Discovering Effective Policies for Land-Use Planning

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Land-Use Optimization

(Globe Observer, 2023)

Global Carbon Budget Imbalance (Friedlingstein et al. 2022):

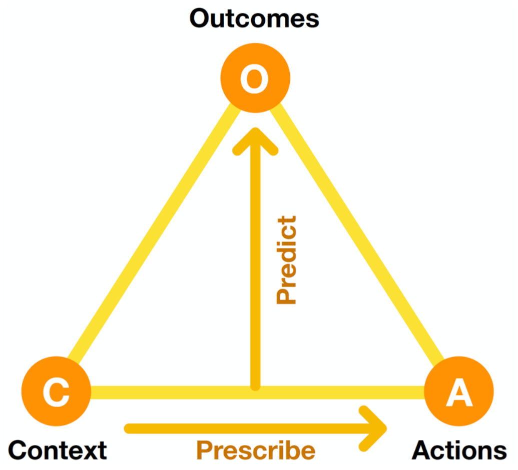
$$B_{IM} = E_{FOS} + E_{LUC} - (G_{ATM} + S_{OCEAN} + S_{LAND})$$

Emissions due to land-use change (ELUC) is a major factor

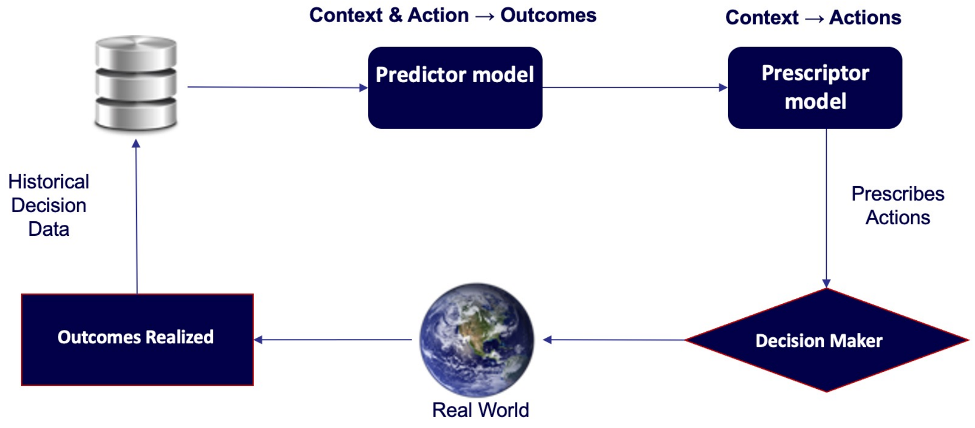
- How much allocated for forest, crops, pasture, range, urban…
- Different amount of carbon release/capture

Optimize to balance carbon emissions vs. economy

Approach: Evolutionary Surrogate-assisted Prescription (ESP)



Conceptual design (Francon et al. 2020)
- Use a predictive model as a surrogate for the world
- Train a predictive model with historical data
  - E.g. a neural net: Context+Actions → Outcomes
  - Supervised training
- Search for a good prescriptive model, i.e. decision strategy
  - E.g. a neural net: Context → Actions
  - Evolutionary optimization



Implementation in Cognizant NeuroAI
- Orchestration of data collection, predictor training, prescriptor evolution, decision-making interface
- A general platform for AI-based decision support

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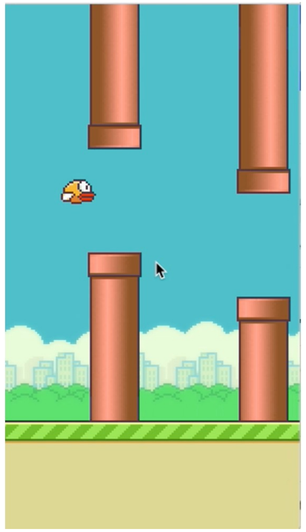
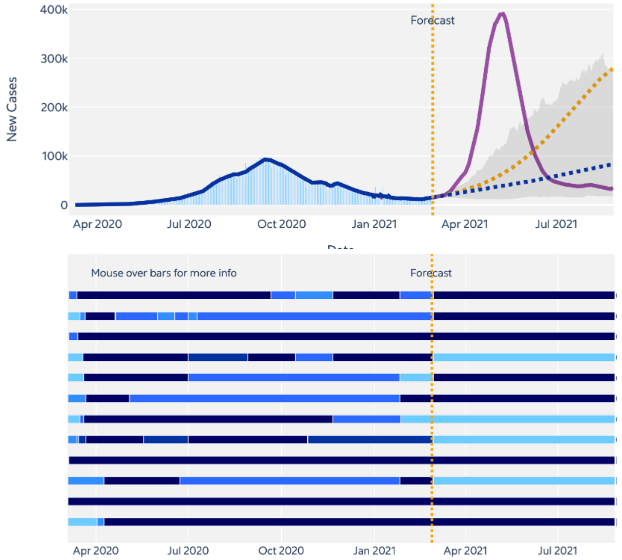
From ESP to Project Resilience



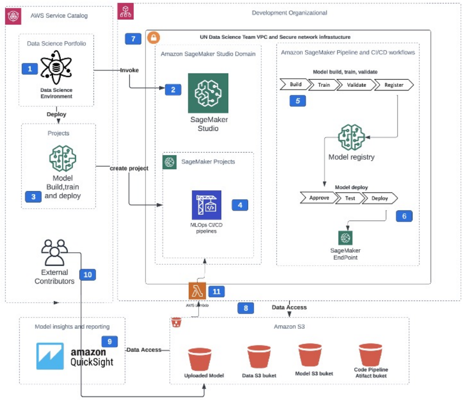


ESP evaluated in several RL tasks (Francon et al. 2020)

- Fast, accurate, sample-efficient, low regret, low variance
- Automatic regularization and curricular learning

Demo on NPI optimization for Covid-19 (Miikkulainen et al. 2021)

- Prediction of cases, prescription of interventions
- Basis for XPRIZE Pandemic Response competition



Motivation for Project Resilience

- Building a public AI utility, hosted by ITU of UN
- Global community can utilize data and AI
- Preparedness, intervention, response to environmental, health, information, social equity challenges

MVP platform built in 2023

Land-Use optimization is its first application

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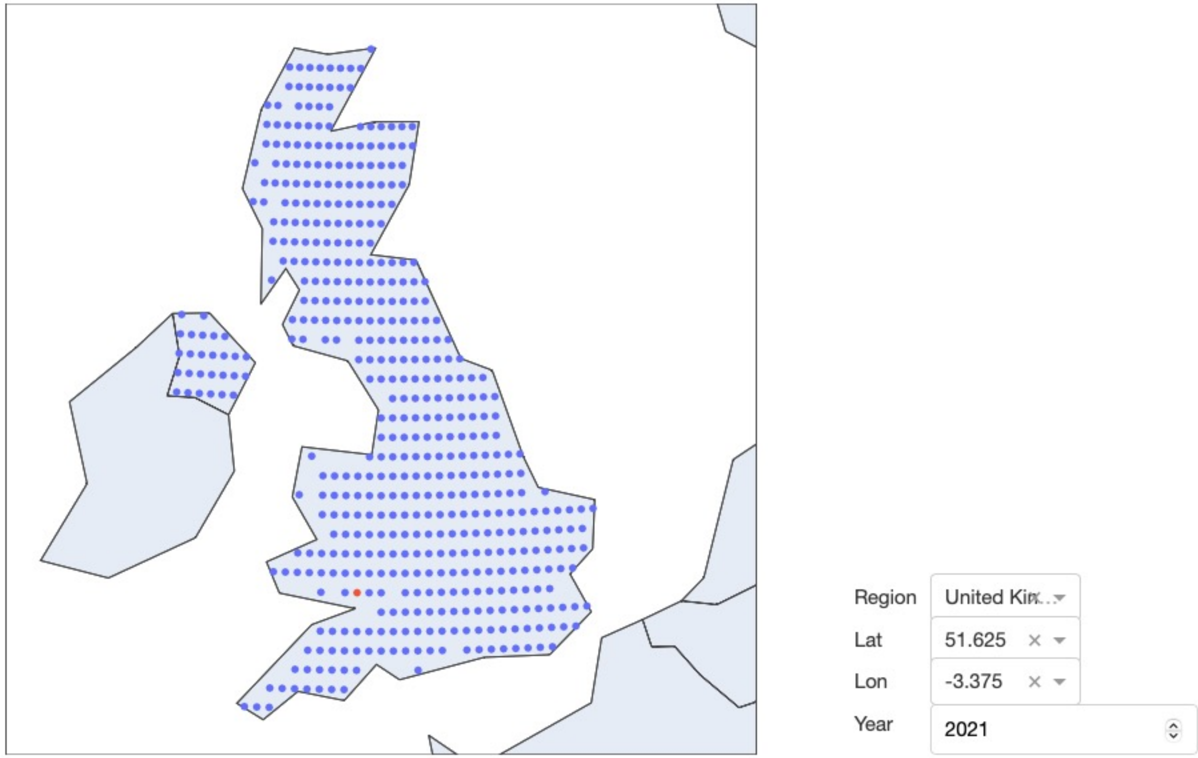
Data Source 1: Historical Land Use



Primary: Vegetation that is untouched by humans

- primf: Primary forest
- primn: Primary nonforest vegetation

Secondary: Vegetation that has been touched by humans

- secdf: Secondary forest
- secdn: Secondary nonforest vegetation

Urban

- urban: Urban areas

Crop

- c3ann: Annual C3 crops (e.g. wheat)
- c4ann: Annual C4 crops (e.g. maize)
- c3per: Perennial C3 crops (e.g. banana)
- c4per: Perennial C4 crops (e.g. sugarcane)
- c3nfx: Nitrogen fixing C3 crops (e.g. soybean)

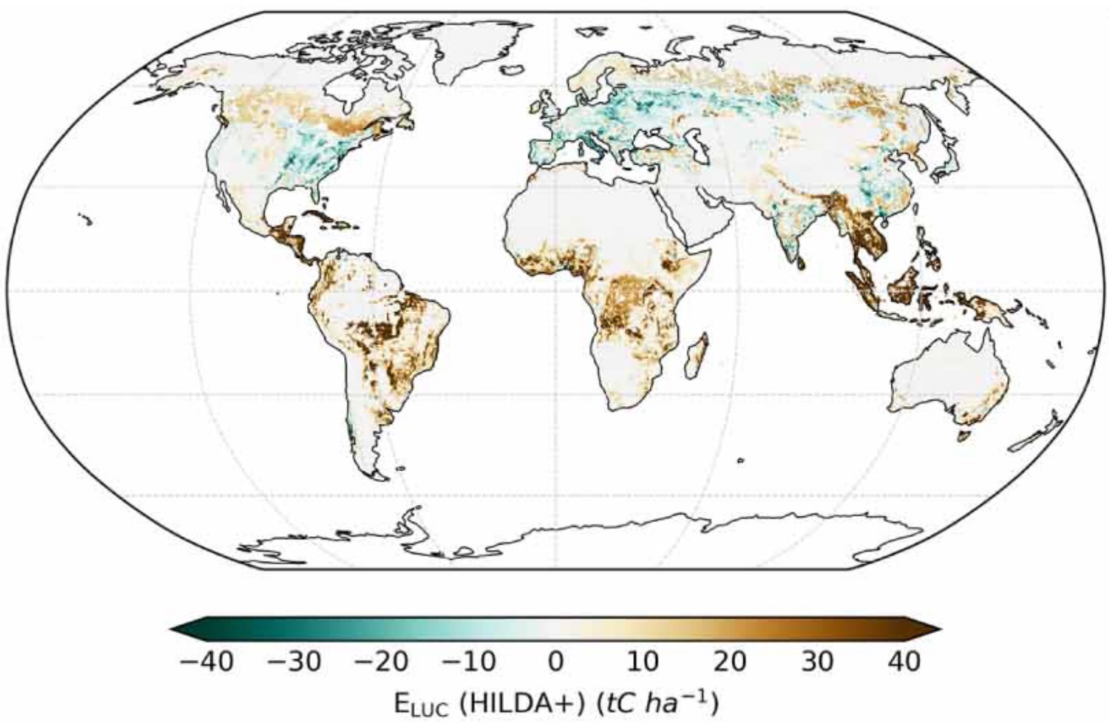
Pasture

- pastr: Managed pasture land
- range: Natural grassland / savannah / desert / etc.

Land-use harmonization project (LUH2) (Hurtt et al. 2020)

- Cells with 0.25x0.25 degree resolution
- Annually 850-2022

Data Source 2: Carbon Emissions from Different Uses



Bookkeeping of Land Use Emissions (BLUE) (Hansis et al. 2015)

- High-fidelity simulation
- Estimates long-term emissions resulting from land-use change (ELUC)

Too slow to run directly as a surrogate

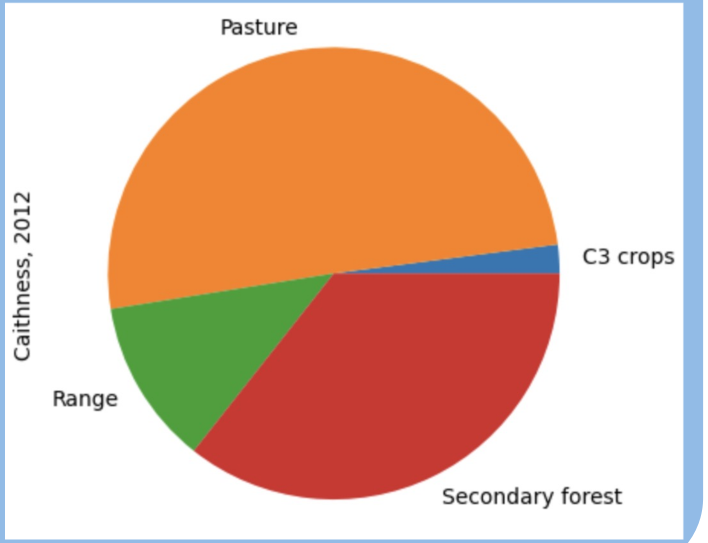
- Prepared a dataset for 1850-2022 by sampling the simulator

Setting Up ESP for Land-Use Optimization

For a given cell and year, what are the smallest changes we can make to reduce emissions as much as possible?

Context

- *Cell, area, year*
- *Land use*



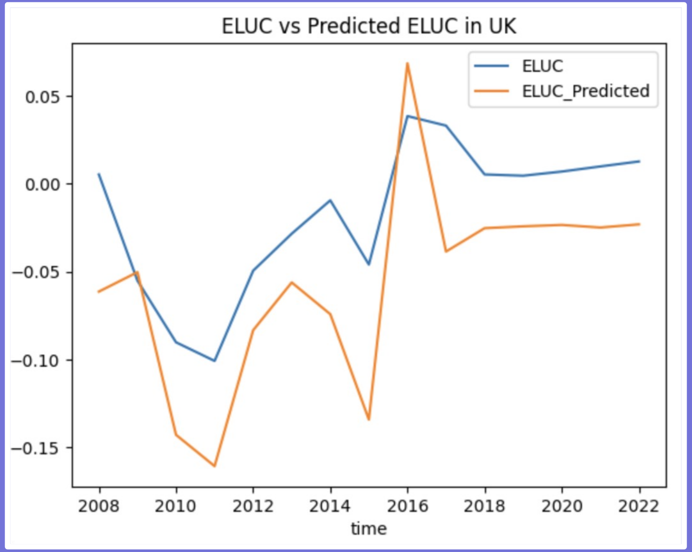
Actions

- *Changes in land use*

C3 crops diff	0.000283
Pasture diff	-0.003074
Range diff	-0.000801
Secondary forest diff	0.003570
Urban diff	0.000000

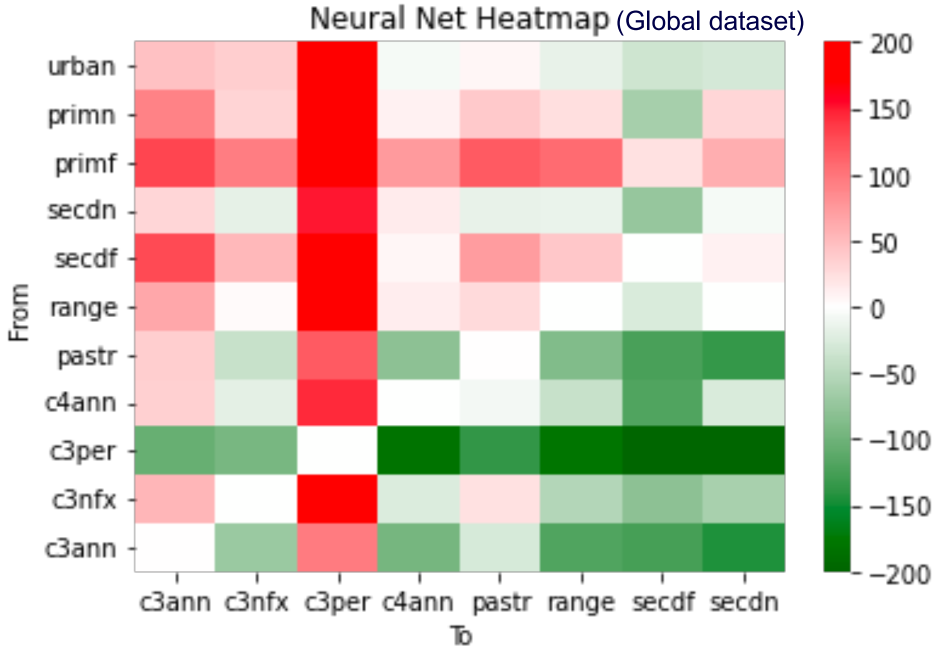
Outcomes

- *Emissions*
- *Change amount*



Training Predictive Models

Model	Train Time	W. Europe	South America	United States	Global
LinReg (EU)	0.1236	0.0331	0.2570	0.1720	0.2204
LinReg (SA)	0.8281	0.1422	0.1549	0.0648	0.1110
LinReg (US)	0.5652	0.1402	0.1467	0.0345	0.0720
LinReg (Global)	11.1449	0.1410	0.1520	0.0366	0.0723
RF (EU)	43.2344	0.0314	0.2373	0.1156	0.2232
RF (SA)	338.2790	0.1722	**0.0715**	0.0462	0.1095
RF (US)	115.4622	0.1559	0.1874	0.0200	0.1120
RF (Global)	255.3720	0.1007	0.0870	0.0257	0.0558
Neural Net (EU)	78.7409	**0.0247**	0.5510	0.3313	0.3493
Neural Net (SA)	1208.0376	0.7950	0.0936	0.1866	0.2195
Neural Net (US)	312.3967	0.3348	0.2164	**0.0196**	0.1319
Neural Net (Global)	186.2248	0.3298	0.2182	0.1309	**0.0530**



Evaluated linear regression, random forest, neural network models
To keep computations feasible:

- Separate models for Global, Europe, South America, US
- NN, LinReg trained with 1851-2011, RF 1982-2011; tested with 2012-2021

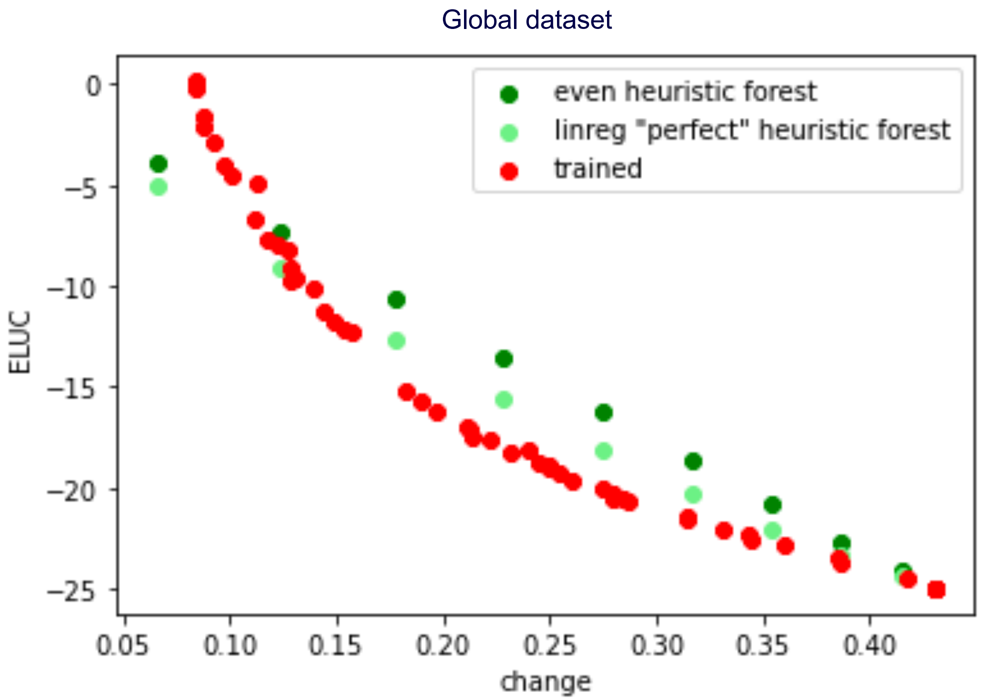
LinReg not sufficient

- Apparently a nonlinear problem

RF does not extrapolate well
Neural networks are the most accurate

- Learn positive and negative changes
- Modulated nonlinearly based on location, area, year

Evolving Prescriptive Models



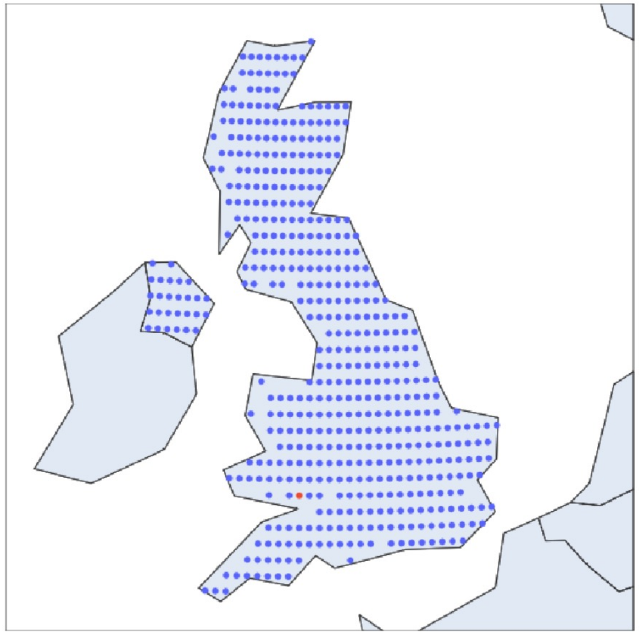
A population of neural networks recommending land-use change for a particular cell and year

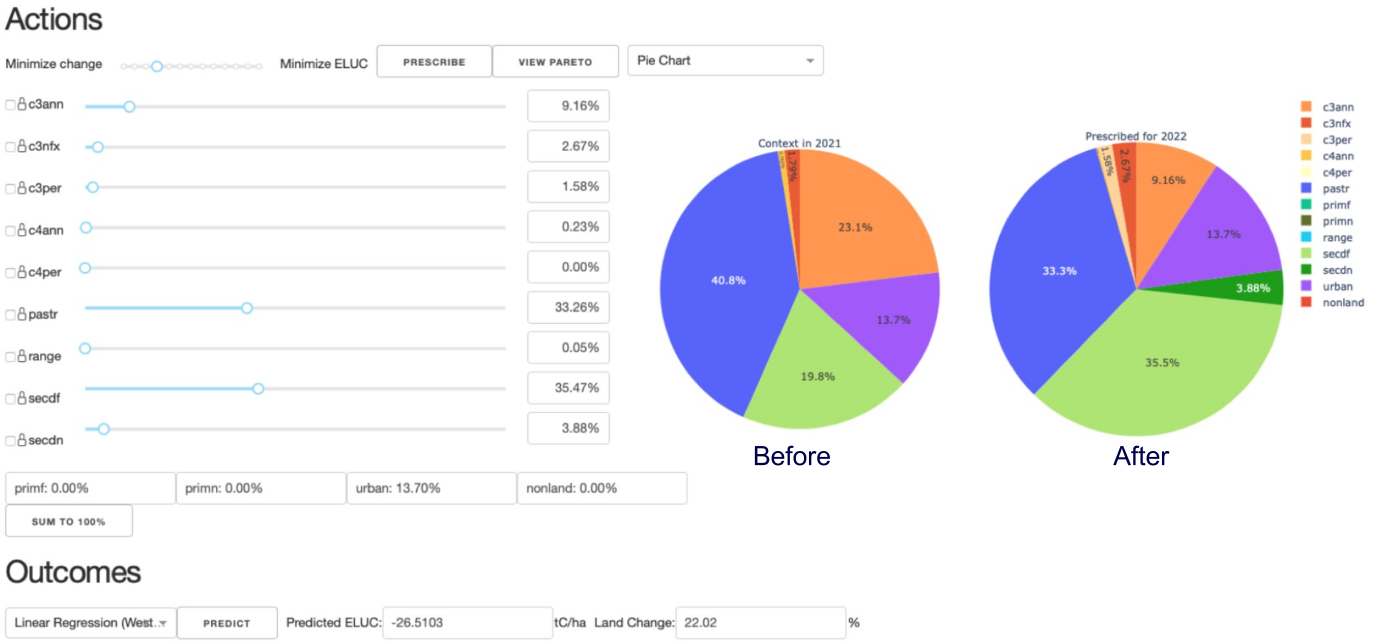
- Evolved against the neural-network predictor
- Trained with a random subset of 1851-2011, tested with 2012-2021

Results in a Pareto front for ELUC/Change tradeoffs

- Better than changing to forest equally, or linearly optimally
- Discovers nonlinearities and exploits them

Interactive Demo

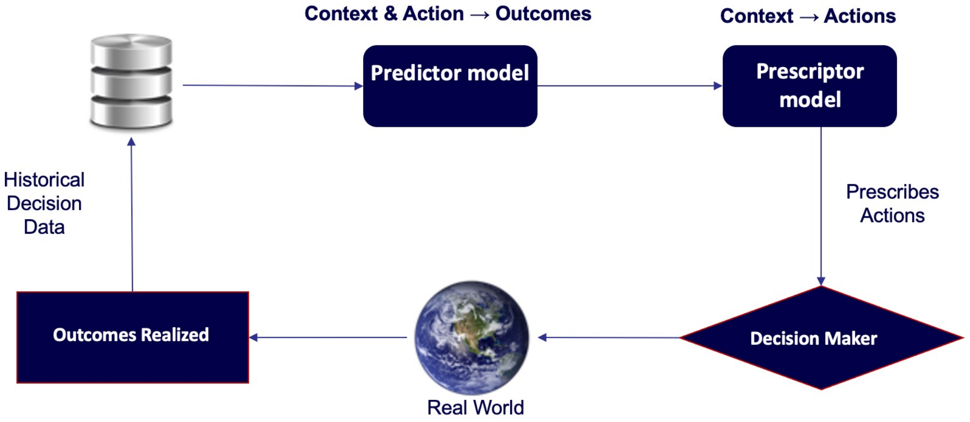


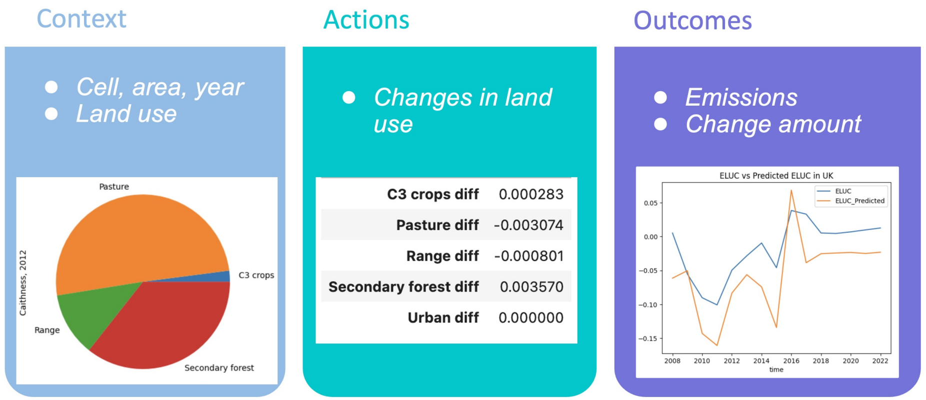


Available at https://landuse.evolution.ml

- Explore different locations and time periods
- Observe actions and modify them
- See their outcomes

Future Work





Project Resilience Platform

- Incorporate e.g. RIO to estimate confidence on predictions: trustworthy
- Evolve a set of rules instead of neural networks: explainable
- Utilize ensembling of different predictive models: improved accuracy

Problem definition and data

- More refined actions, e.g. different crop types: more actionable
- Recommend changes over several years
- Optimize multiple objectives, e.g. food yield, water usage, fertilizer usage

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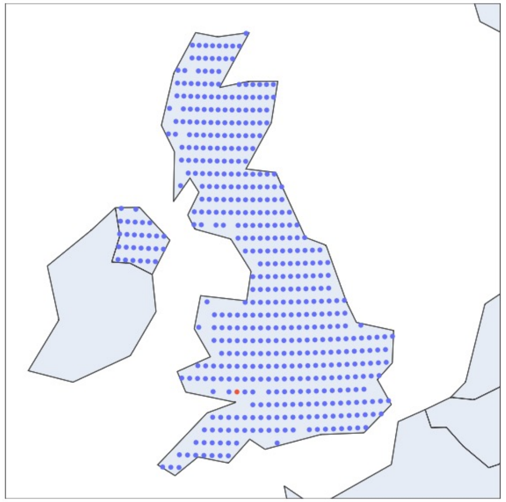
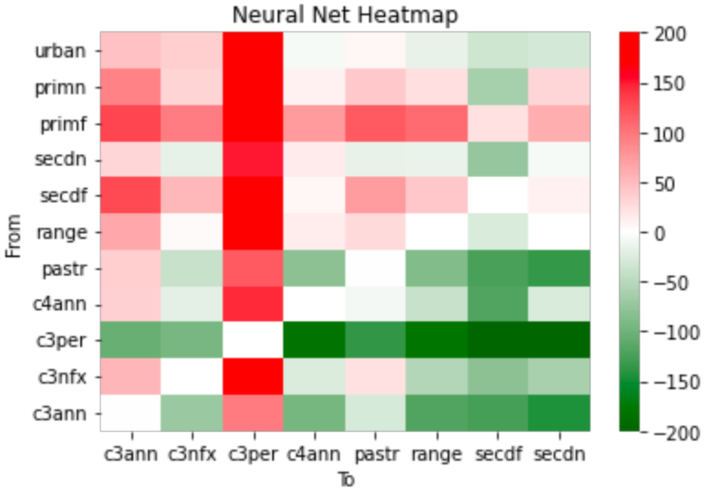
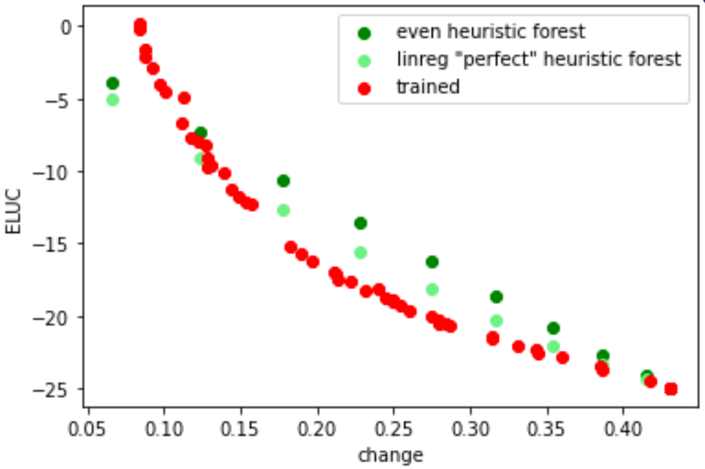
Conclusion



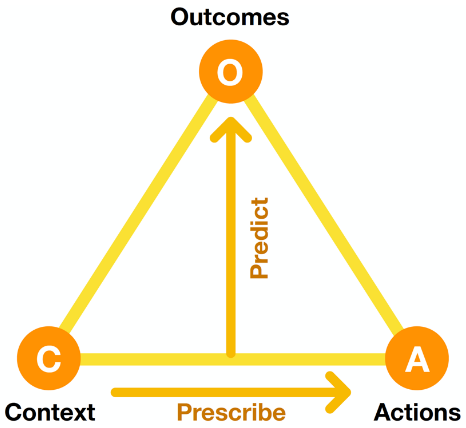




Land-use decisions can have a large impact on climate

Historical data and simulations brought together in ESP
- To predict effects of land-use change
- To discover optimal strategies for land-use change

Can be refined with more precise data and decisions
Eventually to be used to empower decision-makers



Project Resilience: https://www.itu.int/en/ITU-T/extcoop/ai-data-commons/Pages/project-resilience.aspx