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Forest drought impact prediction based on satellite imagery and weather forecasts - a spatially distributed approach using a recurrent deep neural network

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The increased frequency of temperature anomalies and drought events in Switzerland has major ecological implications, with impacts over whole ecosystems. In Swiss forests, the 2018 drought, which was the most severe drought event recorded led to widespread leaf discoloration, premature leaf-shedding, and tree mortality. While work has been carried out to analyse droughts a posteriori, the prediction of potential drought impacts would make it possible to anticipate ecological responses, manage resources and mitigate damage. Current approaches to drought prediction include mechanistic models. However, such models are often limited by data accessibility and resolution to effectively describe local effects. Deep learning models trained on remote sensing and atmospheric data have been applied to drought fore- casting, but face the "black box" issue and often discard domain knowledge on drought mechanisms.

In this work, we propose a spatio-temporal deep learning method for drought forecasting in forests based on Sentinel-2 satellite imagery and weather variables, with the inclusion of topographic and environmental information. Drought is monitored by a proxy of early leaf wilting, using the normalized difference vegetation index (NDVI) that can be derived from Sentinel-2 bands. By predicting future NDVI values of pixels, we predict the potential occurrence of droughts in the short term.

Hand-crafted features based on environmental data are used as input for the model, such as high-resolution topographic features which can capture micro-climatic effects, as well as soil-vegetation-climate relationships. Environmental information is provided to the model through data on soil and forest properties. This explicit modelling with topographic and environmental features increases the model interpretability, compared to models performing feature extraction and based only on image bands.

A sequence model with long short-term memory (LSTM) cells was selected for its capacity to learn long-term dependencies as required in our application. We implement a pipeline to process spatiotemporal data, including data aggregation, normalization, missing data impu- tation and sample pixel timeseries for the prediction task. The model is trained and tested on data between 2015 and 2021, using the mean squared error to evaluate performances. A month (3 timesteps at Sentinel-2 acquisition rate) is forecasted given the past 3 months (9 timesteps) at a specific location. We opt for a "guided prediction" approach where the model has also access to weather forecasts for the future timesteps. The model is trained and tested in different regions in Switzerland to assess its generalization in space. A feature importance study was performed to identify key factors for drought forecasting and further improve the model.

This research combines drought predictors known to have an impact in ecology and hydrology with a guided deep learning model. We offer a method for dealing with heterogeneous spatiotemporal data and train an interpretable model for forecasting potential forest drought.