Discovering Effective Policies for Land-Use Planning

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Land-Use Optimization

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

(Globe Observer, 2023)
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
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
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
  - secdn: Secondary nonforest vegetation
- **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

Outcomes

- Emissions
- Change amount
Training Predictive Models

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
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
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