EGU23-12437, updated on 06 Mar 2024
https://doi.org/10.5194/egusphere-egu23-12437
EGU General Assembly 2023

Forest Drought Impact Prediction based on Spatio-temporal Satellite Imagery and Weather Forecasts -- A Spatio-Temporal Approach using Convolutional LSTM Models

Emine Didem Durukan[1], Selene Ledain[2], Thomas Brunschwiler[3], Devis Tuia[2], Manuel Günther[1], and Benjamin Stocker[4]
[1]University of Zurich, Informatics, Zurich, Switzerland (eminedidem.durukan@uzh.ch)
[2]Ecole Polytechnique Fédérale de Lausanne
[3]IBM Research Europe
[4]University of Bern

Recent hot and dry summers in Europe have had a significant impact on forest functioning and structure. In 2018 and 2019, Central Europe experienced two extremely dry and hot summers. These extremes resulted in widespread canopy defoliation and tree mortality. The objective in this study is to create a predictive model for predicting the density of vegetation, as measured by the NDVI index. We predict NDVI at a horizon of a month utilising data from the previous months as input to determine where and when drought impacts are triggered. Such predictive models should take into account both spatial and temporal dependencies between environmental variables and impacts. We hereon focus on Switzerland's forests as a region of interest to leverage high-quality model input layers and applications to typical stakeholder needs. Widely used vegetation indices and mechanistic land surface models are not effectively informed by the full information contained in Earth Observation data and the observed spatial heterogeneity of land surface greenness responses at hillslope-scale resolution. Effective learning from the simultaneous evolution of climate and remotely sensed land surface properties is challenging. Modern deep learning and machine learning techniques, however, have the capacity to generate accurate predictions while also explaining the relationship between climate and its recent history, the position in the landscape, and influences on vegetation. The task is to predict the future NDVI over forest areas, given past and future weather and surface reflectance. Giving future weather predictions as an input to the model, we are going for a 'guided-prediction' approach where the aim is to exploit weather information from forecasting models in order to increase the predictive power of the model - similar to the EarthNet2021 Challenge. Models are fully data-driven, without feature engineering and trained on spatio-temporal datacubes which can be seen as stacked satellite imagery for a specific geo-location and a timestep of past Sentinel 2 surface reflectance, past (observed) and future (forecasted) climate reanalysis, time-invariant information from a digital elevation model, and land cover map. The data pre-processing step includes implementing a customized dataset for drought impact prediction task, and a customized data sampler in order to be able to sample data (scenes) both spatially and temporally. Additional data operations

include aggregation of the weather data, normalization, and data imputation both on the image-level and missing-day level. For the prediction task, we used Convolutional Long-Short Term Memory models. In the temporal domain, models are trained on the period between 2015-2018, and be validated between 05-2019 and 09-2019. For the test period summer months of 2020 and 2021 will be used. However, in the spatial domain, for the sake of testing the generalizability of the model, different regions were used for train, validate and test processes. In order to asses the models performance on the temporal domain, tests with different training and testing window sizes are used. As for evaluating the performance of the model, Mean Squared Error was used. The project will lay the basis for an early warning platform to enable periodically updated near-term drought-impact forecasts.