Gross Primary Production from Above

Remote Sensing & *Digital Forest*

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UNIVERSITÄT
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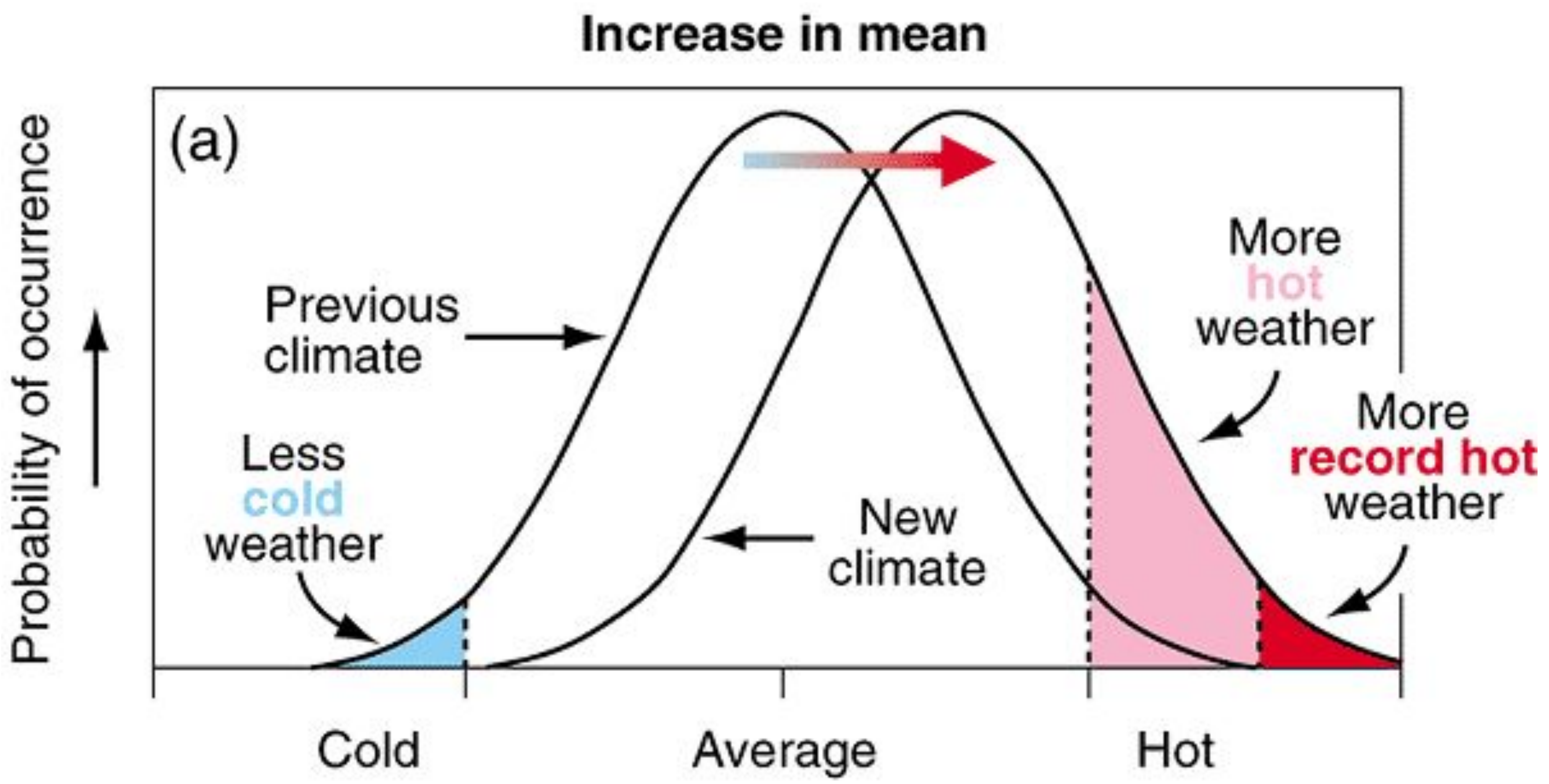
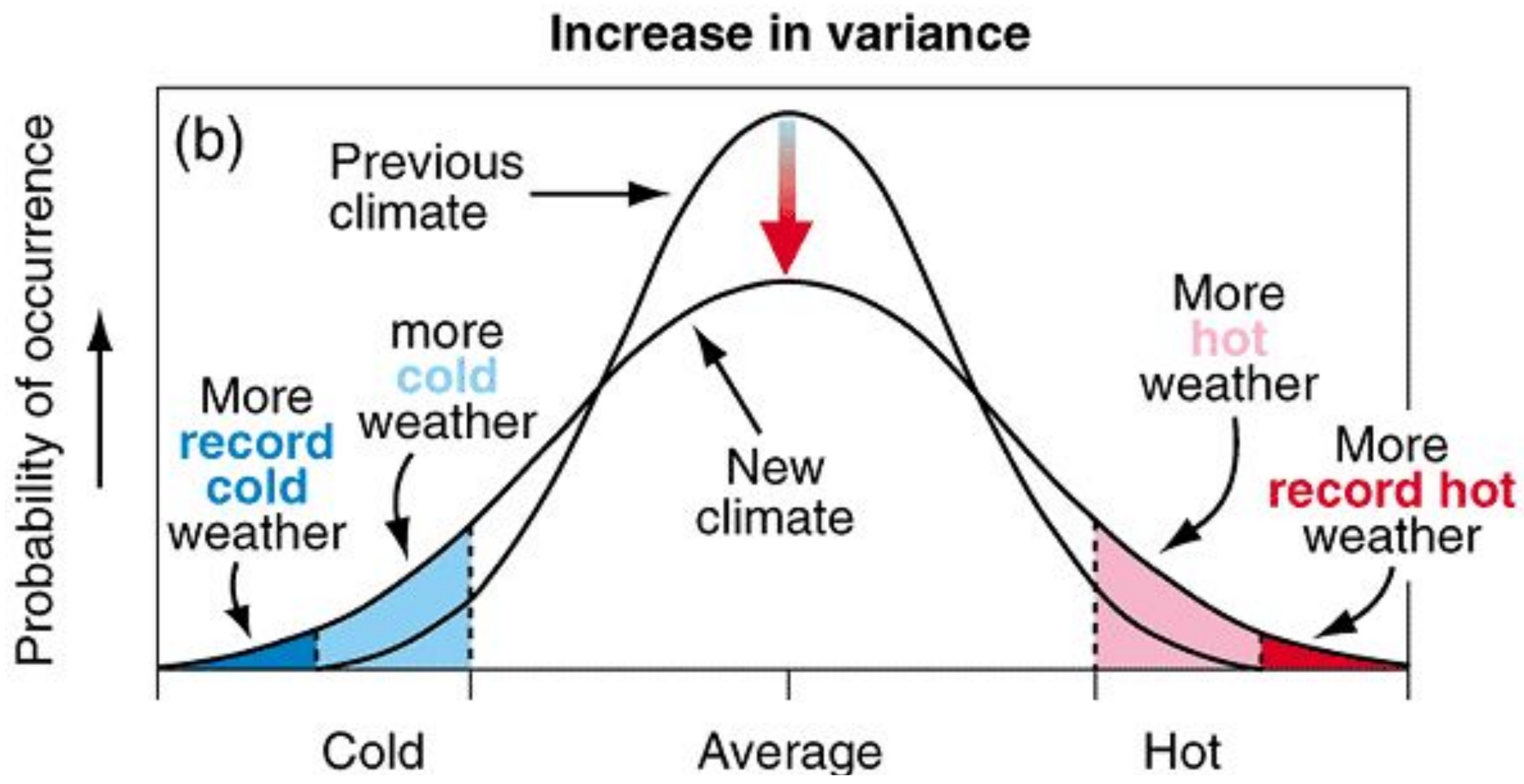
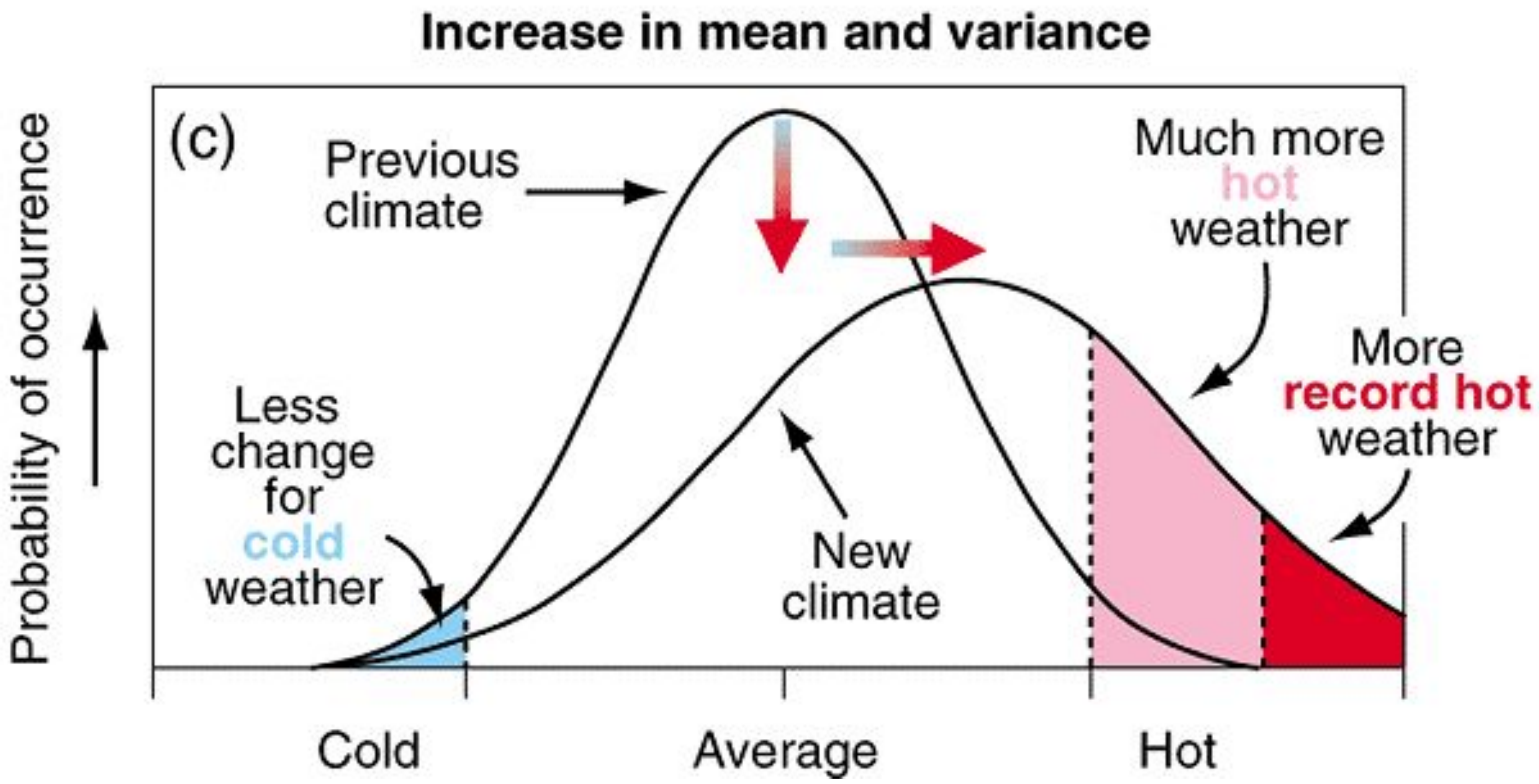
Background

Extremes events and their impact on biosphere

Extreme events are increasing

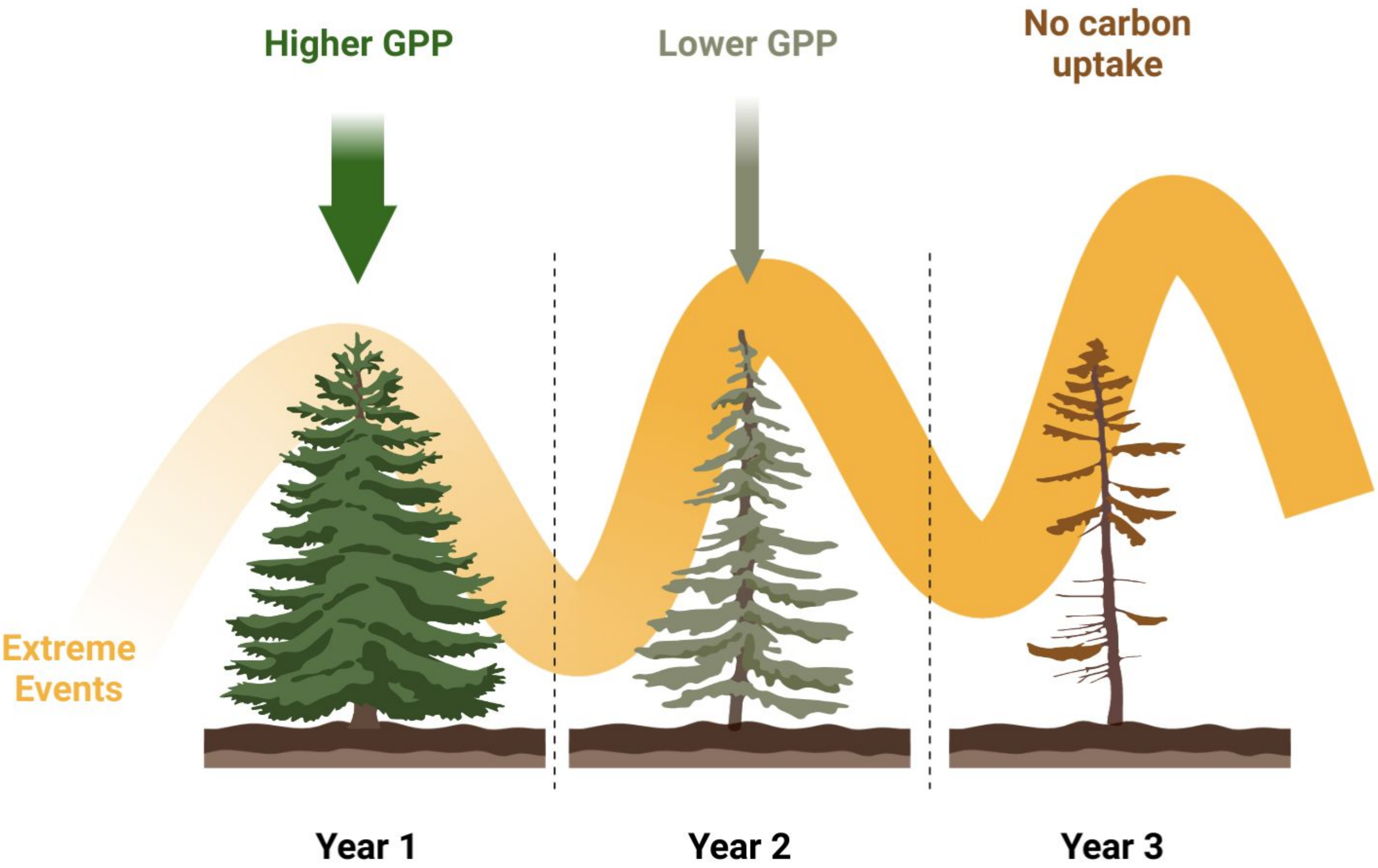






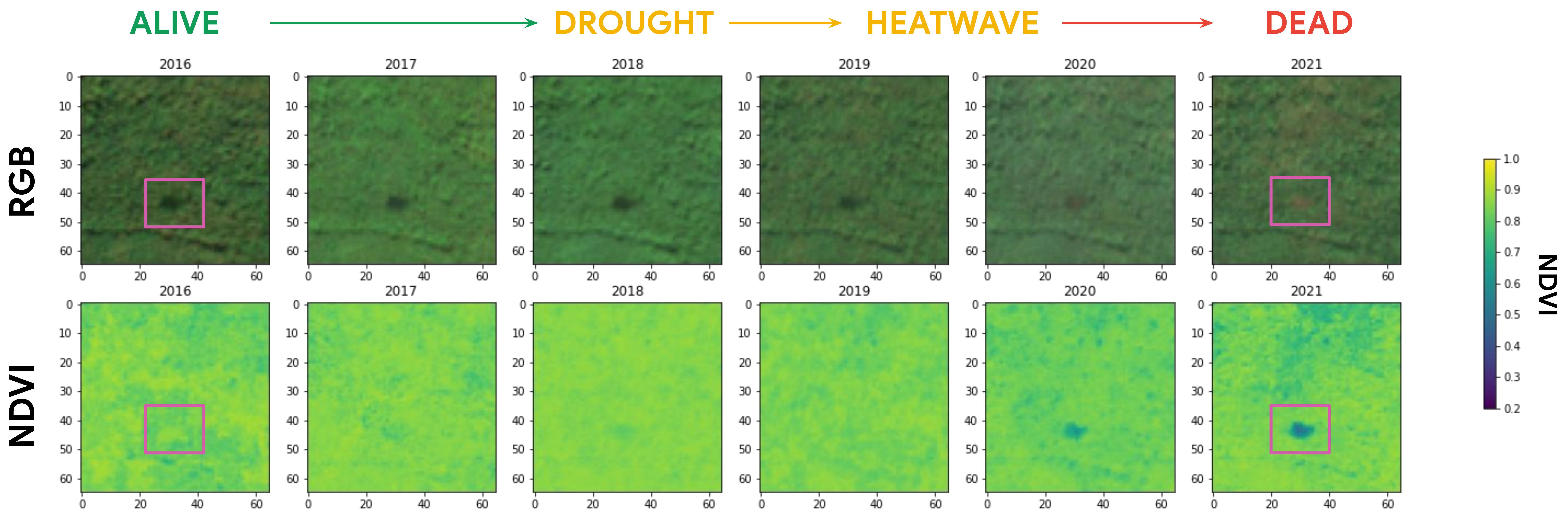
Houghton et al., 2001
IPCC Climate Change 2001

Effects on **carbon uptake**



GPP: Gross Primary Production

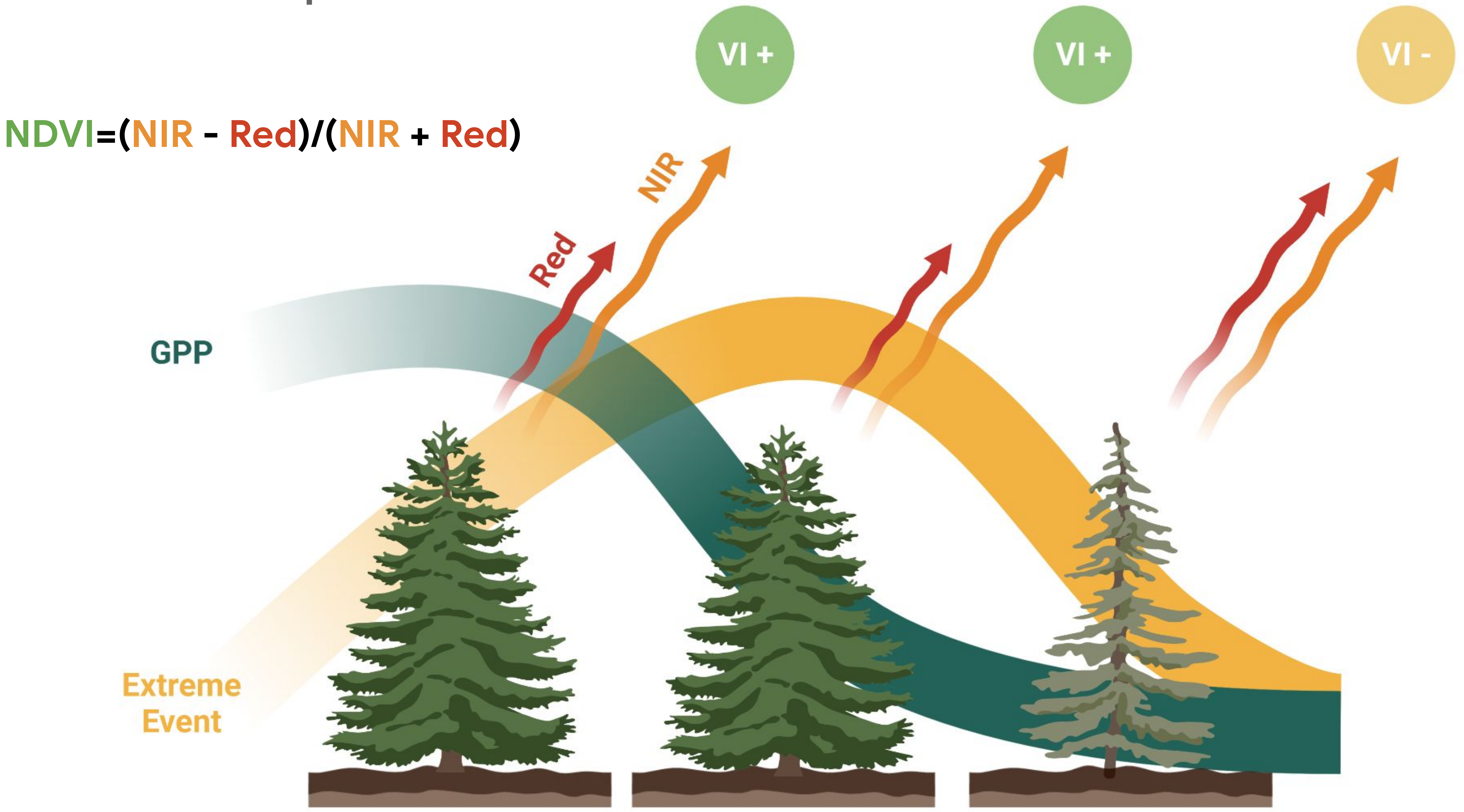
Tree **mortality**



NDVI: Normalized Difference Vegetation Index

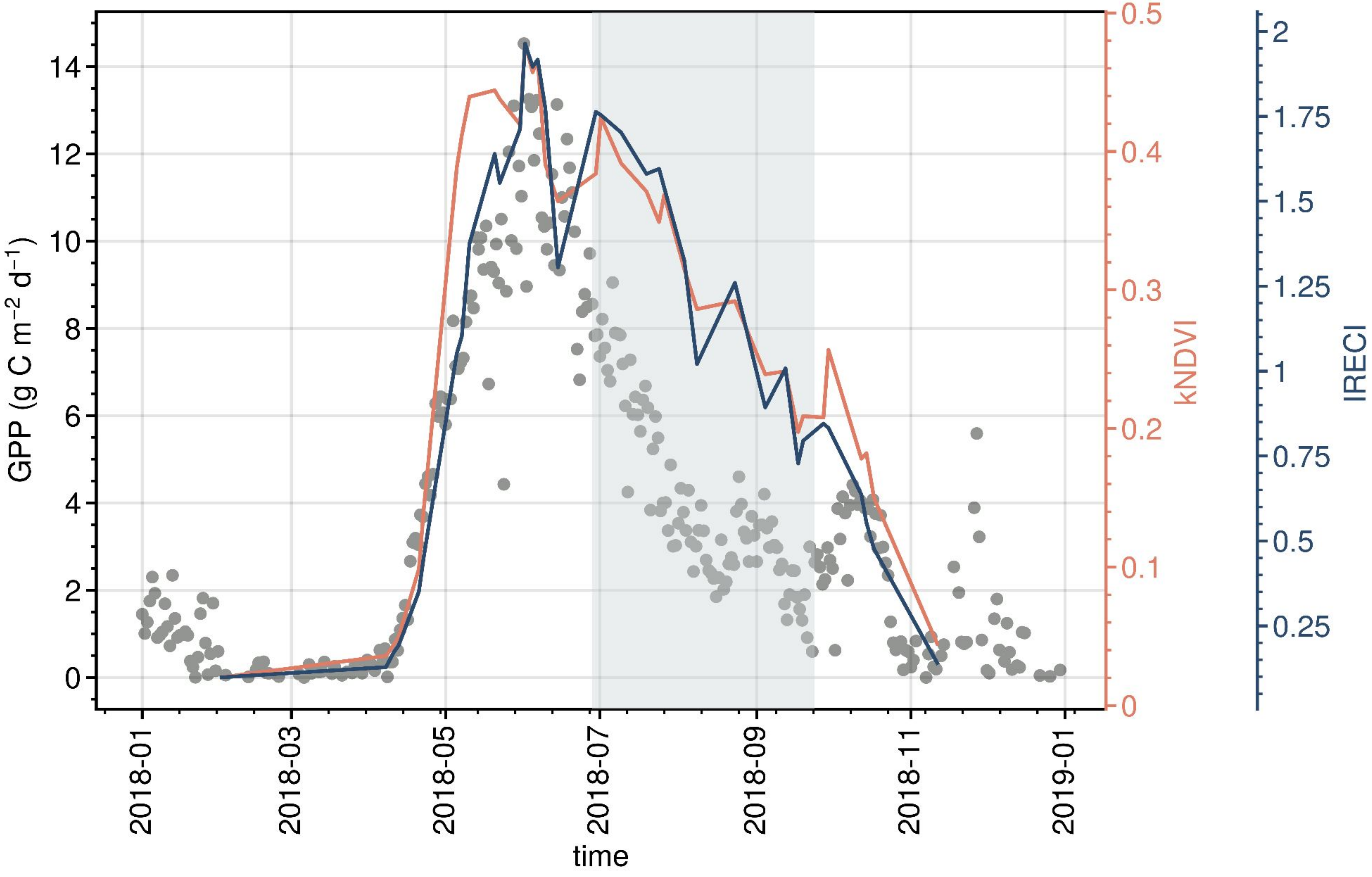
GPP **Downregulation**

Spectral response



NIR: Near-Infrared
VI: Vegetation Index

Instantaneous prediction from RS is **NOT** enough



kNDVI: Kernel NDVI
IRECI: Inverted Red Edge Chlorophyll Index

Hypotheses

1. Exploiting the memory of Remote Sensing signals improves the GPP estimation in forests.

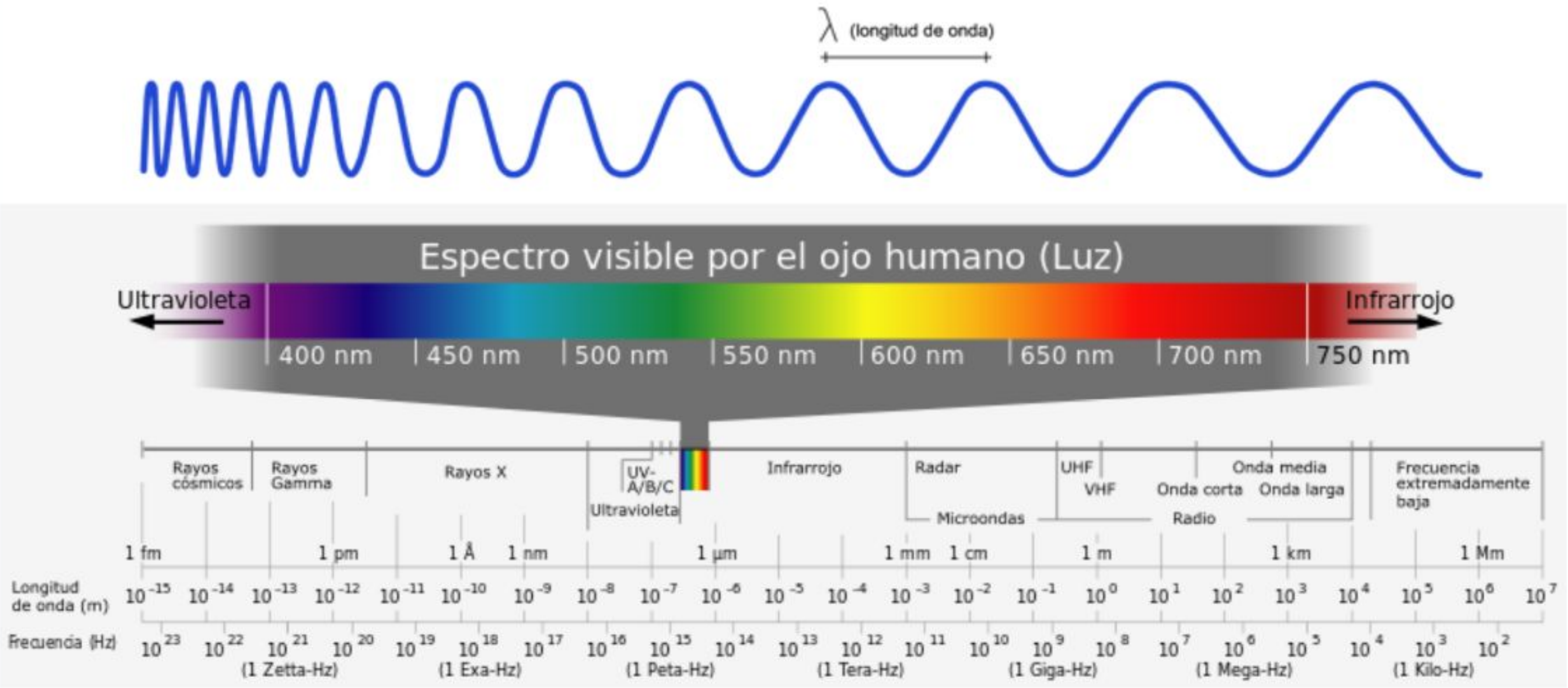
2. Considering the temporal dependencies using Deep Learning improves the GPP prediction during extreme events.

First Chapter

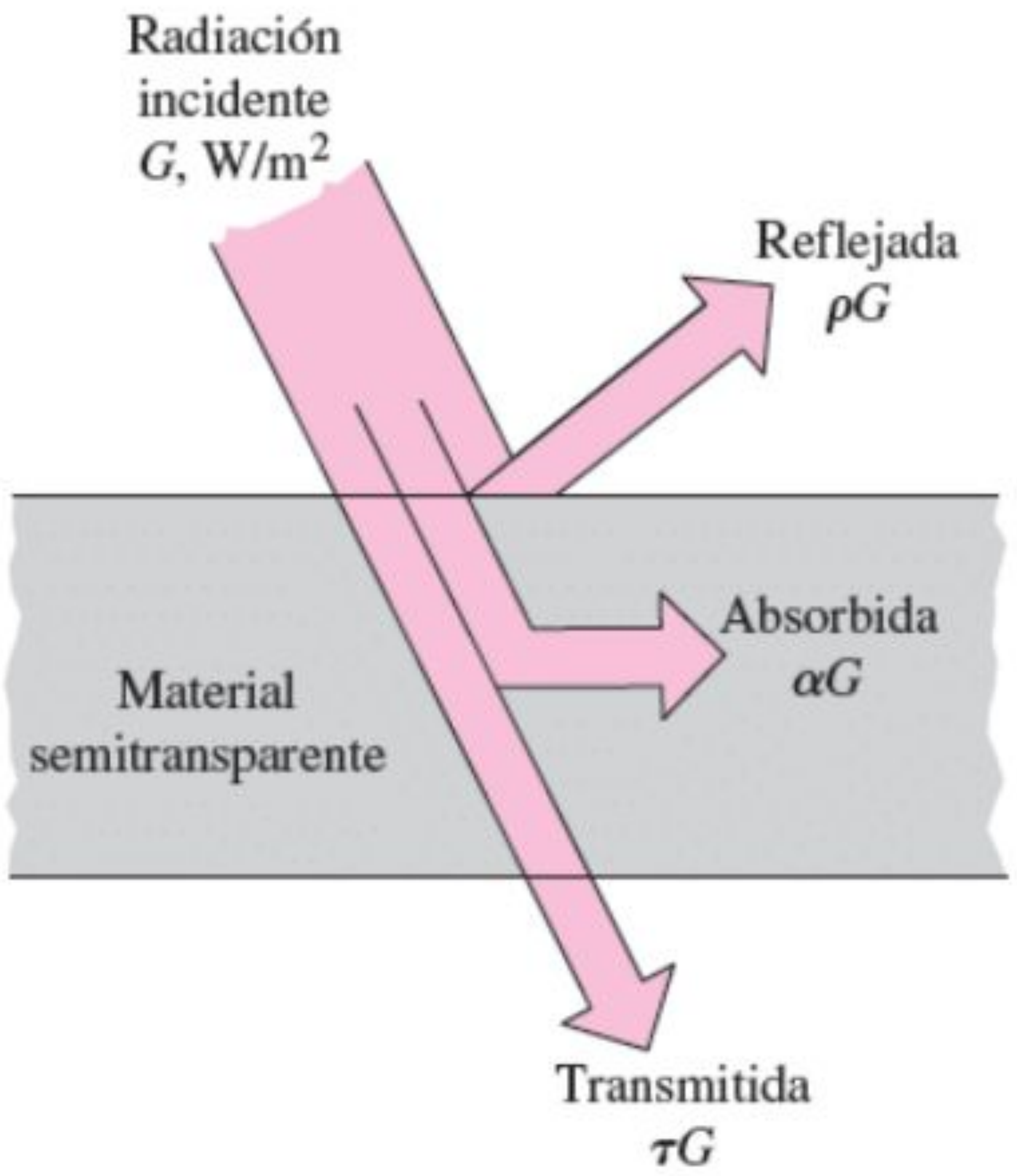
Remote Sensing *(optical)*

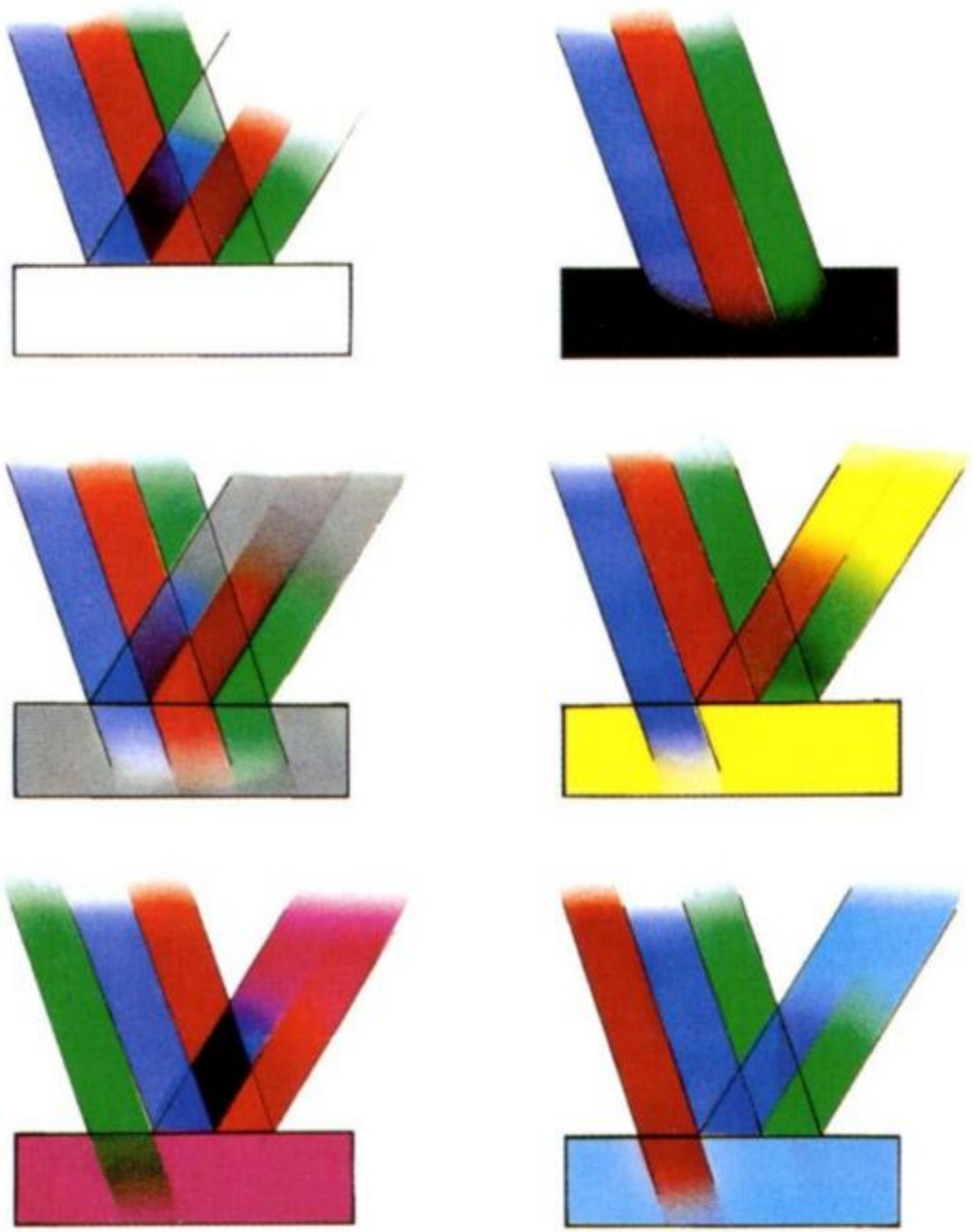
1

Electromagnetic spectrum

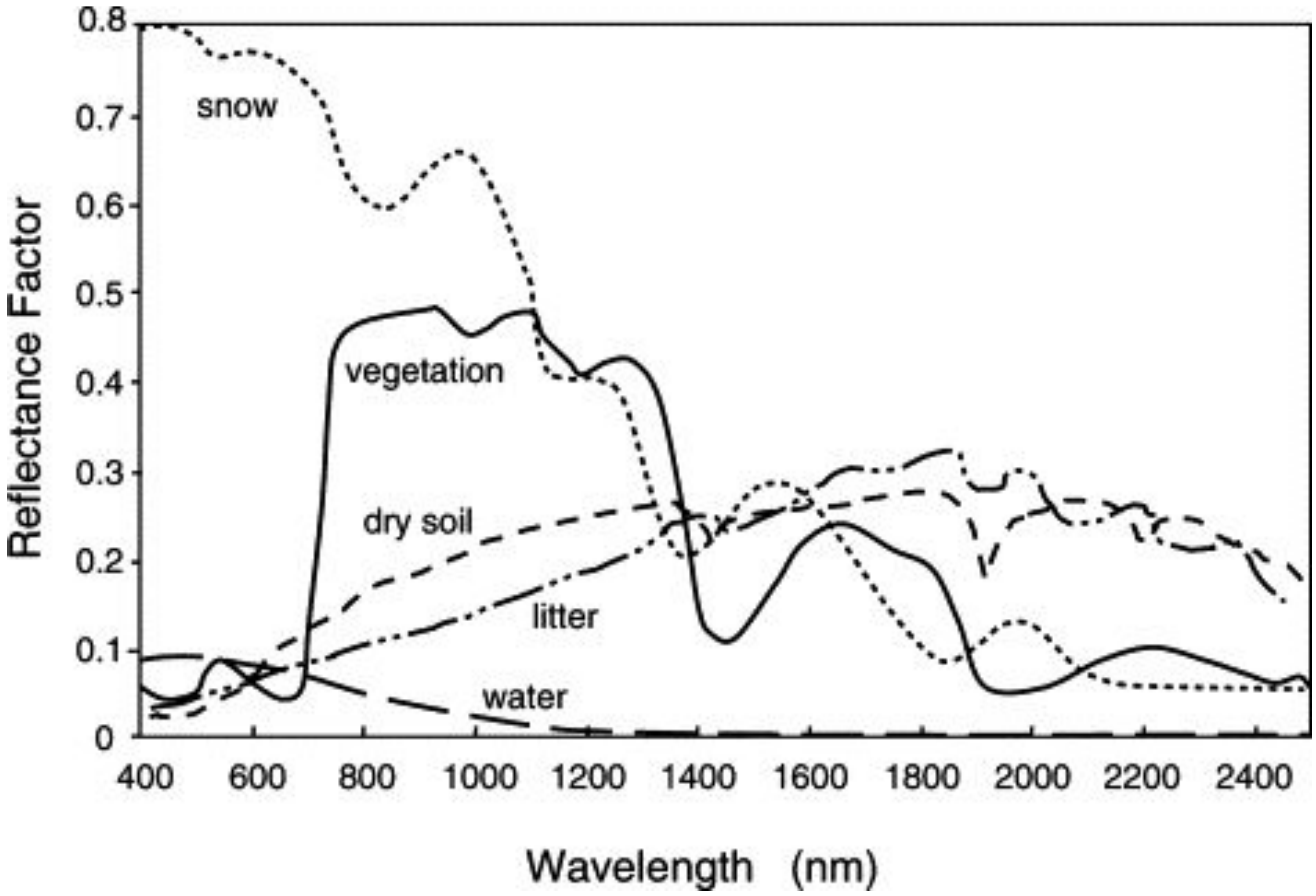


Interacting with **radiation**



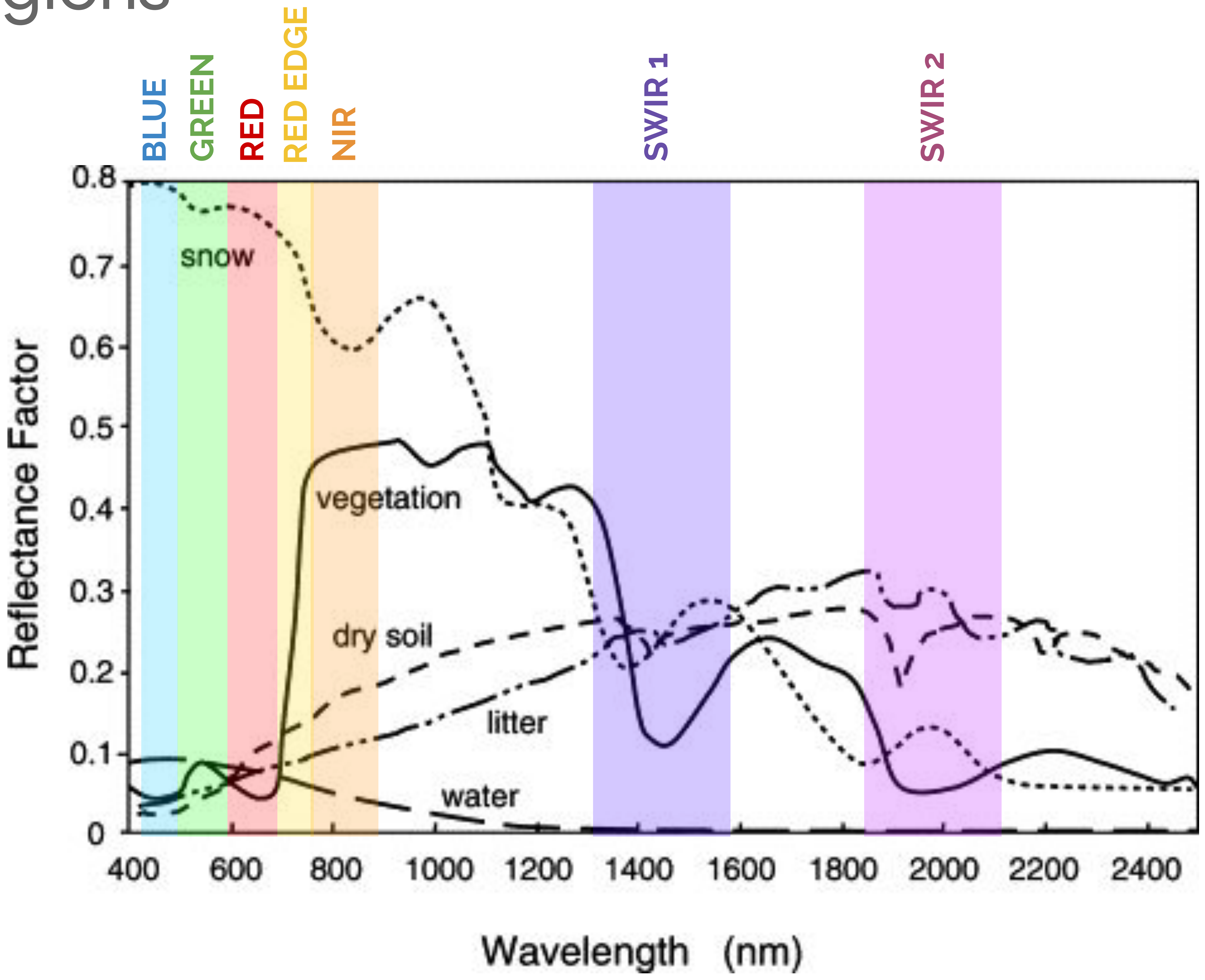


Spectral signature



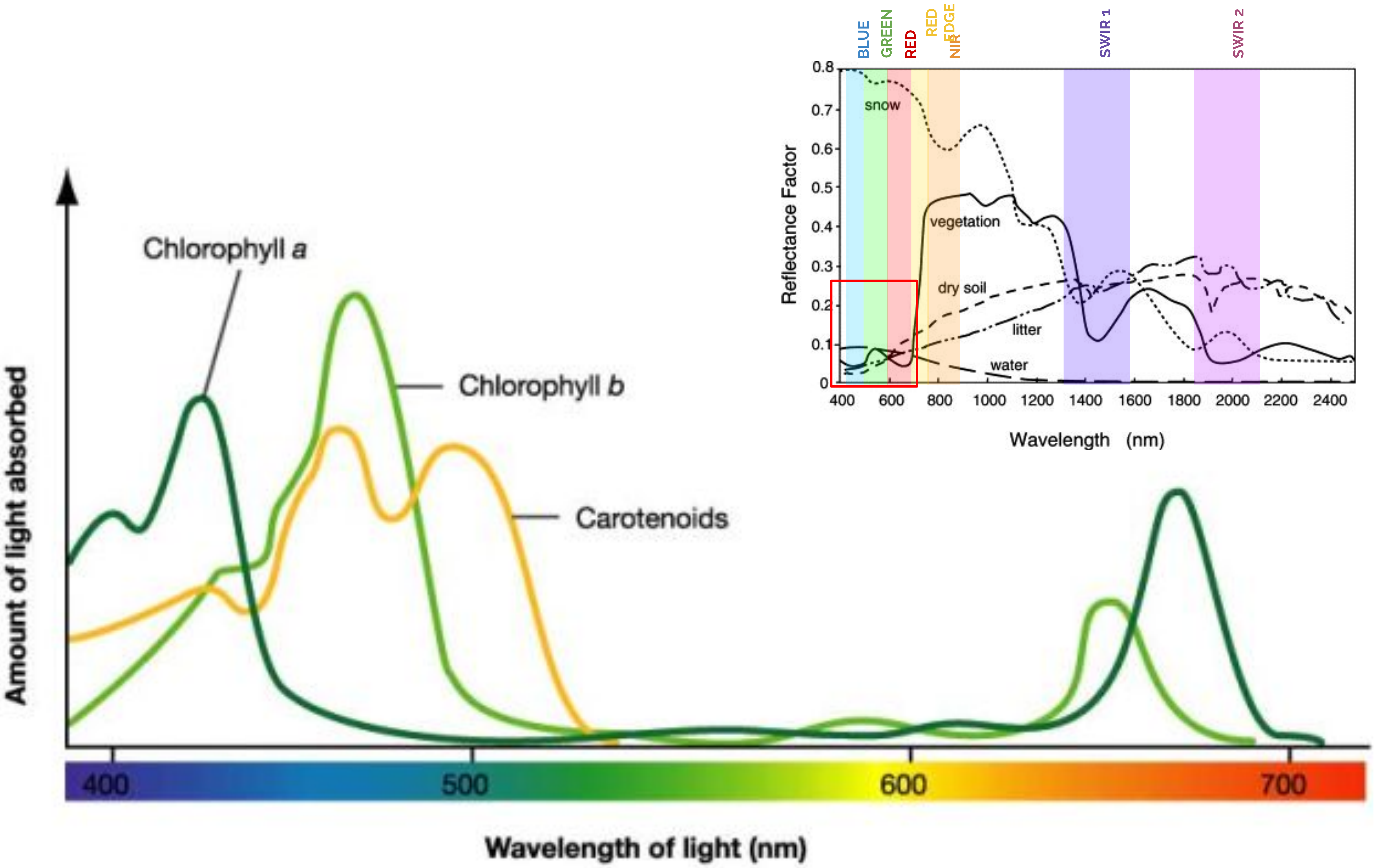
Source image: ([Huete, 2004]())

Broader regions



Source image: ([Huete, 2004]())

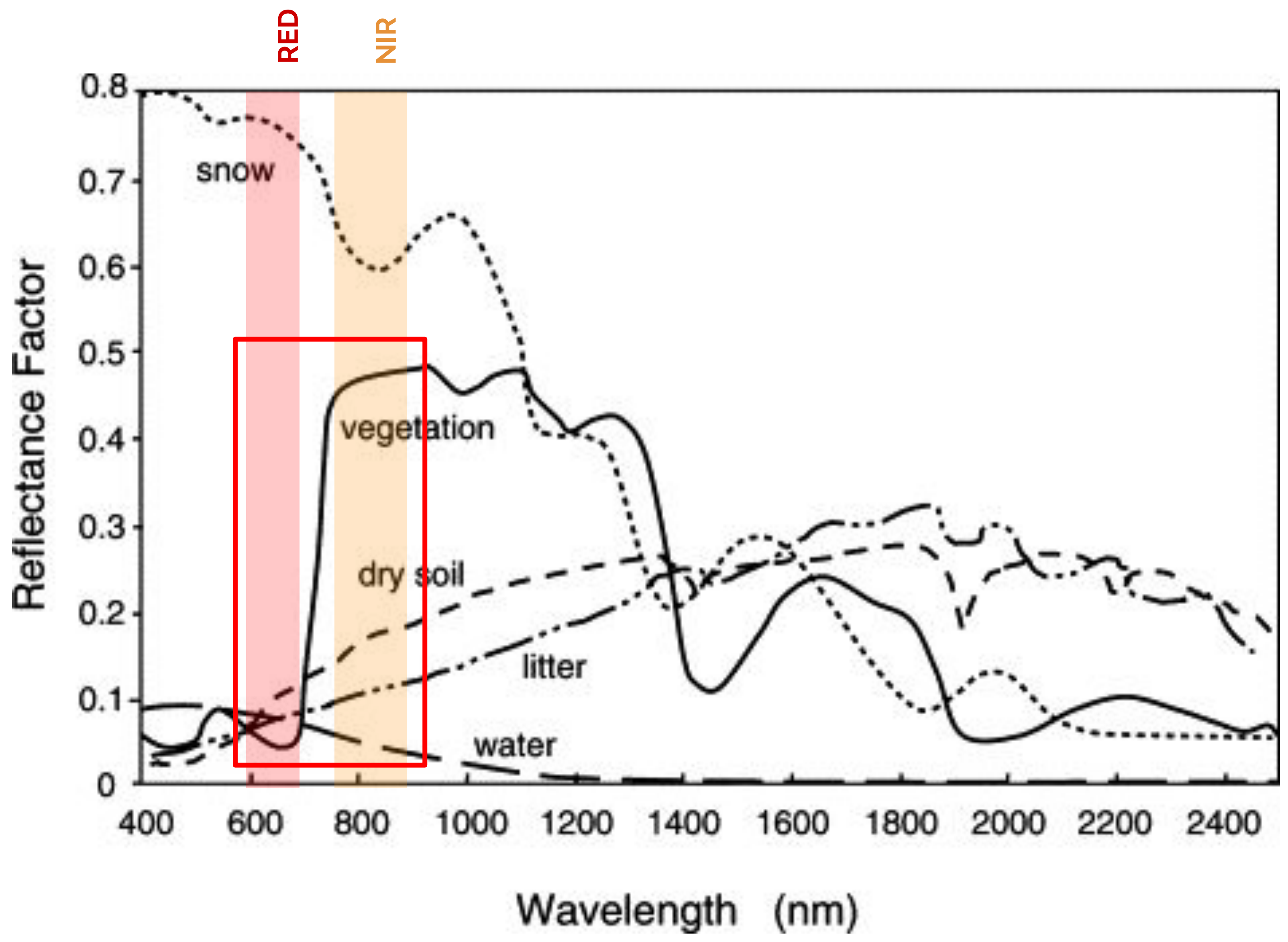
Pigments and photosynthesis



Source image: (Unisciel, 2021)

Spectral indices

NDVI =
(NIR - RED)/(NIR + RED)

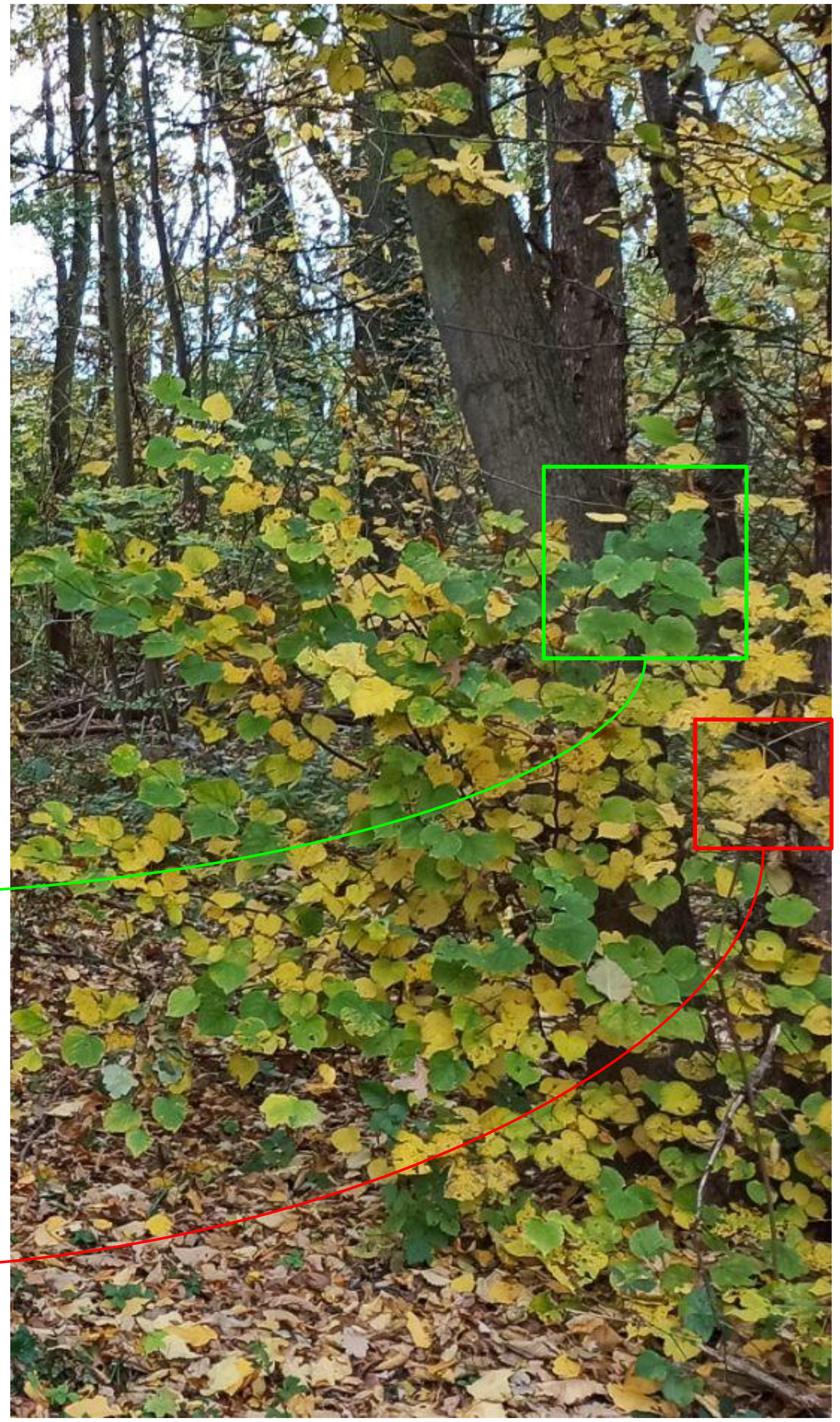


NDVI = 0.75

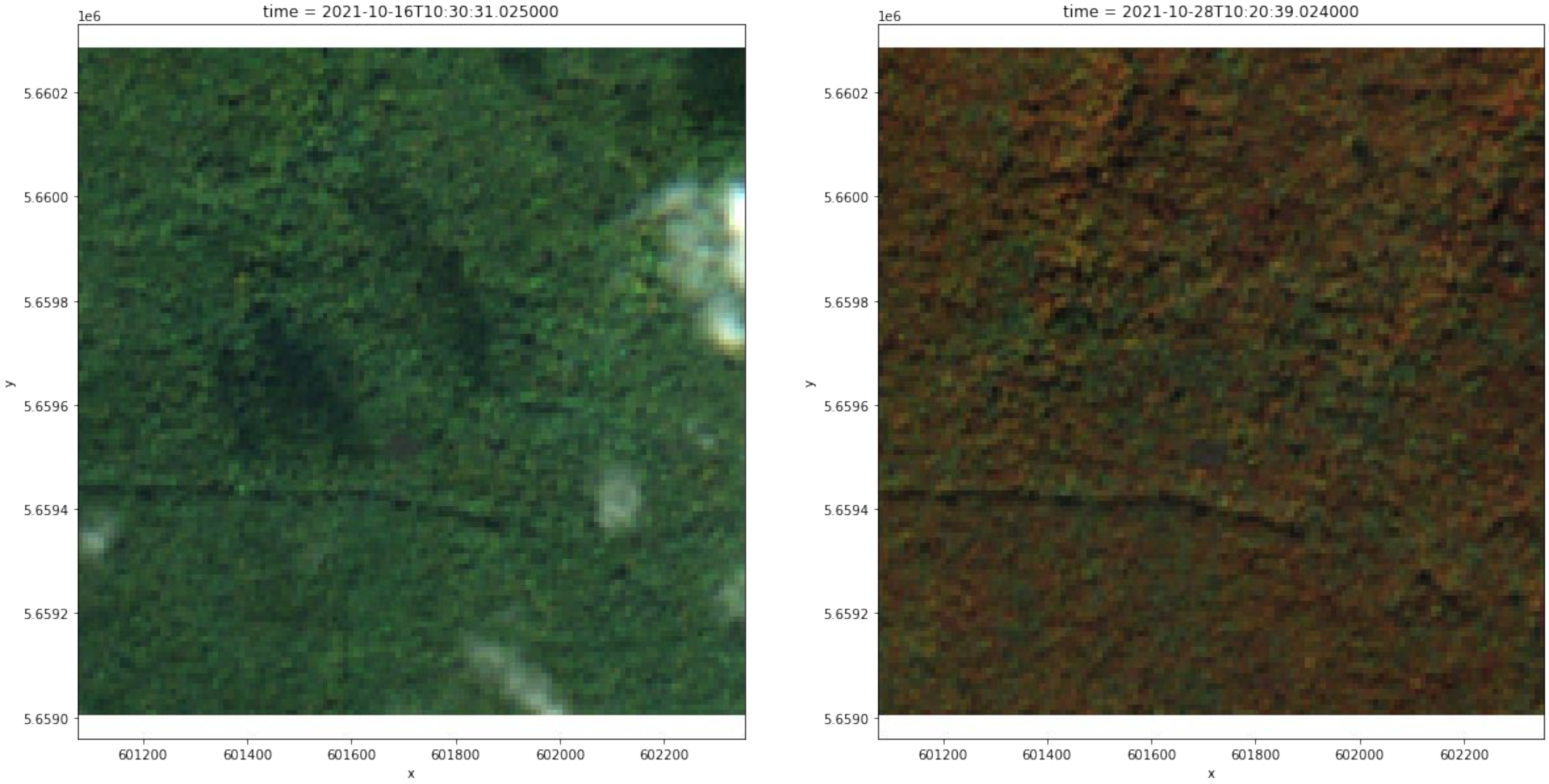
NIR = 0.50
RED = 0.07

NDVI = 0.31

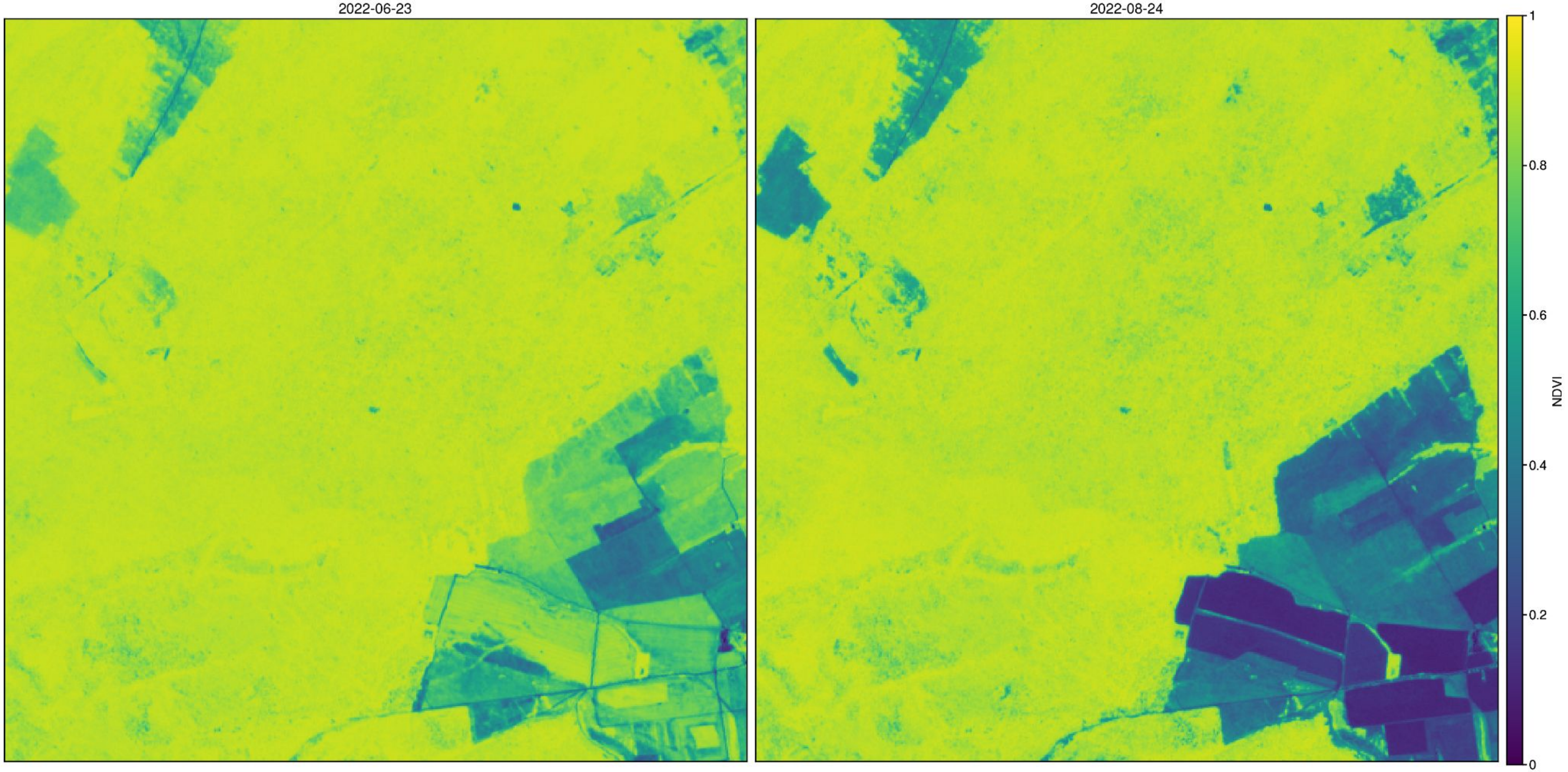
NIR = 0.48
RED = 0.25



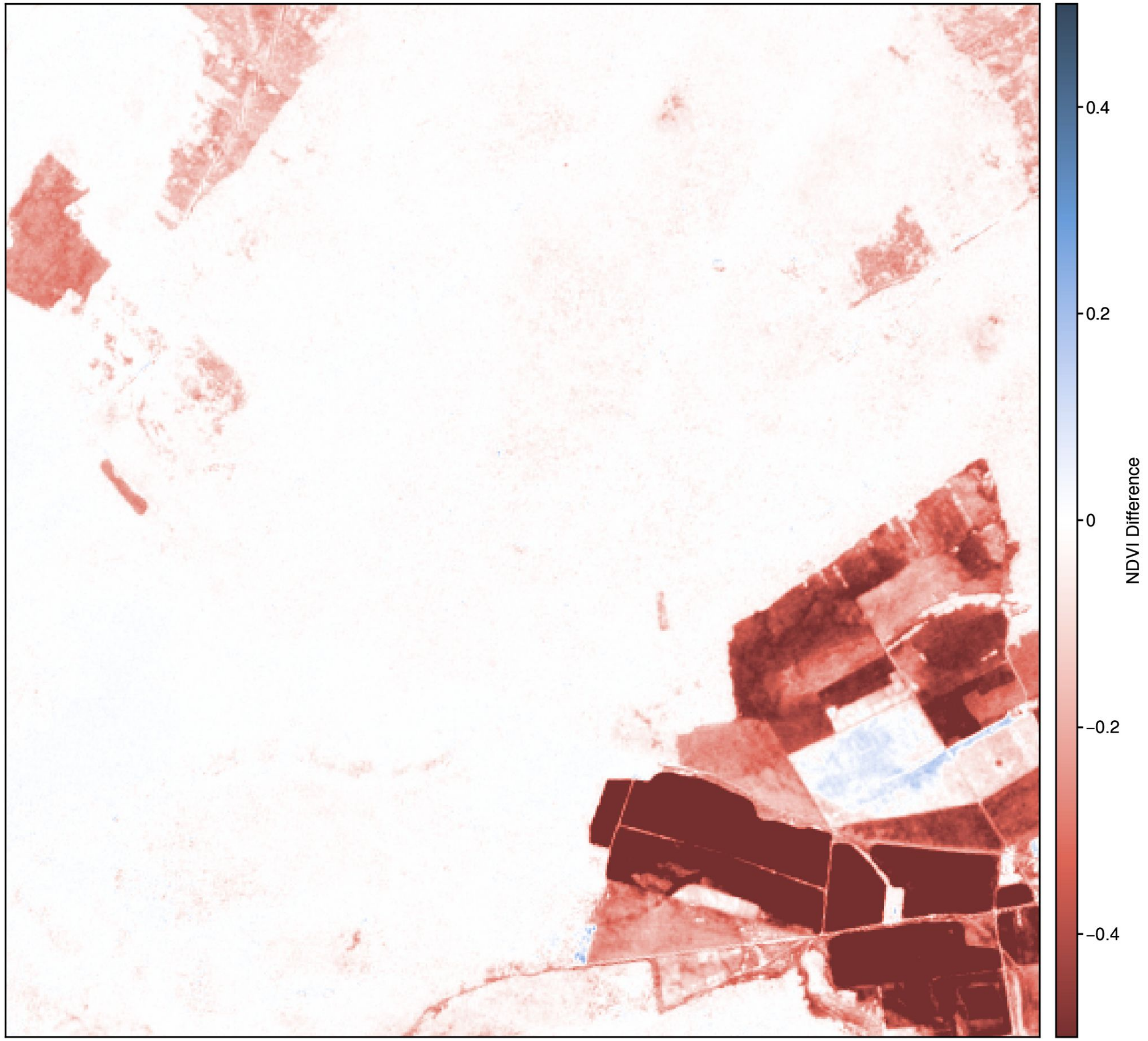
From **satellite imagery**



NDVI: Normalized Difference Vegetation Index

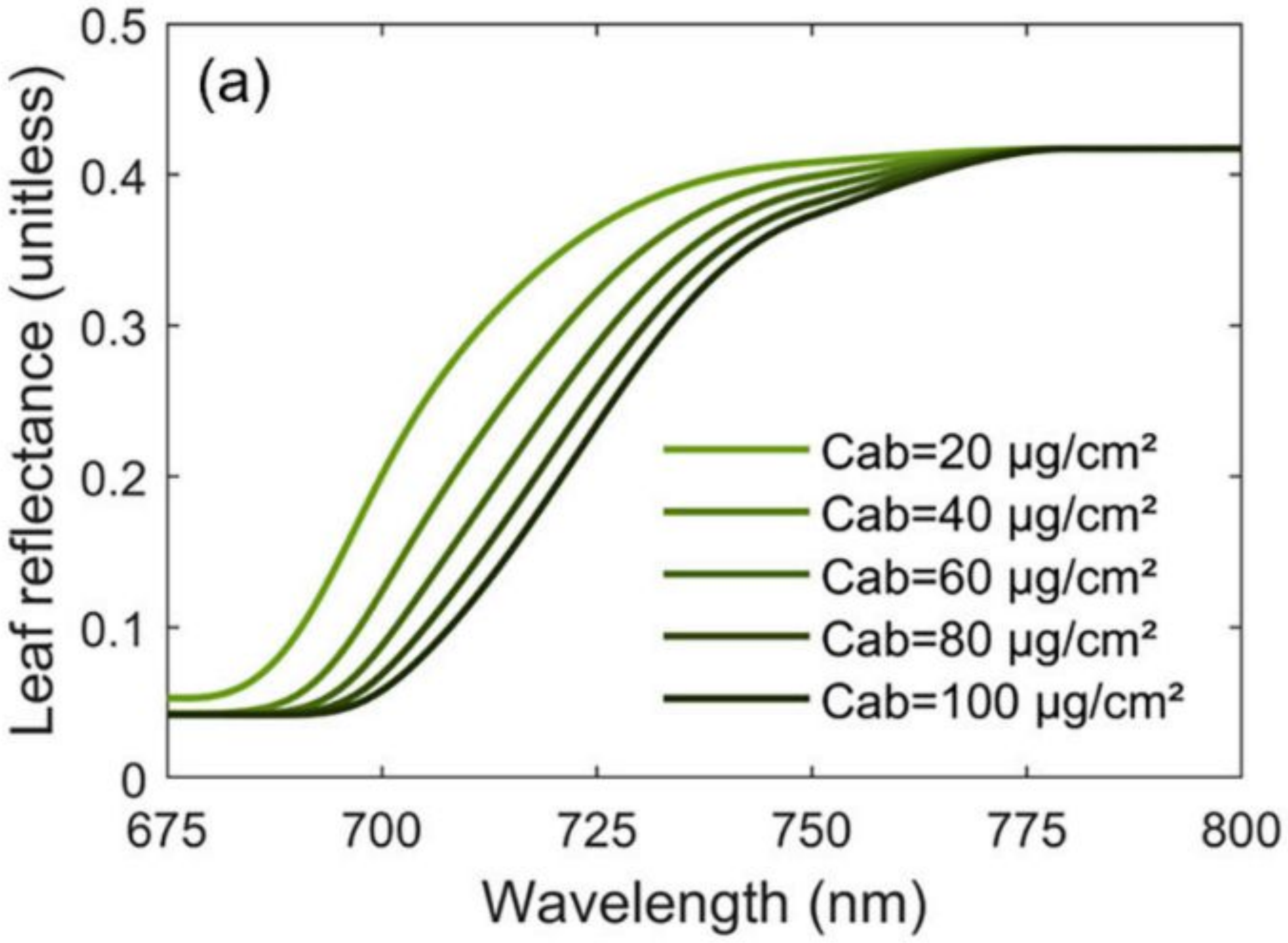


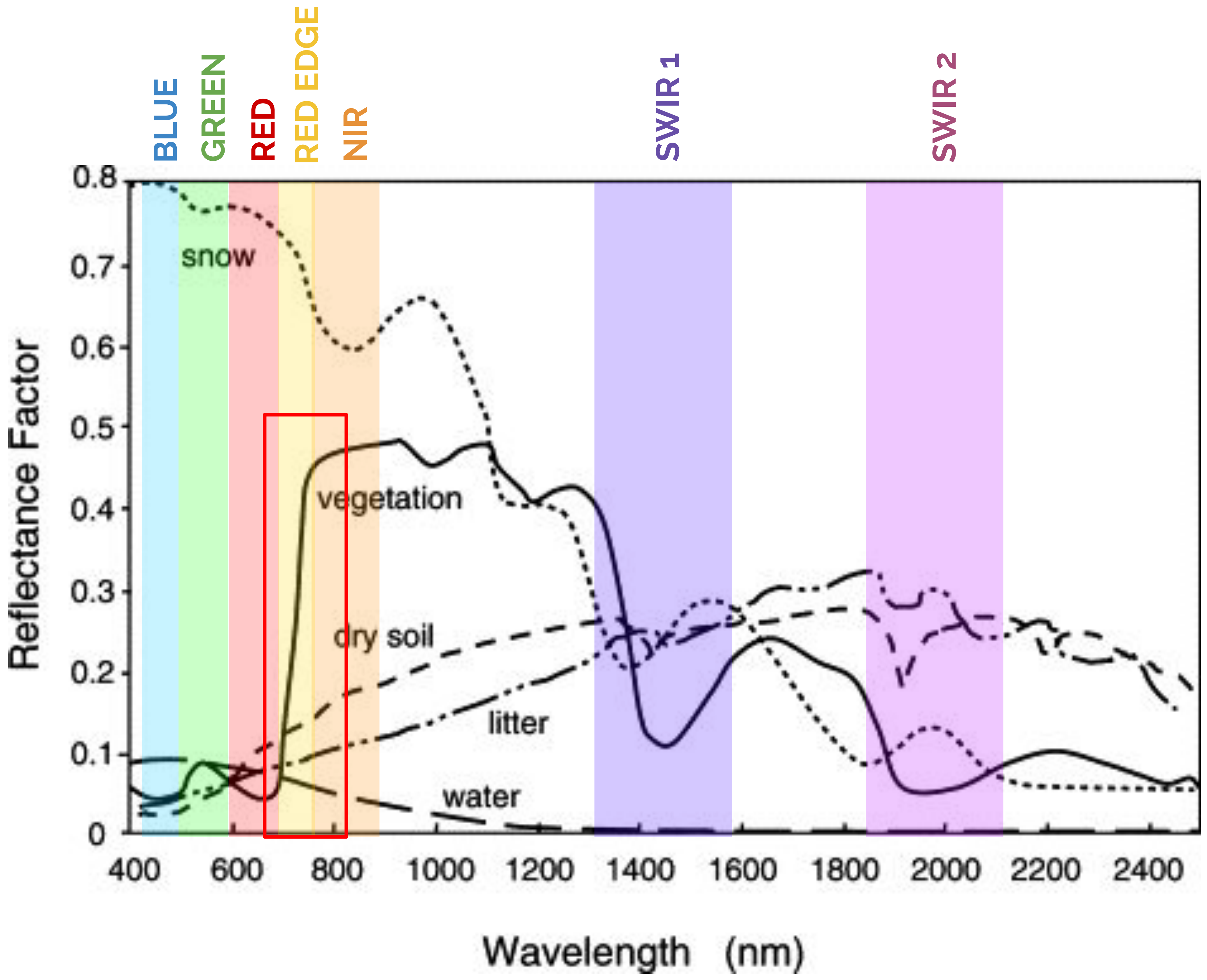
NDVI: Normalized Difference Vegetation Index



NDVI is usually saturated, this is why we see no great differences between both dates.

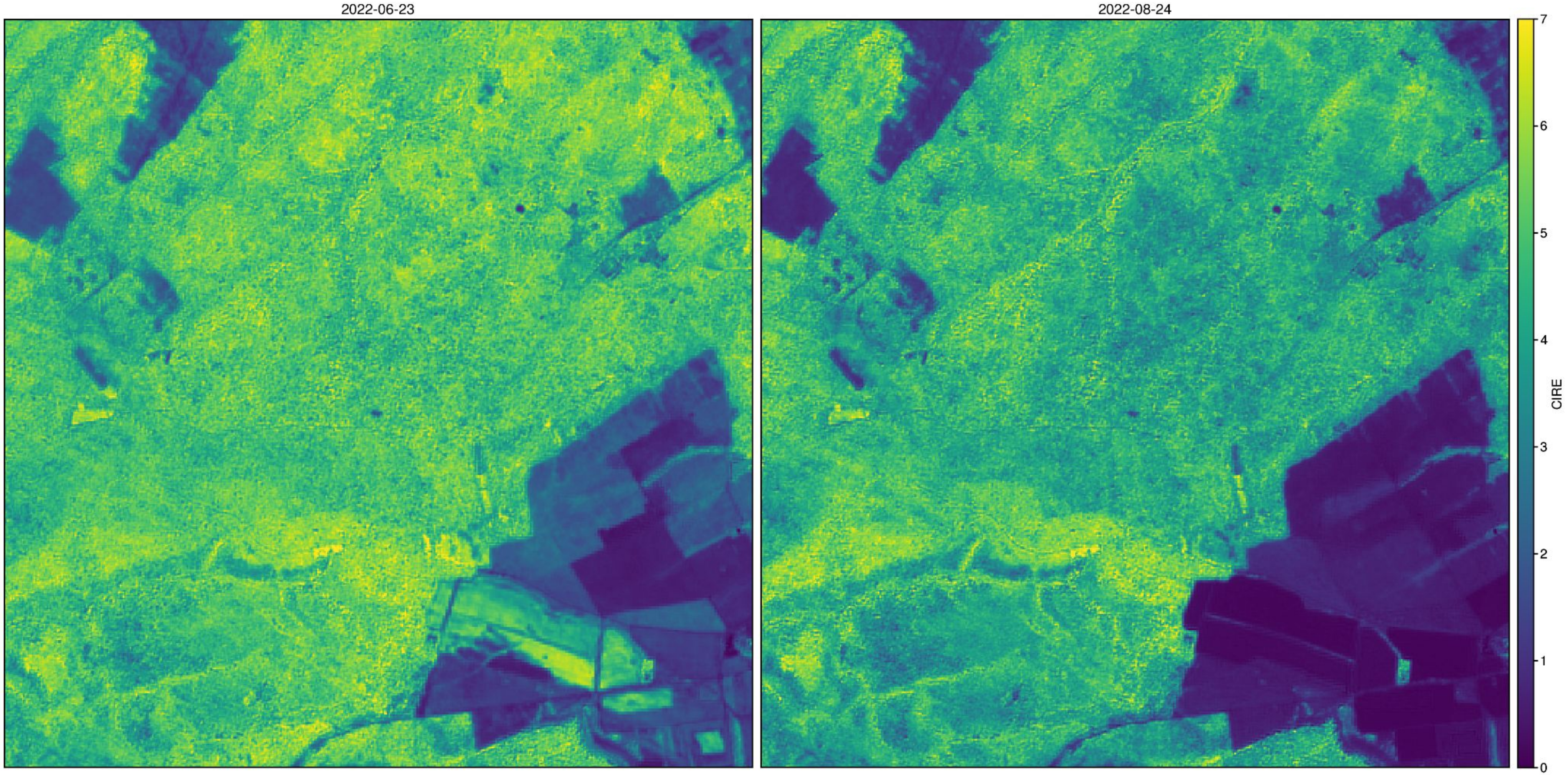
Pushing the **slope** further into NIR: Red Edge



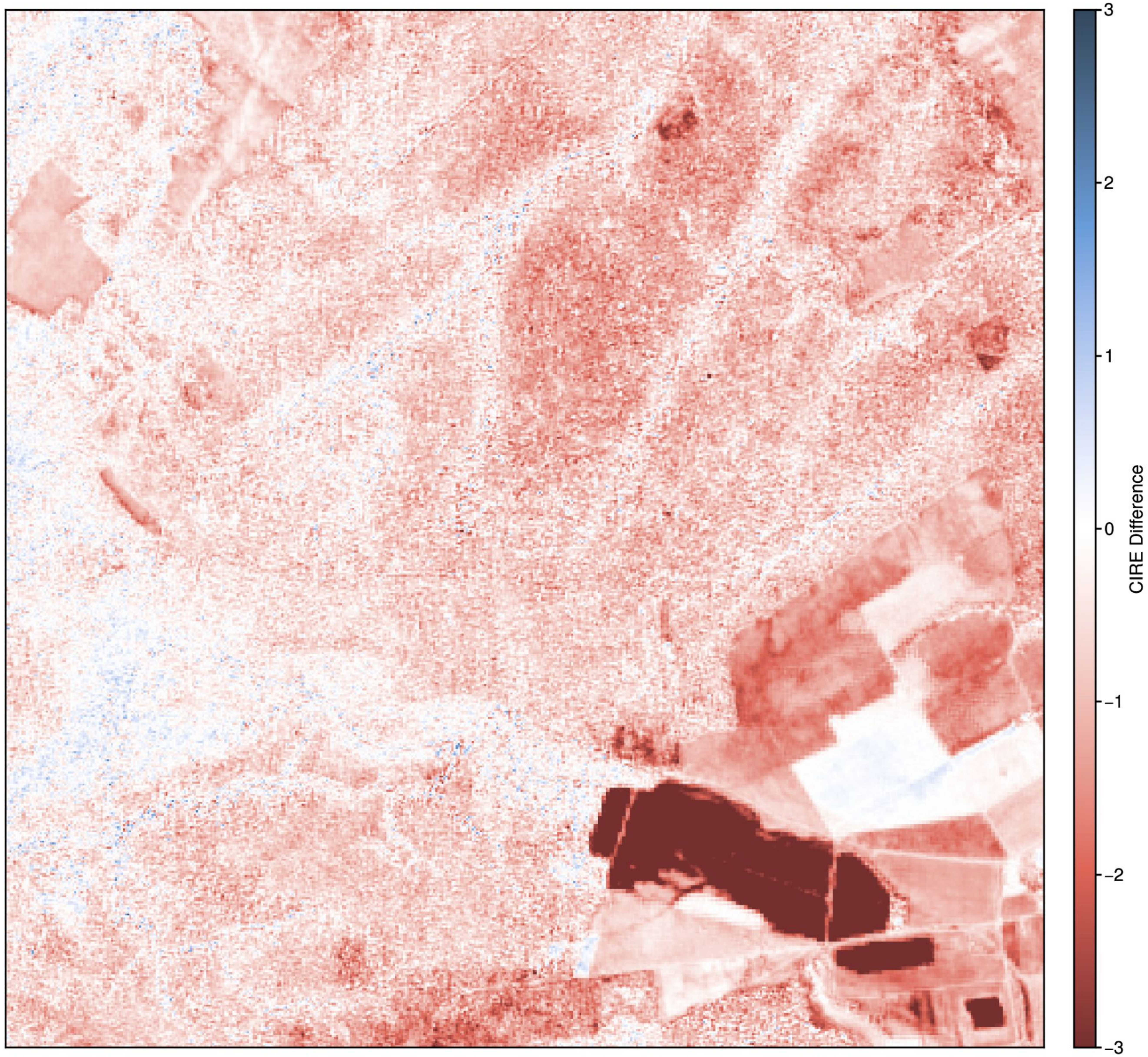


Source image: ([Zeng et al., 2021](#))

CIRE: Chlorophyll Index Red Edge



CIRE: Chlorophyll Index Red Edge



CIRE is another chlorophyll-related index. Its behaviour is close to the IRECI's behaviour.

Spectral Indices

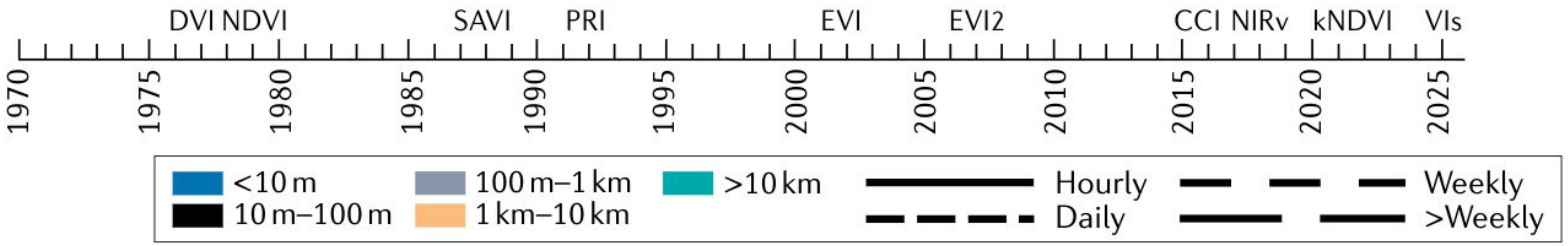
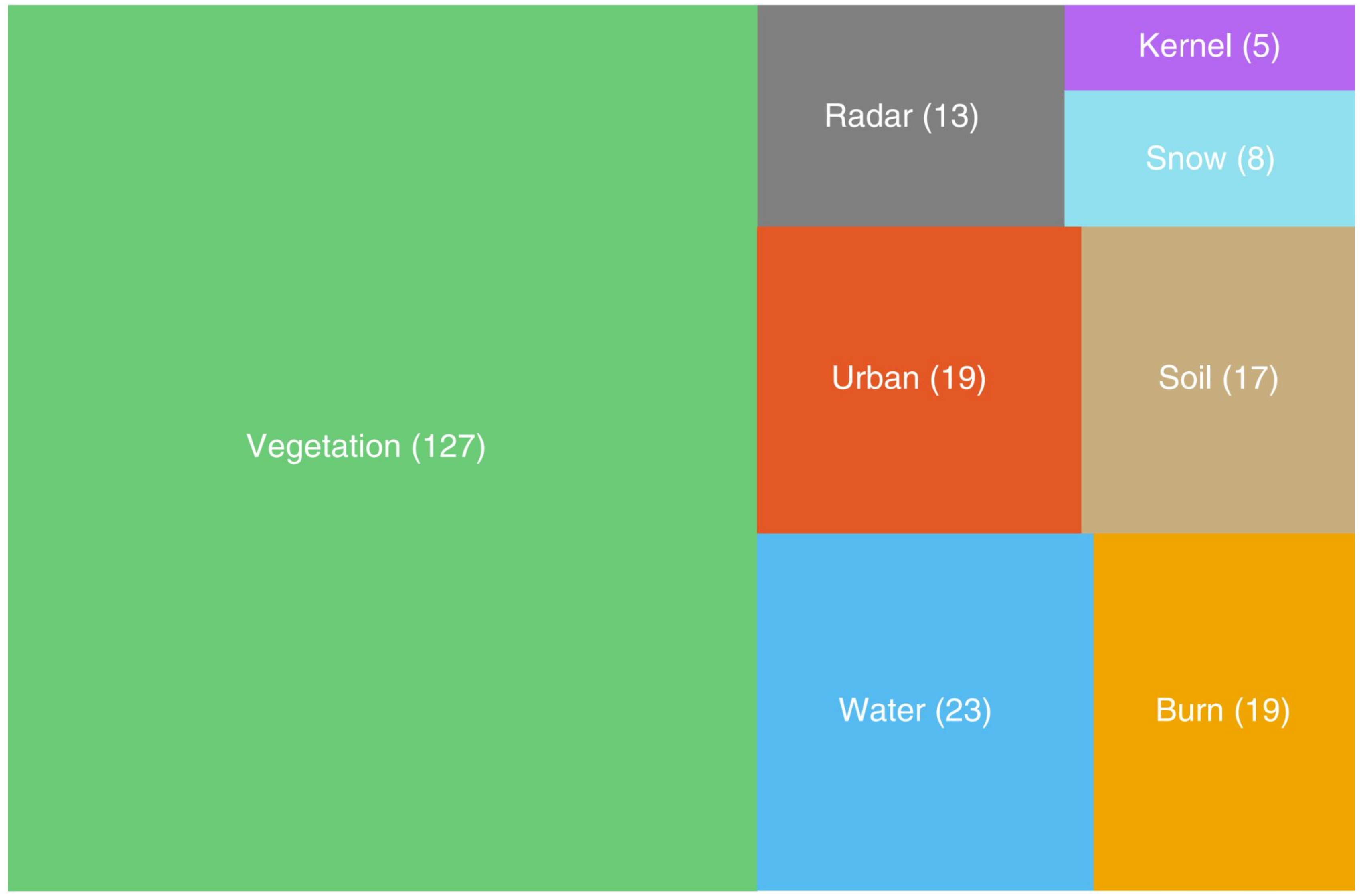


Table 1 | **Selected widely used optical vegetation indices, spectral ranges and references**

Name	Abbreviation	Equation and derivation	Primary applications, advantages and disadvantages
Red–NIR			
Simple ratio[14]	SR	NIR/Red	Structure; simple, but sensitive to the red band atmospheric correction
Normalized difference vegetation index[14–16]	NDVI	(NIR – Red)/(NIR + Red) = (SR – 1)/(SR + 1) = 1 – 2/(SR + 1)	Structure; simple, but sensitive to soil background variations
Modified simple ratio[22]	MSR	$\frac{\mathrm{NIR/Red} - 1}{\sqrt{\mathrm{NIR/Red} + 1}}$	Structure; relatively linear relationship with canopy structure parameters, but with small sensitivity to overstory vegetation
Difference vegetation index[19]	DVI	NIR–Red	Structure; simple, but sensitive to the BRDF effect
Perpendicular vegetation index[19]	PVI	$\sqrt{(\mathrm{NIR}_{soil} - \mathrm{NIR}_{veg})^2 + (\mathrm{Red}_{soil} - \mathrm{Red}_{veg})^2}$	Structure; minimizes soil background influence, but requires the slope and intercept of the soil line
Soil-adjusted vegetation index[4]	SAVI	$(1 + L) \cdot (\mathrm{NIR} - \mathrm{Red})/(\mathrm{NIR} + \mathrm{Red} + L)$	Structure; minimizes soil background influence, but sensitive to the BRDF effect
Two-band version of the enhanced vegetation index (EVI2) without the blue band[27]	EVI2	2.5 · (NIR – Red)/(NIR + 2.4 · Red + 1)	Structure; minimizes soil background influence and no blue band requirement, but sensitive to the BRDF effect
Near-infrared reflectance of vegetation[5]	NIRv	NDVI · NIR	Structure; minimizes soil background influence, but sensitive to the BRDF effect
Hyperspectral near-infrared reflectance of vegetation[160]	NIRvH	$\mathrm{NIR} - \mathrm{Red} - k(\lambda_{NIR} - \lambda_{Red})$	Structure; minimizes soil background influence stronger than NIRv, but sensitive to the BRDF effect
Kernel normalized difference vegetation index[31]	kNDVI	$\tanh(\mathrm{NDVI}^2)$	Structure; higher sensitivity to canopy structural parameters and GPP
Plant phenology index[28]	PPI	$-K \cdot \ln\left(\frac{M - \mathrm{DVI}}{M - \mathrm{DVI}_s}\right)$	Structure; linearly related to green LAI, less severely impacted by snow than NDVI and EVI, and works well for phenology at high latitudes; requires soil DVI
VIS–NIR			
Enhanced vegetation index[25]	EVI	2.5 · (NIR – Red)/(NIR + 6 · Red – 7.5 · Blue + 1)	Structure; minimizes both soil and atmospheric effects, but sensitive to the BRDF effect and requires the blue band
Fluorescence correction vegetation index[29]	FCVI	NIR – VIS	Structure; minimizes soil background influence, but sensitive to the BRDF effect
VIS			
Photochemical reflectance index[49]	PRI	$(R_{531} - R_{570})/(R_{531} - R_{570})$	Physiological; tracks the diurnal changes of photosynthetic activity, but complications associated with diurnal sun angle changes must be reduced
Chlorophyll/carotenoid index[6]	CCI	$\frac{\mathrm{Band}_{11} - \mathrm{Band}_1}{\mathrm{Band}_{11} + \mathrm{Band}_1}$ for MODIS sensor	Physiological and biochemical; tracks the seasonality of daily GPP and phenology for evergreen conifers at multiple spatial scales
Green chromatic coordinate[50,189]	GCC	Green/(Red + Green + Blue)	Physiological; structure; biochemical; sensitive to changes in both carotenoid and chlorophyll, correlates well with GPP seasonality but less so to CCI and PRI, and can be easily acquired using RGB imagery
Red-edge NIR			
Red-edge chlorophyll index[33]	CIred-edge	NIR/RE – 1	Biochemical: chlorophyll; linear relationship between the chlorophyll content in maize and soybean leaves with CIred-edge
Red-edge NDVI[34]	NDVIre	(NIR – RE)/(NIR + RE)	Biochemical: chlorophyll; directly proportional to chlorophyll and indicates leaf senescence
MERIS total chlorophyll index[35]	MTCI	$(R_{750} - R_{710})/(R_{710} - R_{680})$	Biochemical: chlorophyll; correlates strongly with red-edge position and is sensitive to high values of chlorophyll content

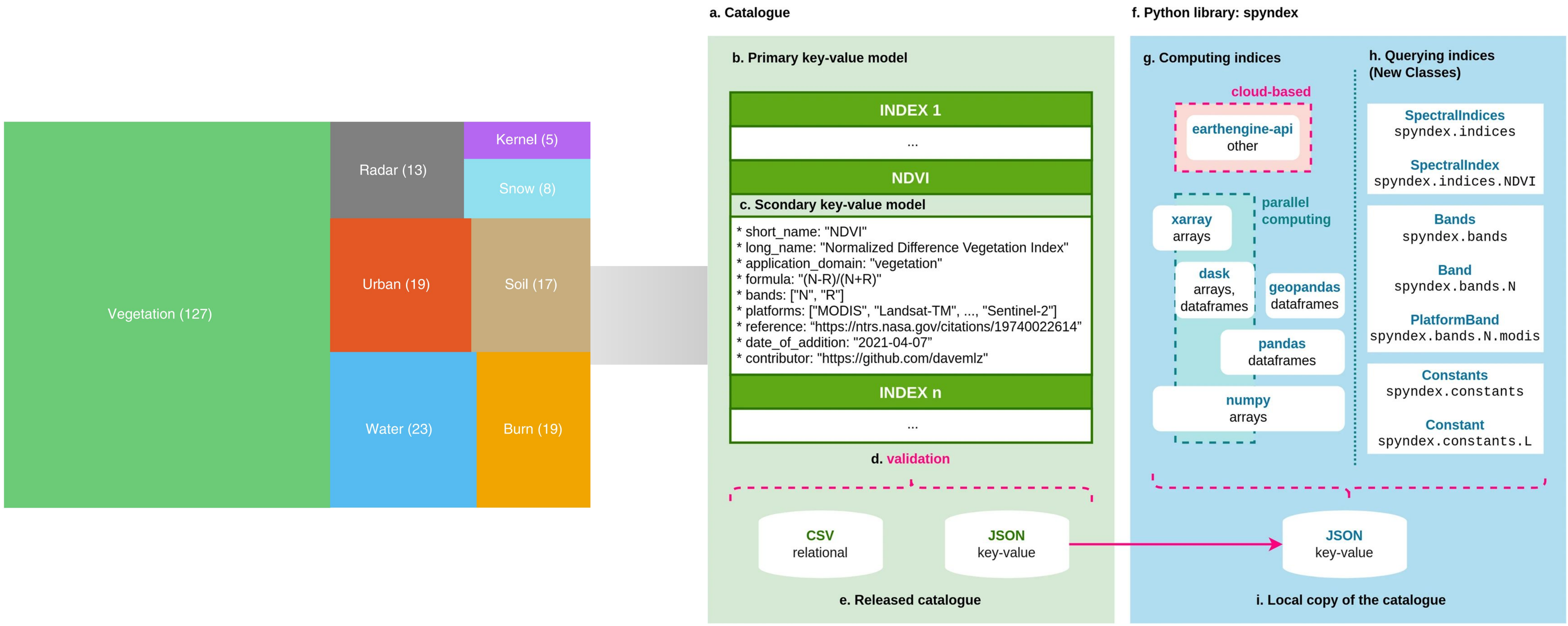
Zeng et al., 2022
Nature Reviews Earth & Environment

Making Spectral Indices **FAIR**



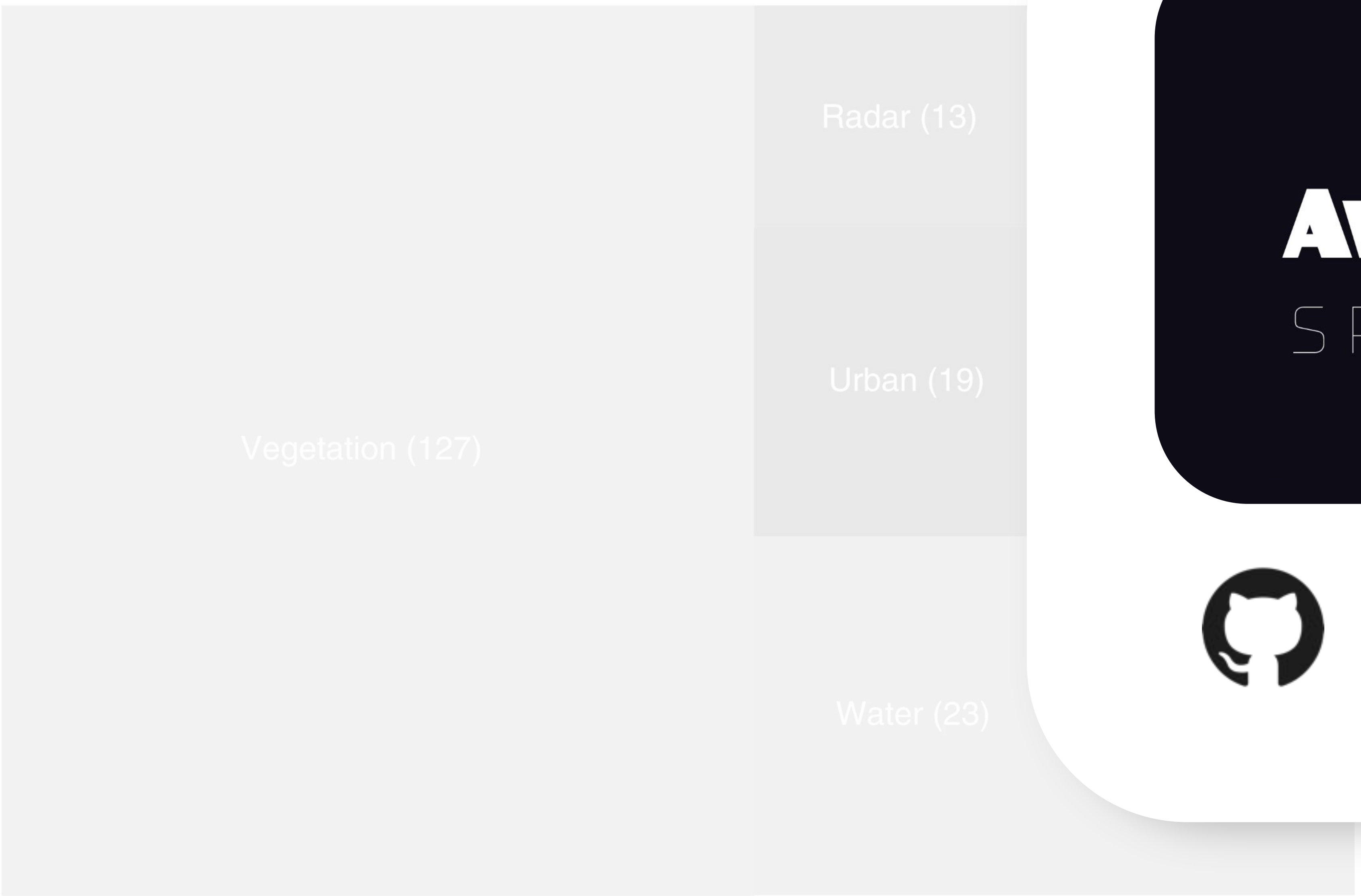
Montero et al., 2023
Scientific Data

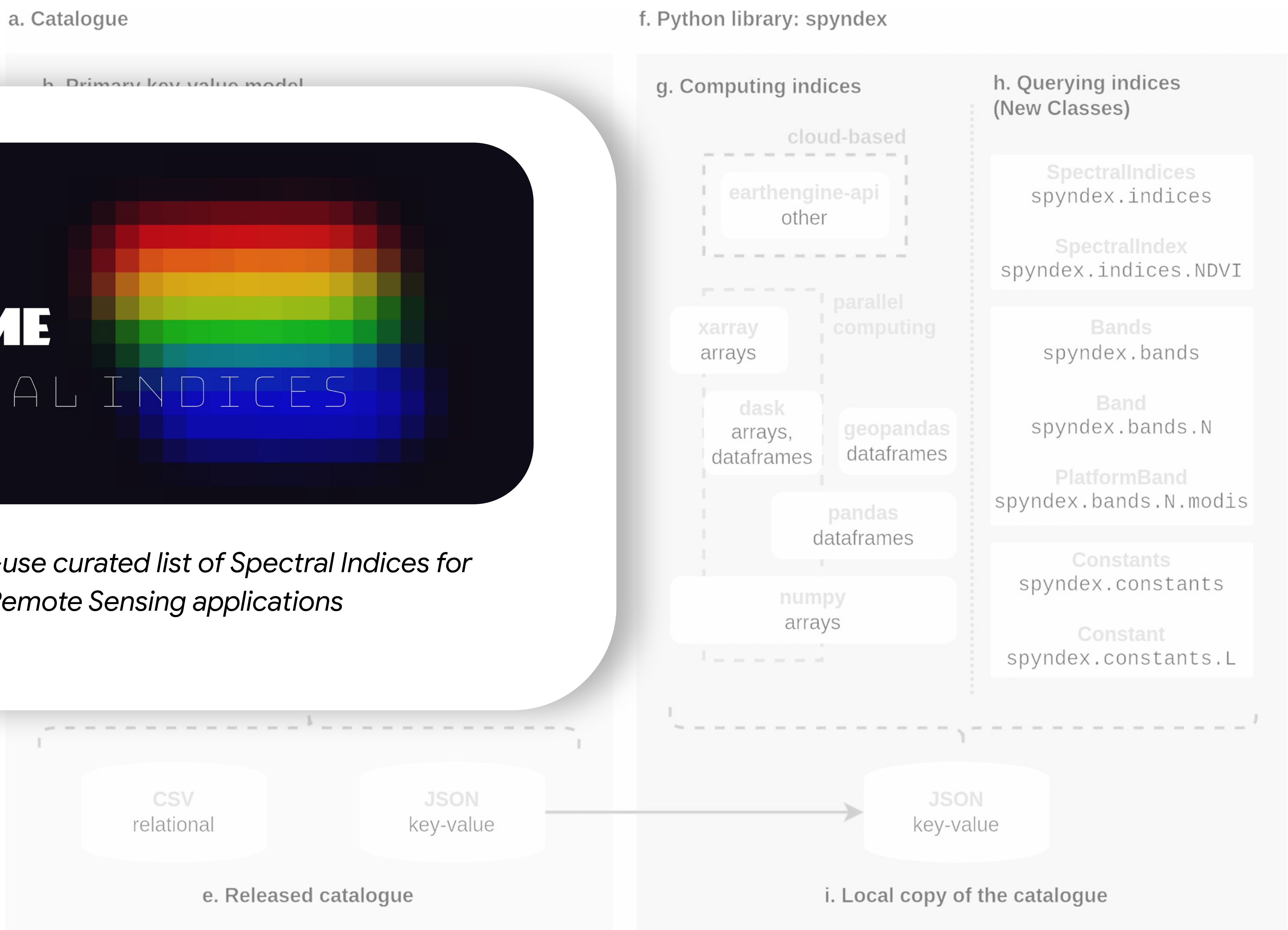
Making Spectral Indices **FAIR**



Montero et al., 2023
Scientific Data

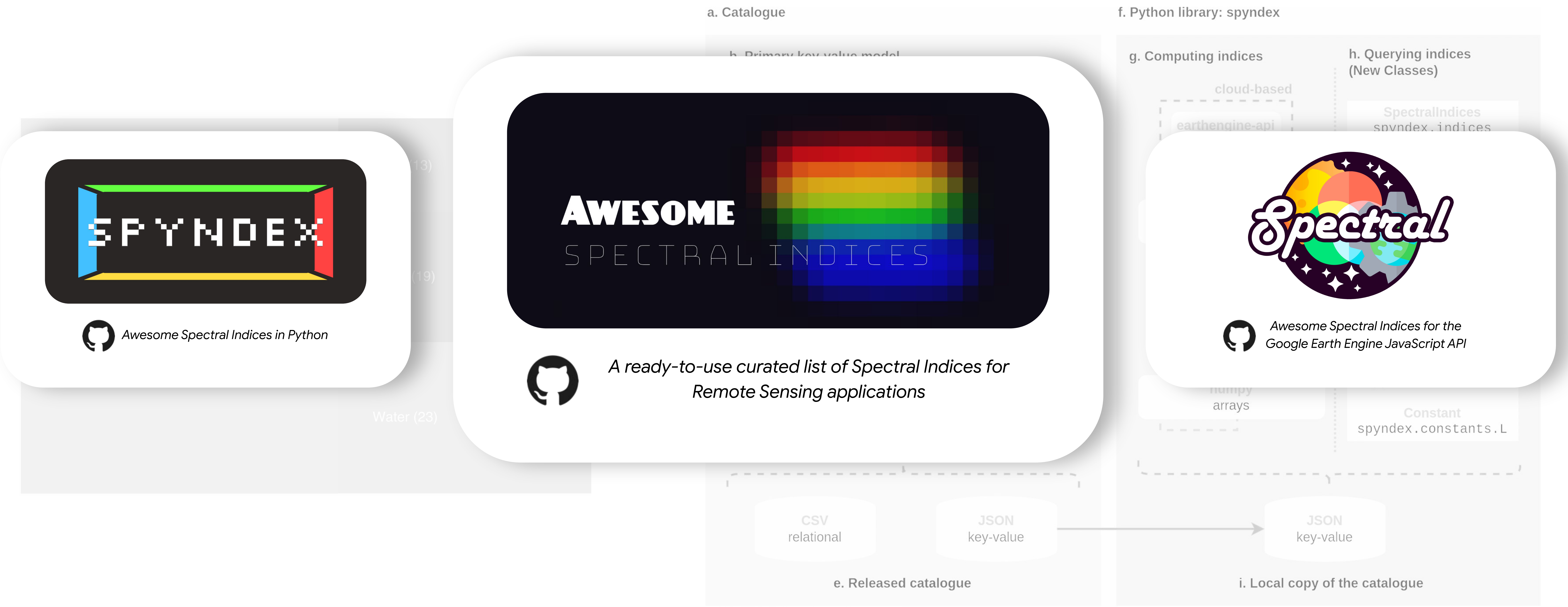
Awesome Spectral Indices



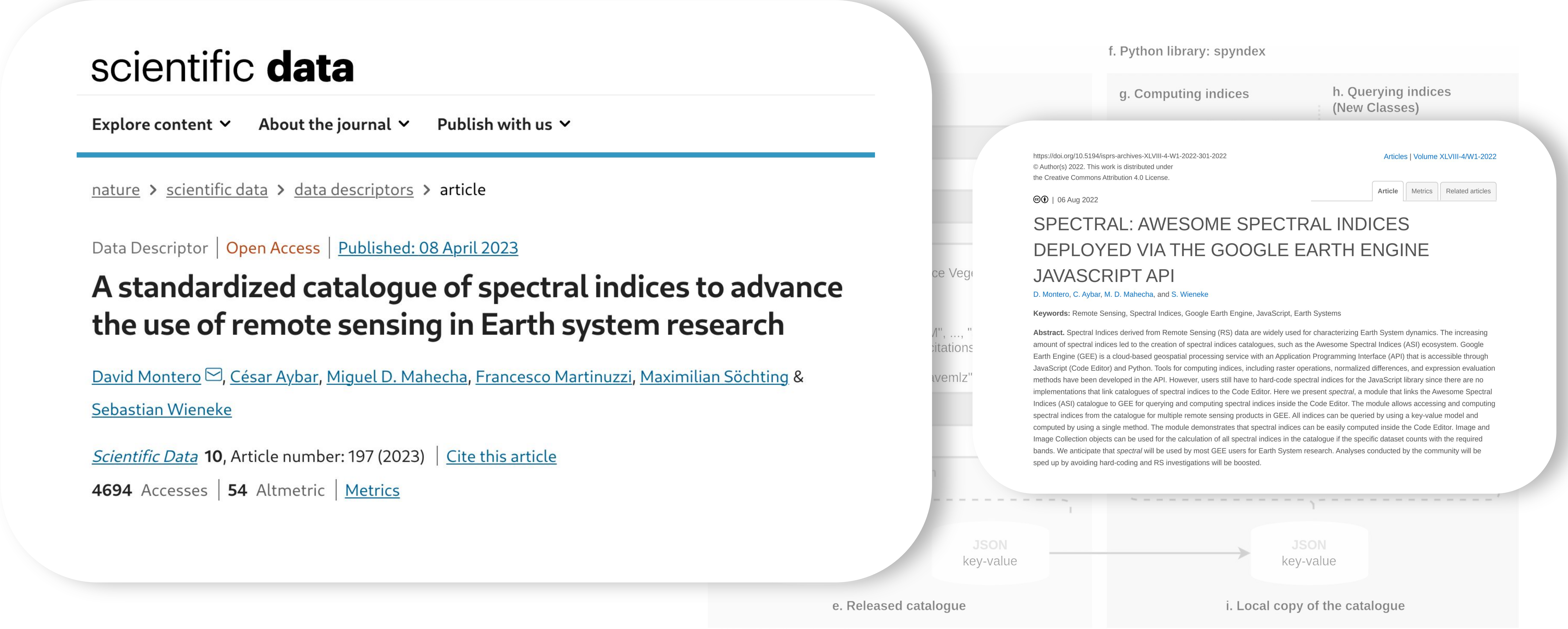


A ready-to-use curated list of Spectral Indices for Remote Sensing applications

Awesome Spectral Indices



Awesome Spectral Indices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A standardized catalogue of spectral indices to advance the use of remote sensing in Earth system research

David Montero, César Aybar, Miguel D. Mahecha, Francesco Martinuzzi, Maximilian Söchting & Sebastian Wieneke

Scientific Data **10**, Article number: 197 (2023) | Cite this article

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06 Aug 2022

SPECTRAL: AWESOME SPECTRAL INDICES DEPLOYED VIA THE GOOGLE EARTH ENGINE JAVASCRIPT API

D. Montero, C. Aybar, M. D. Mahecha, and S. Wieneke

Keywords: Remote Sensing, Spectral Indices, Google Earth Engine, JavaScript, Earth Systems

Abstract. Spectral Indices derived from Remote Sensing (RS) data are widely used for characterizing Earth System dynamics. The increasing amount of spectral indices led to the creation of spectral indices catalogues, such as the Awesome Spectral Indices (ASI) ecosystem. Google Earth Engine (GEE) is a cloud-based geospatial processing service with an Application Programming Interface (API) that is accessible through JavaScript (Code Editor) and Python. Tools for computing indices, including raster operations, normalized differences, and expression evaluation methods have been developed in the API. However, users still have to hard-code spectral indices for the JavaScript library since there are no implementations that link catalogues of spectral indices to the Code Editor. Here we present *spectral*, a module that links the Awesome Spectral Indices (ASI) catalogue to GEE for querying and computing spectral indices inside the Code Editor. The module allows accessing and computing spectral indices from the catalogue for multiple remote sensing products in GEE. All indices can be queried by using a key-value model and computed by using a single method. The module demonstrates that spectral indices can be easily computed inside the Code Editor. Image and Image Collection objects can be used for the calculation of all spectral indices in the catalogue if the specific dataset counts with the required bands. We anticipate that *spectral* will be used by most GEE users for Earth System research. Analyses conducted by the community will be sped up by avoiding hard-coding and RS investigations will be boosted.

Sentinel-2 *(2015 - now) - 5 days*

Name	Units	Min	Max	Scale	Pixel Size	Wavelength	Description
B1				0.0001	60 meters	443.9nm (S2A) / 442.3nm (S2B)	Aerosols
B2				0.0001	10 meters	496.6nm (S2A) / 492.1nm (S2B)	Blue
B3				0.0001	10 meters	560nm (S2A) / 559nm (S2B)	Green
B4				0.0001	10 meters	664.5nm (S2A) / 665nm (S2B)	Red
B5				0.0001	20 meters	703.9nm (S2A) / 703.8nm (S2B)	Red Edge 1
B6				0.0001	20 meters	740.2nm (S2A) / 739.1nm (S2B)	Red Edge 2
B7				0.0001	20 meters	782.5nm (S2A) / 779.7nm (S2B)	Red Edge 3
B8				0.0001	10 meters	835.1nm (S2A) / 833nm (S2B)	NIR
B8A				0.0001	20 meters	864.8nm (S2A) / 864nm (S2B)	Red Edge 4
B9				0.0001	60 meters	945nm (S2A) / 943.2nm (S2B)	Water vapor
B11				0.0001	20 meters	1613.7nm (S2A) / 1610.4nm (S2B)	SWIR 1
B12				0.0001	20 meters	2202.4nm (S2A) / 2185.7nm (S2B)	SWIR 2

Landsat 8 *(2013 - now) but could also be (1974 - now)! - 16 days*

Resolution
30 meters

Bands

Name	Description
SR_B1	Band 1 (ultra blue, coastal aerosol) surface reflectance
SR_B2	Band 2 (blue) surface reflectance
SR_B3	Band 3 (green) surface reflectance
SR_B4	Band 4 (red) surface reflectance
SR_B5	Band 5 (near infrared) surface reflectance
SR_B6	Band 6 (shortwave infrared 1) surface reflectance
SR_B7	Band 7 (shortwave infrared 2) surface reflectance

MODIS *(2000 - now) - daily*

Resolution
500 meters

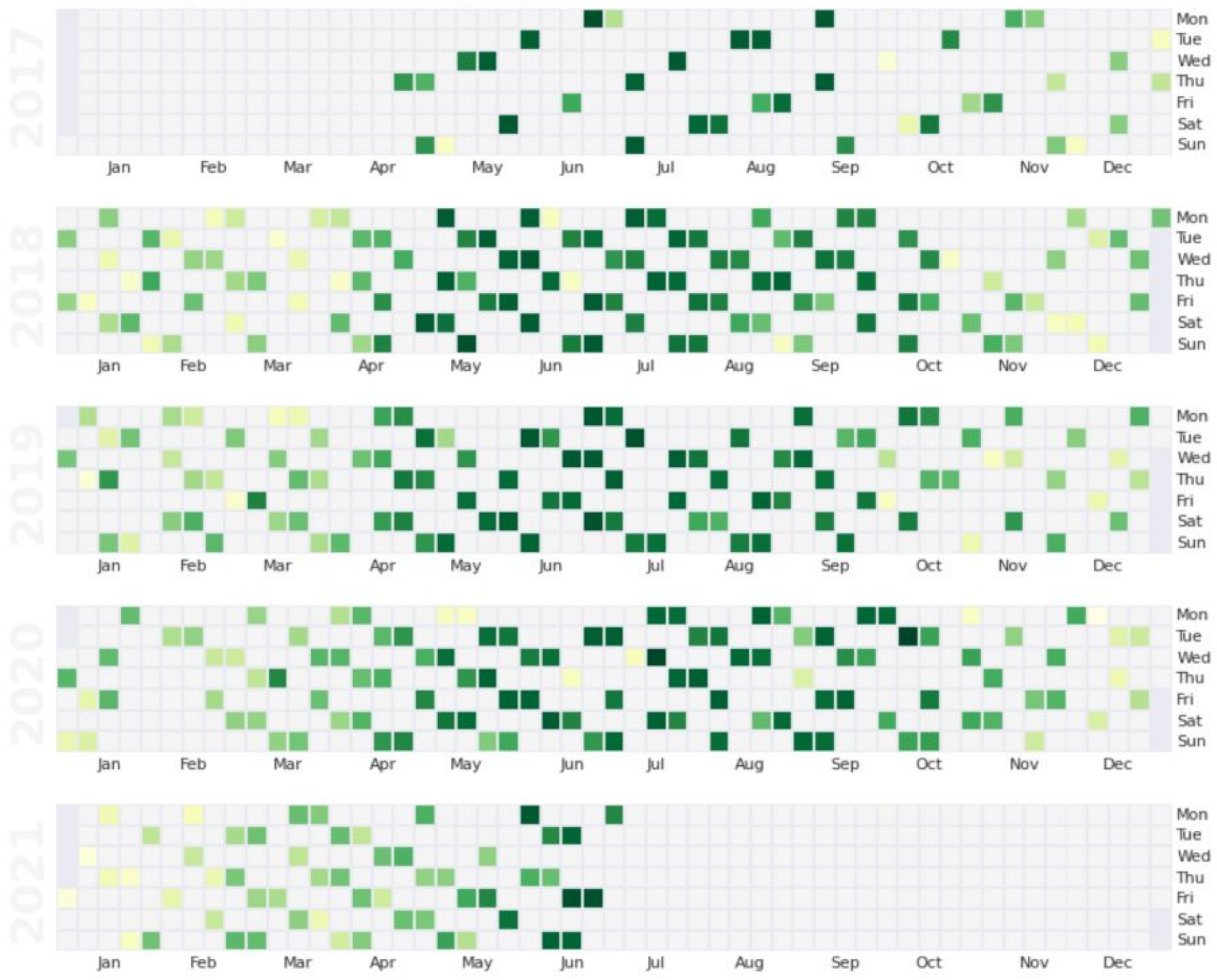
Bands

Name	Wavelength	Description
`Nadir_Reflectance_Band1`	620-670nm	NBAR at local solar noon for band 1
`Nadir_Reflectance_Band2`	841-876nm	NBAR at local solar noon for band 2
`Nadir_Reflectance_Band3`	459-479nm	NBAR at local solar noon for band 3
`Nadir_Reflectance_Band4`	545-565nm	NBAR at local solar noon for band 4
`Nadir_Reflectance_Band5`	1230-1250nm	NBAR at local solar noon for band 5
`Nadir_Reflectance_Band6`	1628-1652nm	NBAR at local solar noon for band 6
`Nadir_Reflectance_Band7`	2105-2155nm	NBAR at local solar noon for band 7

Revisit times matter

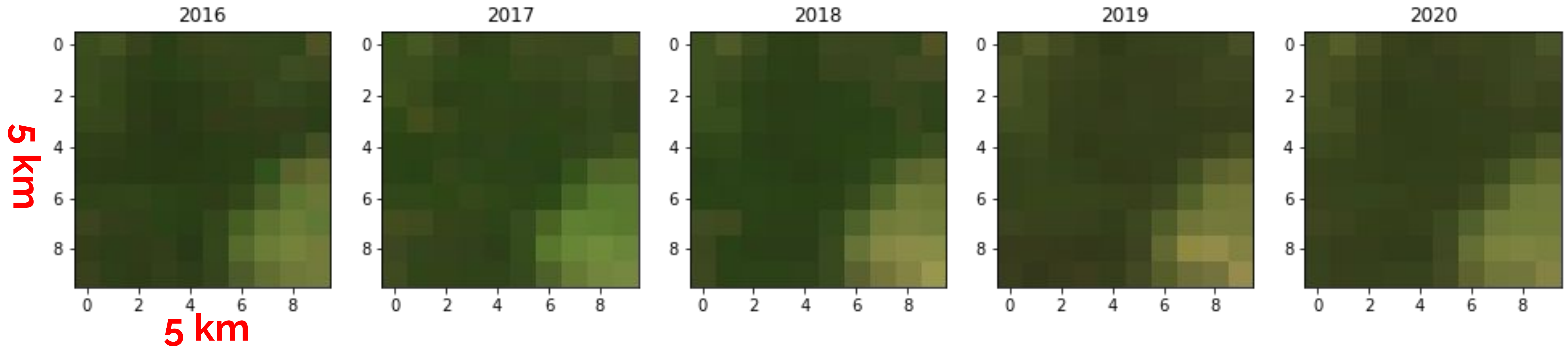
Landsat-8 NDVI

Sentinel-2 NDVI



Tree mortality: Do you see the dead trees?

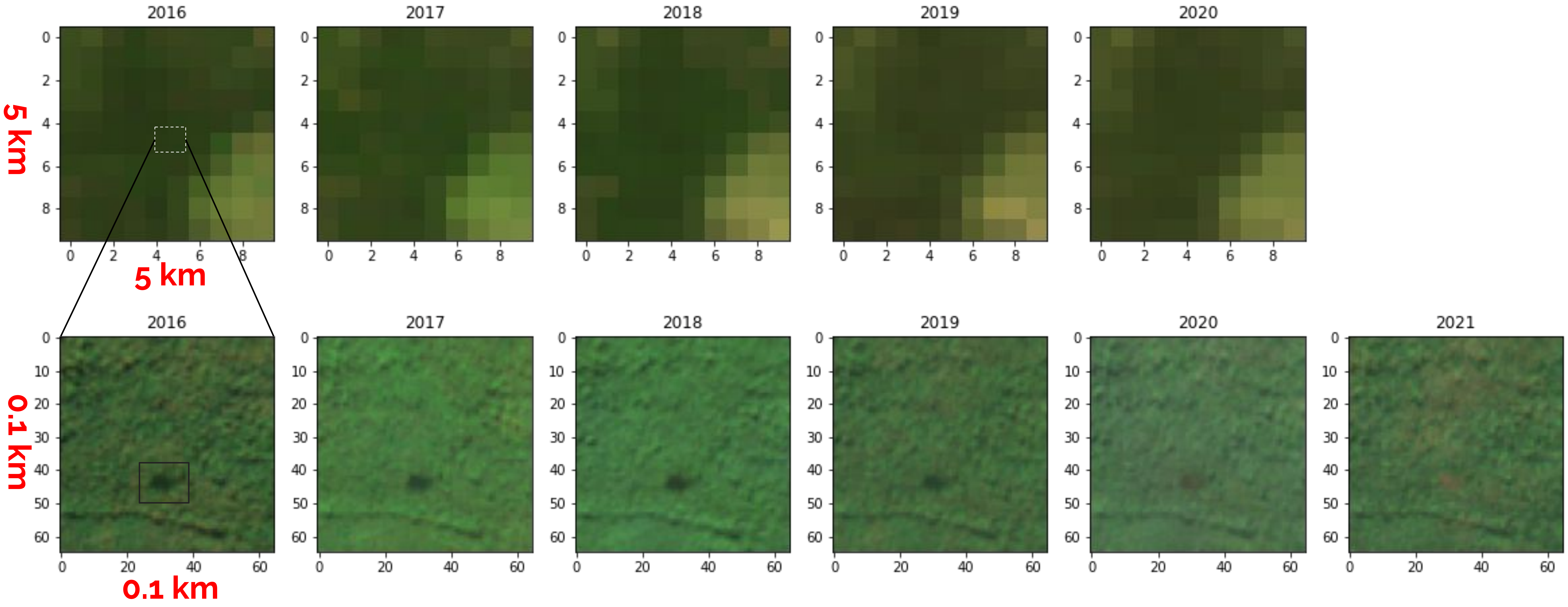
MODIS
RGB
pixel size
500 x 500 m



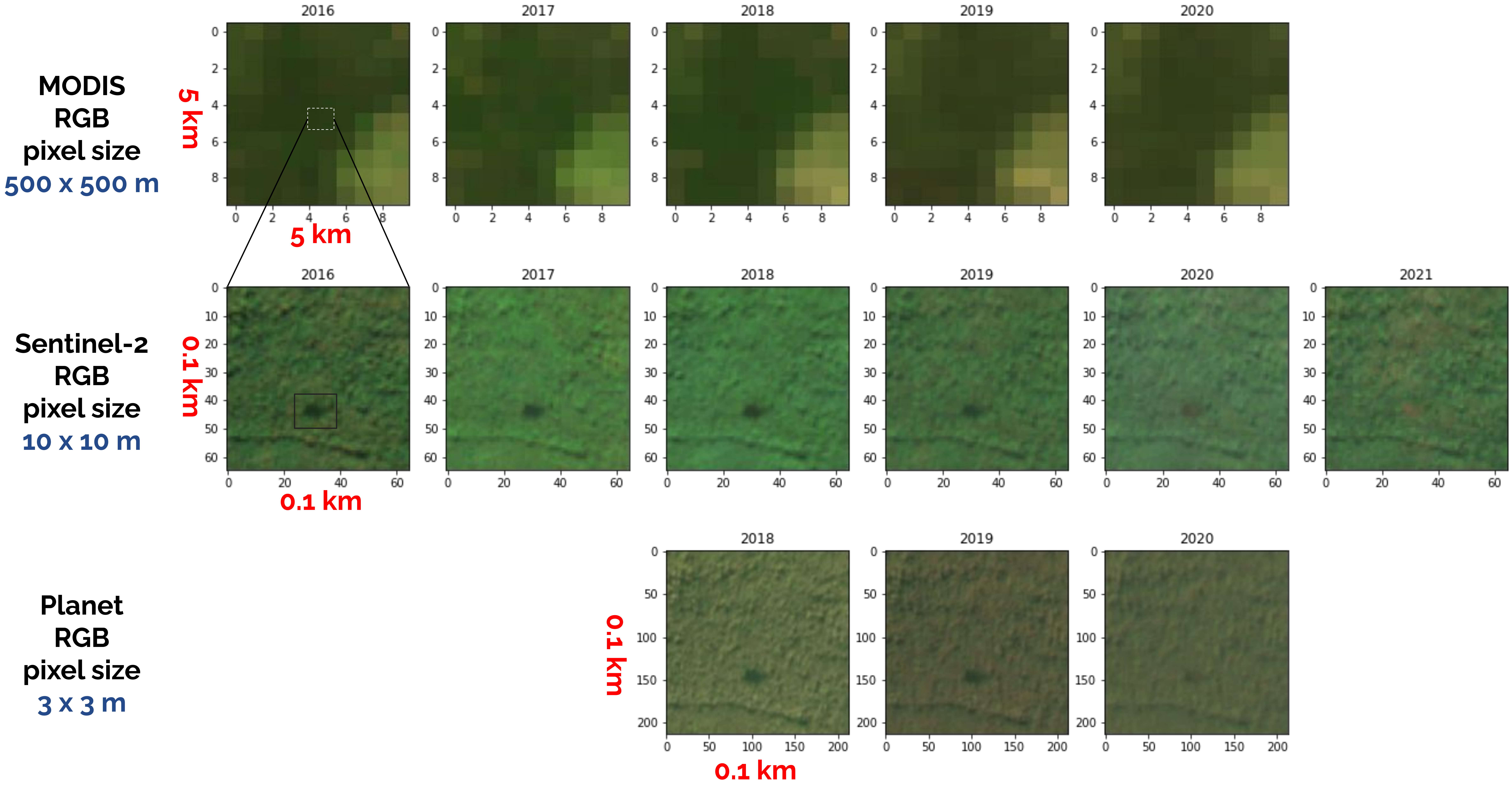
Spatial resolution matters here!

MODIS
RGB
pixel size
500 x 500 m

Sentinel-2
RGB
pixel size
10 x 10 m



Do we need a super **high-resolution image?**



Second Chapter

Data management

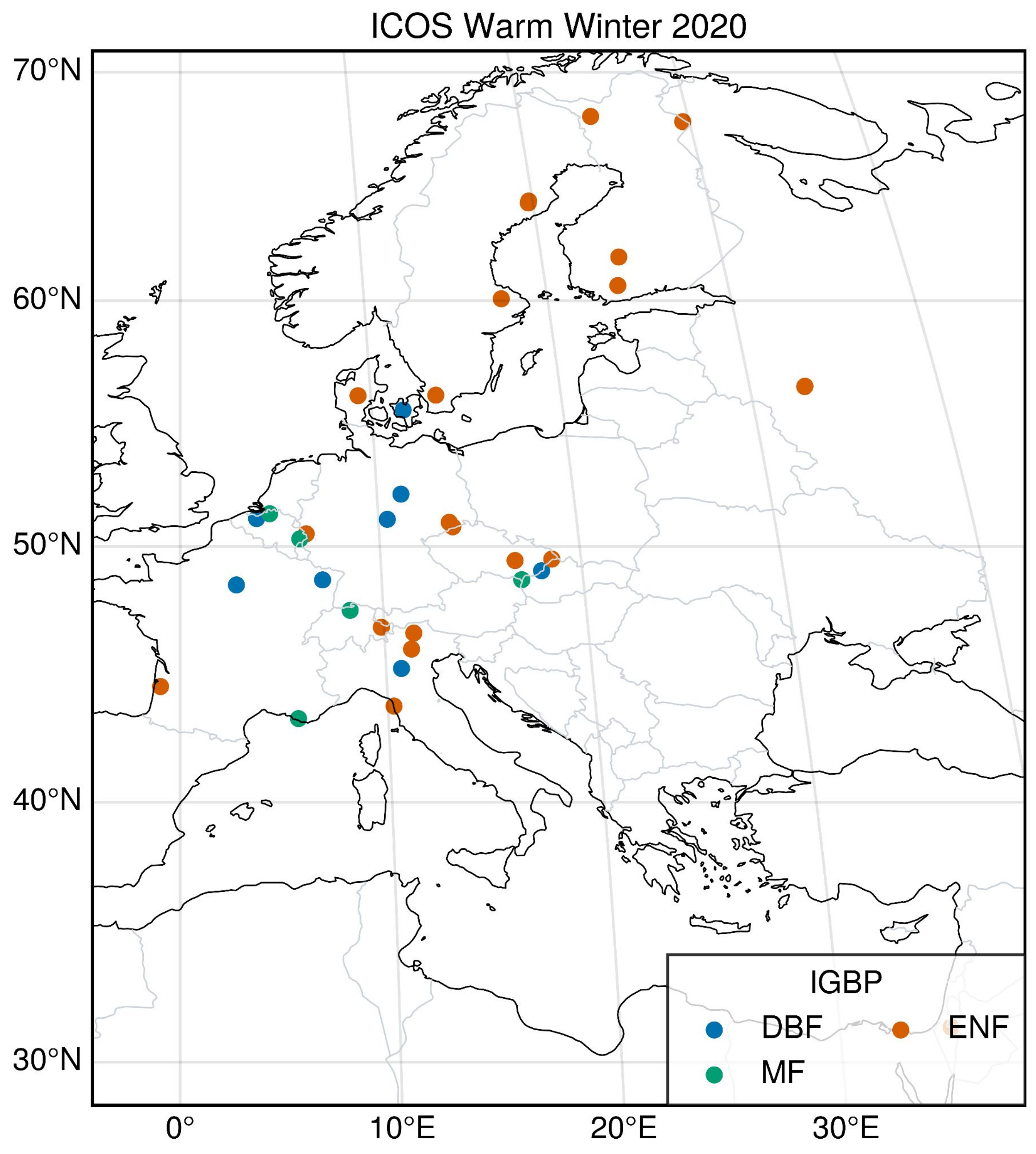
2

Data **gathering**

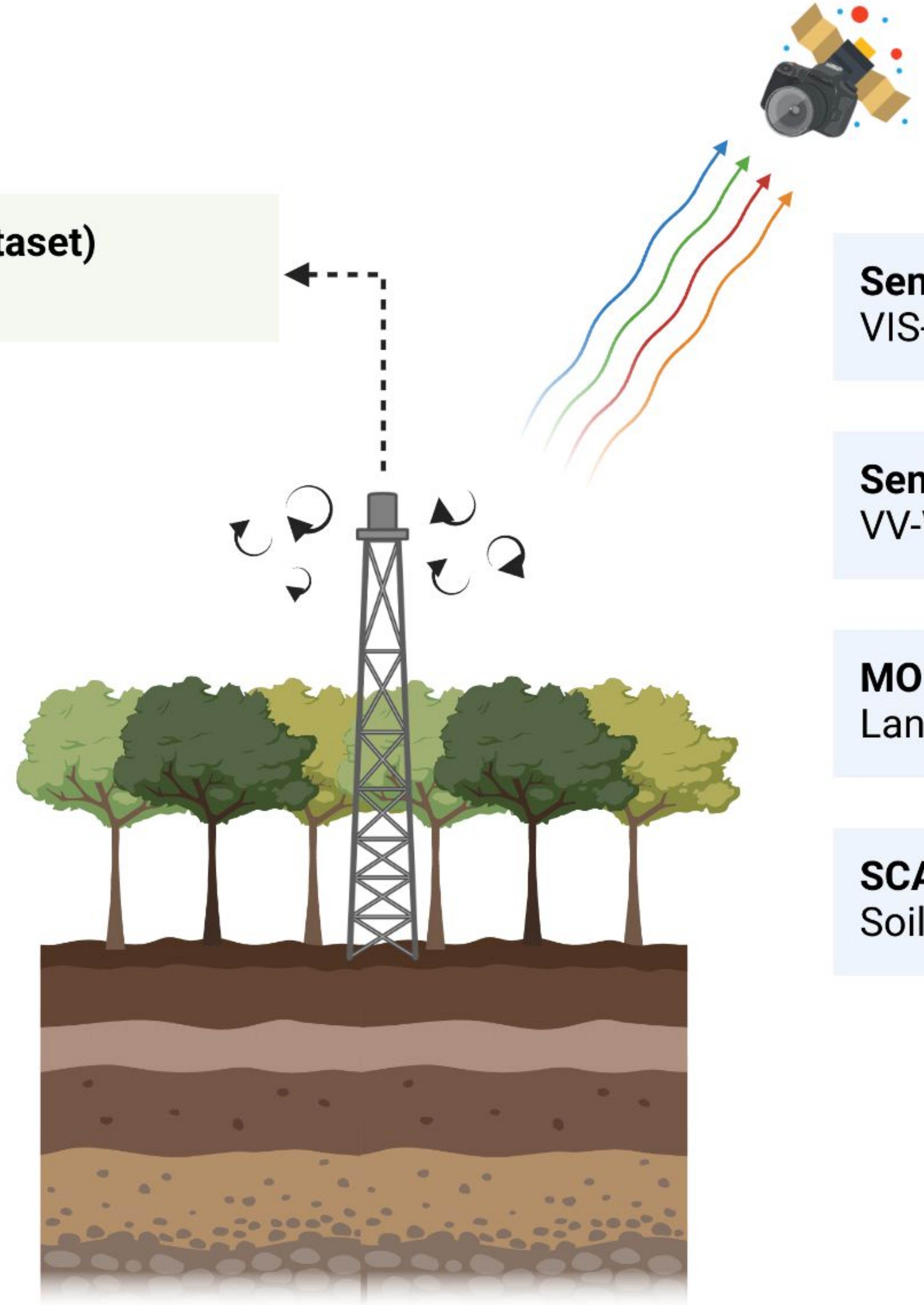
Target

ICOS (2020 Warm Winter Dataset)
Daily GPP ($g\ C\ m^{-2}\ d^{-1}$)

Forests sites



DBF: Deciduous Broadleaved Forest
ENF: Evergreen Needleleaved Forest
MF: Mixed Forest



Sentinel-2
VIS-SWIR Surface Reflectance

Sentinel-1
VV-VH Gamma Flattened Backscattering

MODIS (Terra/Aqua)
Land Surface Temperature

SCATSAR + Sentinel-1
Soil Water Index

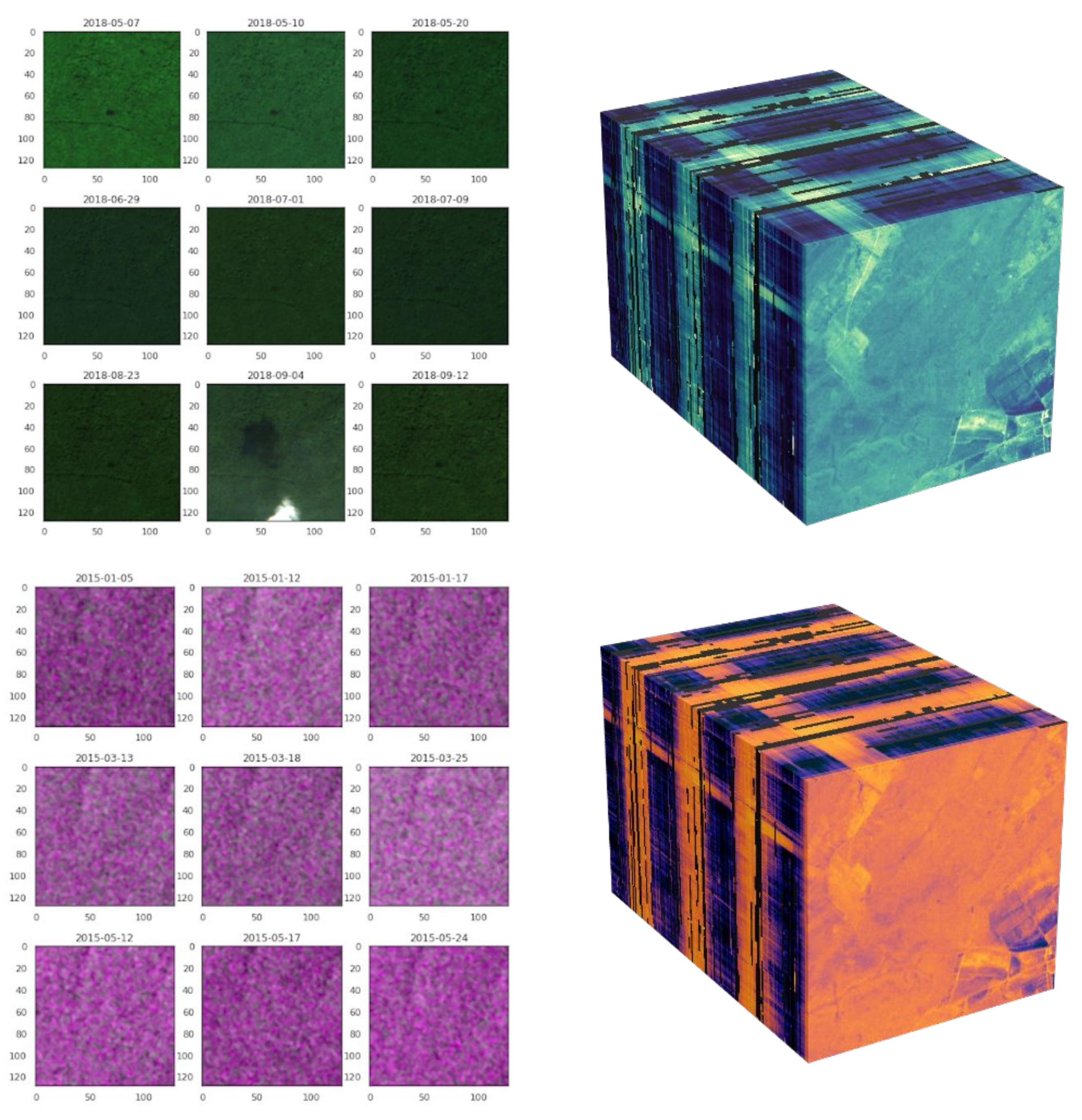
Predictors

Only Remote Sensing products

VIS: Visible Spectrum
SWIR: Shortwave Infrared Spectrum

Data **cubing**

Mini Cubes Generation

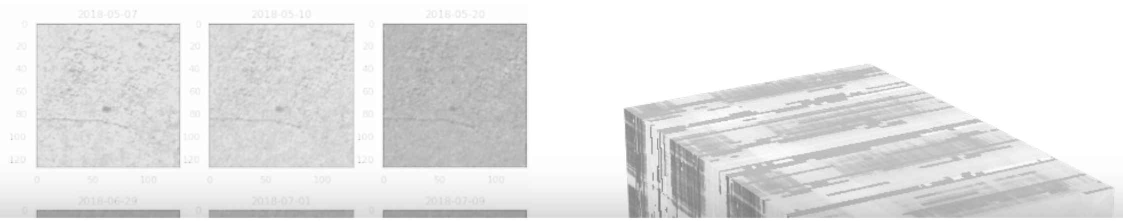


Sentinel-2
VIS-SWIR Surface Reflectance

Sentinel-1
VV-VH Gamma Flattened Backscattering

Data **cubing**

Mini Cubes Generation



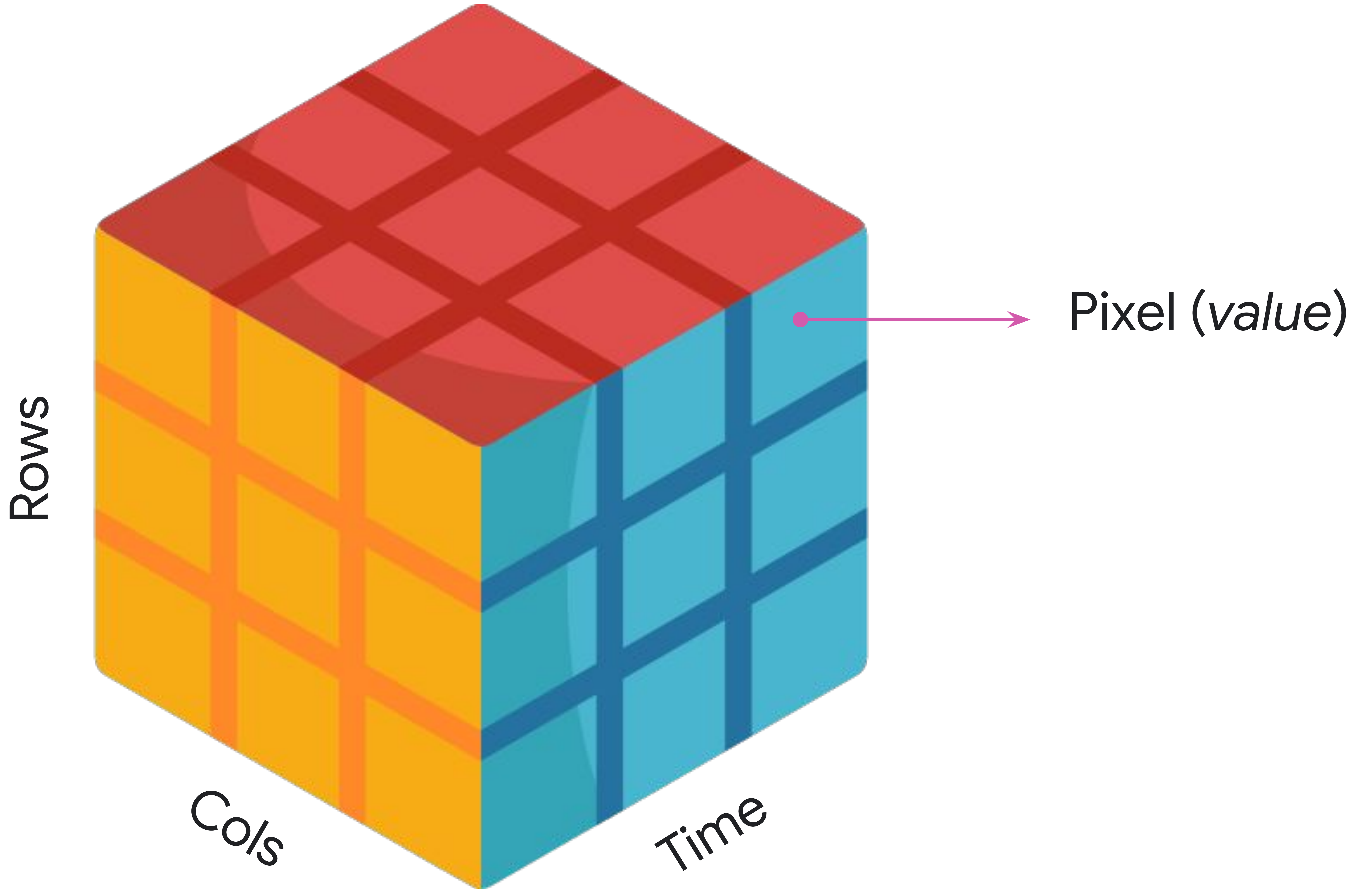
CUBO

Easily create EO mini cubes
from STAC in Python

VIS-SWIR Surface Reflectance

Sentinel-1
VV-VH Gamma Flattened Backscattering

Data **cubes**



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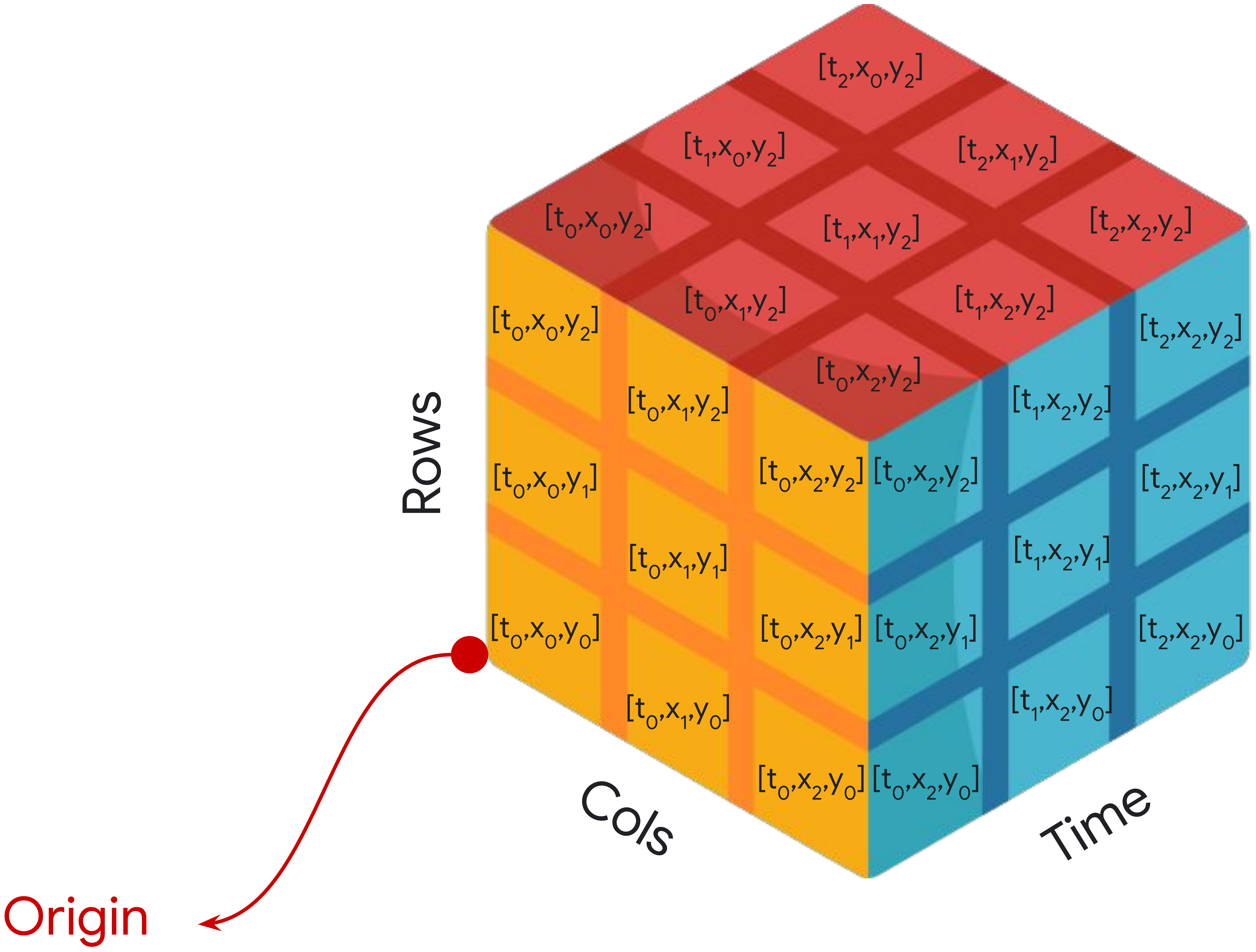
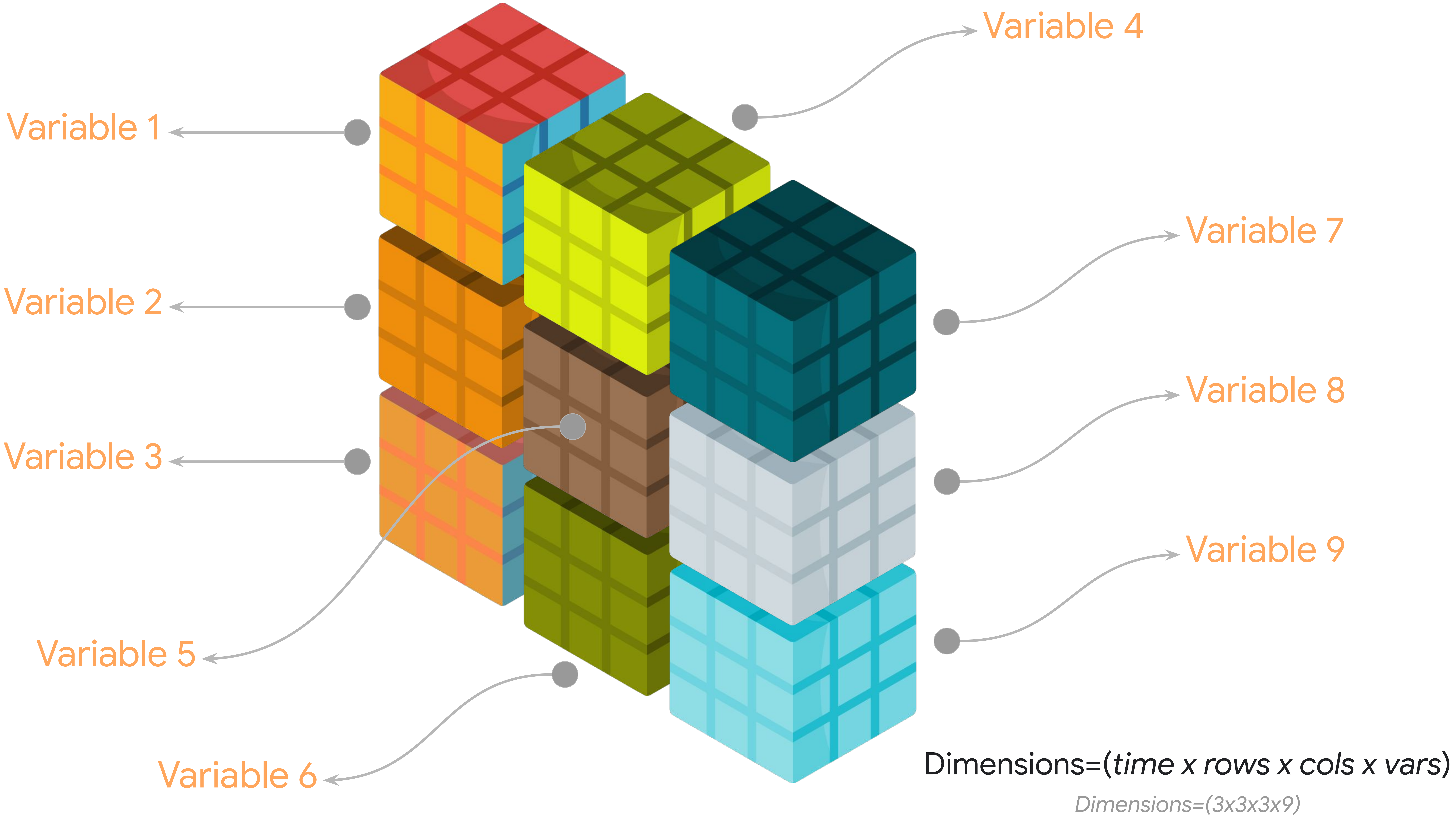
Dimensions=(3x3x3)

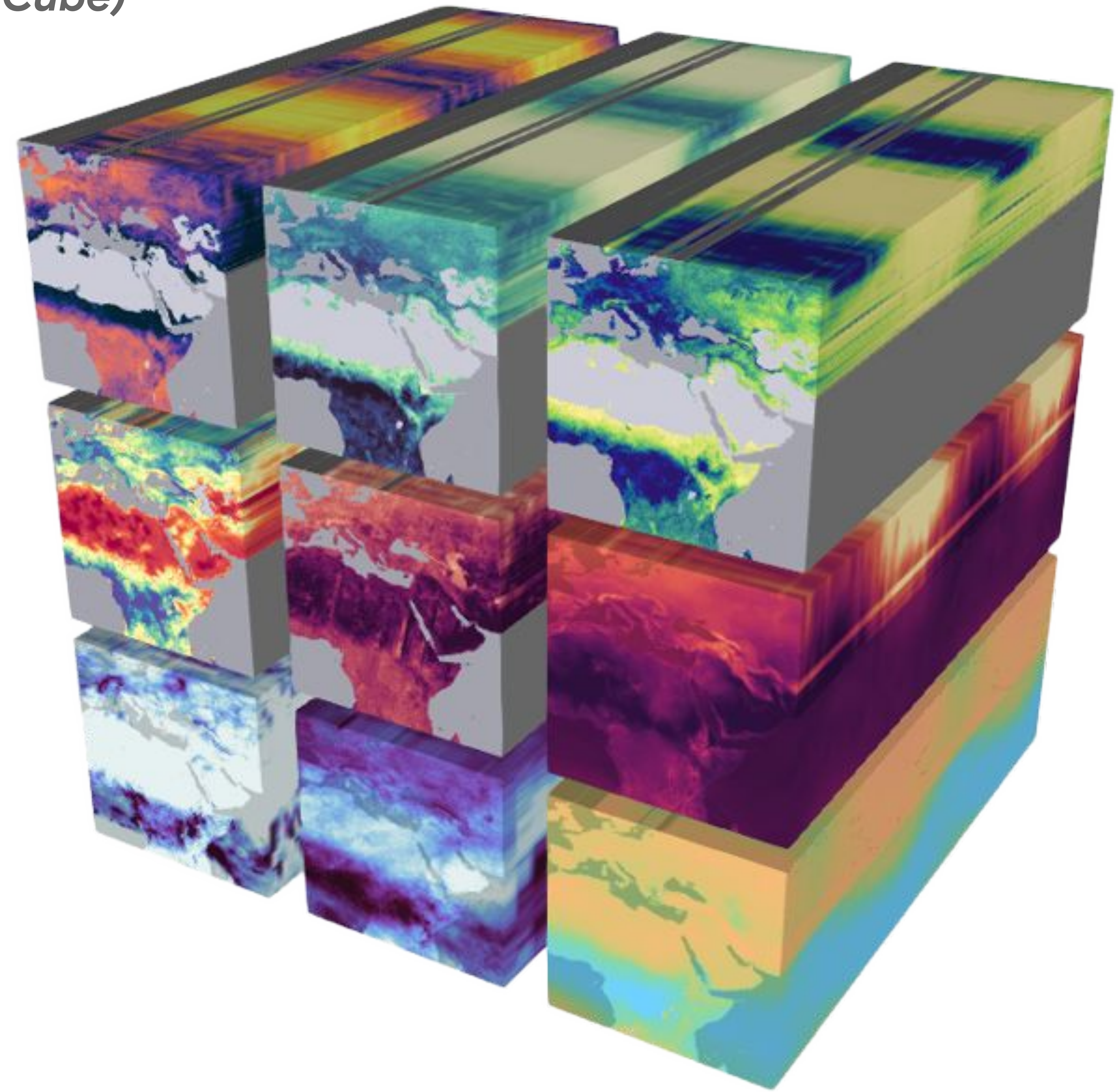


+ CRS

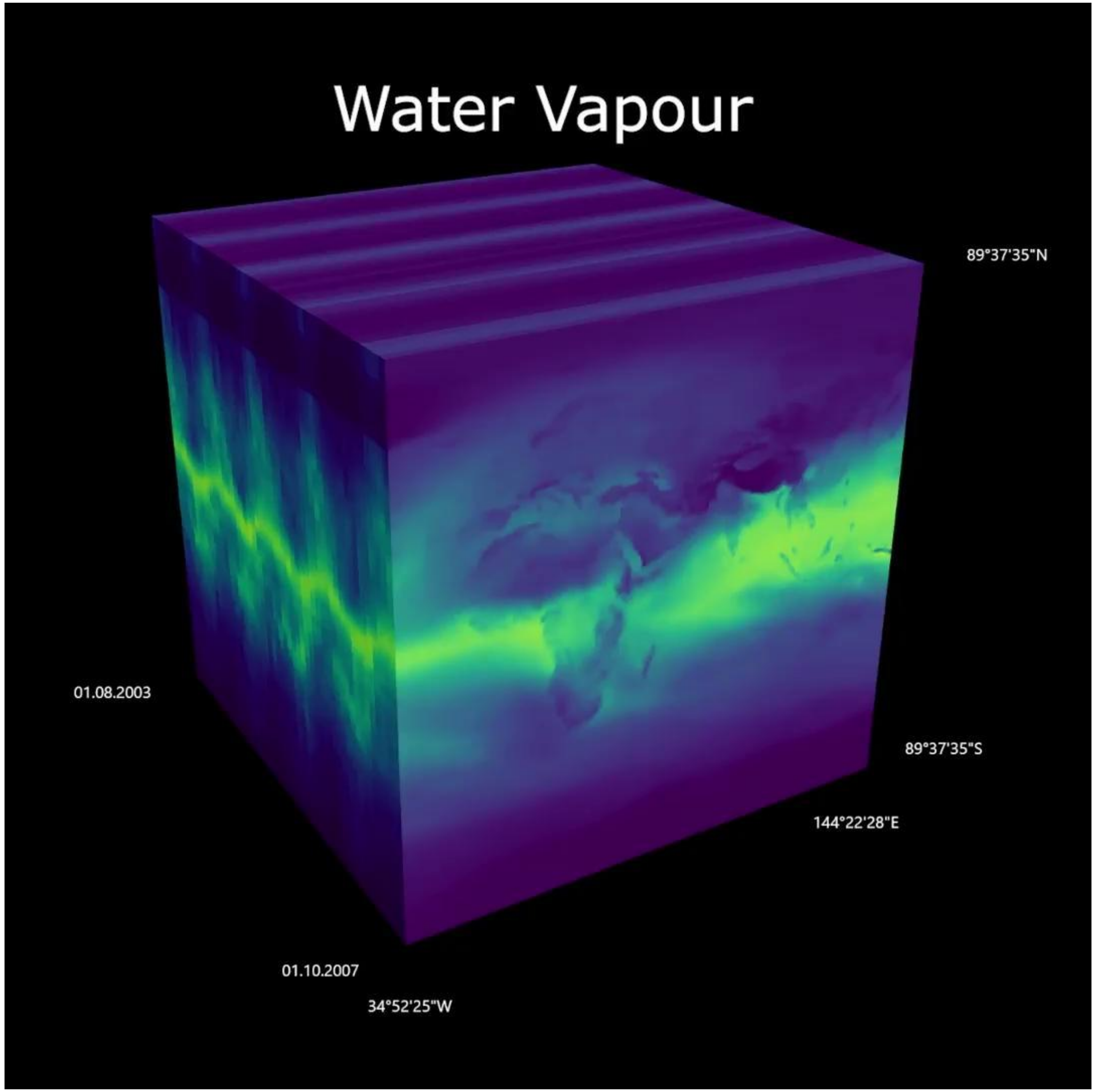
(Coordinate Reference System)


Variable 1
Variable 2
Variable 3
Variable 4
Variable 5
Variable 6
Variable 7
Variable 8
Variable 9
Dimensions=(*time x rows x cols x vars*)
Dimensions=(3x3x3x9)

ESDC *(Earth System Data Cube)*

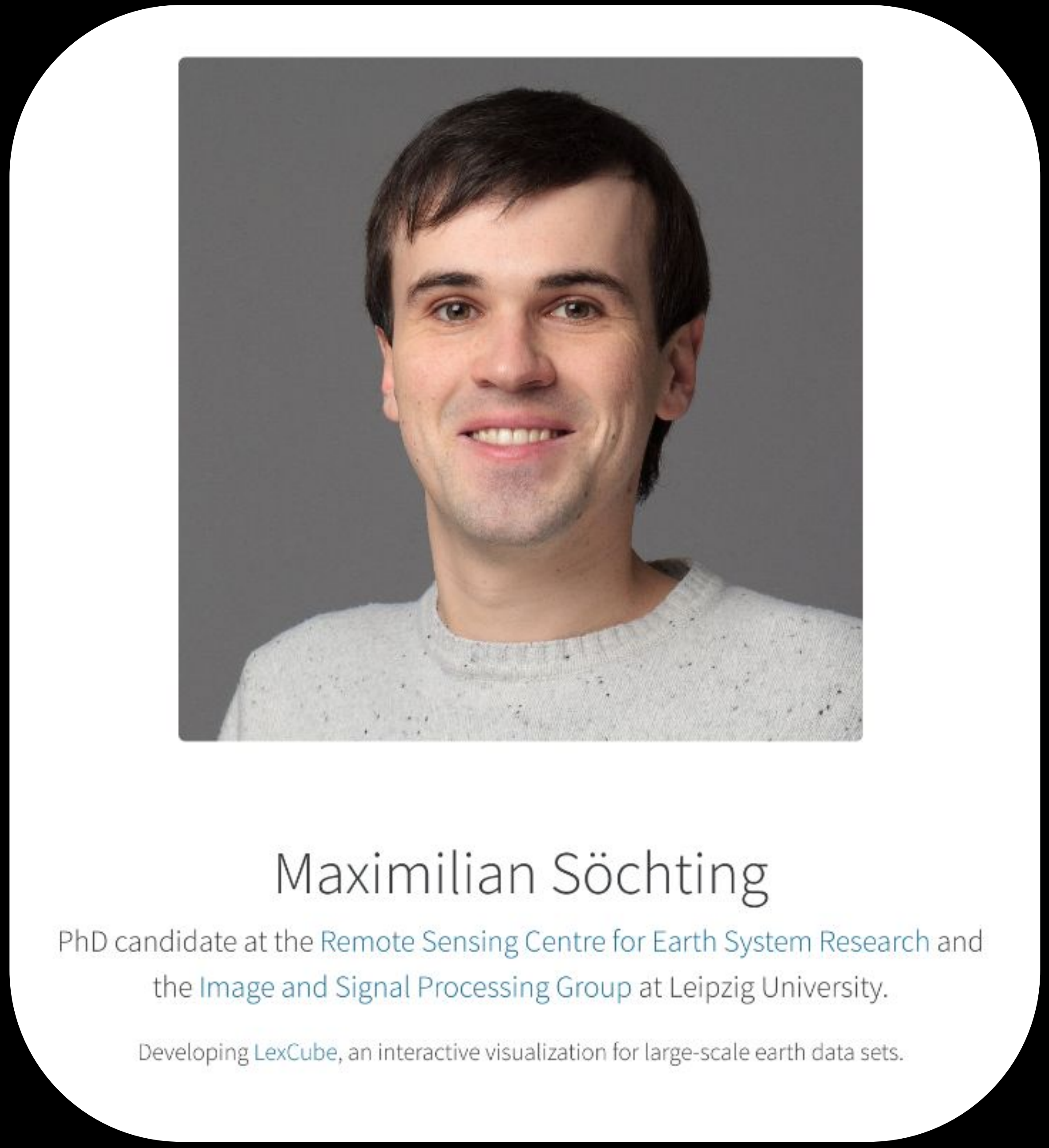


Source: https://doi.org/10.5194/esd-11-201-2020 (Mahecha et al., 2020)

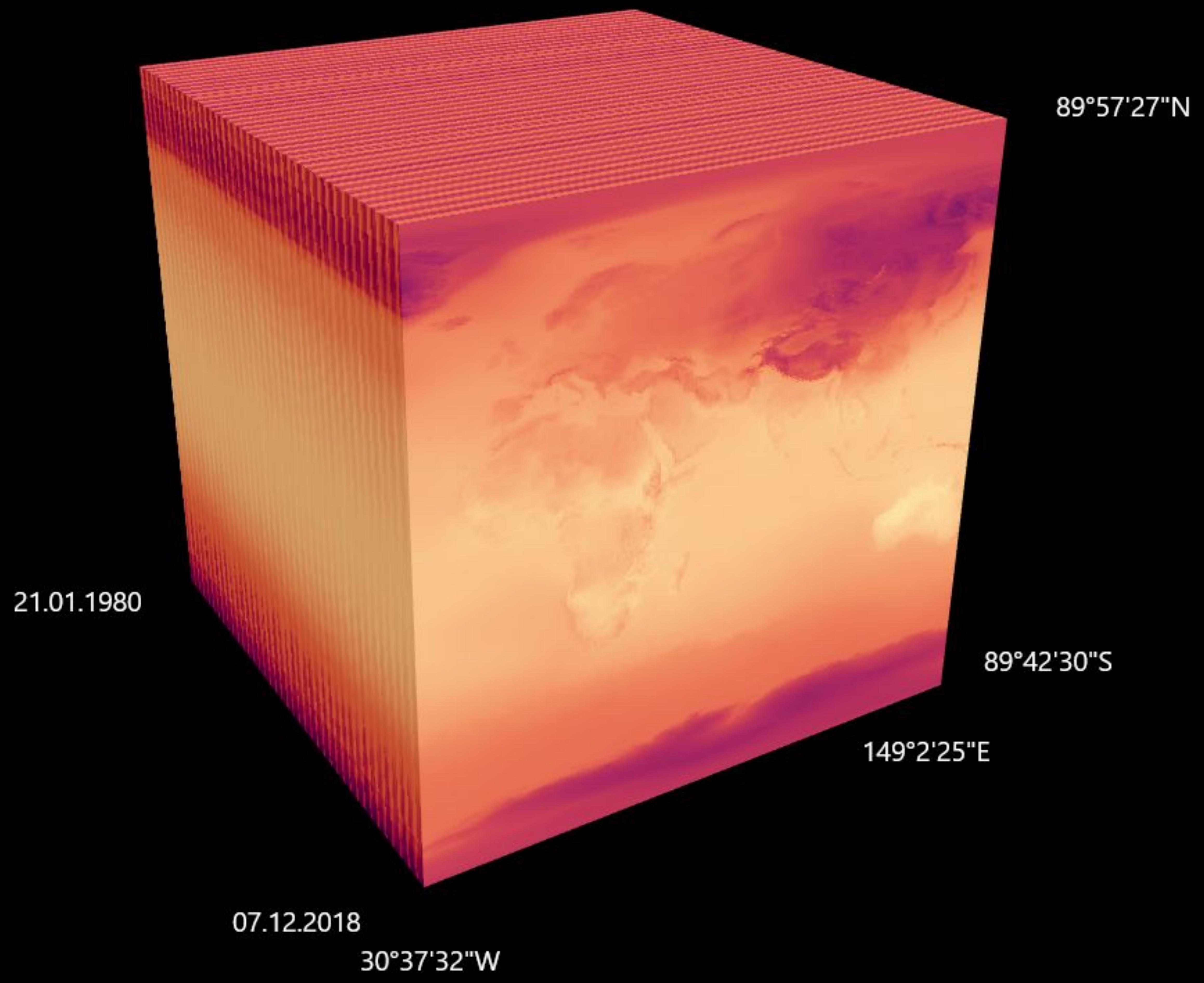


Source: https://www.lexcube.org/

Source: https://msoechting.de/en/

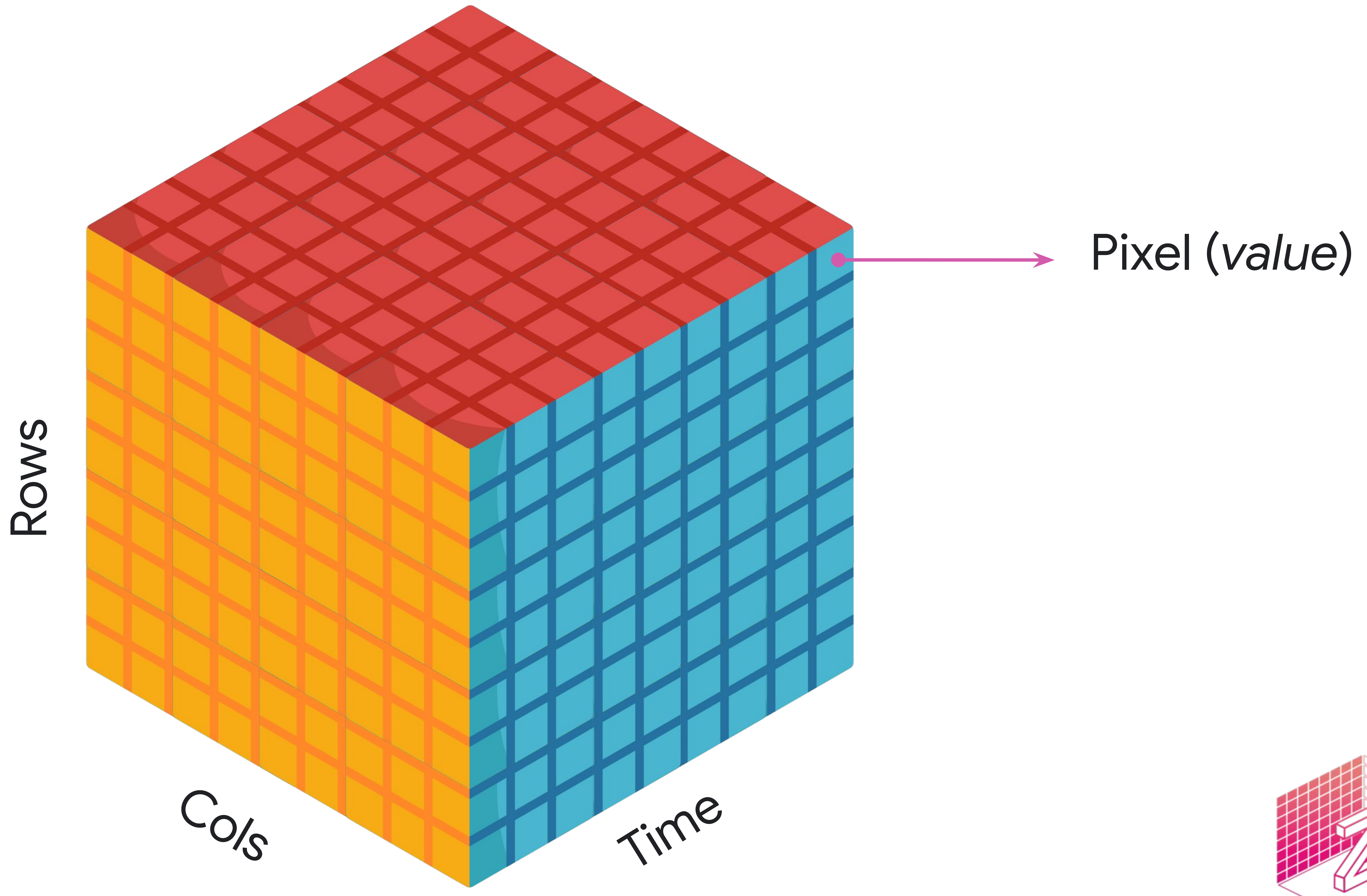


Lexcube.org



2 metre air temperature
Data Source: ERA5
Data attribution and license

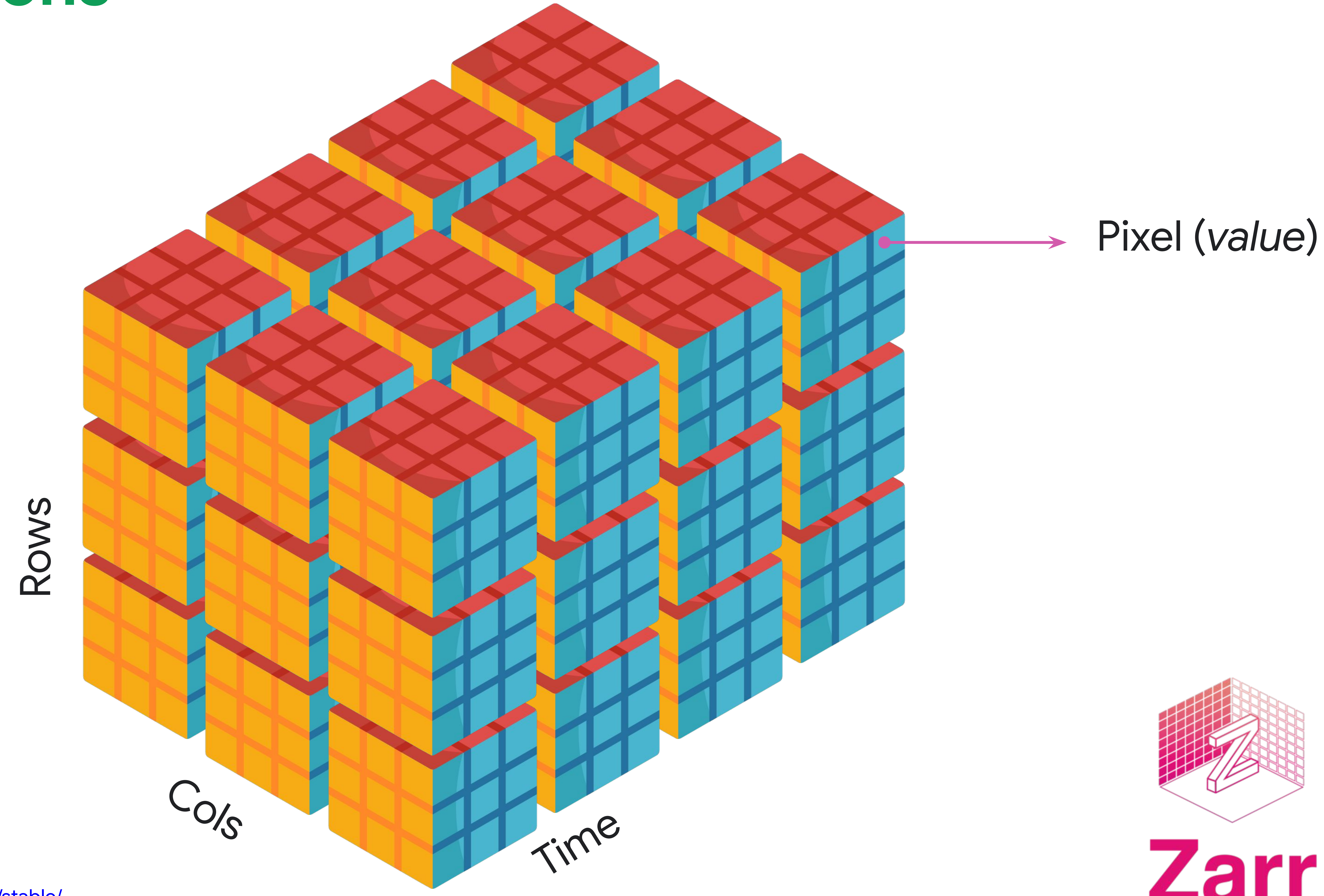
Data cubes can be **super efficient!**



Source: https://zarr.readthedocs.io/en/stable/

Zarr

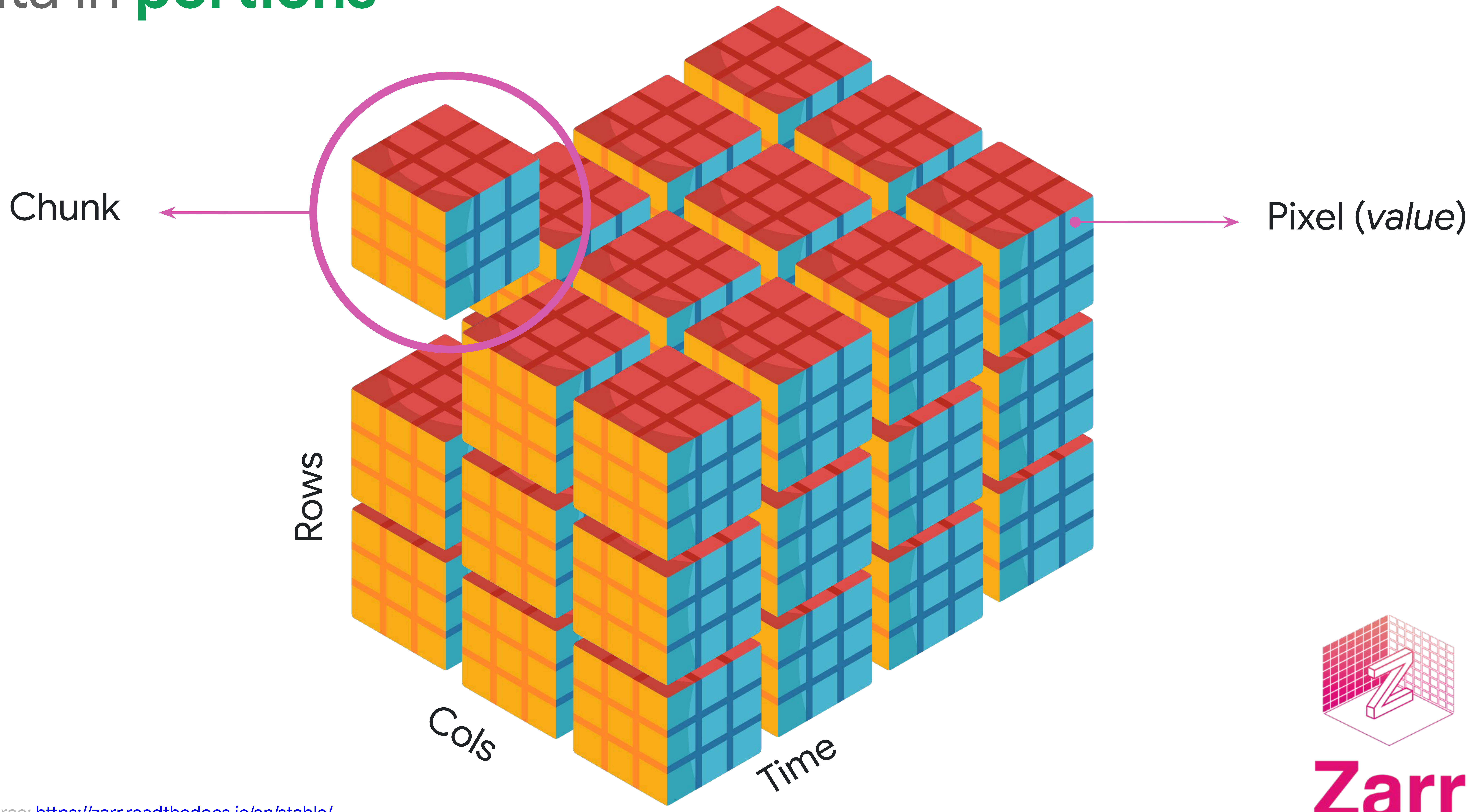
Data in **portions**



Zarr

Source: https://zarr.readthedocs.io/en/stable/

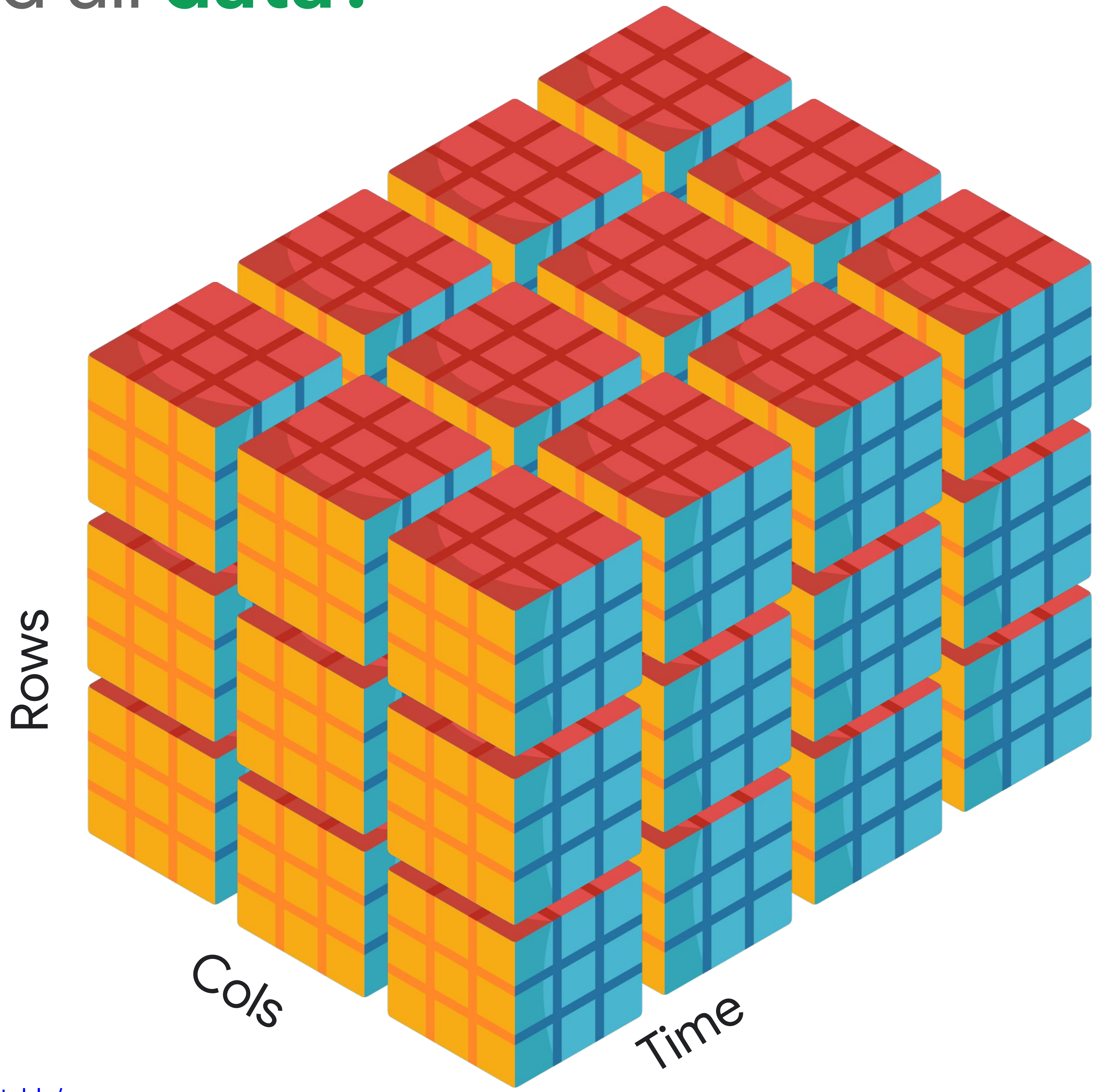
Data in **portions**



Source: https://zarr.readthedocs.io/en/stable/

Zarr

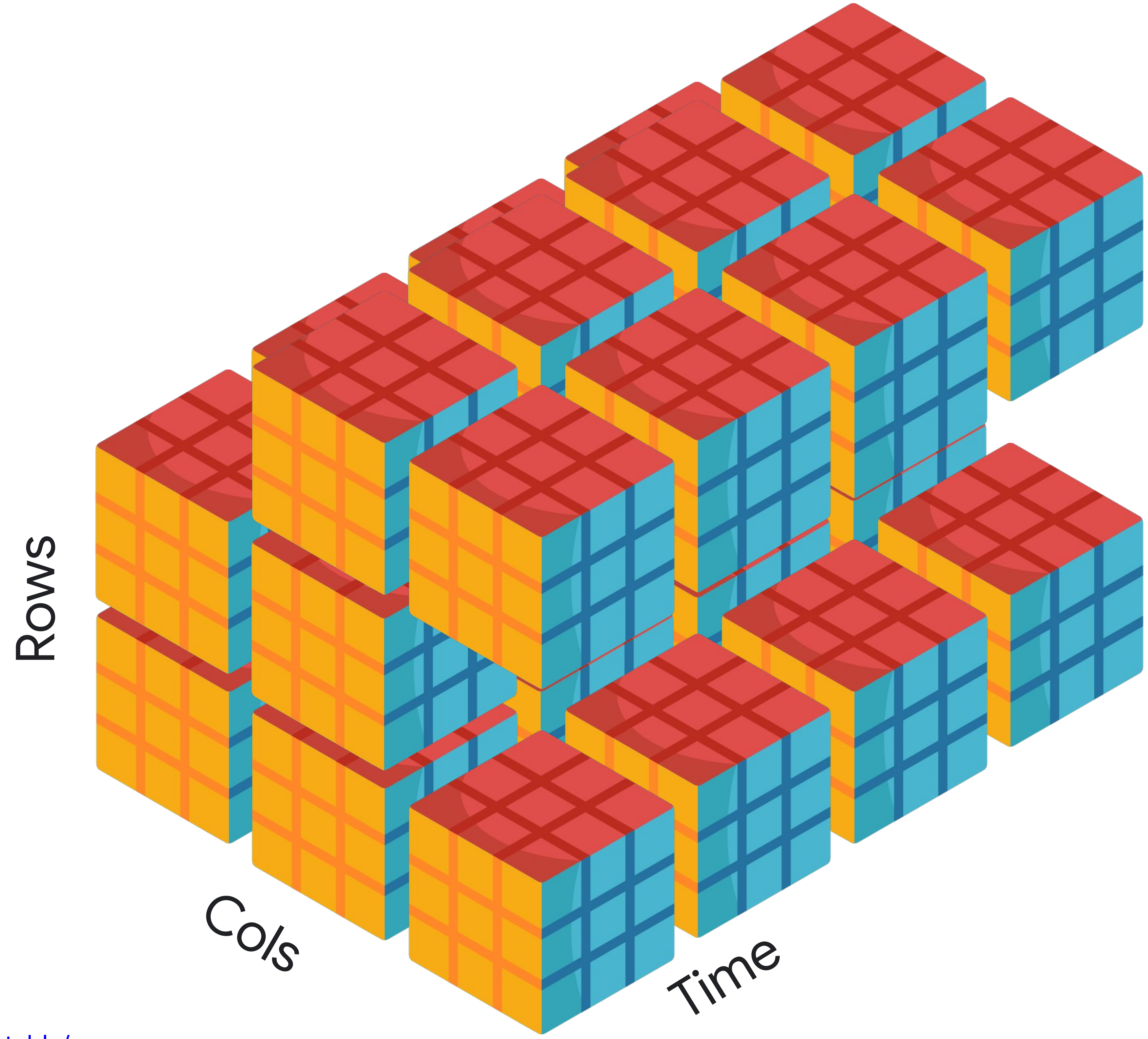
We don't need all **data?**



Source: https://zarr.readthedocs.io/en/stable/

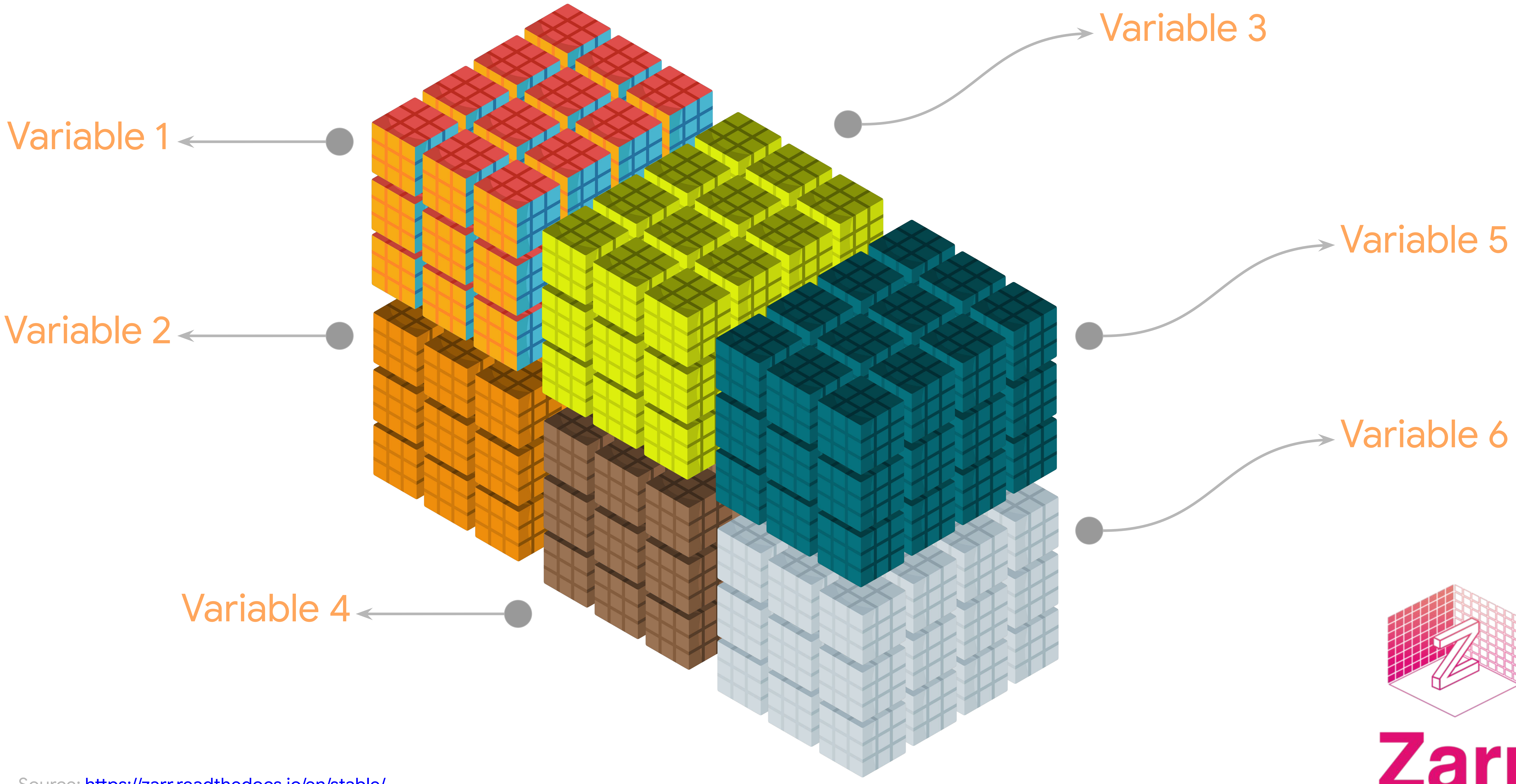
Zarr

No **problem!**



Source: https://zarr.readthedocs.io/en/stable/

Zarr

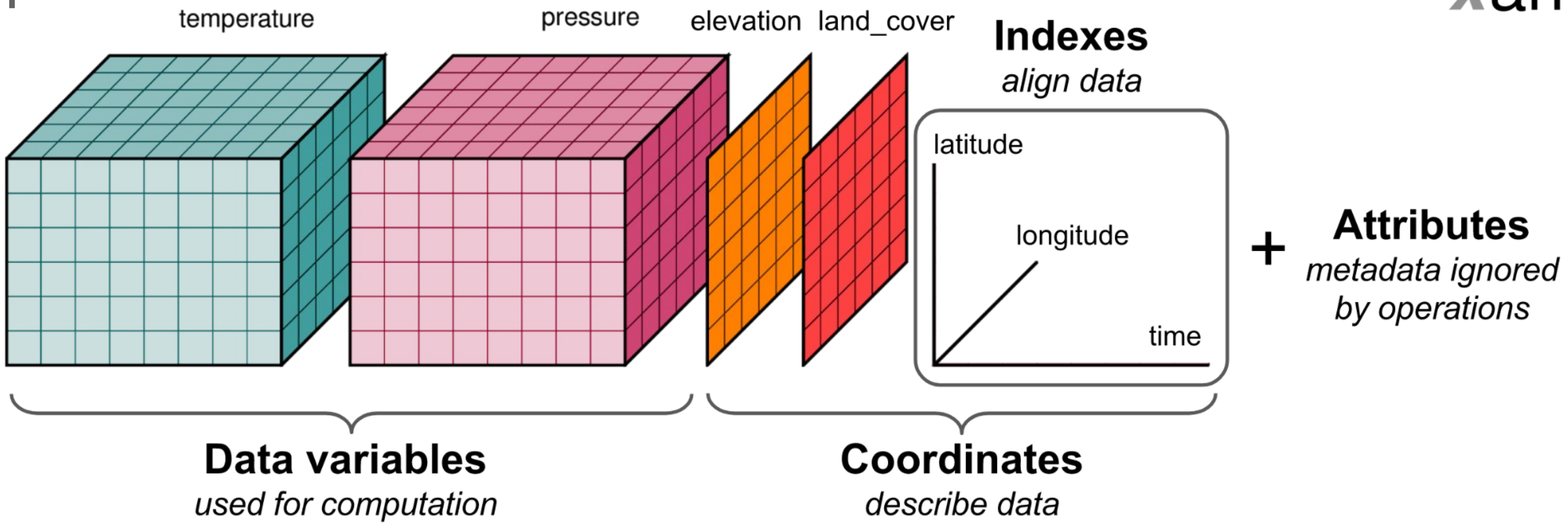


Zarr

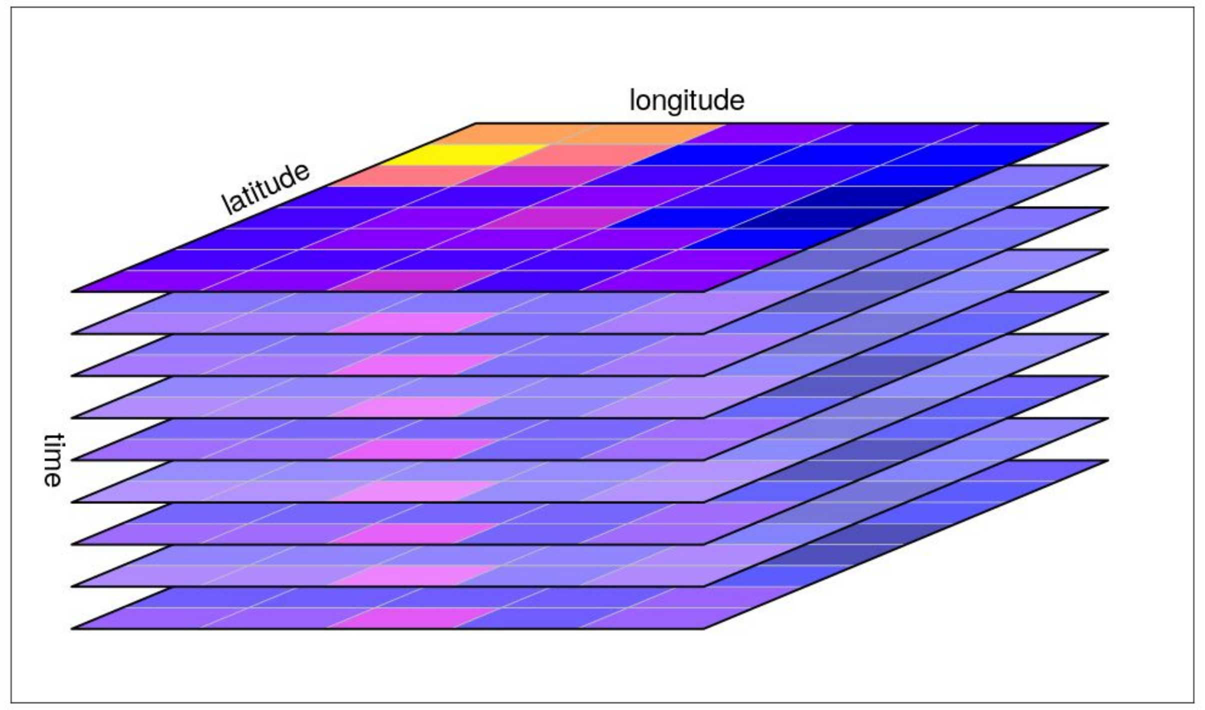
Source: https://zarr.readthedocs.io/en/stable/

python

xarray



stars



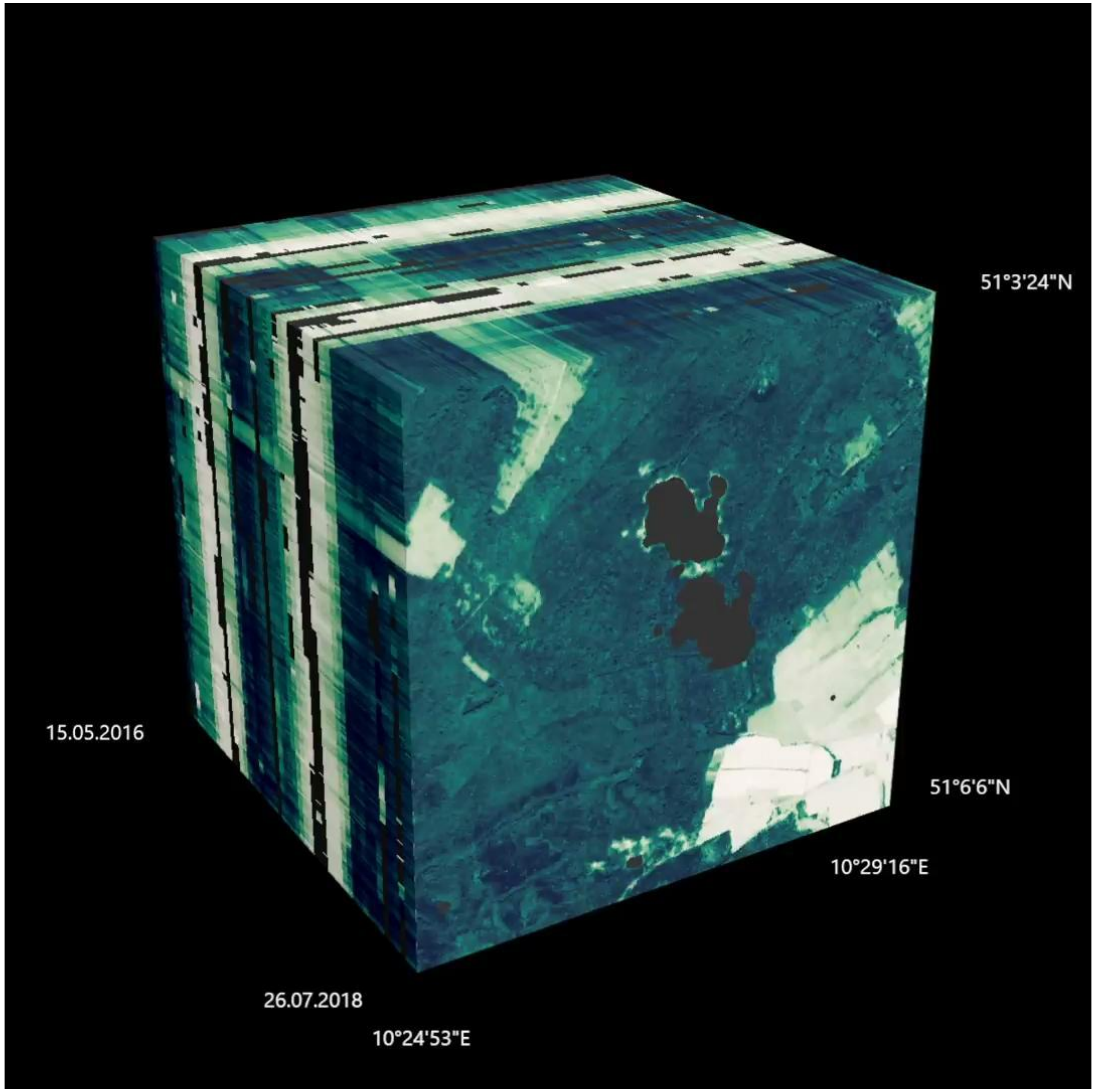
julia

JuliaDataCubes/
YAXArrays.jl

Yet Another XArray-like Julia package

13 Contributors · 64 Issues · 30 Stars · 6 Forks

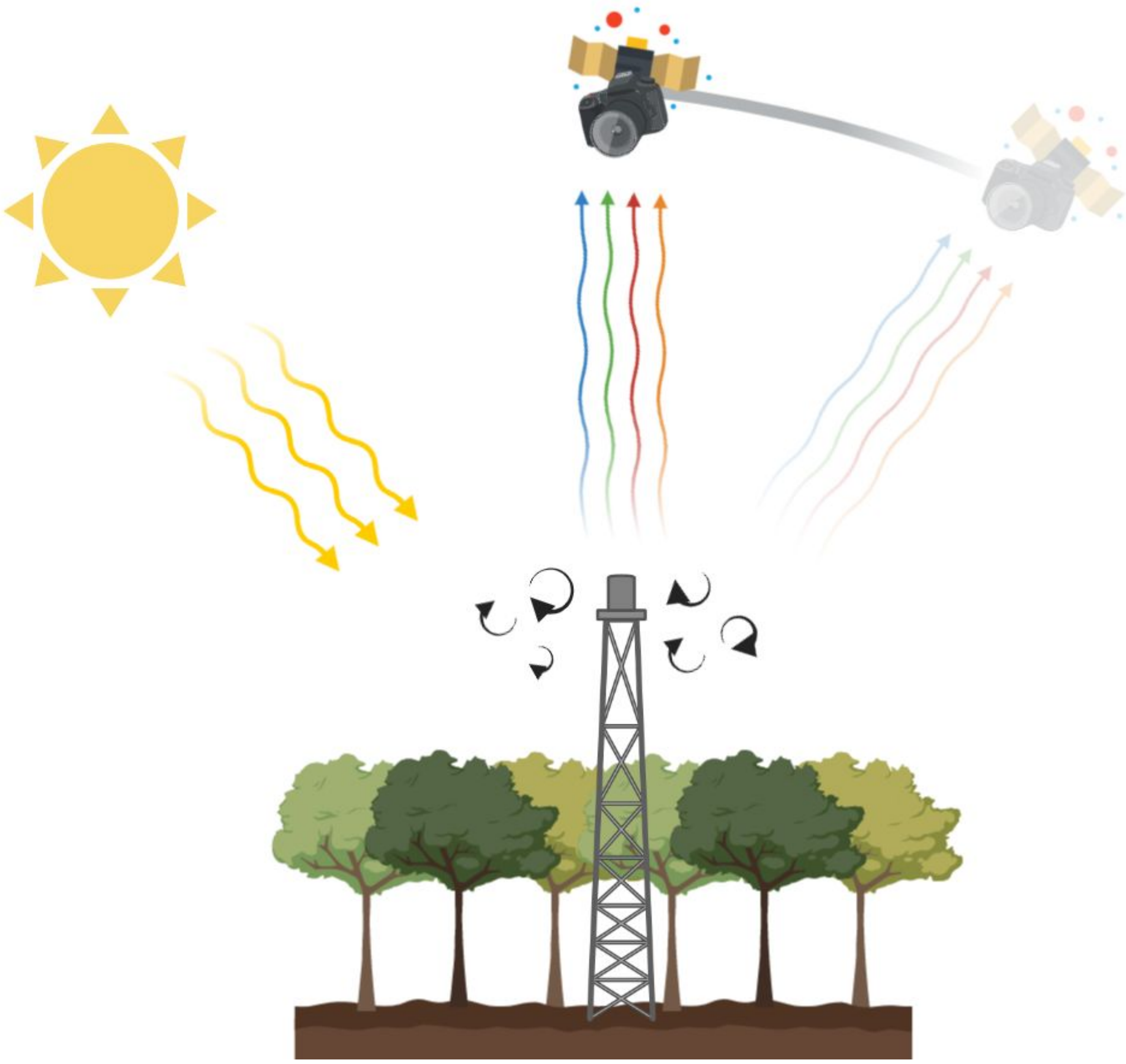
Source: https://github.com/JuliaDataCubes/YAXArrays.jl - https://docs.xarray.dev/en/stable/ - https://r-spatial.github.io/stars/index.html



Source: https://www.lexcube.org/

Data **curation**

Nadir BRDF Reflectance Adjustment



Sentinel-2
VIS-SWIR Surface Reflectance

BRDF: Bidirectional Reflectance Distribution Function

Data **curation**

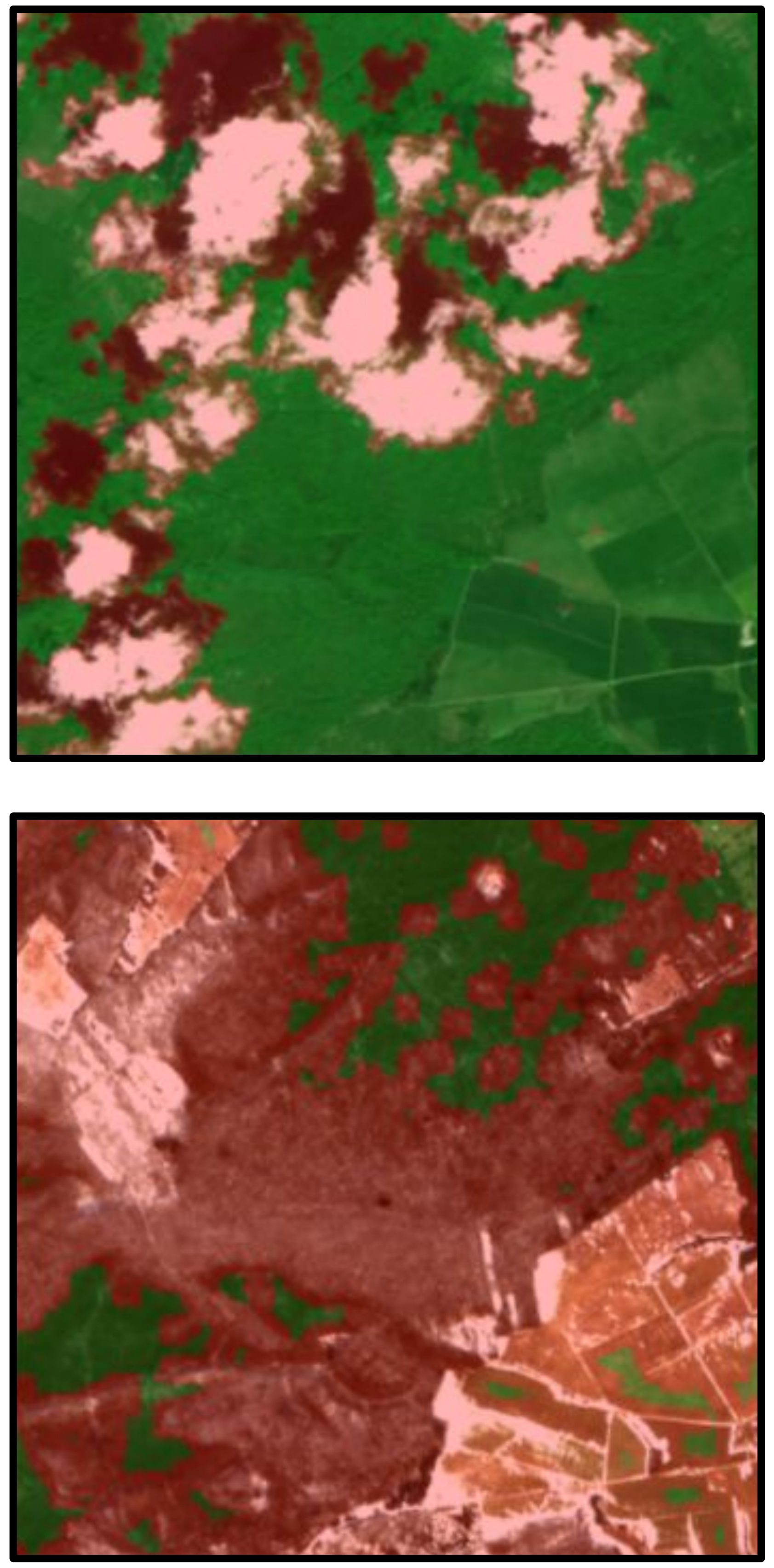
Nadir BRDF Reflectance Adjustment

Nadir BRDF Adjusted Reflectance (NBAR) for Sentinel-2 in Python

Sentinel-2
VIS-SWIR Surface Reflectance

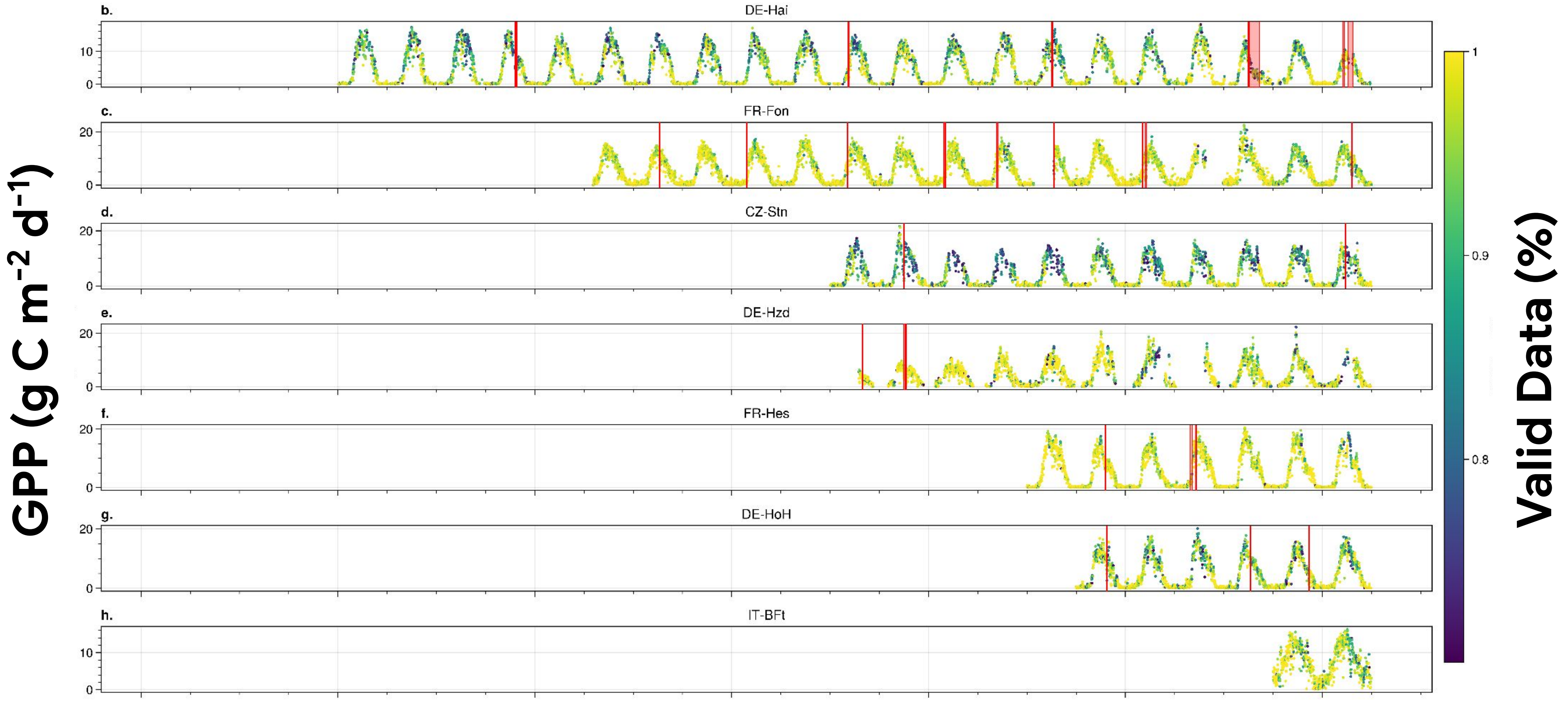
Further data **curation**

Cloud, cloud-shadow and snow masking



Sentinel-2
VIS-SWIR Surface Reflectance

Quality data filtering



ICOS (2020 Warm Winter Dataset)
Daily Gross Primary Production (g C m^2 d^{-1})

Sentinel-2
VIS-SWIR Surface Reflectance

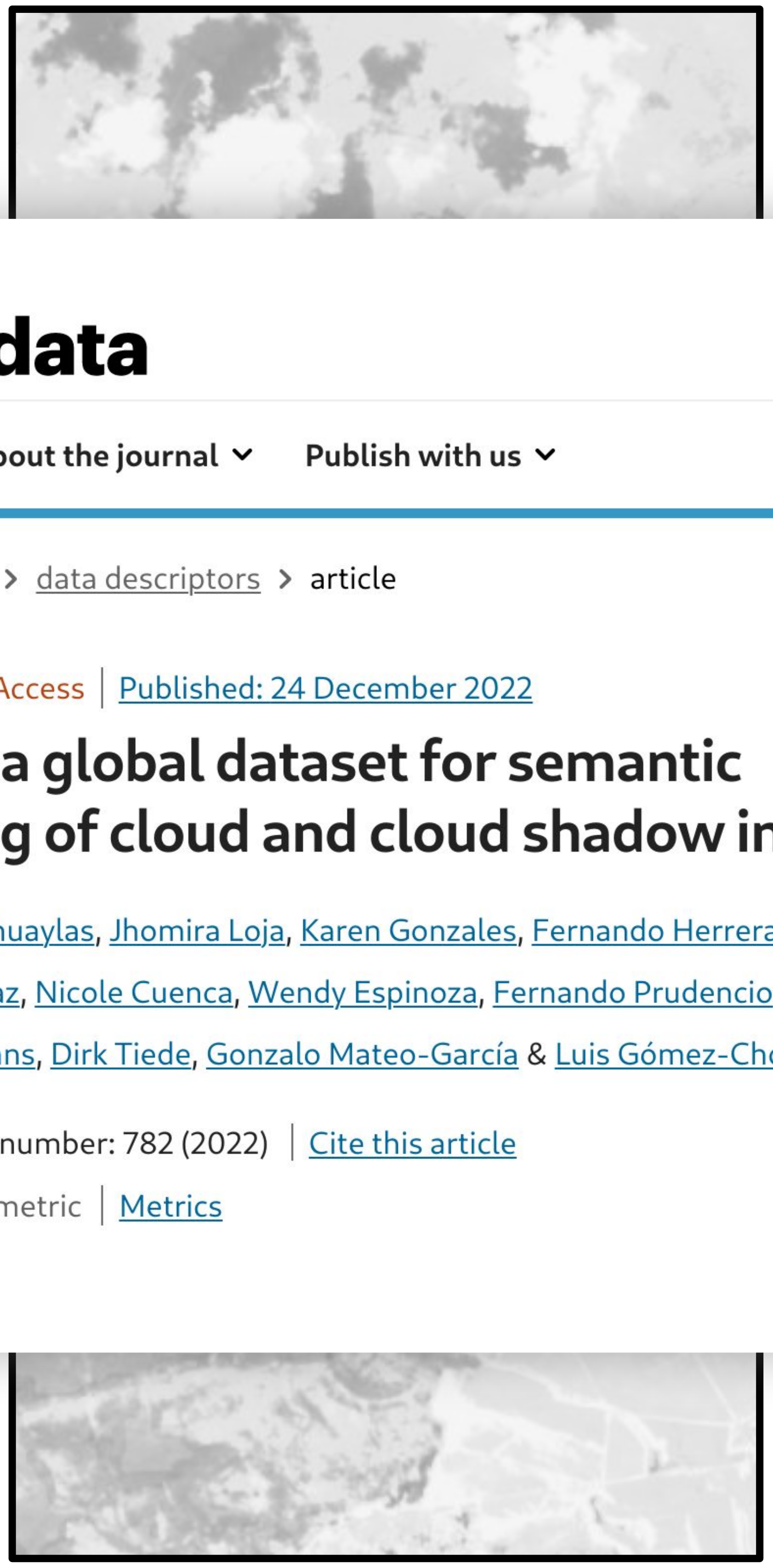
MODIS (Terra/Aqua)
Land Surface Temperature

Sentinel-1
VV-VH Gamma Flattened Backscattering

SCATSAR + Sentinel-1
Soil Water Index

Further data **curation**

Cloud, cloud-shadow and snow masking



scientific **data**

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nature > scientific data > data descriptors > article

Data Descriptor | Open Access | Published: 24 December 2022

CloudSEN12, a global dataset for semantic understanding of cloud and cloud shadow in Sentinel-2

Cesar Aybar, Luis Ysuhuaylas, Jhomira Loja, Karen Gonzales, Fernando Herrera, Lesly Bautista, Roy Yali, Angie Flores, Lissette Diaz, Nicole Cuenca, Wendy Espinoza, Fernando Prudencio, Valeria Llactayo, David Montero, Martin Sudmanns, Dirk Tiede, Gonzalo Mateo-García & Luis Gómez-Chova

Scientific Data 9, Article number: 782 (2022) | Cite this article

Sentinel-2
VIS-SWIR Surface Reflectance

Quality data filtering

ICOS (2020 Warm Winter Dataset)
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VIS-SWIR Surface Reflectance

MODIS (Terra/Aqua)
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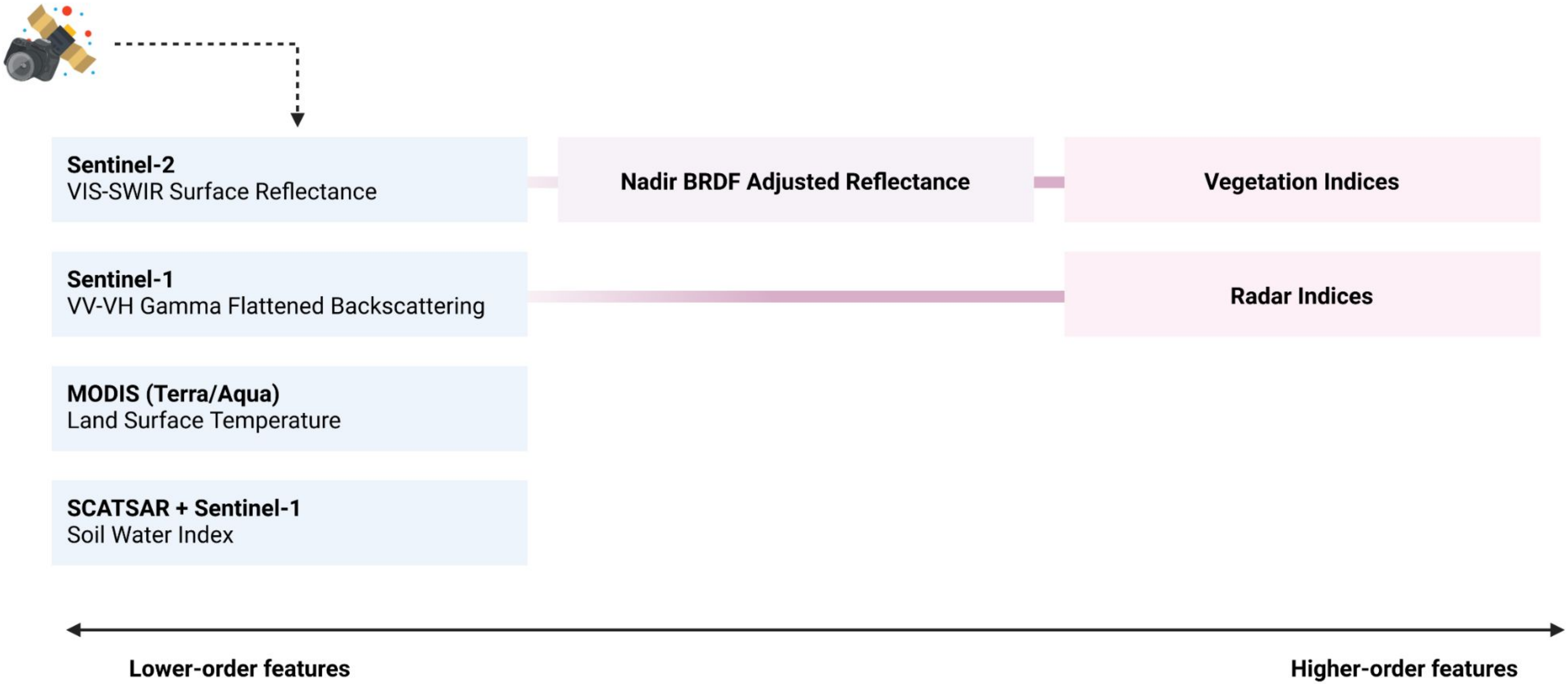
VV-VH Gamma Flattened Backscattering

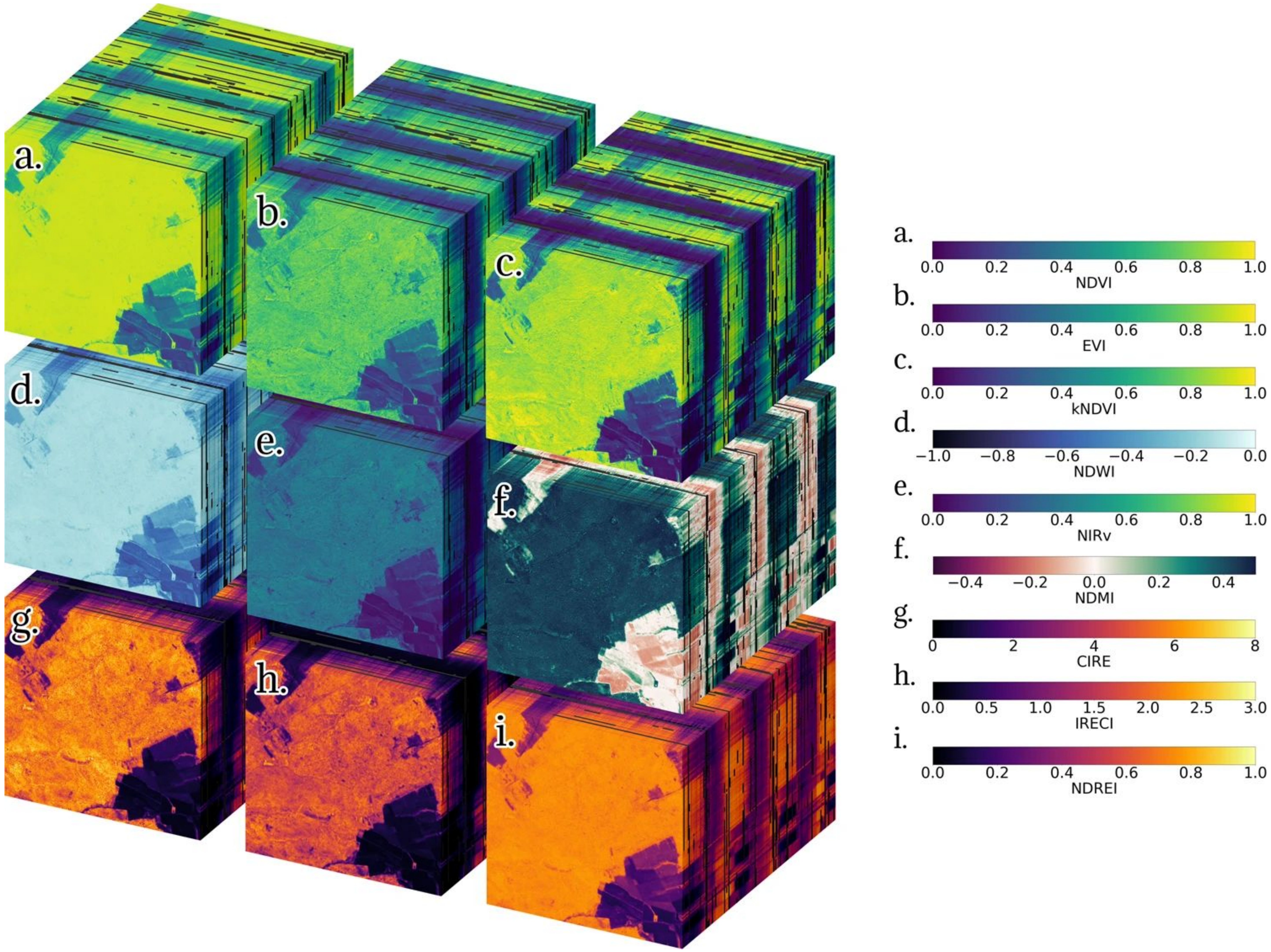
SCATSAR + Sentinel-1
Soil Water Index

Data **engineering**

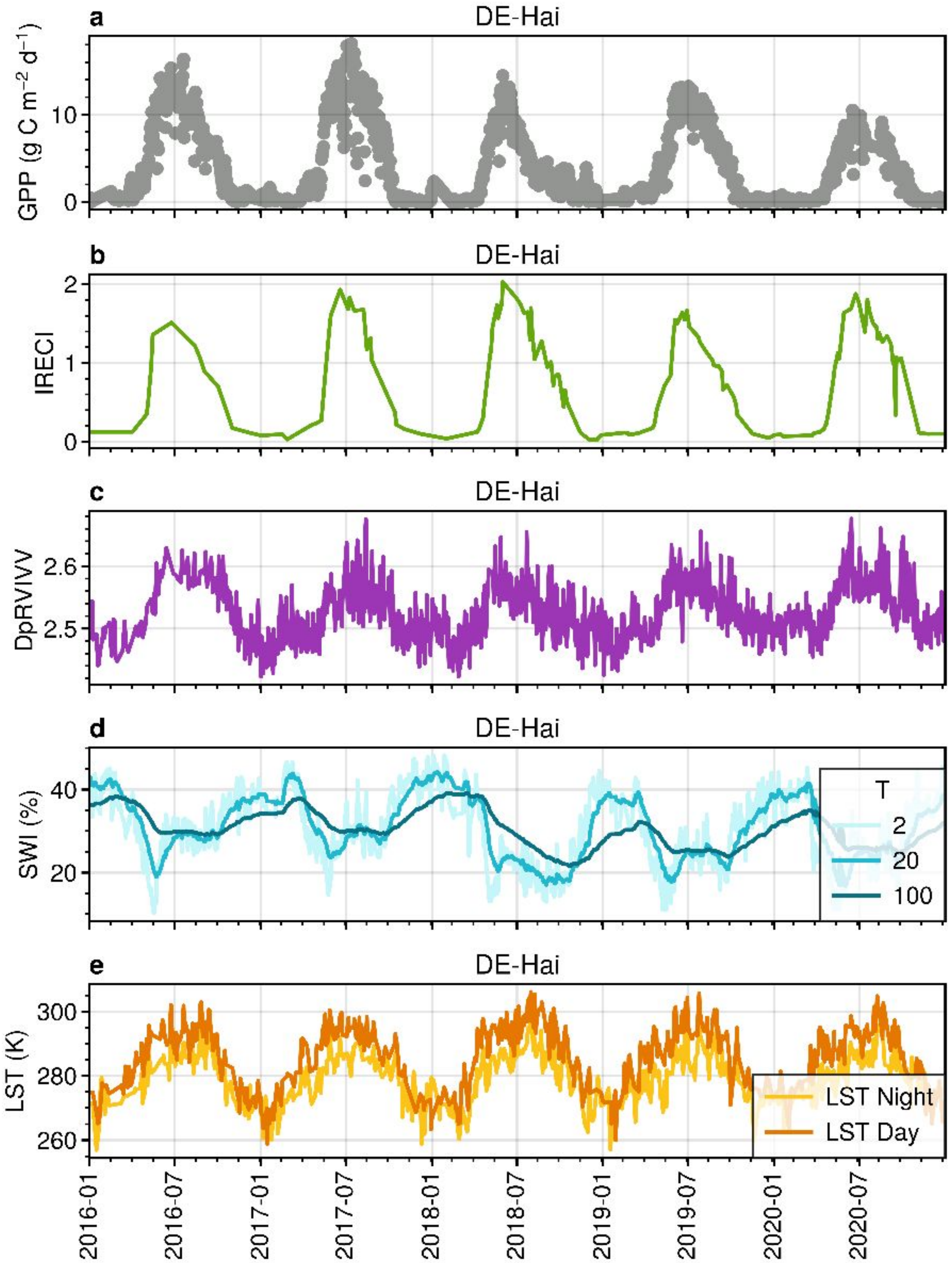


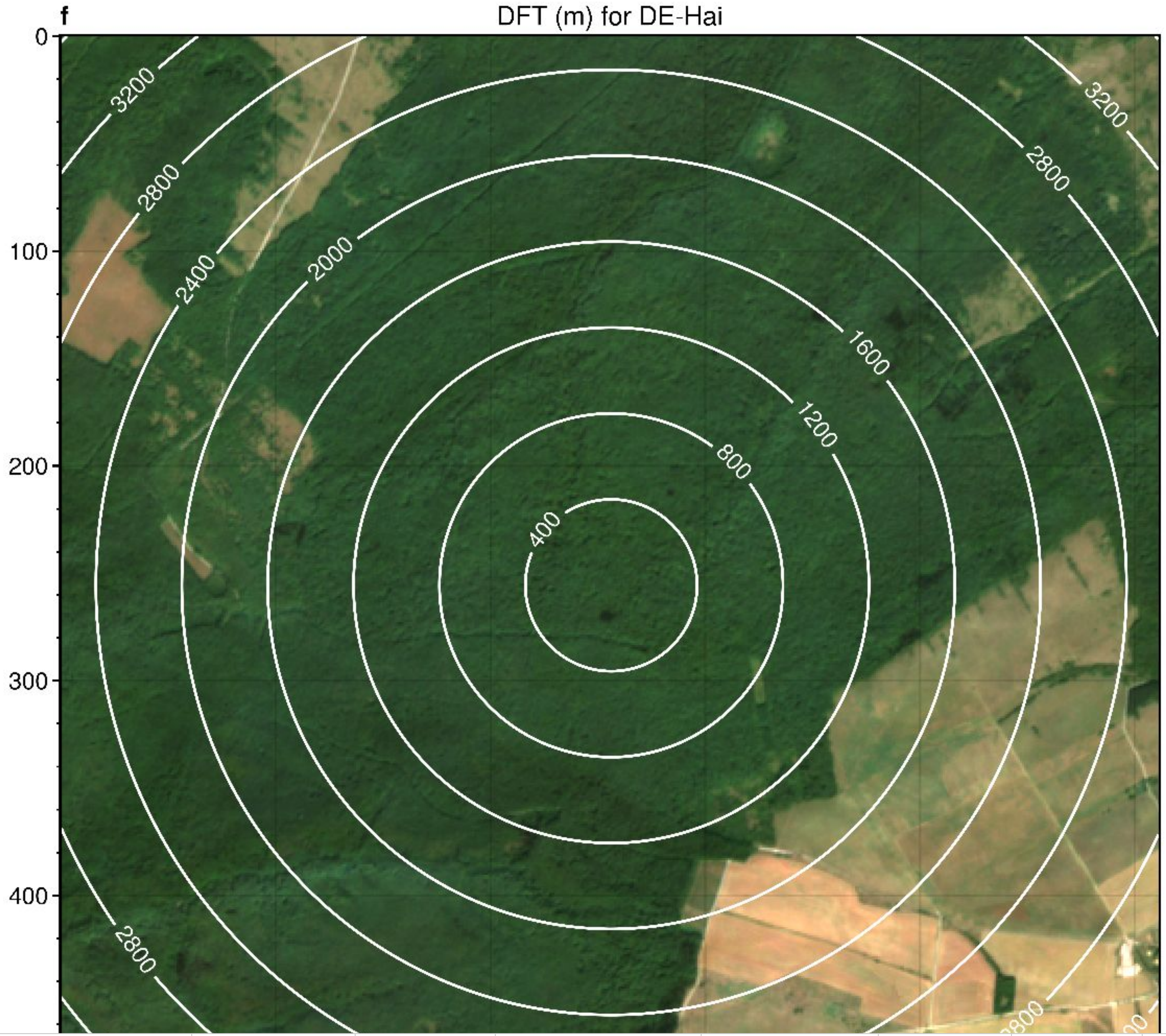
Earth System **Mini** Cubes for **ICOS 2020 WW**

*Sample of 9 VIs from 126 available indices (for Sentinel-2) in Awesome Spectral Indices that were computed

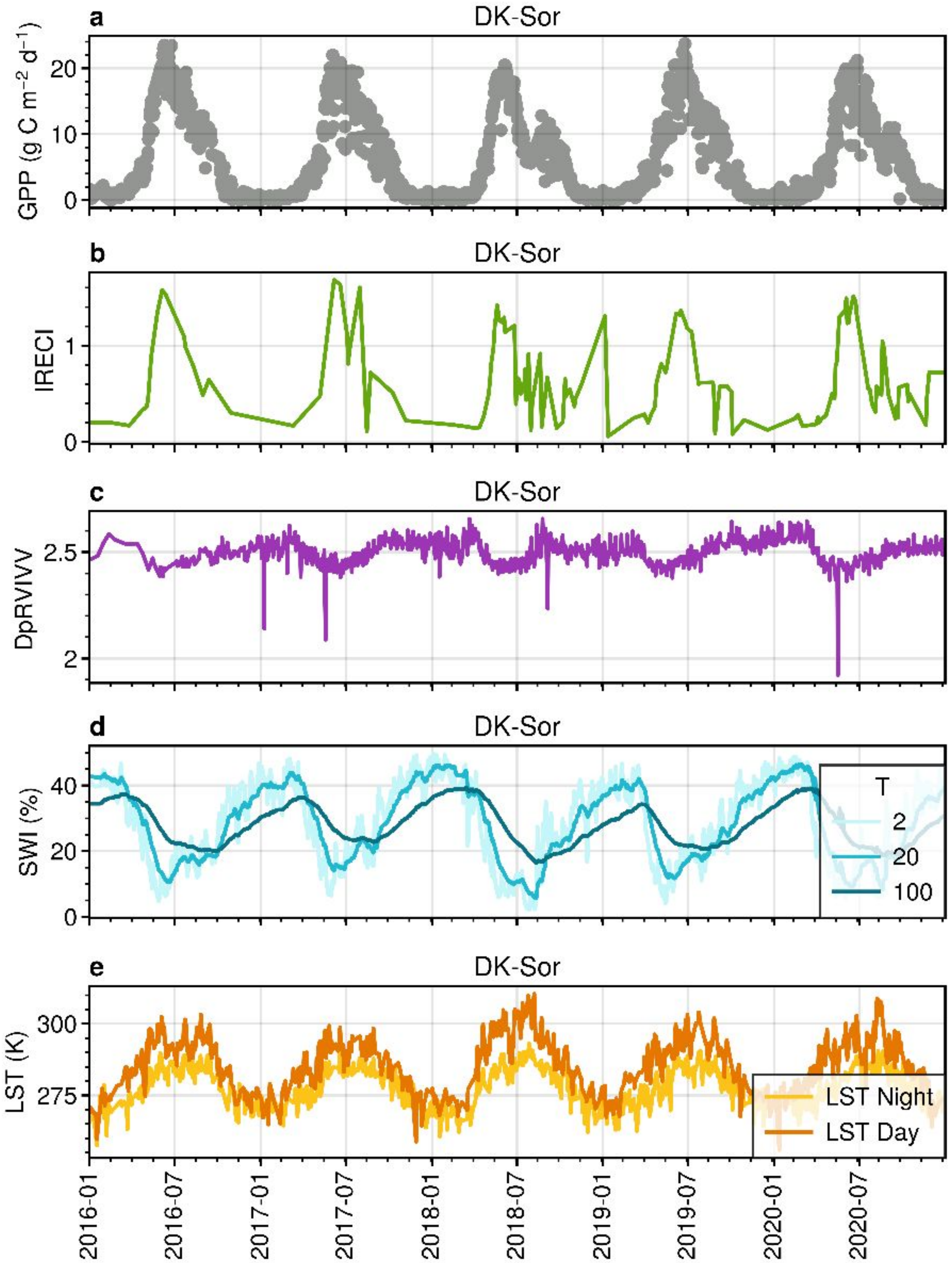


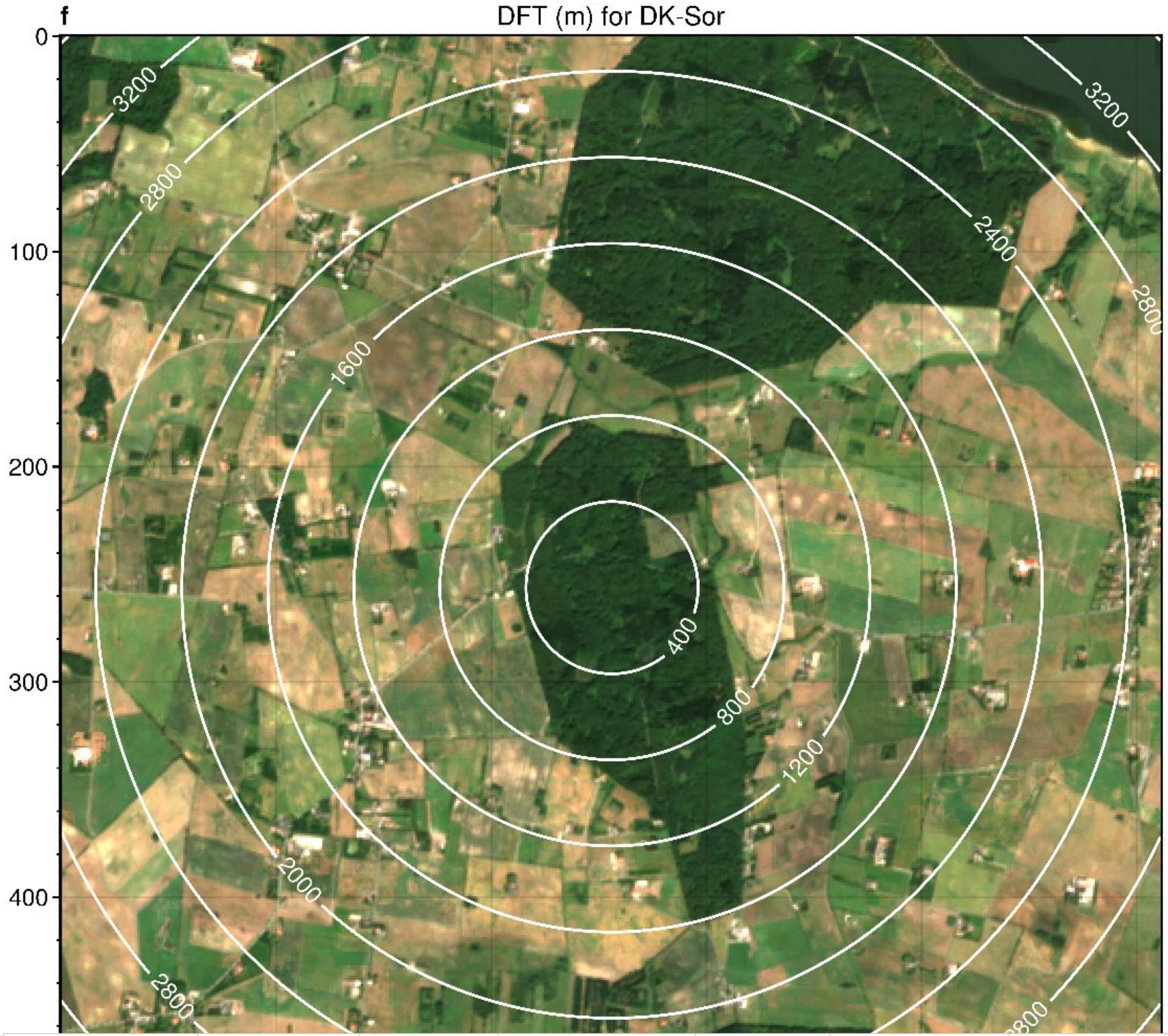
Montero et al., 2023
Scientific Data





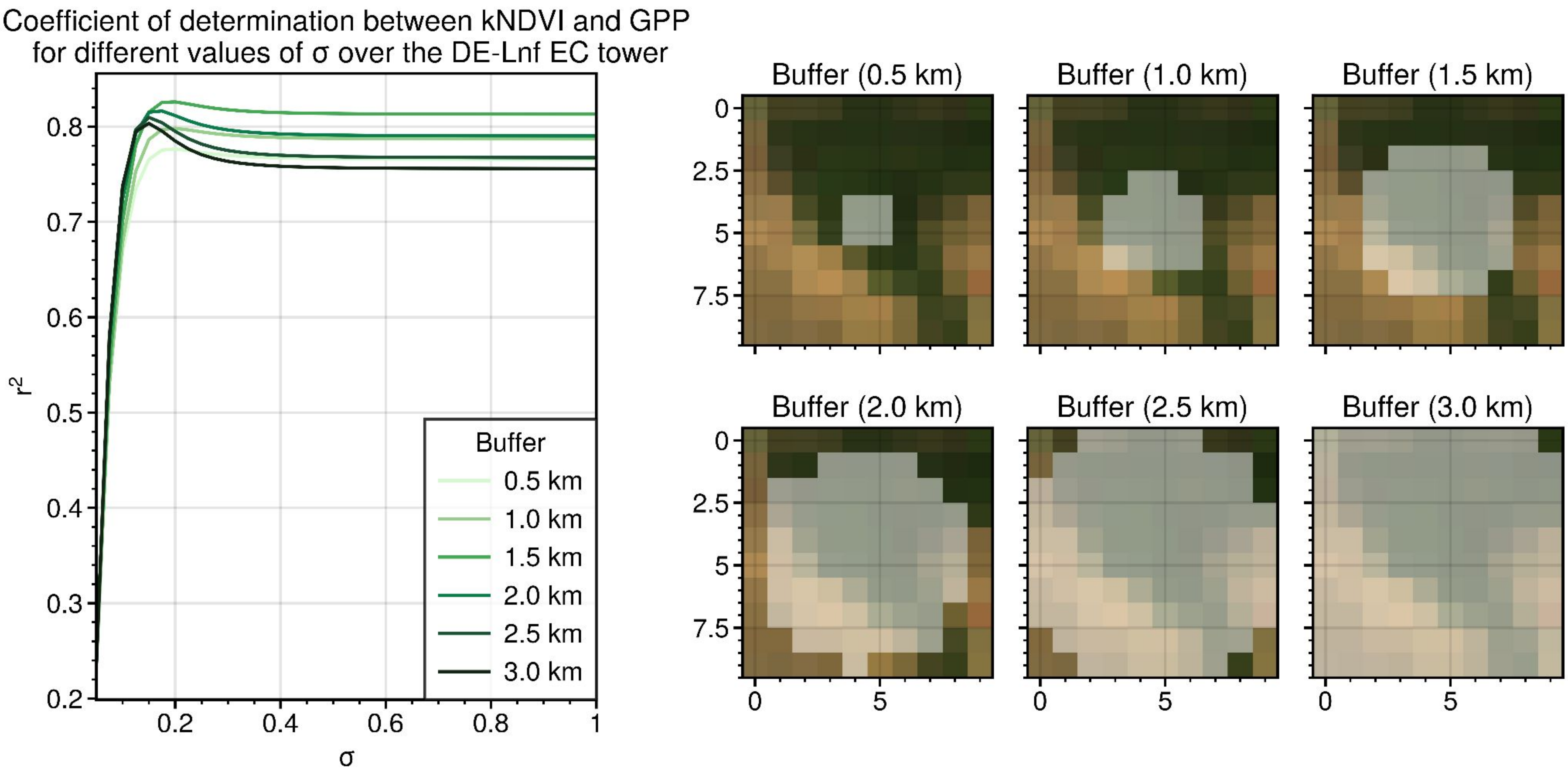
Agriculture	Artificial	Forest	No Vegetation	Pasture	Scrub	Water	Wetland	dft
0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	**500.00**
0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	**1000.00**
0.01	0.00	0.96	0.00	0.03	0.00	0.00	0.00	**1500.00**
0.03	0.00	0.89	0.00	0.08	0.00	0.00	0.00	**2000.00**



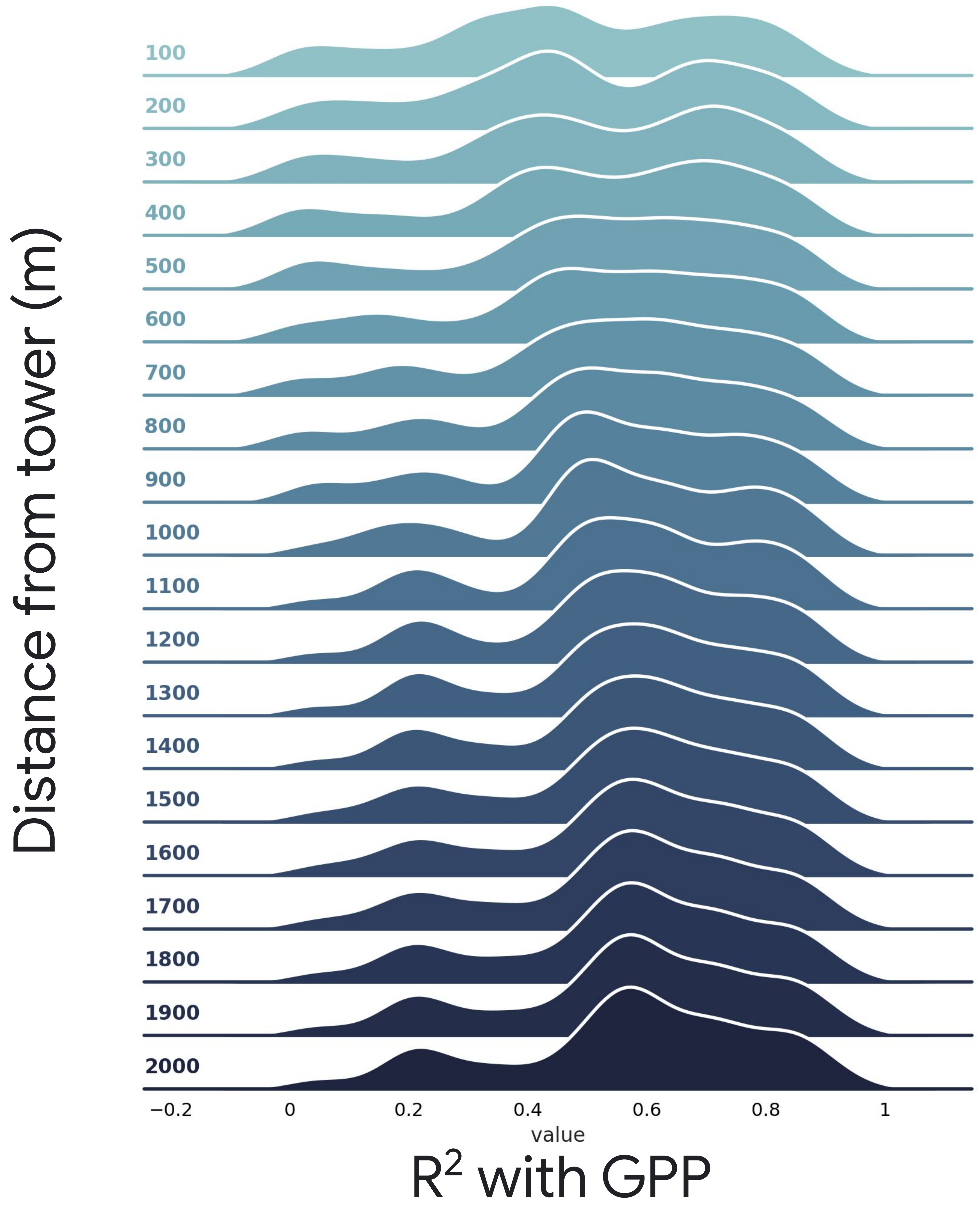


Agriculture	Artificial	Forest	No Vegetation	Pasture	Scrub	Water	Wetland	dft
0.05	0.00	0.95	0.00	0.00	0.00	0.00	0.00	**500.00**
0.54	0.00	0.46	0.00	0.00	0.00	0.00	0.00	**1000.00**
0.71	0.00	0.29	0.00	0.00	0.00	0.00	0.00	**1500.00**
0.78	0.00	0.22	0.00	0.00	0.00	0.00	0.00	**2000.00**

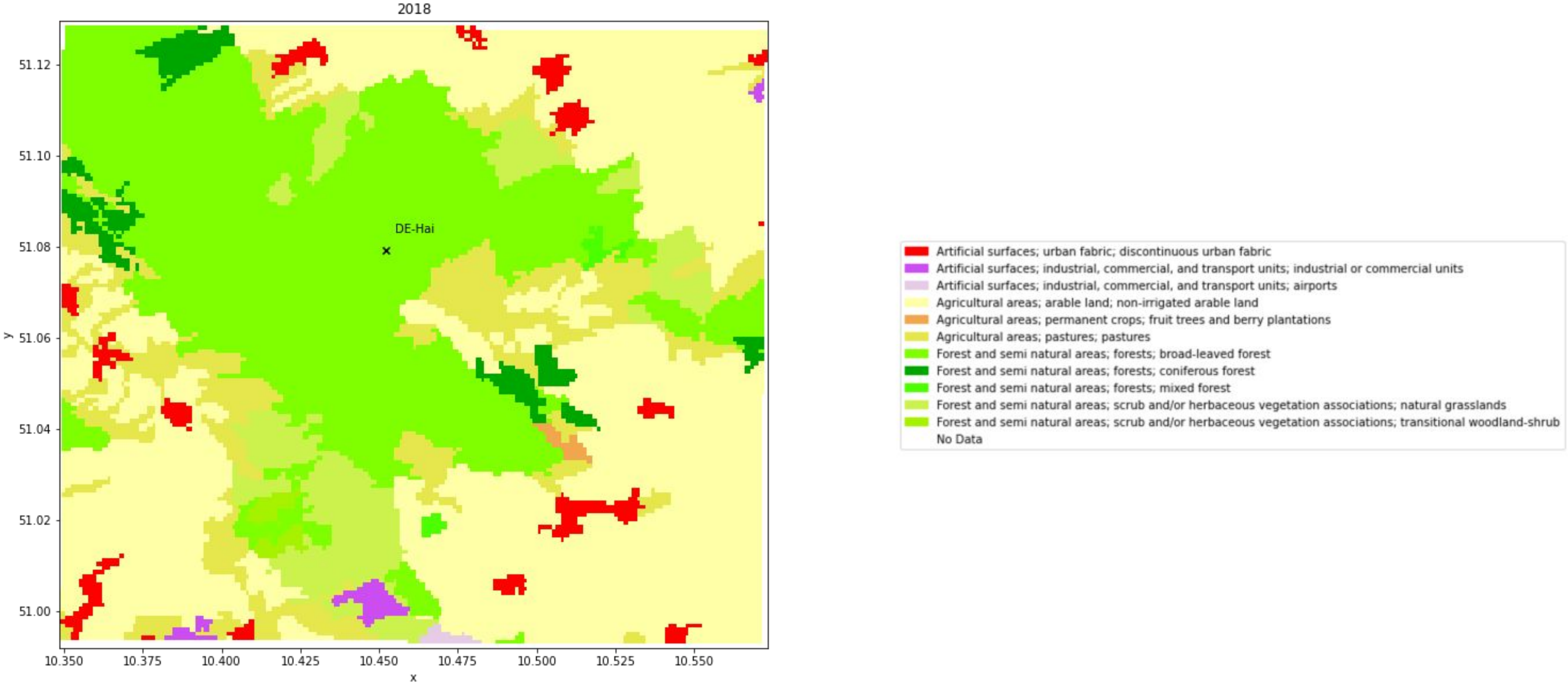
What's the best **area?**



What’s the best **area?**



Land cover **data**



Third Chapter

Machine Learning and Memory

3

Remote Sensing variables

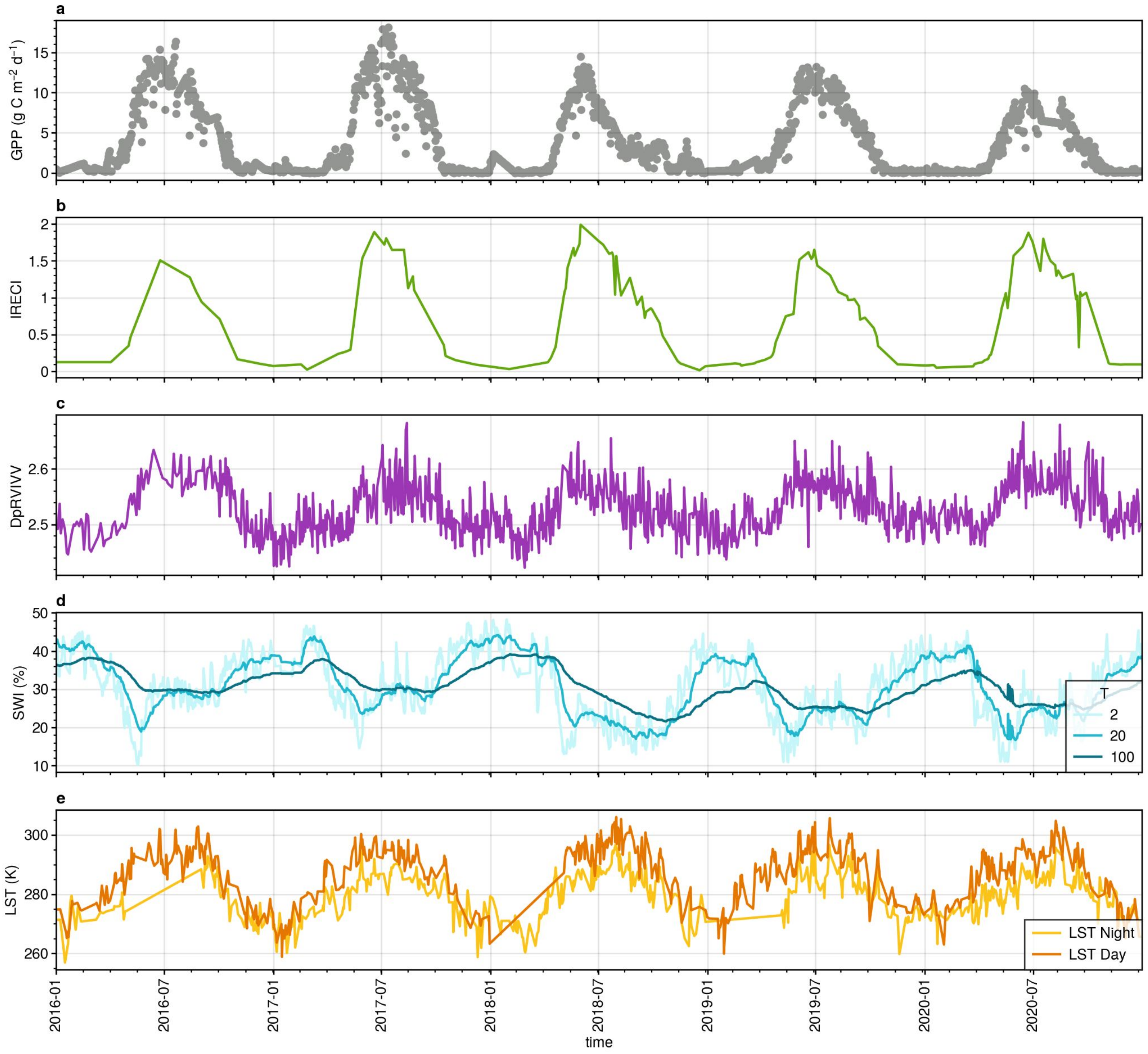
ICOS (2020 Warm Winter Dataset)
Daily GPP (g C m^{-2} d^{-1})

Sentinel-2
VIS-SWIR Surface Reflectance

Sentinel-1
VV-VH Gamma Flattened Backscattering

SCATSAR + Sentinel-1
Soil Water Index

MODIS (Terra/Aqua)
Land Surface Temperature



*Illustrative example with 7 features

Remote Sensing variables

ICOS (2020 Warm Winter Dataset)
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Sentinel-2
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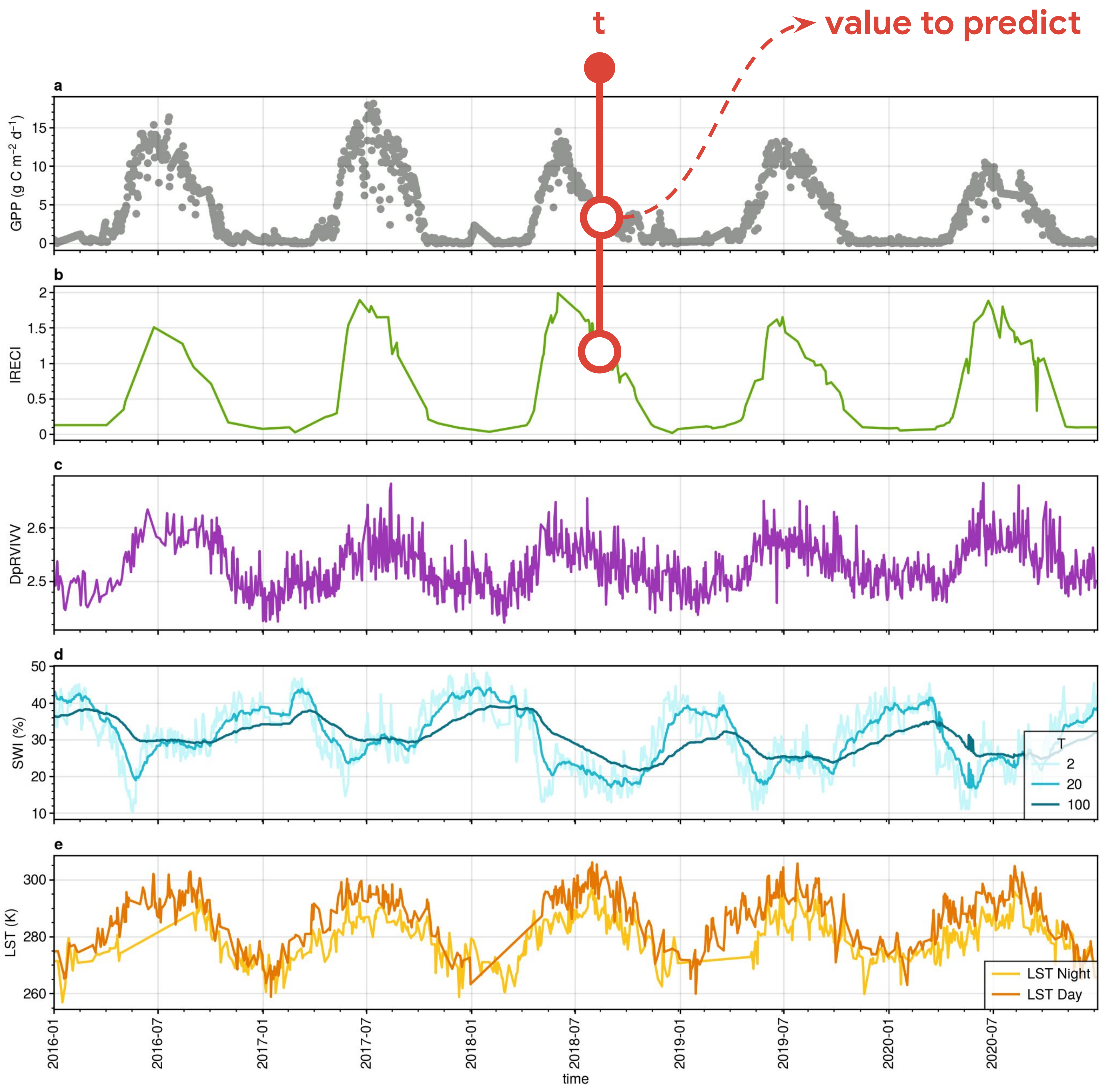
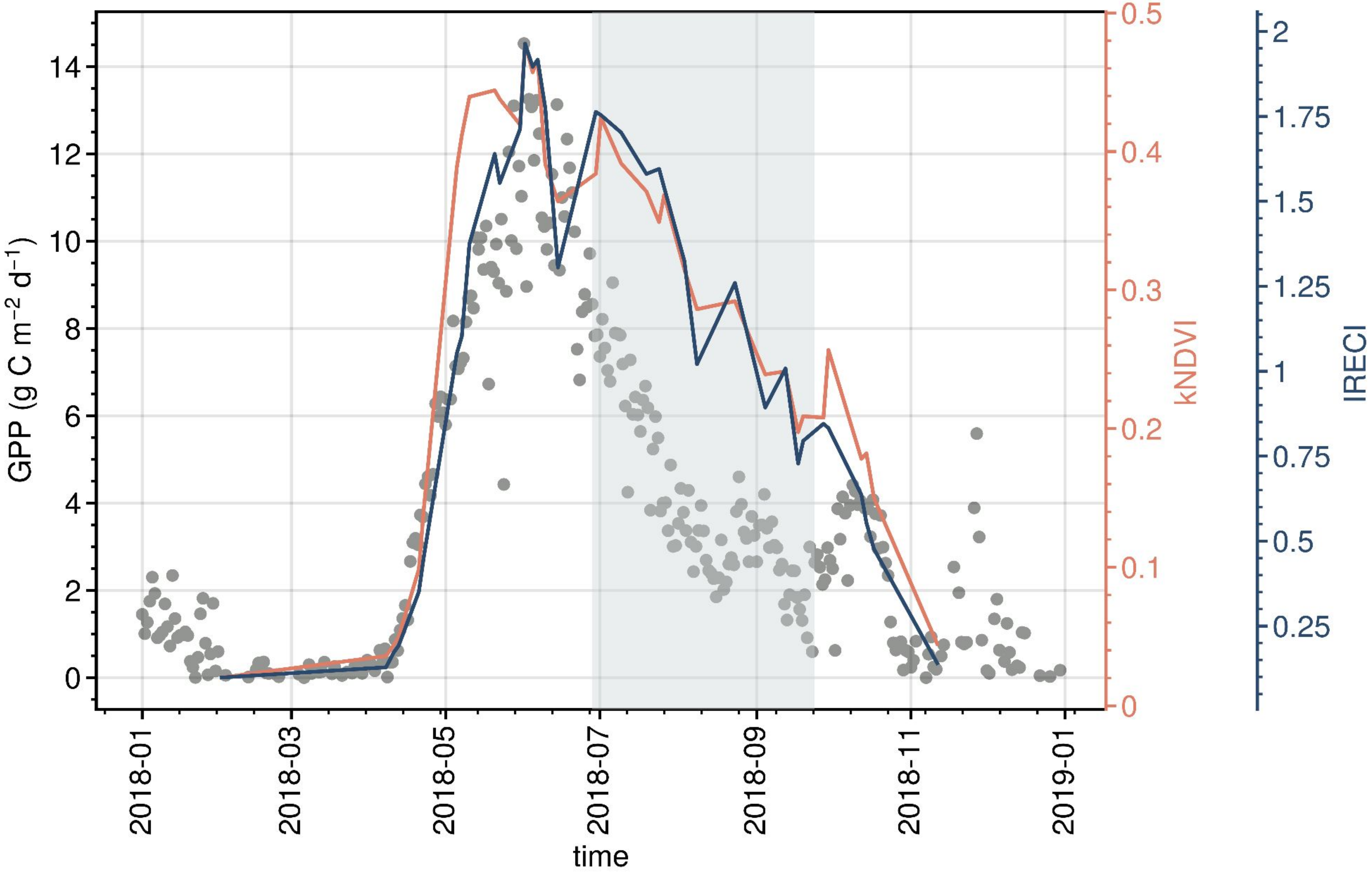


Linear regression



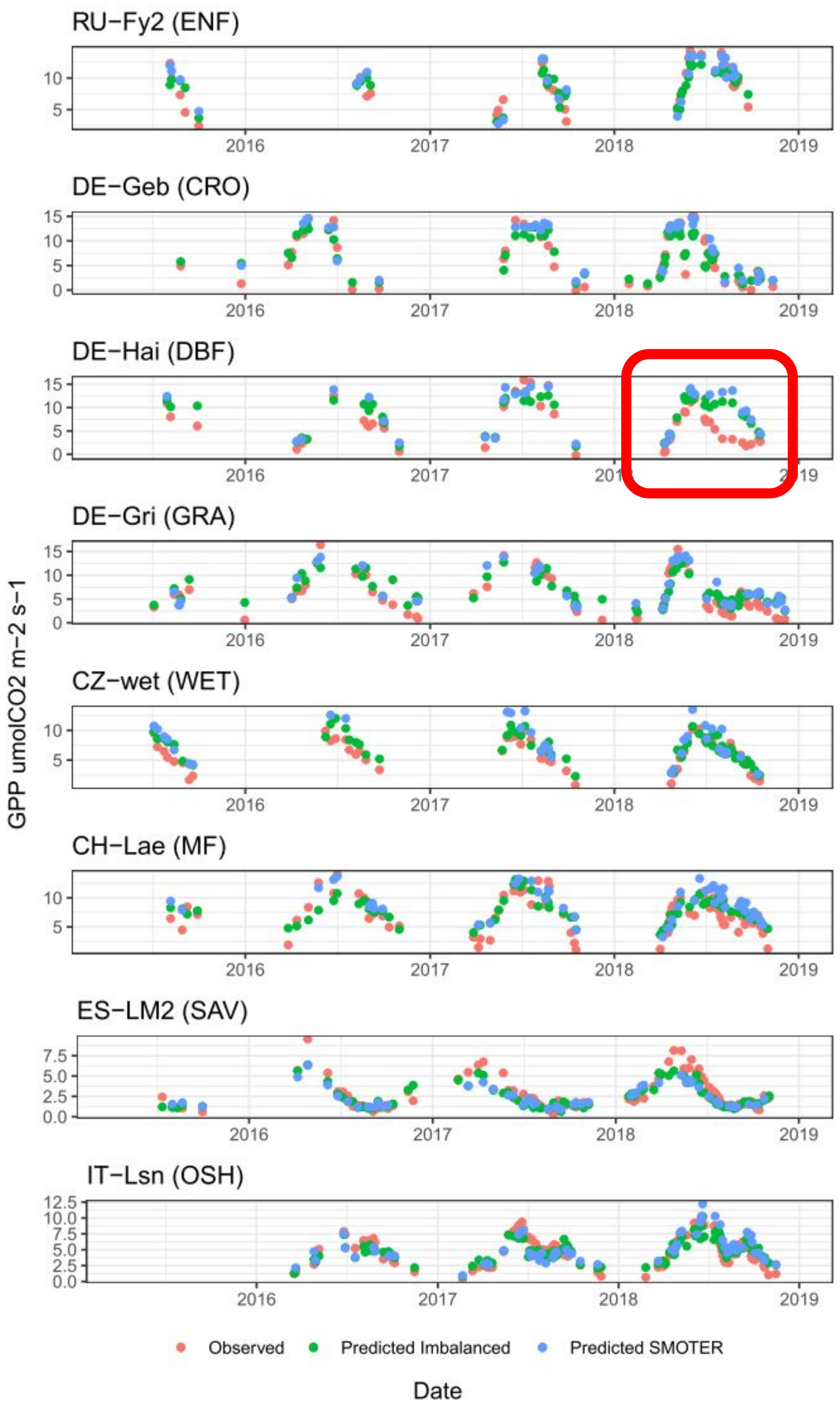
Montero et al., 2023

Poster Session

kNDVI: Kernel NDVI

IRECI: Inverted Red Edge Chlorophyll Index

Random Forests



Pabón-Moreno et al., 2022
IEEE Transactions on Geoscience and Remote Sensing

Memory of Remote Sensing variables

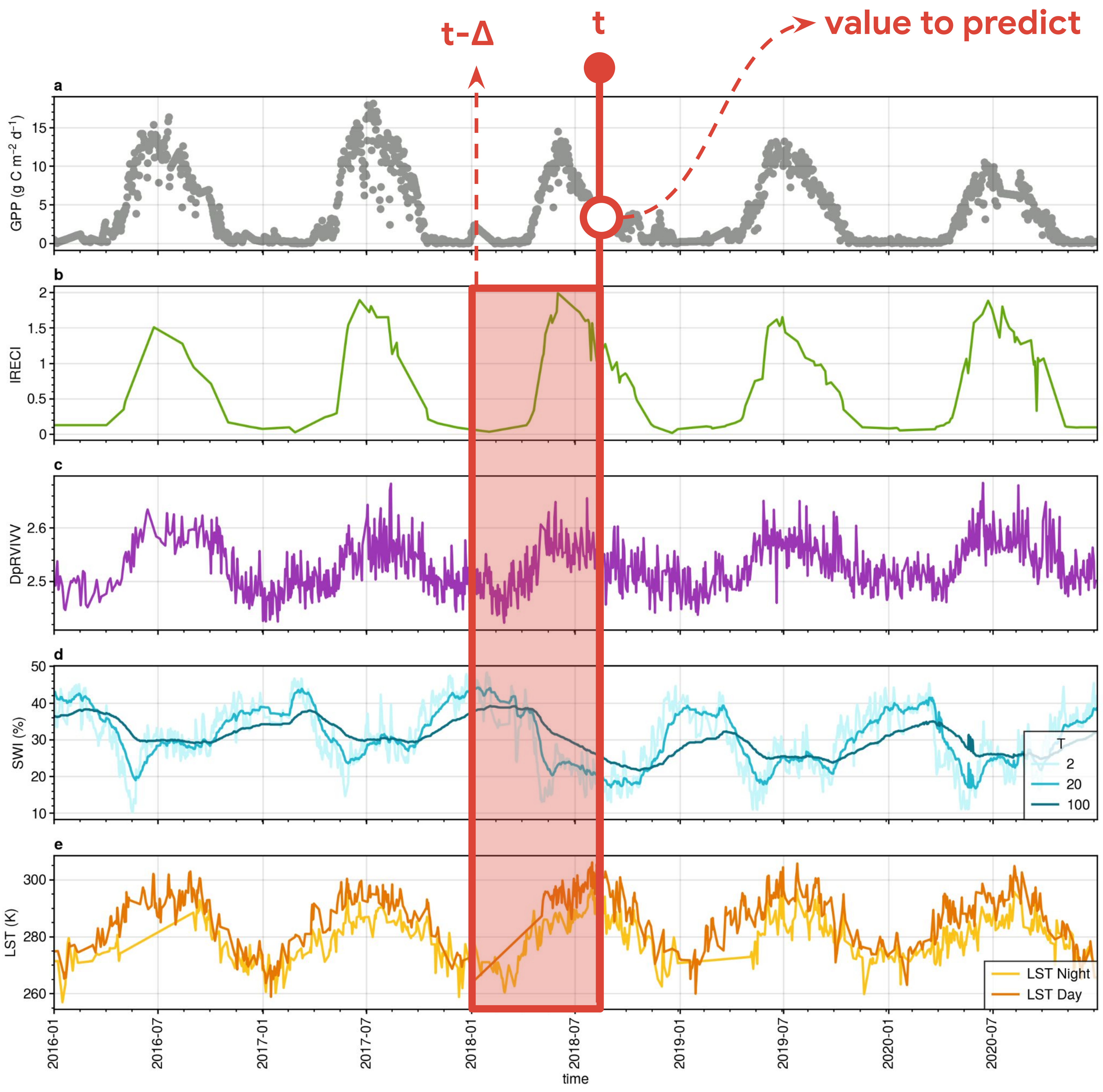
ICOS (2020 Warm Winter Dataset)
Daily GPP (g C m^{-2} d^{-1})

Sentinel-2
VIS-SWIR Surface Reflectance

Sentinel-1
VV-VH Gamma Flattened Backscattering

SCATSAR + Sentinel-1
Soil Water Index

MODIS (Terra/Aqua)
Land Surface Temperature



Memory of Remote Sensing variables

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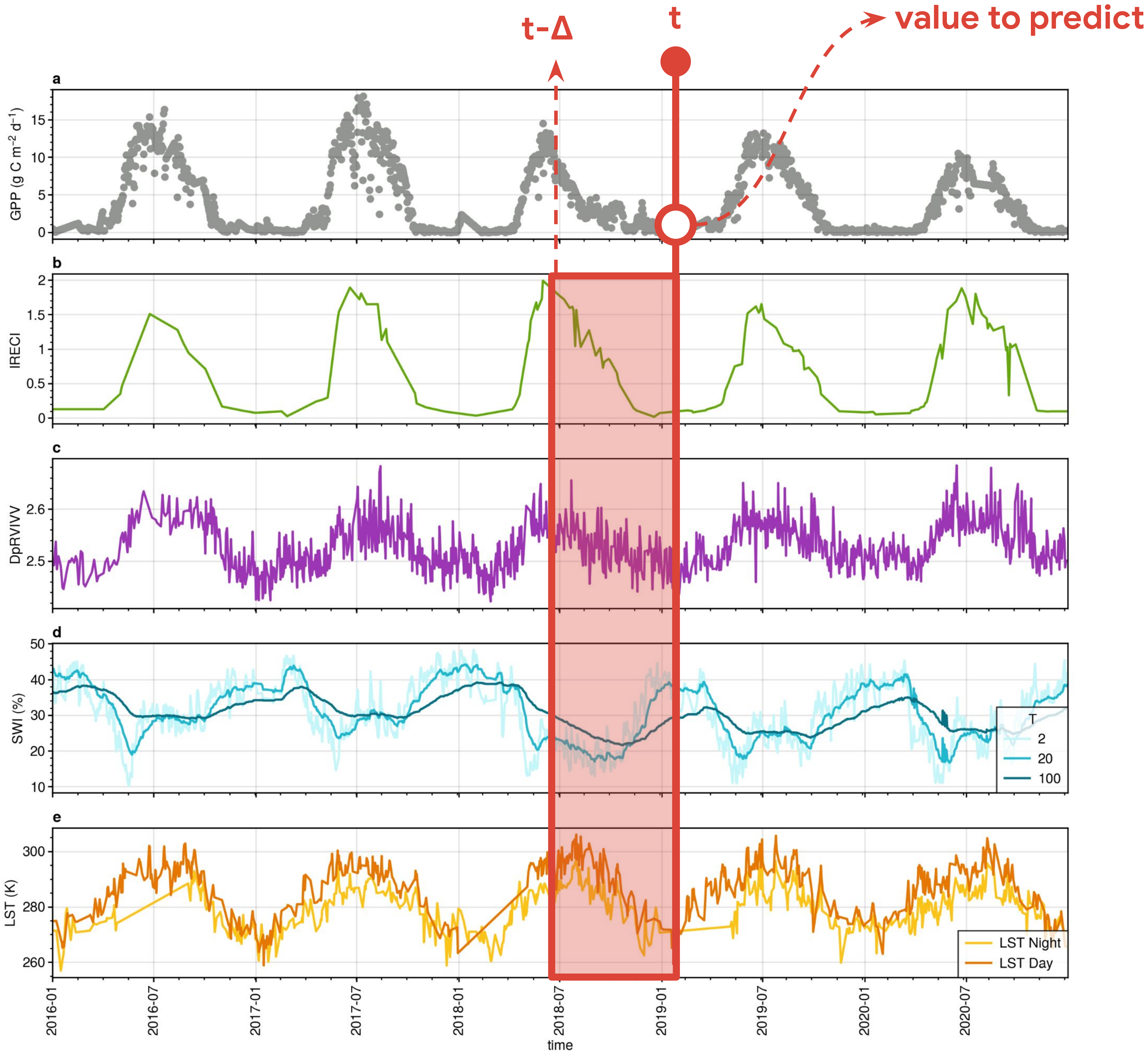
SCATSAR + Sentinel-1
Soil Water Index

MODIS (Terra/Aqua)
Land Surface Temperature



Memory of Remote Sensing variables

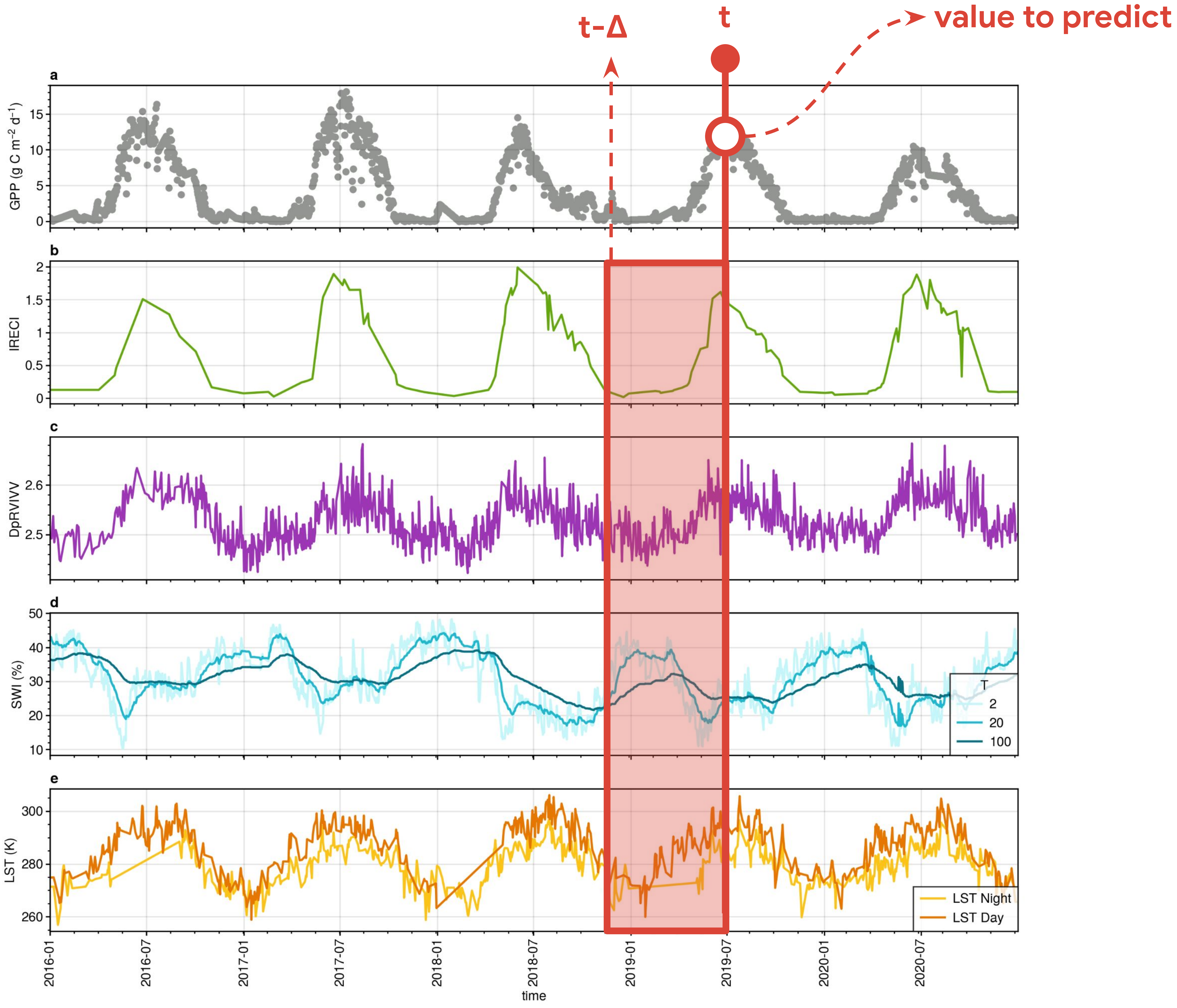
ICOS (2020 Warm Winter Dataset)
Daily GPP (g C m^{-2} d^{-1})

Sentinel-2
VIS-SWIR Surface Reflectance

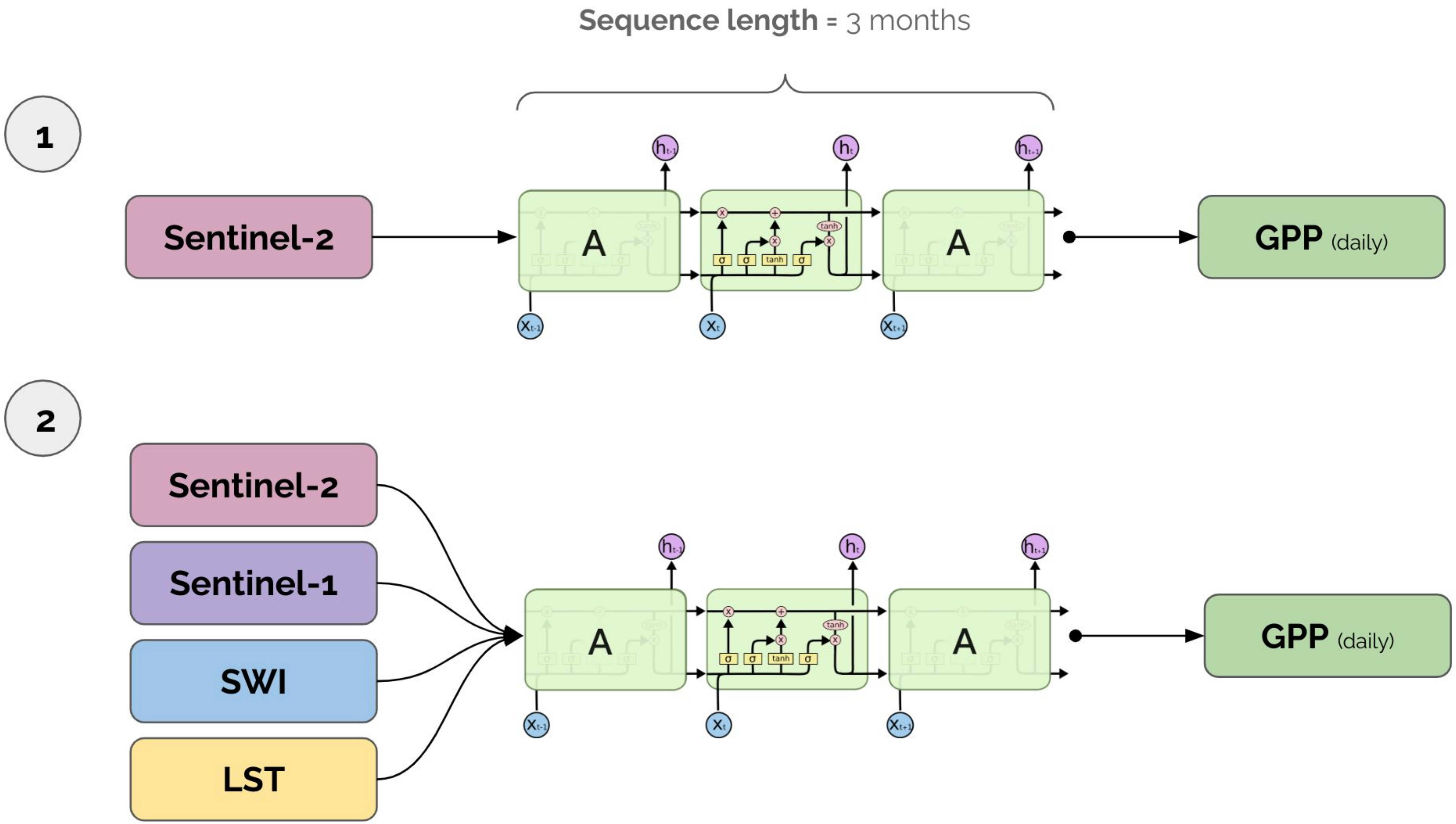
Sentinel-1
VV-VH Gamma Flattened Backscattering

SCATSAR + Sentinel-1
Soil Water Index

MODIS (Terra/Aqua)
Land Surface Temperature



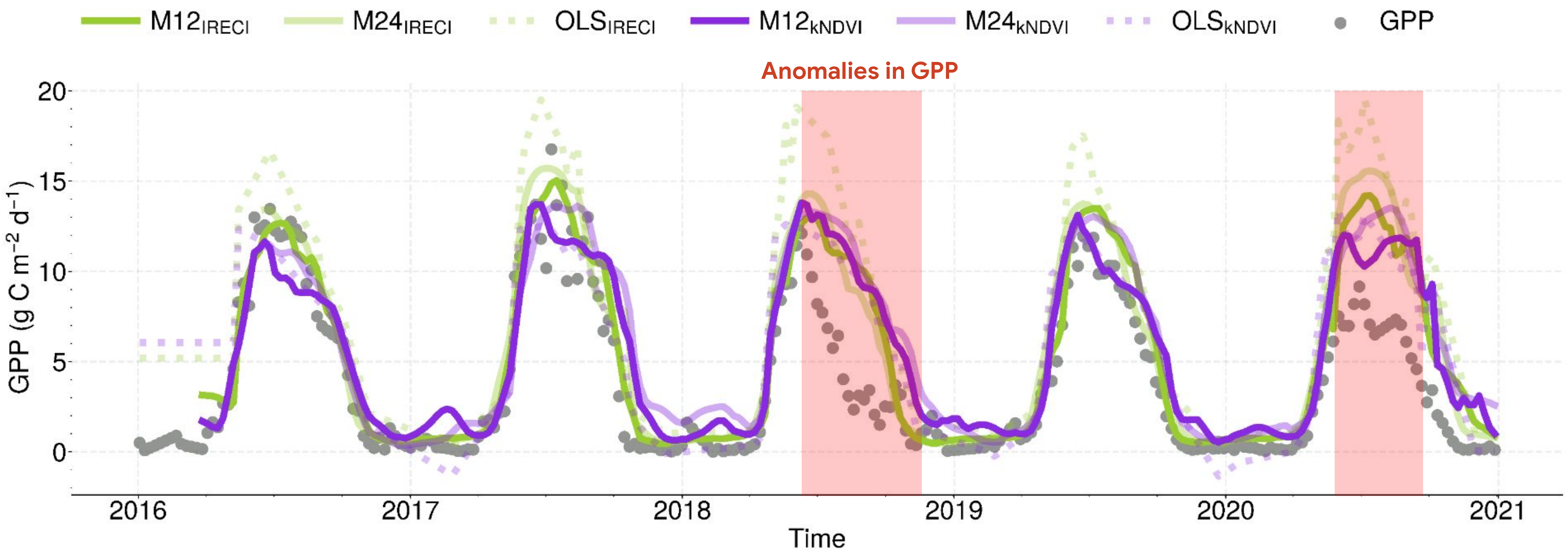
LSTMs


Sequence length = 3 months
1
Sentinel-2
A
A
GPP (daily)
2
Sentinel-2
Sentinel-1
SWI
LST
A
A
GPP (daily)

Exp 1. Using only Sentinel-2

Vegetation Indices

*Using **Sentinel-2** in weekly predictions



IRECI RMSE = **2.85** g C m^{-2} d^{-1}
kNDVI RMSE = **3.03** g C m^{-2} d^{-1}

Montero et al., 2022
Living Planet Symposium 2022

RNN: Recurrent Neural Network

Exp 2. Adding more RS variables

Sentinel-2
VIS-SWIR Surface Reflectance

Vegetation Indices

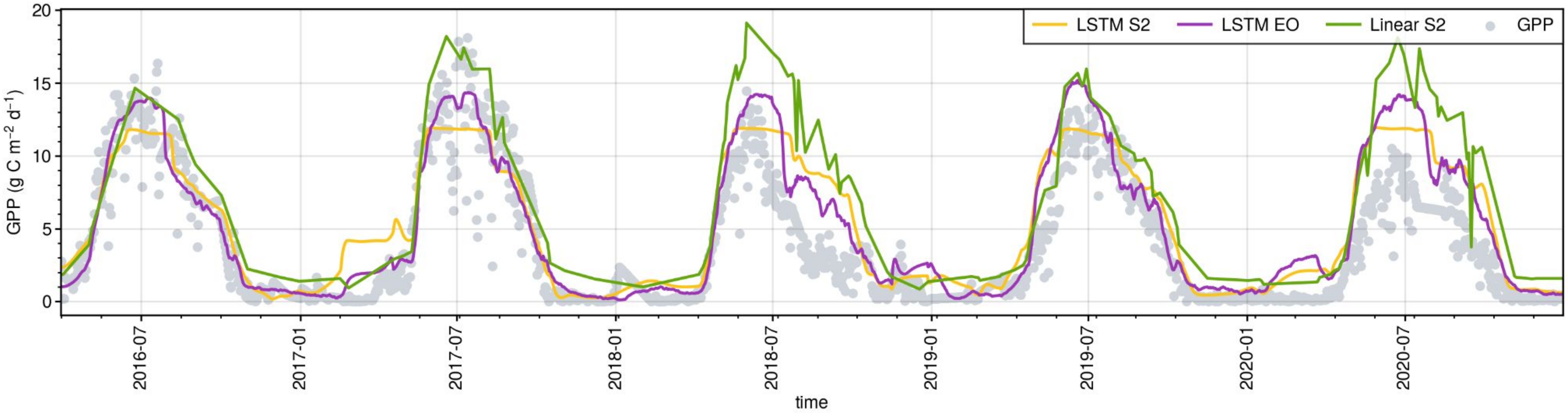
Sentinel-1
VV-VH Gamma Flattened Backscattering

Radar Indices

MODIS (Terra/Aqua)
Land Surface Temperature

SCATSAR + Sentinel-1
Soil Water Index

*Using **all features** in daily predictions



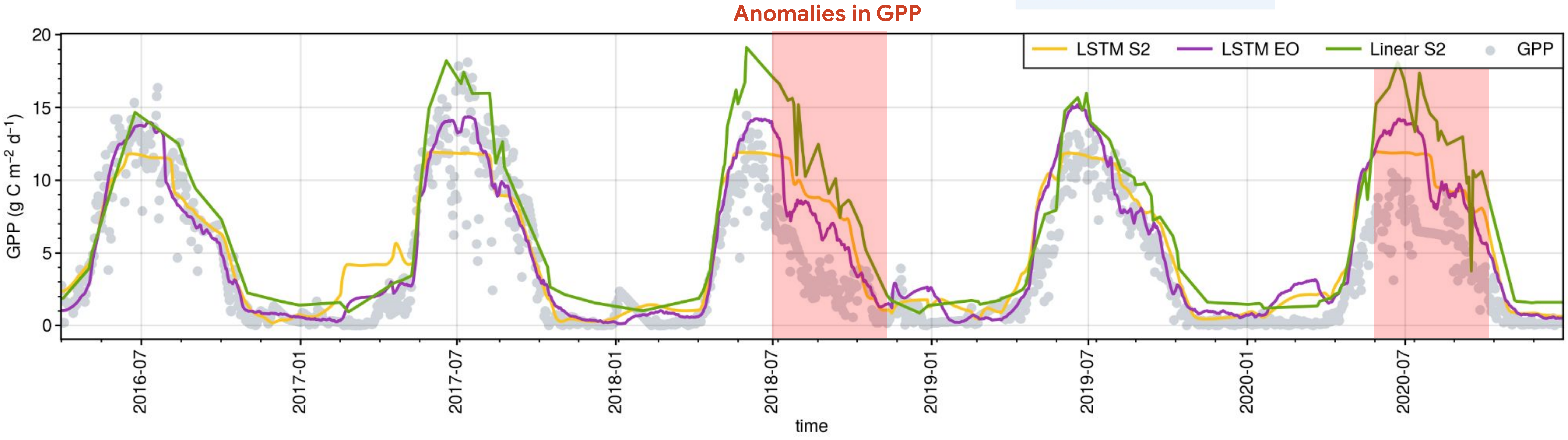
Only Sentinel-2 RMSE = **2.50** g C m^{-2} d^{-1}
Whole EO set RMSE = **2.41** g C m^{-2} d^{-1}

RS: Remote Sensing

Exp 2. Adding more RS variables

Sentinel-2 VIS-SWIR Surface Reflectance	**Vegetation Indices**
Sentinel-1 VV-VH Gamma Flattened Backscattering	**Radar Indices**
MODIS (Terra/Aqua) Land Surface Temperature	
SCATSAR + Sentinel-1 Soil Water Index	

*Using **all features** in daily predictions

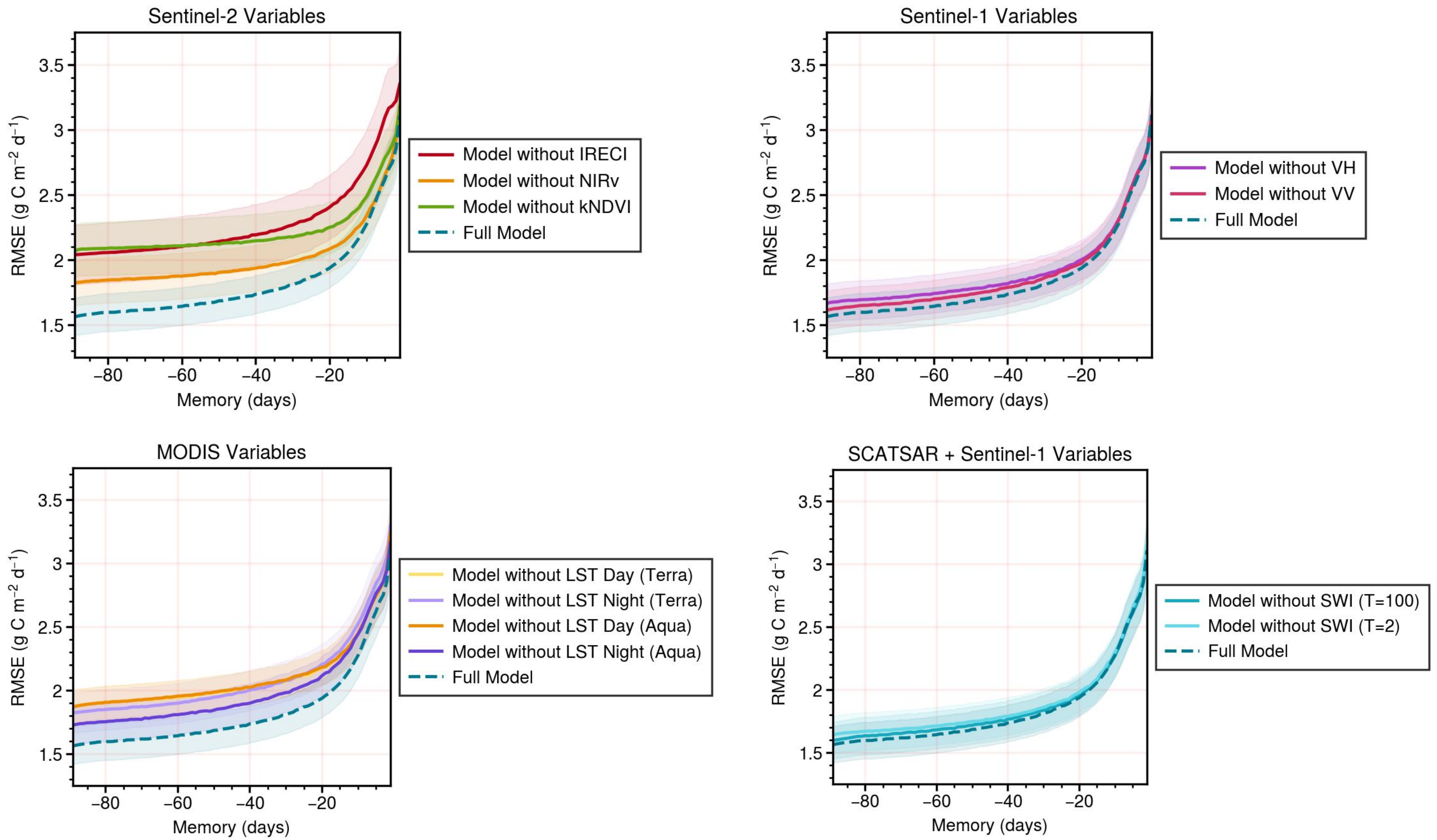


Only Sentinel-2	RMSE = **2.50** g C m^{-2} d^{-1}		RMSE = **5.24** g C m^{-2} d^{-1}
Whole EO set	RMSE = **2.41** g C m^{-2} d^{-1}	*Only extreme events*	RMSE = **4.89** g C m^{-2} d^{-1}

RS: Remote Sensing

Exp 3. The importance of memory

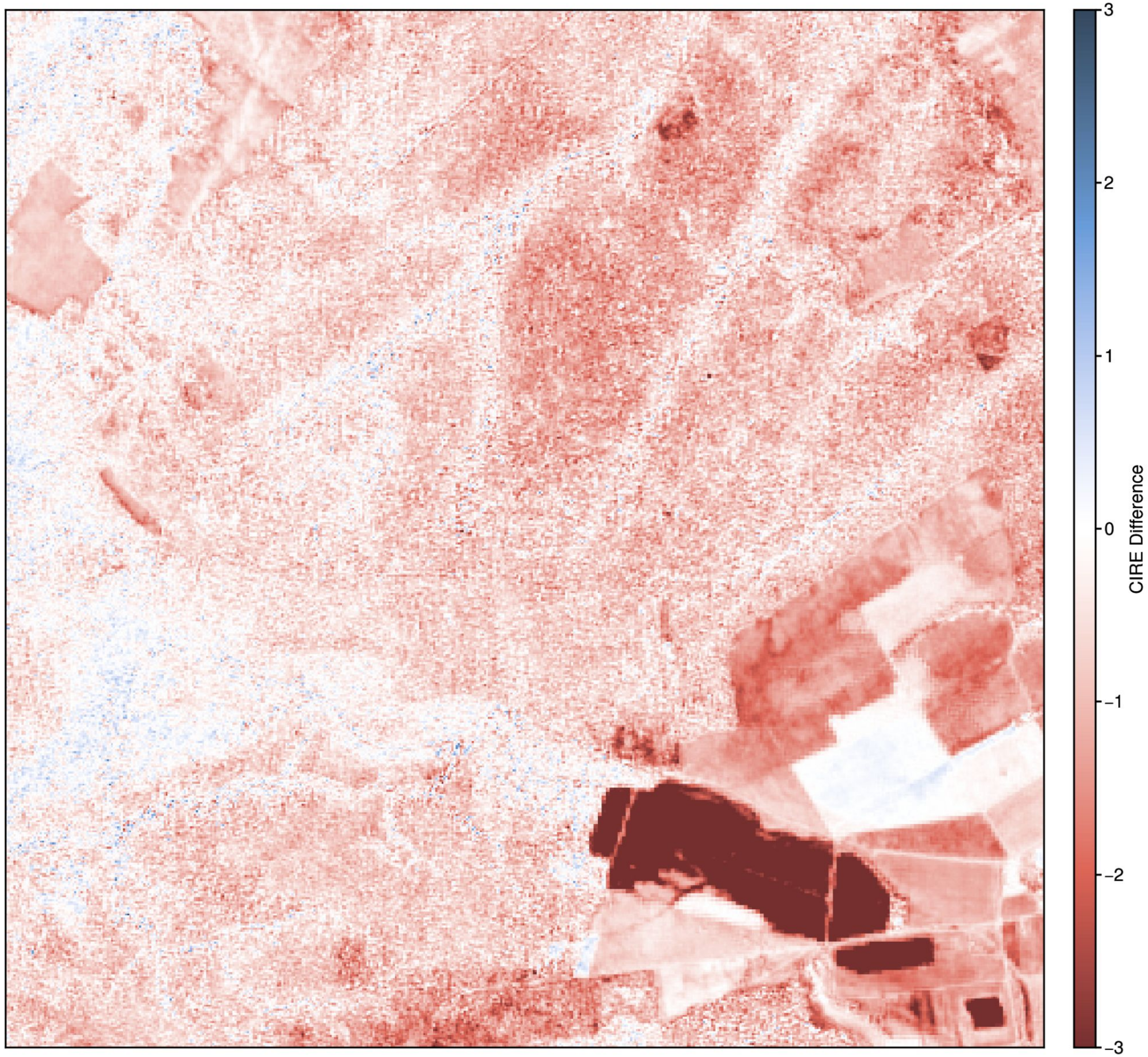
*Using **a test set of features** in **daily** predictions



Fourth Chapter
Additional Inputs?

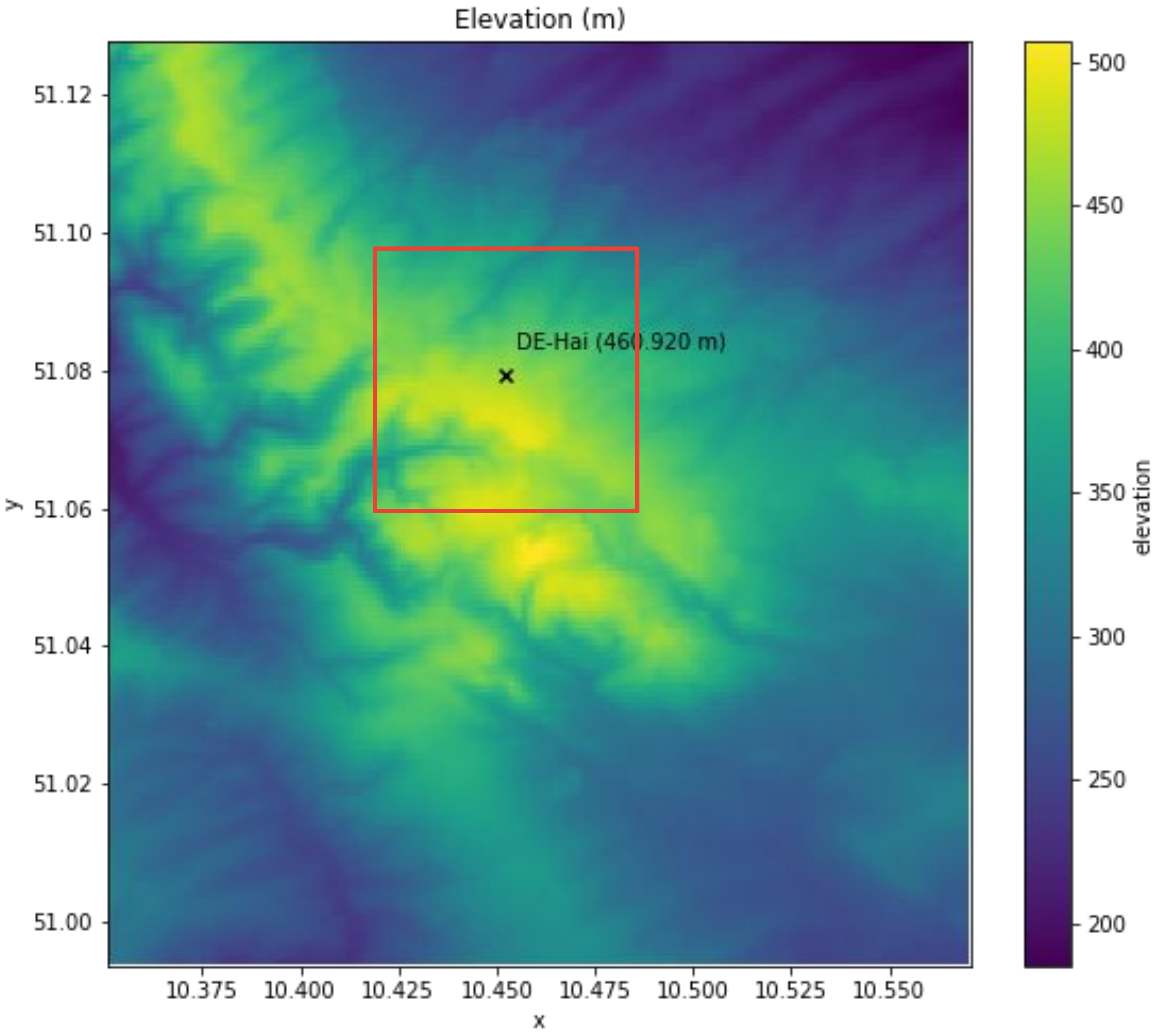
4

CIRE: Chlorophyll Index Red Edge

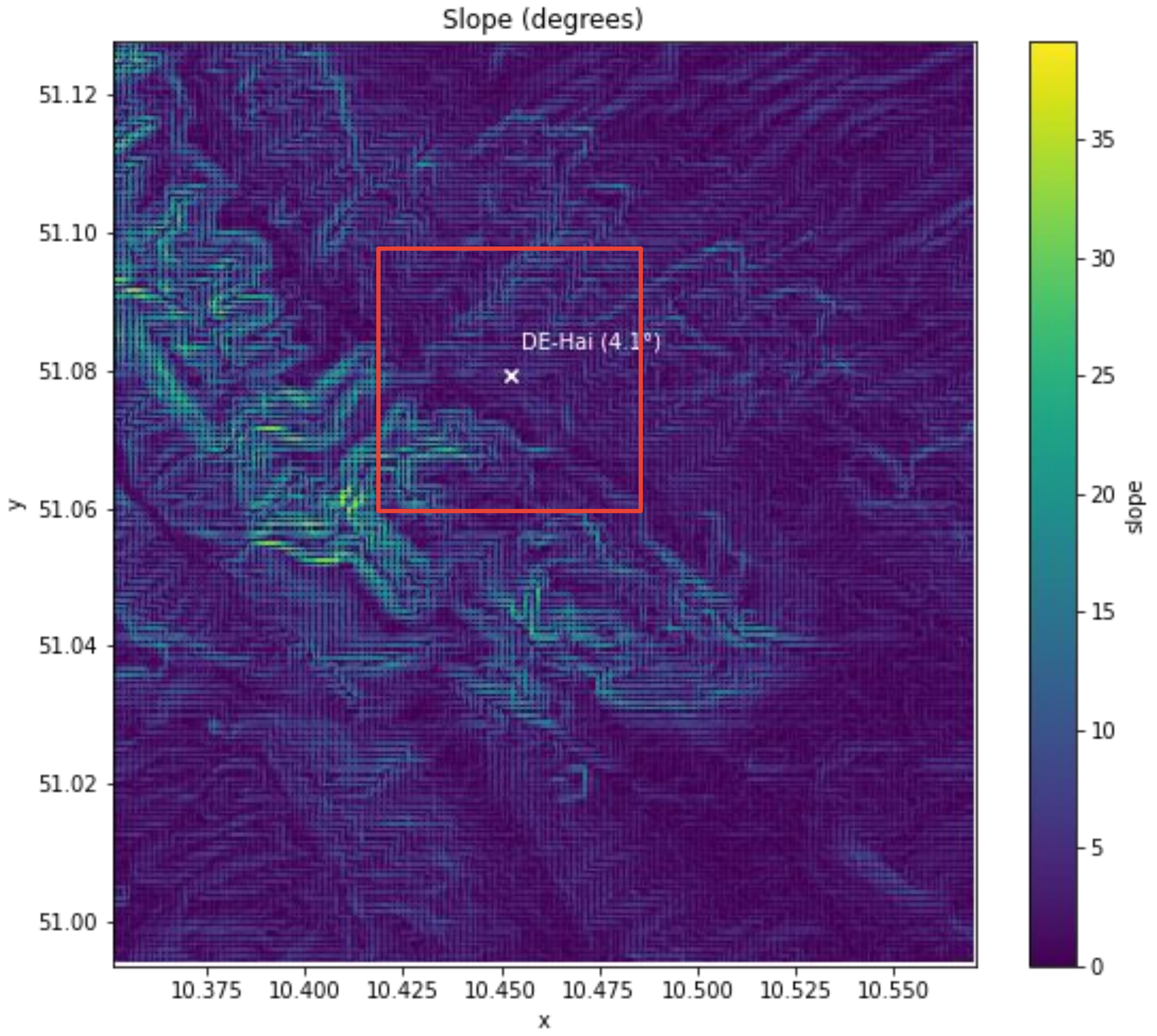


CIRE is another chlorophyll-related index. Its behaviour is close to the IRECI's behaviour.

Topography

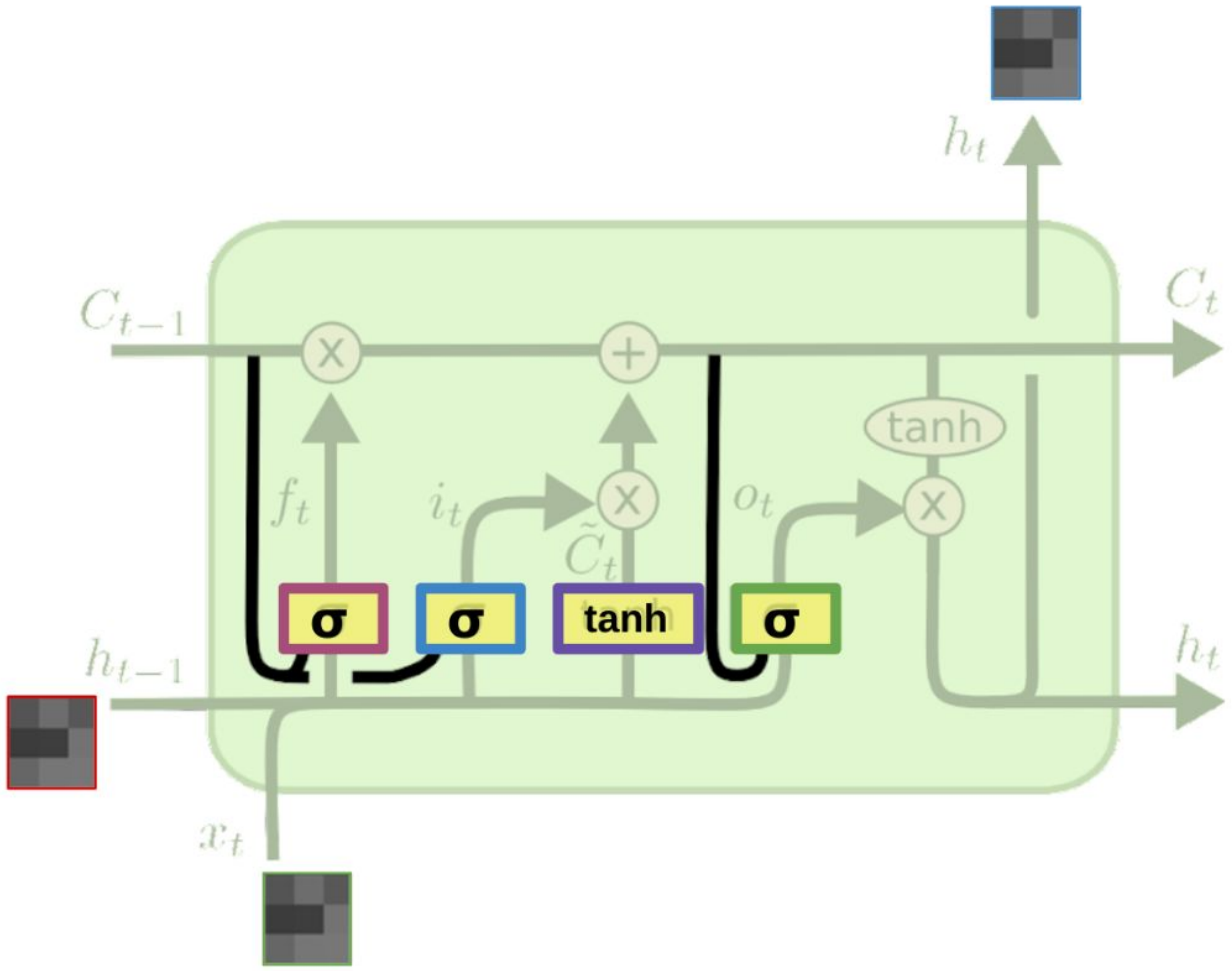


Elevation (m)
DE-Hai (460.920 m)
51.12
51.10
51.08
51.06
51.04
51.02
51.00
y
10.375 10.400 10.425 10.450 10.475 10.500 10.525 10.550
x
500
450
400
350
300
250
200
elevation



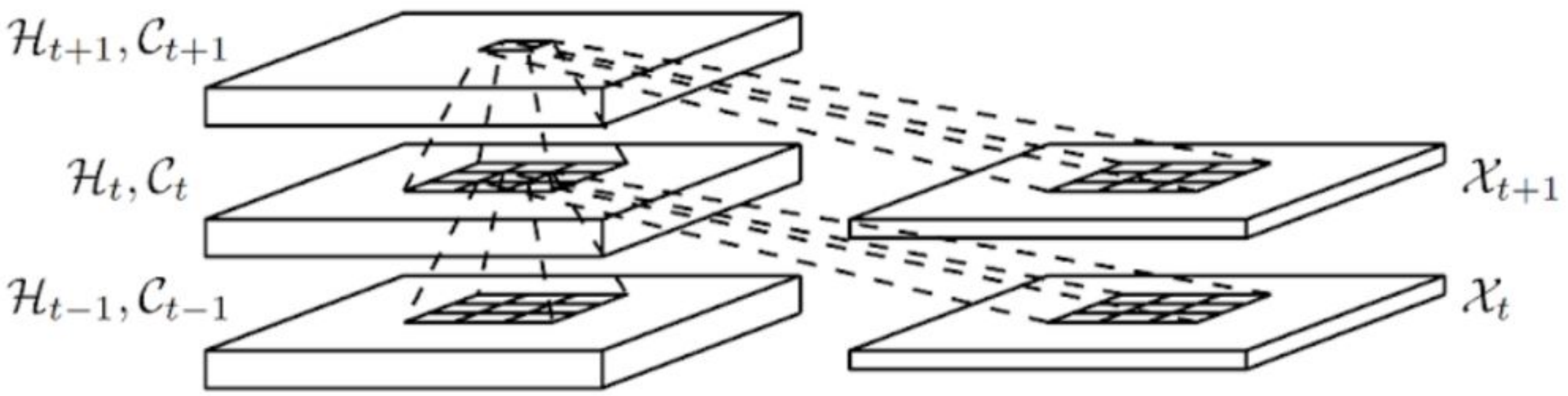
Slope (degrees)
DE-Hai (4.1°)
51.12
51.10
51.08
51.06
51.04
51.02
51.00
y
10.375 10.400 10.425 10.450 10.475 10.500 10.525 10.550
x
35
30
25
20
15
10
5
0
slope

ConvLSTMs



Now we use convolutions!!

$$
\begin{aligned}
i_t &= \sigma(\boxed{W_{xi} * \mathcal{X}_t + W_{hi} * \mathcal{H}_{t-1}} + W_{ci} \circ \mathcal{C}_{t-1} + b_i) \\
f_t &= \sigma(\boxed{W_{xf} * \mathcal{X}_t + W_{hf} * \mathcal{H}_{t-1}} + W_{cf} \circ \mathcal{C}_{t-1} + b_f) \\
\mathcal{C}_t &= f_t \circ \mathcal{C}_{t-1} + i_t \circ \tanh(\boxed{W_{xc} * \mathcal{X}_t + W_{hc} * \mathcal{H}_{t-1}} + b_c) \\
o_t &= \sigma(\boxed{W_{xo} * \mathcal{X}_t + W_{ho} * \mathcal{H}_{t-1}} + W_{co} \circ \mathcal{C}_t + b_o) \\
\mathcal{H}_t &= o_t \circ \tanh(\mathcal{C}_t)
\end{aligned}
$$



Summary

Take-home message

Take-home

1. Exploiting the memory of Remote Sensing signals improves the GPP estimation in forests.

2. Considering the temporal dependencies using Deep Learning improves the GPP prediction during extreme events.

Take-home

1

2

Robust data gathering, curation, and engineering ensures the acquisition of high-quality data for hypothesis testing.

The inclusion of memory from Remote Sensing variables in Deep Learning models improves GPP estimation.

Additional investigation will assess their effectiveness during extreme events.

Take-home

1

Robust data gathering, curation, and engineering ensures the acquisition of high-quality data for hypothesis testing.

The inclusion of memory from Remote Sensing variables in Deep Learning models improves GPP estimation.

2

Additional investigation will assess their effectiveness during extreme events.

Take-home

1

2

Robust data gathering, curation, and engineering ensures the acquisition of high-quality data for hypothesis testing.

The inclusion of memory from Remote Sensing variables in Deep Learning models improves GPP estimation.

Additional investigation will assess their effectiveness during extreme events.

Thank **you**!

PhD Candidate
David Montero Loaiza

RSC4Earth Collaborators
Dr. Sebastian Wieneke
Prof. Dr. Miguel D. Mahecha

Support
Slides

A **standard** was required

Table 2 Standard band naming and the corresponding band number for different platforms.

From: A standardized catalogue of spectral indices to advance the use of remote sensing in Earth system research

Band	Standard	Landsat			Sentinel		Terra/Aqua
		TM	ETM+	OLI	MSI-2A	MSI-2B	MODIS
Aerosols	A			1 (440.0)	1 (442.7)	1 (442.3)	
Blue	B	1 (485.0)	1 (485.0)	2 (480.0)	2 (492.4)	2 (492.1)	3 (469.0)
Green 1	G1						11 (531.0)
Green	G	2 (560.0)	2 (560.0)	3 (560.0)	3 (559.8)	3 (559.0)	4 (555.0)
Yellow	Y						
Red	R	3 (660.0)	3 (660.0)	4 (655.0)	4 (664.6)	4 (665.0)	1 (645.0)
Red Edge 1	RE1				5 (704.1)	5 (703.8)	
Red Edge 2	RE2				6 (740.5)	6 (739.1)	
Red Edge 3	RE3				7 (782.8)	7 (779.7)	
Near Infrared	N	4 (830.0)	4 (835.0)	5 (865.0)	8 (832.8)	8 (833.0)	2 (858.5)
Near Infrared 2	N2				8A (864.7)	8A (864.0)	
Water Vapour	WV				9 (945.1)	9 (943.2)	
Short-wave Infrared 1	S1	5 (1650.0)	5 (1650.0)	6 (1610.0)	11 (1613.7)	11 (1610.4)	6 (1640.0)
Short-wave Infrared 2	S2	7 (2215.0)	7 (2220.0)	7 (2200.0)	12 (2202.4)	12 (2185.7)	7 (2130.0)
Thermal Infrared	T	6 (11450.0)	6 (11450.0)				
Thermal Infrared 1	T1			10 (10895.0)			
Thermal Infrared 2	T2			11 (12005.0)			

Central wavelengths in nm are specified for each platform in parenthesis.

A **standard** was required

Table 2 Standard band naming and the corresponding band number for different platforms.

From: A standardized catalogue of spectral indices to advance the use of remote sensing in Earth system research

$$\mathrm{NDVI} = (\rho_{\mathrm{NIR}} - \rho_{\mathrm{red}}) \,/\, (\rho_{\mathrm{NIR}} + \rho_{\mathrm{red}})$$

$$E_{\mathrm{NDVI}} = \ll (\mathrm{N} - \mathrm{R})/(\mathrm{N} + \mathrm{R}) \gg$$

Band	Standard	Landsat			Sentinel		Terra/Aqua
							DIS
Aerosols							
Blue							69.0)
Green 1							531.0)
Green	G	2 (560.0)	2 (560.0)	3 (560.0)	3 (559.8)	3 (559.0)	4 (555.0)
Yellow	Y						
Red	R	3 (660.0)	3 (660.0)	4 (655.0)	4 (664.6)	4 (665.0)	1 (645.0)
Red Edge 1	RE1				5 (704.1)	5 (703.8)	
Red Edge 2							
Red Edge 3							
Near Infrared							58.5)
Near Infrared 2							
Water Vapour	WV				9 (945.1)	9 (943.2)	
Short-wave Infrared 1	S1	5 (1650.0)	5 (1650.0)	6 (1610.0)	11 (1613.7)	11 (1610.4)	6 (1640.0)
Short-wave Infrared 2	S2	7 (2215.0)	7 (2220.0)	7 (2200.0)	12 (2202.4)	12 (2185.7)	7 (2130.0)
Thermal Infrared	T	6 (11450.0)	6 (11450.0)				
Thermal Infrared 1	T1			10 (10895.0)			
Thermal Infrared 2	T2			11 (12005.0)			

Central wavelengths in nm are specified for each platform in parenthesis.

A **standard** was required

Table 3 Standard additional parameters naming and the spectral indices where they are used.

From: A standardized catalogue of spectral indices to advance the use of remote sensing in Earth system research

Parameter	Standard	Spectral Indices
Gain Factor	g	EVI
Canopy Background Adjustment	L	EVI, EVI2, MNLI, SARVI, SAVI, SAVIT
First Coefficient for the aerosol resistance term	C1	EVI, kEVI
Second Coefficient for the aerosol resistance term	C2	EVI, kEVI
c correction factor	cexp	OCVI
n exponent for the SR power operation	nexp	GDVI
α weighting coefficient	alpha	BWDRVI, NDPI, WDRVI
β calibration parameter	beta	$NDSI_{ns}$
γ weighting coefficient	gamma	ARVI
ω weighting coefficient	omega	MBWI
$f(\Delta)$ adjustment factor for terrain shadows distortion	fdelta	SEVI
Soil line slope	sla	ATSAVI, SAVI2, TSAVI, WDVI
Soil line intercept	slb	ATSAVI, SAVI2, TSAVI
Photosynthetically Active Radiation	PAR	NIRvP
Soil slope parameter	k	NIRvH2
Center wavelength of band A (nm)	lambdaA	DVI+, NDGI, NIRvH2
Kernel function of A and B	kAB	kEVI, kNDVI, kRVI, kVARI

Computing Spectral Indices easily

Python

Awesome Spectral Indices in Python

A ready-to-use curated list of Spectral Indices for Remote Sensing applications

Awesome Spectral Indices for the Google Earth Engine JavaScript API

```python
idx = spyndex.computeIndex(
    index=["NDVI", "NIRv", "kNDVI"],
    N=da.sel(band="B08"),
    R=da.sel(band="B04"),
    kNN=1.0,
    kNR=spyndex.computeKernel(
        kernel="RBF",
        a=da.sel(band="B08"),
        b=da.sel(band="B04"),
        sigma=da.sel(band=["B08","B04"]).mean("band").median("time")
    )
)
```

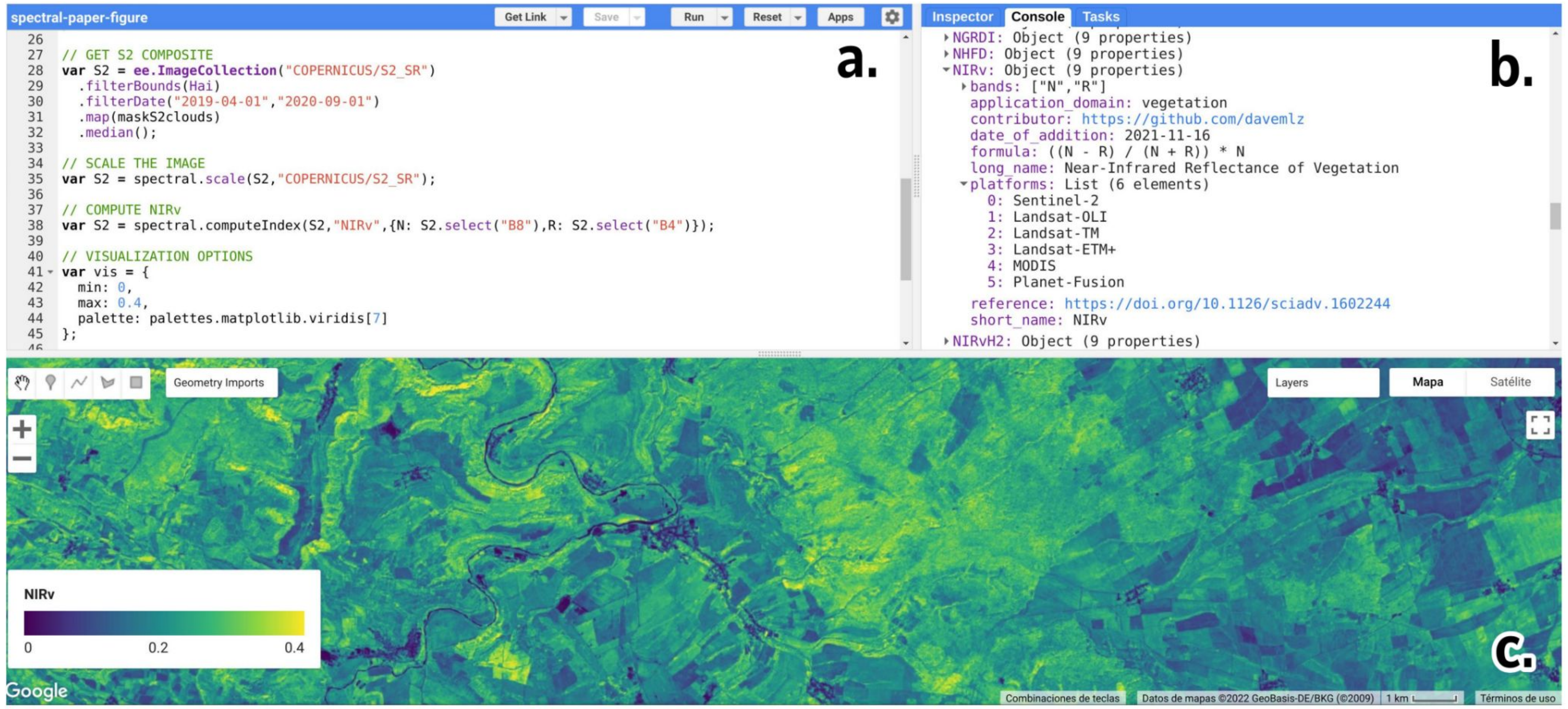
Computing Spectral Indices easily

Google Earth Engine

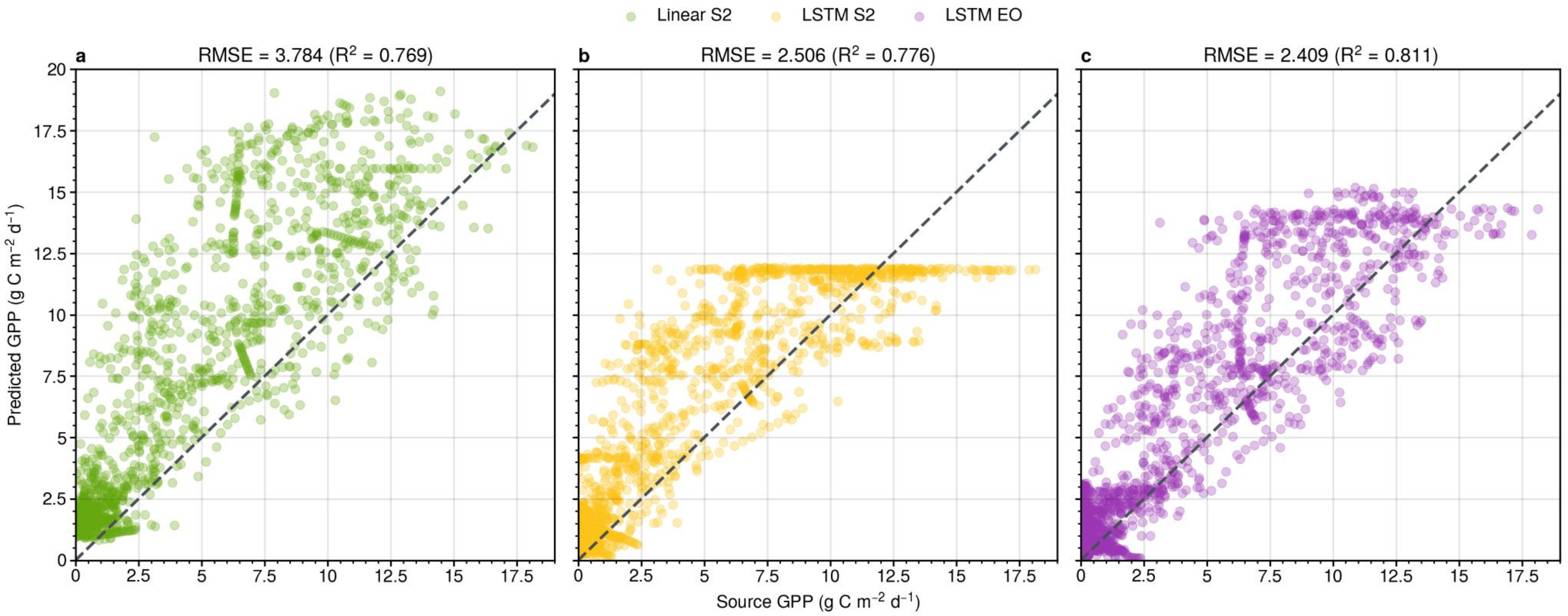
Awesome Spectral Indices in Python

A ready-to-use curated list of Spectral Indices for Remote Sensing applications

Awesome Spectral Indices for the Google Earth Engine JavaScript API



Exp 2. Scatter plots



Exp 2. Scatter plots under extreme events