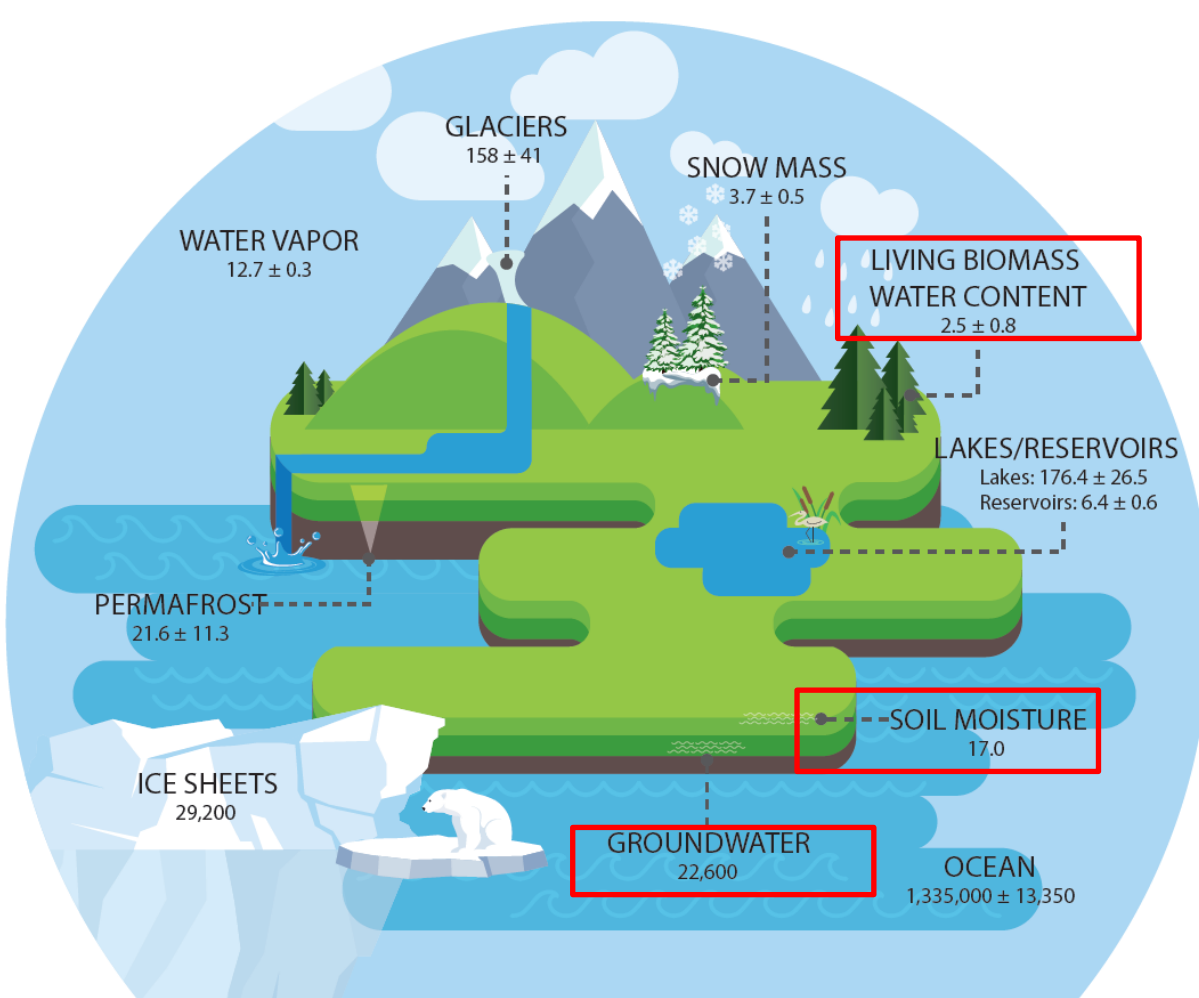


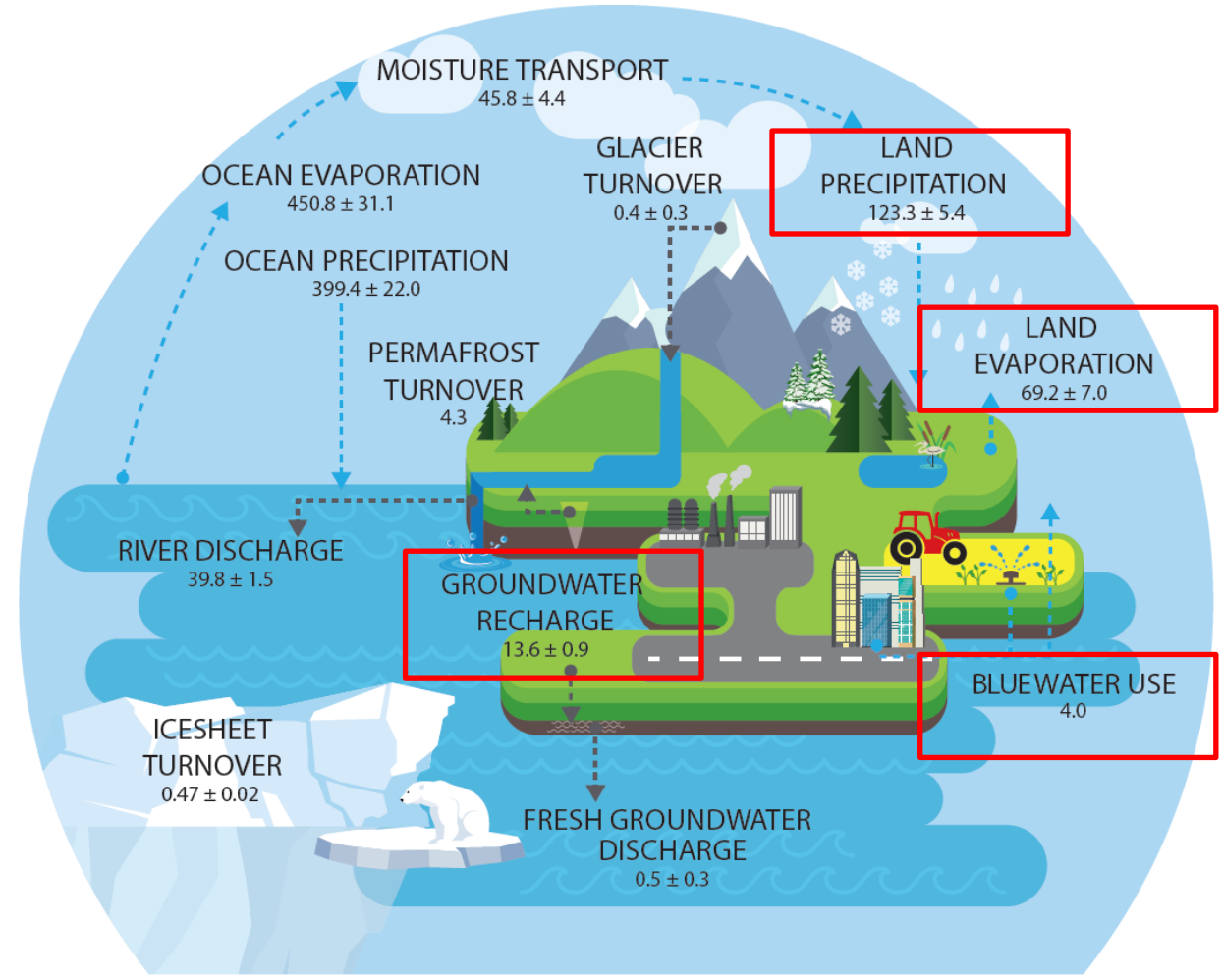
# ESA Land Training course '22

## *Drought monitoring and forecasting*

Wouter Dorigo, Wolfgang Preimesberger, Mariette Vreugdenhil

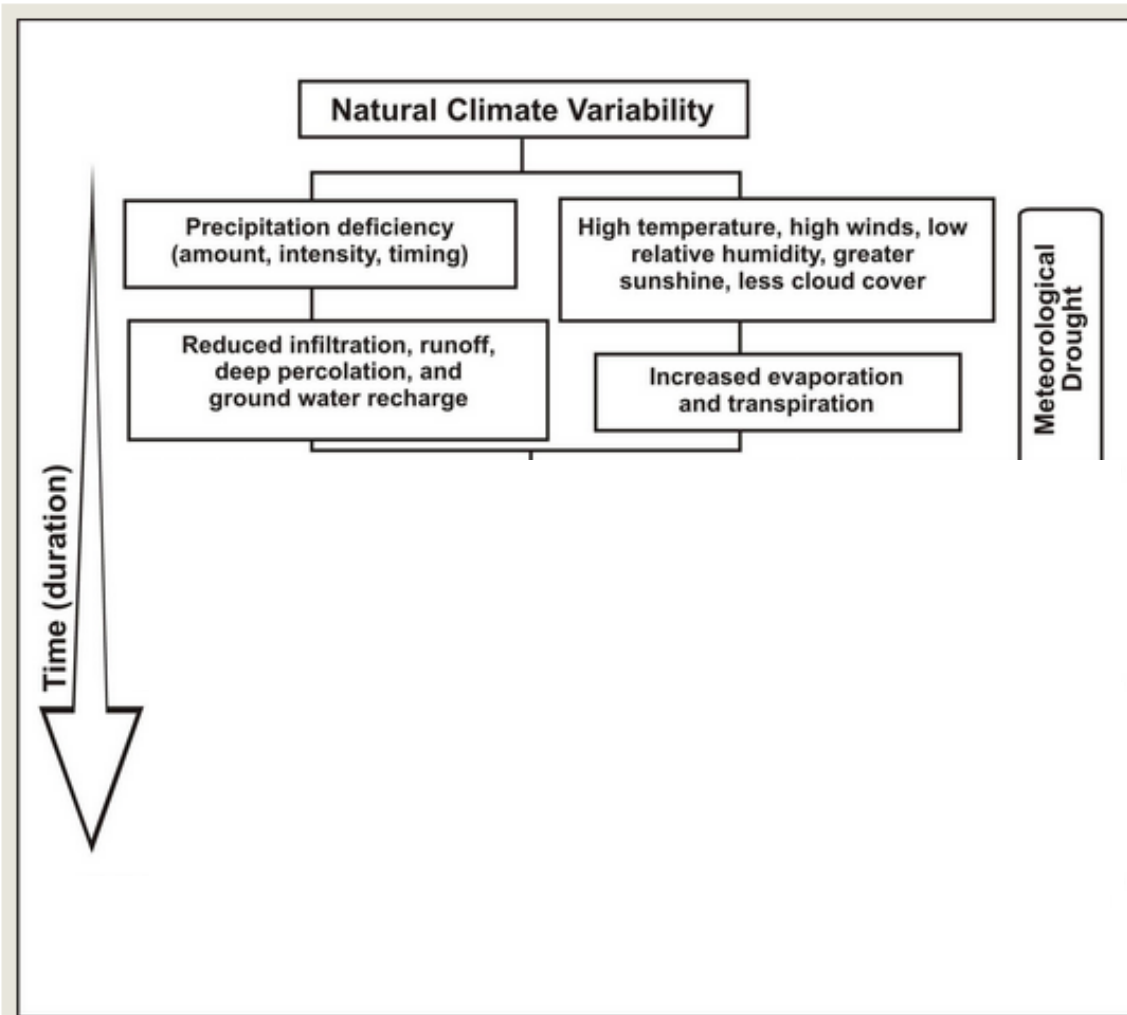


**GLOBAL WATER STORAGES**  
[10<sup>3</sup> km<sup>3</sup>]



**GLOBAL WATER CYCLE FLUXES**

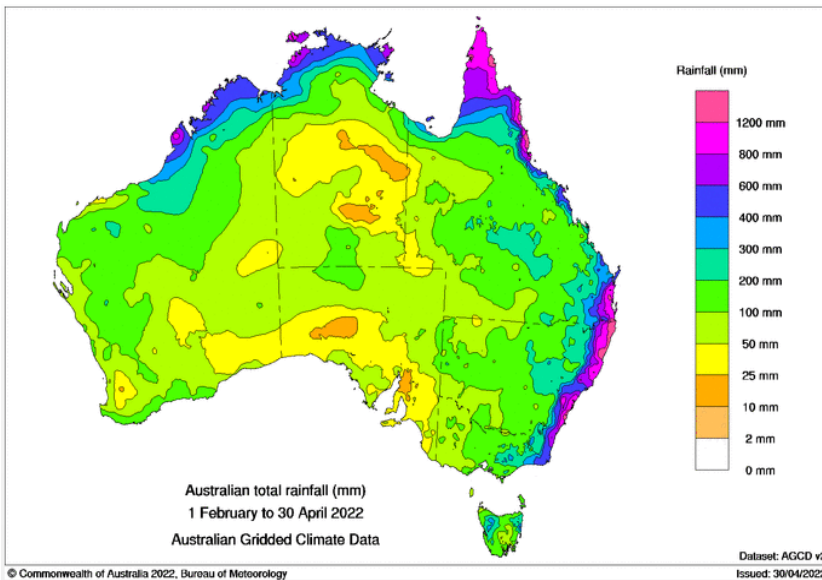
[10<sup>3</sup> km<sup>3</sup>y<sup>-1</sup>] [Dorigo et al., 2021]



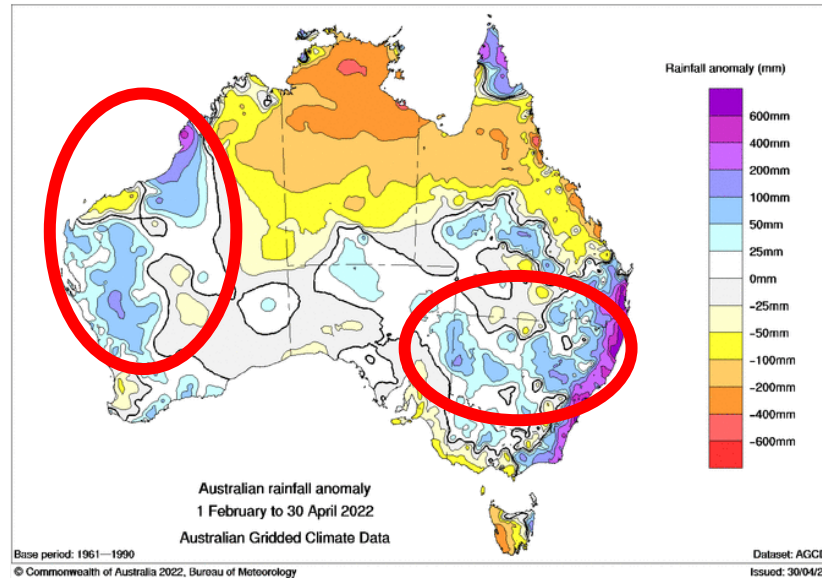
Sequence of drought occurrence and impacts for commonly accepted drought types. All droughts originate from a deficiency of precipitation or meteorological drought but other types of drought and impacts cascade from this deficiency. (Source: National Drought Mitigation Center, University of Nebraska-Lincoln, U.S.A.)

- Drought is not a physical variable but an indicator of deviating conditions, and can be expressed in various ways

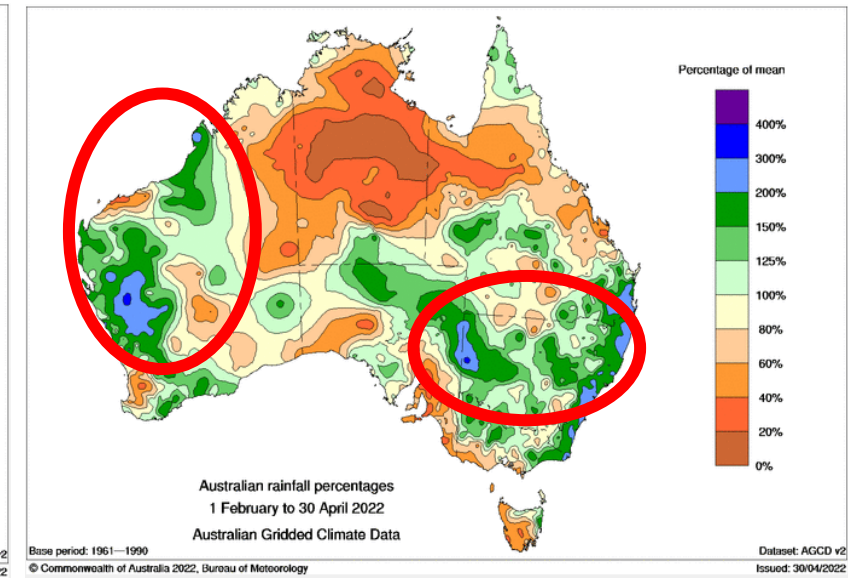
Rainfall January-April 2022 [mm]



Anomaly from long-term mean rainfall [mm]

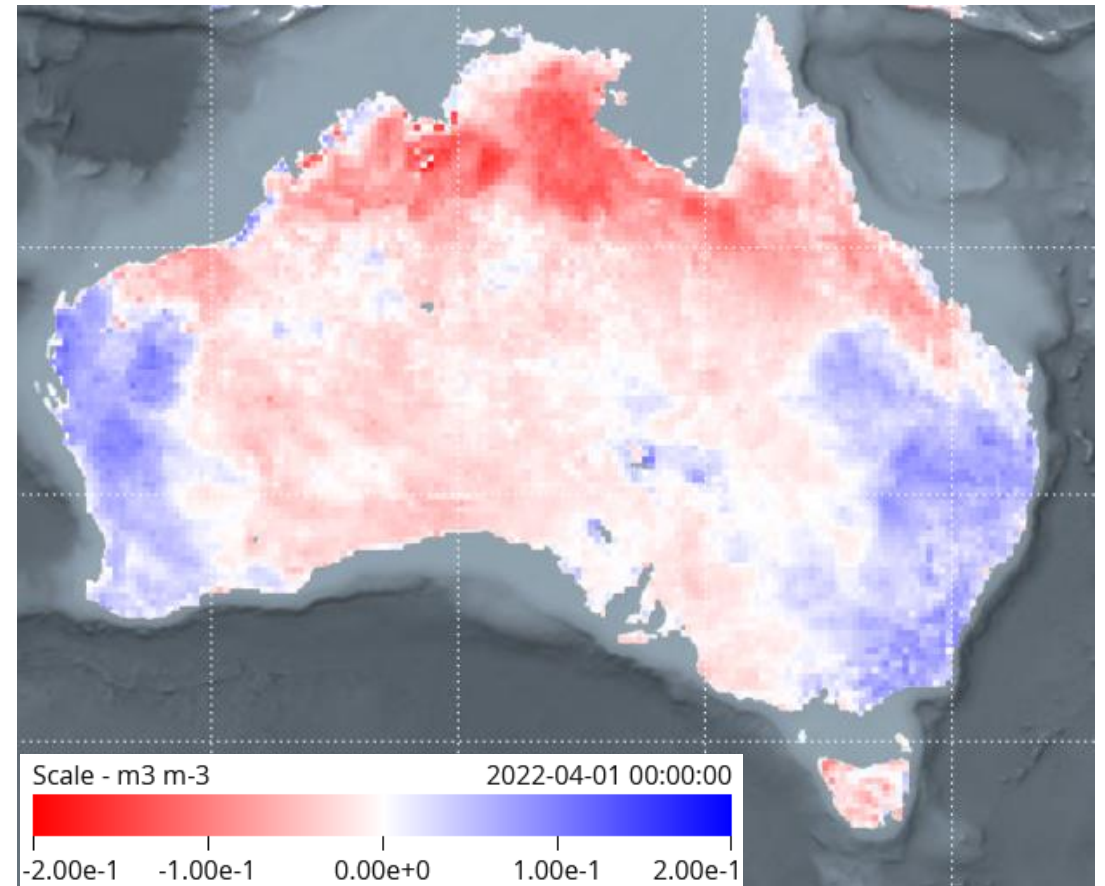
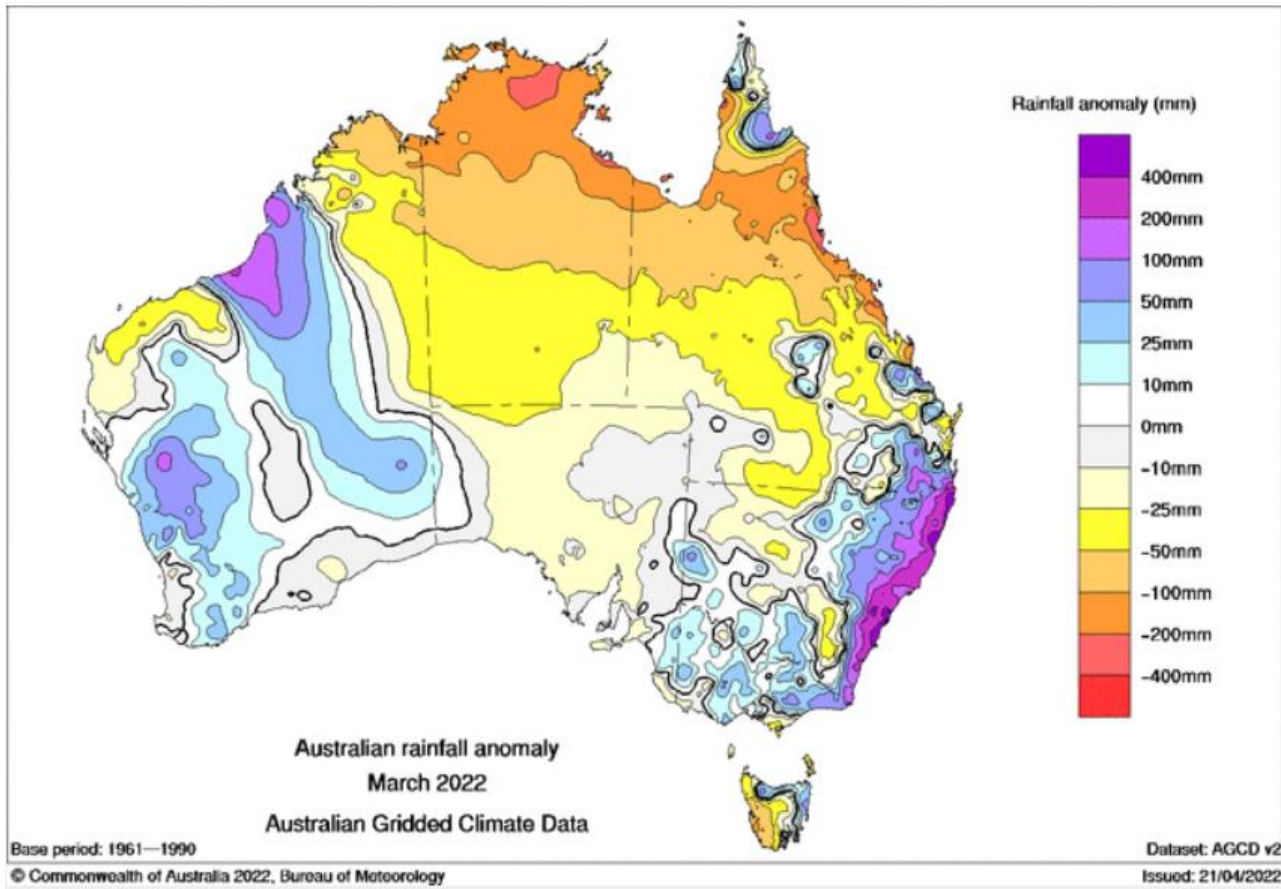


Percentages of long-term mean rainfall [mm]



<http://www.bom.gov.au/climate/maps/rainfall/?variable=rainfall&map=totals&period=3month&region=nat&year=2022&month=03&day=31>

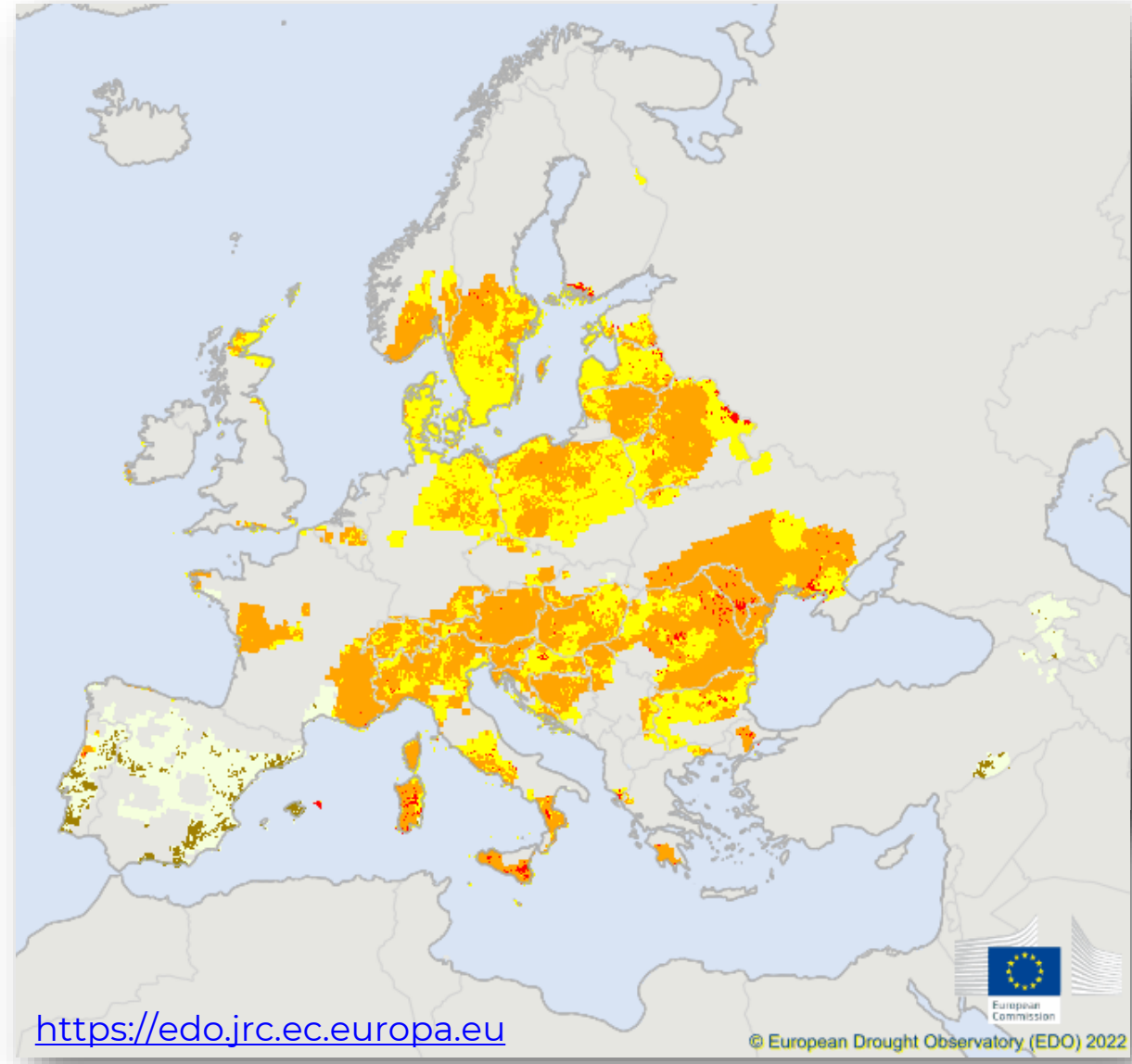
- Anomalies in precipitation and multi-satellite C3S soil moisture for March 2022



<http://www.bom.gov.au/climate/maps/rainfall/>

<https://dataviewer.geo.tuwien.ac.at/>

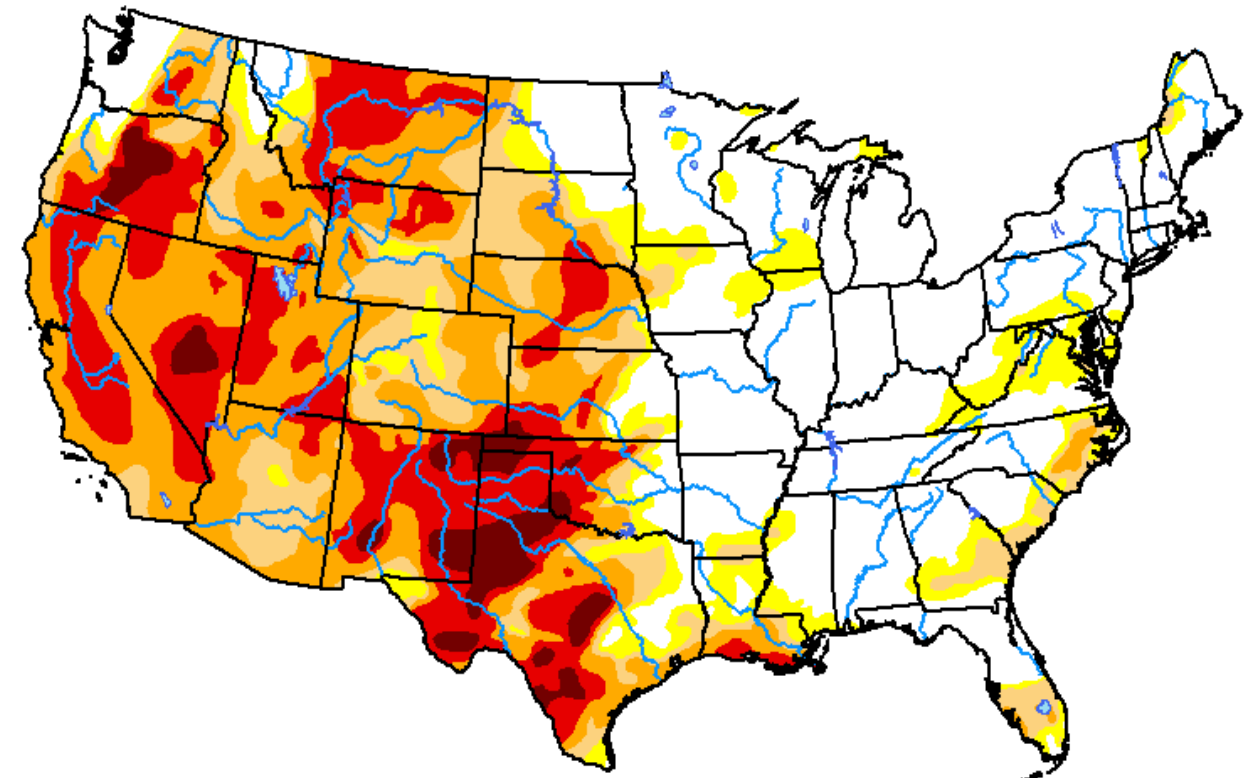
- Drought indicators:
  - › **Soil Moisture Anomaly (SMA)**
  - › **Standardized Precipitation Index (SPI)**
  - › **Anomaly of Vegetation Condition (FAPAR Anomaly)**
  - › **Low-Flow Index (LFI)**
  - › **Heat and Cold Wave Index (HCWI)**
  - › **Combined Drought Indicator (CDI):**  
Integrates information on anomalies of precipitation, soil moisture and satellite-measured vegetation condition into a single index that is used to monitor both the onset of agricultural drought and its evolution in time and space.



- Drought is commonly expressed as an index, and fed with (Earth) observations
- Indices can be used to measure severity and duration
- Many variations have been developed
  - › Standardized Precipitation Index (SPI), using Precipitation only
  - › Standardised Precipitation-Evapotranspiration Index (SPEI), using P and potential ET
  - › Palmer Drought Severity Index (PDSI), based on P and T
  - › Self-calibrating PDSI
  - › And many more...

Map released: April 28, 2022

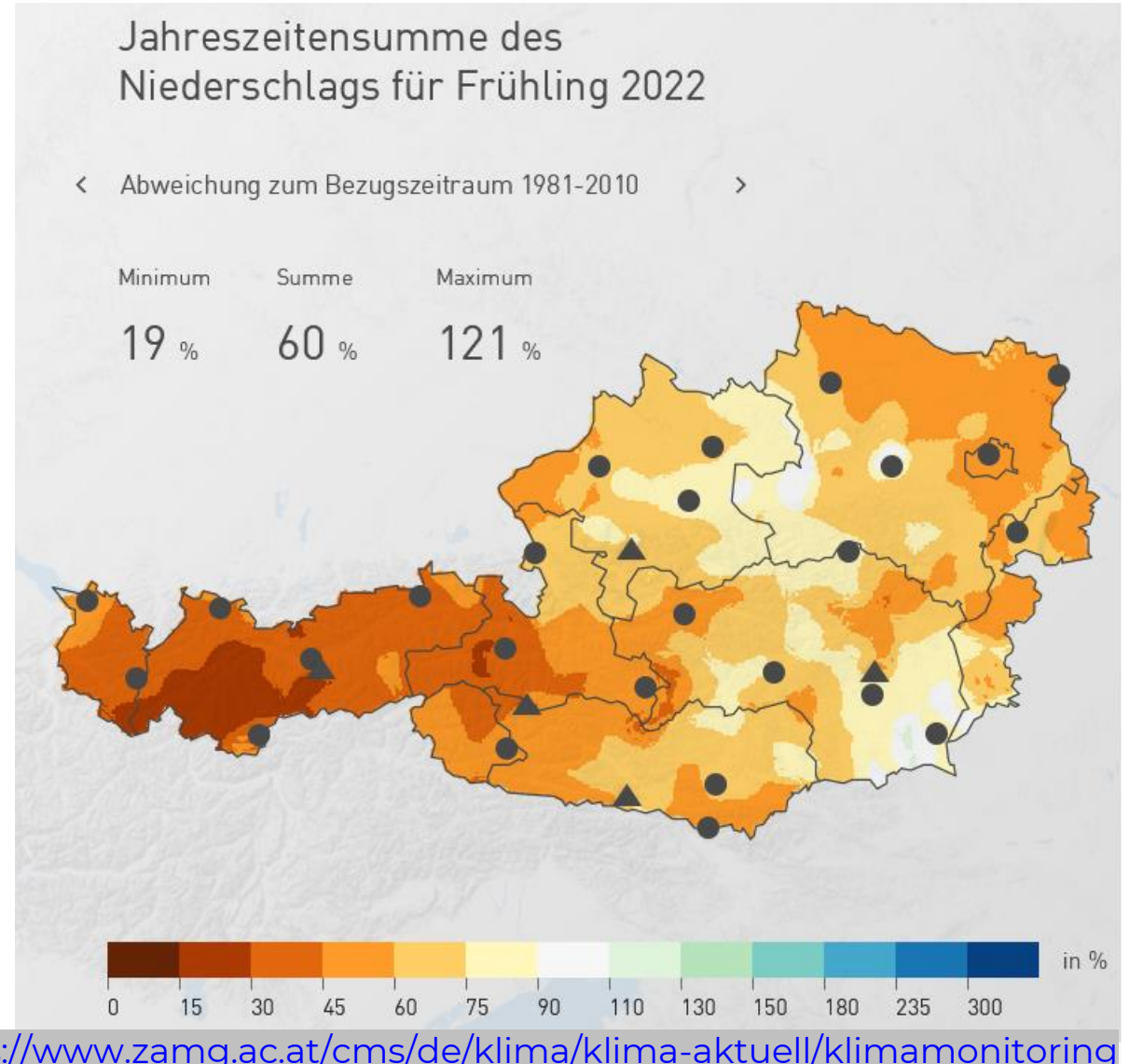
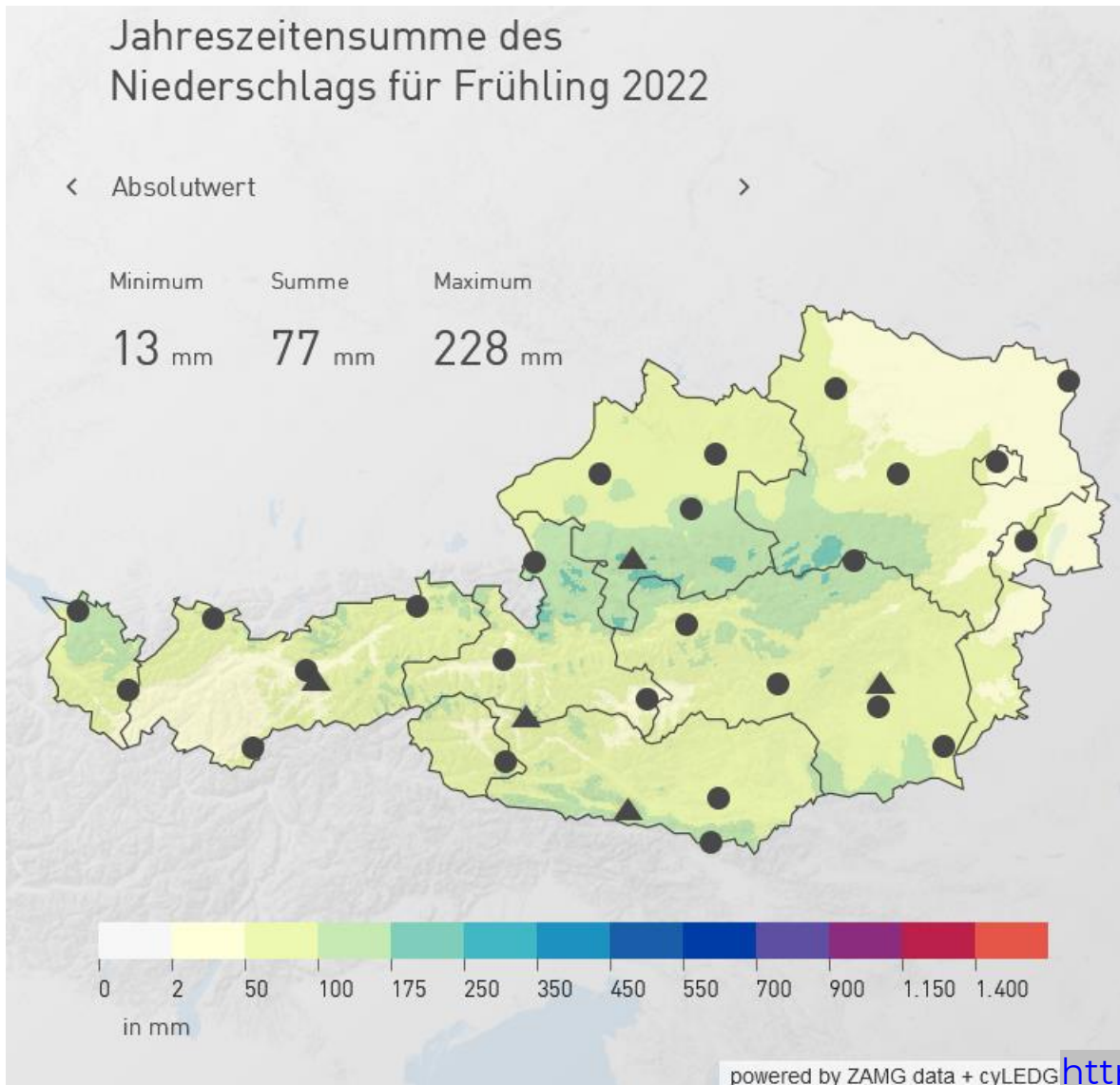
Data valid: April 26, 2022



- Categorisation depends on index

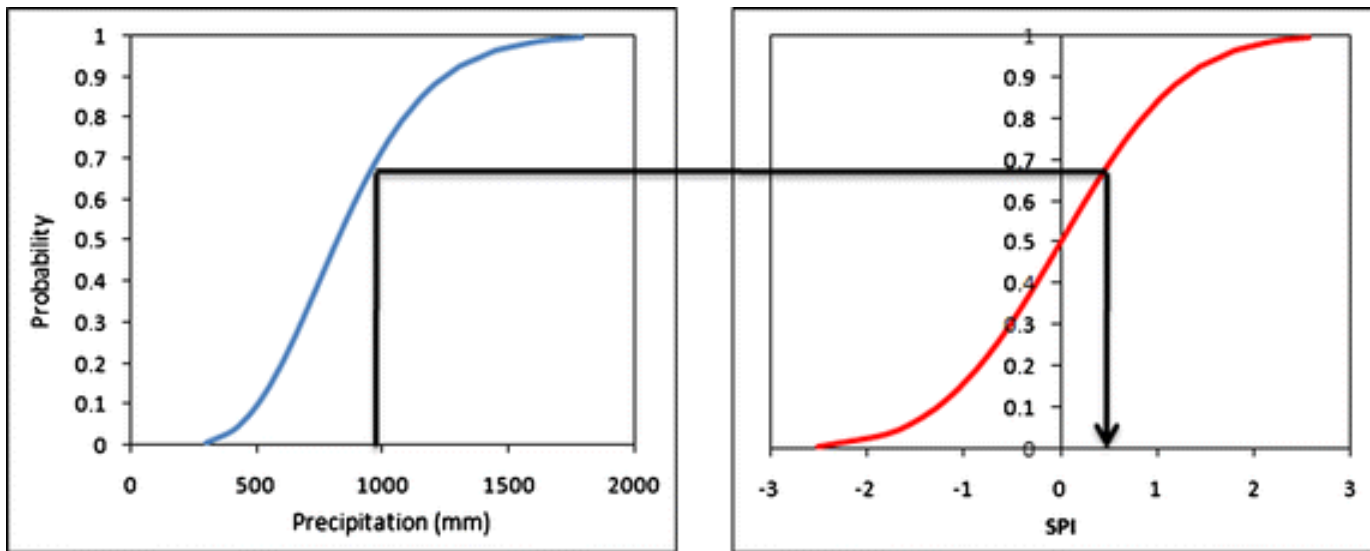
Category	Description	Possible Impacts	Ranges				
			Palmer Drought Severity Index (PDSI)	CPC Soil Moisture Model (Percentiles)	USGS Weekly Streamflow (Percentiles)	Standardized Precipitation Index (SPI)	Objective Drought Indicator Blends (Percentiles)
D0	Abnormally Dry	Going into drought: <ul style="list-style-type: none"> <li>▪ short-term dryness slowing planting, growth of crops or pastures</li> </ul> Coming out of drought: <ul style="list-style-type: none"> <li>▪ some lingering water deficits</li> <li>▪ pastures or crops not fully recovered</li> </ul>	-1.0 to -1.9	21 to 30	21 to 30	-0.5 to -0.7	21 to 30
D1	Moderate Drought	<ul style="list-style-type: none"> <li>▪ Some damage to crops, pastures</li> <li>▪ Streams, reservoirs, or wells low, some water shortages developing or imminent</li> <li>▪ Voluntary water-use restrictions requested</li> </ul>	-2.0 to -2.9	11 to 20	11 to 20	-0.8 to -1.2	11 to 20
D2	Severe Drought	<ul style="list-style-type: none"> <li>▪ Crop or pasture losses likely</li> <li>▪ Water shortages common</li> <li>▪ Water restrictions imposed</li> </ul>	-3.0 to -3.9	6 to 10	6 to 10	-1.3 to -1.5	6 to 10
D3	Extreme Drought	<ul style="list-style-type: none"> <li>▪ Major crop/pasture losses</li> <li>▪ Widespread water shortages or restrictions</li> </ul>	-4.0 to -4.9	3 to 5	3 to 5	-1.6 to -1.9	3 to 5
D4	Exceptional Drought	<ul style="list-style-type: none"> <li>▪ Exceptional and widespread crop/pasture losses</li> <li>▪ Shortages of water in reservoirs, streams, and wells creating water emergencies</li> </ul>	-5.0 or less	0 to 2	0 to 2	-2.0 or less	0 to 2





Spring precipitation in Austria 2022 in comparison to 1981-2010 in %. 100% equals the long-term average. <https://www.zamg.ac.at/cms/de/klima/klima-aktuell/klimamonitoring>

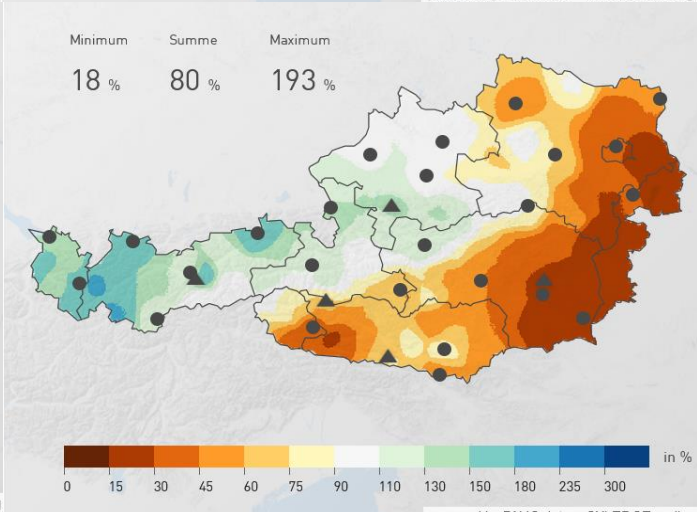
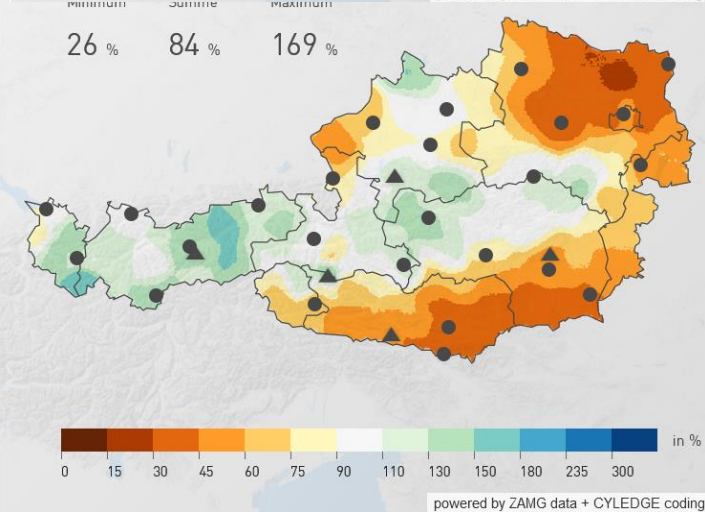
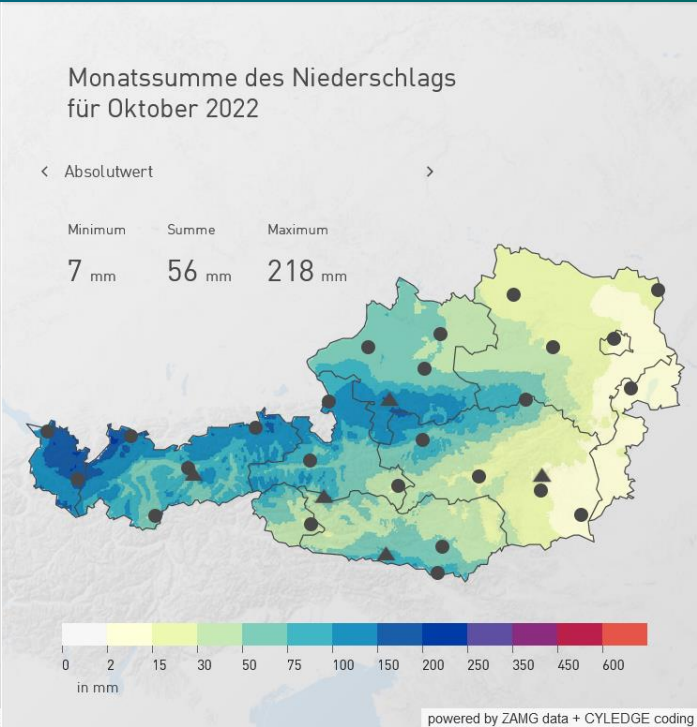
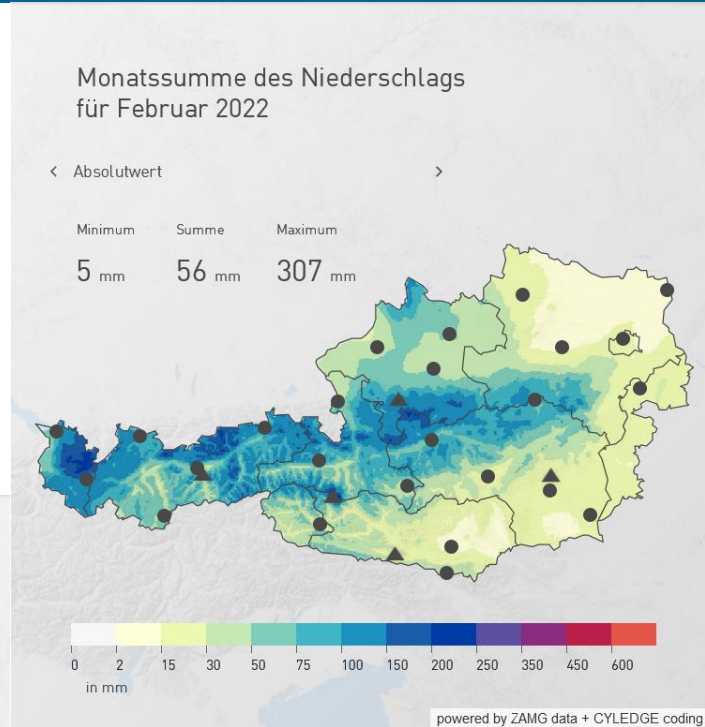
SPI fits actual, long-term precipitation record to probability distribution (left), which is then transformed into a normal distribution (right) so that the mean SPI for the location and desired period is zero and the SPI is expressed by a z-score



**Table 1. SPI values**

2.0+	extremely wet
1.5 to 1.99	very wet
1.0 to 1.49	moderately wet
-.99 to .99	near normal
-1.0 to -1.49	moderately dry
-1.5 to -1.99	severely dry
-2 and less	extremely dry

- Two basic assumptions
  - › Variability of precipitation is much higher than that of other variables, (e.g., T and  $ET_{pot}$ )
  - › Precipitation and other variables are stationary (i.e., they have no temporal trend)



- Individual distribution needs to be fitted for each season individually

<https://www.zamg.ac.at/cms/de/klima/klima-aktuell/klimamonitoring>

- Can be computed at multiple time aggregates (1, 2, 3, 12 months etc) representing different process time scales

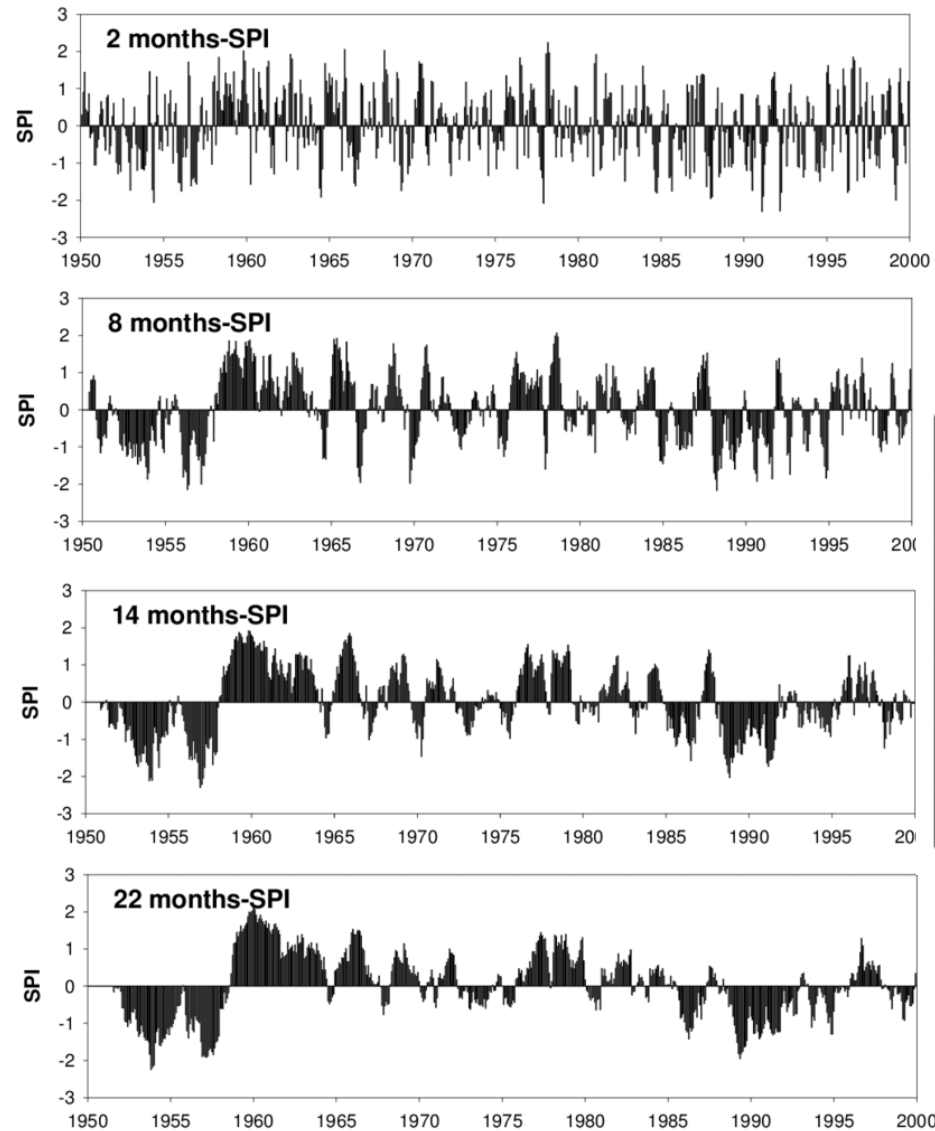
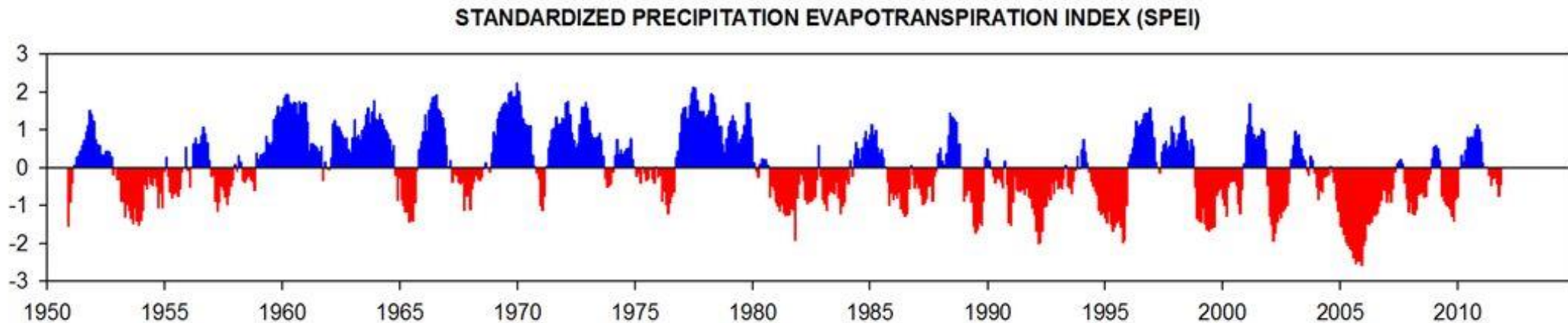
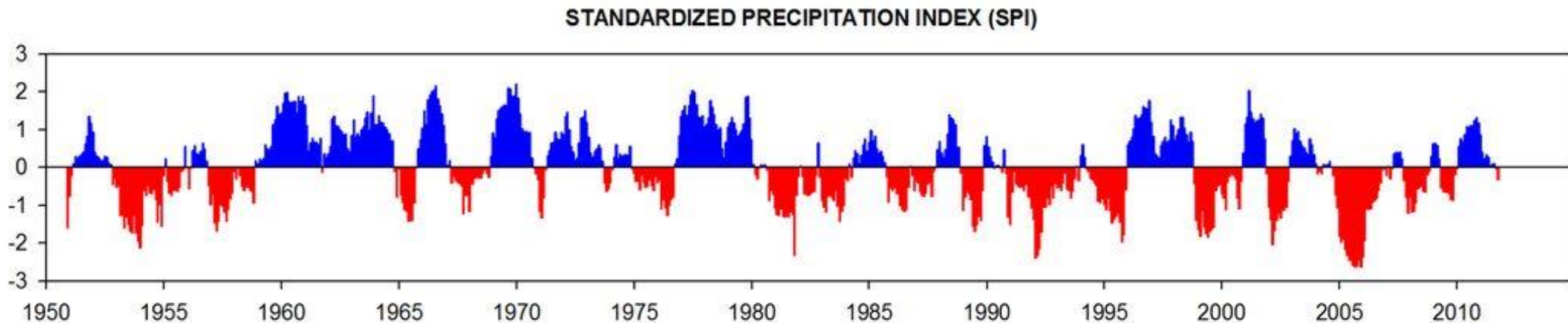


Table 1. SPI values

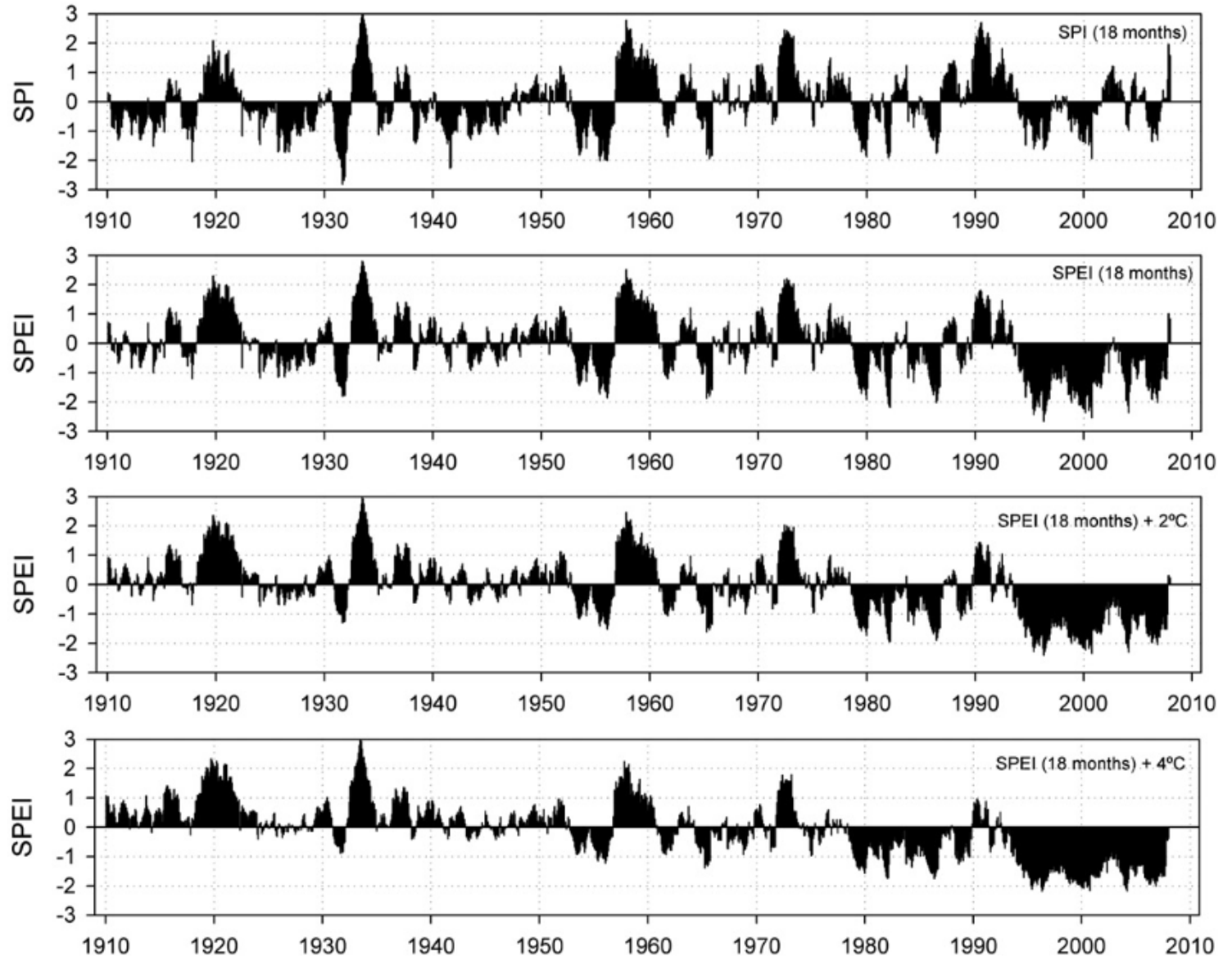
2.0+	extremely wet
1.5 to 1.99	very wet
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-.99 to .99	near normal
-1.0 to -1.49	moderately dry
-1.5 to -1.99	severely dry
-2 and less	extremely dry

[Vicente-Serrano, 2005]

- Climatic water balance (precipitation minus evapotranspiration)
  - › Includes the impact of (rising) temperature



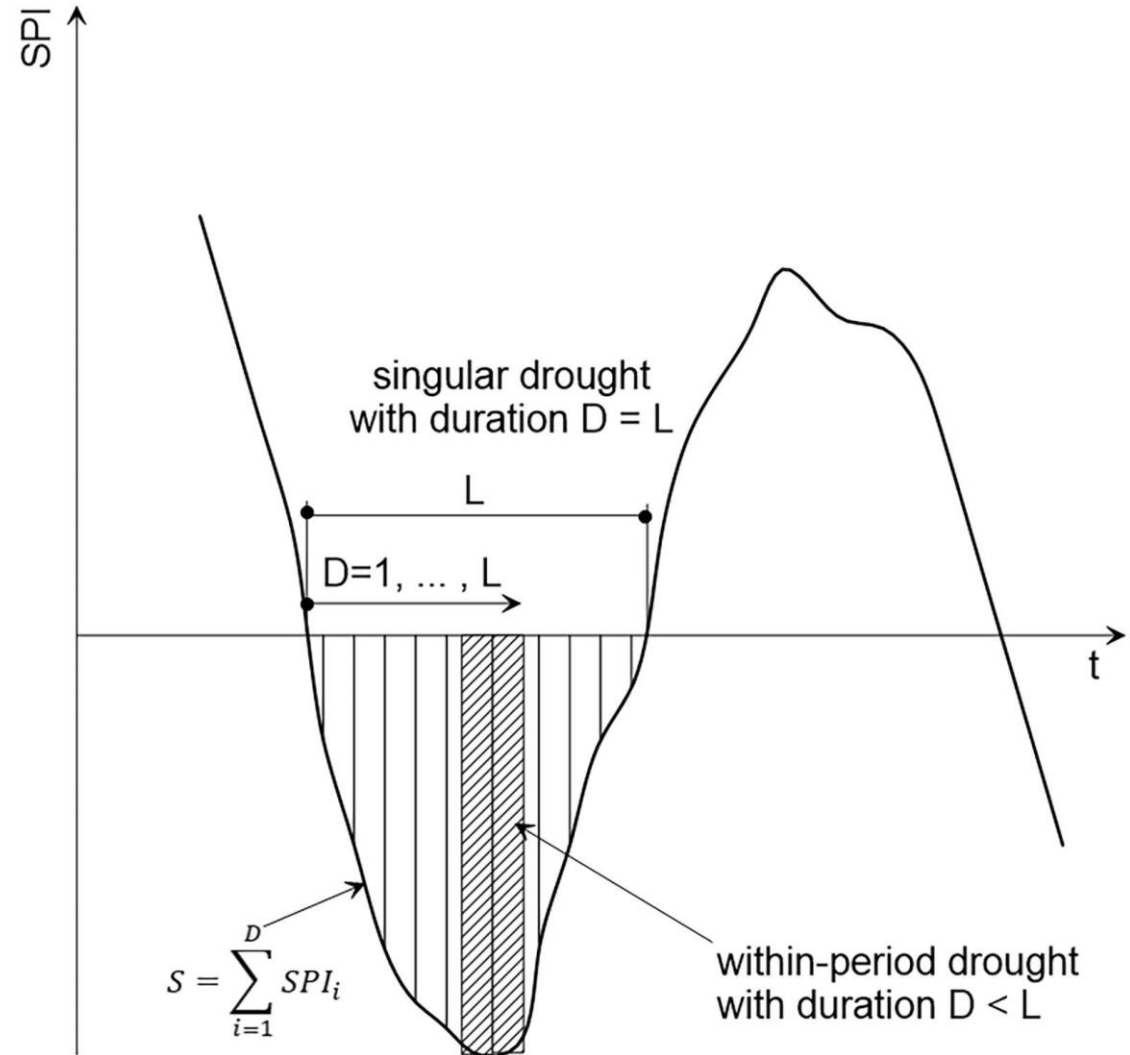
Impact of temperature under 2 °C and 4 °C global warming scenario



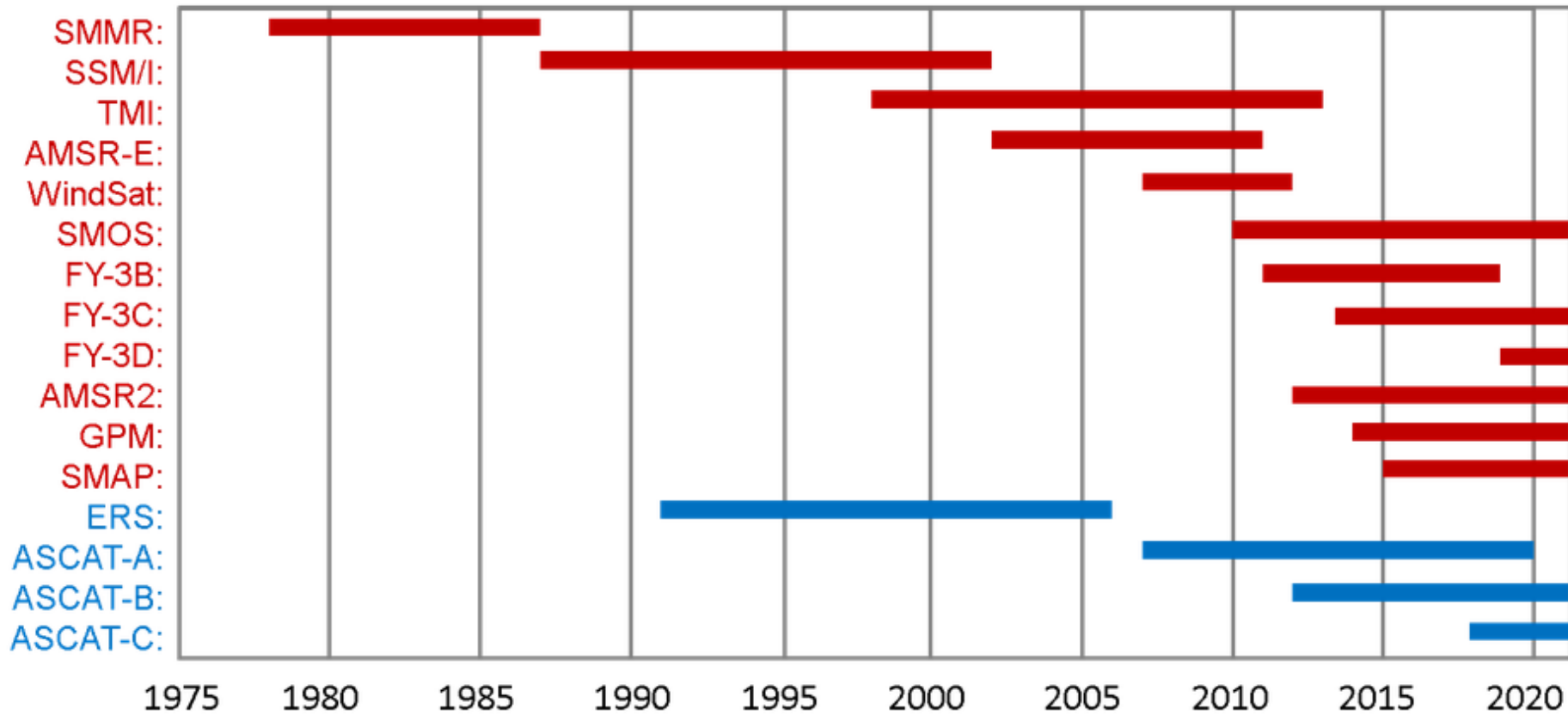
[Vicente-Serrano, 2010]

- **Drought duration (D):** Number of consecutive days with index < 0
- **Drought severity (S):** The accumulation of negative index (e.g. SPI) values preceded and followed by positive SPI values is called severity.
- **Drought intensity (I):** The intensity is obtained by dividing the severity to the drought duration

[Cavus and Aksoy, 2020]

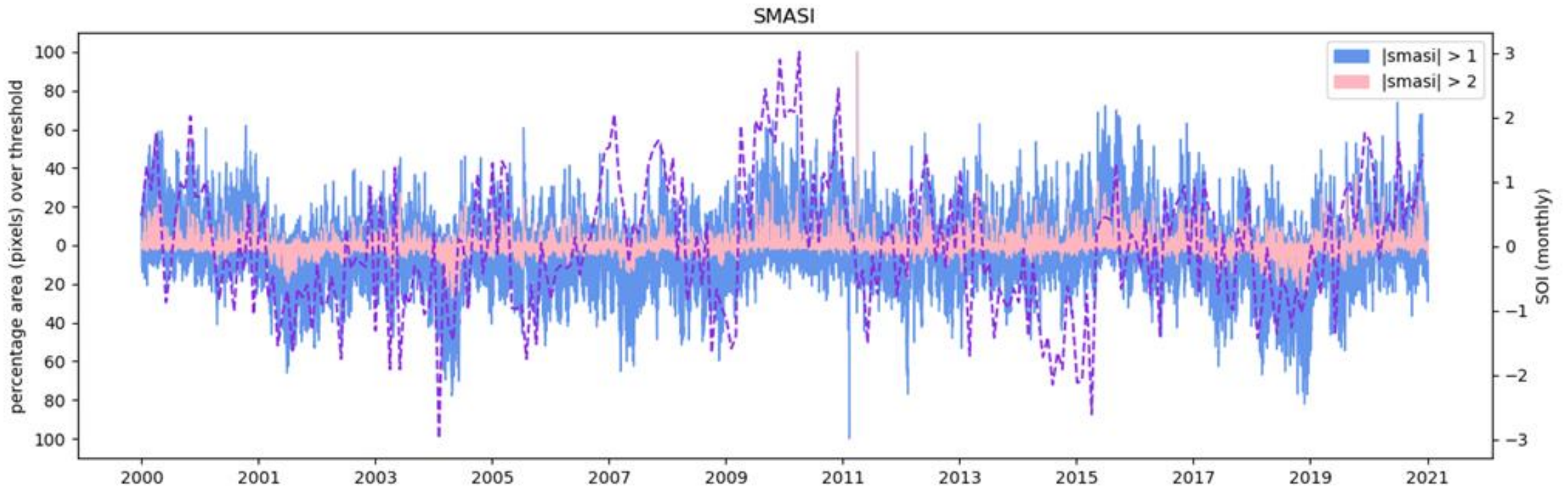


- Z-scores can in principle be computed for any dataset of sufficient length
- Use of multiple satellite missions (e.g., ESA CCI SM) allows for a more robust assessment over longer time periods



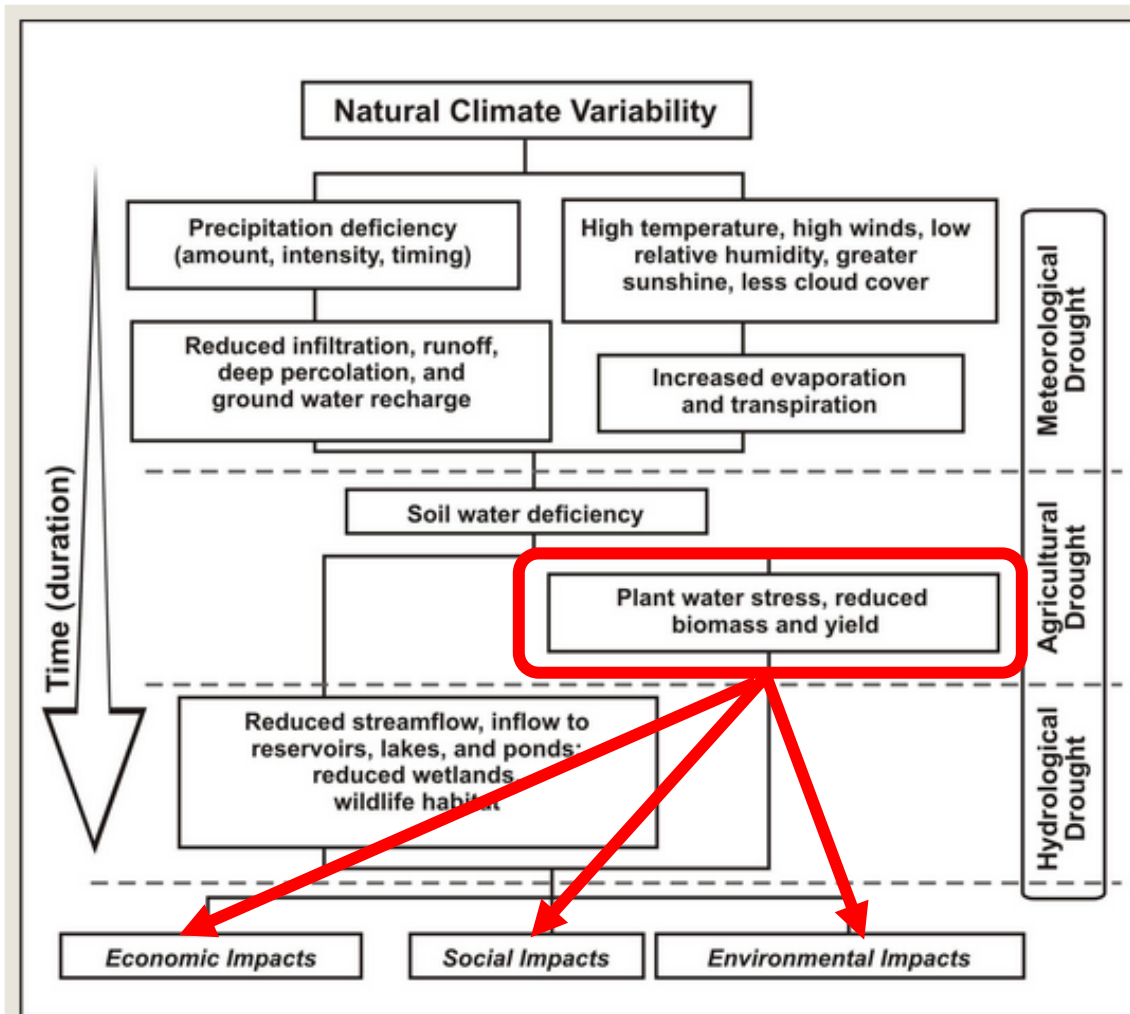


- Soil Moisture Anomaly Standardised Index shows severity of anomalies
  - › Example for Australia, where moisture is strongly driven by El Nino Southern Oscillation (ENSO), as indicated by the Southern Oscillation Index (SOI)

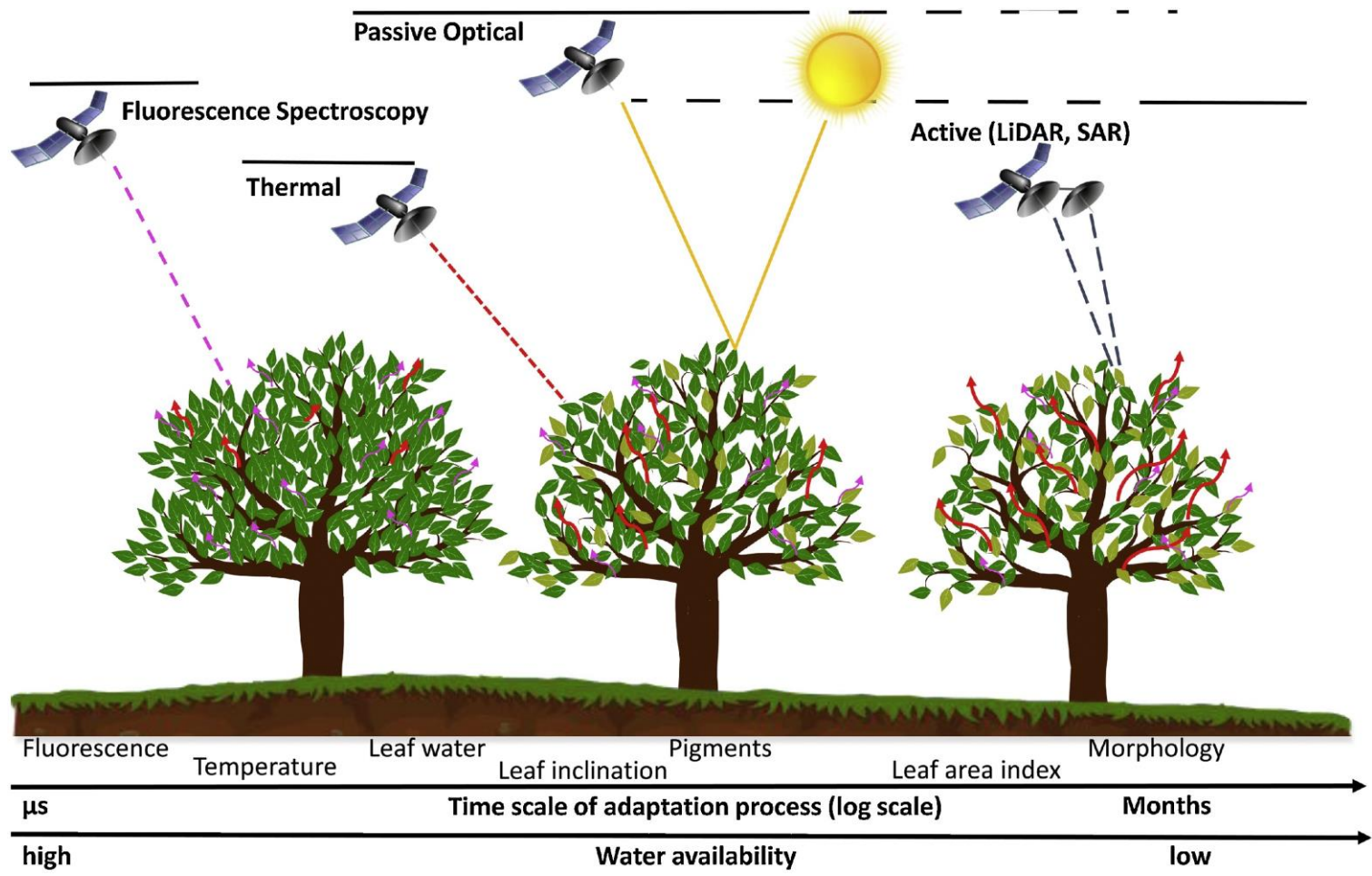
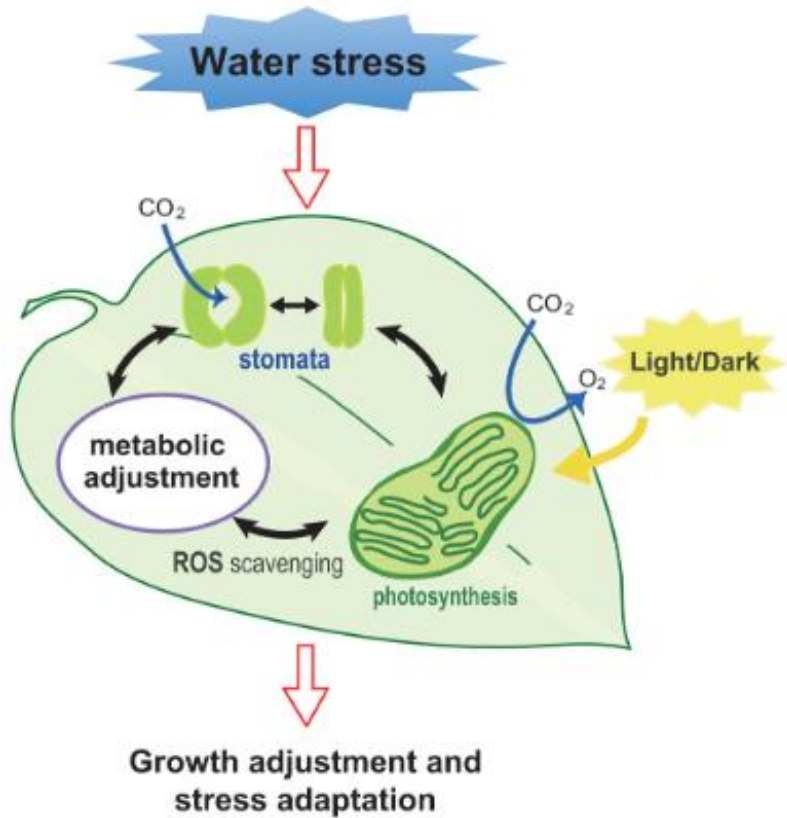


A photograph of a cornfield with mature, golden-brown plants. The sky is clear and blue. A white rectangular box is overlaid on the center of the image, containing blue text.

**Microwave remote sensing for assessing  
drought impacts on vegetation**



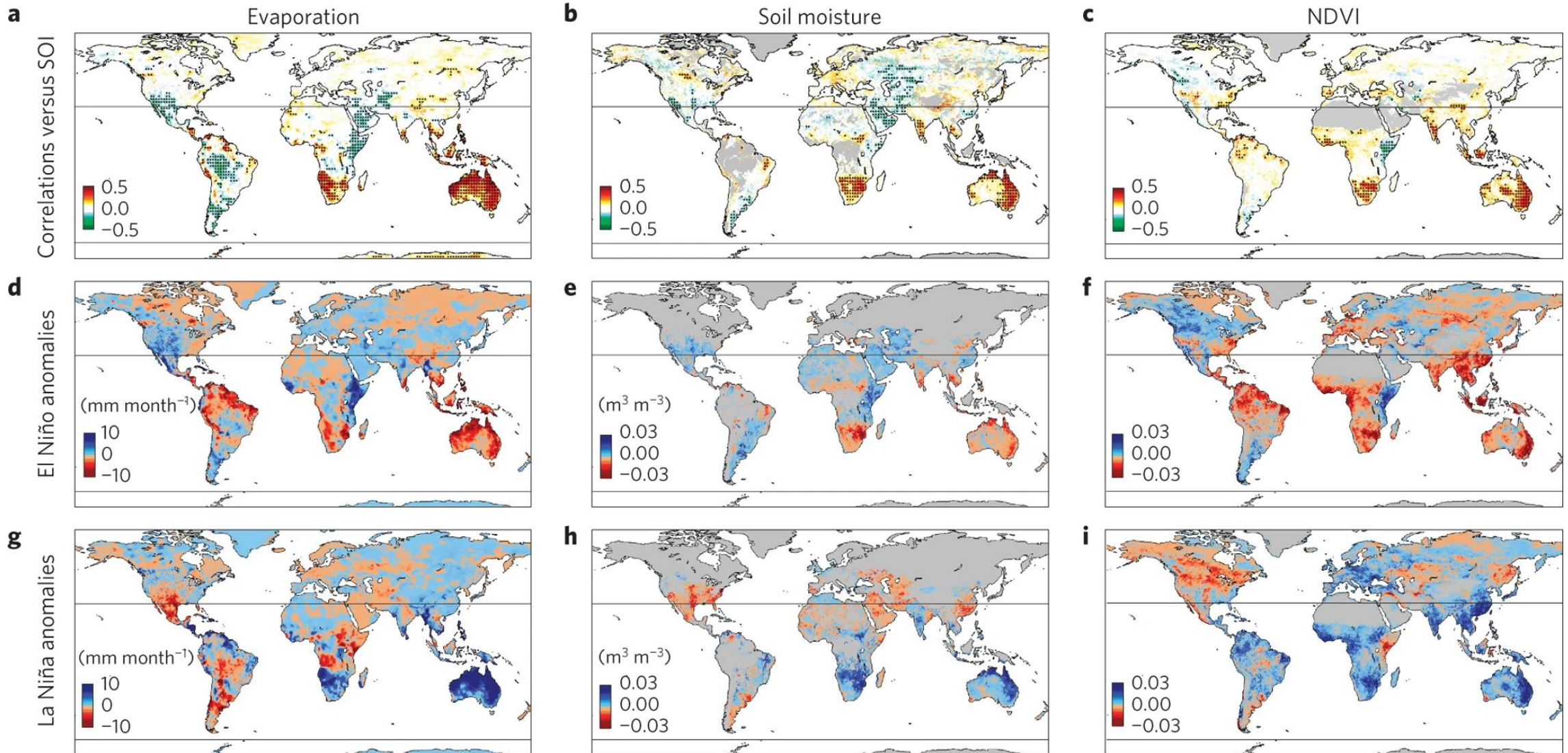
Sequence of drought occurrence and impacts for commonly accepted drought types. All droughts originate from a deficiency of precipitation or meteorological drought but other types of drought and impacts cascade from this deficiency. (Source: National Drought Mitigation Center, University of Nebraska-Lincoln, U.S.A.)



[Osakabe et al. 2014]

\* Removal of Reactive Oxygen Species (ROS) released by changed metabolism

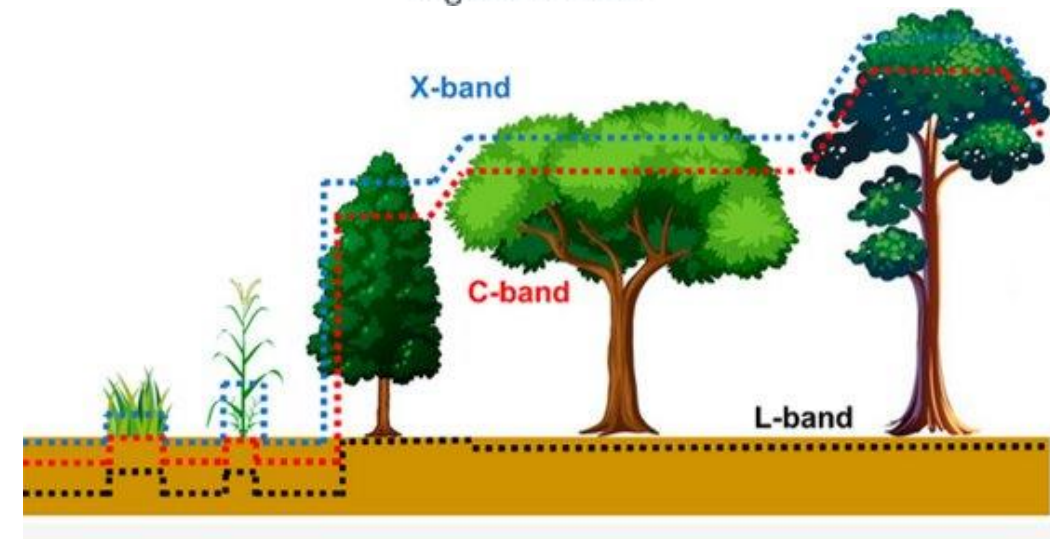
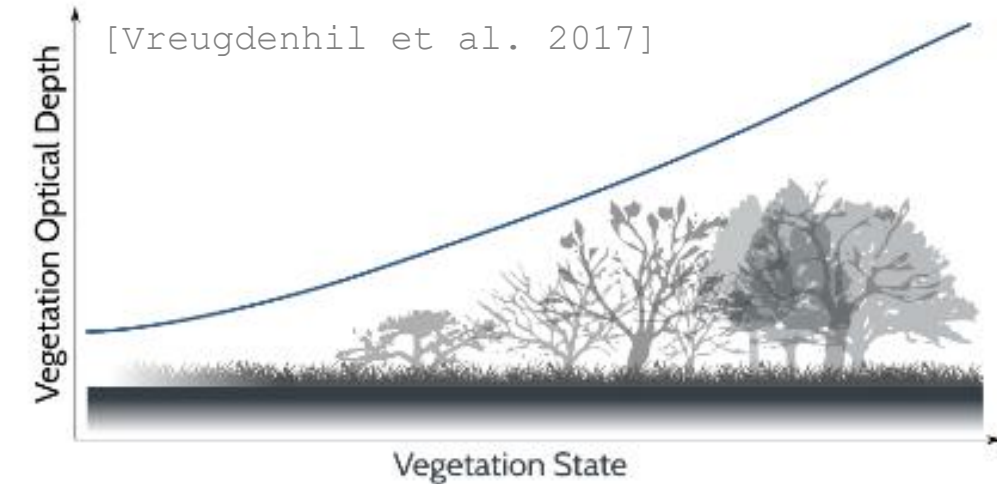
[Damn et al. 2018]



[Miralles et al. 2014]

# Microwave remote sensing for vegetation dynamics

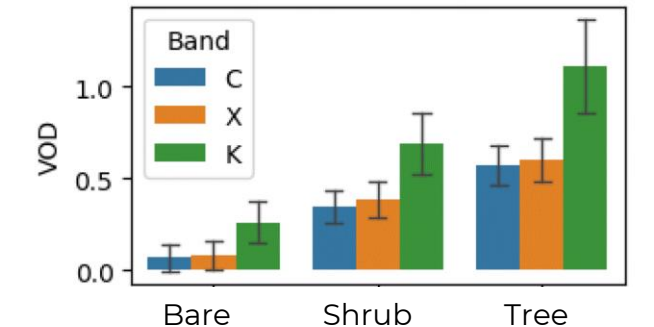
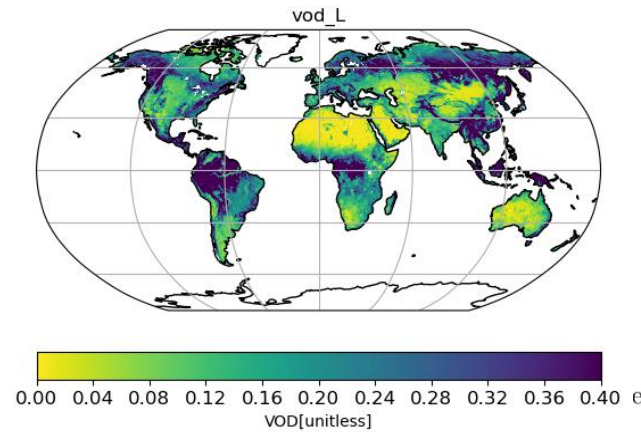
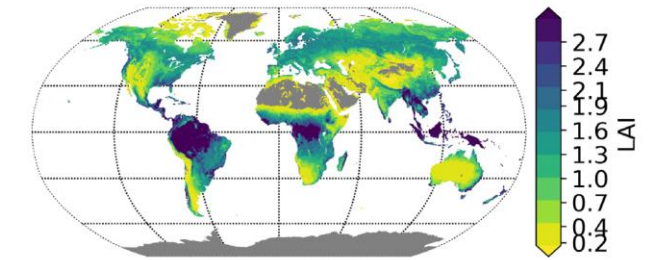
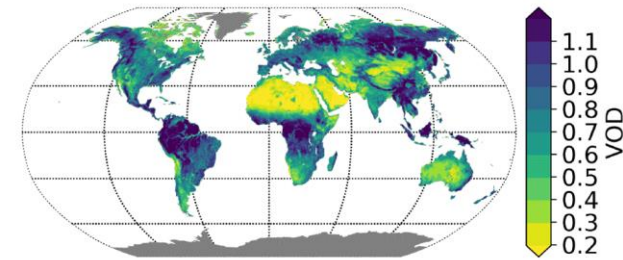
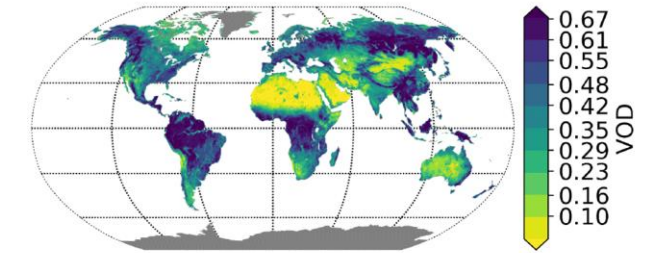
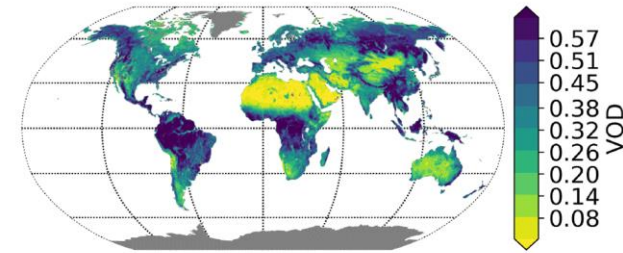
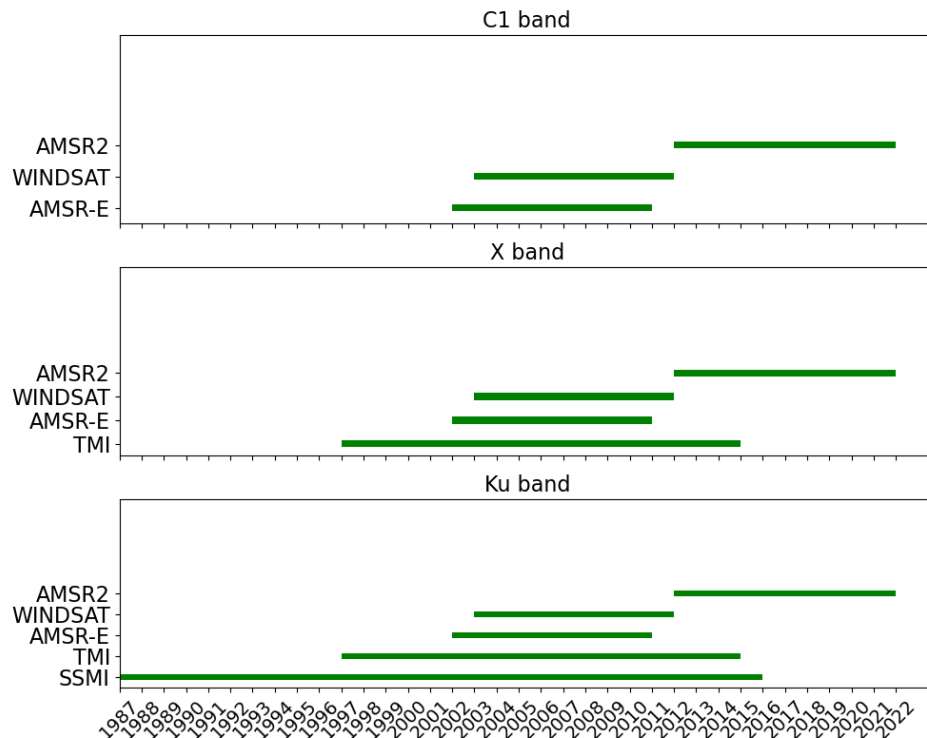
- **Vegetation Optical Depth (VOD)** quantifies the attenuation of (microwave) radiation by vegetation.
  - › Related to **vegetation water content** and **biomass**
  - › Signal depends on **wavelength**
  - › Typically retrieved from **L-, C-, X-, and Ku-band**
- Retrieval algorithms seek to separate vegetation signal from soil signal, e.g.,
  - › **TU Wien method** for radar observations (See Vreugdenhil LTC22)
  - › **Land Parameter Retrieval Model** (VU/NASA/VanderSat/Planet) for radiometer data



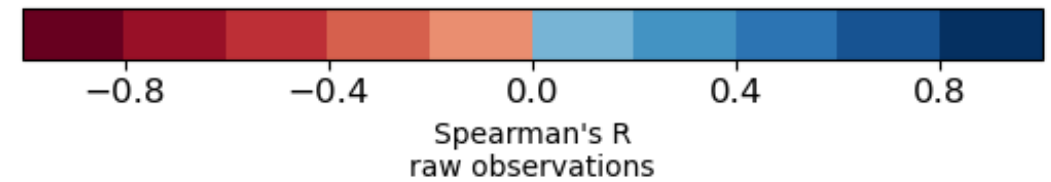
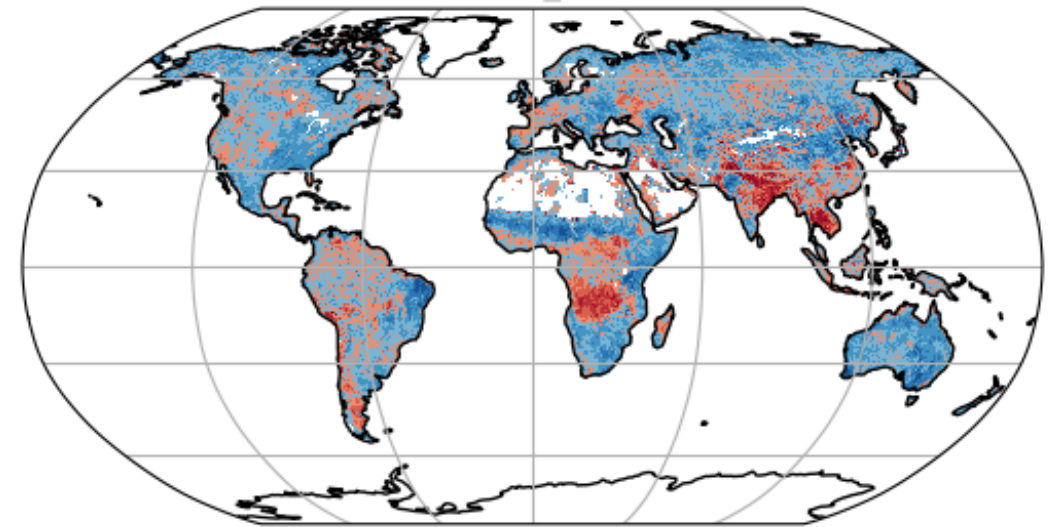
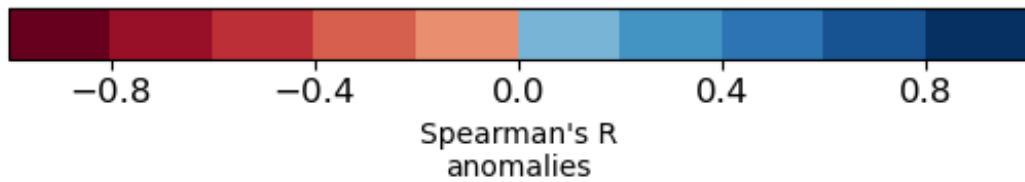
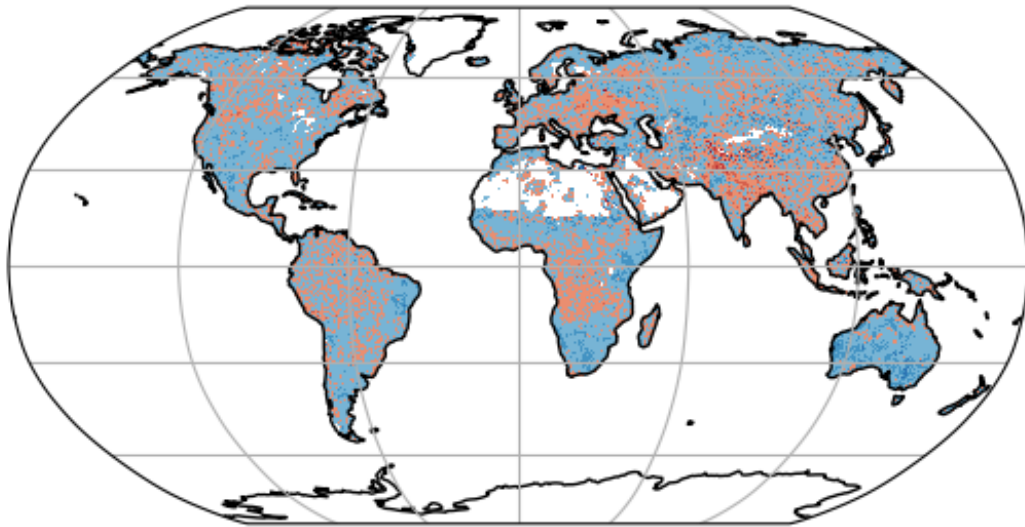
[Frappart et al. 2020]

Long-term, harmonized VOD, derived from multiple radiometer datasets

- Separate VODCA products for C-, X-, Ku-band
- 0.25° spatial sampling
- Daily, 1987 - 2021
- <https://doi.org/10.5281/zenodo.2575599>



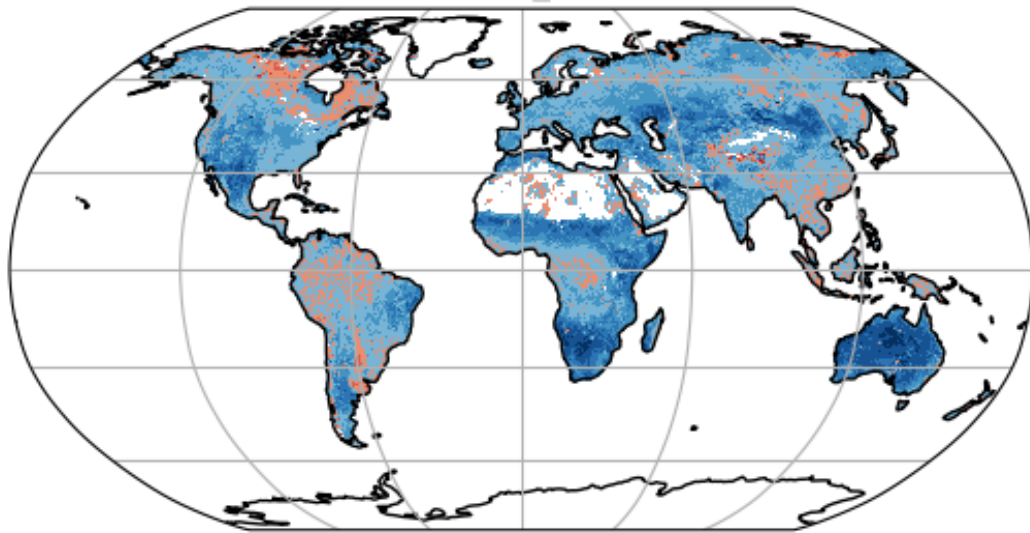
[Moesinger et al. 2020; 10.5194/essd-12-177-202]



(2010-2019)

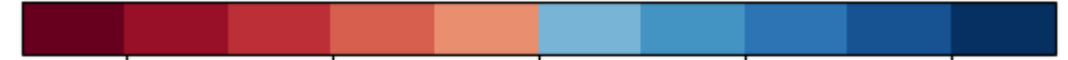
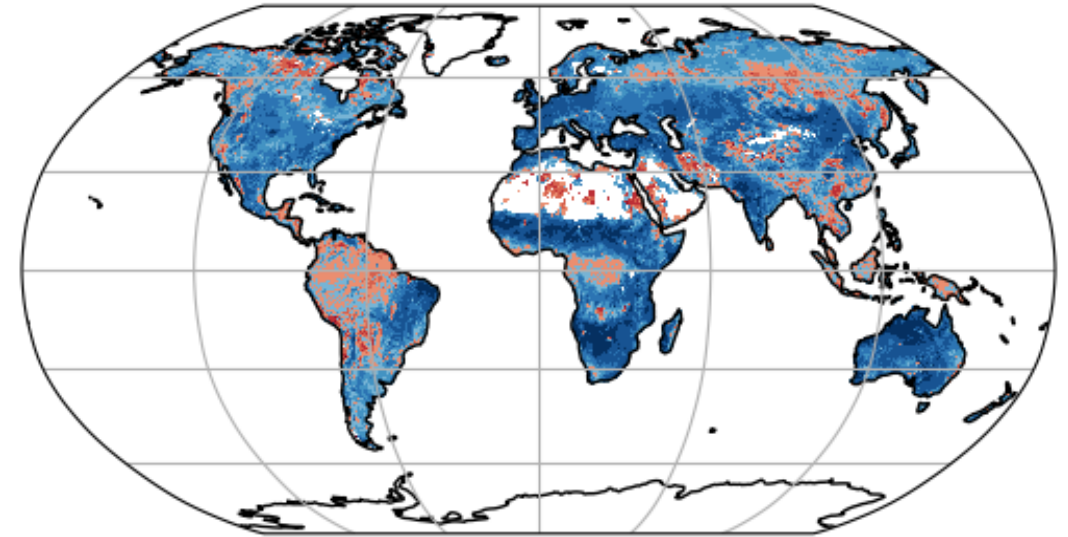
[Moesinger et al. 2020; 10.5194/essd-12-177-202]





-0.8      -0.4      0.0      0.4      0.8

Spearman's R anomalies

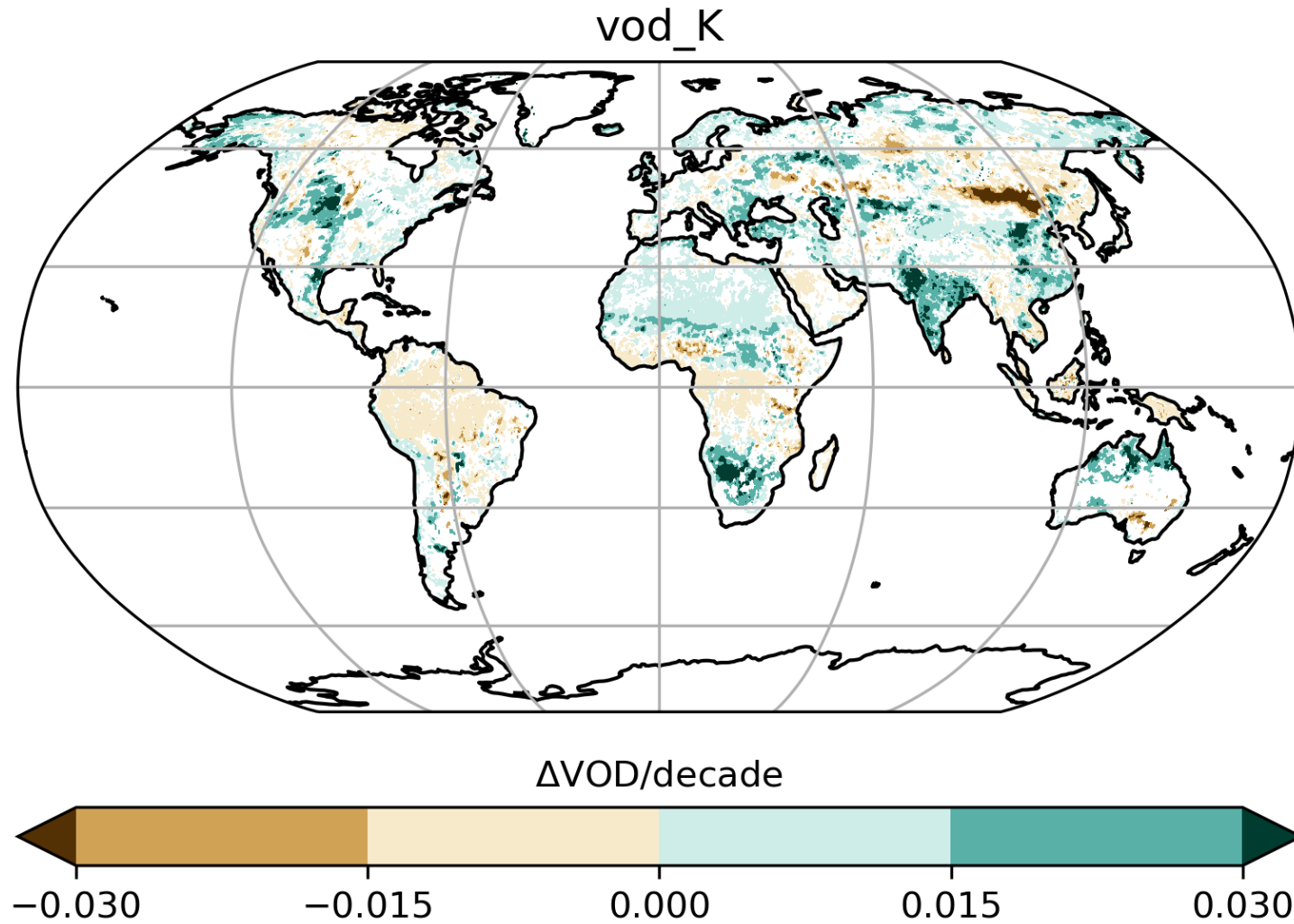


-0.8      -0.4      0.0      0.4      0.8

Spearman's R raw observations

**(2002-2017)**

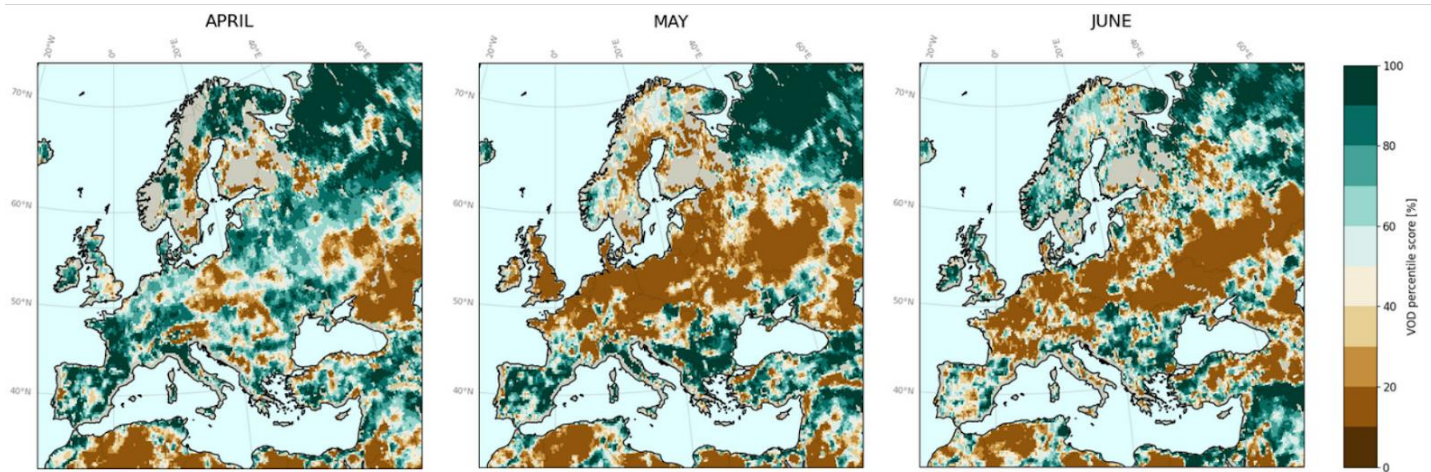
[Moesinger et al. 2020; 10.5194/essd-12-177-202]



[Moesinger et al., 2020; 10.5194/essd-12-177-202]

## C3S European State of the Climate 2021

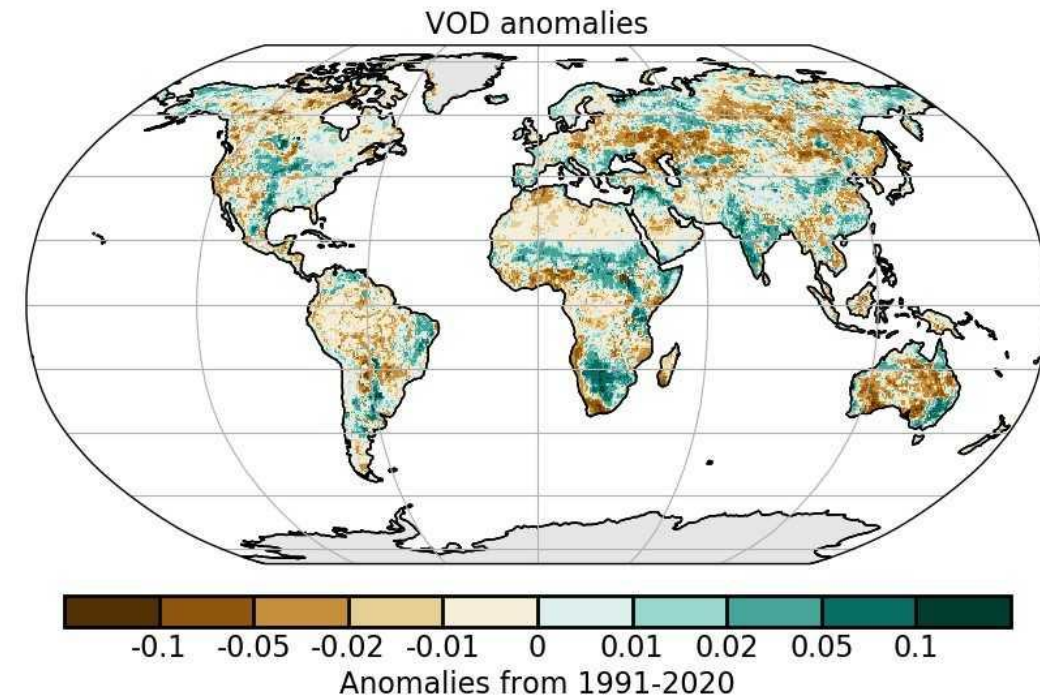
- Impact of late spring frost on vegetation



Data Source: VOD Climate Archive (VODCA) Credit: TU Wien/ VanderSat B. V. Reference period: 1991-2020



## NOAA/BAMS State of the Climate 2021

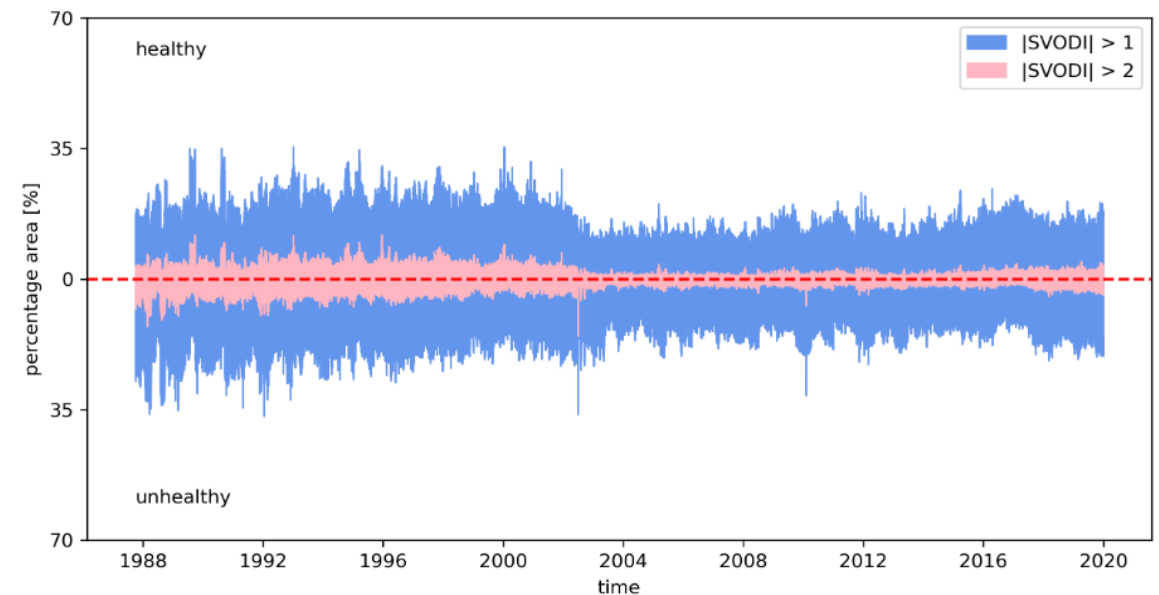
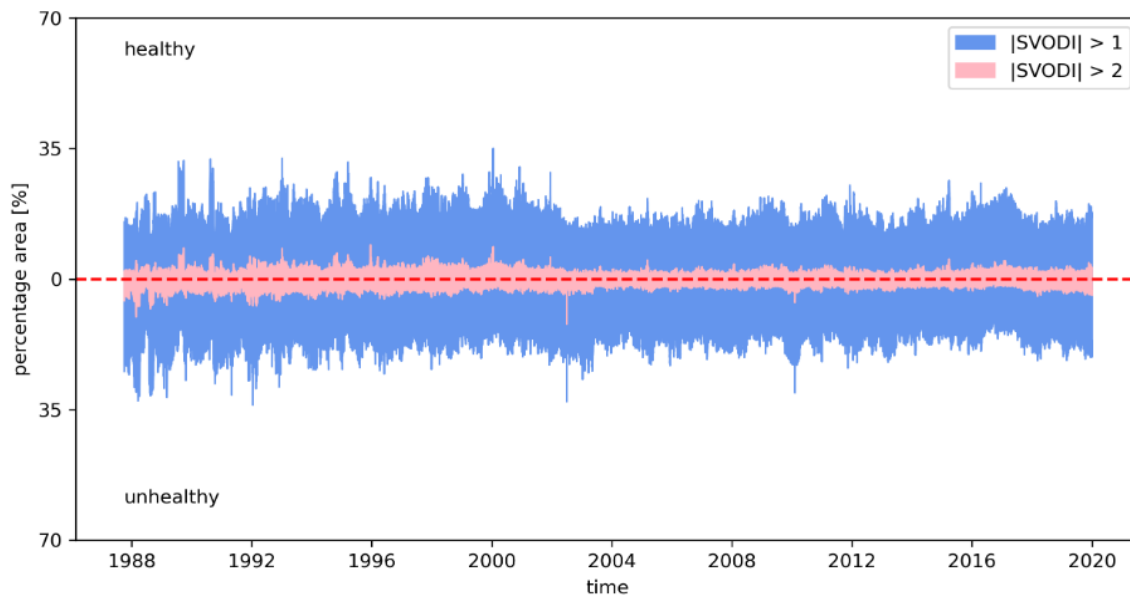


[Dorigo et al., 2021]

Monthly ranking of VOD for April, May and June 2021, relative to 1991-2020, expressed in percentiles

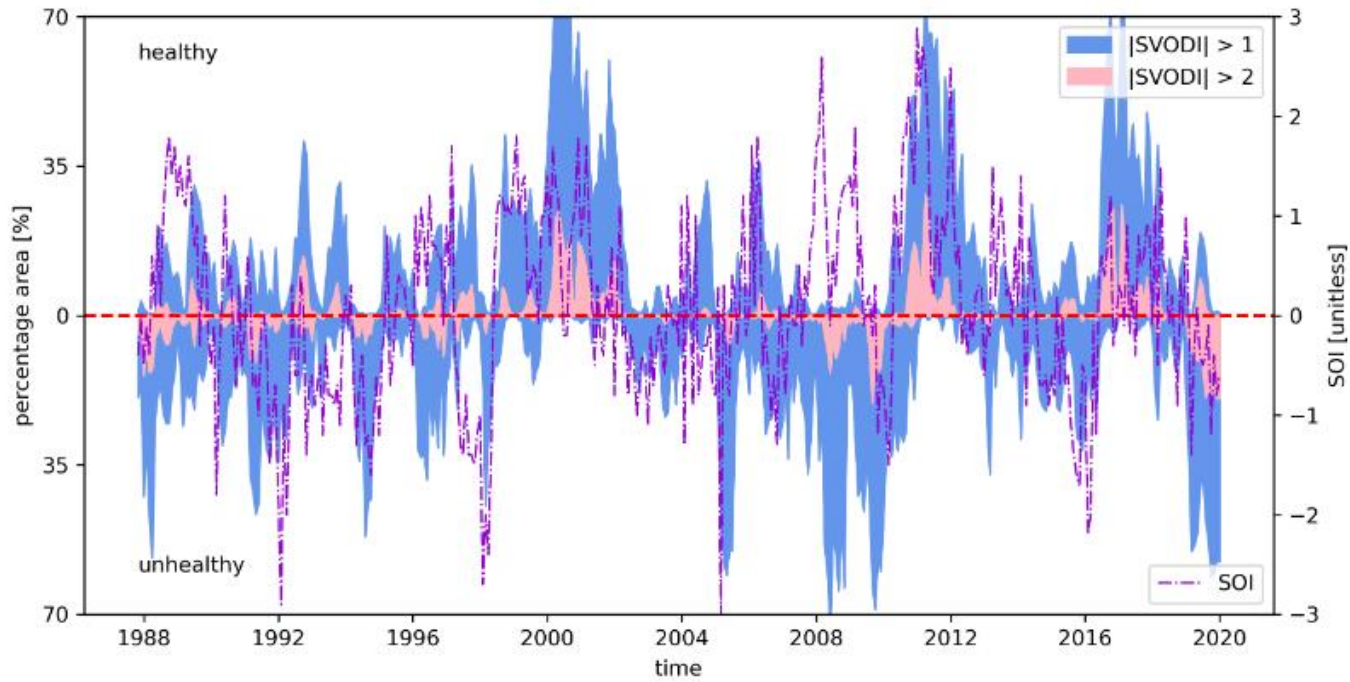
SVODI is a long-term (1987 - present), daily, global vegetation condition monitoring dataset combining on C-, X- and Ku-band VOD from multiple sensors

- Improves spatio-temporal sampling
- Uses a probabilistic merging method to deal with the varying instrument noise and sampling density of the data, similar as for SMASI



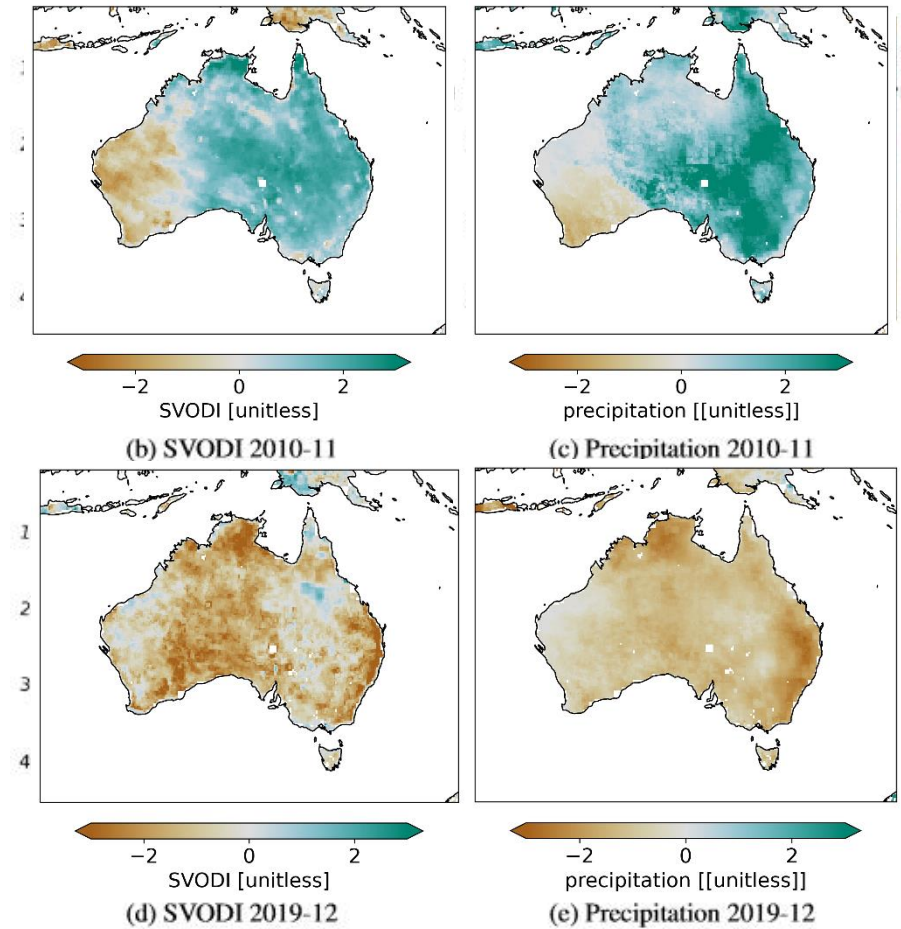
Example of abnormal and extreme counts for probabilistic (left) and non-probabilistic (right) merging

[Moesinger et al., 2022; 10.5194/bg-2021-360]

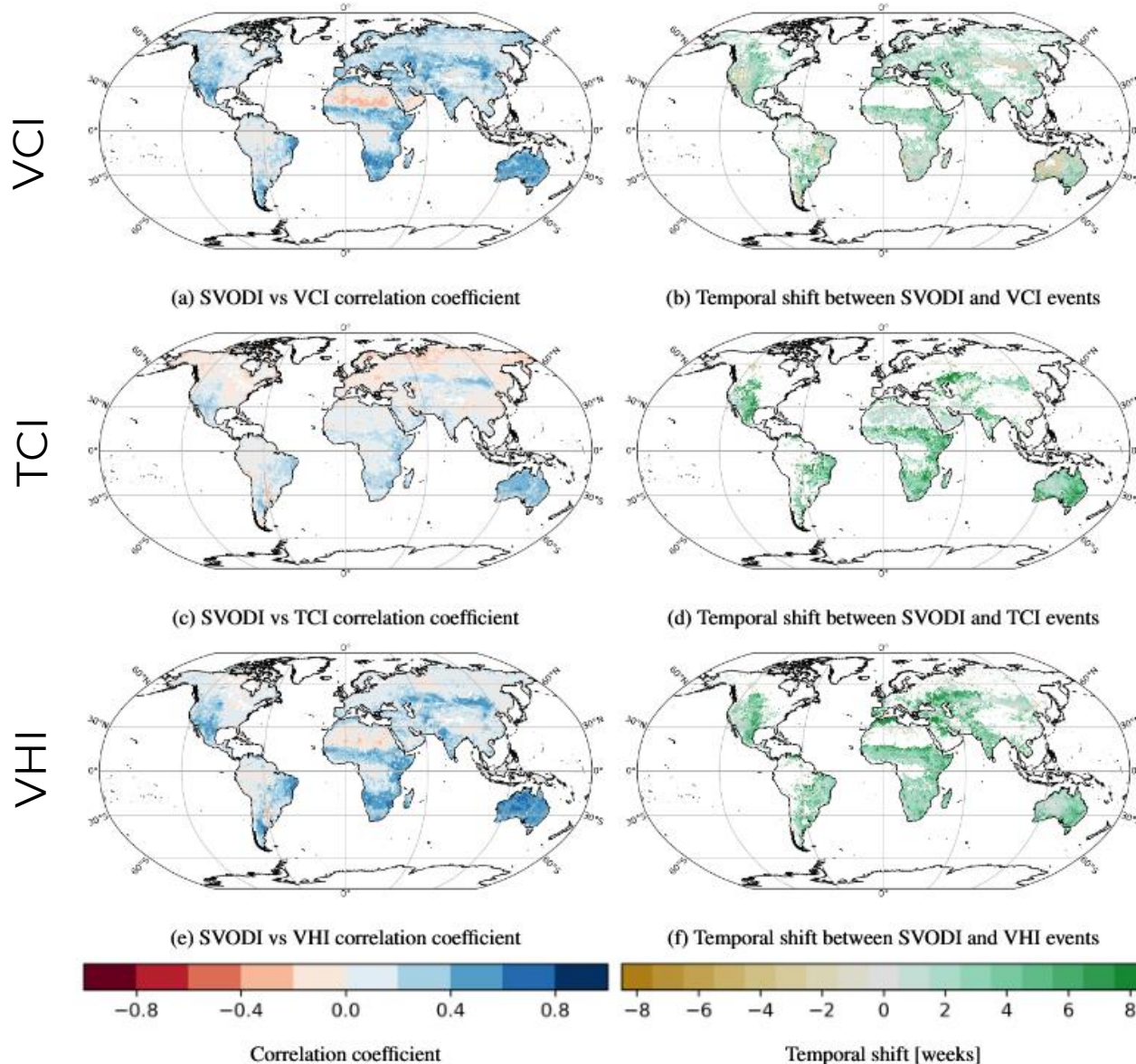


Fraction of percentage area of  $|SVODI| > 1 > 2$  for central Australia along with Southern Oscillation Index

[Moesinger et al., 2022; 10.5194/bg-2021-360]



SVODI and standardized precipitation anomalies for 2010-11 and 2019-12



Correlation and temporal shift (in weeks) between SVODI and optical **vegetation indices**:

- Vegetation Condition Index (VNIR)
- Temperature Condition Index (thermal)
- Vegetation Health Index (optical + thermal)

SVODI anomalies usually **follow** those from optical data: Thermal > VNIR > Microwave

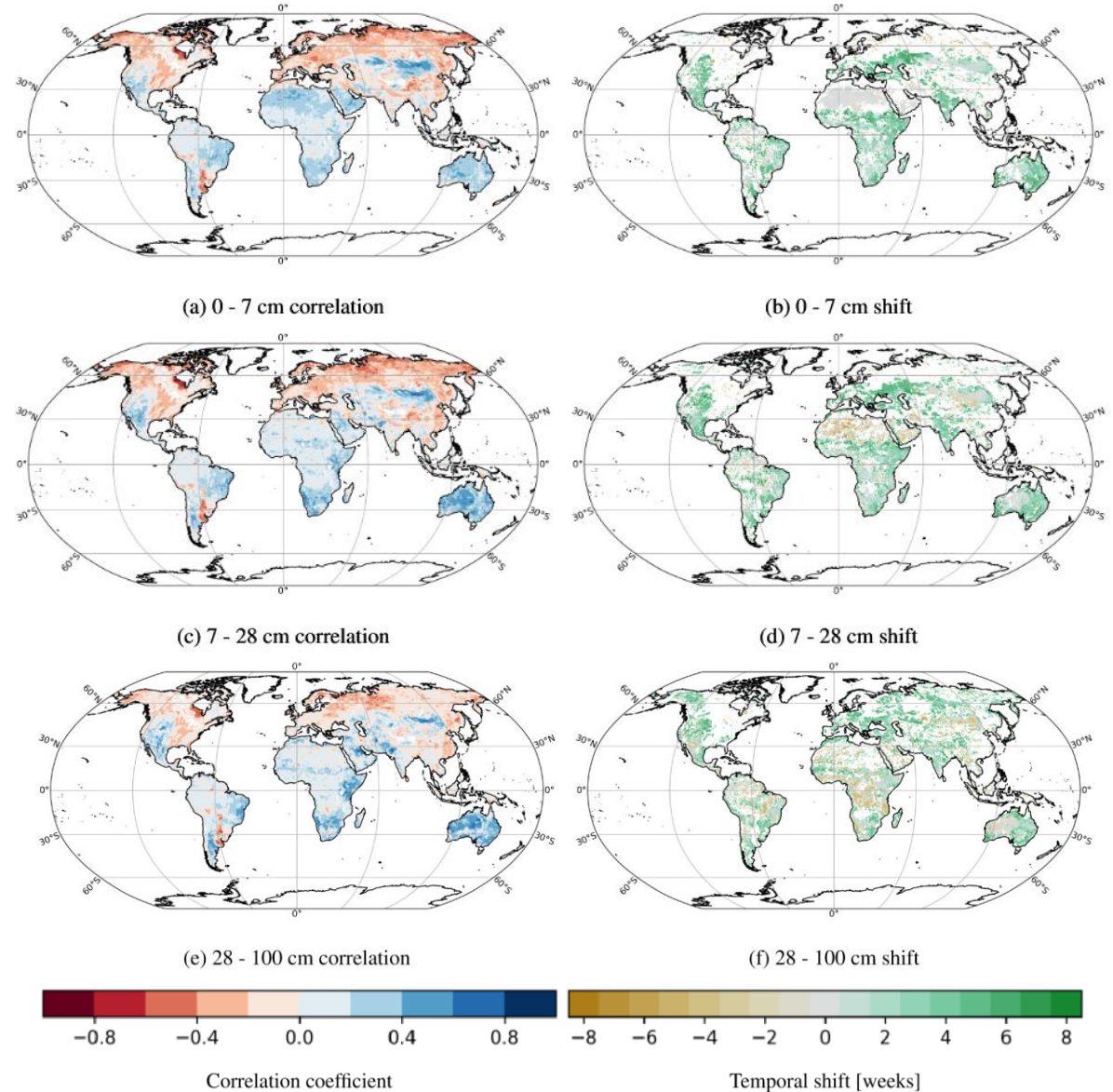
Sign of **advanced vegetation stress** (loss of vegetation water content, and stress in deeper soil layers)

[Moesinger et al., 2022; 10.5194/bg-2021-360]

Correlation and temporal shift (in weeks) between SVODI and ERA5 Soil Moisture:

- 0-7 cm
- 7-28 cm
- 28-100 cm

Apart from very dry regions, correlations generally **increase** with deeper layers



[Moesinger et al., 2022; 10.5194/bg-2021-360]

- **VOD** profits from long heritage of high frequency (C-, X-, Ku) microwave missions, making it a powerful source to study climate (change) impacts on vegetation and plant hydraulics
- **VODCA** allows monitoring temporal and spatial dynamics in above-ground biomass
  - › Ku-, X-, and C-band more sensitive to foliage biomass than L- and P-band
  - › Particularly useful for drylands, agriculture, pastures
- **SVODI** allows to assess the impact of extreme events and water cycle variability on global vegetation dynamics

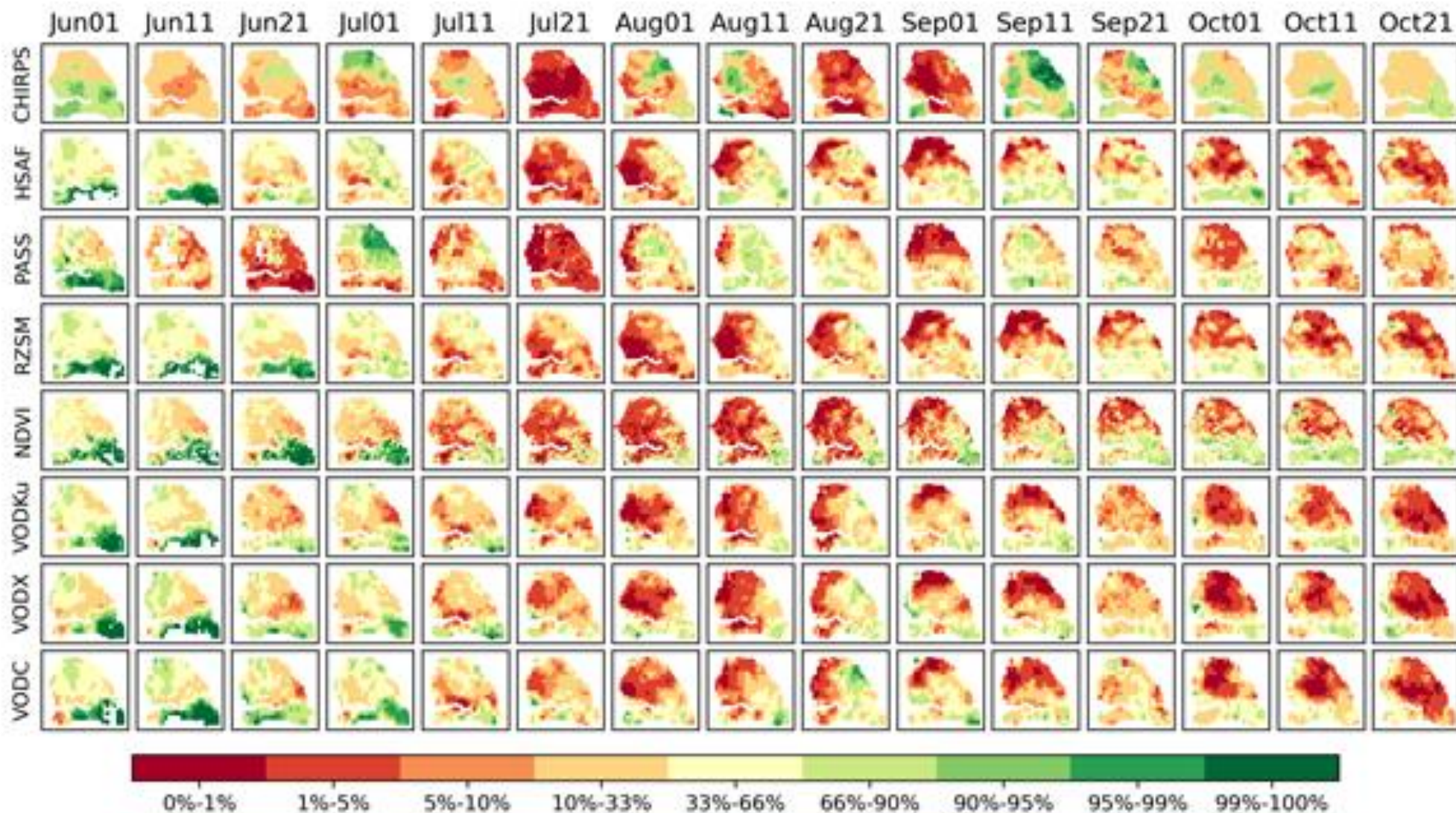




**Drought impact monitoring and yield forecasting**

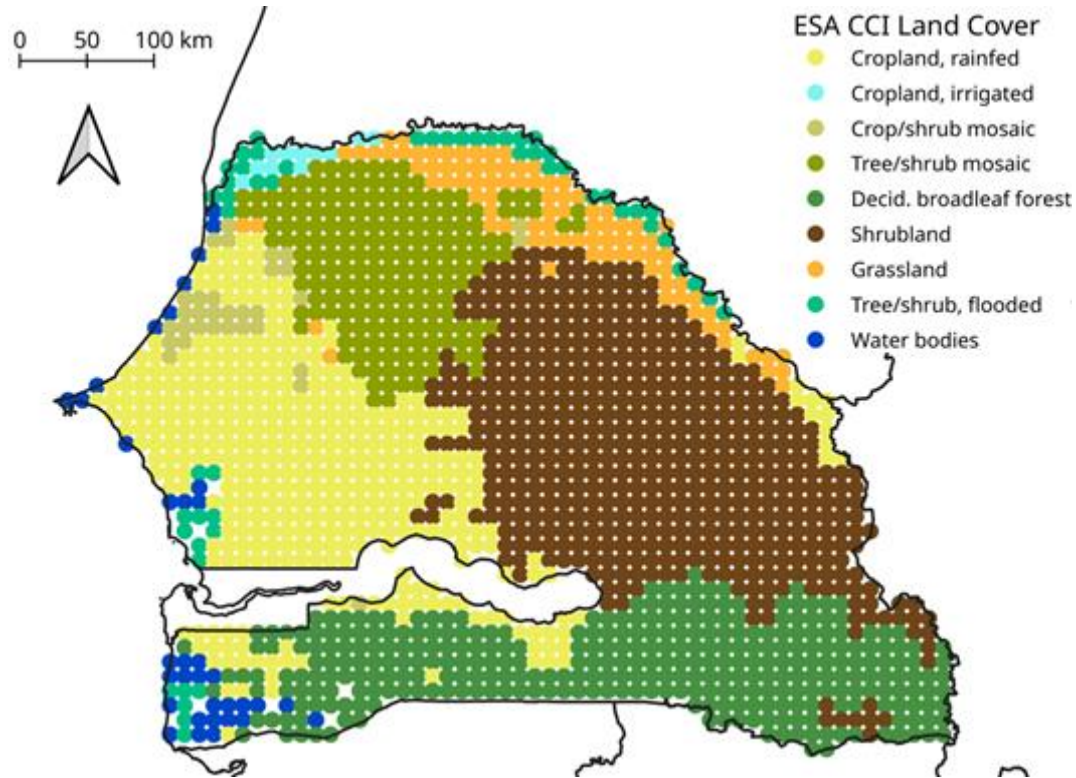
# Senegal 2014 drought

- Impact in multiple indicators
- Strongly water-limited region

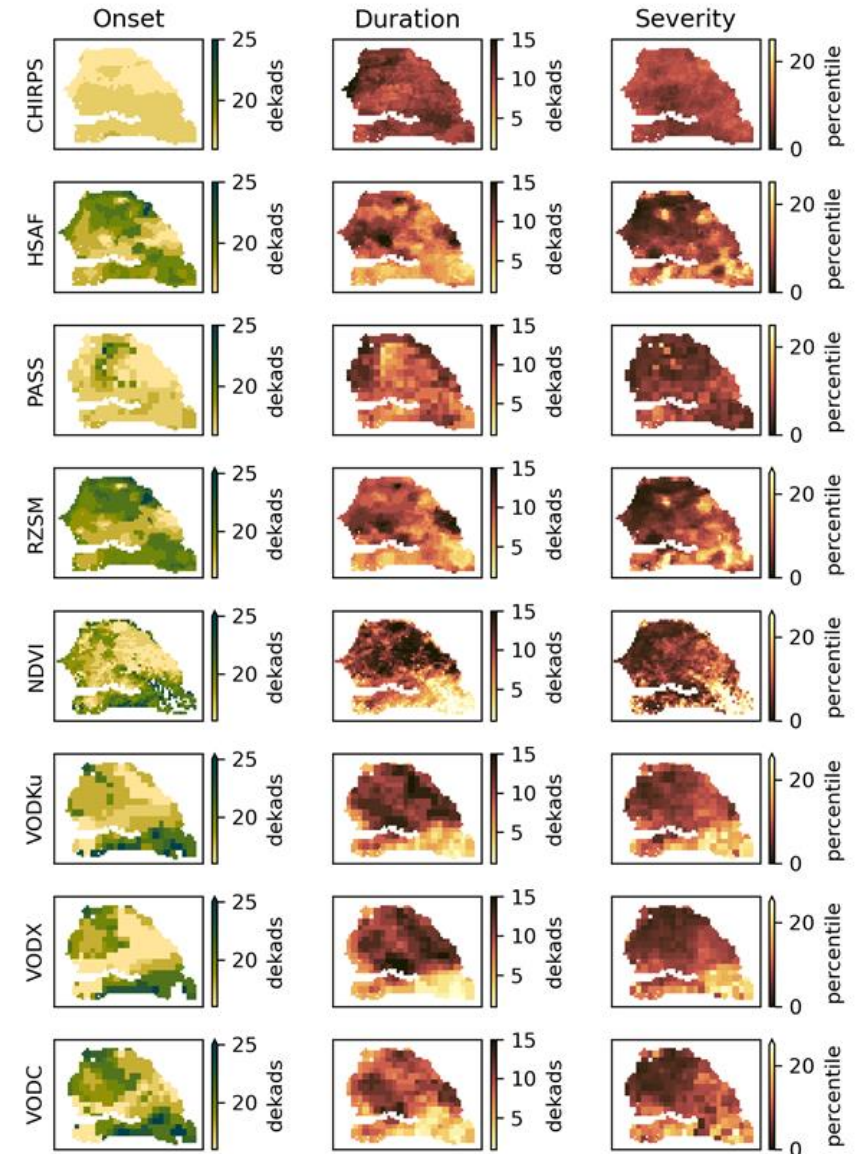


[Vreugdenhil, Pfeil et al., 2022]

- Drought impact carries the signature of land cover



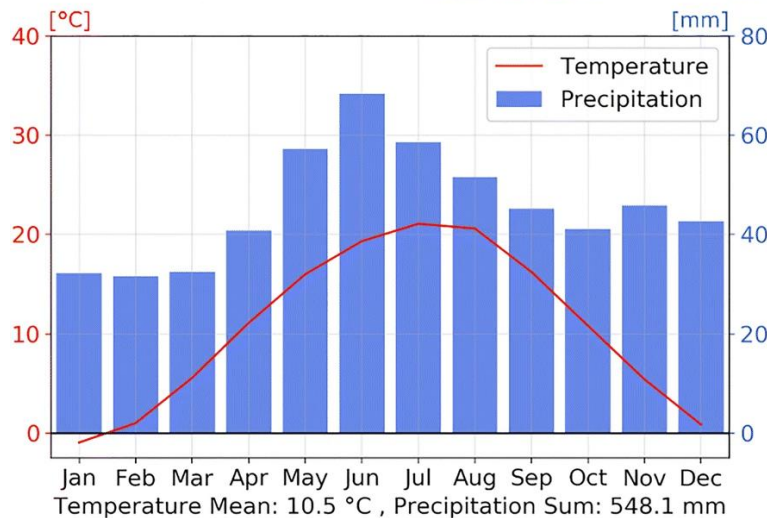
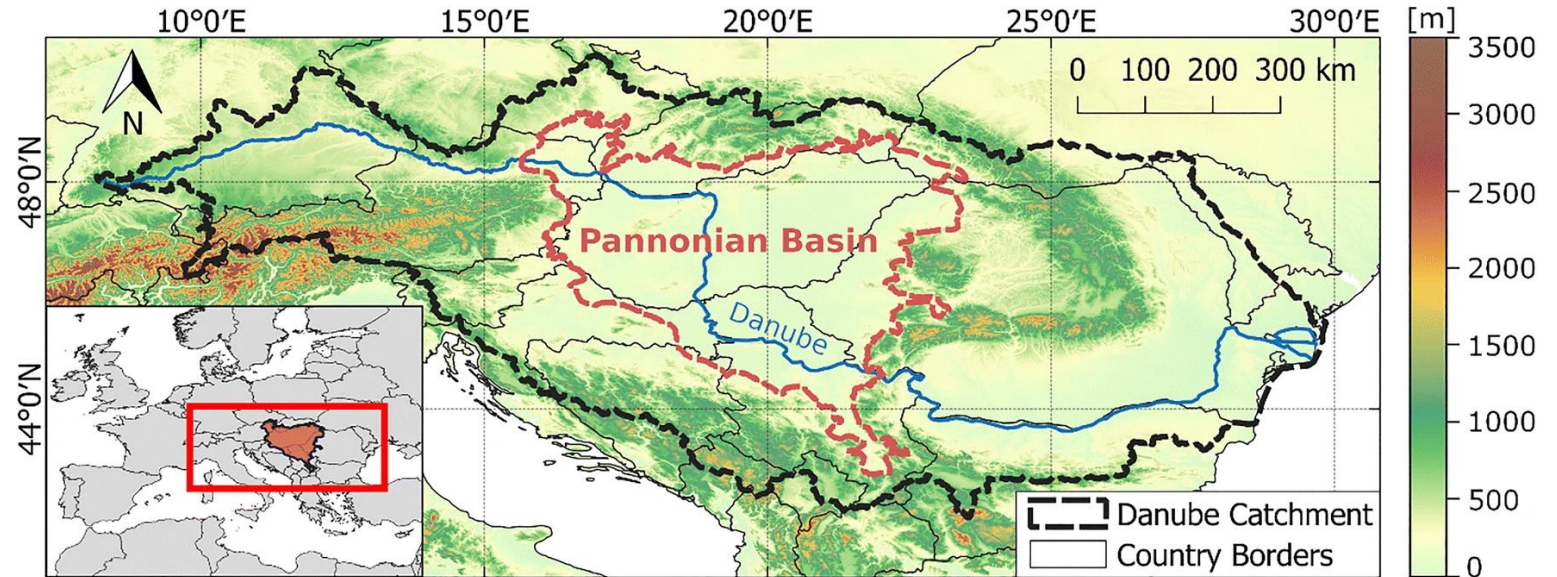
[Vreugdenhil, Pfeil et al., 2022]



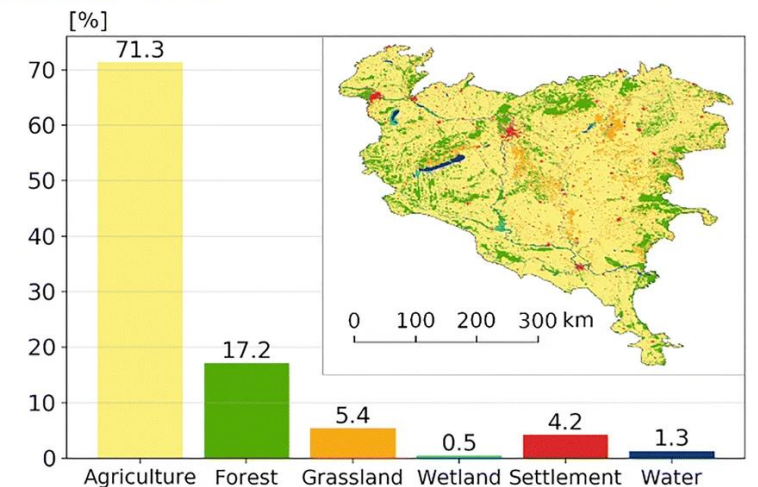
Sheltered, with relatively low levels of precipitation (< 600 mm/year)

High dependency of population on agriculture: 10-20% of population; >70% of area

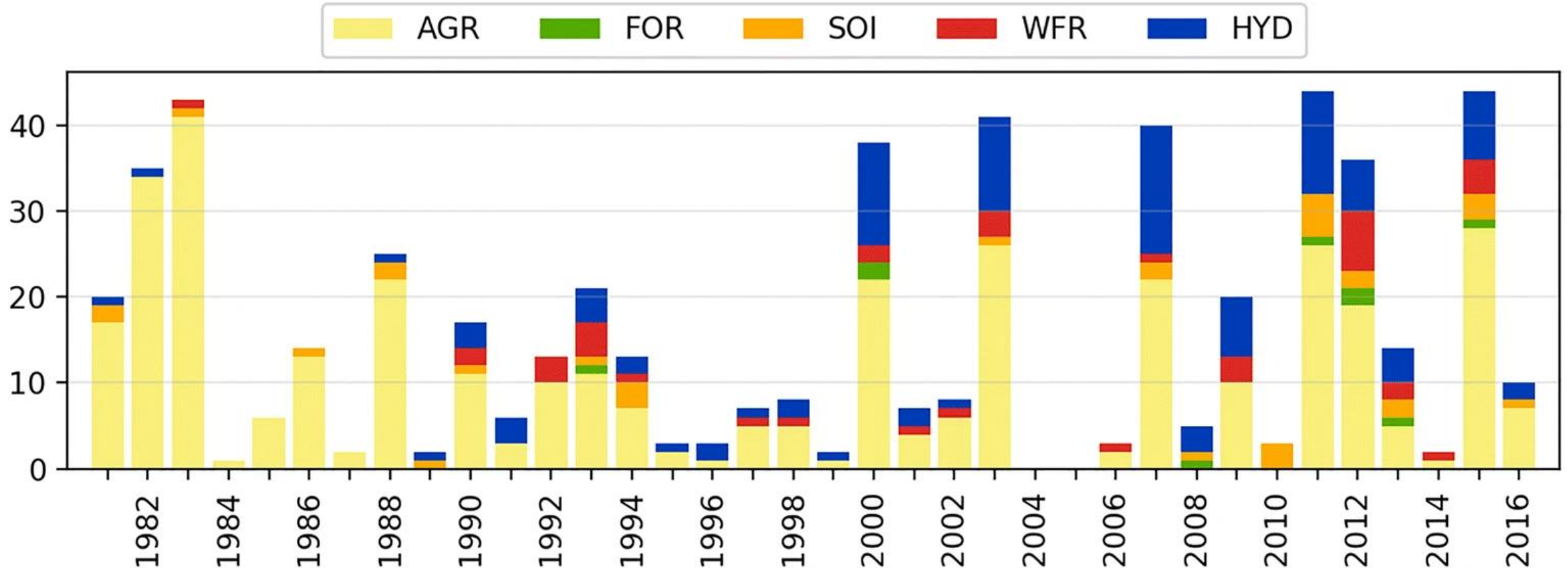
Mainly rain-fed



[Crocetti et al., 2020]



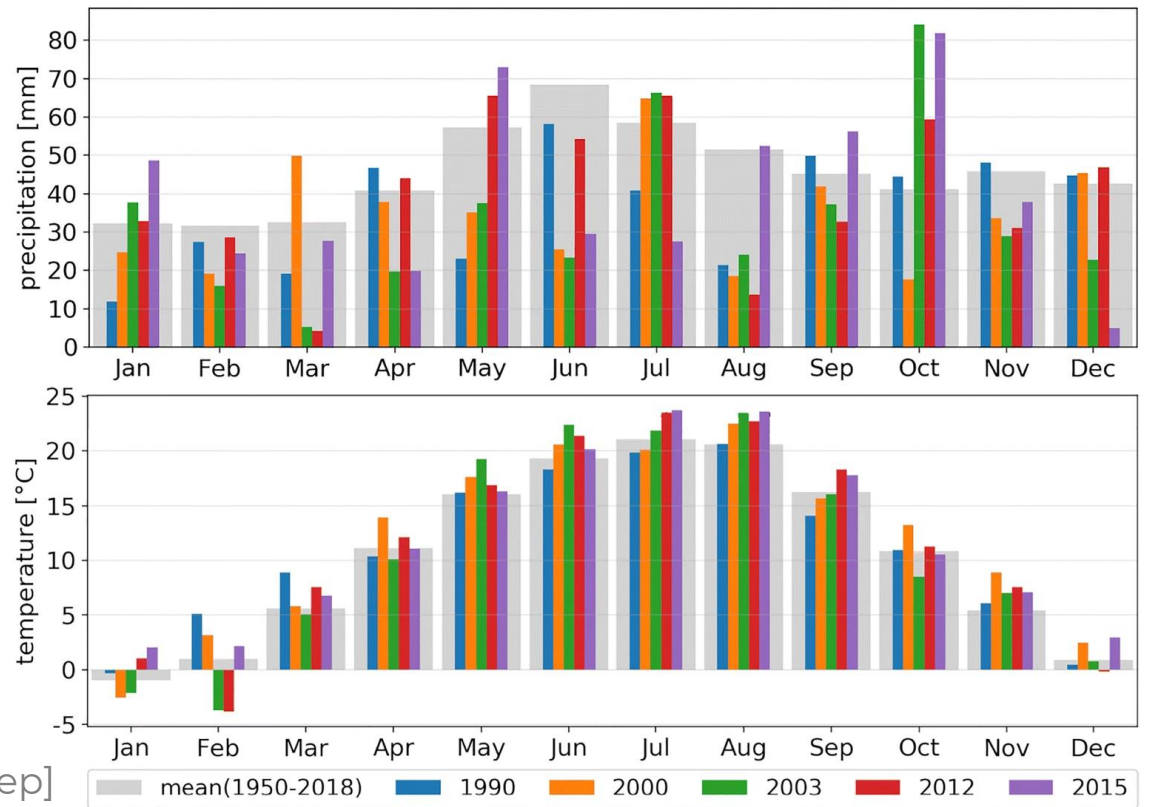
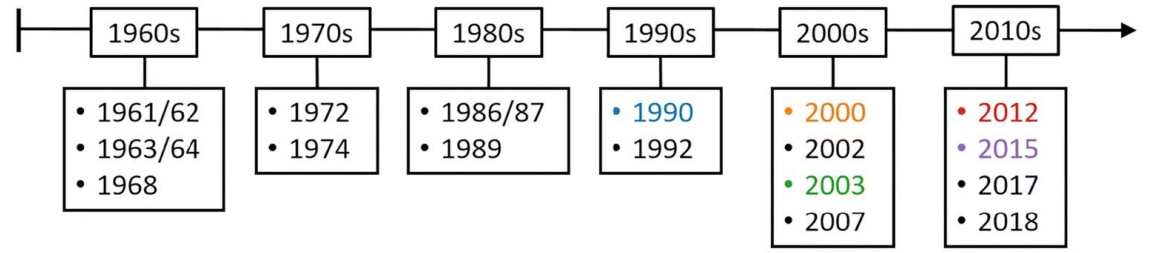
Reported by various media



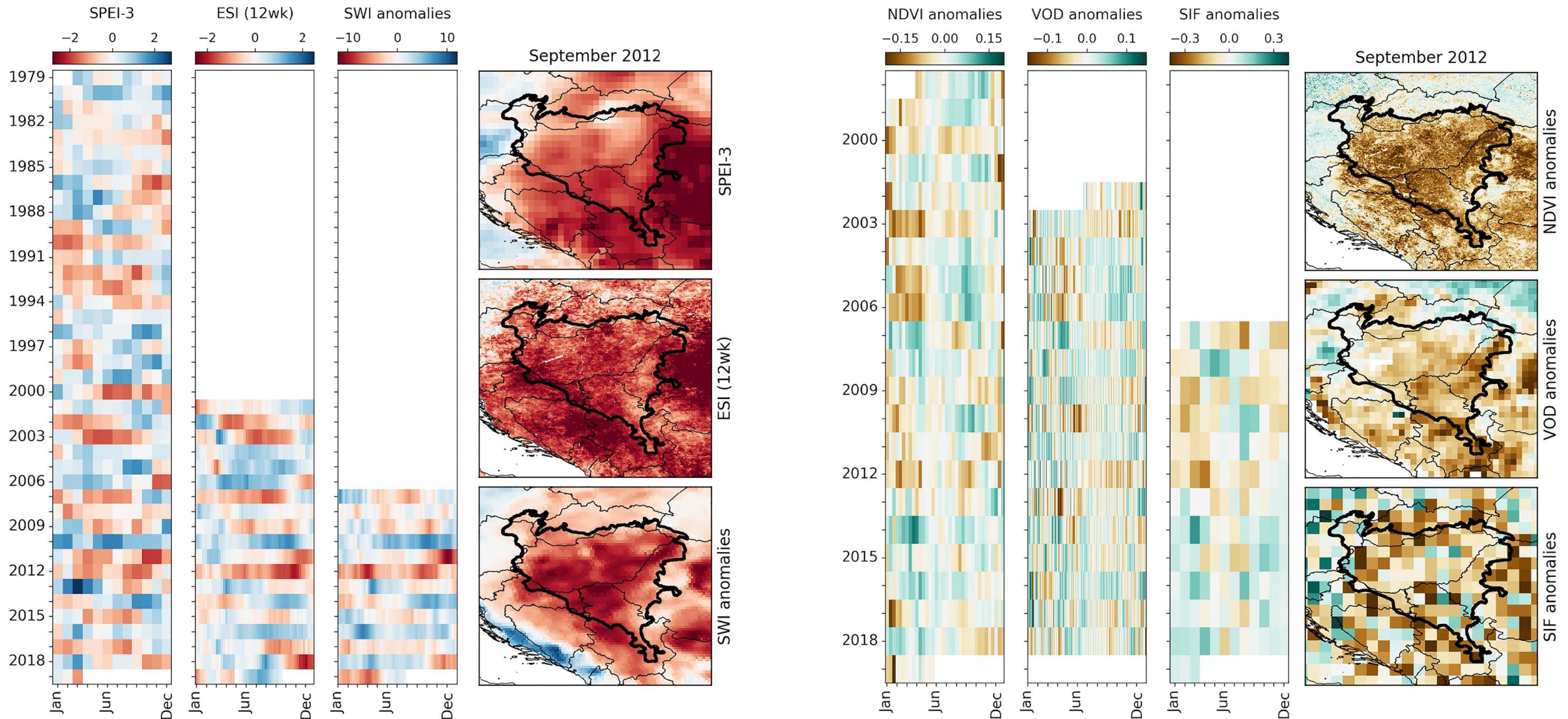
AGR|Agriculture - FOR|Forests - SOI|Soils - WFR|Wildfires - HYD|Hydrology

[Crocetti et al., 2020]

- Several drought episodes in the last decades caused significant crop yield losses
  - › 2003, 2007, 2012, 2015, 2017, 2018
  
- Mean yield loss of 20-30% for all regions
  
- Further exacerbated by climate change



[Bueechi et al., in prep]



[Crocetti et al., 2020]

- Numerous EO-based crop yield models have been developed and applied
  - › Process-based
  - › Machine learning
  
- Application over large areas possible using EO data, reanalysis and meteorological observations
  
- Extreme weather conditions complicate accurate crop yield forecasts

The ARYA crop yield forecasting algorithm: Application to the main wheat exporting countries

B. Franch<sup>a,b,\*</sup>, E. Vermote<sup>c</sup>, S. Skakun<sup>b,c</sup>, A. Santamaria-Artigas<sup>b,c</sup>, N. Kalecinski<sup>b,c</sup>, J.-C. Roger<sup>b,c</sup>, I. Becker-Reshef<sup>b</sup>, B. Barker<sup>b</sup>, C. Justice<sup>b</sup>, J.A. Sobrino<sup>a</sup>

Towards regional grain yield forecasting with 1 km-resolution EO biophysical products: Strengths and limitations at pan-European level

Raúl López-Lozano<sup>a,\*</sup>, Gregory Duveiller<sup>a,b</sup>, Lorenzo Seguini<sup>a</sup>, Michele Meroni<sup>a</sup>, Sara García-Condado<sup>a</sup>, Josh Hooker<sup>a</sup>, Olivier Leo<sup>a</sup>, Bettina Baruth<sup>a</sup>

Statistical modelling of crop yield in Central Europe using climate data and remote sensing vegetation indices

Anikó Kern<sup>a</sup>, Zoltán Barcza<sup>b,c,d,\*</sup>, Hrvoje Marjanović<sup>e</sup>, Tamás Árendás<sup>f</sup>, Nándor Fodor<sup>f</sup>, Péter Bónis<sup>f</sup>, Péter Bognár<sup>a</sup>, János Lichtenberger<sup>a,g</sup>

**In-season performance of European Union wheat forecasts during extreme impacts**

Seasonal weather forecasts for crop yield modelling in Europe

glar, S. Garcia Condado, S. Karetzos, R. Leckerf, & M. van den Berg

Pierre Cantelaube & Jean Statistical modelling of drought-related yield losses using soil moisture-vegetation remote sensing and multiscale indices in the south-eastern Europe

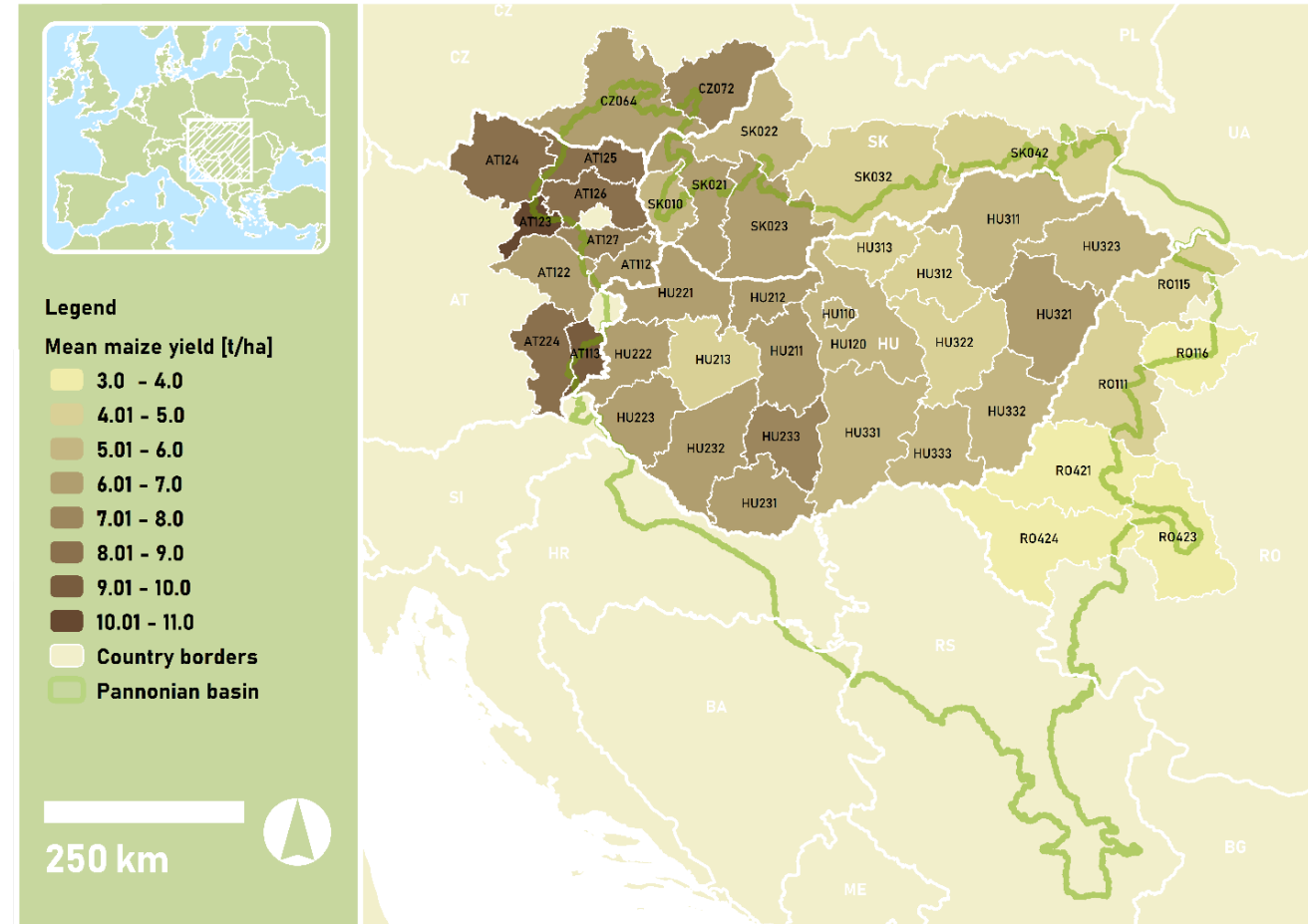
Vera Potopová<sup>a,\*</sup>, Miroslav Trnka<sup>b,c</sup>, Pavel Hamouz<sup>a</sup>, Josef Soukup<sup>a</sup>, Tudor Castravet<sup>d</sup>

**Yield estimation and forecasting for winter wheat in Hungary using time series of MODIS data**

Péter Bognár<sup>a</sup>, Anikó Kern<sup>a</sup>, Szilárd Pásztor<sup>a</sup>, János Lichtenberger<sup>b</sup>, Dávid Koronczay<sup>a</sup> and Csaba Ferencz<sup>a</sup>



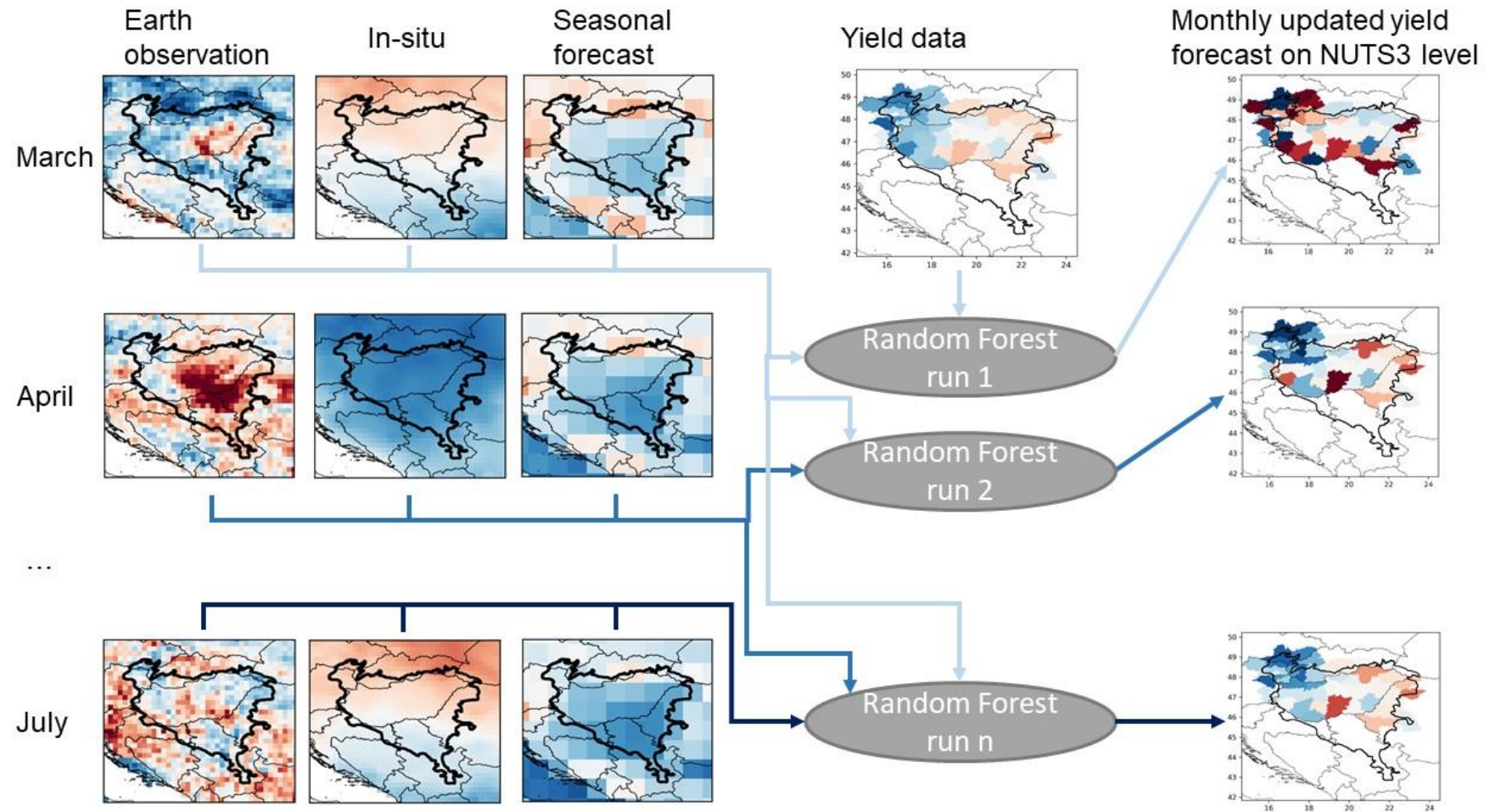
- Develop a forecasting system based on random forests:
  - › Wheat, harvested in July
  - › Maize, harvested in September
  
- 41 NUTS3 regions
  - › 2002-2016
  
- Assess its skill:
  - › in normal years and
  - › years of severe drought
  
- Assess the contribution of various drivers:
  - › Per crop type
  - › At different times during the growing season



- Temperature
- Water availability
  - › Precipitation
  - › Soil moisture
  - › Drought indices
- Crop status: VOD, NDVI, LAI
- Drought indices SPEI and ESI for specific drought information
- Seasonal forecasts of precipitation and temperature
- Detrended anomalies

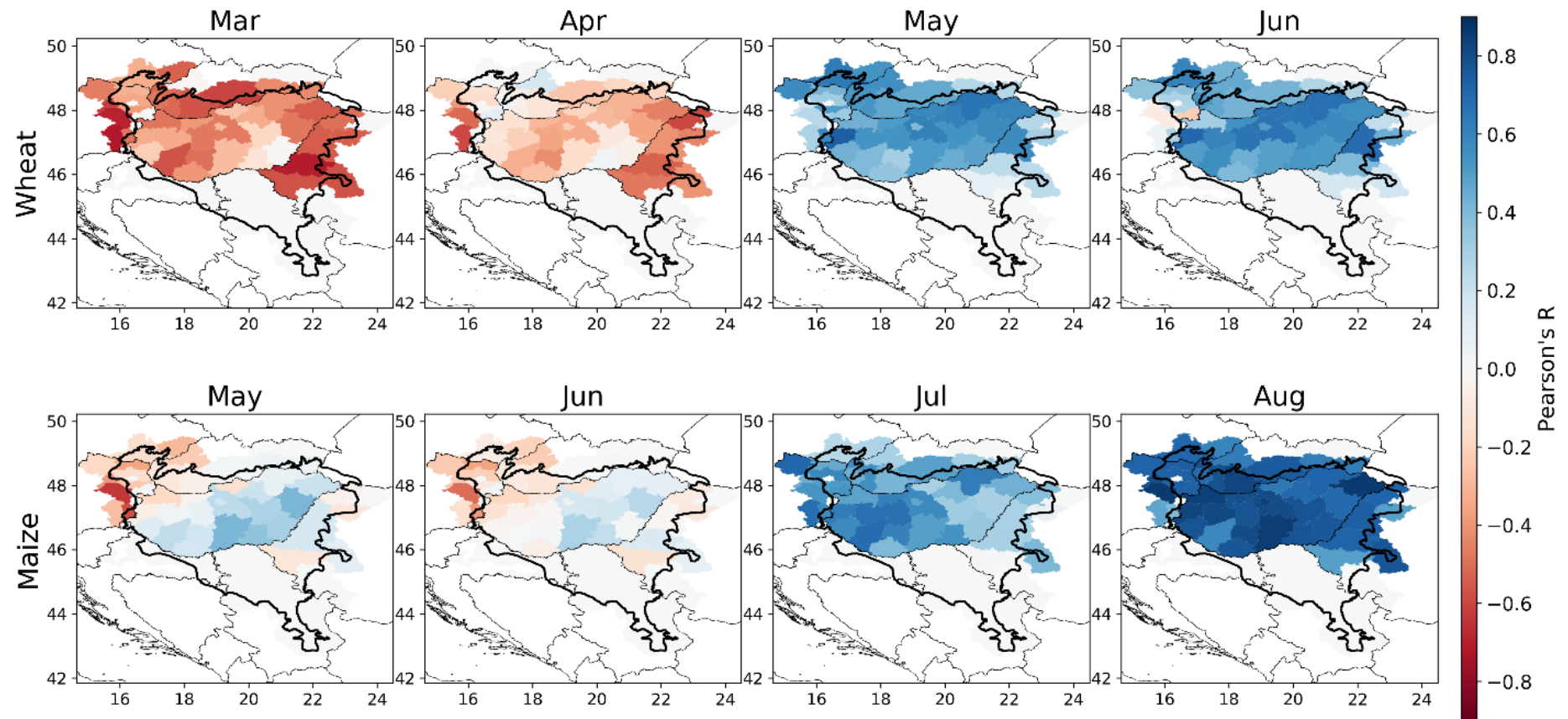
Dataset	Source	Spatial Resolution	Temporal Resolution
<b>Earth Observation</b>			
Soil Moisture	ESA CCI	0.25°	daily
Soil Water Index	ESA CCI	0.25°	daily
VOD Ku-Band	VODCA	0.25°	daily
NDVI	CGLS	0.01°	10-daily
LAI	CGLS	0.01°	10-daily
ESI (1 and 3 months)	MODIS	0.05°	weekly
<b>Reanalysis</b>			
Temperature	ERA5-Land	0.1°	daily
Growing Degree Days	ERA5-Land	0.1°	monthly
SPEI (1 and 3 months)	ERA5	0.25°	monthly
<b>Seasonal forecasts</b>			
Precipitation	ECMWF	1°	monthly
Temperature	ECMWF	1°	monthly
<b>In situ data</b>			
Temperature	E-OBS	0.25°	daily
Precipitation	E-OBS	0.25°	daily
Fraction of wet days	E-OBS	0.25°	monthly

- Crop yield forecasts with lead times up to 4 months before harvest
- Feature importance to assess impact of predictors
- Monthly updated with latest data
- Cross-validation leaving 3 years out in blocked periods



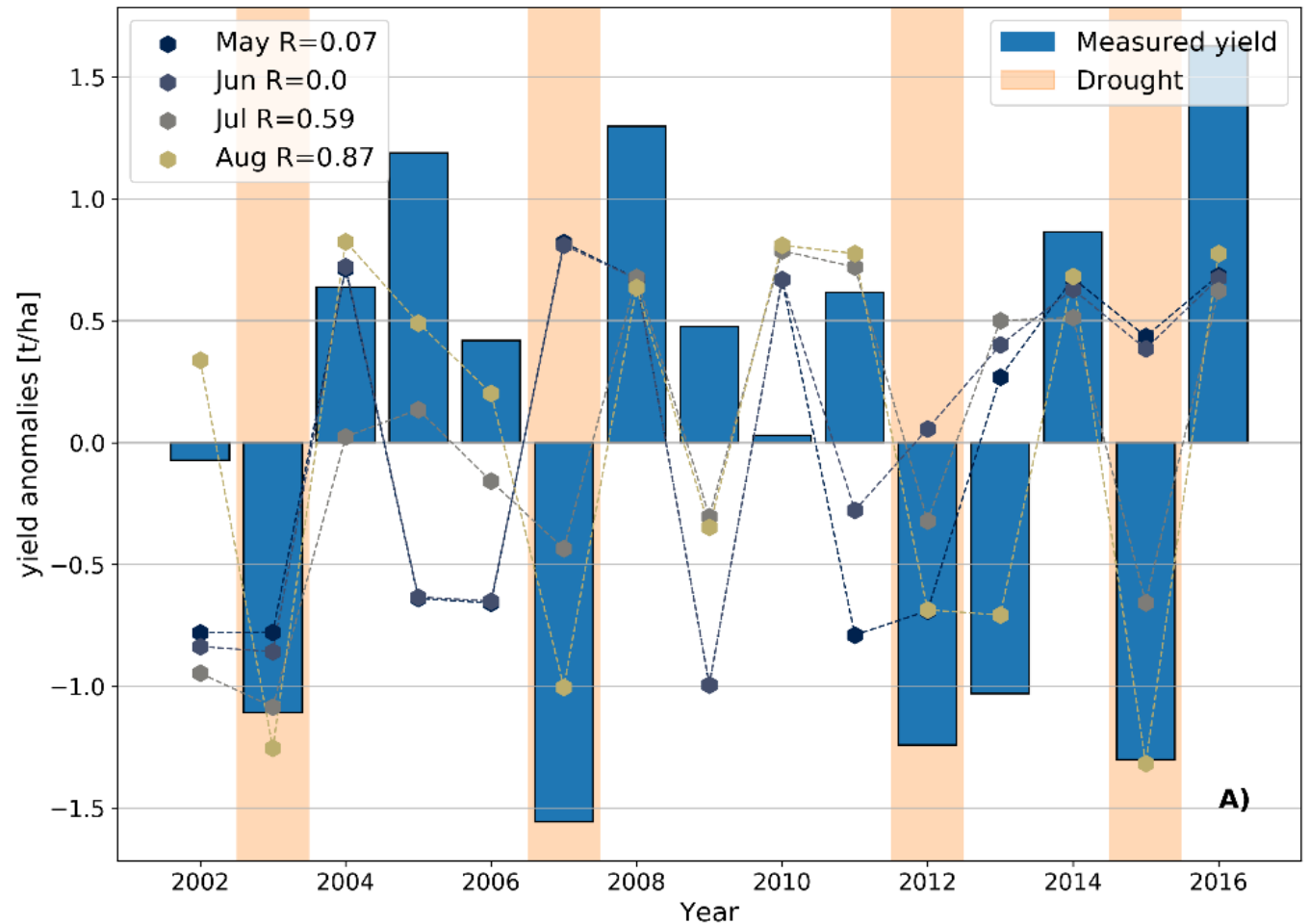
[Bueechi et al., in prep]

- For all regions, predicted and observed yields have high correlations 2 months before harvest (NUTS3 and mean of Pannonian basin)



[Bueechi et al., in prep]

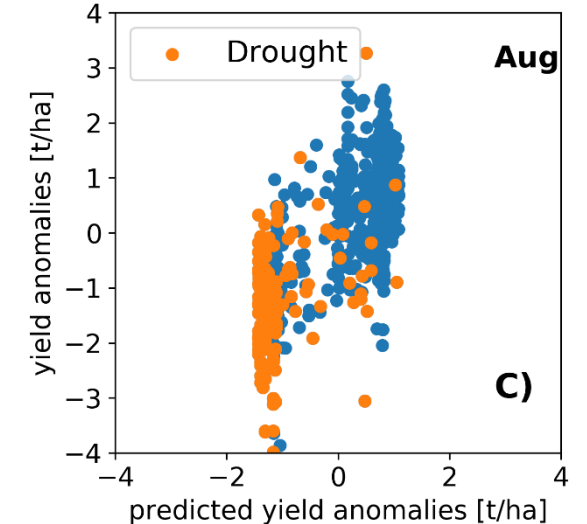
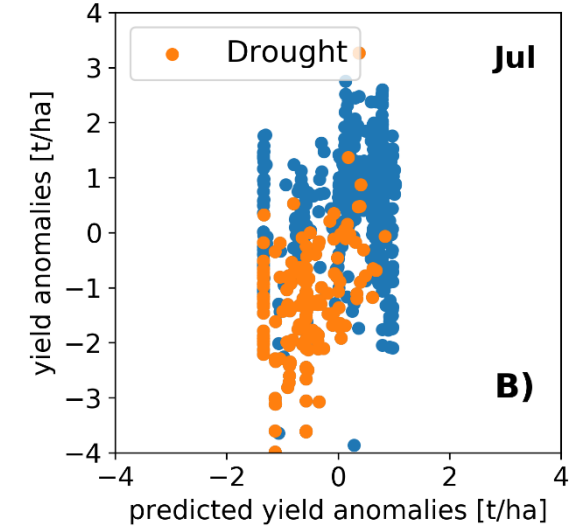
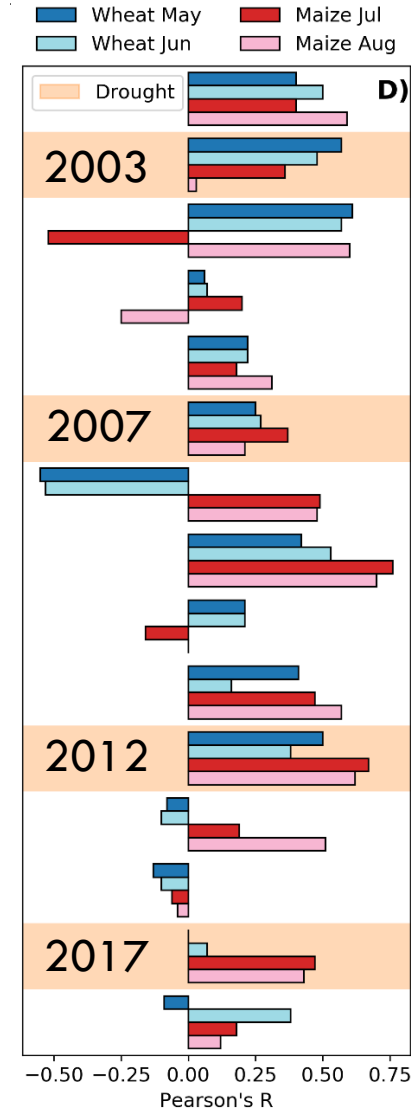
- Highest correlations to predict Pannonian basin mean maize yield the month before harvest ( $R=0.87$ )
- Model detects negative anomalies in drought years from around 2 months prior to harvest



[Bueechi et al., in prep]

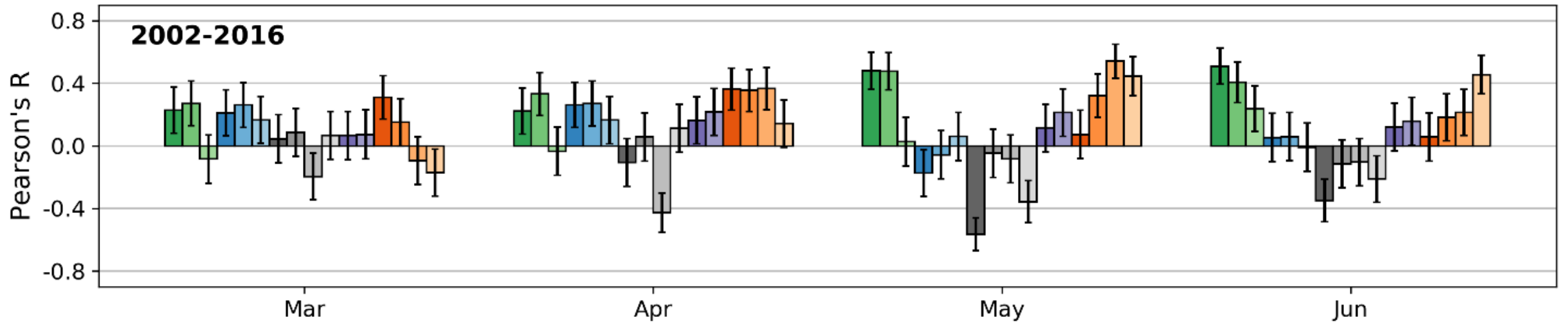
- Model is **poor in distinguishing** crop yields between different NUTS3 regions
  - Low yearly performance (spatial correlations)
  - High spatial correlations of yields and predictors
  - Coarse resolution of predictors

	Overall (R)	Drought (R)
Maize Jul	0.51	0.36
Maize Aug	0.67	0.33
Wheat May	0.41	0.47
Wheat Jun	0.47	0.44



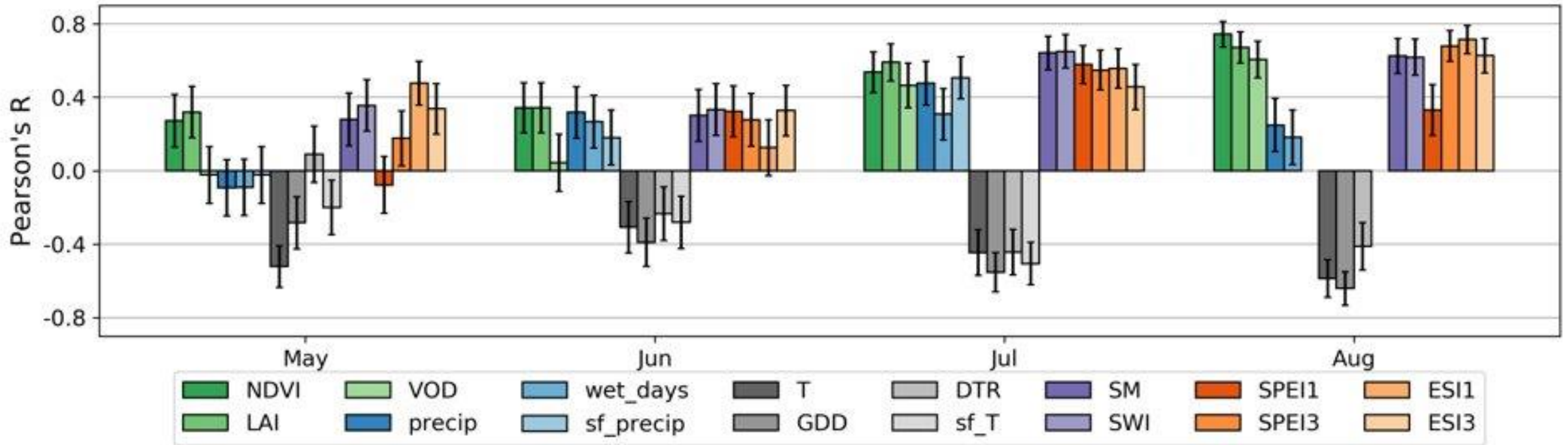
[Bueechi et al., in prep]

- Increase in correlation between predictors and wheat yields towards last two months
- Soil moisture little impact in addition to SPEI
- Crop condition most important predictor



[Bueechi et al., in prep]

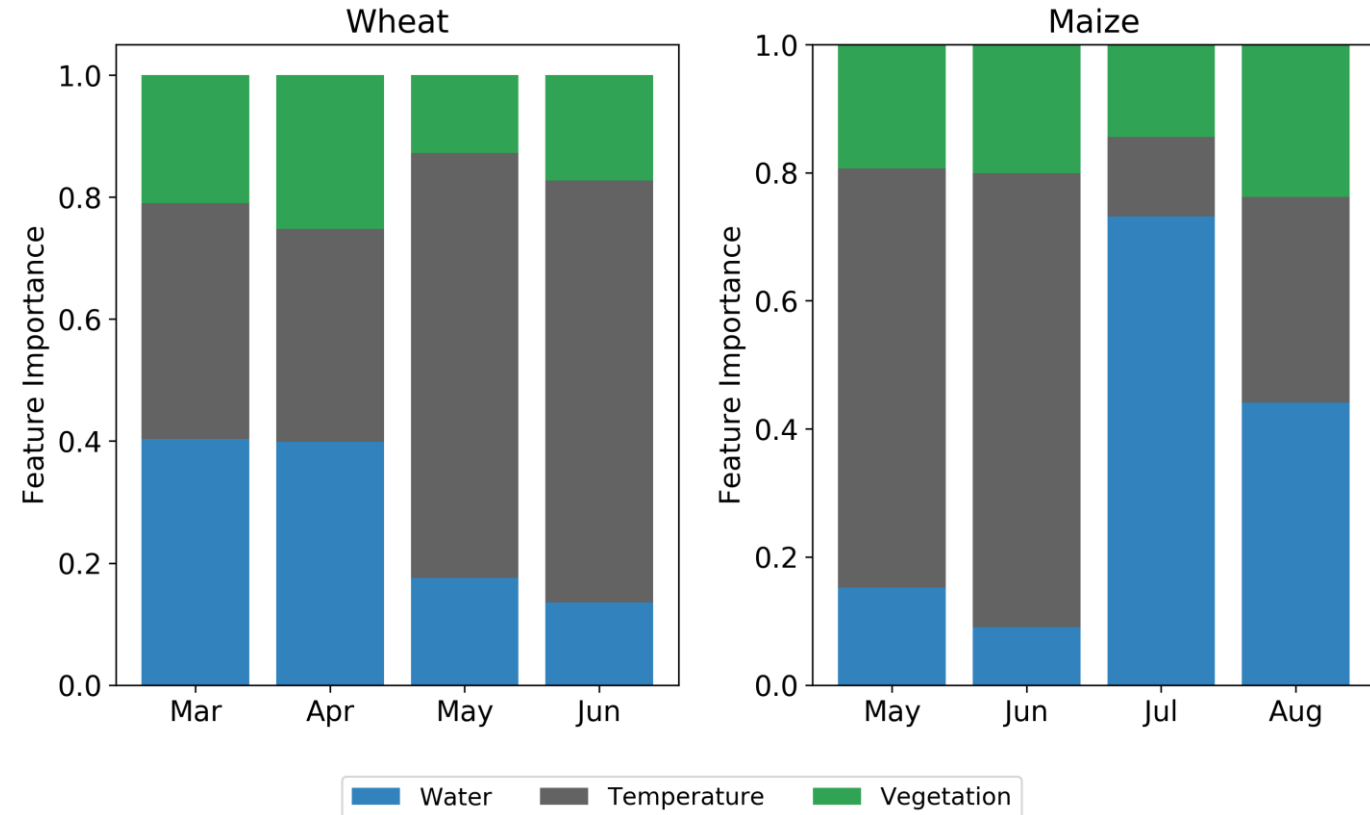
- Large increase in correlation between predictors and maize yields towards last two months
- Surface and root-zone soil moisture have highest correlations in July
- Crop indicators largest skill shortly before harvest



[Bueechi et al., in prep]



- Large changes of the feature importance from first to last two months
  
- Wheat
  - › Temperature main control overall
  - › Water (SPEI3 and soil moisture) mostly at beginning of growing season
  
- Maize
  - › Temperature main control in first months
  - › Water main control in last months



- Wheat and maize yield forecasts show reasonable performance **from around two months before harvest** for interannual variabilities
  - › Wheat is mainly dependent on the **temperature** - maize on water availability
  - › **Soil moisture and crop state** provide **key information** during last two months before harvest
- Crop yield losses in years of **severe drought underestimated** - negative anomalies are correctly early detected
- **High spatial autocorrelations** make it difficult to distinguish between regions

What else do we need from satellites?

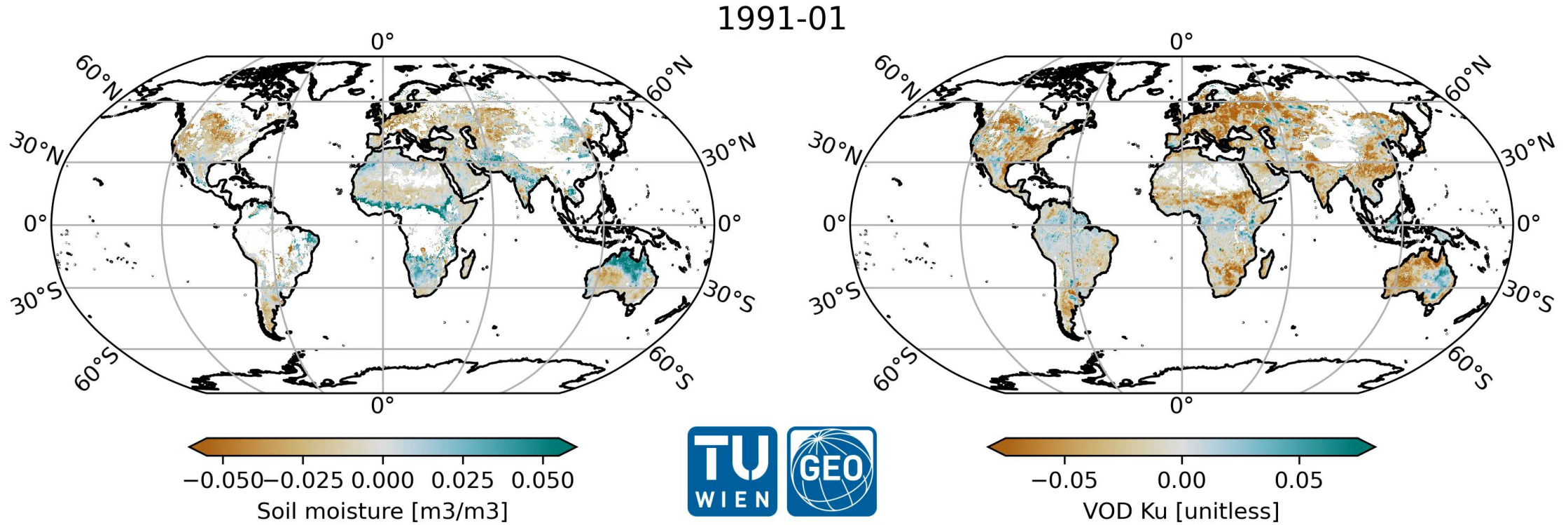
- Improving spatial and temporal resolutions to improve regional model performance; toward **field-scale** prediction
  - › Sentinel-1 soil moisture, Sentinel-2 crop variables
- Using **novel EO datasets** to better capture key variables like temperature and water availability
  - › LSTM temperature, Fluorescence from FLEX
- **Dub-daily observations** for better capturing of plant response to drought and heat stress?

- **ESA CCI Soil Moisture**
  - [climate.esa.int/en/odp/](https://climate.esa.int/en/odp/)
- **C3S Soil Moisture**
  - [cds.climate.copernicus.eu/](https://cds.climate.copernicus.eu/)
- **International Soil Moisture Network**
  - [ismn.earth](https://ismn.earth)
- **Vegetation Optical Depth Climate Archive (VODCA)**
  - [doi.org/10.5281/zenodo.2575599o](https://doi.org/10.5281/zenodo.2575599o)
- **SVODI**
  - [doi.org/10.5281/zenodo.7114654](https://doi.org/10.5281/zenodo.7114654)
- **VODCA2GPP**
  - [doi.org/10.48436/1k7aj-bdz35](https://doi.org/10.48436/1k7aj-bdz35)
- **QA4SM**
  - [qa4sm.eu](https://qa4sm.eu)
- **Data Viewer**
  - [dataviewer.geo.tuwien.ac.at](https://dataviewer.geo.tuwien.ac.at)



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