Empowering a sustainable future

How remote sensing-based image analysis can contribute

Mareike Dorozynski

How to define Sustainability?

Planetary boundaries

- Concept:

  stability and resilience of the Earth system

- Goal:

  estimation of the safe space for human development

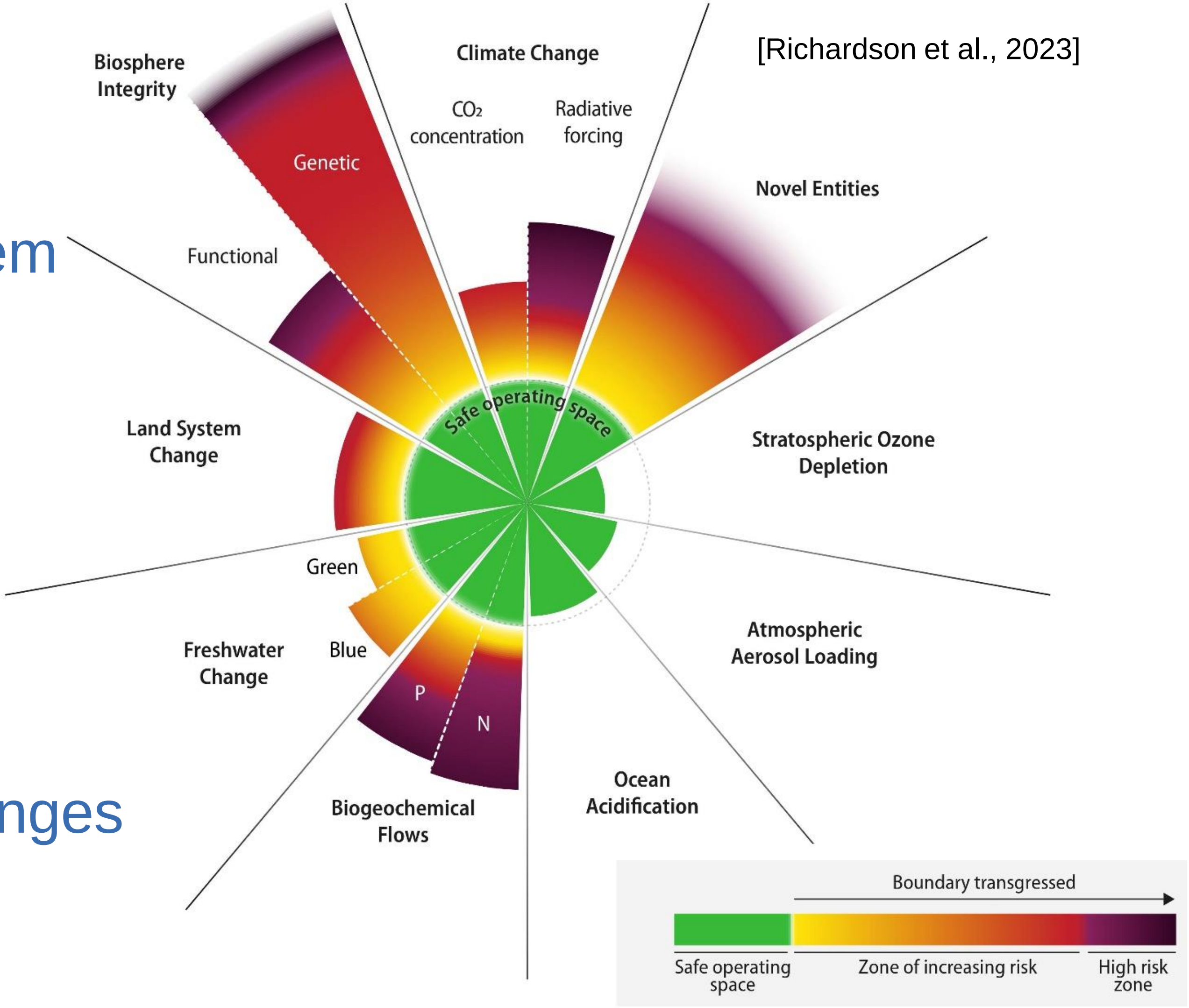
- Transgressing boundaries:

  increases the risk of environmental changes

  → 2023: 6 of 9 boundaries crossed

  (2009: 3 crossed)

[Richardson et al., 2023]



Richardson, K., Steffen, W., Lucht, W., Bendtsen, J., Cornell, S. E., Donges, J. F., ... & Rockström, J. (2023). Earth beyond six of nine planetary boundaries. *Science advances*, *9*(37), eadh2458. https://doi.org/10.1126/sciadv.adh2458

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Why is this of interest?

Ecosystem services

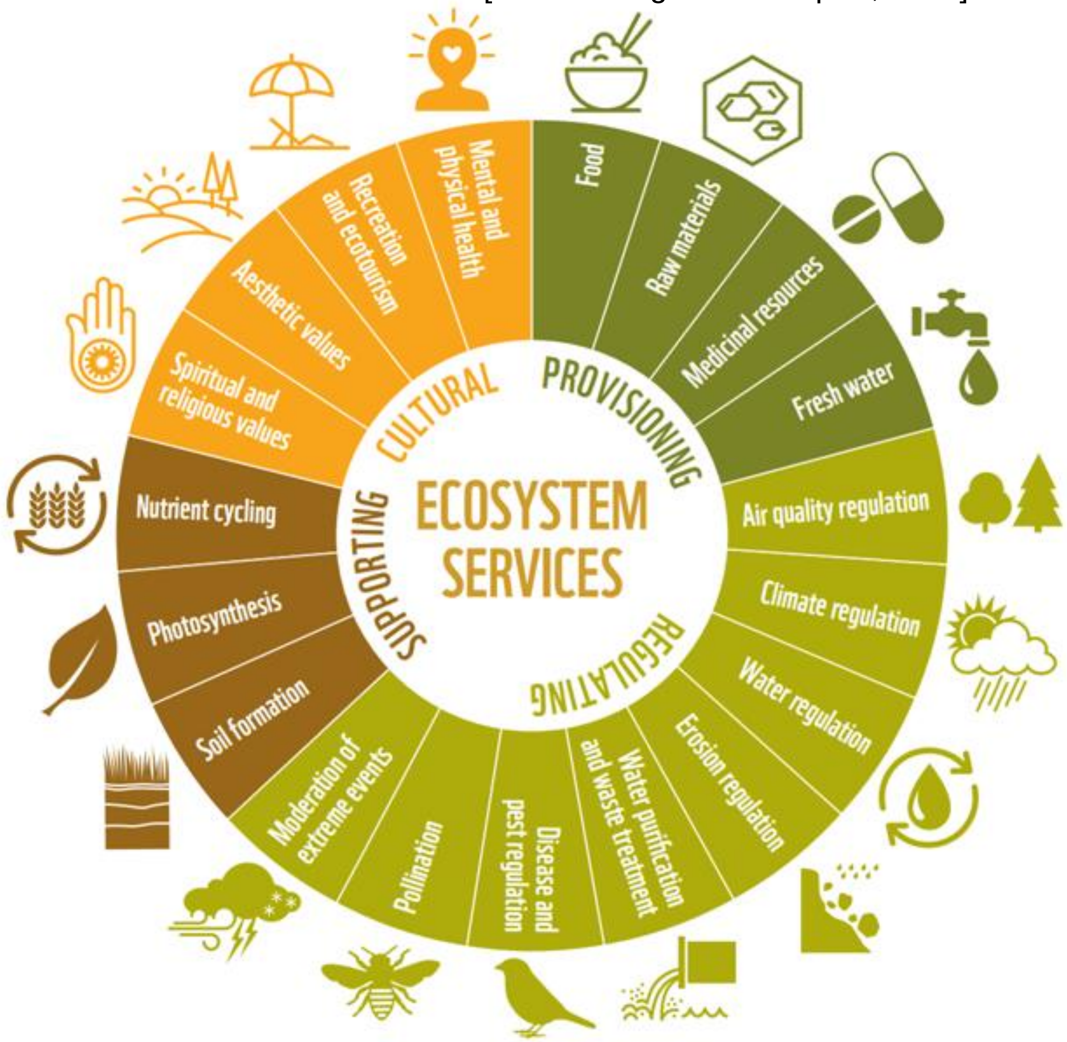
- Concept:

  benefits for humanity from natural capital

- Example of forest ecosystems:
  - Lock up carbon, release oxygen 
  - Are recreational areas 
  - Provide fuelwood 
  - Provide food 
  - …

→ We require healthy ecosystems

[WWF-Living Planet Report, 2016]



WWF. 2016. Living Planet Report 2016. Risk and resilience in a new era. WWF International, Gland, Switzerland

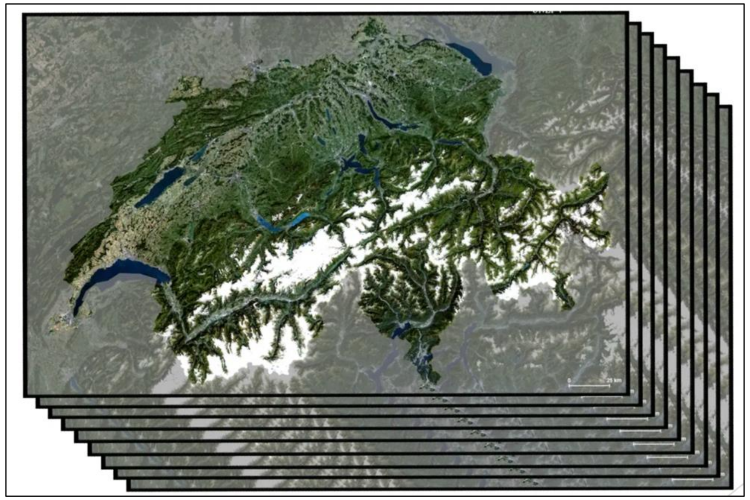
What can we do?

- We = surveyor, geodesists, photogrammetrists, remote sensing experts

- Our strength = monitoring and data analysis:
  - Current status
  - Past status (if data available)
  - Forecasting
  - Identification of trends
  - Monitoring of actions

→ Provide information about the environment in a short time at a large scale

[ESA, Sentinel-2]



[Swiss Data Cube]

Requirements: How can we do that?

- Interdisciplinary work: model + interpretation of data
- Combination of data: 3D (LiDAR, high models), optical (satellite, aerial), hyperspectral (EnMAP, FLEX, …), Radar, topography (maps, information systems), tabular data
- Combination of epochs: multi-temporal approaches and analysis
- Combination of tasks: multi-task, geometry und semantics
- Forecasting: prediction of the future

→ Required directions: multi-disciplinary, multi-source (multi-scale, multi-modal, multi-sensor, …), multi-task, multi-temporal

Forest damage forecasting

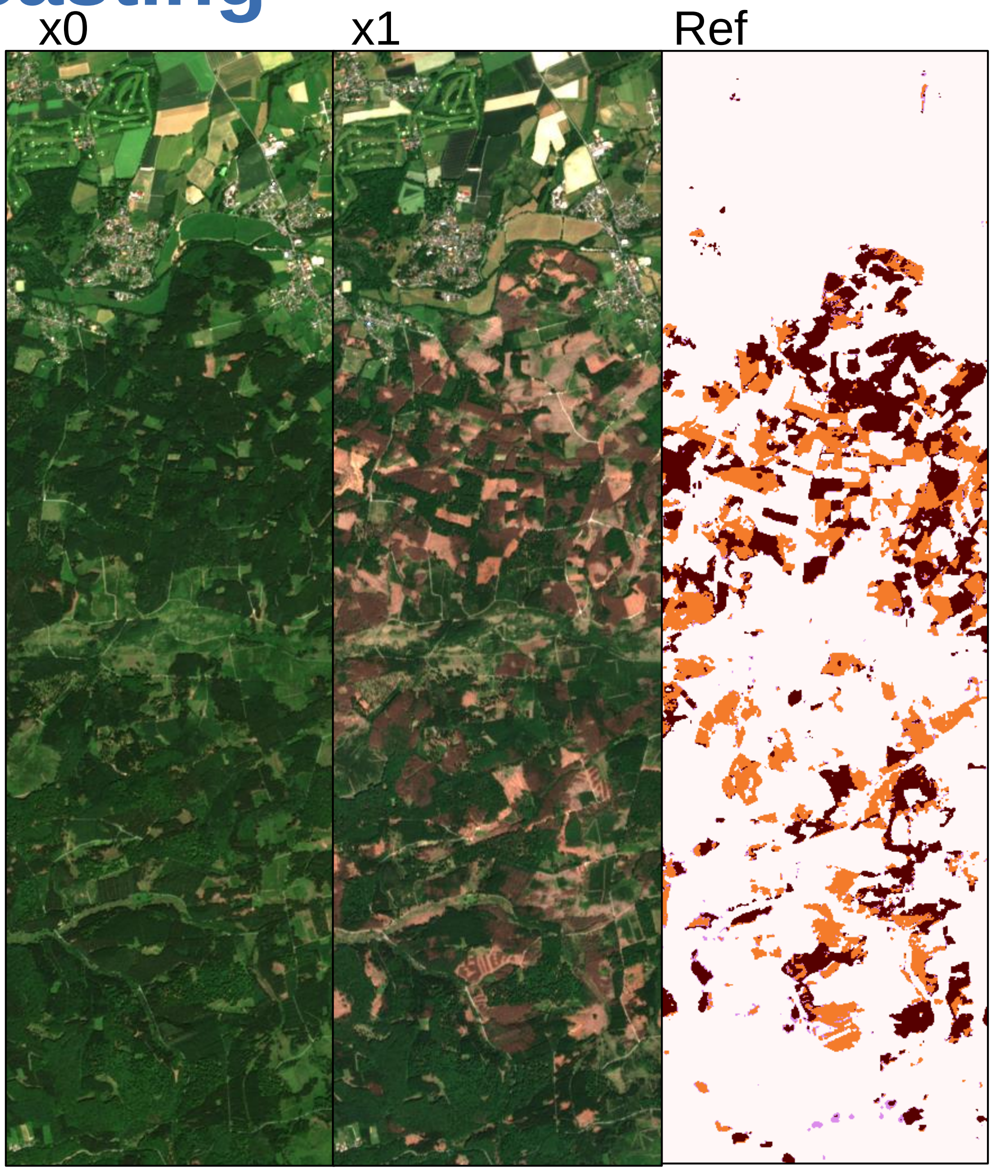
Goal: detection of early signs for upcoming damage and prediction of remaining life time

Data:
- Sentinel 2 image time series
- bi-temporal reference for degradation


Dennis Wittich

Class structure

- No forest / Healthy forest
- Forest died
- Area got “cut”



Wittich D., Rottensteiner F., Voelsen M., Heipke C., Müller S. (2022): Deep learning for the detection of early signs for forest damage based on satellite imagery. In: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences V-2-2022, pp. 307–315.

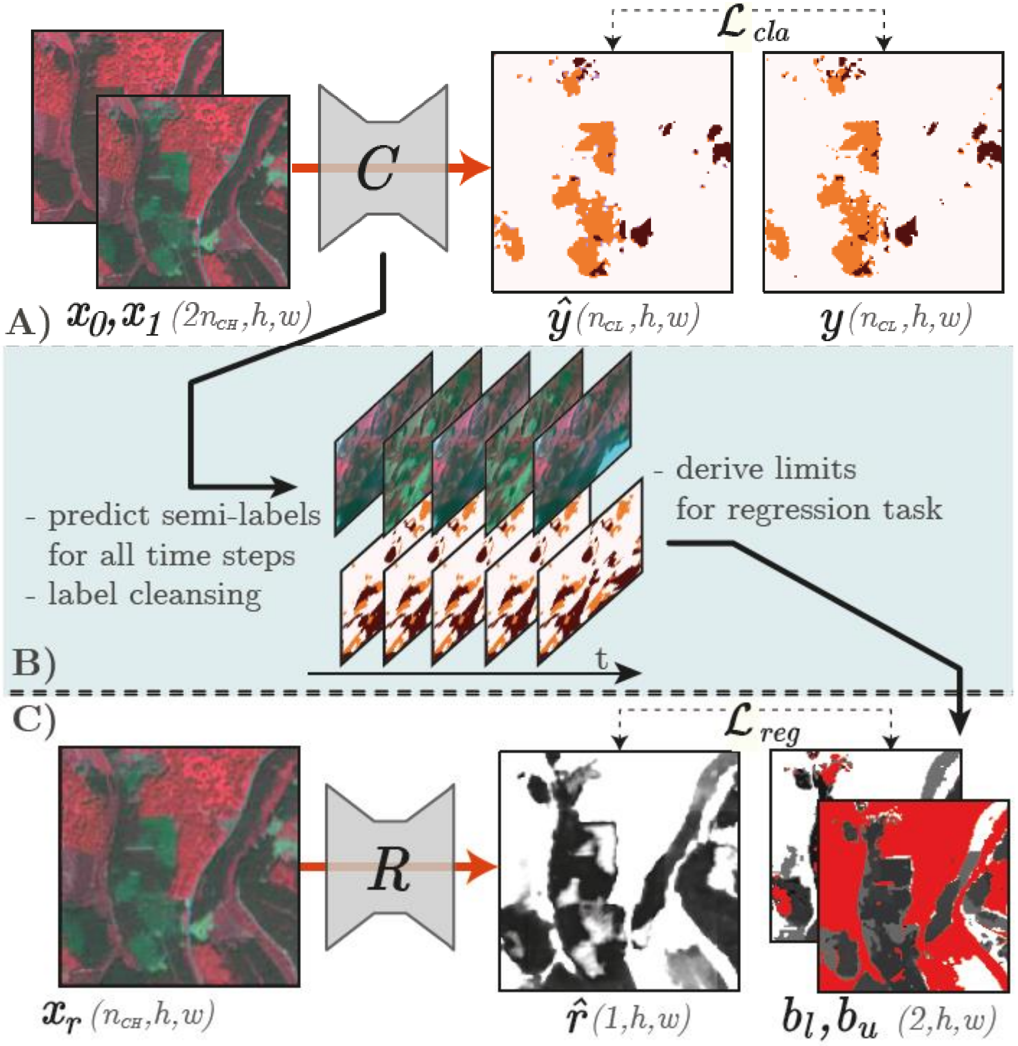
Forest damage forecasting

Idea: 3-stage approach with regression for remaining life-time (RLT)

A) Train C for prediction of vitality loss
→ bi-temporal pixel-wise classification

B) Apply C to image time series („living“/“dead“)
→ derive reference intervals for RLT (known period in which the forest died)

C) Train R based on known RLT intervals



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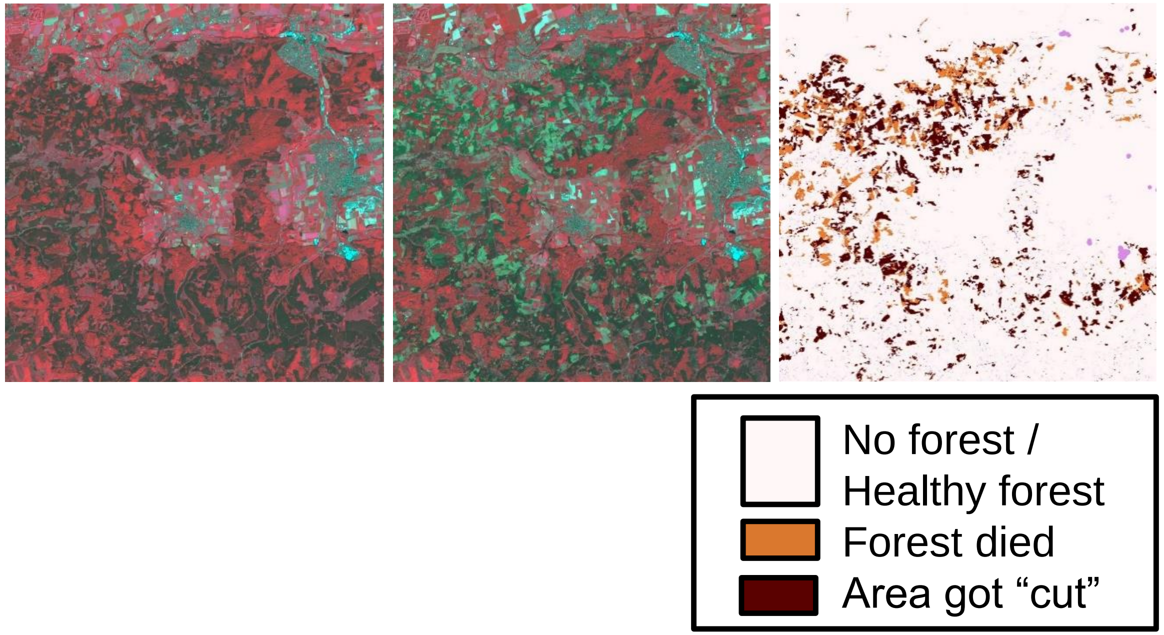
Forest damage forecasting

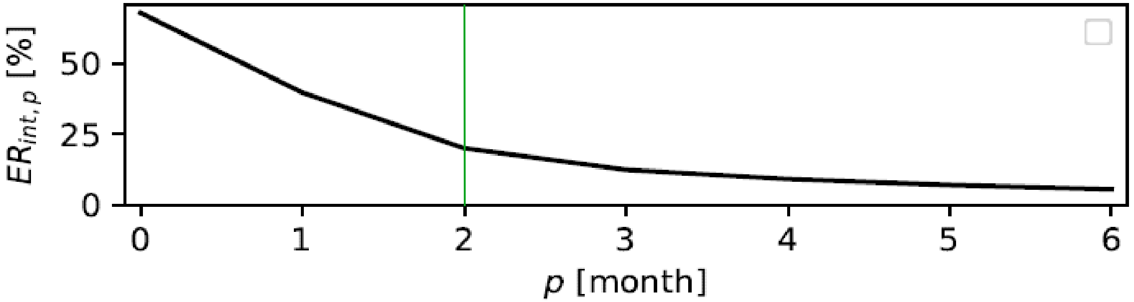
Training data:

- Sentinel-2 images (2017-2021)
  - ~50 time steps
- Vitality change reference
  - 7 image pairs



Results:

- Pixel-wise classification of vitality loss:
  - Mean F1: 94.2±0.2%
- Prediction of remaining life-time:
  - Error < 2 months for 80%



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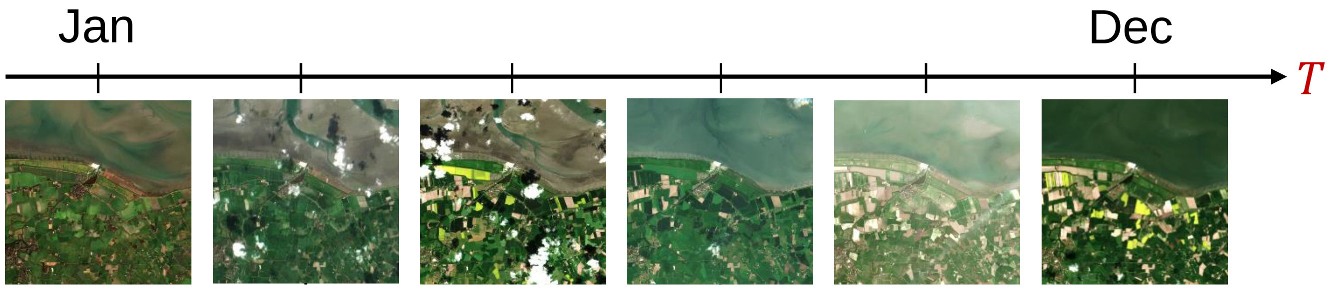
Multi-temporal land cover classification

Goal: Analysis and monitoring of Earth‘s surface (short term trends and changes)

Data:

- Sentinel image time series
  - high temporal resolution
  - medium spatial resolution
- Existing topographic database
  - noisy land cover information



Mirjana Voelsen

Voelsen, M., Rottensteiner, F. & Heipke, C. (2024): Transformer Models for Land Cover Classification with Satellite Image Time Series. Journal of Photogrammetry, Remote Sensing and Geoinformation Science. https://doi.org/10.1007/s41064-024-00299-7

Multi-temporal land cover classification

Idea: exploit temporal context in a multi-temporal classification

A) Temporal encoding (TE)

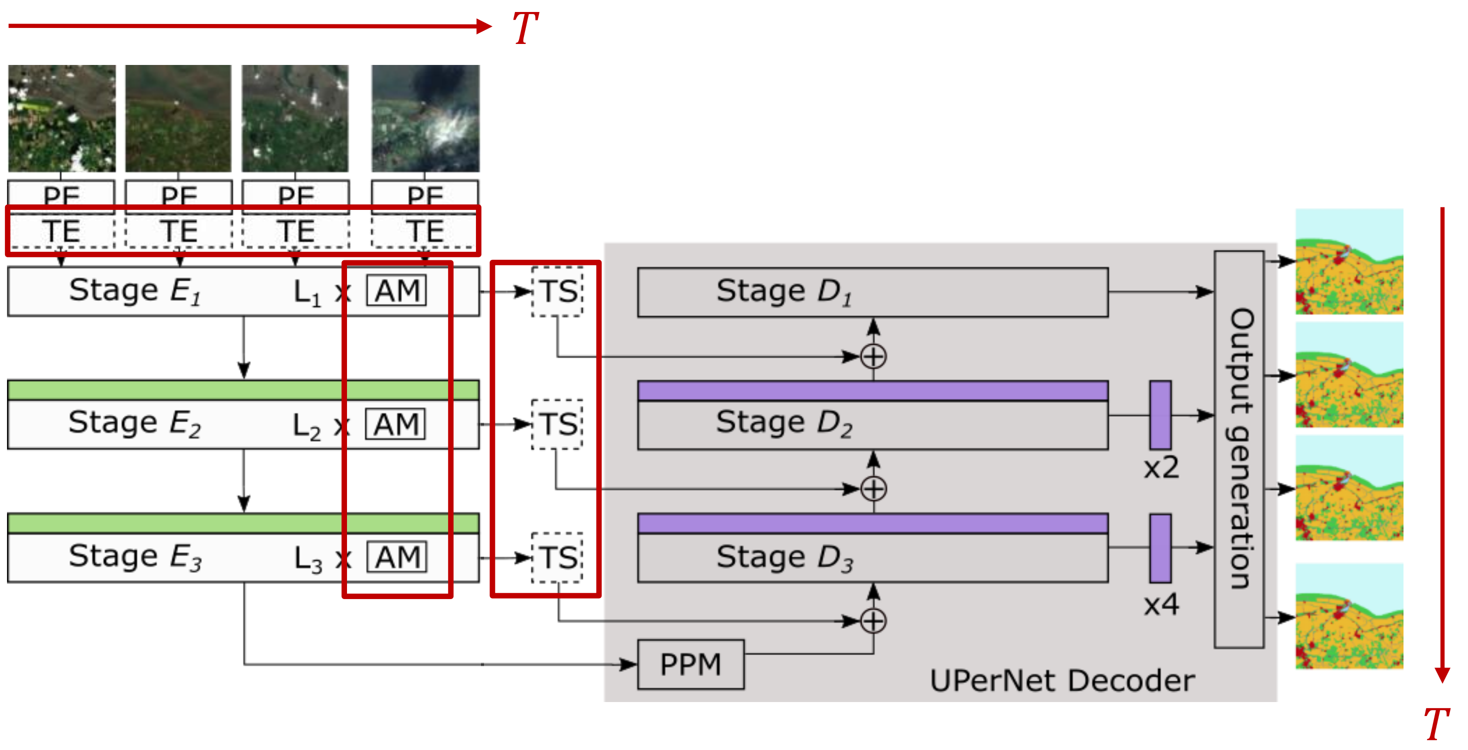
→ temporal position per image

B) Spatio-temporal attention (AM)

→ focus on important features

C) Temporal weighting (TS)

→ focus on important epochs for spatial reconstructions



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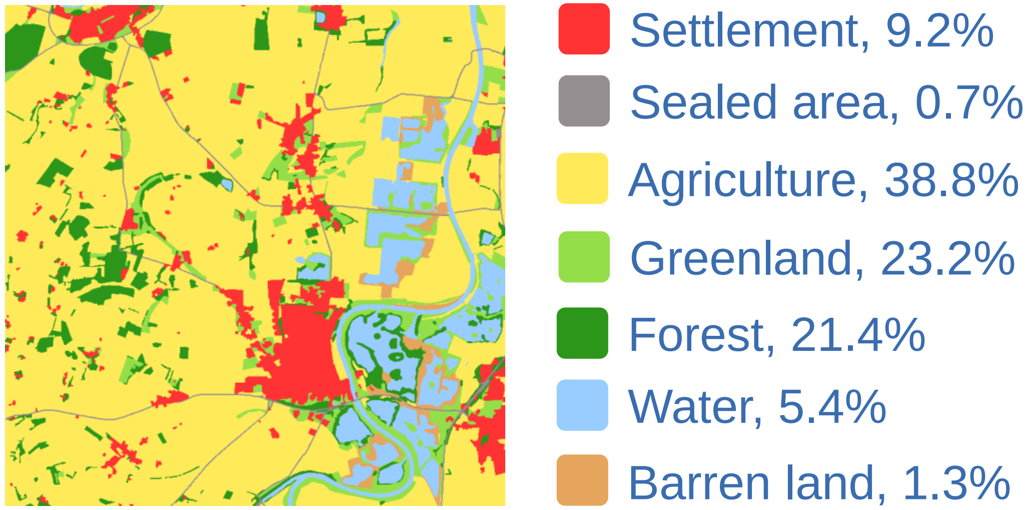
Multi-temporal land cover classification



Training Data:

- Sentinel-2 images (2019-2022)
  - RGBIR channels used
- ATKIS-based labels all 3 months (T=12)
  - aggregated to 7 classes

Results:

Corrected test data:

- Mean F1: 67.9±0.6%
- OA: 82.4±0.4%

Sentinel ATKIS Reference Prediction

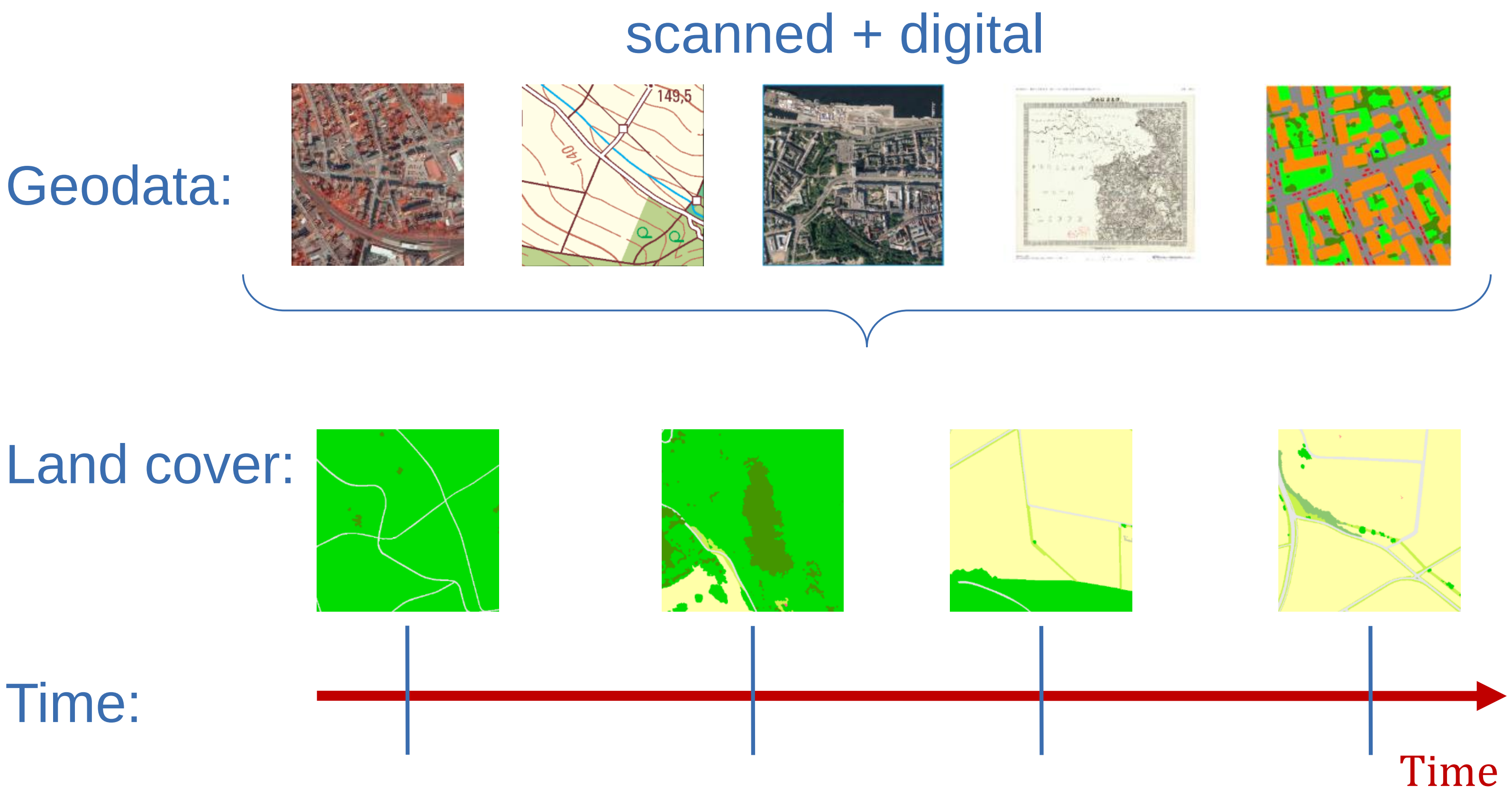
Voelsen, M., Rottensteiner, F. & Heipke, C. (2024): Transformer Models for Land Cover Classification with Satellite Image Time Series. Journal of Photogrammetry, Remote Sensing and Geoinformation Science. https://doi.org/10.1007/s41064-024-00299-7

Gauß Centre: the temporal change of geospatial data

Goal: Analysis and monitoring of Earth‘s surface (long term trends and changes)

Data: multi-temporal geodata

- Aerial imagery
- Satellite imagery
- Topographic maps



Gauß-Zentrum
für Geodäsie und Geoinformation

Gauss centre: the temporal change of geospatial data

Idea: Exploit land cover information contained in multiple data sources

A) Extract features from both modalities

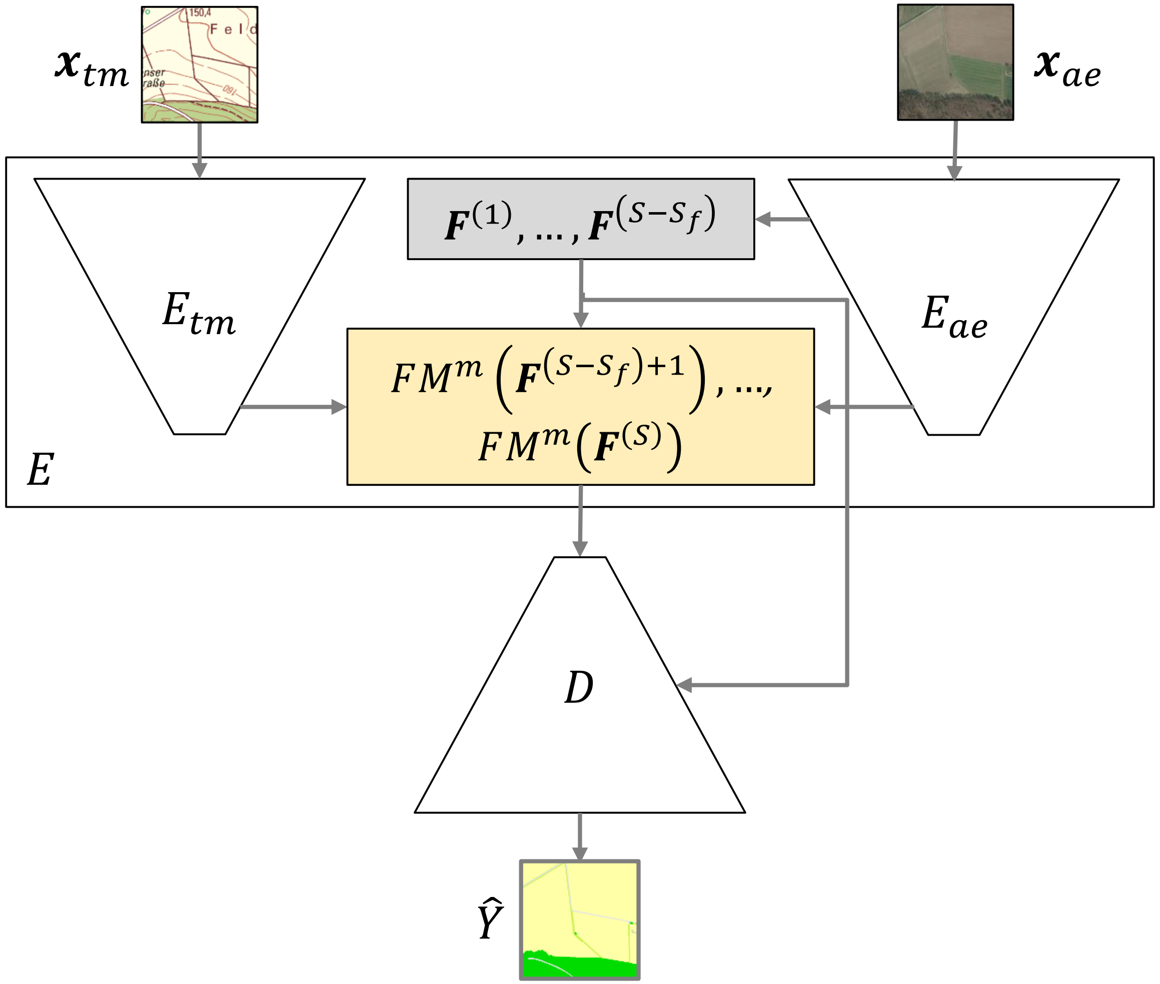
→ uni-modal features

B) Multi-modal feature fusion FM^m

→ focus on more informative modality

C) Decoding of the label map $\hat{Y}$

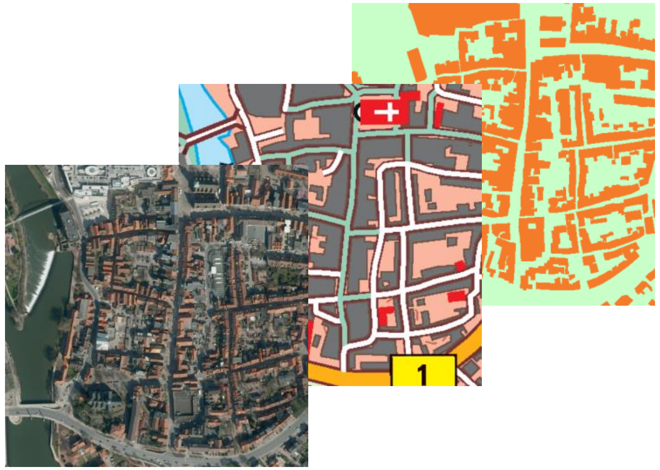
→ exploit uni-modal and multi-modal features



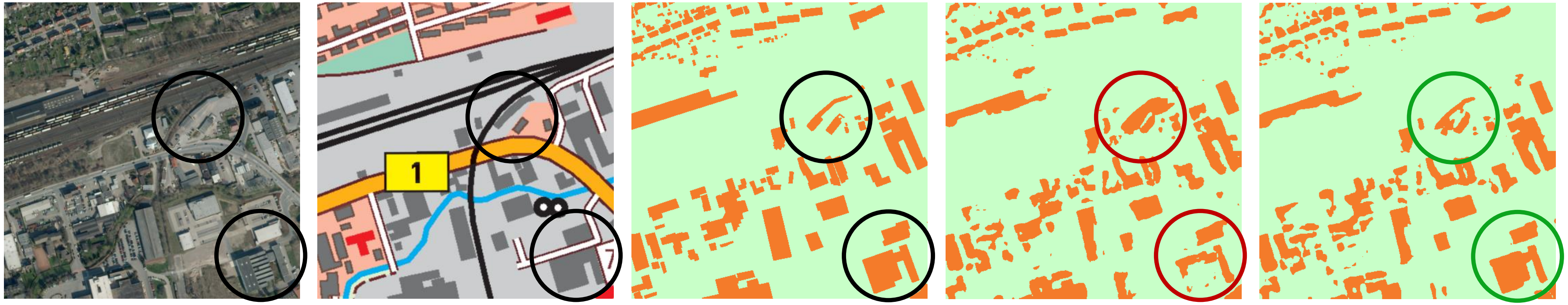
Gauss centre: the temporal change of geospatial data

Training:

- Multi-modal inputs
  - Topographic maps (TM25)
  - Digital Orthophotos (DOP)
- Manual reference for buildings



Results:



DOP | TM25 | Y | $\hat{Y}$(DOP) | $\hat{Y}$(DOP, TM25)

	$\hat{Y}$(DOP)	$\hat{Y}$(DOP, TM25)
Mean F1:	89.2±0.5%	**90.1**±0.3%
Building F1:	83.8±0.7%	**85.1**±0.3%

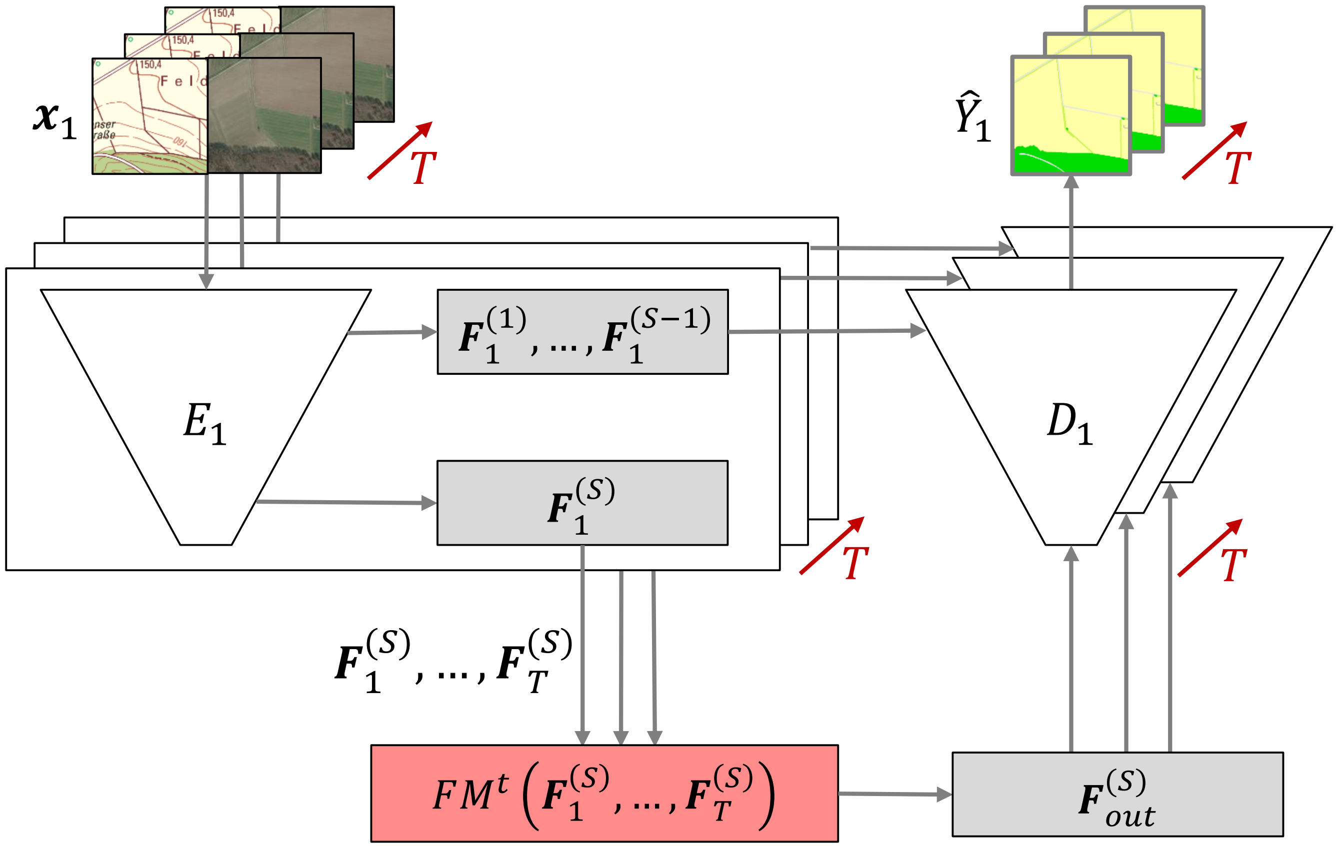
Gauss centre: the temporal change of geospatial data

Idea: Exploit temporal context in multi-modal classification

A) Extract uni-modal and multi-modal features for T epoch
→ feature set per epoch

B) Multi-temporal feature fusion FM^t
→ focus on informative epochs

C) Decoding one label map per epoch



Revisiting Requirements

- Interdisciplinary work: More outreach required.

- Combination of data:
- Combination of epochs:
- Combination of tasks:

Tackling issues related to

- selection of data sources,
- application of models at a larger scale,
- consideration of related tasks.

- Forecasting: Approaches required that
  - predict future states of ecological indicators (application),
  - consider useful interdependencies (methodology).

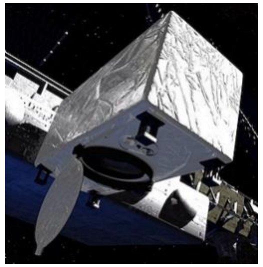
(One) Vision for contributing to a Sustainable Future

- Goal: evolution of
  - Tree species
  - Tree height
  - Tree biomass
  - Tree health
- Methods:
  - multi-modal
  - multi-task
  - domain adaptation (space, time)
  - for data of new sensors
  - multi-temporal
  - forecasting

[ESA, Sentinel-2]

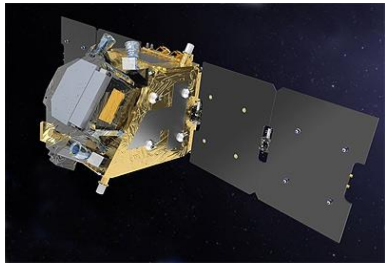
optical

[NASA, GEDI]

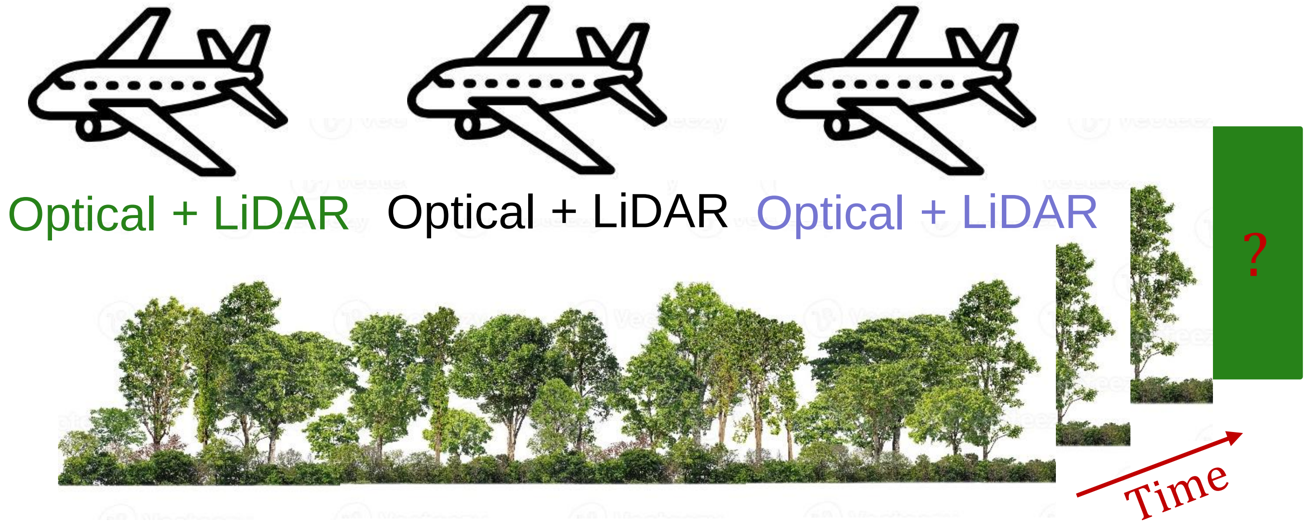


LiDAR

[ESA, FLEX]



fluorescence
(launch: 2025)



Optical Remote Sensing for Sustainability Group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