GainForest: Scaling Climate Finance for Forest Conservation using Interpretable Machine Learning on Satellite Imagery

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Abstract

Designing effective REDD+ policies, assessing their GHG impact, and linking them with the corresponding payments, is a resource intensive and complex task. GainForest leverages video prediction with remote sensing to monitor and forecast forest change at high resolution. Furthermore, by viewing payment allocation as a feature selection problem, GainForest can efficiently design payment schemes based on the Shapley value.

1. Introduction

Climate change is arguably humanity's primary challenge, demanding urgent, decisive action in line with the Paris Agreement. Land use is a key component, accounting for approximately 25% of total greenhouse gases (GHG). Land use includes a wide range of critical issues, from deforestation and forest degradation through agriculture. The domain is particularly challenging, given that the world's growing population and rising standards of living exert an increasing pressure on food and consumer goods production, both of which may lead to conflicting objectives with climate change and biodiversity.

The REDD+ program (Reducing Emissions from Deforestation and Forest Degradation), is UNFCCCs scheme for the reduction of emissions caused by forest protection measures. However, designing effective REDD+ policies and actions, assessing their GHG impact, and linking them with the corresponding payments, is a resource-intensive and complex task for which there is considerable room for improvement also with respect to private sector involvement.

There are delays in implementation, inconsistencies in the reported data, insufficient levels of transparency, and as a result a lack of actionable projects. Current efforts fall short for fully leveraging the process and technology options available today. The net result is insufficient climate action in the land management domain (including biodiversity protection) and a collective failure to meet the climate targets set.

We propose GainForest, an interpretable machine learning system that addresses concrete needs to improve the efficiency and effectiveness of Measurement, Reporting and Verification (MRV) processes in relation to forest conservation efforts and climate finance instruments that rely on MRV in order to incentivise sustainable land-use practices, as well as Payment for Ecosystem Services and biodiversity schemes that promote public and private investment in sustainable land-use activities.

GainForest integrates large amounts of unlabeled satellite imagery with labelled authoritative data from forest zoning and plot ownership to predict land use change. Interpretable machine learning approaches can then be used to guide fair performance and model-based climate payments.

2. Predicting Forest Change

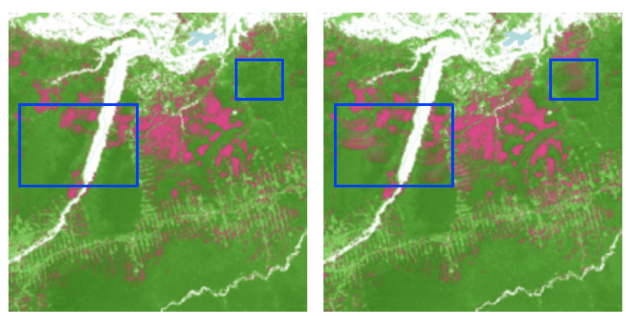

Figure 1. Given past deforestation (pink) patterns from Global Forest Watch (left image), a video prediction model is able to forecast in which regions a deforestation pattern is likely going to spread to in the near future (blue boxes, right image)

Remote sensing, such as satellite imagery, is getting increasingly important in ecosystem monitoring. Although it provides a huge supply of data and detailed resolutions (Digital Globe provides imagery up to 0.3m per pixel), many downstream tasks, however, are constrained by a lack of

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labels. Thus, current forest change alert systems such as FORMA (Wheeler et al., 2018) are constrained to train shallow supervised classifiers on handcrafted features to detect clear cuts in low resolutions (250m per pixel). Furthermore, in humid regions where clouds are covering large parts of forests, it can sometimes take months until forest change is detected and an alert is raised. Assessment of forest change suitable for performance-based payments such as the UN's REDD+ program is usually limited on a yearly basis (often leveraging a mosaic of numerous clear satellite imagery combined with on-site measurements).

2.1. Leveraging Spatial and Temporal Dependencies

Recent research demonstrated (Jean et al., 2018; Xie et al., 2016), that we can leverage spatial dependencies and transfer learning techniques to pre-train efficient representations with deep learning models that allow us to fully leverage the high resolutions of modern satellite imagery. Moreover, by additionally considering the temporal dependencies of remote sensing data we can reformulate land use change prediction as a video prediction task (Lee et al., 2018) (see Figure 1), enabling us to forecast the spread of deforestation up to a daily basis[1]. Accurate image forecasting models can support MRV decisions under uncertainty (e.g. predicting deforestation areas in cloudy images) and can be combined with additional authoritative data such as forest zoning and plot ownership.

2.2. Local Stakeholder Engagement as Active Learning

Machine learning models predicting forest change in high resolutions offer a valuable opportunity to engage and reward local stakeholders for climate action. Local stakeholders in respective regions can be queried by the model (e.g. via a mobile app) and incentivized to confirm or deny (uncertain) predictions of the model on-site. Responses can then be queried and used as future labels by the model using active learning.

3. Performance-Based Payments Based on Feature Value Contribution

One of the challenges of performance-based payments such as REDD+ is how to distribute the payment from investors and donors to the local stakeholders. A natural way of tackling the attribution problem is to adopt a game-theoretic viewpoint, where each stakeholder is modelled as a player in a coalitional game and the usefulness of a player from any subset of contributors is characterized via a utility function. The Shapley value (SV) (Shapley, 1953) is a classic method in cooperative game theory to distribute the total gains generated by the coalition of all players and has been applied to problems in various domains in environmental science. The reason for its broad adoption is that the SV defines a unique profit allocation scheme that satisfies a set of properties with appealing real-world interpretations, such as fairness, rationality, and additivity.

[1]Assuming we are leveraging Planet's daily satellite imagery coverage

By defining our climate utility function as machine learning model and our stakeholders as feature input (see Figure 2), we can solve the payment allocation problem as a feature selection problem and leverage the efficient SV computation techniques that has been applied to ML feature selection (Cohen et al., 2005; Sun et al., 2012; Mokdad et al., 2015; Jia et al., 2019; Lundberg & Lee, 2017). Climate investors can then use the assigned SV for their investment decisions.

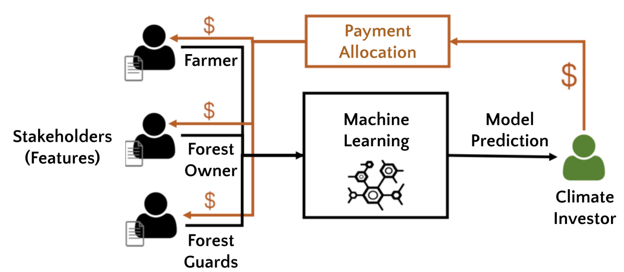

Figure 2. We can solve the payment allocation problem as feature selection problem

4. Discussion

Machine learning-based MRVs for forest change combined with the exponential data growth in remote sensing can scale forest conservation efforts by providing more fine-grained predictions under uncertainty. Additionally by leveraging techniques from interpretable machine learning such as efficient SV calculation, we can reframe payment allocation problems as efficient feature selection problems, potentially guiding climate investors in their decision making.

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