CHARLES UNIVERSITY
Faculty of Science
Department of Applied Geoinformatics and Cartography
EO4Landscape Laboratory Team

REMOTE SENSING TIME SERIES IN FOREST ECOSYSTEMS:

Introduction into Remote Sensing Methods Using Optical Data

Associate professor Přemysl Štych, Ph.D. and Josef Laštovička, Ph.D.
Prague 5th July 2023 – TAT 2023

https://eo4landscape.natur.cuni.cz/
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LinkedIn: eo4landscape-research-group

The Department of Applied Geoinformatics and Cartography

- Education and research in the fields of:
  - *GIS a geodatabases*
  - *Remote sensing and photogrammetry*
  - *Cartography*
  - *Computational geometry, algorithm development & programming*
  - *Geodetic and surveying methods of data collection*

EO4Landscape Research Team

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- Earth Observation (EO)
  - *Advanced classification methods using remote sensing data, Time Series, Normalization methods of remote sensing data, Big Data, Cloud computing and satellite data - Google Earth Engine, Sentinel Hub*
- Land Use/Land Cover (LUCC)
  - *Long-term Land Use/Land Cover Change, Driving forces of LUCC*
- 3D
  - *Visualization of the dynamic landscape changes in 3D*
- Web GIS technologies and maps services
  - *Visualization of landscape changes, in-situ data collection*
- Capacity building and education in GIS and EO

EO4Landscape Research Team

- Assoc. Prof. Přemysl Štych – head of team
- RNDr. Josef Laštovička, Ph.D. – researcher, professor assistant
- Mgr. Daniel Paluba – PhD student
- Mgr. Jan Svoboda – PhD student
- Mgr. Natalia Kobliuk – PhD student
- Mgr. Jiří Šandera – PhD student

- *Master and bachelor students*

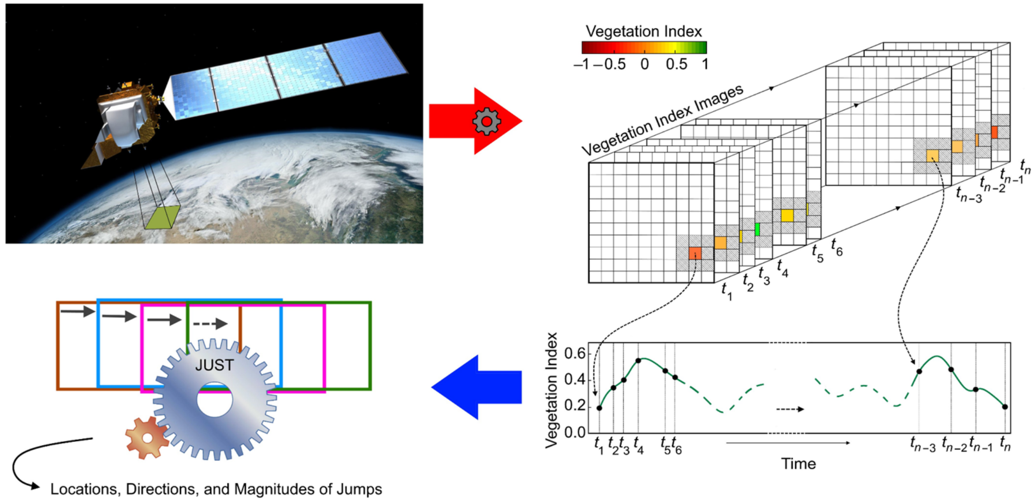
[*http://eo4landscape.natur.cuni.cz*](http://eo4landscape.natur.cuni.cz)

Selected Papers in Forest Ecosystems

#	Citation	IF (2021)	Open Access
1	Štych, P., Paluba, D., Laštovička, J., Outrata, D., Hladký, R., 2018. Hodnocení změn krajinného pokryvu bývalého vojenského újezdu Brdy pomocí dálkového průzkumu Země. Bohemia cent. 51–73.	-	Yes
2	Paluba, D., Štych, P., Laštovička, J., 2018. Hodnotenie metód a dát DPZ pre účely klasifikácie krajinnej pokrývky na príklade bývalých vojenských obvodov Brdy a Ralsko. Kartogr. List. / Cartogr. Lett. 26, 76–90.	-	Yes
3	Stych, P., Jerabkova, B., Lastovicka, J., Riedl, M., Paluba, D., 2019a. A Comparison of Worldview-2 and Landsat 8 Images for the Classification of Forests Affected by Bark Beetle Outbreaks Using a Support Vector Machine and a Neural Network: A Case Study in the Sumava Mountains. Geosci. 9.	-	Yes
4	Svoboda, J., Štych, P., Laštovička, J., Paluba, D., Kobliuk, N., 2022. Random Forest Classification of Land Use, Land-Use Change and Forestry (LULUCF) Using Sentinel-2 Data—A Case Study of Czechia. Remote Sens. 14.	5.349	Yes
5	Senf, C., Laštovička, J., Okujeni, A., Heurich, M., van der Linden, S., 2020. A generalized regression-based unmixing model for mapping forest cover fractions throughout three decades of Landsat data. Remote Sens. Environ. 240.	13.850	No
6	Lastovicka, J., Svec, P., Paluba, D., Kobliuk, N., Svoboda, J., Hladky, R., Stych, P., 2020. Sentinel-2 Data in an Evaluation of the Impact of the Disturbances on Forest Vegetation. Remote Sens. 12.	5.349	Yes
7	Hladky, R., Lastovicka, J., Holman, L., Stych, P., 2020. Evaluation of the influence of disturbances on forest vegetation using Landsat time series; a case study of the Low Tatras National Park. Eur. J. Remote Sens. 53, 40–66.	3.168	No
8	Stych, P., Lastovicka, J., Hladky, R., Paluba, D., 2019c. Evaluation of the Influence of Disturbances on Forest Vegetation Using the Time Series of Landsat Data: A Comparison Study of the Low Tatras and Sumava National Parks. ISPRS Int. J. Geo-Information 8, 71.	3.099	No
9	Paluba, D., Laštovička, J., Mouratidis, A., Štych, P., 2021. Land cover-specific local incidence angle correction: A method for time-series analysis of forest ecosystems. Remote Sens. 13.	5.349	Yes

Remote Sensing Data Time Series

- Our ability to identify changes over time has changed because:
  - The availability of long-term satellite data sets
    - *Landsat (30+ years)*
    - *MODIS (18 years)*
    - *Sentinel-2 A,B (8 years)*
  - Increased computing power and cloud computing Improved processing methods

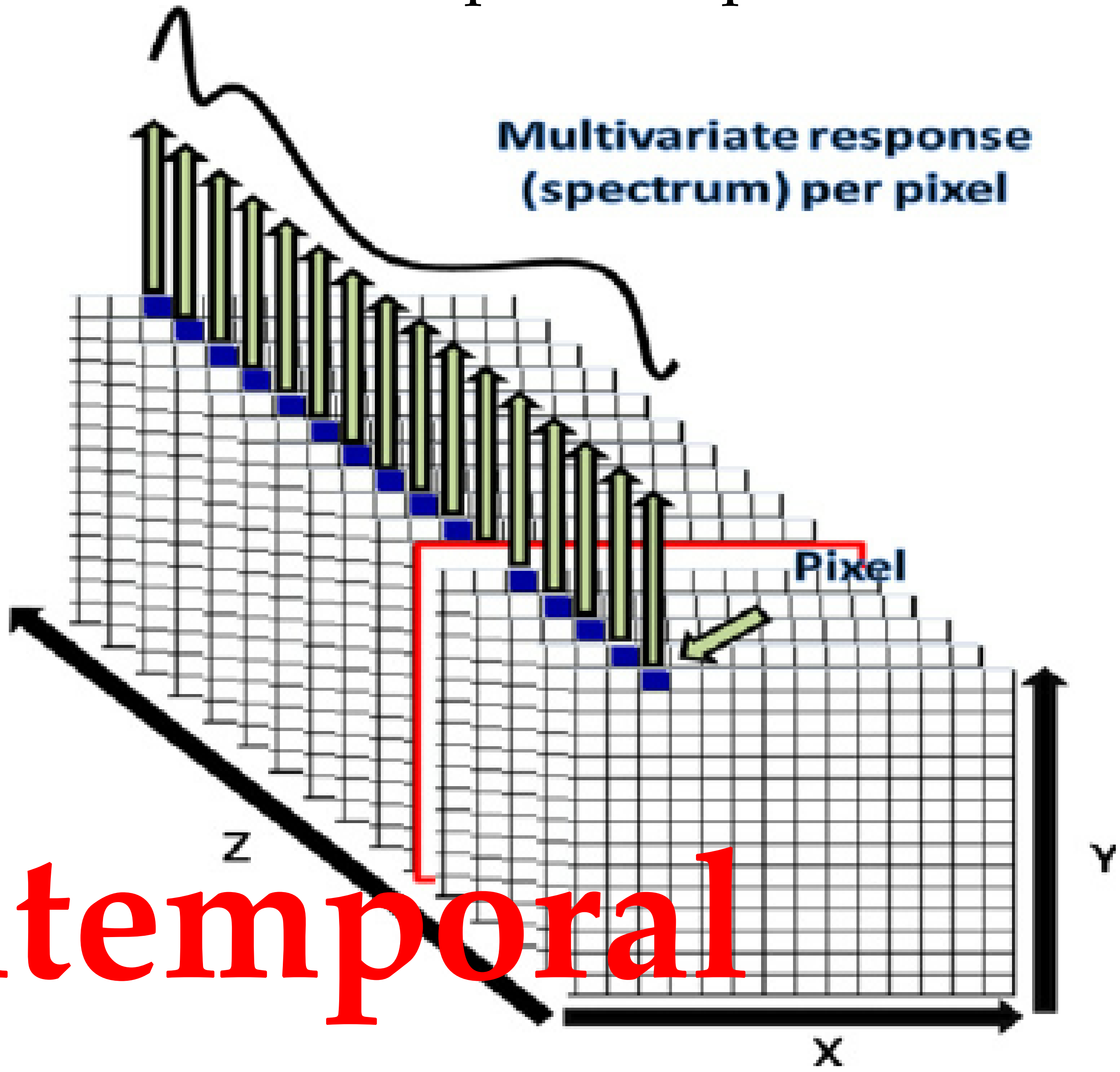


Ghaderpour, E., Vujadinovic, T. 2020. Change Detection within Remotely Sensed Satellite Image Time Series via Spectral Analysis. Remote Sens., 12, 4001. https://doi.org/10.3390/rs12234001

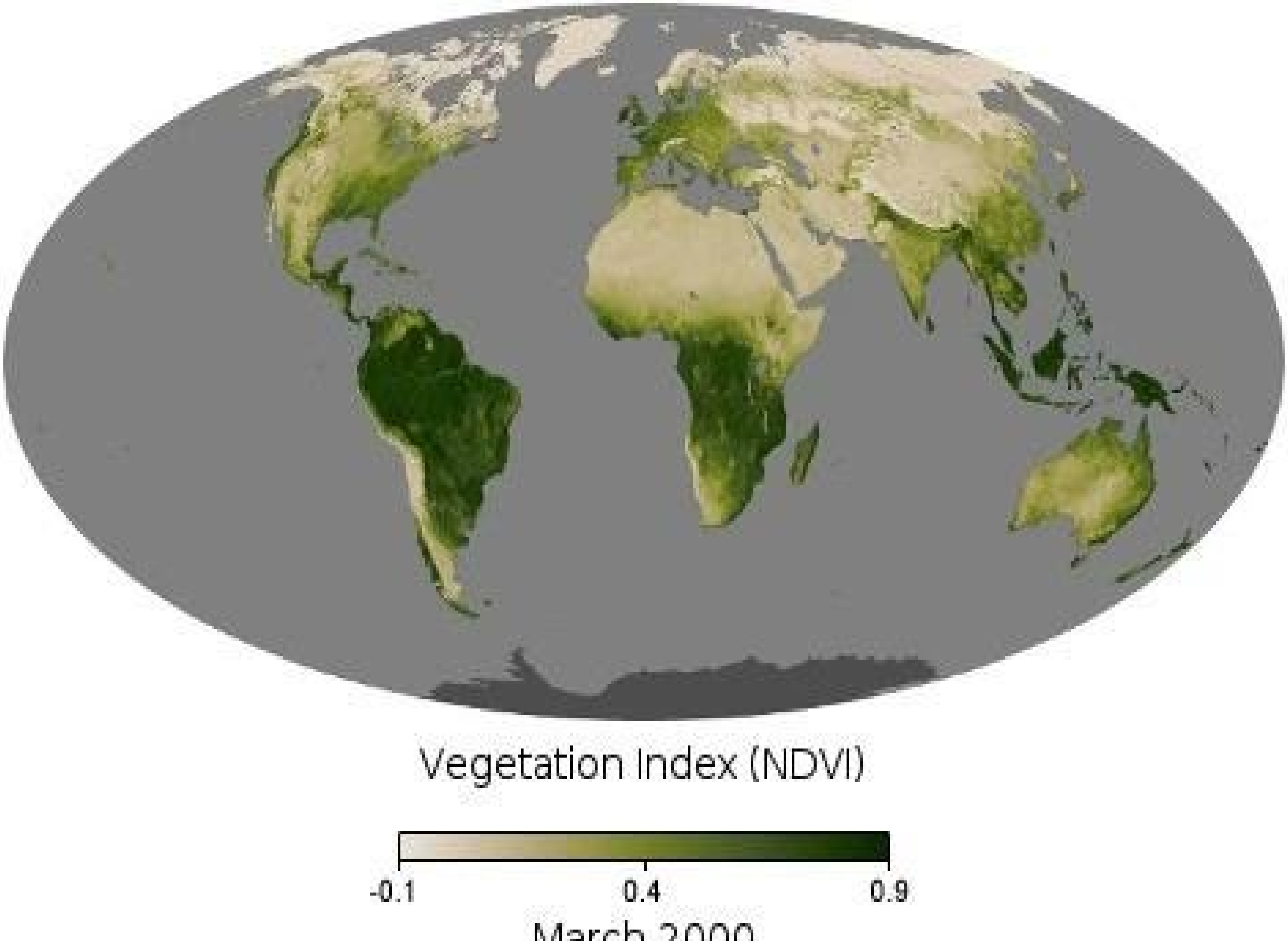
Data Time Series

- Time series data is a collection of observations obtained through repeated measurements over time.
- Time series refers to a chain of data points observed and recorded in a time order over a specific period.
- It represents the output obtained from monitoring and tracking specific events or processes.

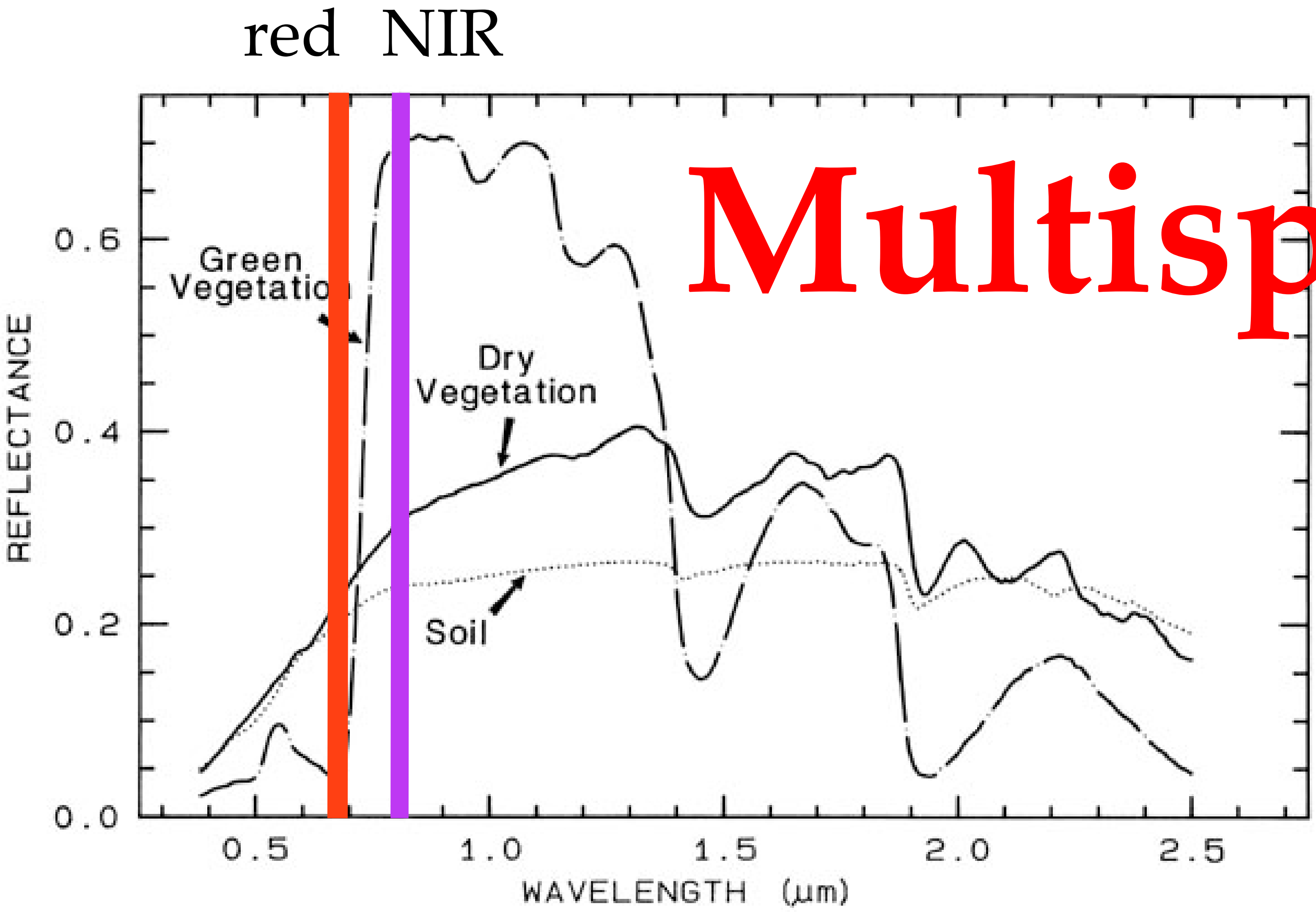
multi-temporal response

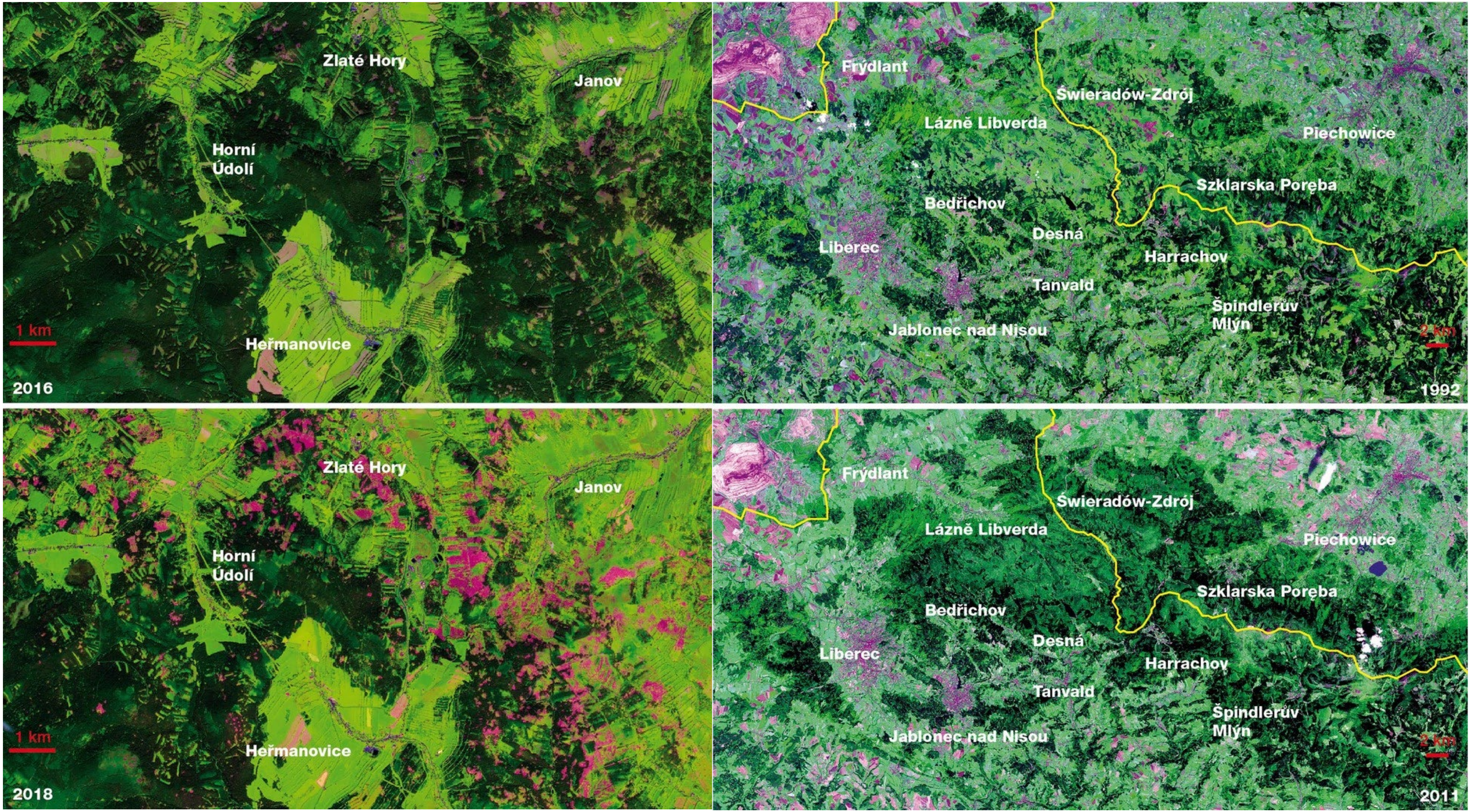


Multitemporal


Vegetation Index (NDVI)
-0.1
0.4
0.9
March 2000

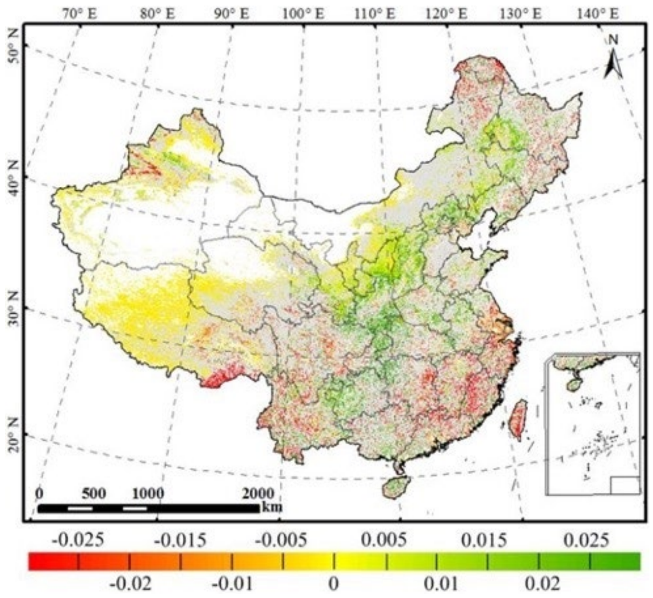
Multispectral

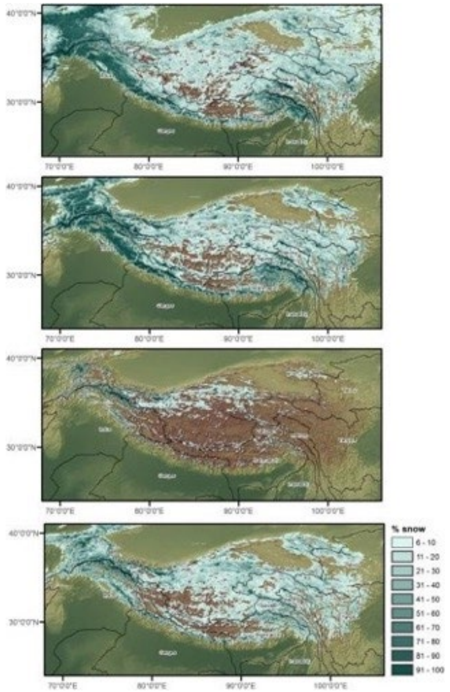



Zlaté Hory
Janov
Horní
Údolí
1 km
Heřmanovice
2016
Frýdlant
Świeradów-Zdrój
Lázně Libverda
Piechowice
Szklarska Poręba
Bedřichov
Desná
Liberec
Harrachov
Tanvald
Špindlerův
Mlýn
Jablonec nad Nisou
2 km
1992
Zlaté Hory
Janov
Horní
Údolí
1 km
Heřmanovice
2018
Frýdlant
Świeradów-Zdrój
Lázně Libverda
Piechowice
Szklarska Poręba
Bedřichov
Desná
Liberec
Harrachov
Tanvald
Špindlerův
Mlýn
Jablonec nad Nisou
2 km
2011

Annual vs. Seasonal Trends

- Annual Trends
  - *Annual land cover/land use changes over long time periods*
  - *Ex: Trends in vegetation greenness in China*
  - *Annual mean Leaf Area Index (LAI) during 2000-2014 from MODIS These data were used to analyze the change in evapotranspiration and water yield*
- Seasonal Trends
  - *Driven by annual temperature and/or precipitation*
  - *Ex: Snow cover monitoring in the Himalayas*
  - *Seasonal snow cover based on MODIS snow cover time series from Mar 2000 to Feb 2008. (Winter, (top), Spring, Summer, Autumn (bottom) The values show the percentage of time that a pixel was snow-covered during the season within the time period*



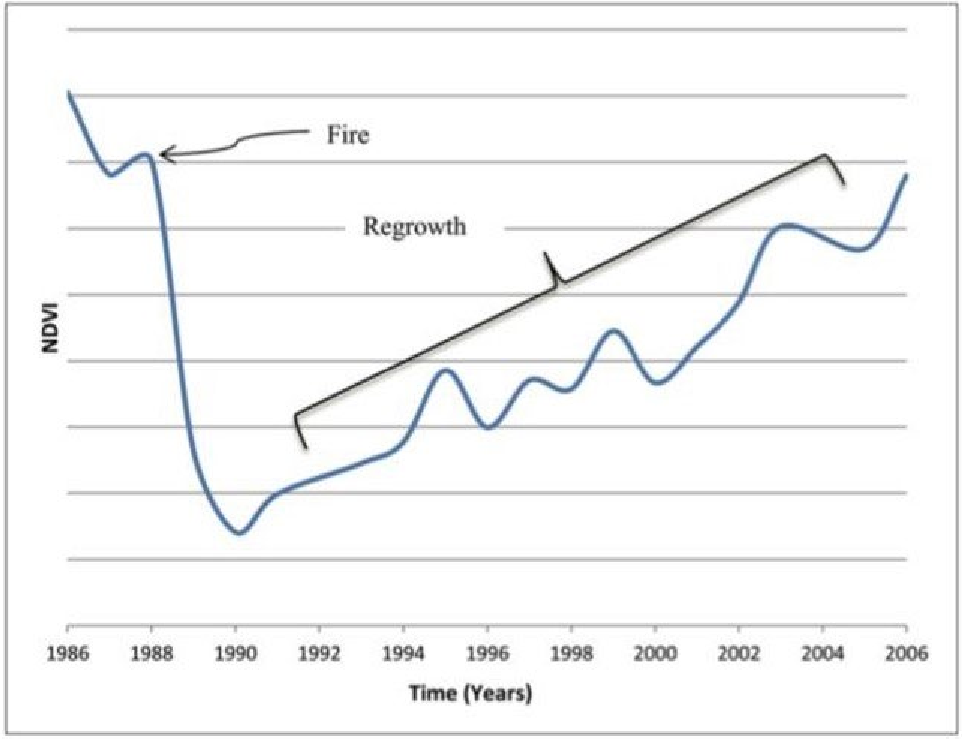


Liu, Y., Xiao, J., Ju, W., Xu, K., Zhou, Y., Zhao, Y. 2016. Recent trends in vegetation greenness in China significantly altered annual evapotranspiration and water yield. Environ. Res. Lett. 11, 094010. https://10.1088/1748-9326/11/9/094010. (top image)
Immerzeel, W.W., Droogers, P., de Jong, S.M. and Bierkens, M.F.P. 2009. Large-Scale Monitoring of Snow Cover and Runoff Simulation in Himalayan River Basins Using Remote Sensing. Remote Sens. Environ., 113, 40–49. https://doi.org/10.1016/j.rse.2008.08.010 (bottom image)

Gradual vs. Abrupt Changes

- Gradual changes:
  - *Land degradation*
  - *Forest recovery*

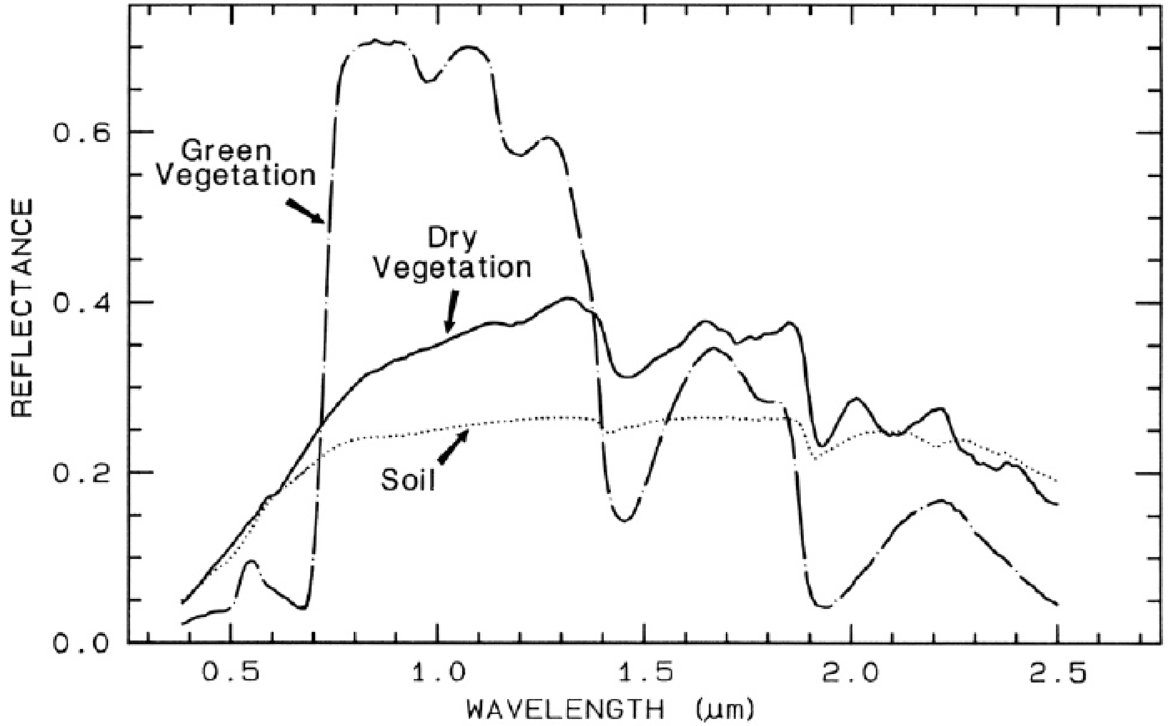
- Abrupt changes:
  - *Wildfire*
  - *Deforestation*
  - *Urban development*



Franks, S., Masek, J.G., Turner, M.G. 2013. Monitoring forest regrowth following large scale fire using satellite data-A case study of Yellowstone National Park, USA. Eur. J. Remote Sens., 46:1, 551–569. https://10.5721/EuJRS20134632

Time Series of Forest Disturbance and Recovery

- Used for:
  - *Mapping disturbance patterns*
  - *Establishment of historic relationships between human and natural disturbance drivers – Urban development vs. insects*
- Evolution of post-disturbance recovery
- Two Primary Approaches:
  - *Deviations (short events)*
  - *Trends (long-term events)*



Clark, R. 1999. Spectroscopy of Rocks and Minerals, and Principles of Spectroscopy, in: Rencz, A. (ed.), Remote Sens. for the Earth Scien., 3–58, New York. (= Manual of Remote Sensing 3).

Introduction to Forest Ecosystem Problems in Central Europe

- Research focused on the observation of disturbances in forest ecosystems
- Bark beetle calamities (Ips typographus, in combination with wind calamities and drought)
- Observations of selected sites before disturbance, during disturbance and during the forest regeneration phase in the Czech Republic, Slovakia and Germany

Photo: J. Laštovička (2017)

Photo: R. Hladký (2017)

#	Classification of TS Methods by Zhu 2017	
	Level 1 (Method Group)	**Level 2 (Method Subgroup)**
1	Thresholding	-
2	Differencing	Classification
		SMA
		Spectral / Index
3	Segmentation	-
4	Trajectory	Hypothesized Trajectory
		Multi-date Classification
5	Statistical Boundary	-
6	Regression	-

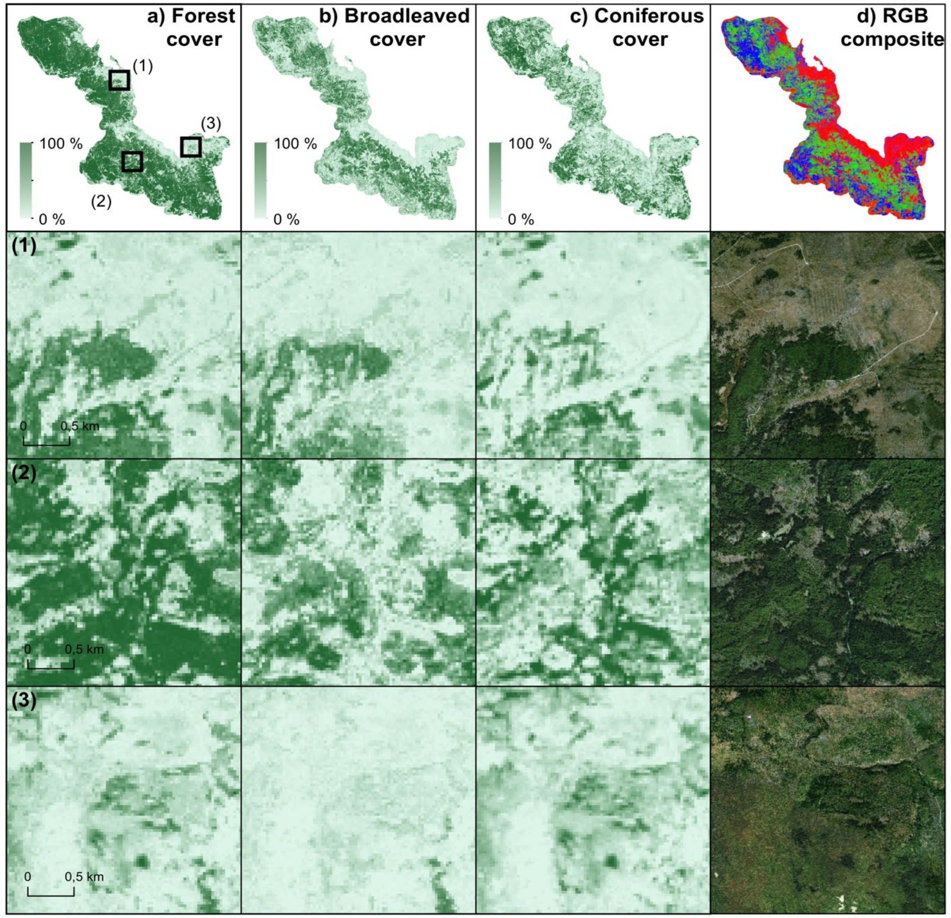
Classification of TS Menthods by Zhu 2017 Completed by EO4Landscape
Level 3 (Processing and P*reprocessing* Subgroup)

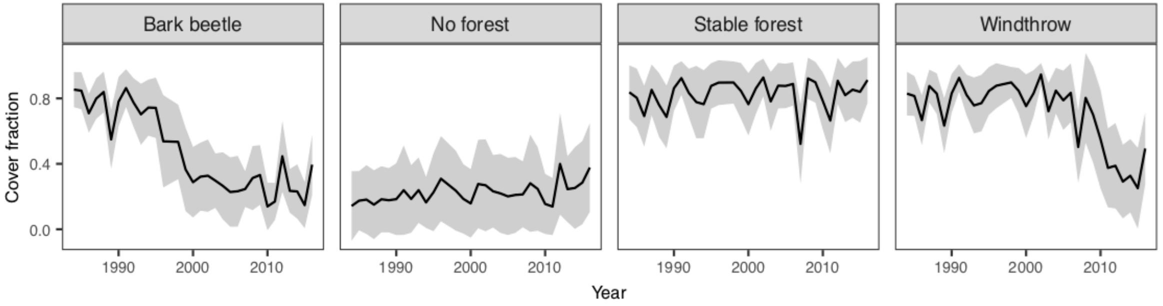
Per-pixel Classification
Object Classification
Linear Unmixing
Nonlinear Unmixing
Raw SR_1 / BOA Data
Relative Radiometric Normalization
Sensors Harmonization
Sensors Cross-calibration

Are sub-pixel classification methods, commonly used for hyperspectral data (Okujeni et al. 2013), suitable for forest surface detection with multispectral data?

1. Suitability of sub-pixel classification for detection of bark beetle calamities

- Tested Unmixing methods on Landsat data time series
- The different levels of land cover were created: forest and non-forest areas
- Two methods: SVR and RFR
- The forest areas were then divided into coniferous and deciduous areas using fractions
- Very high spatial resolution CIR aerial imagery was used to assess accuracy and endmembers
- RMSE (classification error relative to reference data) of 0.18 for SVR and 0.20 for RFR for forest stands
- RMSE 0.23 for both SVR and RFR for coniferous forests
- RMSE 0.24 for SVR and 0.25 for RFR for broadleaved forests

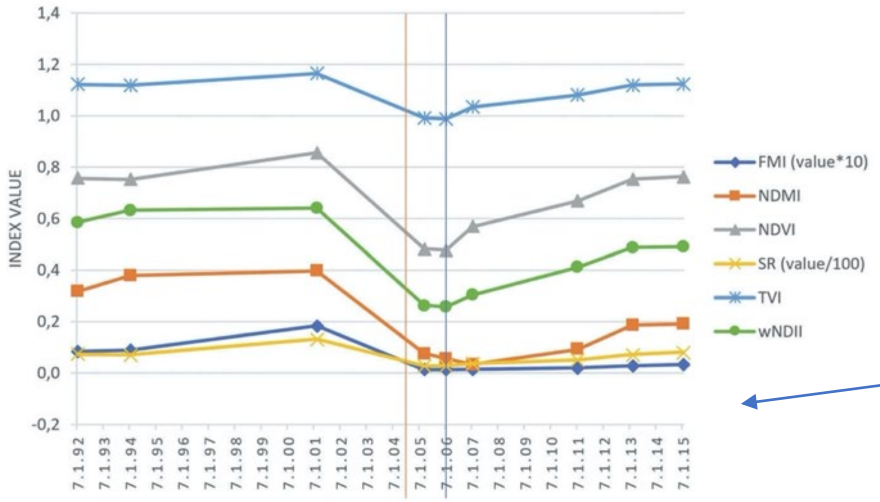


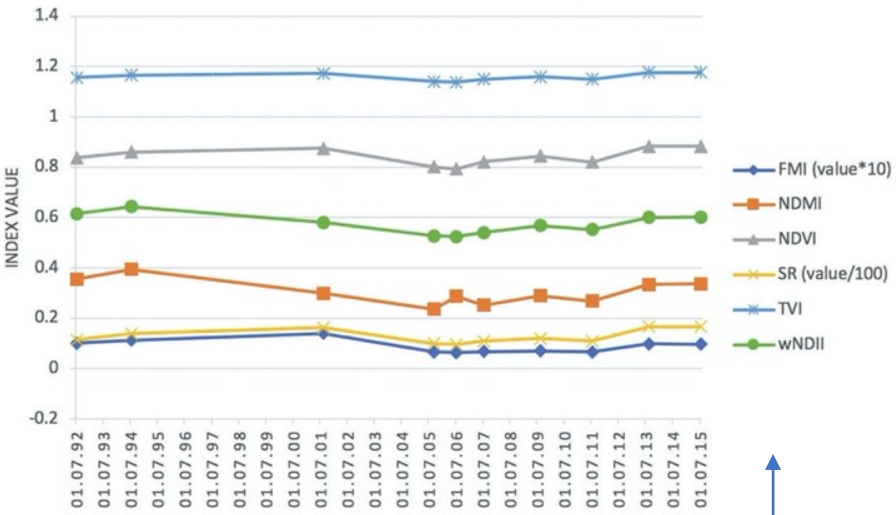


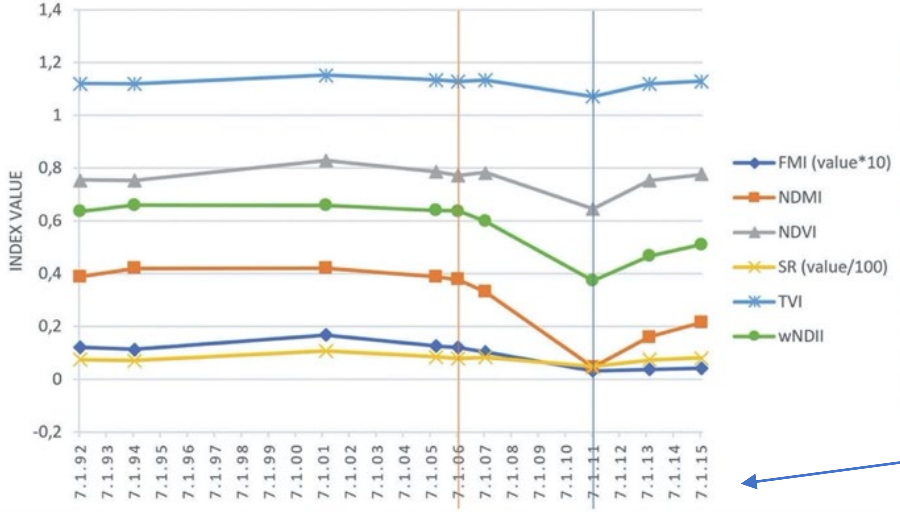
Which of the frequently used vegetation indices (e.g. Jin and Sader 2005, Hais et al. 2009, Musilová 2012) is the most suitable for observing disturbance, regeneration and early infection phases?

Is it possible to use short Sentinel-2 time series to observe the evolution of forest ecosystems after disturbance?

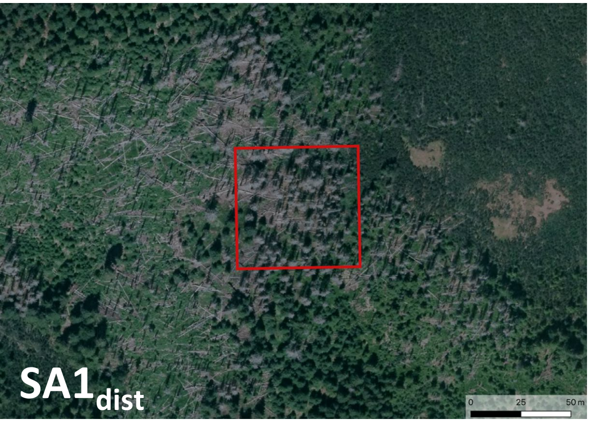
2. Assessment of forest ecosystem change using Landsat and Sentinel-2

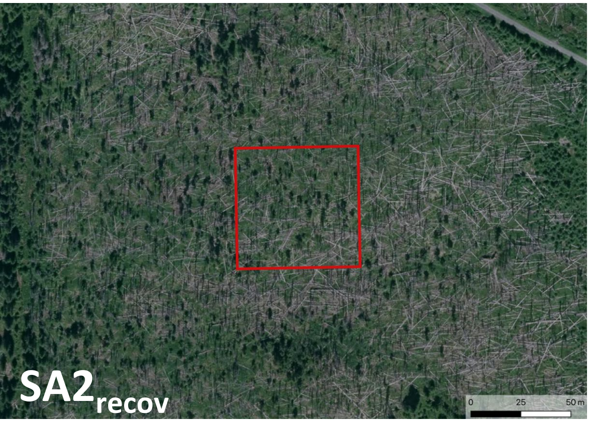


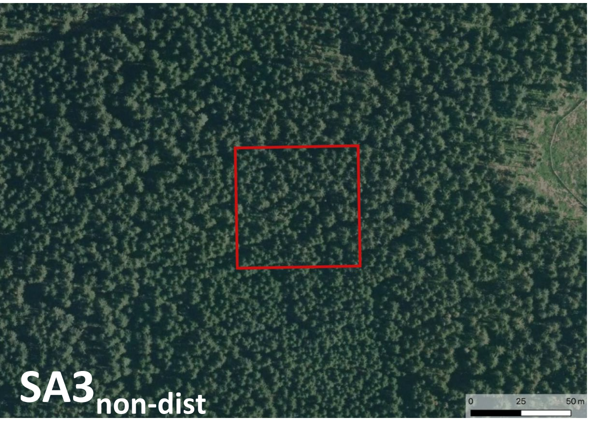


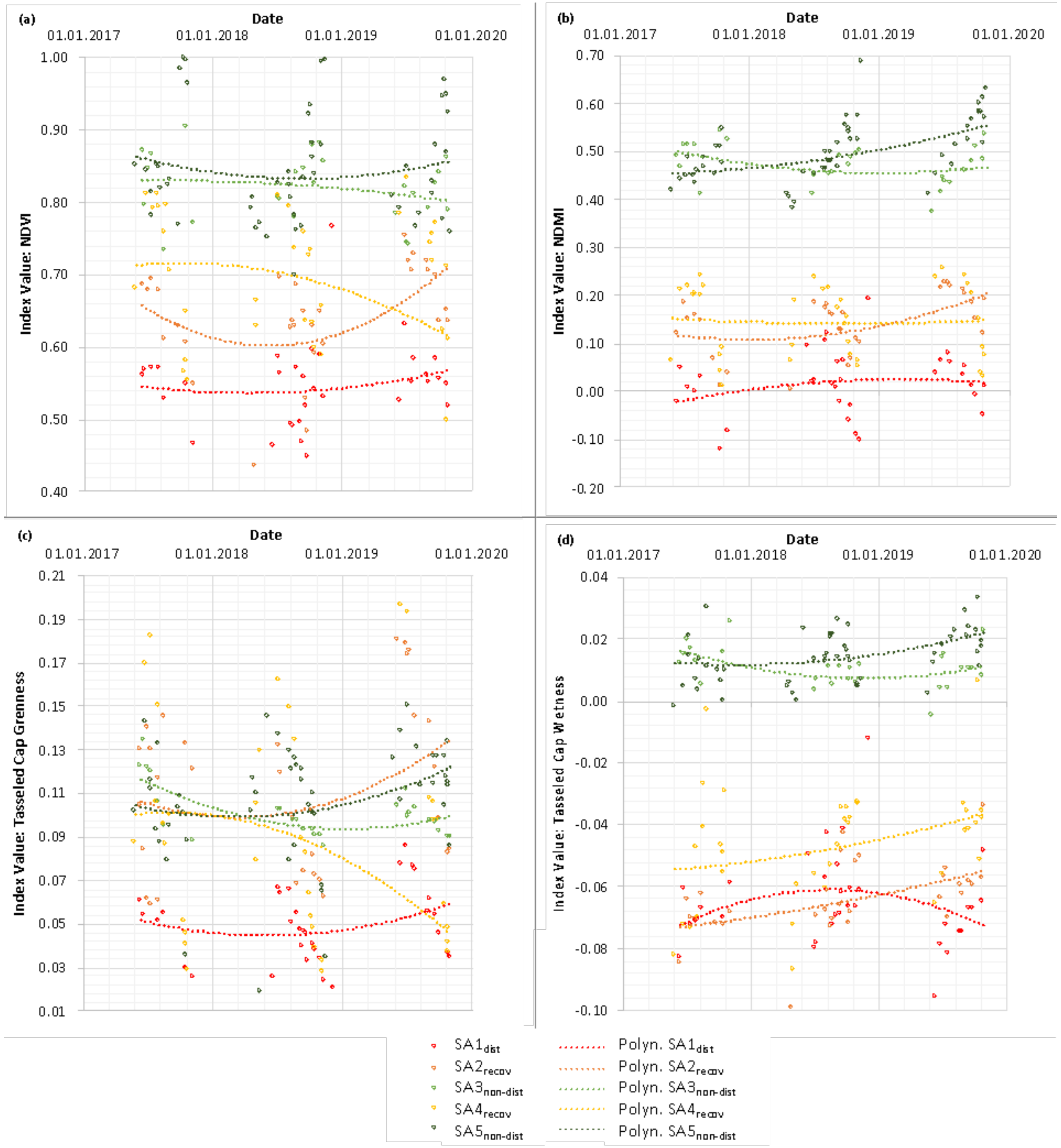


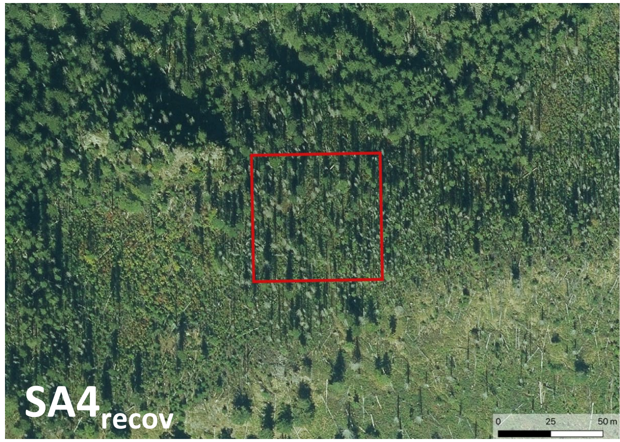
Photos: R. Hladký (2017)

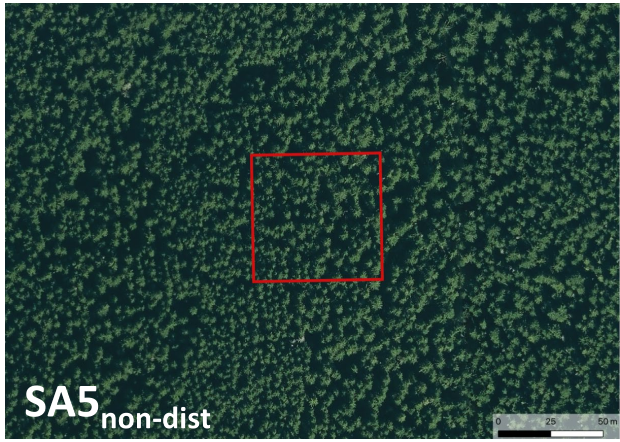

SA1$_{dist}$
0 25 50 m


SA2$_{recov}$
0 25 50 m


SA3$_{non-dist}$
0 25 50 m


(a)
Date
01.01.2017
01.01.2018
01.01.2019
01.01.2020
Index Value: NDVI
1.00
0.90
0.80
0.70
0.60
0.50
0.40
(b)
Date
01.01.2017
01.01.2018
01.01.2019
01.01.2020
Index Value: NDMI
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
-0.10
-0.20
(c)
Date
01.01.2017
01.01.2018
01.01.2019
01.01.2020
Index Value: Tasseled Cap Greenness
0.21
0.19
0.17
0.15
0.13
0.11
0.09
0.07
0.05
0.03
0.01
(d)
Date
01.01.2017
01.01.2018
01.01.2019
01.01.2020
Index Value: Tasseled Cap Wetness
0.04
0.02
0.00
-0.02
-0.04
-0.06
-0.08
-0.10
SA1$_{dist}$
SA2$_{recov}$
SA3$_{non-dist}$
SA4$_{recov}$
SA5$_{non-dist}$
Polyn. SA1$_{dist}$
Polyn. SA2$_{recov}$
Polyn. SA3$_{non-dist}$
Polyn. SA4$_{recov}$
Polyn. SA5$_{non-dist}$


SA4$_{recov}$
0 25 50 m


SA5$_{non-dist}$
0 25 50 m

How do the phases of forest ecosystem recovery after disturbance differ in the no-management zones of Šumava NP compared to the intervention areas of Low Tatras NP?

Can these phases be distinguished using satellite data?

3. Comparison of the evolution of forest health in selected sites in the Czech Republic and Slovakia

- The selected study areas were in NP Šumava and NP Low Tatras
- Both sites are geographically different, but they were connected by similar events of wind and bark beetle calamities
- Different regenerative evolution of each habitat was shown to be caused by different forestry and conservation intervention policies in the studied sites
- In most of the Slovak sites studied, dead trees were removed or new trees were planted, which was shown to accelerate the onset of regeneration
- Slower, spontaneous habitat regeneration was demonstrated at the Šumava sites, but with a diverse composition of vegetation species


Photo: R. Hladký (2017)

3. Selection of a suitable vegetation index to detect different developmental stages of disturbance, forest recovery phase after disturbance or sites without forest damage

- Difference indices: NDVI, NDMI, SR, TVI, FMI and wNDII
- Orthogonal indices: TCW and TCG
- NDMI, wNDII, NDVI and TCW suitable for disturbance observations
- NDMI has also enabled observation of the early stages of bark beetle infection
- NDMI for observation of the recovery phase
- The NDMI index perfectly reflected the ongoing phases of each observed site
- The NDMI is suitable for all phases

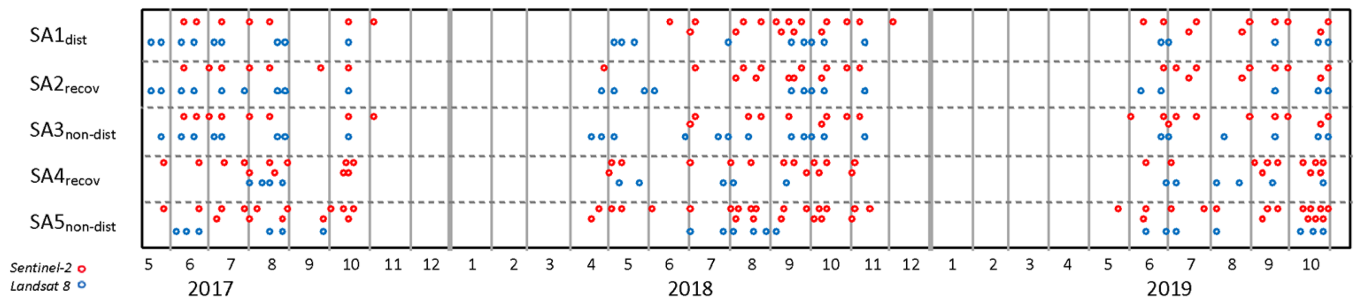
What is the effect of using both Sentinel-2A and Sentinel-2B satellites on the temporal resolution?

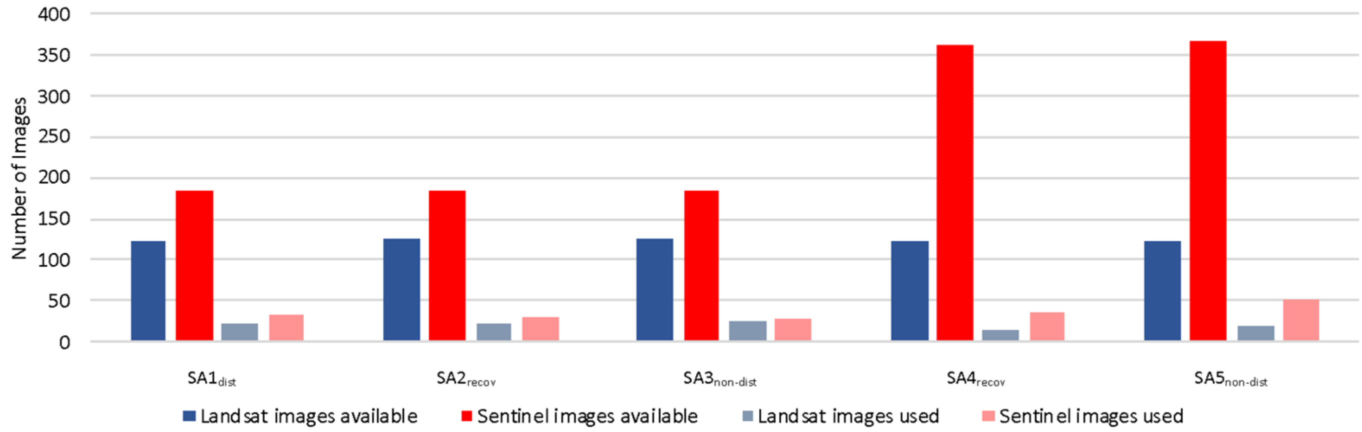
What is the difference in temporal resolution between Landsat 8 and Sentinel-2 data?

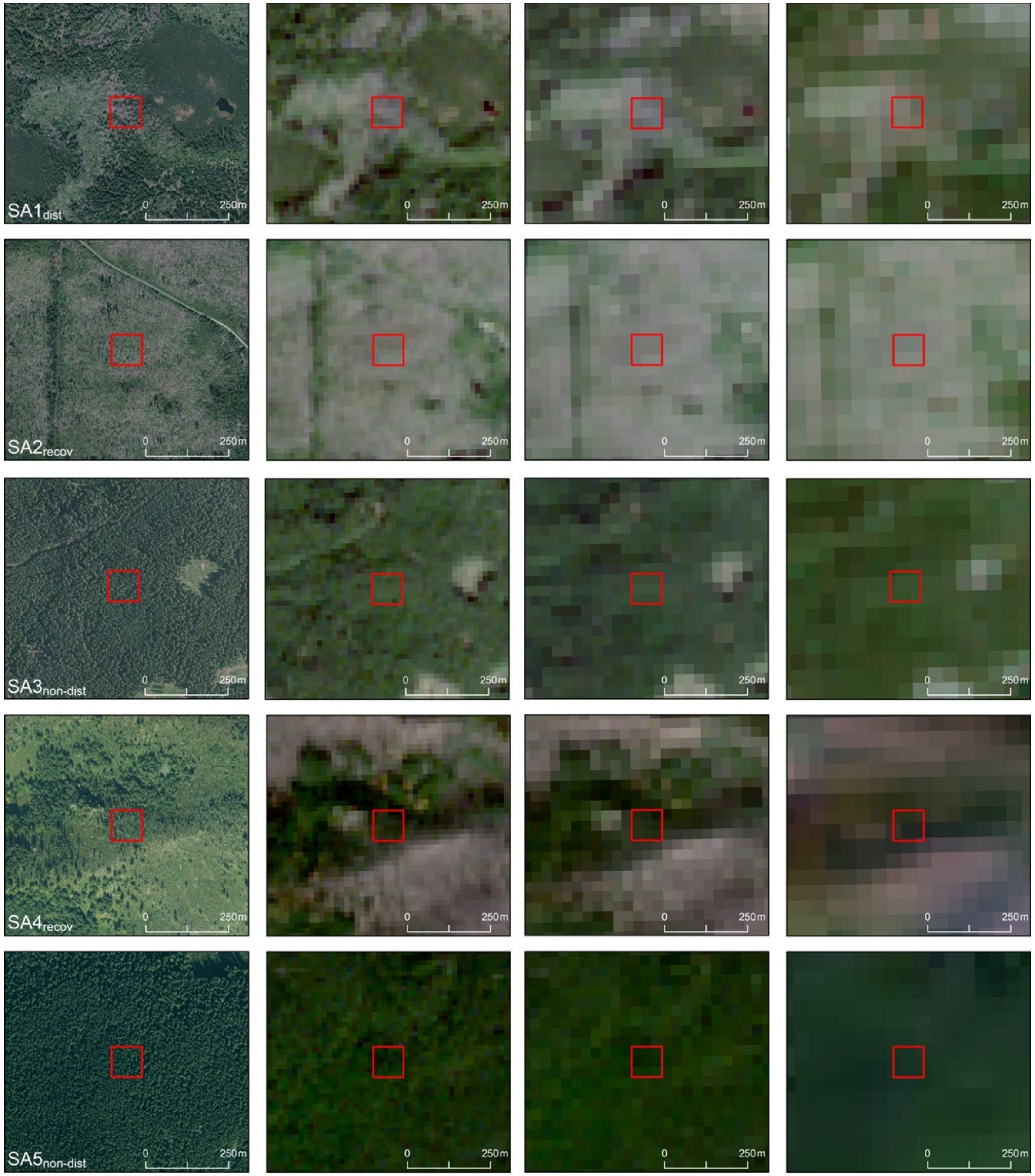
What allows the higher spatial resolution of Sentinel-2 data to better resolve within forest ecosystems?

5. Landsat 8 and Sentinel-2 data differences in spectral, spatial and temporal resolution

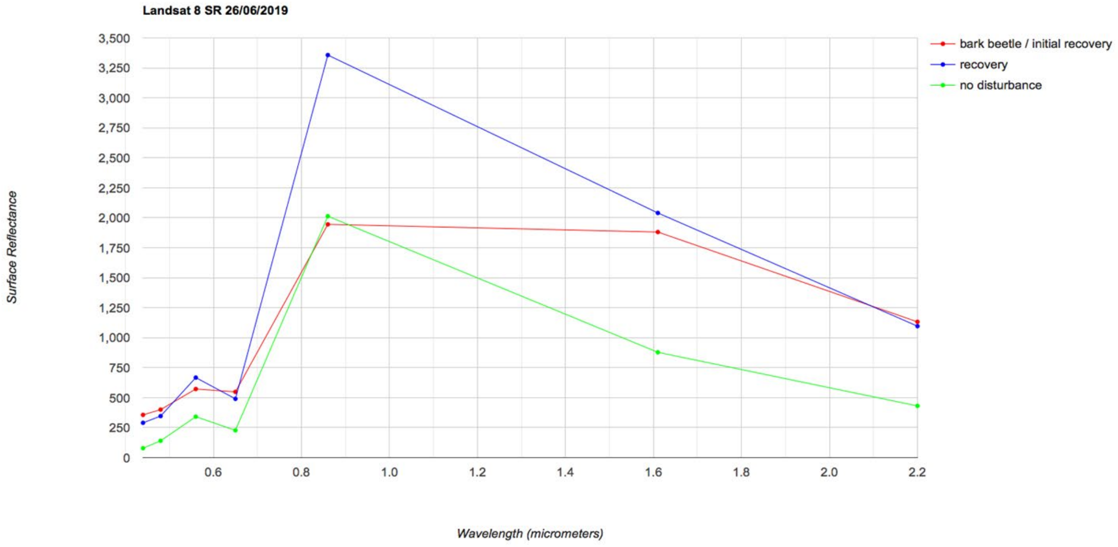
- Sentinel-2 data had a similar temporal resolution to Landsat 8 data at the beginning of its existence
- In 2017, Sentinel-2A was complemented by Sentinel-2B, resulting in a significant increase in temporal resolution and a much higher number of images captured
- A total of 625 Landsat images and 1284 Sentinel-2 images were acquired for five selected sites in Sumava and the Low Tatras during the period 28 March 2017 - 31 December 2019
- Thanks to the improved spatial resolution of Sentinel-2 (10/20 m), clouds, cloud shadows, cirrus clouds and tree shadows can be more accurately detected visually

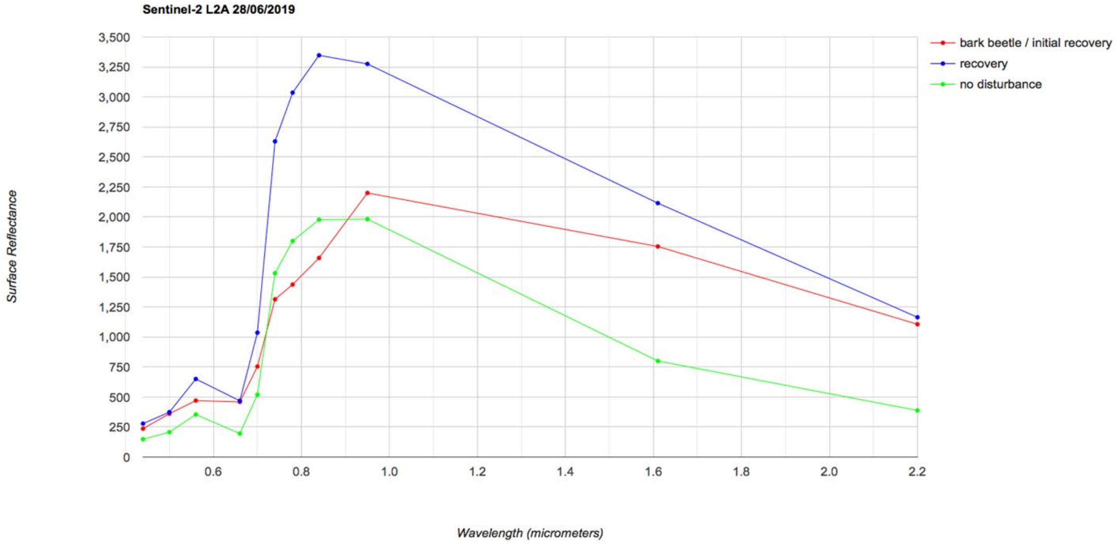






Orthophoto (~0.25 m/pixel) | Sentinel-2 (10 m/pixel) | Sentinel-2 (20 m/pixel) | Landsat 8 (30 m/pixel)





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Franks, S., Masek, J.G., Turner, M.G. 2013. Monitoring forest regrowth following large scale fire using satellite data-A case study of Yellowstone National Park, USA. Eur. J. Remote Sens., 46:1, 551–569. https://10.5721/EuJRS20134632

Hais, M., Jonášová, M., Langhammer, J., Kučera, T., 2009. Comparison of two types of forest disturbance using multitemporal Landsat TM/ETM+ imagery and field vegetation data. Remote Sens. Environ. 113, 835–845. https://doi.org/https://doi.org/10.1016/j.rse.2008.12.012

Immerzeel, W.W., Droogers, P., de Jong, S.M. and Bierkens, M.F.P. 2009. Large-Scale Monitoring of Snow Cover and Runoff Simulation in Himalayan River Basins Using Remote Sensing. Remote Sens. Environ., 113, 40–49. https://doi.org/10.1016/j.rse.2008.08.010

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Liu, Y., Xiao, J., Ju, W., Xu, K., Zhou, Y., Zhao, Y. 2016. Recent trends in vegetation greenness in China significantly altered annual evapotranspiration and water yield. Environ. Res. Lett. 11, 094010. https://10.1088/1748-9326/11/9/094010

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Okujeni, A., van der Linden, S., Tits, L., Somers, B., Hostert, P., 2013. Support vector regression and synthetically mixed training data for quantifying urban land cover. Remote Sens. Environ. 137, 184–197. https://doi.org/10.1016/j.rse.2013.06.007

Senf, C., Laštovička, J., Okujeni, A., Heurich, M., van der Linden, S., 2020. A generalized regression-based unmixing model for mapping forest cover fractions throughout three decades of Landsat data. Remote Sens. Environ. 240. https://doi.org/10.1016/j.rse.2020.111691

Zhu, Z., 2017. Change detection using landsat time series: A review of frequencies, preprocessing, algorithms, and applications. ISPRS J. Photogramm. Remote Sens. 130, 370–384. https://doi.org/10.1016/j.isprsjprs.2017.06.013


Photo: J. Laštovička

Thank you for your attention. Time for your questions.

Next: Daniel Paluba – SAR Data in Forest Ecosystems

Stych and Lastovicka (2023)

stych@natur.cuni.cz and josef.lastovicka@natur.cuni.cz