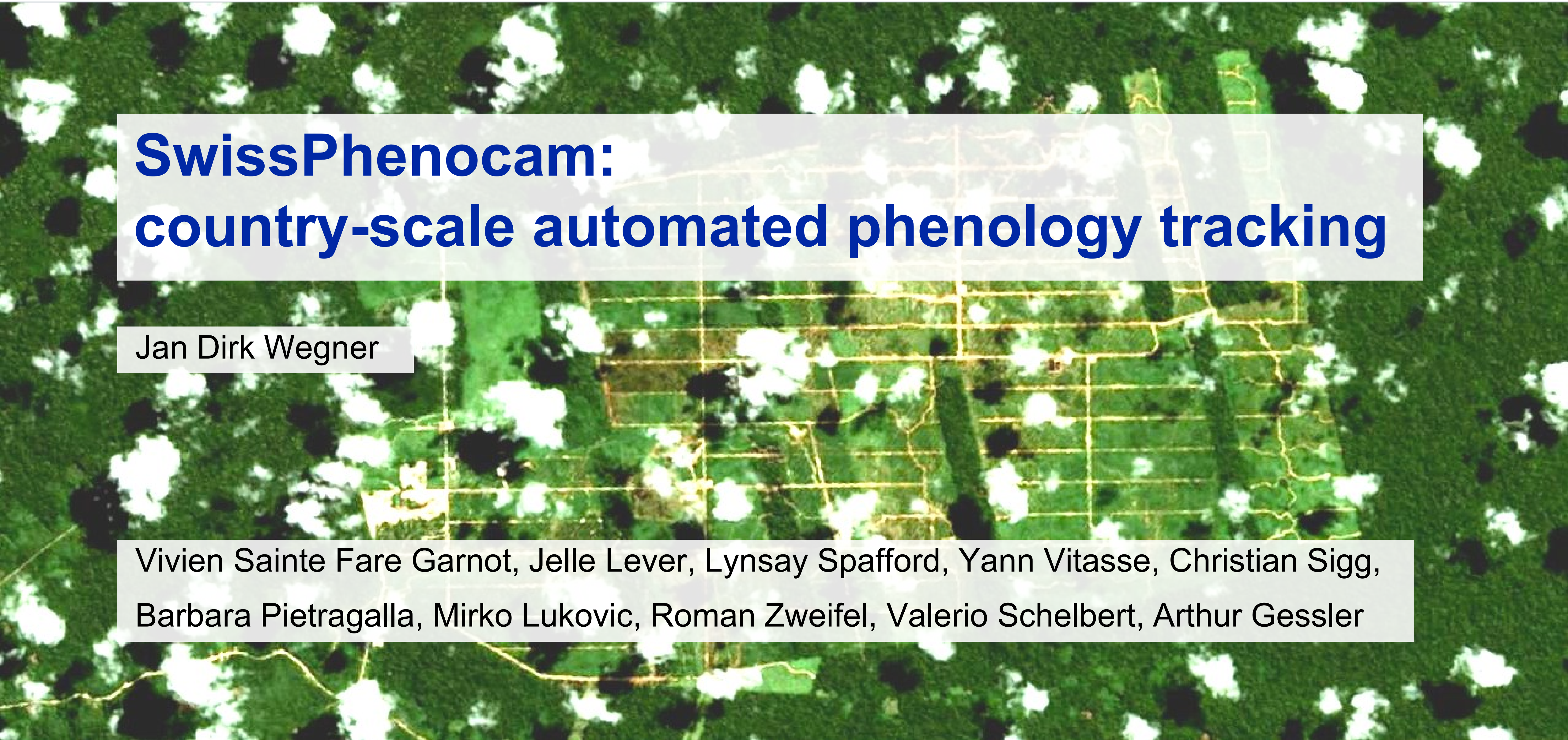
University of Zurich[UZH]
Eidg. Forschungsanstalt für Wald, Schnee und Landschaft WSL
Federal Office of Meteorology and Climatology MeteoSwiss
EcoVision
Department of Mathematical Modeling and Machine Learning (DM³L)



SwissPhenocam: country-scale automated phenology tracking

Jan Dirk Wegner

Vivien Sainte Fare Garnot, Jelle Lever, Lynsay Spafford, Yann Vitasse, Christian Sigg, Barbara Pietragalla, Mirko Lukovic, Roman Zweifel, Valerio Schelbert, Arthur Gessler

SwissPhenocam: Map and predict tree phenology in Switzerland automatically

Leaf unfolding

Flowering

Fruit maturation

Leaf colouration

- understand phenology to anticipate the effects of climate change on species interactions, biodiversity, ecosystems, carbon cycle etc.
- Aim: predict date of a given phenological event for a given species
- Existing approaches: process-based (mechanistic) models and traditional ML

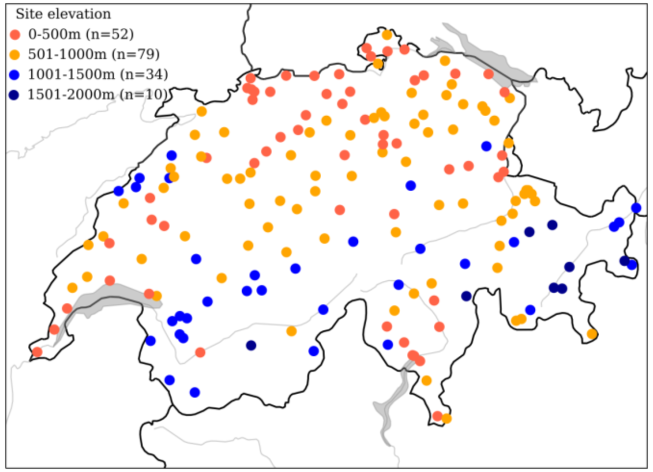
University of Zurich[UZH]
Eidg. Forschungsanstalt für Wald, Schnee und Landschaft WSL
Federal Office of Meteorology and Climatology MeteoSwiss
EcoVision
Department of Mathematical Modeling and Machine Learning (DM³L)

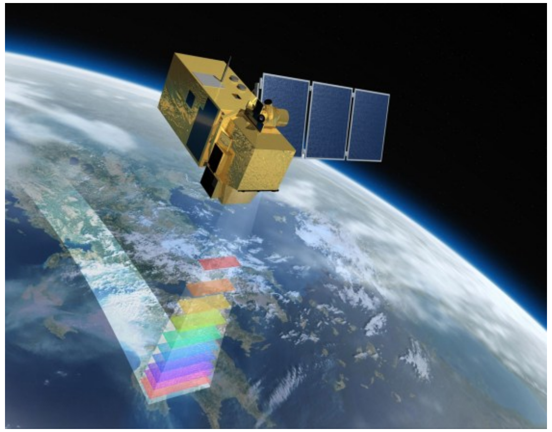
Combination of in-situ, webcam, climate and satellite data time-series

RoundShot webcams:
- 150+ relevant for phenological tracking
- annotation of the data of 34 sites

Phenology of individual trees at Swiss national scale

Swiss Phenology network:
- 175 sites
- 70 years of data
- 9 species
- >40k observations





University of Zurich[UZH]

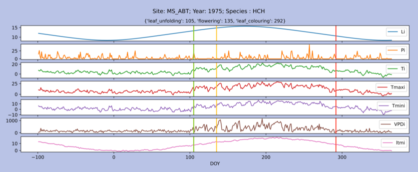
WSL Eidg. Forschungsanstalt für Wald, Schnee und Landschaft WSL

Federal Office of Meteorology and Climatology MeteoSwiss

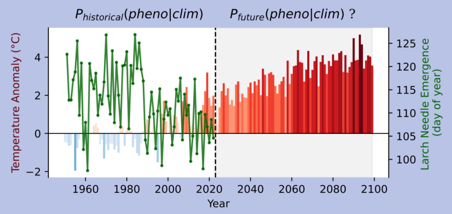
EcoVision

Department of Mathematical Modeling and Machine Learning (DM^3L)

1. Climate time series as input data (no webcam or satellite imagery)

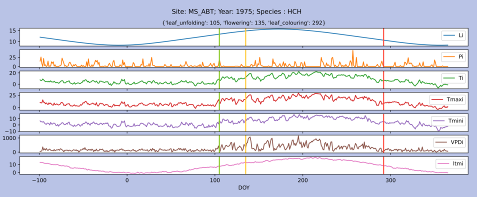


2. Making deep phenology models robust to climate change



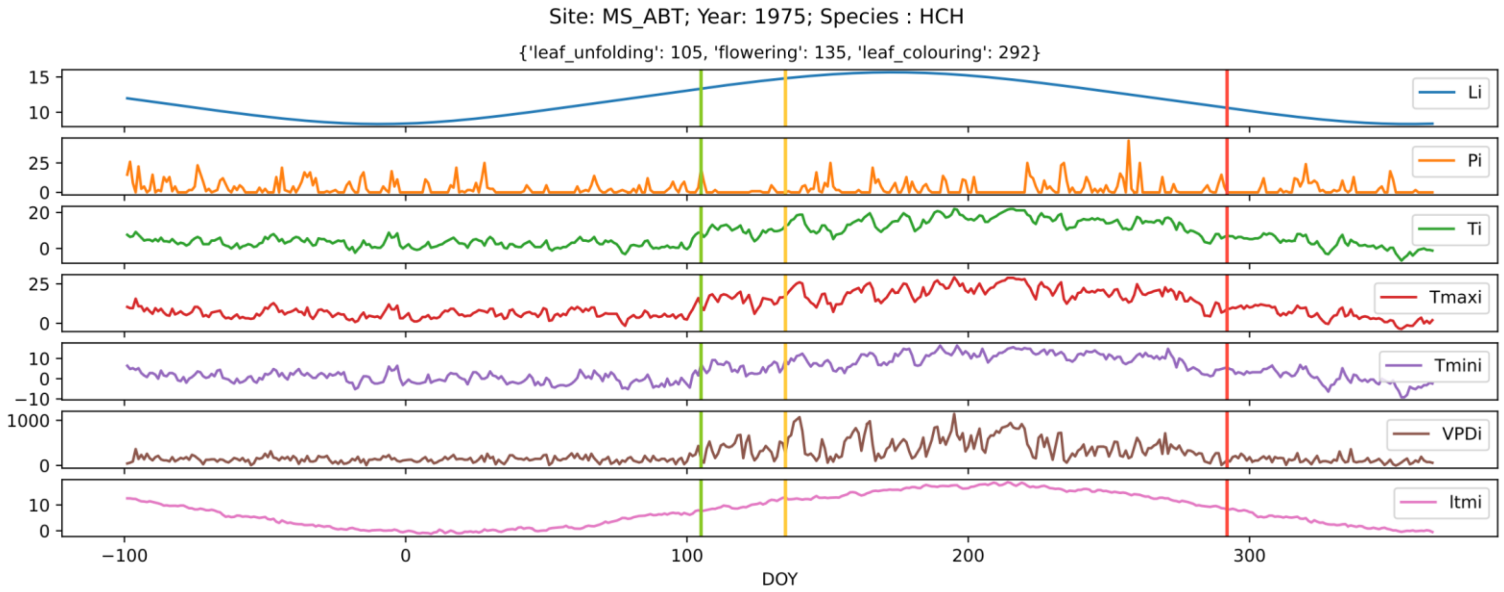
3. Webcam image time-series for phenology modeling via greenness

4. Joint modeling of image and climate time-series



1. Climate time series as input data (no webcam or satellite imagery)

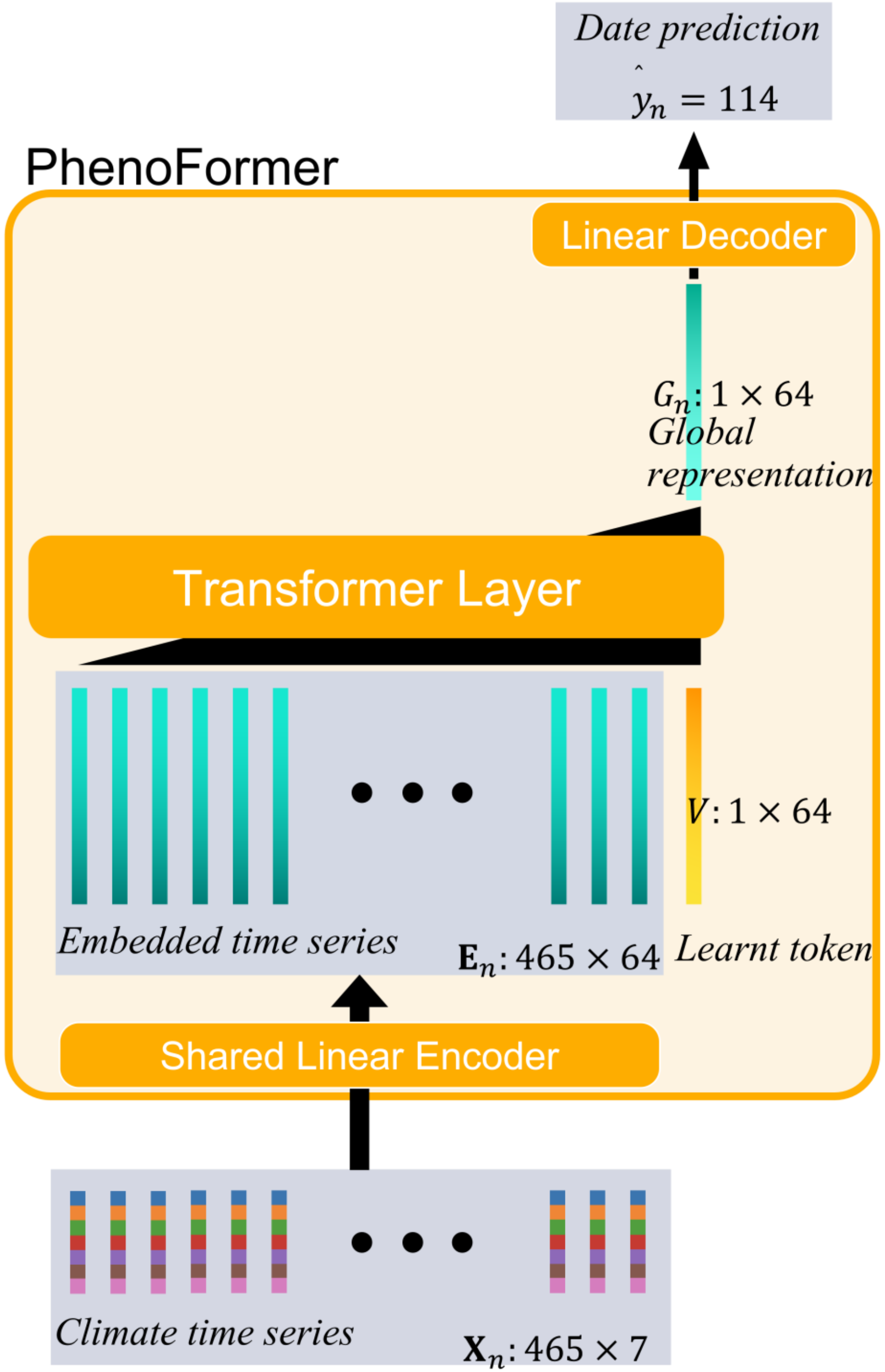
- Temperature, precipitation, water vapour pressure deficit, daily photoperiod
- Daily time series sampled at the location of each site of the Swiss Phenology Network and for each year



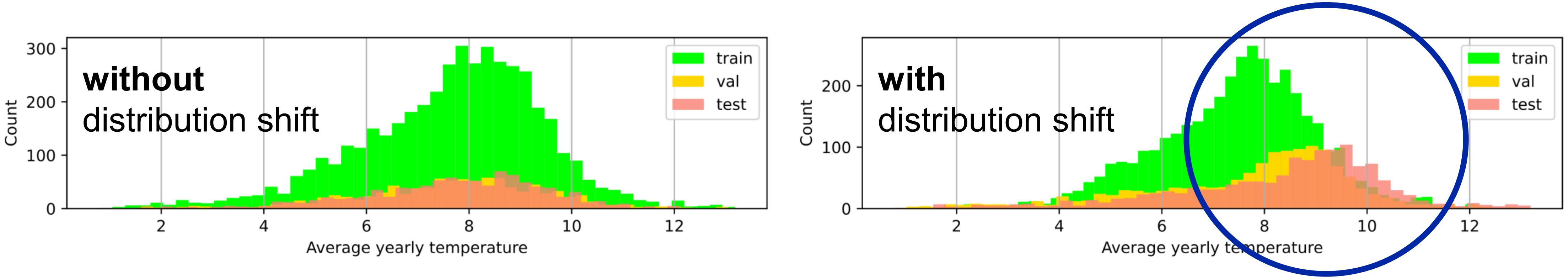
T	mean daily temperature ($^\circ C$)
T_{min}	minimum daily temperature ($^\circ C$)
T_{max}	maximum daily temperature ($^\circ C$)
ltm	long term daily mean temperature over a 30-year period ($^\circ C$)
P	daily precipitation sum (mm)
VPD	daily average water vapour pressure deficit (Pa)
L	daily photoperiod (hours)

PhenoFormer approach

- Attention-based architecture for phenology modeling with
  - Temporally shared linear encoder
  - Transformer layer + learnt token ➔ global embedding
  - Linear decoder ➔ event date prediction
- “Lightweight” model with approx. 35k trainable parameters
- Optimized with MSE loss + Adam



PhenoFormer results

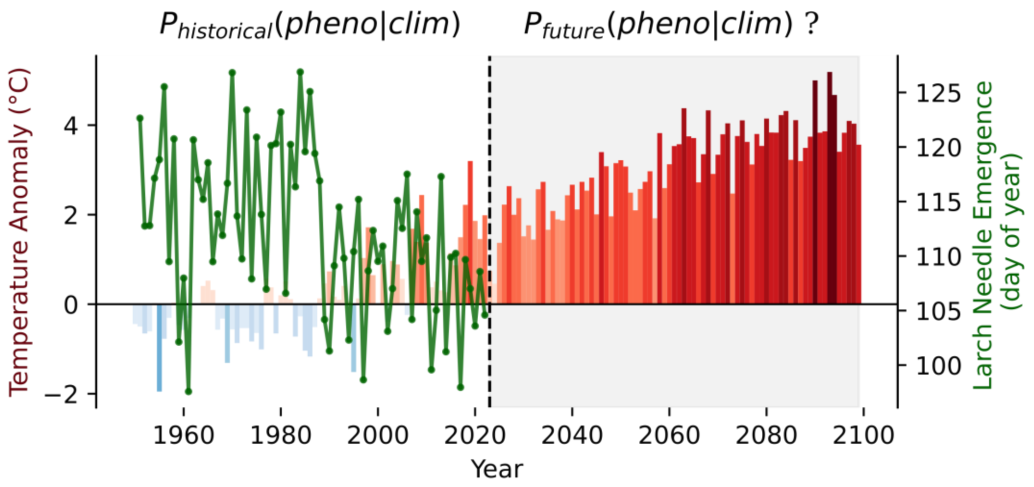


- **without** distribution shift: PhenoFormer slightly better than traditional ML (-0.2 day RMSE) and process-based models (-0.9 day RMSE)

- **with** distribution shift: PhenoFormer better than traditional ML (-1.1 day) and similar to process-based models (+0.1 day RMSE) ➔ *without specific OOD treatment*

2. How to make deep phenology models more robust to climate change?

- Climate change induces a continuous data distribution shift
- Shift is visible both on covariates and labels
- Breaks the i.i.d. hypothesis → poorer generalisation of ML models
- Process models more robust, but even they show a drift in optimal parameters over time
- **MId-feature RANk-adversarial Domain Adaptation (MIRANDA):** toward climate change-robust ecological forecasting with deep learning



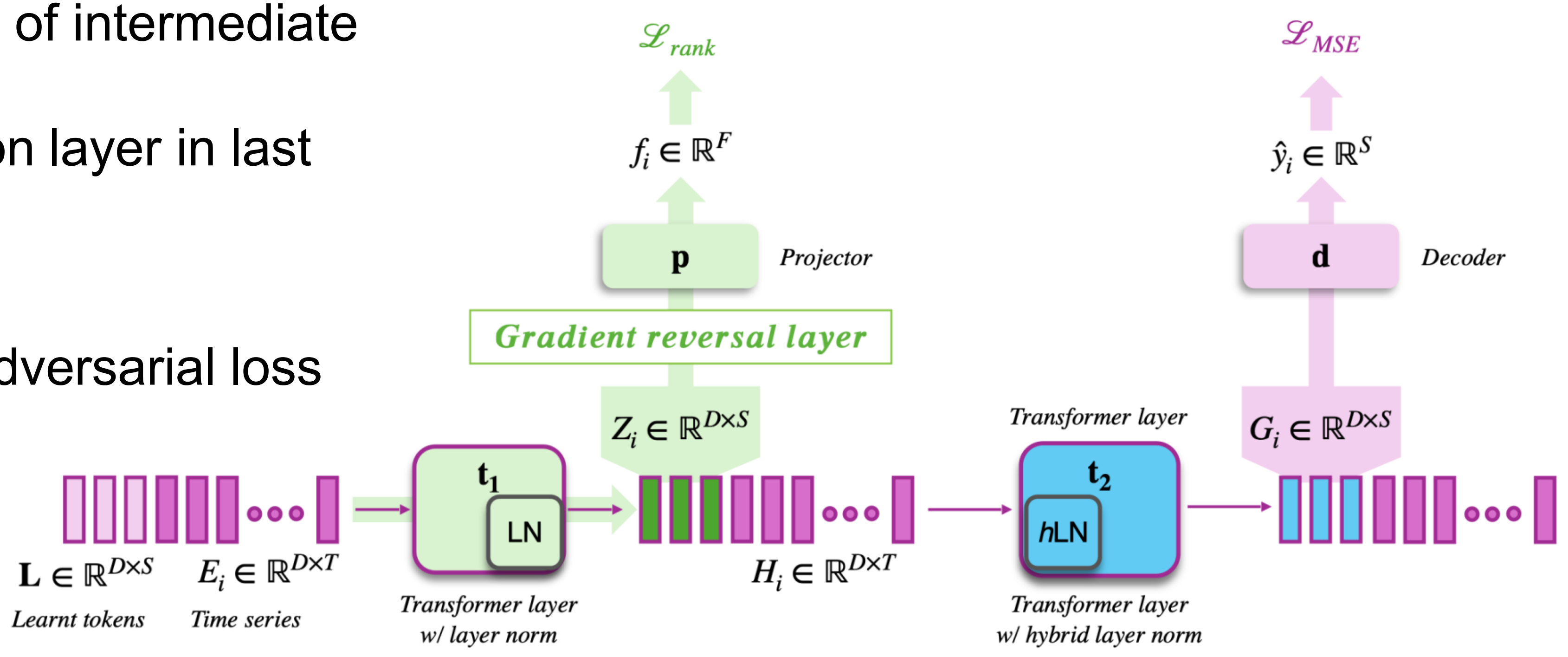
MIRANDA overview & first results

Combined covariate and label shift:

- Enforce invariance of intermediate representations
- hybrid normalisation layer in last transformer layer

Domain continuity:

- with rank-based adversarial loss



➔ **Outperforms deep learning baselines, but process model still on par or better (with longer training times though)**

3. Webcam image time-series for phenology modeling via greenness

- Webcam image archive with high spatial and temporal resolution
- Panoramic high-resolution views
- Heterogenous sources (weather cams, ski resorts, hotels, cities…)
- Between 1 and 144 images per day, every day
- Up to 14 year history

University of Zurich[UZH]
Eidg. Forschungsanstalt für Wald, Schnee und Landschaft WSL
Federal Office of Meteorology and Climatology MeteoSwiss
EcoVision
Department of Mathematical Modeling and Machine Learning (DM³L)

Image annotation campaign across Switzerland

Manual polygon annotations in images and expert site visits for species identification:

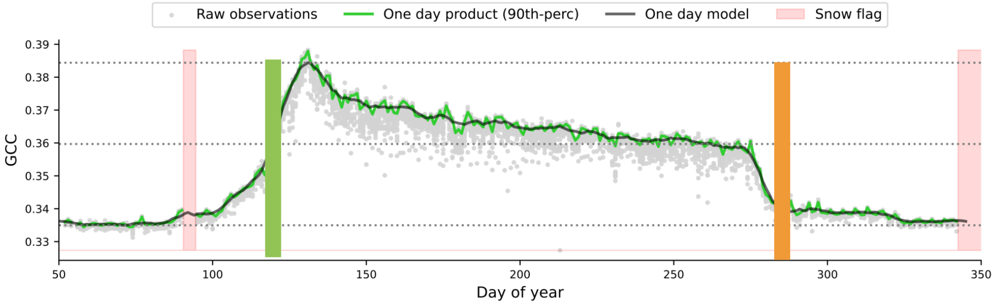
➔ 1788 individual trees identified

➔ 1361 groups of trees identified

Overview of modeling pipeline

Image time series

- Snow filtering
- Greenness extraction



Greenness time series

Transition date extraction

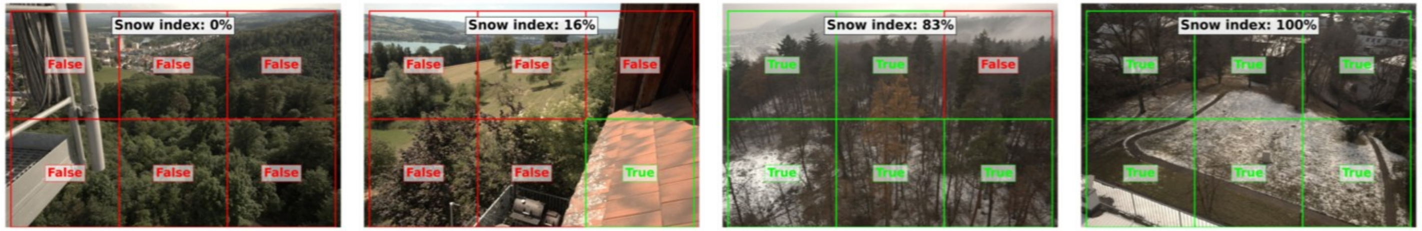
GreenUp 50% : DOY 118
GreenDown 25% : DOY 281

Phenological dates

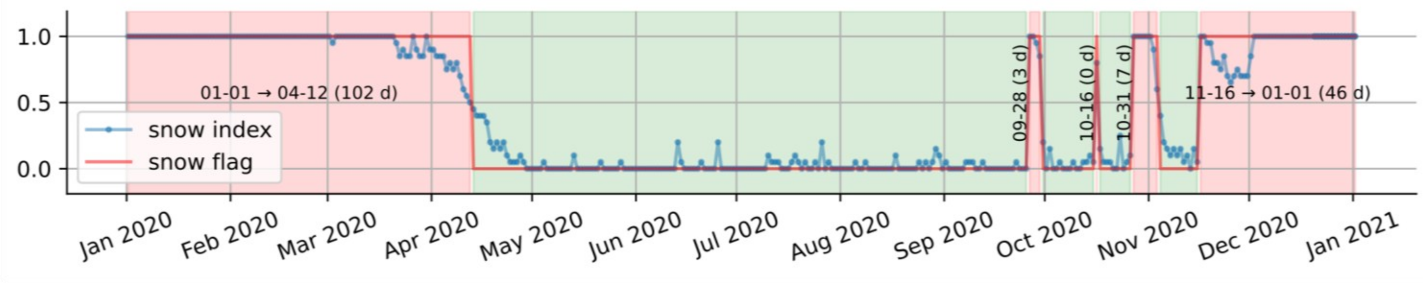
University of Zurich[UZH]
Eidg. Forschungsanstalt für Wald, Schnee und Landschaft WSL
Federal Office of Meteorology and Climatology MeteoSwiss
EcoVision
Department of Mathematical Modeling and Machine Learning (DM³L)

Snow detection with VLM

(a) Example of snow detection on a panorama image



(b) Analysis image 1 (c) Analysis image 2 (d) Analysis image 3 (e) Analysis image 4



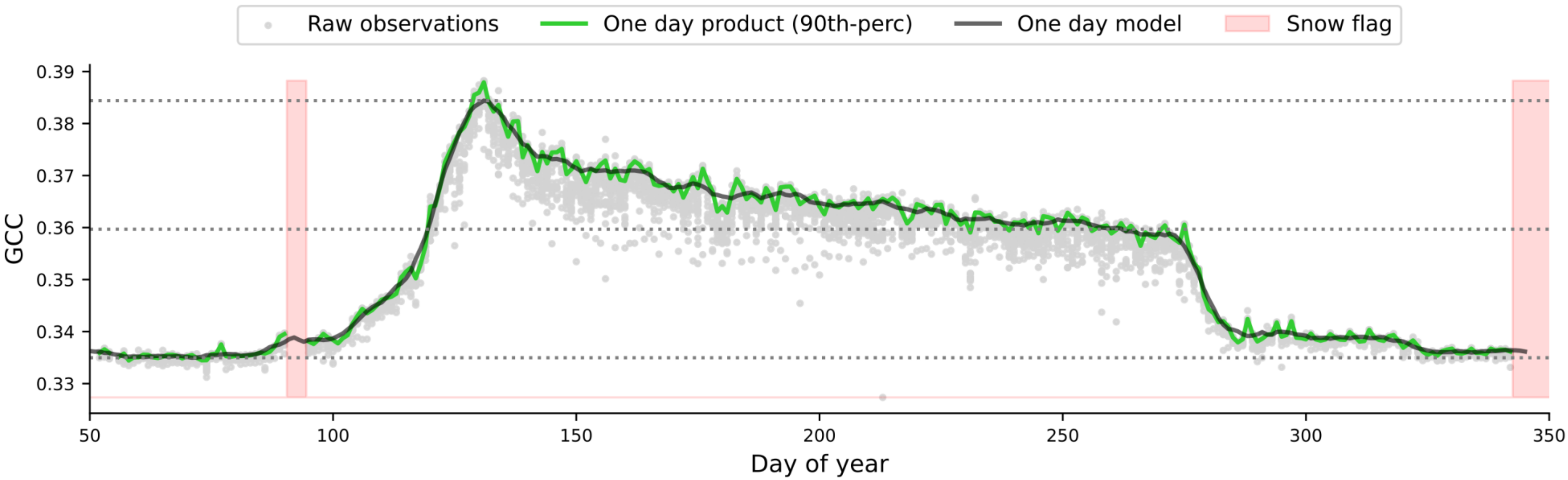
(f) Binary snow flag

- Qwen2-VL-2B-Instruct Prompt:

"Does this webcam image show visible snow on the foreground ground, vegetation, or structures? "
"Answer only with 'yes' or 'no'."

- Patch-based processing+majority vote
- Performance on 1k labelled images:
  - 98% Accuracy and 95% F1-score
- 1-day temporal closing as post-processing

University of Zurich UZH
WSL Eidg. Forschungsanstalt für Wald, Schnee und Landschaft WSL
Federal Office of Meteorology and Climatology MeteoSwiss
EcoVision
Department of Mathematical Modeling and Machine Learning (DM³L)



For each tree polygon

- Ignore snowy dates
- Extract Green Chromatic Coordinate (GCC) from all other observations (GCC = G / (R + G + B))
- Compute the one-day 90th-percentile → 1 day GCC product
- Compute smoothed time seres → 1 day GCC model

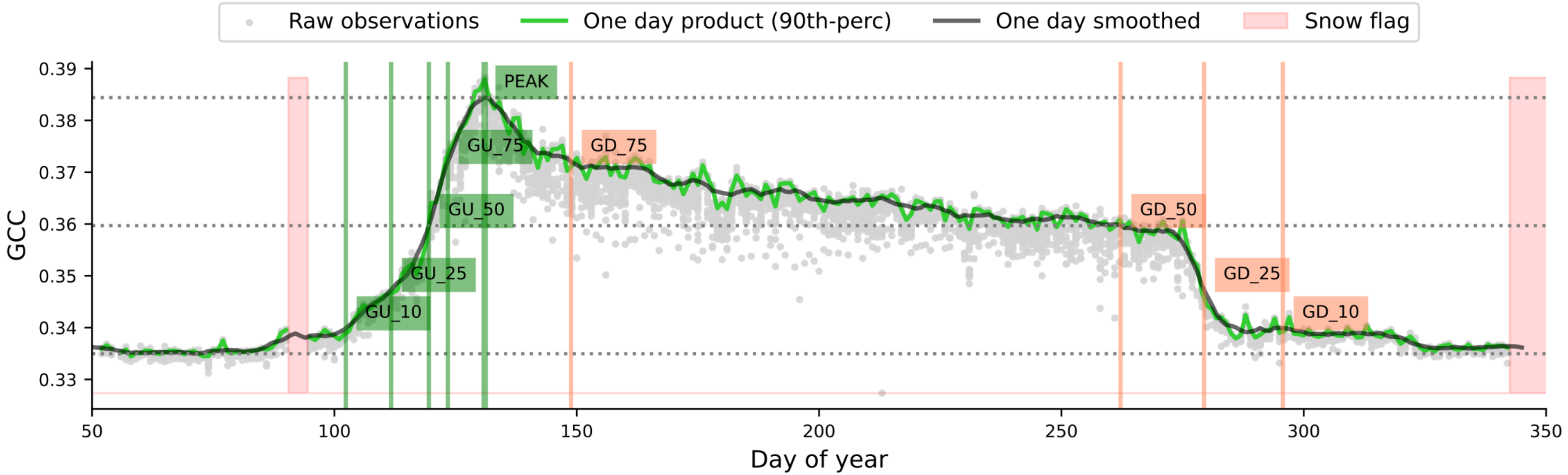
University of Zurich[UZH]

Eidg. Forschungsanstalt für Wald, Schnee und Landschaft WSL

Federal Office of Meteorology and Climatology MeteoSwiss

EcoVision

Department of Mathematical Modeling and Machine Learning (DM³L)



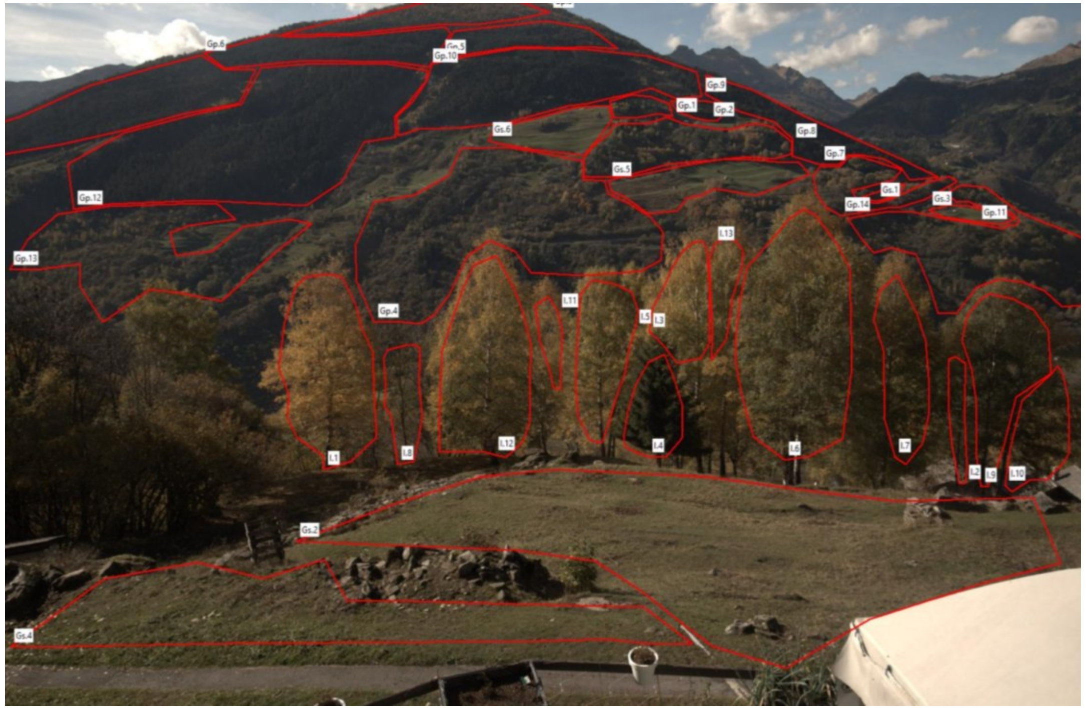
Greenness-based phonological date extraction:

- Greenness amplitude determined between DOY 60 and 320
- Green-Up X% : upwards crossing of X% of amplitude
- Green-Down X% : downwards crossing of X% of amplitude
- Monte-Carlo uncertainty estimation

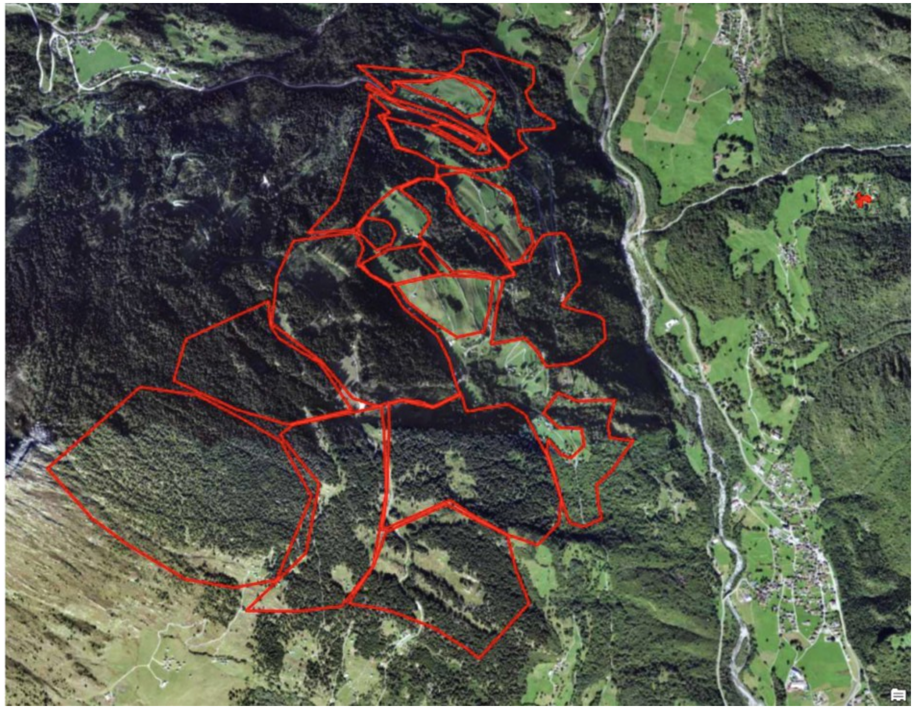
Results:

- Notable effect of elevation on season onset
- No clear effect for autumn phenology
- Measured phenological dates are in line with MeteoSwiss' means

Comparison with satellite imagery



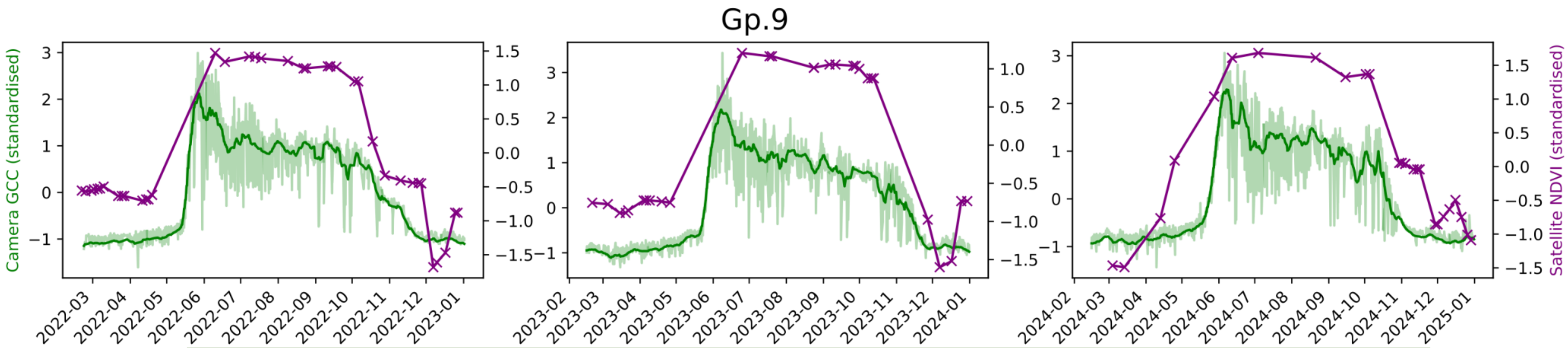
Camera view (Olivone)



Orthophoto (Olivone)

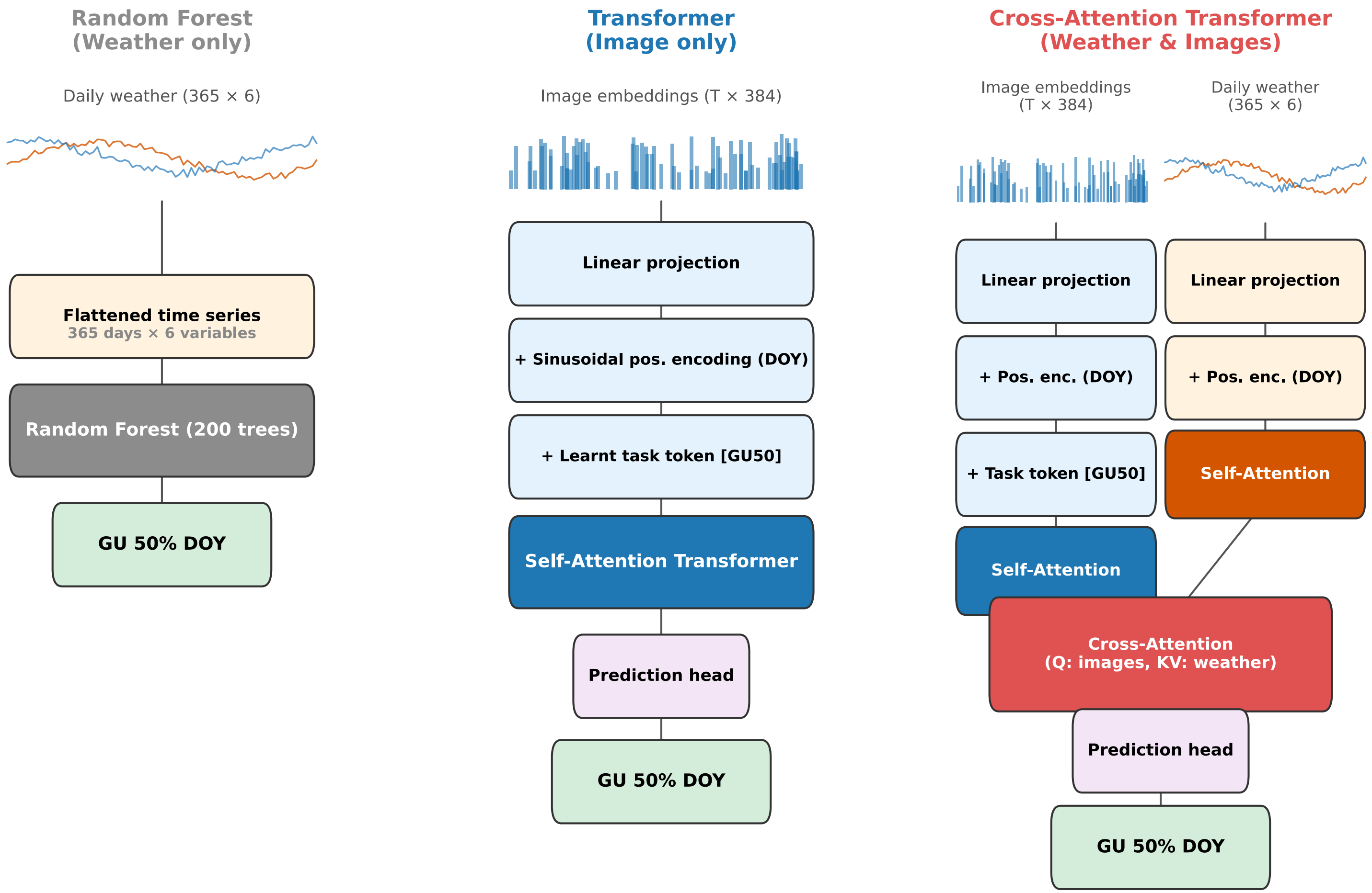
Geo-referencing of polygons with mono-plotting tool enables comparison of satellite and phenocam signal

Example in Brunasco (Ticino)



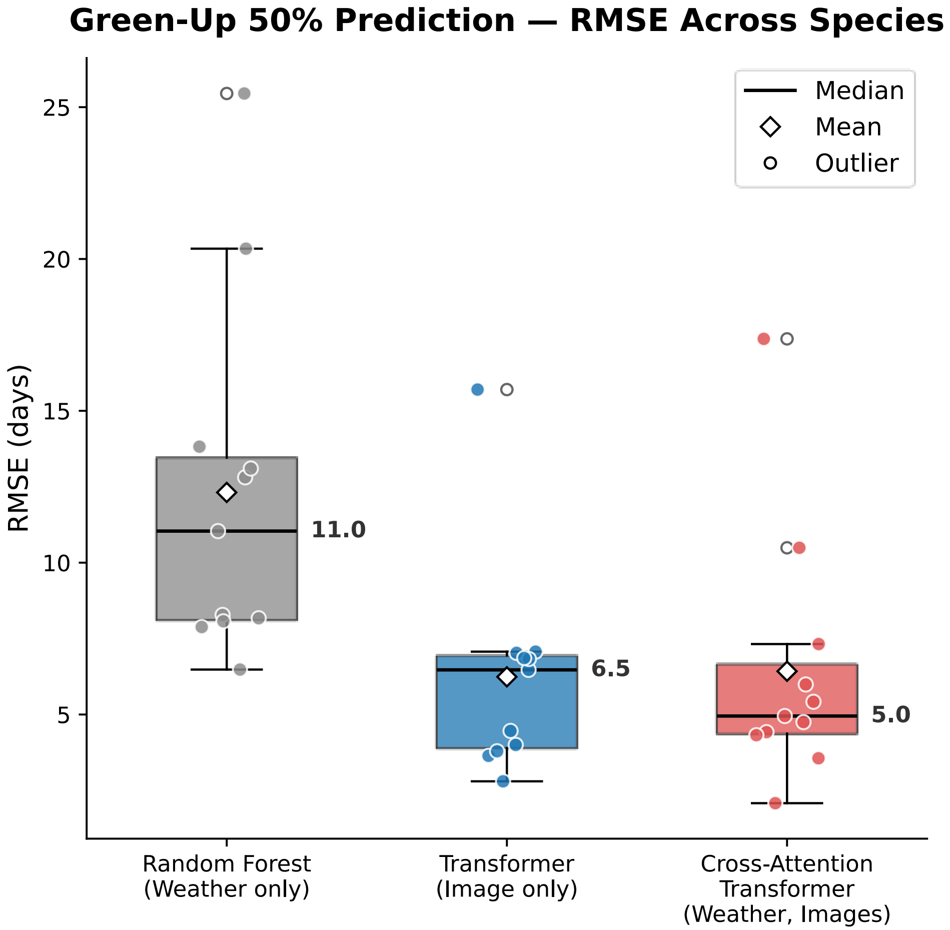
Green-up period is often covered by clouds which prevent monitoring Sentinel-2

4. Joint modeling of image and climate time-series



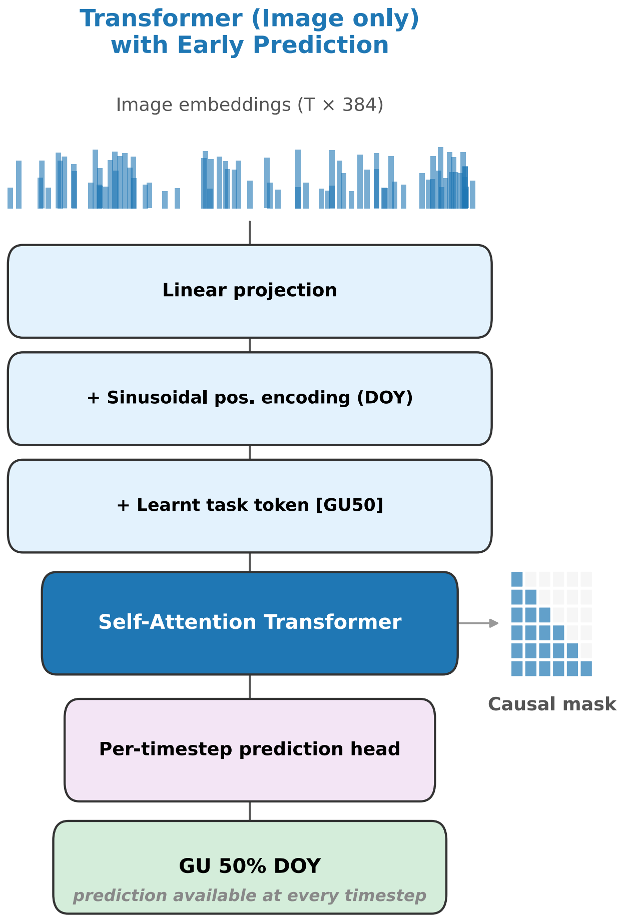
Green-Up 50% prediction results

- cross-attention transformer (weather, images) median RMSE of 5 days.
- average performance only slightly behind the transformer (image only) model (diamond markers).
- cross-attention transformer (weather, images) still under development ➔ we hope to achieve continuously better performance with combined weather and image inputs.



Towards nowcasting tree phenology

- All slides before: use full time-series to estimate phenological events back in time
- Nowcasting: estimate phenological events for the most recent point in time, e.g., "What species and where show 50% green-up today across Switzerland?"
- Add causal mask to self-attention transformer to predict for most recent day ➔ under development



Summary

- Successful extraction of reliable phenological signal
  - At individual tree level → enables species-specific monitoring
  - Using non-specialised webcams and climate data → potential for larger coverage

Open milestones until end of the project:

- Add full nowcasting capability
- Real-time ecosystem stress and recovery prediction
- Uncertainty estimation for all model outputs
- Forecasting tree phenology under different climate scenarios

1.Tackling the inherent interdisciplinarity of Earth System monitoring through innovative, silo-overcoming collaboration addressing individual cycles as well as interactions across all cycles

"Exploration of new approaches and methods should be facilitated more strongly. Also, joint efforts are needed to ensure the continued development of existing observing systems and ideally to close critical measurement gaps. Next-generation numerical weather and climate prediction models simulate an increasing number of Earth System elements and should be recognised, utilised and exploited as a natural platform for collaboration." (1st Swiss National GAW/GCOS Symposium 2021: White Paper)

➔ The SwissPhenocam project explores new approaches and methods. We introduce novel deep learning and computer vision methods custom-designed for tree phenology prediction based on a collaboration between Data Science, Ecology, Weather and Climate Research. All deep learning models are linked to state-of-th-art mechanistic knowledge on phenology. This allows us to pick up subtle patterns in multi-modal data, to scale to national scale (and beyond), to ground data-driven estimates in well-established ecological theory, and to automate phenology prediction. Our project improves and reinvents an existing observing system and closes a critical measurement gap.