Discovering Effective Policies for Land-Use Planning

Risto Miikkulainen[1,2], **Olivier Francon**[2], **Daniel Young**[2], **Elliot Meyerson**[2], **Jacob Bieker**[3], **Hugo Cunha**[2], **and Babak Hodjat**[2]
[1]The University of Texas at Austin; [2]Cognizant AI Labs; [3]Open Climate Fix

Abstract

How areas of land are allocated for different uses, such as forests, urban, and agriculture, has a large effect on carbon balance, and therefore climate change. Based on available historical data on changes in land use and a simulation of carbon emissions/absorption, a surrogate model can be learned that makes it possible to evaluate the different options available to decision-makers efficiently. An evolutionary search process can then be used to discover effective land-use policies for specific locations. Such a system was built on the Project Resilience platform [5] and evaluated with the Land-Use Harmonization dataset [4] and the BLUE simulator [3]. It generates Pareto fronts that trade off carbon impact and amount of change customized to different locations, thus providing a potentially useful tool for land-use planning.

1 Introduction

One of the main factors contributing to climate change is how much land area is allocated for different uses [2]. Forests in general absorb more carbon than e.g. crops and ranges, yet such uses are essential for the economy. Land-use patterns must therefore be planned to maximize carbon absorption while maintaining economic viability.

An approach for land-use optimization was developed as part of Project Resilience, a non-profit project hosted by the ITU agency of the United Nations [5]. The goal is to provide decision-makers with a tool to know how their land-use choices affect CO2 fluxes in the long term, and make suggestions for optimizing these choices. More specifically, the tool is designed to answer three questions: (1) For a geographical grid cell, identified by its latitude and longitude, what changes to the land usage can be made to reduce CO2 emissions? (2) What will be the long-term CO2 impact of changing land usage in a particular way? (3) What are the optimal land-use choices that can be made with minimal cost and maximal effect?

The approach is based on the Evolutionary Surrogate-assisted Prescription method [1]. The idea is to first utilize historical data to learn a surrogate model on how land-use decisions in different contexts affect carbon emissions. Then, this model is used to evaluate candidates in an evolutionary search process for good land-use change policies. As a result, a Pareto front is generated of solutions that trade off reduction in carbon emissions and the amount of change in land use. Each point in the Pareto front represents an optimal policy for that tradeoff. To make the results trustworthy, the tool allows the decision-maker to explore modifications to these policies, and see the expected effect. In the future, it should also be possible to evaluate confidence of the predictions, evolve rule sets to make the policies explainable, and utilize ensembling and further objectives and preferences to make them more accurate. Thus, the tool harnesses several techniques in machine learning to provide a practical tool for decision-makers in optimizing land-use decisions.

This paper provides a short summary; for details, see the full paper [7]. An interactive demo of the system is at `https://landuse.evolution.ml`.

2 Background

Evolutionary Surrogate-assisted Prescription (ESP; [1]) is an approach for optimizing decision-making in a variety of domains (Figure 1). The main idea is that a decision policy can be represented as a neural network, or a set of rules, and a good policy can be discovered through population-based search, i.e. using evolutionary computation techniques. However, each

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candidate must be evaluated, which is difficult to do in many real-world applications. Therefore, a surrogate model of the world is learned from historical data, predicting how good the resulting outcomes are for each decision in each context.

ESP was first evaluated in reinforcement learning tasks such as function approximation, cart-pole control, and the flappybird game, and found to discover significantly better solutions, find them faster, and with lower regret than standard approaches such as direct evolution, DQN, and PPO. A major application to decision-making was developed for optimizing strategies for non-pharmaceutical interventions (NPIs) in the COVID-19 pandemic [6]. This approach was extended to an XPRIZE competition on Pandemic Response, which in turn forms the blueprint for Project Resilience [5], an ITU/UN collaborative effort to tackle global problems. Land-use optimization is the first application being developed under Project Resilience.

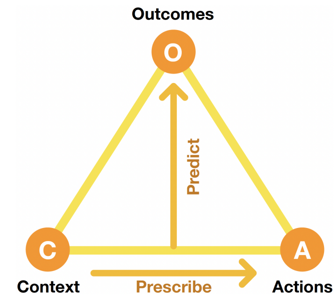

Figure 1: The ESP Decision Optimization Method. A predictor is trained with historical data on how given actions in given contexts led to specific outcomes. It is then used as a surrogate in order to evolve prescriptors, i.e. neural networks that implement decision policies resulting in the best possible outcomes.

3 Land-Use Optimization Task

The data for carbon emissions (Emissions resulting from Land-Use Change, ELUC) originate from a high-fidelity simulation called Bookkeeping of Land-Use Emissions (BLUE; [3]). BLUE is designed to estimate the long-term CO2 impact of committed land use. "Committed emissions" means all the emissions that are caused by a land-use change event are attributed to the year of the event. BLUE is a bookkeeping model that attributes carbon fluxes to land-use activities. While in principle a simulator can be used as the surrogate model for ESP, in practice the simulations are too expensive to carry out on demand during the search for good policies. Therefore, the team in charge of the BLUE model performed a number of simulations covering a comprehensive set of situations for 1850-2022, resulting in a dataset that could be used to train an efficient surrogate model.

The Land-Use Change (LUC) data is provided by the Land-Use Harmonization project (LUH2; [4]). A land-use harmonization strategy estimates the fractional land-use patterns, underlying land-use transitions, and key agricultural management information, annually for the time period 850-2100 at 0.25 x 0.25 degree resolution.

Based on these data, the modeling approach aims to understand the domain in two ways: (1) In a particular situation, what are the outcomes of the decision maker's actions? (2) What are the decisions that result in the best outcomes, i.e. the lowest carbon emission and cost for each tradeoff between them? The data is thus organized into context, action, and outcome variables.

Context describes the problem the decision maker is facing, i.e. a particular grid cell, a point in time when the decision has to be made, and the usage of the land at that point. More specifically it consists of latitude and longitude and the area of the grid cell, the year, and the percentage of land used in each LUH2 category (as well as nonland, i.e. sea, lake, etc.).

Actions represent the choices the decision-maker faces. How can they change the land? In the study of this paper, these decisions are limited in two ways: First, decision-makers cannot affect primary land. The idea is that it is always better to preserve primary vegetation; destroying it is not an option given to the system. Technically, it is not possible to re-plant primary vegetation. Once destroyed, it is destroyed forever. If re-planted, it would become secondary vegetation. Second, decision-makers cannot affect urban areas. The needs of urban areas are dictated by other imperatives, and optimized by other decision makers. Therefore, the system cannot recommend that a city should be destroyed, or expanded.

Outcomes consist of two conflicting variables. The primary variable is ELUC, i.e. emissions from land-use change. It consists of all CO2 emissions attributed to the change, in metric tons of carbon per hectare (tC/ha), obtained from the BLUE simulation. A positive number means carbon is emitted, a negative number means carbon is captured. The secondary variable is the cost of the change, represented by the percentage of land that was changed. This variable is calculated directly from the actions. There is a trade-off between these two objectives: It is easy to reduce emissions by changing most of the land, but that would come at a huge cost. Therefore, decision-makers have to

Model	Train Time(s)	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**

Table 1: Mean absolute errors of the models trained on each region, evaluated on each region.

minimize ELUC while minimizing land change at the same time. Consequently, the result is not a single recommendation, but a Pareto front where each point represents the best implementation of each tradeoff given a balance between the two outcomes.

4 Models

The system consists of the predictor, trained with supervised learning on the historical data, and the prescriptor, trained through evolution.

Given the context and actions that were performed, the **predictive model** estimates the outcomes. In this case, since the cost outcome can be calculated directly, only the ELUC is predicted by the model. That is, given the land usage of a specific location, and the changes that were made during a specific year, the model predicts the CO2 long-term emissions directly caused by these changes. Any predictive model can be used in this task, including a neural network, random forest, or linear regression. As usual, the model is fit to the existing historical data and evaluated with left-out data.

Given context, the **prescriptive model** suggests actions that optimize the outcomes. The model has to do this for all possible contexts, and therefore it represents an entire strategy for optimal land use. The strategy can be implemented in various ways, including decision trees, sets of rules, or neural networks. The approach in this paper is based on neural networks. The optimal actions are not known, but the performance of each candidate strategy can be measured (using the predictive model), therefore the prescriptive model needs to be learned using search techniques. Standard reinforcement learning methods such as PPO and DQN are possible; the experiments in this paper use evolutionary optimization, i.e. conventional neuroevolution [8]. As in prior applications of ESP [1, 6], the network has a fixed architecture of two fully connected layers; its weights are concatenated into a vector and evolved through crossover and mutation.

5 Experiments

In preliminary experiments, it turned out to be difficult to achieve high accuracy globally in a single model. Therefore, separate models were trained on different subsets of countries: Western Europe, South America, and the United States. Three different predictive models were evaluated: linear regression (LinReg), Random Forests (RF), and neural networks (Neural Net). They were trained with a sampling of data upto 2011, and were tested with data from [2012-2021].

As shown in Table 1, in each region the models trained on that region performed the best. The LinReg models performed consistently the worst, suggesting that the problem includes significant nonlinear dependencies. RF performed significantly better; however, RF does not extrapolate well beyond the training examples. In contrast, neural nets both capture nonlinearities and extrapolate well, and turned out to be best models overall. Therefore, the global neural net surrogate was used to evolve the prescriptors.

The prescriptors were evolved and tested with the same training and testing sets as the global neural net. The prescriptors were fixed fully connected neural networks with two layers of weights. Their weights were initially random, and modified by crossover and mutation. They received the current land-use percentages as their input, and their outputs specified the suggested changed land-use percentages; they were then given to the predictor to estimate the change in ELUC. The outputs were compared to the inputs to calculate the change percentage.

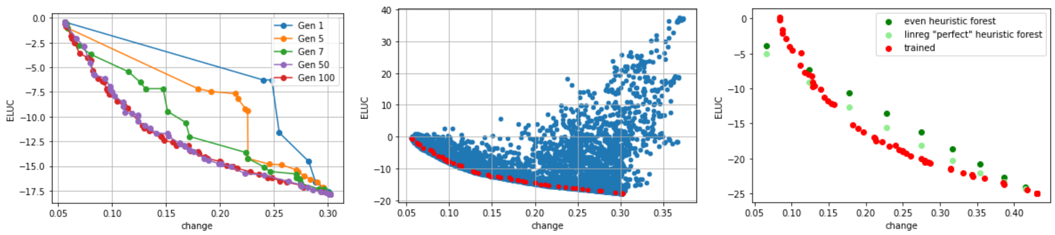

Figure 2: Prescriptor evolution and performance. (Left) Evolution of the Pareto front; (middle) Distribution of all prescriptors created during evolution; (right) Comparison to even and optimal linear heuristic baselines.

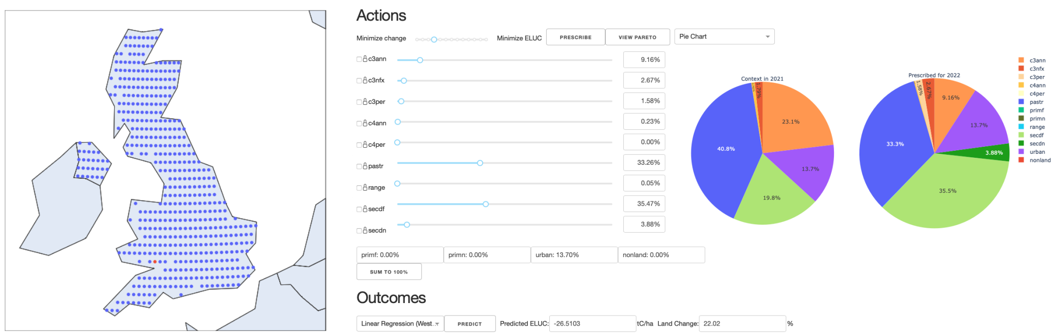

Figure 3: A suggested land-use change for a given location. (*a*) The location is indicated by the red dot among the UK grid cells. (*b*) One prescriptor is chosen from the Pareto front spanning minimal change and minimal ELUC (top left). The current land use is shown on the left pie chart and the recommended on on the right pie chart. This prescriptor recommends decreasing pasture and annual C3 crops and increasing secondary forest and secondary non-forest vegetation, resulting in a 26.5% decrease in carbon emissions with a 22.0% change. The user can then select different solutions from the Pareto front and modify the sliders manually to explore alternatives.

Figure 2 demonstrates the progress of evolution towards increasingly better prescriptors, i.e. those that represent better implementations of each tradeoff of the ELUC and change objectives. They represent a wide variety of tradeoffs, and a clear set of dominant solutions that constitute the final Pareto front (red dots). That set is returned to the decision-maker, who can then select the most preferred one to be implemented. Importantly, the evolved Pareto front dominates two linear baselines: one where land is converted to forest from all other types evenly, and another where other land types are converted to forest in a decreasing order of emissions. This result suggests that the approach is able to learn and utilize nonlinear interactions, and therefore results in better solutions for land-use than obvious heuristics.

Figure 3 shows a screenshot of an interactive demo of the trained models (available at `https://landuse.evolution.ml`). It allows the user to explore different locations, see the prescribed actions for them, and their outcomes. It is also possible to modify those actions and see their effect, thus evaluating the user's skills as a decision-maker compared to that of machine learning.

For more details on the experiments as well as future work, please see the full paper [7].

6 Conclusion

Land-use policy is an area of climate change where local decision-makers can have a large impact. In this paper, historical data and simulation technology are brought together to build an efficient machine-learning model that can predict the outcomes of these decisions efficiently for different contexts. An evolutionary optimization process is then used to identify effective policies, balancing the cost of land-use change and its effect in reducing carbon emissions. Machine learning methods can thus play an important role in empowering decision-makers on climate change issues.

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