

Scaling Connectivity Conservation Planning with Deep Reinforcement Learning

ML4EO 2026

Exeter, UK

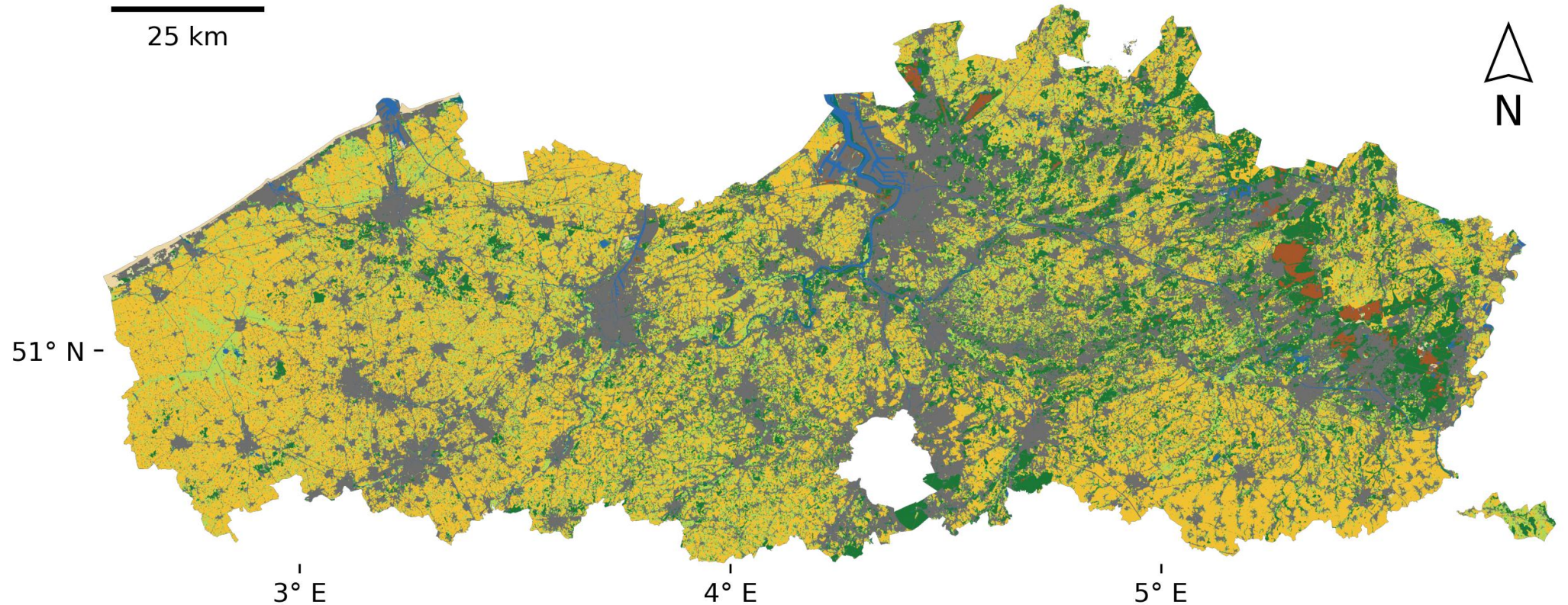
Pieter Wytynck & Kato Vanpoucke

RESEARCH INSTITUTE
NATURE AND FOREST



KU LEUVEN

Habitat fragmentation in northern Belgium



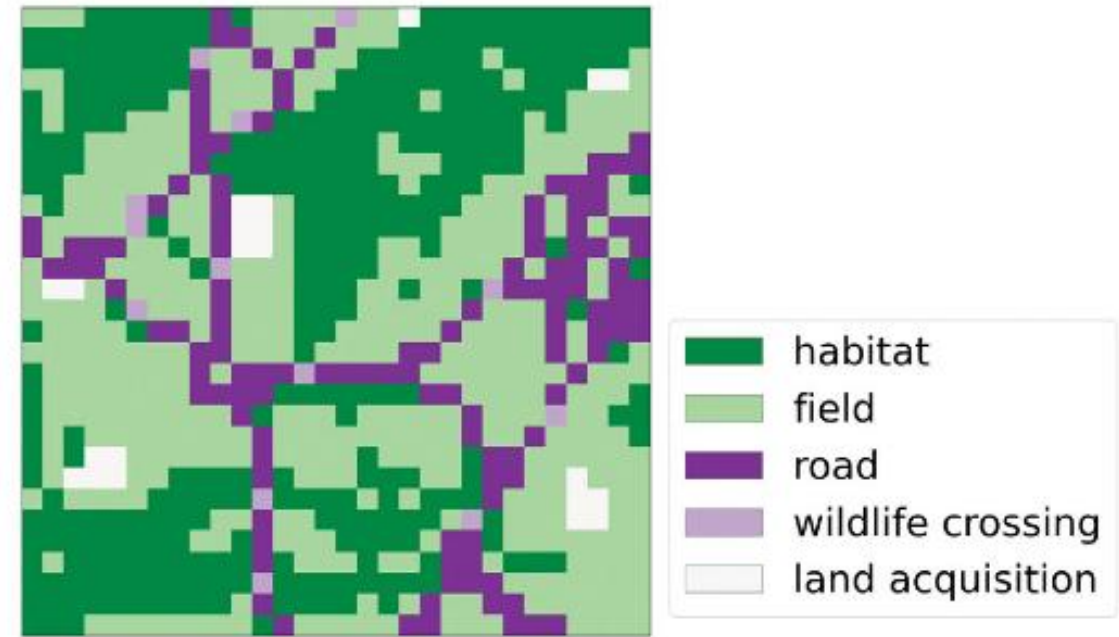
52% agriculture

29% built-up

11% forest

What is connectivity conservation planning?

- Optimize landscape connectivity within budget constraints
- This is a difficult problem
 - If we can only choose between 1000 non-habitat cells and we only need to choose 10 cells → **2.63×10^{23} unique solutions**

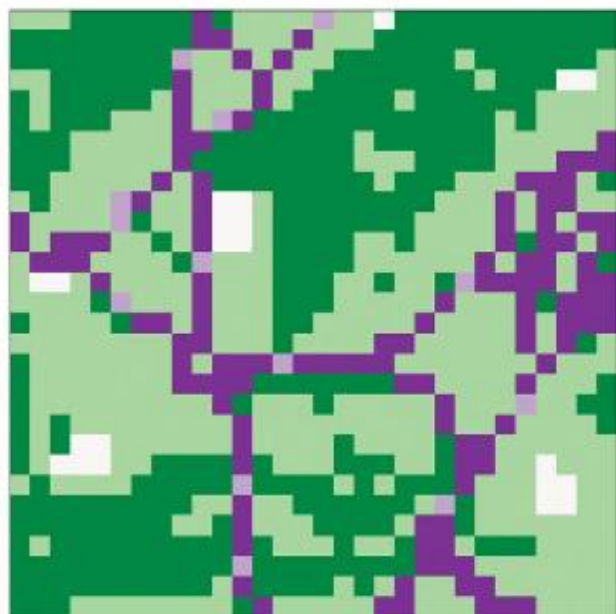


Hamonic et al. 2025



7.5×10^{18} grains of sand on Earth

What is connectivity conservation planning?

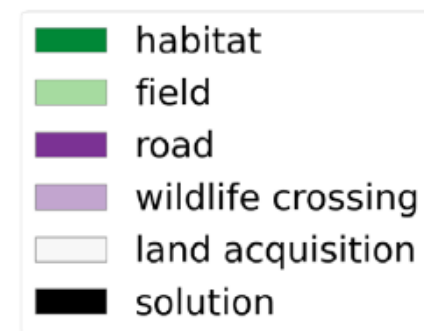


30x30 pixels



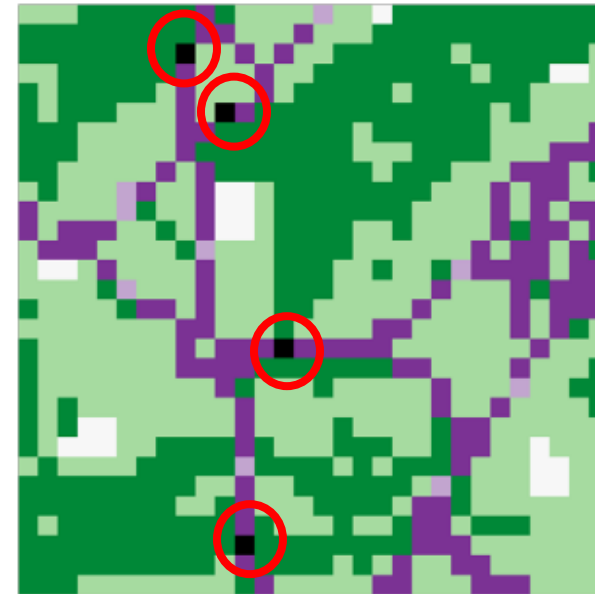
Optimal solution

Hamonic et al. 2025

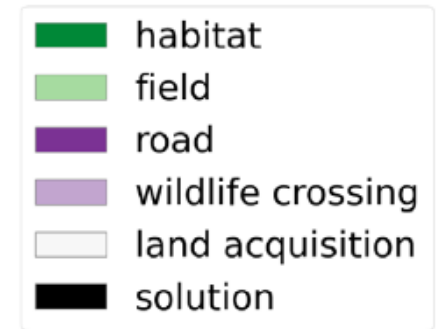


What is connectivity conservation planning?

- ✓ Optimality
- ✗ Exponential growth of problem with number of options

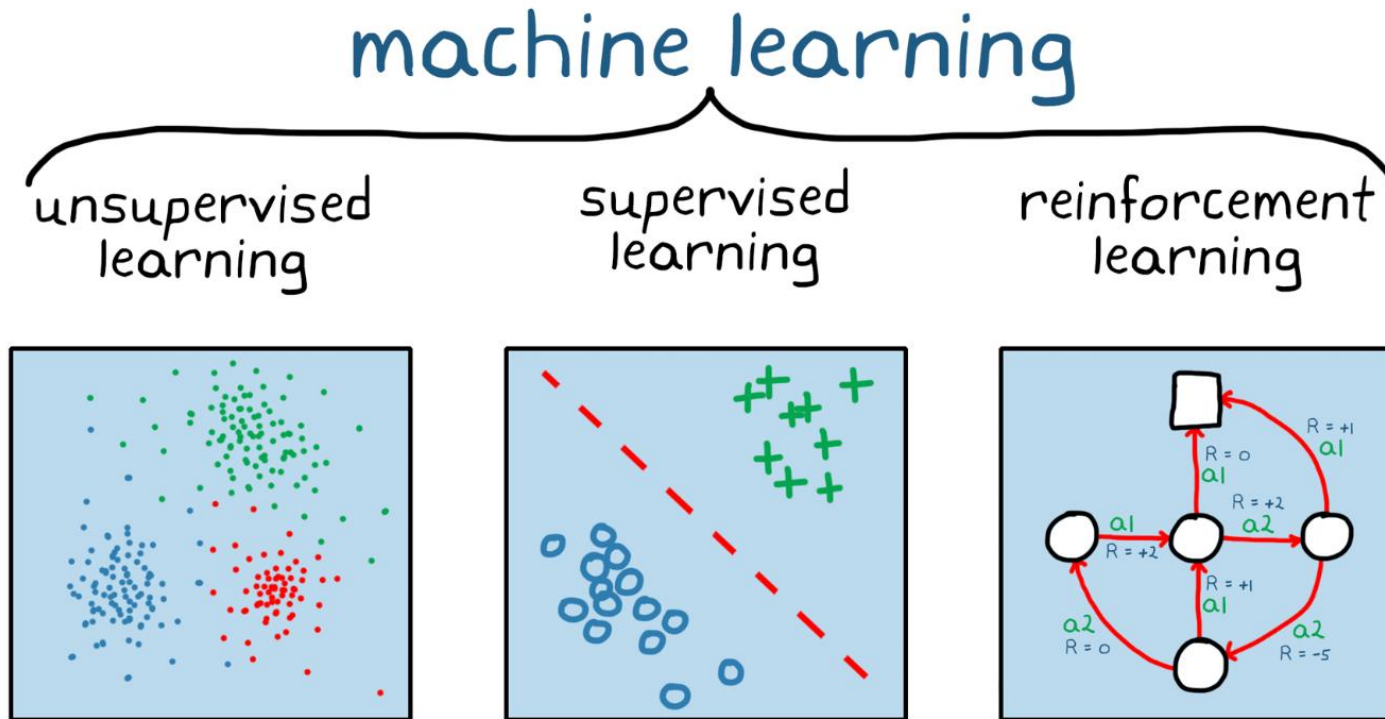


Hamonic et al. 2025



Optimal solution

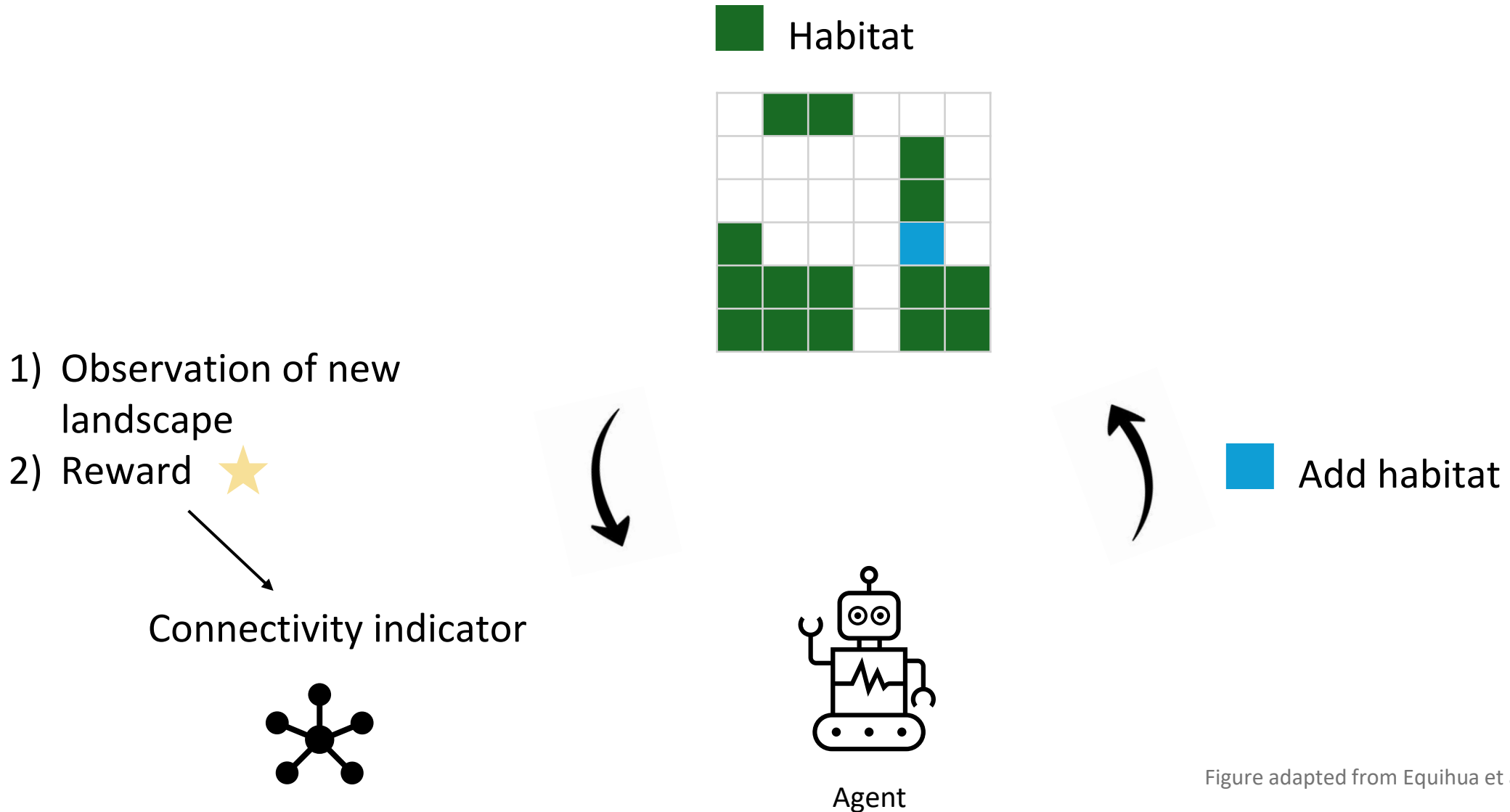
What is deep reinforcement learning?



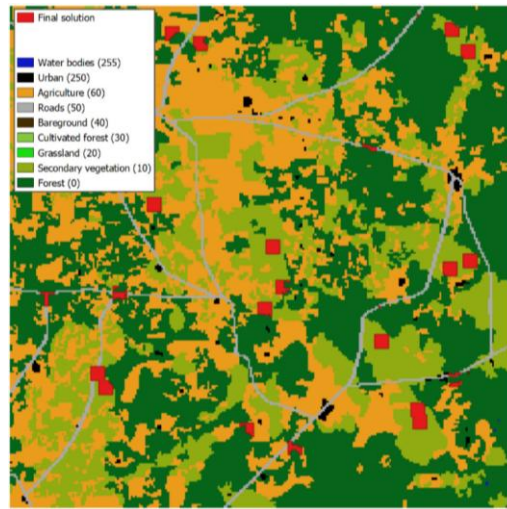
Learning by trial and error



How to combine both?

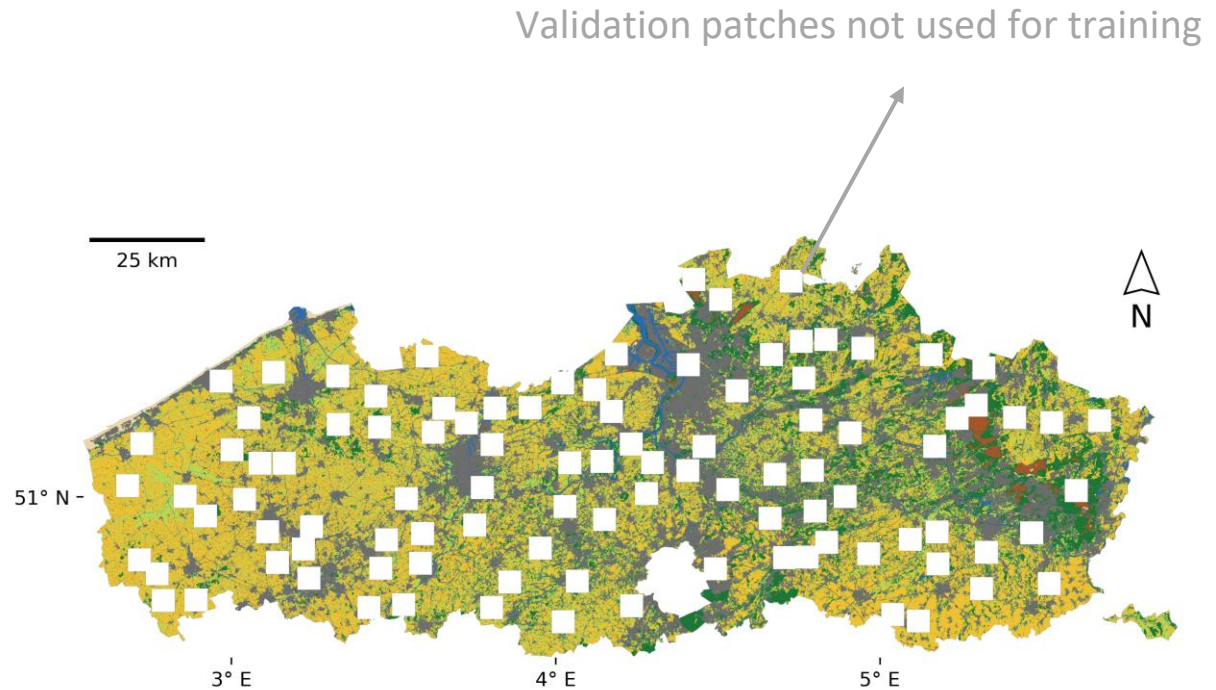


Creating a generalized model

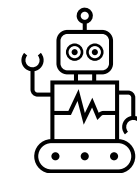


Equihua et al. (2024)

Single patch
250x250



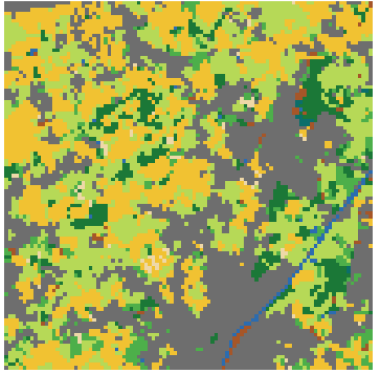
Entire map



= U-net

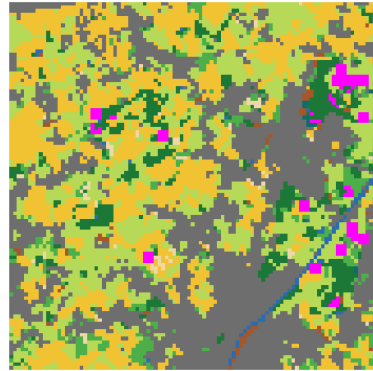
Training a generalized model

Step 0



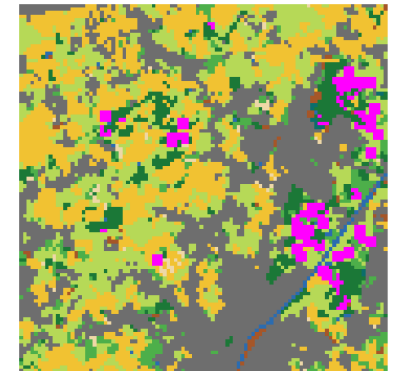
Budget = 10.000

Step 20

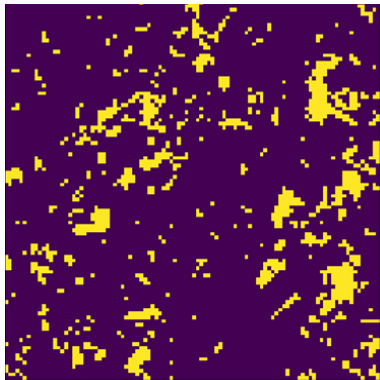


Budget ↓
Connectivity ↑

Step 59



Budget = 0
Connectivity ↑↑



Connectivity

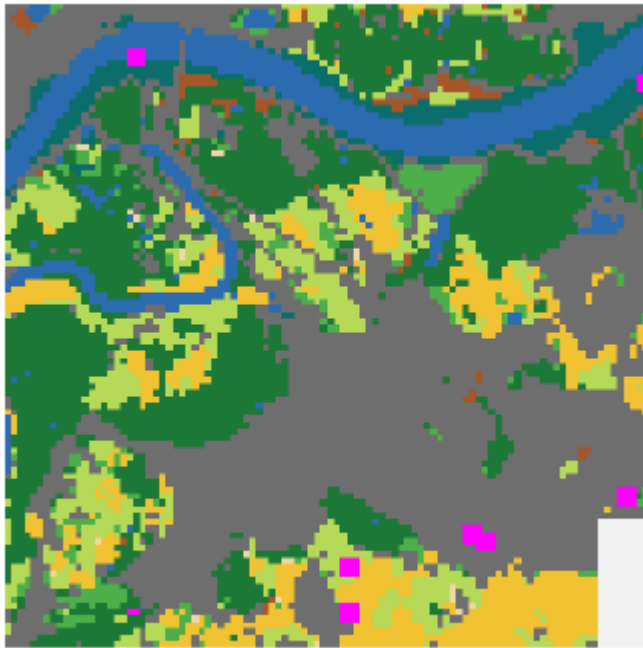
255	Urban
Habitat -> 0	Forest
60	Agricultural field
20	Agricultural grassland
10	Heathland and scrub

Costs

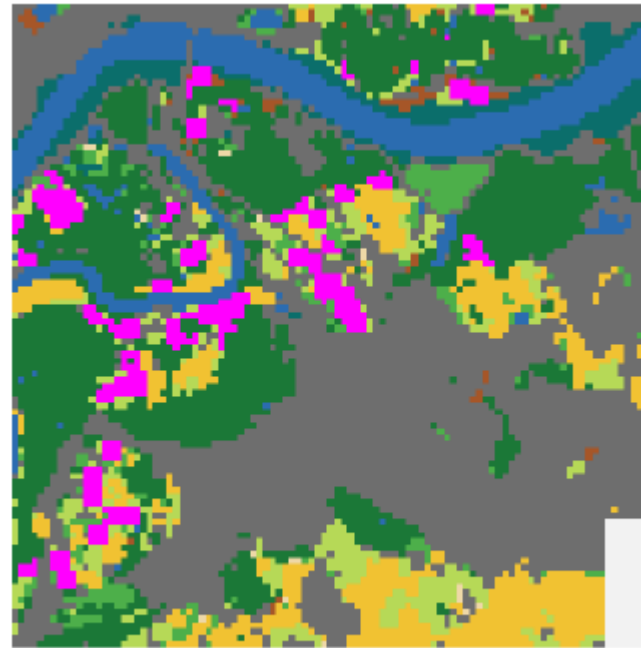
40	Dune & fallow
255	Water
40	Swamp
Habitat -> 0	Natural grassland

Does the model generalize?

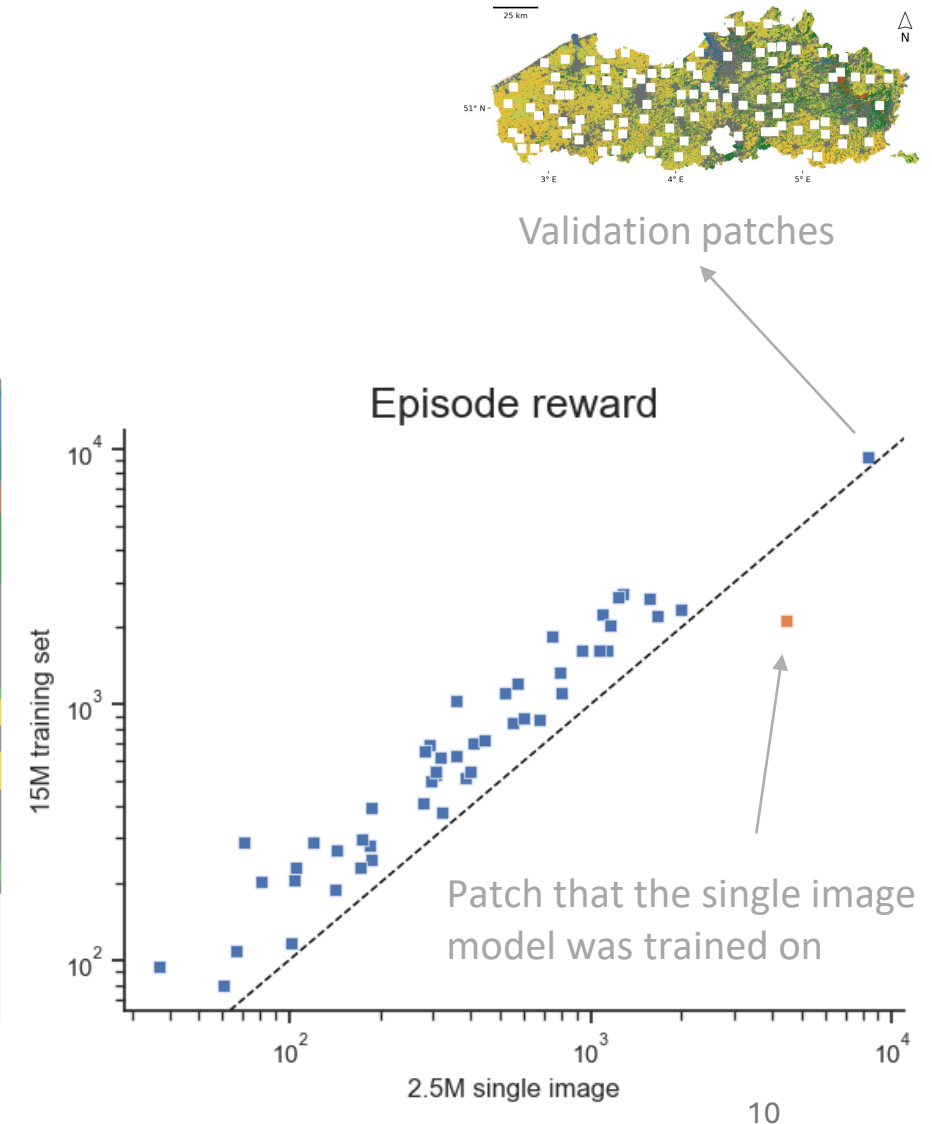
- Yes, model learns to connect habitats!
 - ✗ No optimal solutions
 - ✓ Scalable



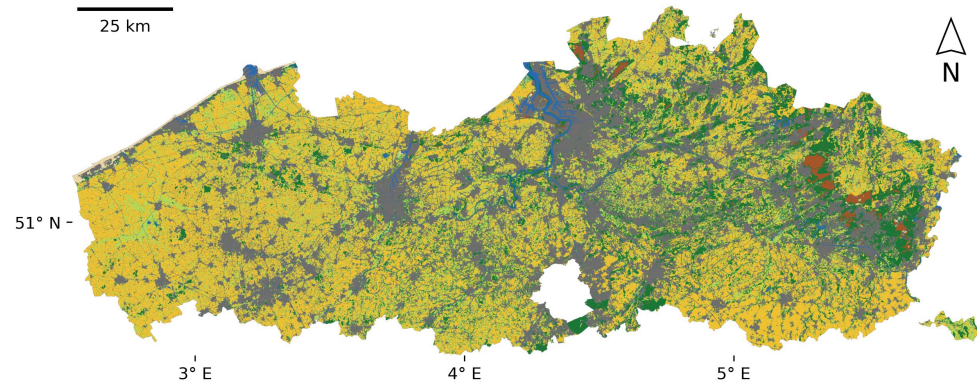
Random agent.



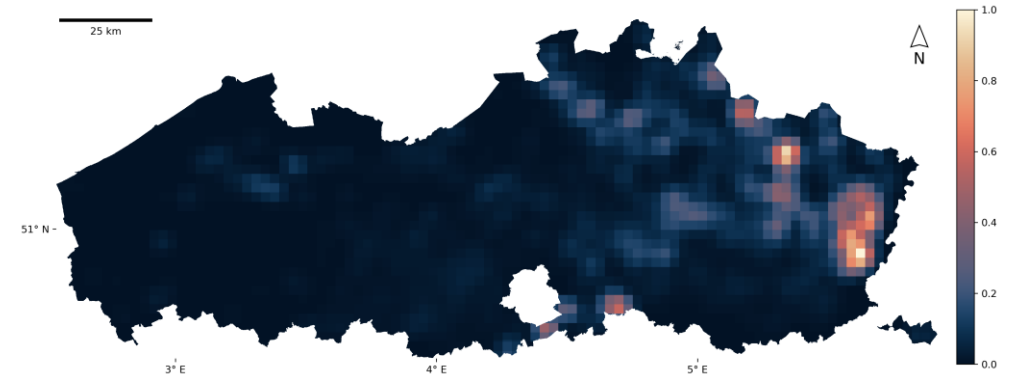
Agent after 15M training steps.



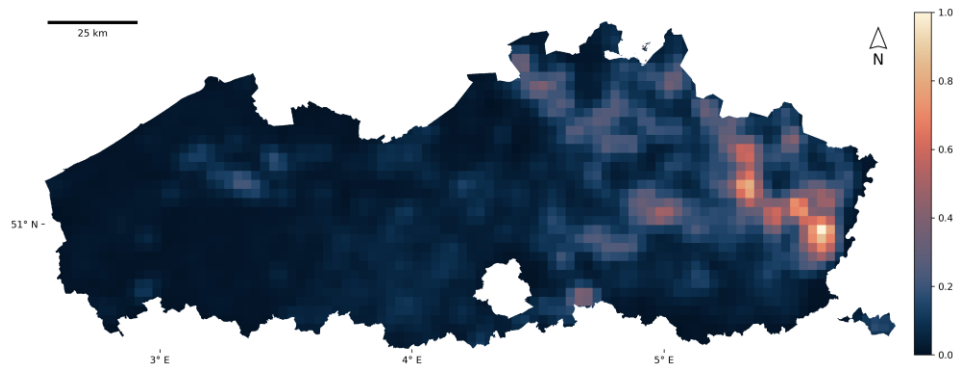
Restoration potential in northern Belgium



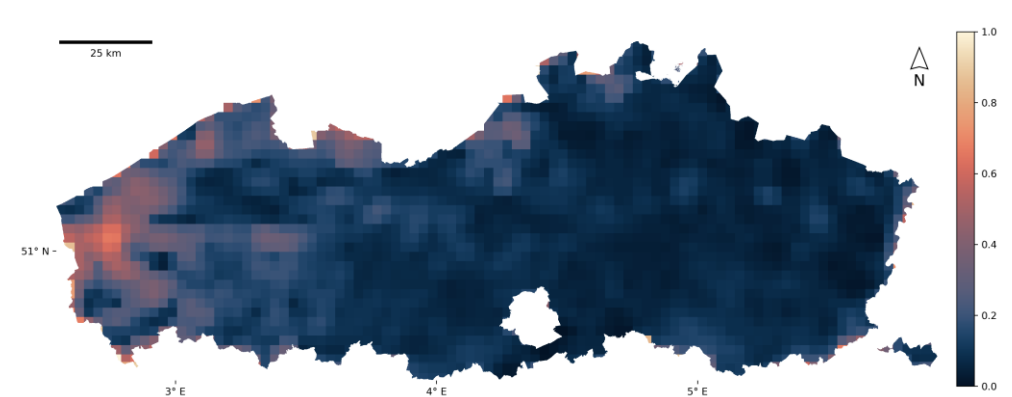
Land use map



(1) Current connectivity



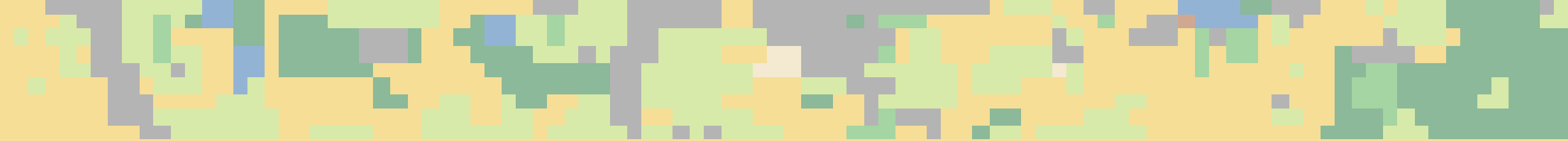
(2) Improved connectivity



(3) Relative improvement (log)

Key takeaways

- Scalable, but not optimal solutions (yet?)
- Complementary to traditional tools
- Potential for spatial planning



Thank you!

Funding

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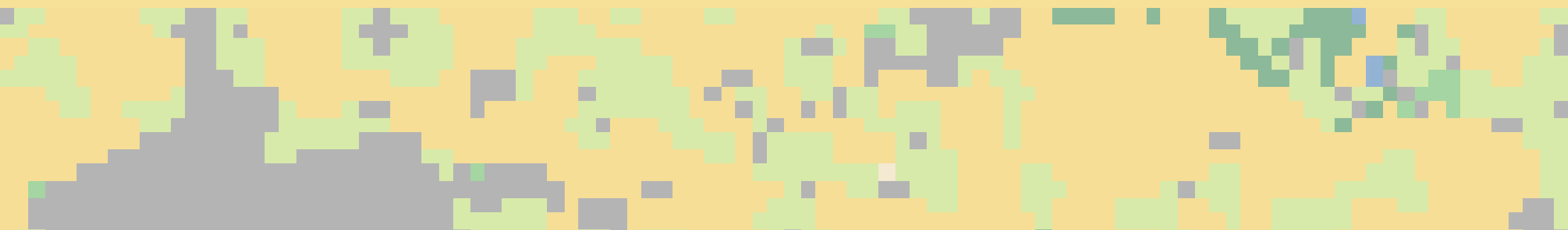
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References

Equihua, J., Beckmann, M., & Seppelt, R. (2024). Connectivity conservation planning through deep reinforcement learning. *Methods in Ecology and Evolution*, 15(4), 779–790.

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