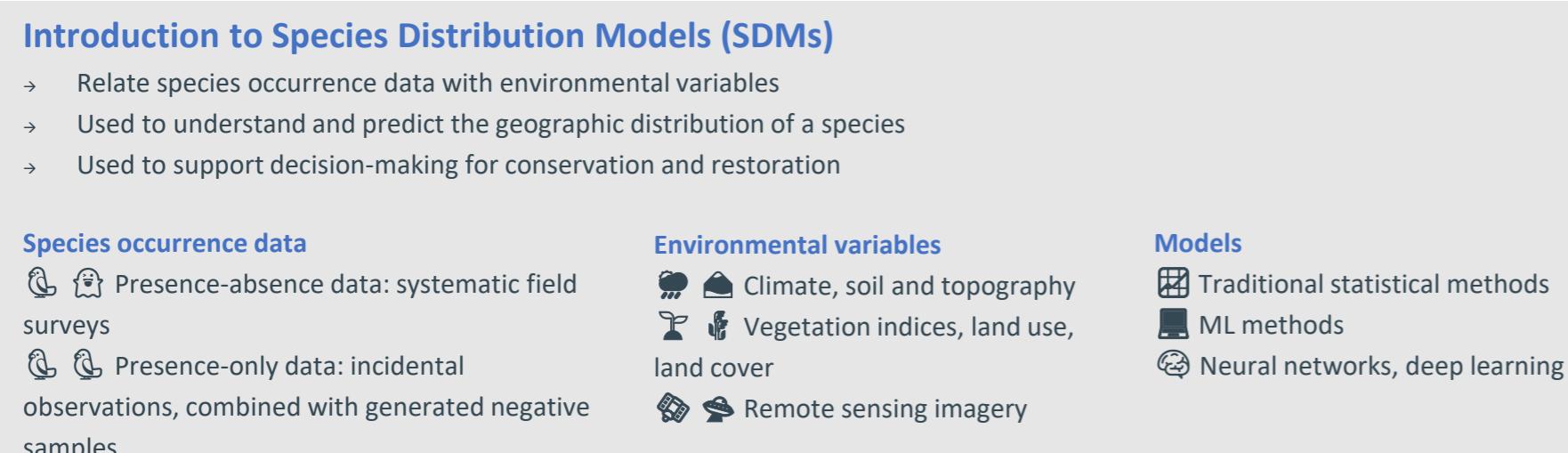
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Our work

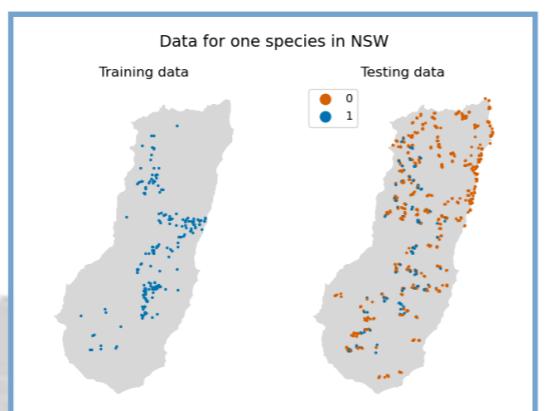
How do neural networks perform compared to well-established methods for SDMs?

Dataset: benchmark dataset [1]: tabular data for 225 species from 6 regions. Train on presence-only, test on presence-absence.

Model: multi-layer perceptrons (MLPs) with:

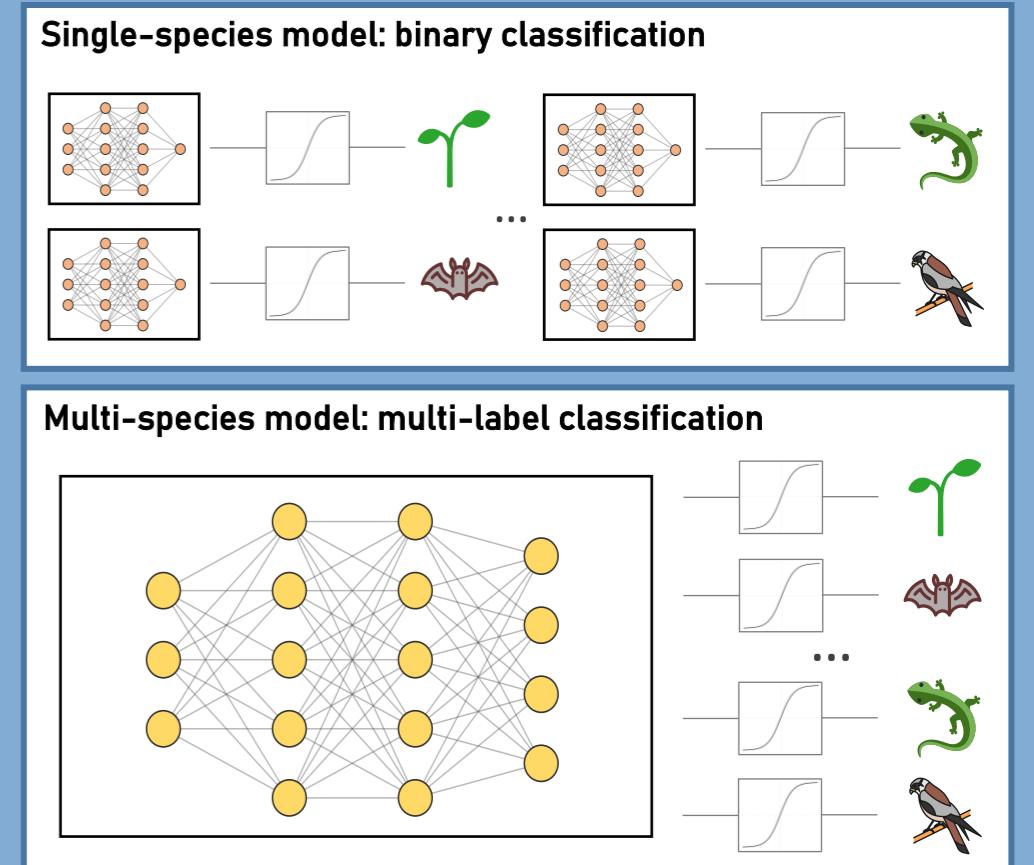
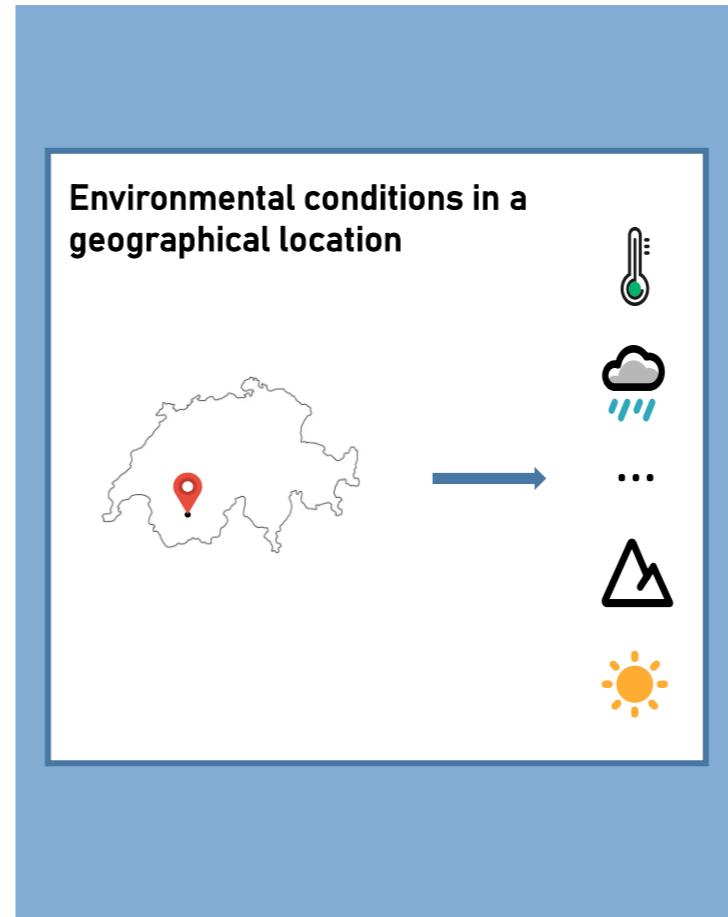
- binary classification for single-species models
- multi-label classification for multi-species models

Loss function: weighted binary cross-entropy



References

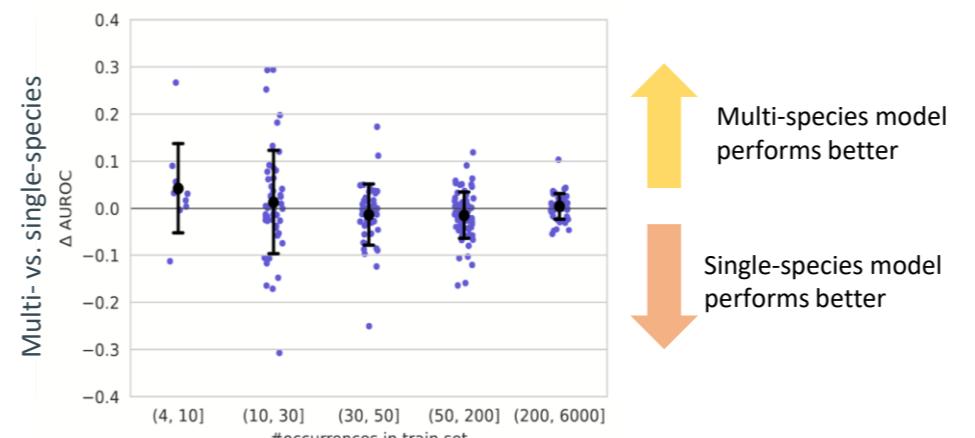
- [1] Elith, Jane, et al. "Presence-only and presence-absence data for comparing species distribution modeling methods." *Biodiversity informatics* 15.2 (2020): 69-80.
- [2] Valavi, Roozbeh, et al. "Predictive performance of presence-only species distribution models: a benchmark study with reproducible code." *Ecological Monographs* 92.1 (2022): e01486.



Results

Mean AUROC across species for each region

	AWT	CAN	NSW	NZ	SA	SWI	
[2]	MaxEnt	0.686	0.584	0.713	0.738	0.804	0.809
	XGBoost	0.653	0.568	0.706	0.720	0.788	0.815
Ours	Random Forest	0.675	0.572	0.718	0.746	0.813	0.818
	Ensemble	0.683	0.580	0.723	0.749	0.806	0.812
Ours	Single-species MLP	0.666	0.589	0.688	0.715	0.799	0.808
	Multi-species MLP	0.617	0.605	0.708	0.714	0.803	0.815



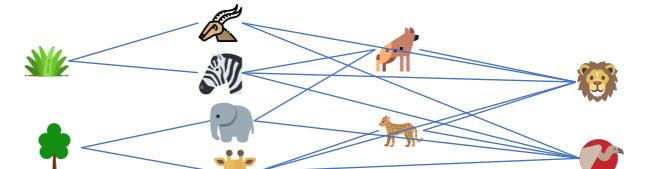
Future directions

More complex deep learning based SDMs involving and combining:

- Multi-modal data providing, for example, geospatial and temporal context



- Biological and ecological information through **knowledge-guided** machine learning



- Transfer learning, model **pre-training**

