How to use the power of AI to reduce the impact of climate change on Switzerland

Recommendations for the Swiss society and economy to become more resilient against the impact from a radically changing climate

Make key technologies broadly available and overcome challenges through key methodologies in climate- and AI-related fields.

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8.7 Case-Study #6: Vegetation Health Forecasting

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8.7.1 Vegetation Health Forecasting Service Description

Ecosystem services and vegetation productivity are sensitive to climate and weather anomalies. Meteorological extreme events can drive large variability in agricultural yields, can impair forest health and services, and can trigger ecological disturbances, including wildfires. Adverse climate impacts on vegetation are expressed, for example, through reduced crop growth or wood production, tree mortality, reduced carbon uptake and storage. AI has spurred and will enable new developments in vegetation health monitoring and forecasting to inform management decisions in agriculture, forestry and ecosystem conservation and restoration. However, it remains challenging to connect information of what can be observed with predictions for what stakeholders seek to understand.

Developments in AI for vegetation health monitoring and forecasting are fundamentally driven by the increasing volume, accessibility, and diversity of Earth Observation (EO) data and near-range remote sensing techniques. A range of applications and long-standing challenges have seen new advances thanks to AI, including field-scale plant disease detection and vegetation health monitoring[129], drought stress detection and monitoring[130] [131], carbon cycle monitoring[132], or phenology, plant growth, and crop yield forecasts in agricultural settings and forests[133] [134] (Lees et al., 2020).

In Switzerland, climate anomalies and extreme events with impacts on ecosystems are mostly related to summer drought and heat, late frost, hail, floods, and windstorms. Impacts of hail, floods, and windstorms are primarily determined by the magnitude of the meteorological forcing. In contrast, impacts by heat, drought and frost are strongly determined by the predisposition of the ecosystem to the meteorological forcing and are subject to the ecosystem's evolution and meteorological conditions over past weeks to months (or even years). They are the focus of this sub-chapter.

Vegetation monitoring and ***impact detection*** uses continuous ecosystem monitoring and EO data for "now-casting" (state estimation, quantification of anomaly levels from current or recent measurements). In contrast, near-term *forecasts* for weeks to months lead time and *projections* for decades lead time under novel climates rely on models of how the abiotic environment (climate, CO_2, soils, topography) drives ecosystem responses. AI has great potential for impact detection, now-casting, and near-term forecasting, but is limited for long-term projections because relevant model training data from current observations do not cover novel climates and CO_2.

Modelling ecosystems and climate impacts on forests and agricultural systems is challenging due to the nature and diversity of biotic processes that often vary between species or even individual plants, and due to landscape heterogeneity at small spatial scales, arising from topography, variations of soils and bedrock, and land use. These spatial variations underlie large variations in vegetation *exposure* to abiotic stress. Nevertheless, a rich history of dynamic vegetation and land surface modelling based on

[129] https://doi.org/10.1186/s13007-019-0479-8
[130] https://www.biorxiv.org/content/early/2022/08/17/2022.08.16.504173
[131] http://arxiv.org/abs/2303.16198
[132] https://www.nature.com/articles/s41597-019-0076-8
[133] https://www.sciencedirect.com/science/article/pii/S0168169923001096
[134] https://doi.org/10.1080/01431161.2017.1410296

mechanistic models has been established that climate impacts on vegetation are, to a certain extent, predictable[135]. AI bears promise in making best use of the recent surge in high-resolution EO data (10-500 m) and continuous ecosystem monitoring data for reliable, data-informed and stakeholder-relevant forecasts (e.g., yields, growth, carbon balance) beyond the coarse-resolution (50-100 km global) of land surface model simulations available today.

AI-guided impact detection, monitoring, and forecasts will be important for guiding management decisions in agriculture and forestry, revenue planning and insurances, and for early warning of impacts by climate extreme events guiding adaptation measures. The relevance of AI-tools for drought impact forecasting is depicted in (Figure 8.9). Solutions will have to be found for implementing regular updates of now-casting and forecasting outputs based on continuously ingested EO and ecosystem data. Projections, including trained models, will have to be made accessible through web applications and open-access APIs.

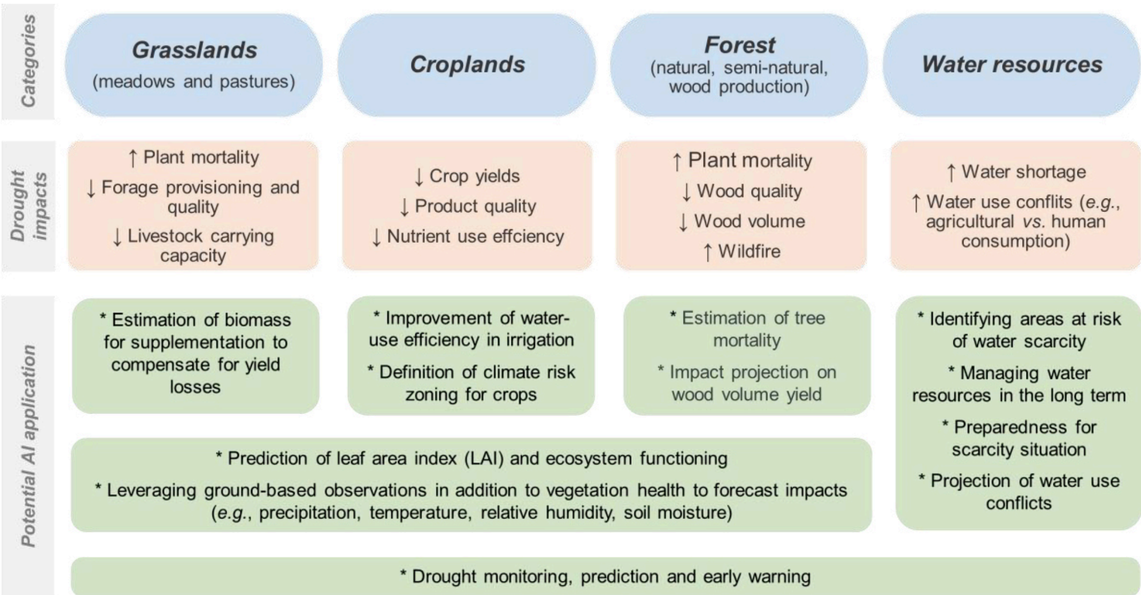

Figure 8.9: Use of AI tools associated to remotely sensed vegetation health for drought impact forecasting.

8.7.2 Methodology of Vegetation Health Forecasting: Data and AI Workflow Implementation

AI will be most successful if it can be effectively informed by the most abundant data sources. Satellite-based EO generates the most voluminous data and will continue to play a central role for vegetation monitoring, impact detection and forecasting. The most widely used EO data for vegetation is derived from multispectral satellite-remote sensing of surface reflectance in the optical, near-infrared, and thermal range, commonly sourced from the MODIS, Landsat, and Sentinel missions[136]. For certain modelling applications and target variables, information may be enhanced by LiDAR (Light Detection and Ranging), microwave, or near-range remote sensing using unmanned aerial vehicles (UAVs) or field phenotyping infrastructure in demonstration and research settings.

Vegetation monitoring and forecasting requires EO data from satellites with relatively frequent revisit times to capture the seasonal evolution and the response to weather anomalies that evolve over days to weeks. Frequent cloud cover limit data availability of satellite remote sensing data in the visible range. This further enhances the necessity for high temporal resolution. To generate stakeholder-

[135] https://royalsocietypublishing.org/doi/10.1098/rstb.2017.0304
[136] https://doi.org/10.1038/s41477-021-00952-8

relevant information, spatialized forecasts should be provided at scales of 100-500 m for forests and 10-50 m for agricultural settings. The freely available EO data from Sentinel-2 (min. 5-daily, 20 m) and MODIS/VIIRS (daily, 200 m) missions satisfy the spatial and temporal requirements for such applications. Higher resolution (10–100 cm) EO data will provide information at the level of individual trees and may enable stress impact and tree mortality detection and forecasts[137], potentially considering species information, in the future.

Vegetation impact forecasts informed by weather predictions may be provided with lead times of 1–10 days and may be driven by medium-range to extended-range weather forecasts (up to 1.5 months). Although affected by stochasticity in the weather, persistent atmospheric conditions may be forecasted with sufficient reliability. And although ecological quantities vary at multiple temporal scales and are highly heterogenous in space (soils, species, landscape), ecological systems are typically not stochastic *per se*, making ecological forecasting a highly relevant and achievable target[138].

With the available data, a machine learning model can be trained, needs to be evaluated, and will be deployed in case quality criteria like accuracy and generalization can be met (Figure 8.10).

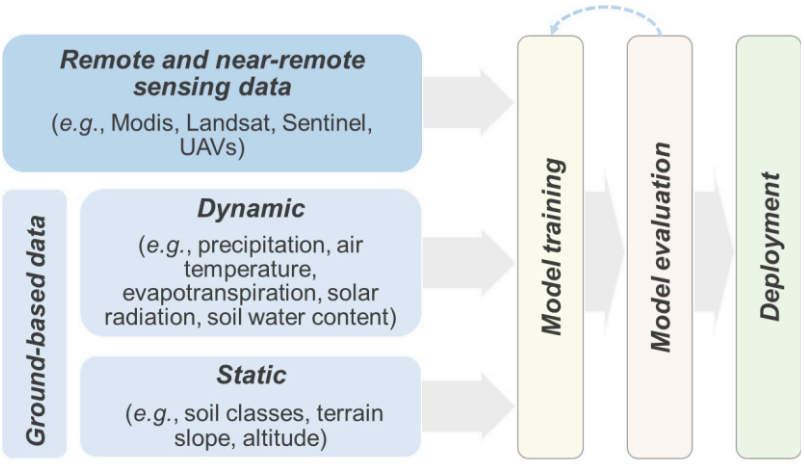

Figure 8.10: A basic workflow of machine learning application to forecast drought impacts on vegetation health based on remote sensing, near-remote sensing and ground-based data.

8.7.3 Current Limitations & Recommendation for Vegetation Health Forecasting Services

Stakeholder-relevant impact monitoring often requires data indirectly related to observable space-based quantities. For instance, obtaining labeled data for training ML-based crop yield predictions is laborious or subject to data use restrictions. Also, technical challenges have to be resolved for treating heterogenous data, combining the information of only indirectly related but abundant EO data with more directly related but sparse target data.

Alternatively, impact detection and forecasting can target EO-derived variables directly. For example, anomaly detection algorithms in surface reflectance data show promise for early intervention in vegetation health. However, challenges arise from varied tree species and topographical differences. Forecasting the Normalized Difference Vegetation Index (NDVI), using past evolution, weather, and predictors like topography and soil, enables operational drought forecasting. Such NDVI forecasting models may also serve as *foundational models* for related, more directly stakeholder-relevant

[137] https://doi.org/10.5194/egusphere-egu23-5917
[138] https://pnas.org/doi/full/10.1073/pnas.1710231115

variables. Challenges related to variable tree species compositions, topographical heterogeneity, and data quality will have to be addressed.

The data richness from EO poses challenges in data handling for effective analysis and model training and causes costs for data storage and ML training. Various data cube services are now available (Google Earth Engine, Microsoft Planetary Computer, IBM PAIRS, Swiss Data Cube), host Petabyte-scale EO and climate data, and freely provide (limited) compute resources. Combining their rich data resources with data-side computing environments for efficient ML training and inference will lower the bar of entry to AI for vegetation monitoring and forecasting at scale.

Many of the AI applications for ecosystem forecasting mentioned in this section are in a development stage. Applications of ecosystem now-casting and continuous monitoring are established (Zweifel et al. 2021; Thomas et al., 2023)[139] but are partial in geographic coverage or are not continuously up-dated.

An integration of multiple EO and ecosystem monitoring data streams for low-latency anomaly detection, early warning services for stakeholder-relevant variables, and spatialized forecasts of climate impacts is achievable and will be critically needed for climate-smart planning of ecosystem management. User-friendly tools for predicting drought impacts on crop yields or early warning systems for crop pests and diseases management would be examples of applications of AI leveraging increasingly abundant vegetation index data with finer temporal and spatial resolution.

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[139] https://lwf.wsl.ch/de/