DROUGHT MONITORING AND CROP YIELD FORECASTING

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→ THE EUROPEAN SPACE AGENCY

Please download data for todays practical

https://ruhr-uni-bochum.sciebo.de/s/H4qH9M48S9yyypQ

Or directly from eo-college

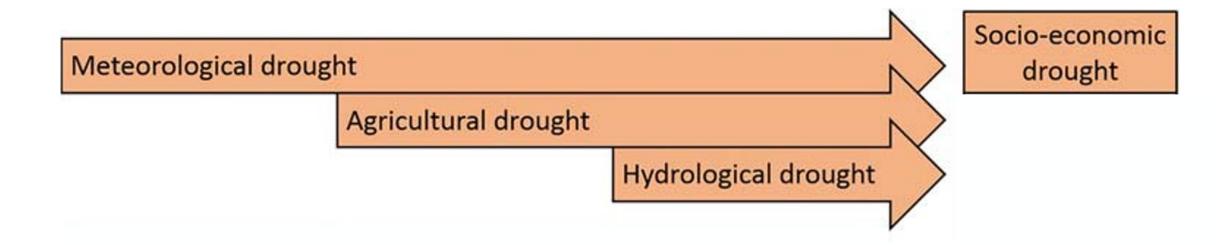→ THE EUROPEAN SPACE AGENCY

What is drought?

- Drier than normal condition leading to water shortage
- Impacts on environment and economy

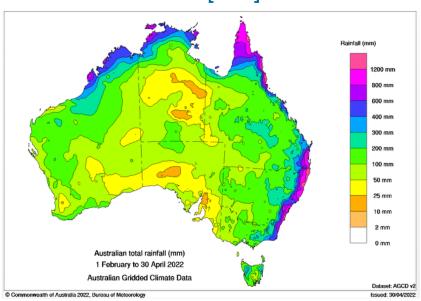→ THE EUROPEAN SPACE AGENCY

Drought types

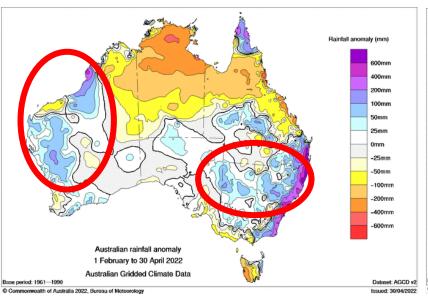[Crocetti et al, 2020]

How do we quantify drought?

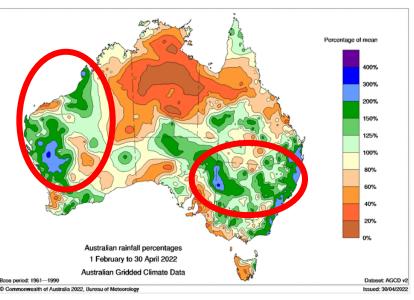- Drought is not a physical variable but an indicator of deviating conditions, and can be expressed in various ways

Rainfall January-April 2022 [mm]

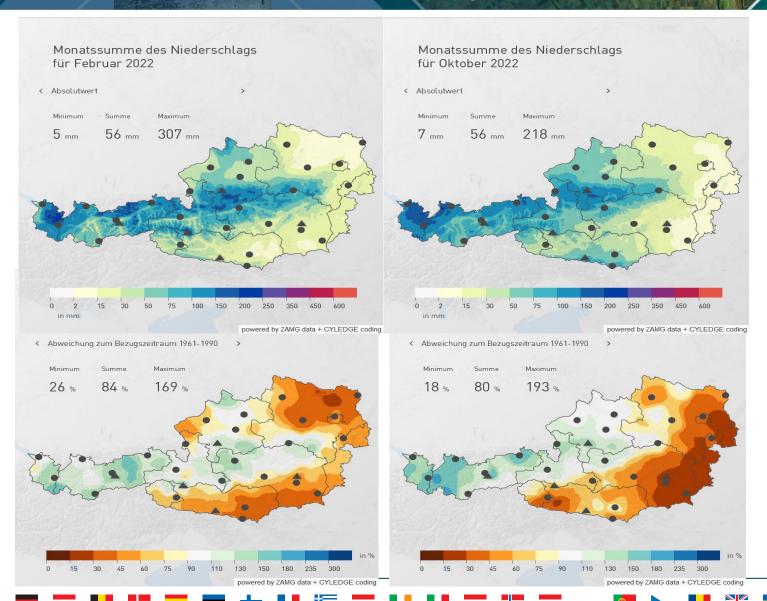### Anomaly from long-term mean rainfall [mm]

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
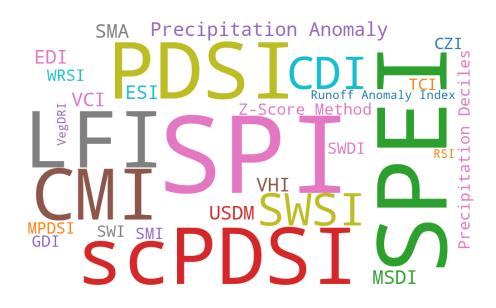
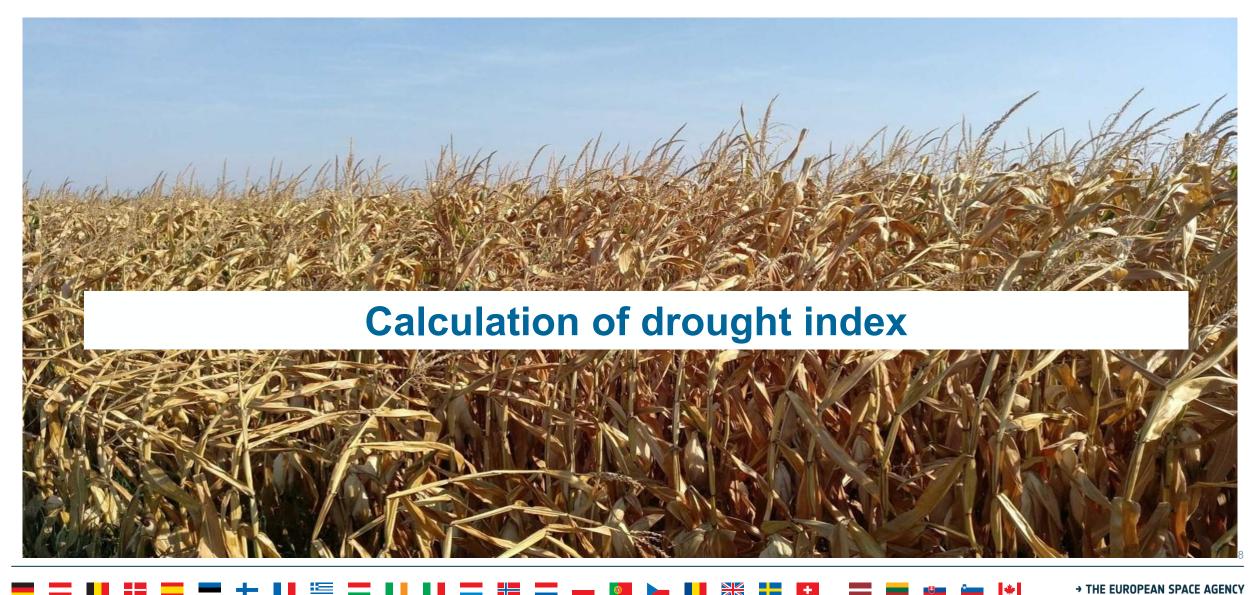# Also seasonal differences need to be accounted for

Different scenario of drought for different seasons

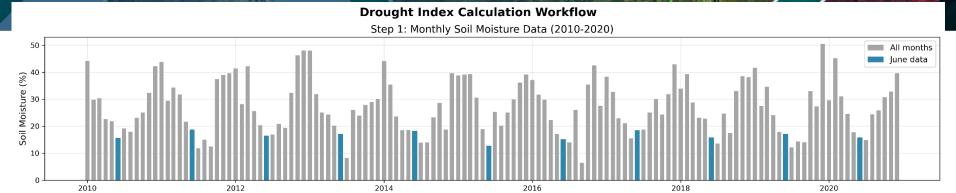https://www.zamg.ac.at/cms/de/klima/klima-aktuell/klimamonitoring

Drought Indices

Indices -> standardized values **express moisture deficit**:

- Standardized Precipitation Index (SPI), using Precipitation only
- Standardized 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…

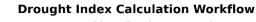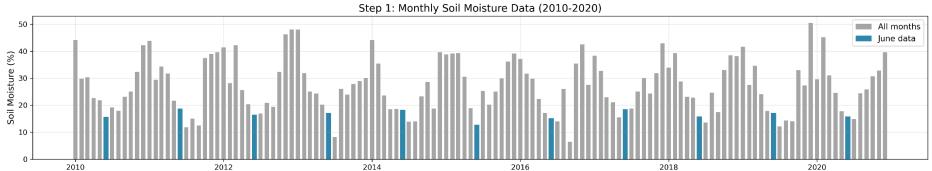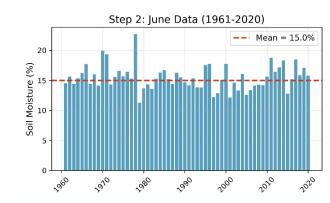# Calculation of drought index

How is drought index calculated?

Drought Index Calculation Workflow
Step 1: Monthly Soil Moisture Data (2010-2020)

Example of standardization with normal distribution fitting (z-score)

How is drought index calculated?

Drought Index Calculation Workflow
Step 1: Monthly Soil Moisture Data (2010-2020)

Step 2: June Data (1961-2020)

Example of standardization with normal distribution fitting (z-score)

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Example of standardization with normal distribution fitting (z-score)

How is drought index calculated?

Example of standardization with normal distribution fitting (z-score)
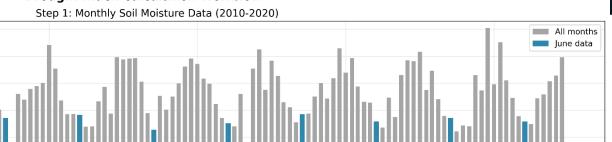
How is drought index calculated?

Example of standardization with normal distribution fitting (z-score)

How is drought index calculated?

Example of standardization with normal distribution fitting (z-score)

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Example of standardization with normal distribution fitting (z-score)

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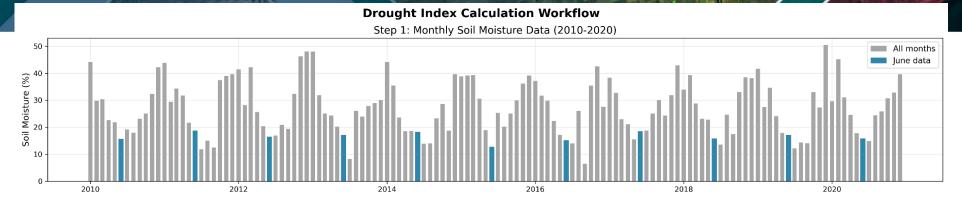
SPI fits actual, long-term precipitation record to probability (gamma) distribution (left), which is then transformed into a normal distribution (right) so that the mean SPI for the location and desired period is zero and the SPI is expressed by a z-score

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)

1. Probability Density Function

Standardized Precipitation Index

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What does drought index say?

Understanding Drought Index Values:
Negative = Drier than Normal, Positive = Wetter than Normal

Drought Monitoring

Standardized Precipitation Index

- ➢ Can be computed at multiple time aggregates (1, 2, 3, 12 months etc.) representing different process time scales
- ➢ Short aggregation period = short-term effect (flash droughts);
- ➢ Long-aggregation period = long-term effect (hydrological drought)
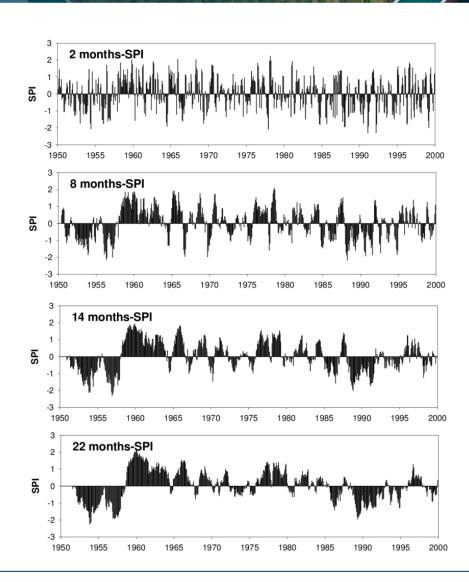
Table 1. SPI values

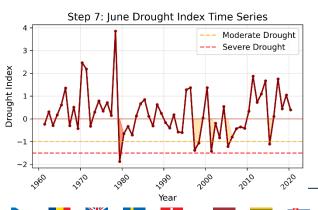|	
2.0+	extremely wet
1.5 to 1.99	very wet
1.0 to 1.49	moderately wet
-.99 to .99	near normal
-1.0 to -1.49	moderately dry
-1.5 to -1.99	severely dry
-2 and less	extremely dry

[Vicente-Serrano, 2005]

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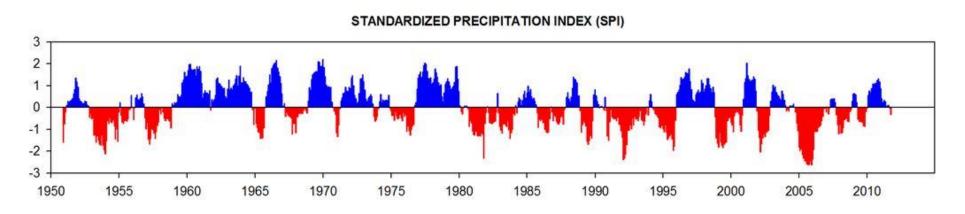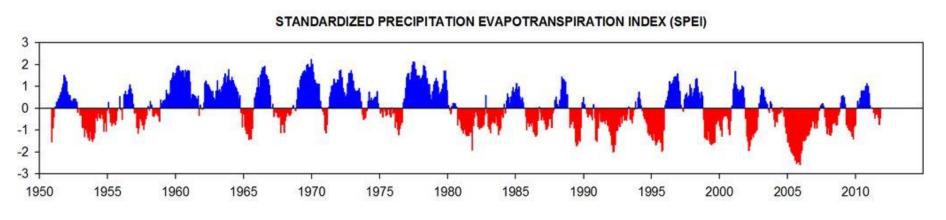
Standardized Precipitation Evapotranspiration Index

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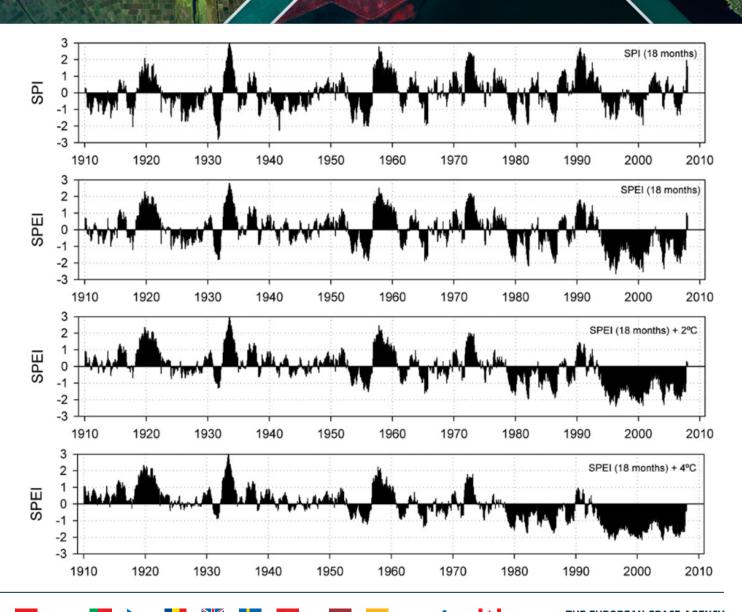
> Includes the impact of (rising) temperature

STANDARDIZED PRECIPITATION INDEX (SPI)

STANDARDIZED PRECIPITATION EVAPOTRANSPIRATION INDEX (SPEI)

SPI vs SPEI in warming climate

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

- progressive temperature
  increase between 1910 to 2007
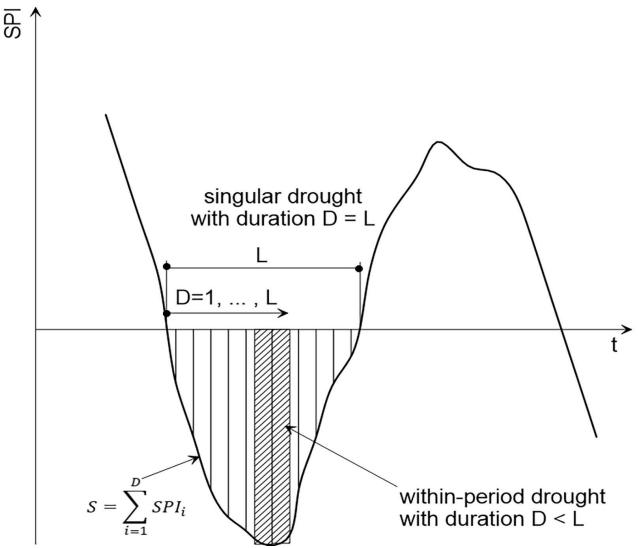
[Vicente-Serrano, 2010]

Drought duration (D): Number of consecutive days with index <0

Drought severity (S): The accumulation of negative index (e.g. SPI) values preceeded and followed by positive SPI values is called severity.
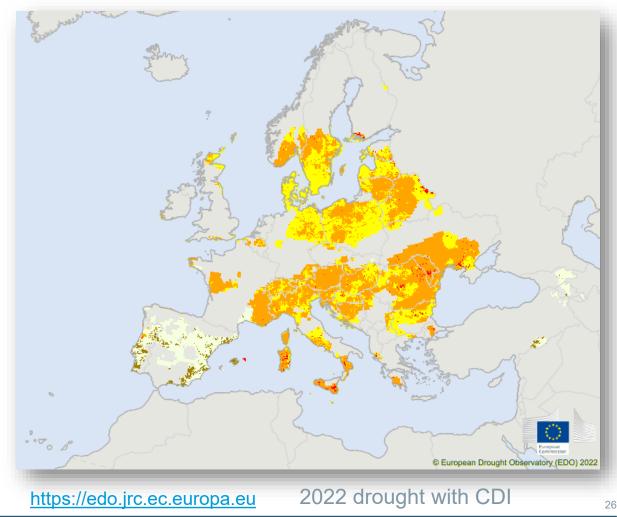
Drought intensity (I): The intensity is obtained by dividing the severity to the drought duration

singular drought with duration D = L

L

D=1, ... , L

$$S = \sum_{i=1}^{D} SPI_i$$

within-period drought with duration D < L

European Drought Observatory (EDO)

Drought indicators:

- **Soil Moisture Anomaly** (SMA)

- **Standardized Precipitation Index** (SPI)

- **Anomaly of Vegetation Condition** (FAPAR Anomaly)

- **Low-Flow Index** (LFI)

- **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.
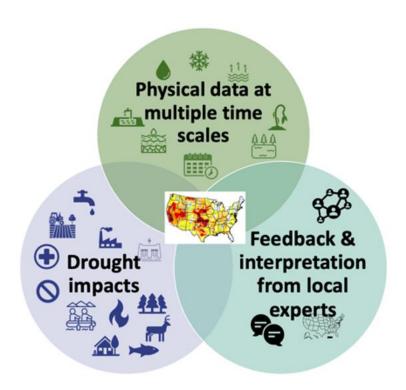
© European Drought Observatory (EDO) 2022

https://edo.jrc.ec.europa.eu   2022 drought with CDI

Drought Monitoring Systems
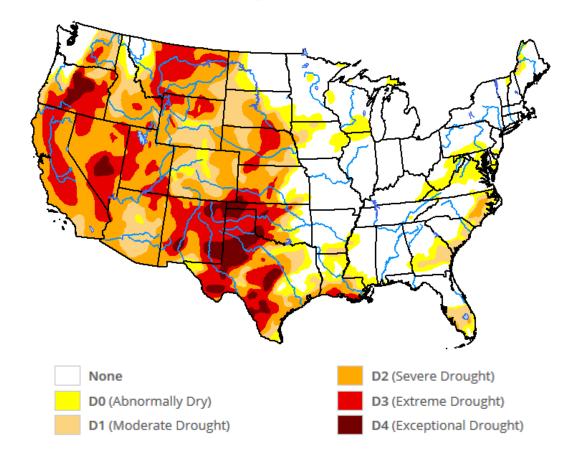
United States Drought Monitor

https://droughtmonitor.unl.edu/CurrentMap.aspx

Map released: April 28, 2022
Data valid: April 26, 2022

None	D2 (Severe Drought)
D0 (Abnormally Dry)	D3 (Extreme Drought)
D1 (Moderate Drought)	D4 (Exceptional Drought)

ESA Land Training Course 2025 – Bueechi, Luintel

Earth Observation for drought monitoring
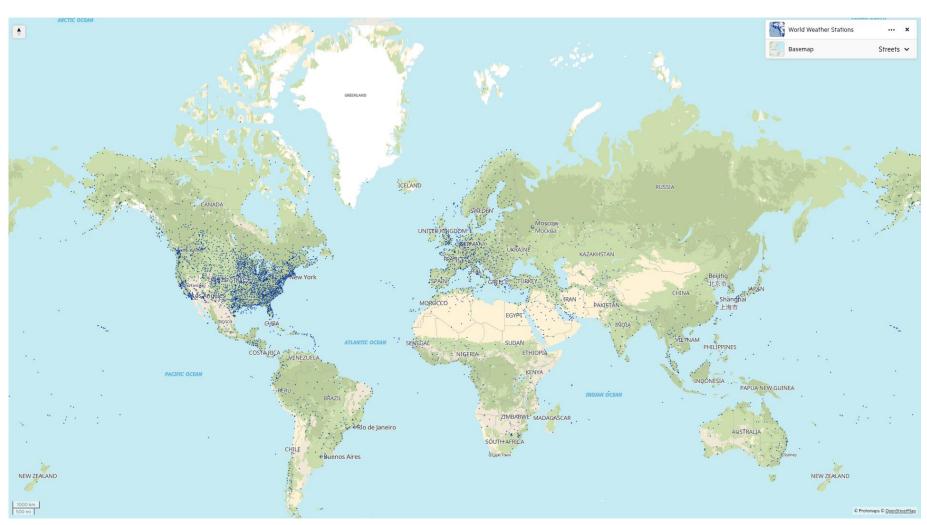
Why Earth Observation?

- Large area coverage
- Continuous data
  - Space
  - Time
- Beyond climate variables
  - Vegetation
- Near-real time
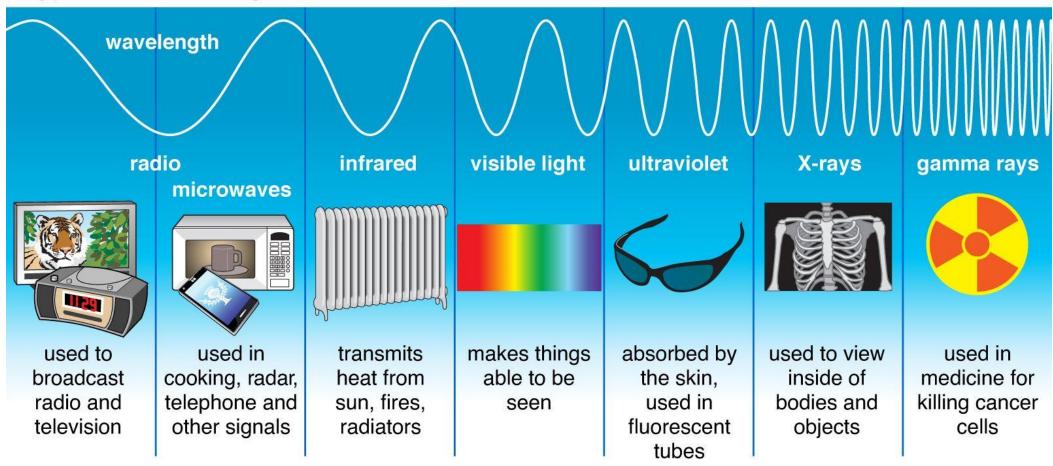
https://koordinates.com/layer/13361-world-weather-stations/

Types of Electromagnetic Radiation
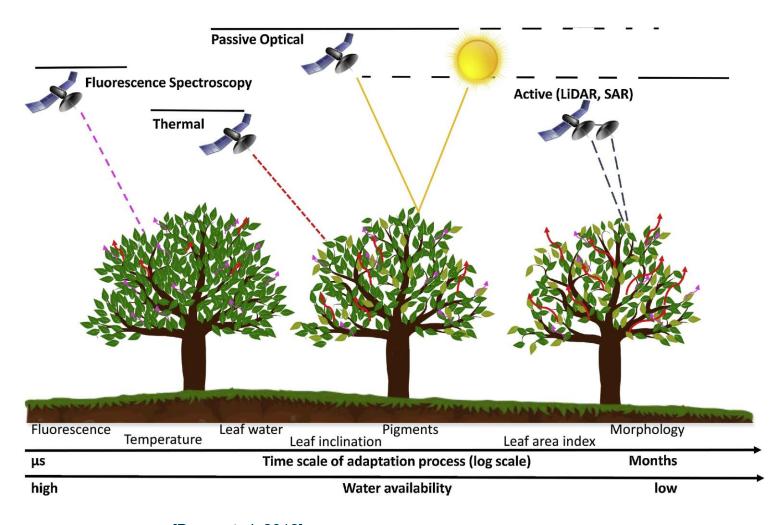
© Encyclopædia Britannica, Inc.

A plant's reaction to water stress

* Removal of Reactive Oxygen Species (ROS) released by changed metabolism
[Osakabe et al. 2014]
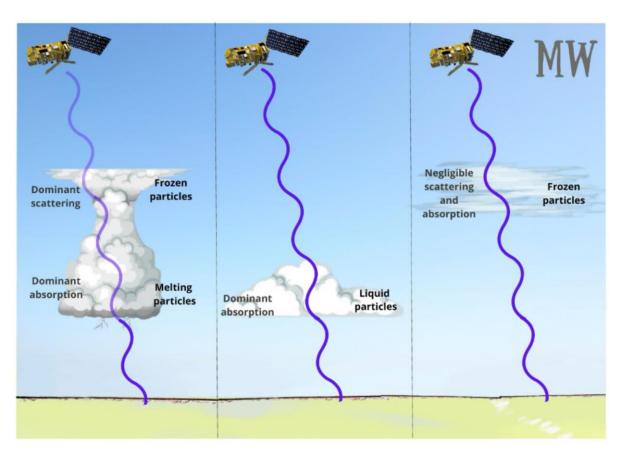
[Damn et al. 2018]
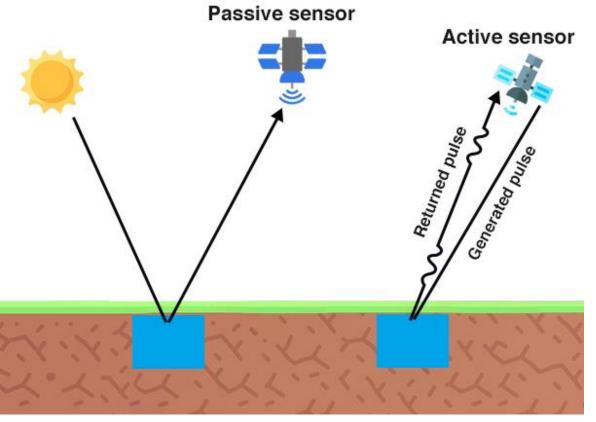
Why Microwave Sensors?

All weather – cloud penetration

How it works?

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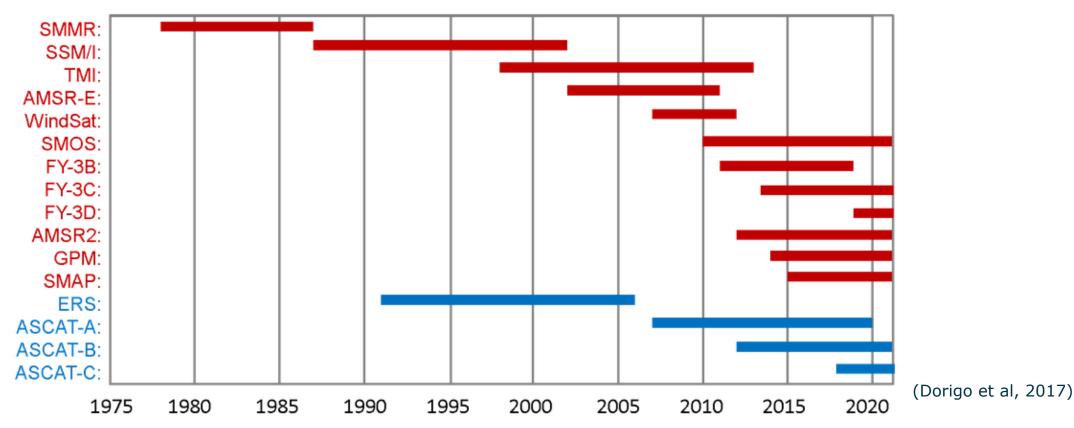
Satellite soil moisture for drought monitoring
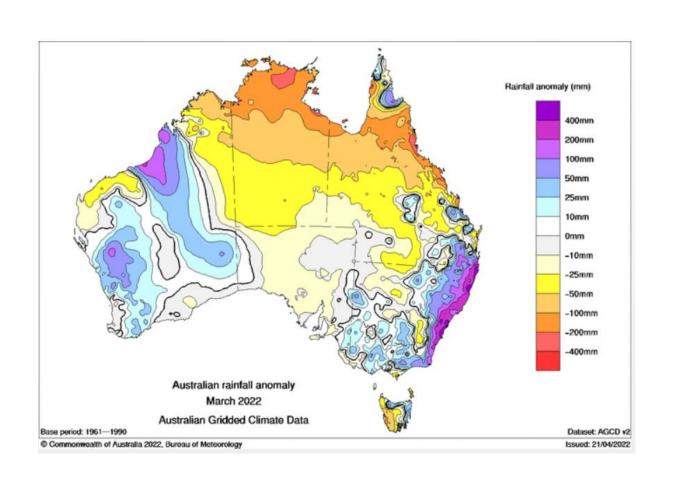
- ESA CCI SM data generated merging SM data from different sensors
- Use of multiple satellite missions allows for a more robust assessment over longer time periods (>45 years)
- Z-scores can in principle be computed for any dataset of sufficient length

(Dorigo et al, 2017)
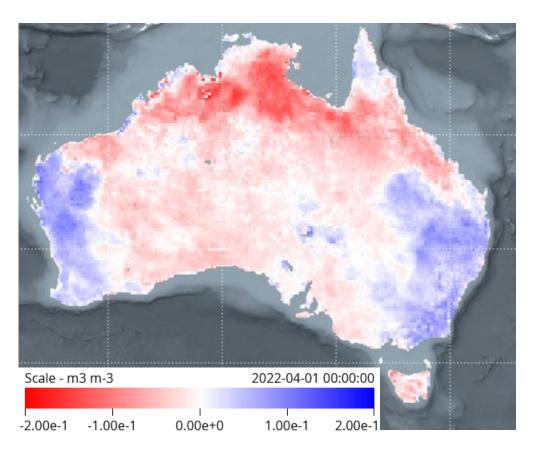
Satellite soil moisture-based drought monitoring

Anomalies in precipitation and multi-satellite ESA CCI SM for March 2022

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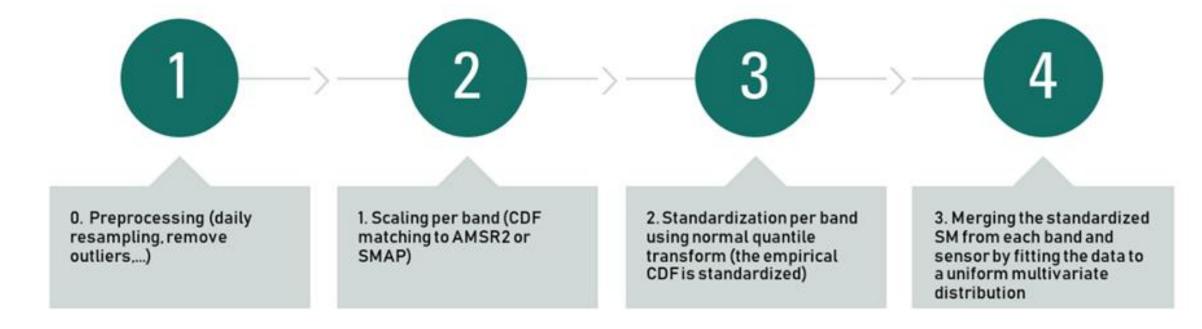
SMASI - A drought index for soil moisture
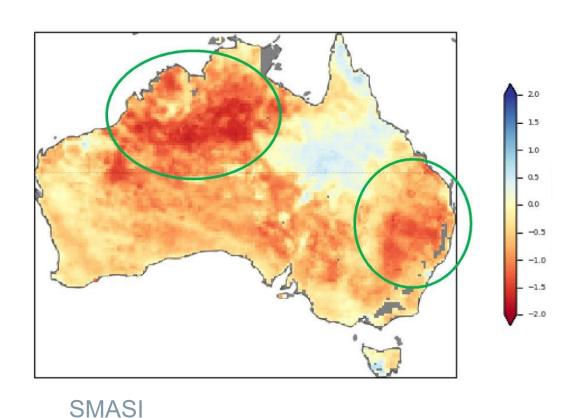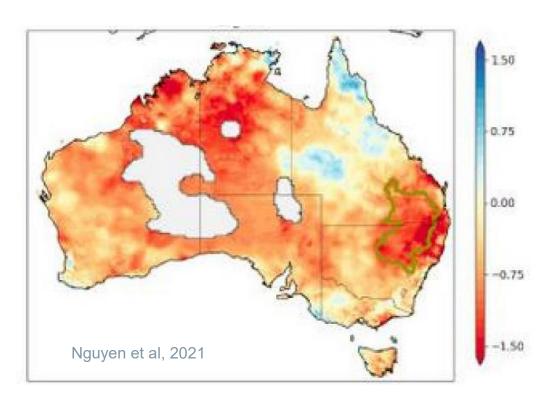
- Soil Moisture Anomaly Standardized Index (SMASI)

  o Merged standardized anomaly of soil moisture products from multiple satellite sensors as in ESA
    CCI soil moisture product (AMSR2, GPM, SMAP, SMOS, ASCAT)

  o 30-day moving window

1 — 0. Preprocessing (daily resampling, remove outliers,...)

2 — 1. Scaling per band (CDF matching to AMSR2 or SMAP)

3 — 2. Standardization per band using normal quantile transform (the empirical CDF is standardized)

4 — 3. Merging the standardized SM from each band and sensor by fitting the data to a uniform multivariate distribution

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SMASI
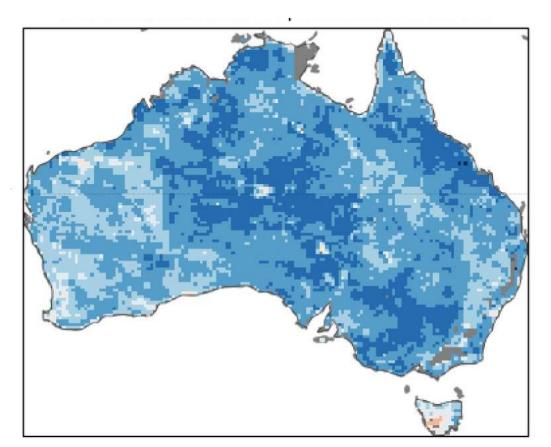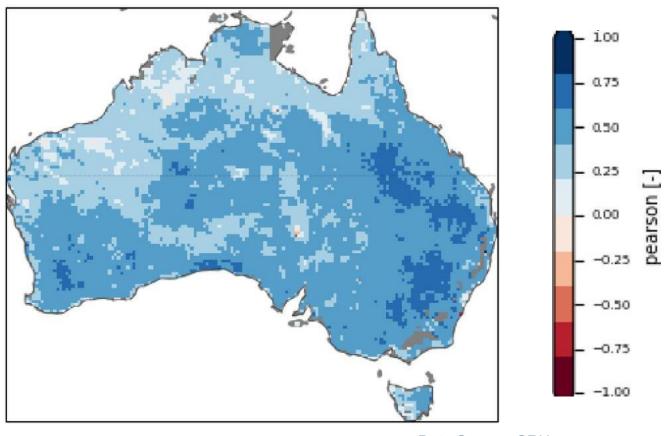
Evaporative stress index (ESI)

Nguyen et al, 2021

2019 December monthly mean follows spatial pattern ESI based on ground observation

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Correlation between SMASI and scPDSI
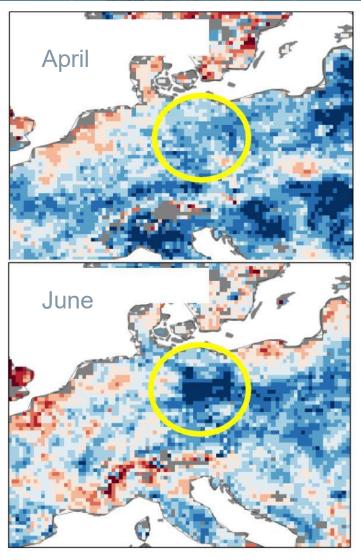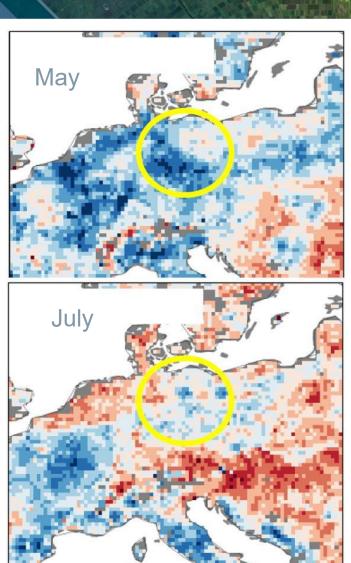
Correlation between SMASI and SPEI

Data Source: CRU

Ability to detect small scale rapid change in moisture

April

May

June

July

Rapid change from wet to dry in 2013 in Europe

Spring 2013: sufficient precipitation leads to high soil water, especially in May, SMASI > 0

June 2013: heavy precipitation leading to massive flooding in the Elbe area, SMASI > 1

July 2013: rapid decrease of soil moisture also detected with SMASI (short-term event).
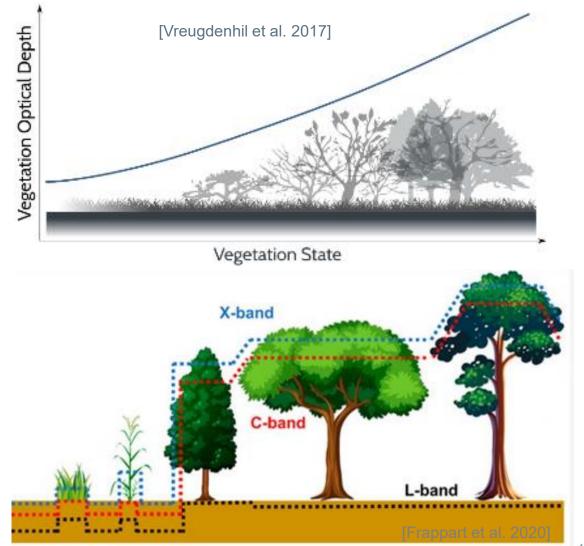
Porcu, Federico et. al. (2019). *Data record on extreme events by CAL and by hazard.*

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Microwave remote sensing for assessing drought impacts on vegetation

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 Ku-, X-, C-, and L-band (increasing wavelength)

- Retrieval algorithms seek to separate vegetation signal from soil signal, e.g.,
  - TU Wien method for radar observations
  - Land Parameter Retrieval Model (VU/NASA/VanderSat/Planet) for radiometer data

[Vreugdenhil et al. 2017]

[Frappart et al. 2020]

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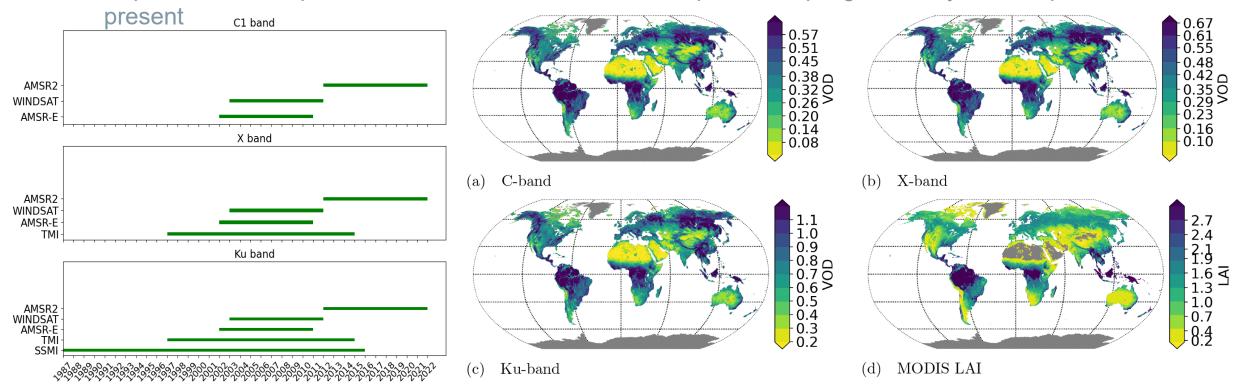
VODCA - The VOD Climate Archive

- Long-term, harmonized VOD, derived from multiple radiometer datasets (Zotta et al, 2024; 10.48436/t74ty-tcx62)
  - Separate VODCA products for C-, X-, Ku-band 0.25° spatial sampling and daily time step 1987-to present

(a) C-band

(b) X-band

(c) Ku-band

(d) MODIS LAI
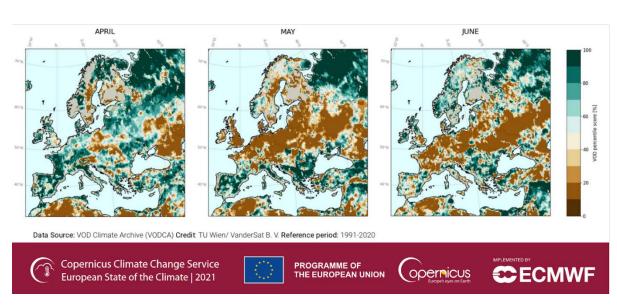
[Moesinger et al. 2020; 10.5194/essd-12-177-202]

VODCA - State of the Climate
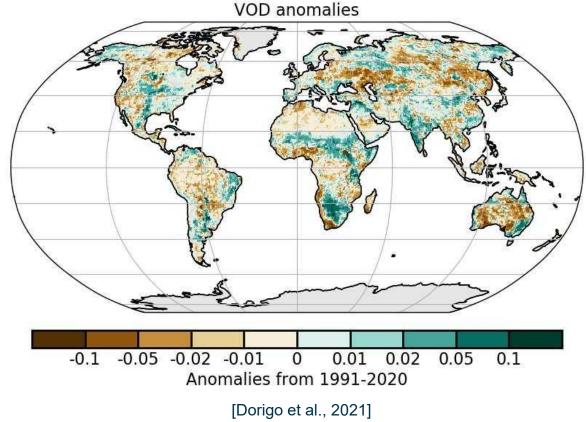
C3S European State of the Climate 2021

- Impact of late spring frost on vegetation

Data Source: VOD Climate Archive (VODCA) Credit: TU Wien/ VanderSat B. V. Reference period: 1991-2020
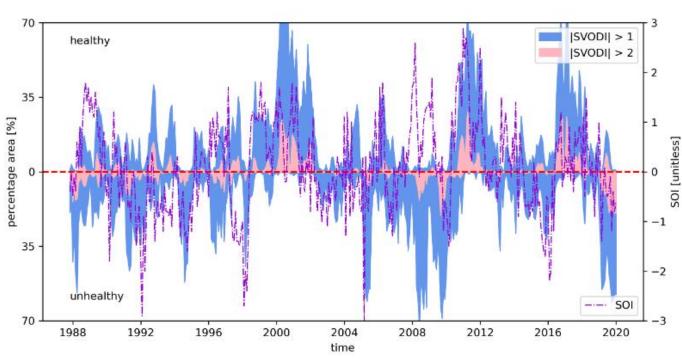
NOAA/BAMS State of the Climate 2021

VOD anomalies

Anomalies from 1991-2020

[Dorigo et al., 2021]
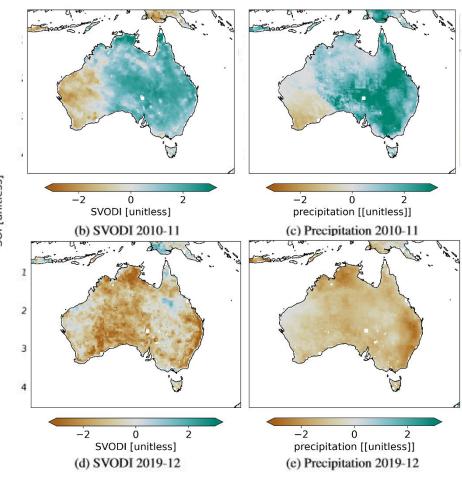
SVODI-Standardized VOD Index

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]

(b) SVODI 2010-11

(c) Precipitation 2010-11

(d) SVODI 2019-12

(e) Precipitation 2019-12

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

Summary

➤ Drought is drier than long-term average condition

➤ Drought is usually expressed as negative standardized values

➤ Earth observation helps continuous drought monitoring at large spatial scale

➤ Microwave sensors can observe earth surface at all weather

➤ Merged satellite soil moisture products such as ESA CCI soil moisture product and related drought index such as SMASI provide long term data for drought monitoring

➤ Vegetation condition monitoring using VOD and SVODI monitor vegetation response to drought

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Food security in a changing climate

Climate change threatens food security

Accurate crop models reduce
crop yield losses and their impacts on society

Earth observation and machine learning
are ideal tools for crop modelling

Climate change threatens food security

- Increasing intensity and frequencies of drought and heatwaves

- Large crop yield losses in recent years

- Arid countries with generally lower crop yields more affected

Reduce impacts of crop yield losses on society

- Different ways to adjust:
  - Reduce losses
    - Early detect stressors like pests and droughts
    - Improve fertilization / irrigation
    - Use "better crops"

  - Improve efficiency
    - Better guide import and export / operate stocks
    - -> reduce food waste!

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Crop yield forecasting

- Crop yield forecasts...

  - … facilitate decision-making

    - Operate stocks

    - Surplus of crops for export

    - How much import is required?

  - … allow farmers to adjust practices

    - Optimize use of fertilizers / irrigation

    - Choose optimal crop to plant

Why Earth observation?

Key information on crop health and growing conditions

Available throughout the season

Global and near-real-time

High spatial and temporal detail

Vast amount of data freely available

Esa.int

Why machine learning?

Increasing availability of high-performance hardware – Supercomputers

Easy accessibility of software

     E.g. Tensorflow, Scikit-learn

     Easy to use

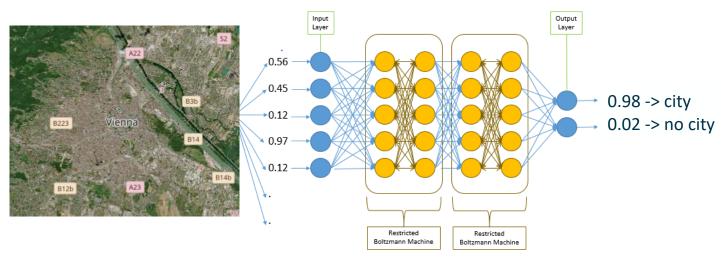   Accessibility for many people while physical models are only for specialists

     Often faster and less computationally expensive than physical models

Learns from data

Tuwien.at

0.98 -> city
0.02 -> no city

Copernicus.eu / codeproject.com

Machine learning and Earth observation

ML and EO are a perfect fit

Very flexibel models meet vast amount of diverse data
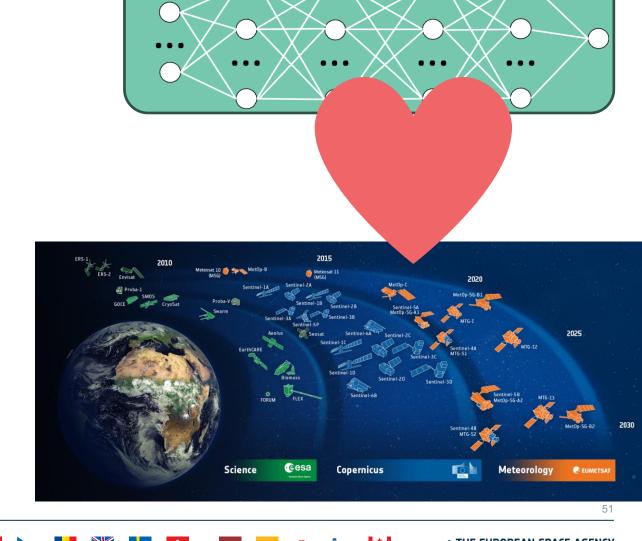
Combining: multispectral, thermal, microwave data

    All providing key information about crops

        Multispectral show state of the crops

        Microwave detects water content in vegetation and soils

        Thermal data for evaporation and temperature
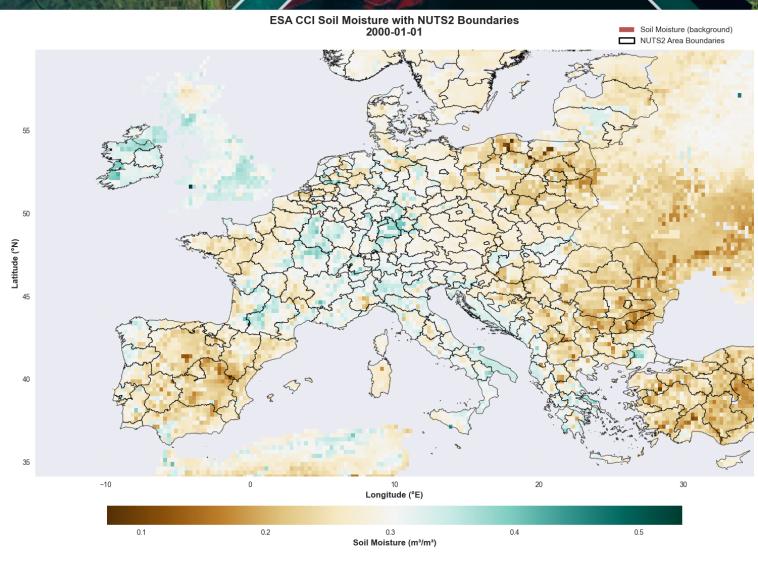
Crop yield forecasting – how to?

Requirements:

Crop yield data

Reasonable predictors

Basic knowledge about ML models

ESA CCI Soil Moisture with NUTS2 Boundaries
2000-01-01

Location / area

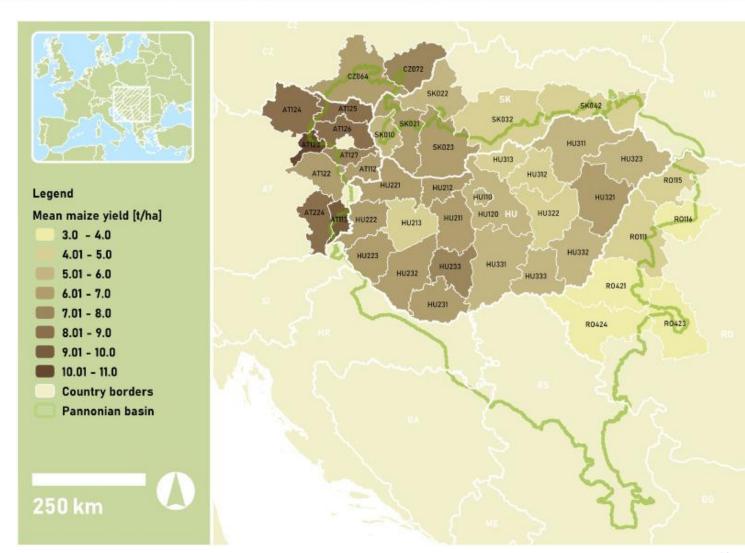> Can be at subfield, field, regional, and national level

Crop yield

> Usually tonnes / ha

Crop type
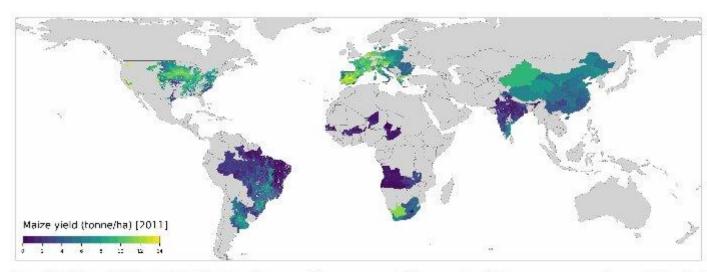
> E.g. maize, winter wheat, spring barley, soybean

Year

Phenology / sowing and harvest date

Legend
Mean maize yield [t/ha]

- 3.0 – 4.0
- 4.01 – 5.0
- 5.01 – 6.0
- 6.01 – 7.0
- 7.01 – 8.0
- 8.01 – 9.0
- 9.01 – 10.0
- 10.01 – 11.0
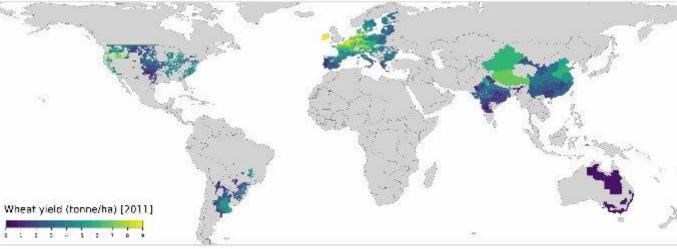- Country borders
- Pannonian basin

250 km

Bueechi et al., 2023

Crop yield data sources

- National statistical offices

- Farmers

- CYBench
  - https://cybench.agml.org
- Eurostat
  - https://agri4cast.jrc.ec.europa.eu/
- FAOstat
  - https://www.fao.org/faostat/en/#data
- USDA
  - https://quickstats.nass.usda.gov/

Cybench.agml.org

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Predictors

Ideally:

Longterm and consistent

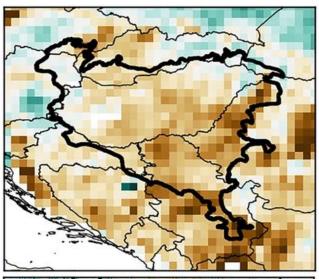Providing key information on crop growth

Examples:

Earth observation

Copernicus, ESA CCI, CGLS, Landsat, MODIS...

Reanalysis (e.g. AgERA5)

In-situ data

Seasonal weather forecasts

Crocetti et al., 2020

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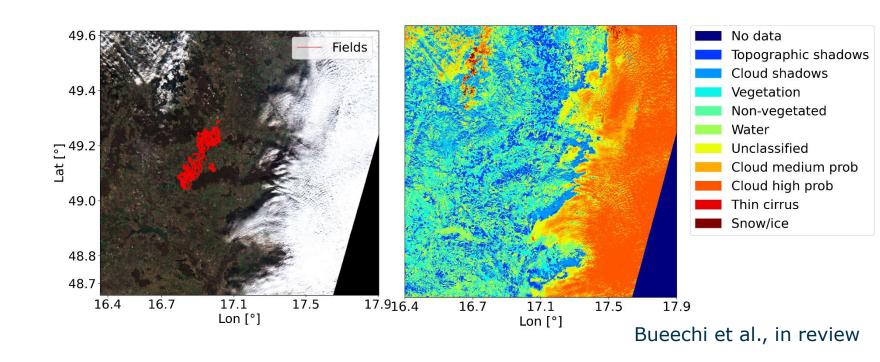Spatial resampling

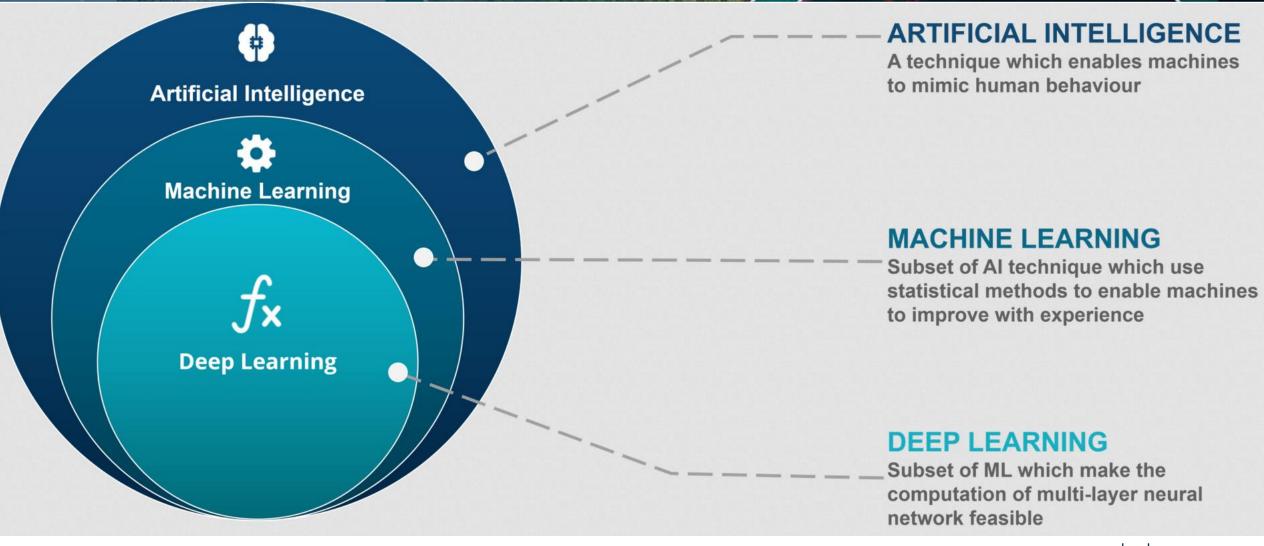   Extract data for region

Cloud filtering

Outlier removal

Calculate requried indices

Temporal resampling

Bueechi et al., in review

Machine Learning – what is it?

ARTIFICIAL INTELLIGENCE
A technique which enables machines to mimic human behaviour

MACHINE LEARNING
Subset of AI technique which use statistical methods to enable machines to improve with experience

DEEP LEARNING
Subset of ML which make the computation of multi-layer neural network feasible

Artificial Intelligence

Machine Learning

Deep Learning

edureka.co

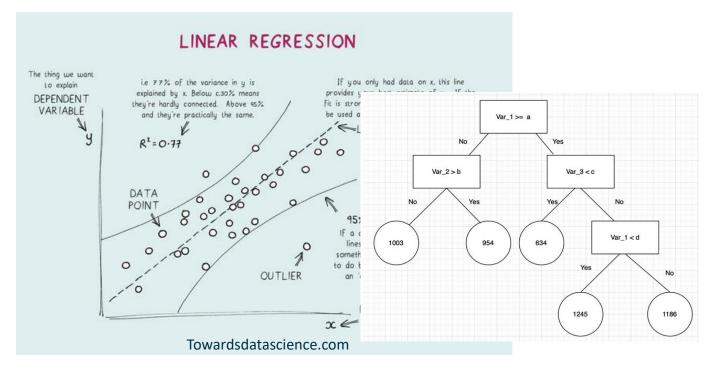→ THE EUROPEAN SPACE AGENCY

ESA Land Training Course 2025 – Bueechi, Luintel

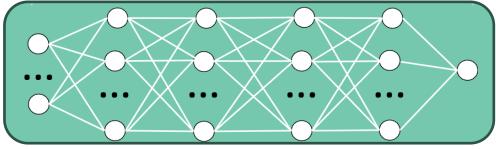# Machine learning models

Classical approaches:

- Linear regression

- Tree based algorithms

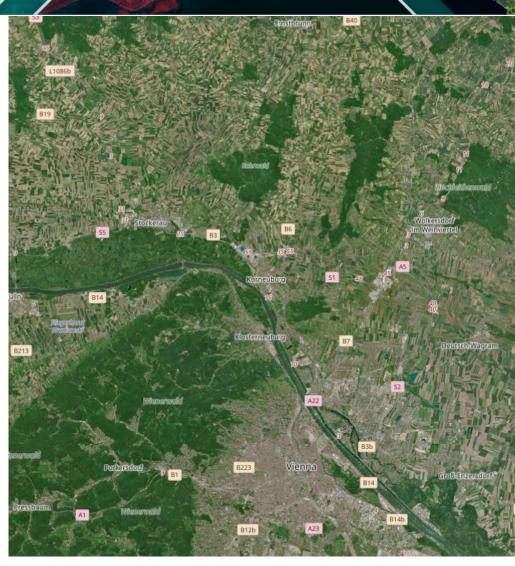- Artificial Neural Networks

- ...

Towardsdatascience.com

Machine learning models

Classical approaches

DO NOT CONSIDER Spatial and temporal dependencies

Such dependencies are very typical in Earth science

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Machine learning models

Deep learning approaches for time-series forecasting

    Recurrent / Convolutional Neural Networks
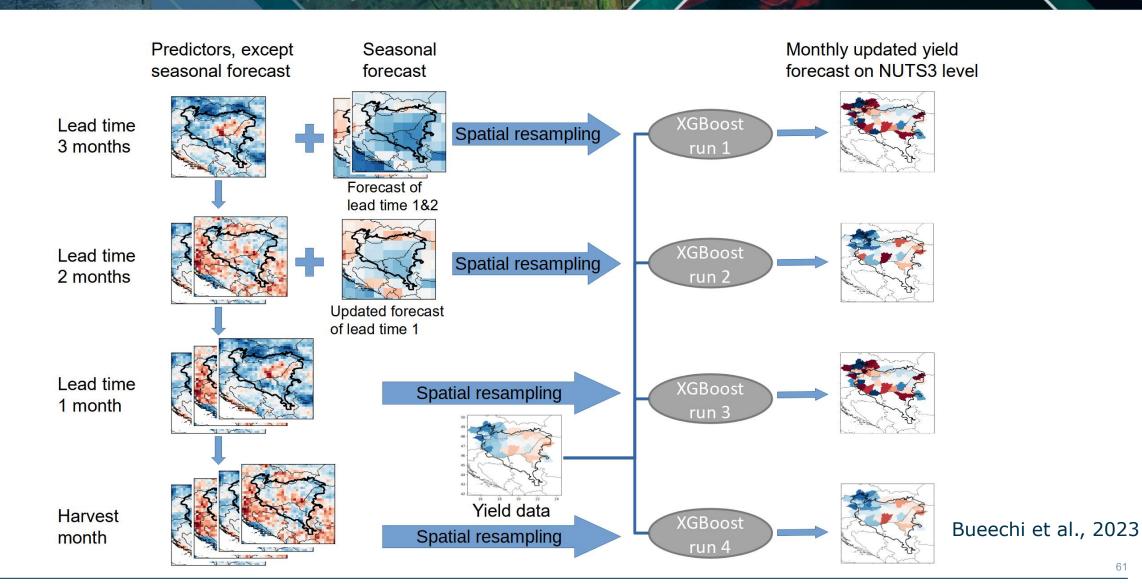

    Transformers

Other novel DL approaches

    Physics informed AI

        Makes use of prior human knowledge about dependency of target and predictor variables

    Transfer learning

        Method to train and use the model in different (related) domains

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Methods

Predictors, except seasonal forecast

Seasonal forecast

Monthly updated yield forecast on NUTS3 level

Lead time 3 months

Forecast of lead time 1&2

Spatial resampling

XGBoost run 1

Lead time 2 months

Updated forecast of lead time 1

Spatial resampling

XGBoost run 2

Lead time 1 month

Spatial resampling

XGBoost run 3

Yield data

Harvest month

Spatial resampling

XGBoost run 4

Bueechi et al., 2023

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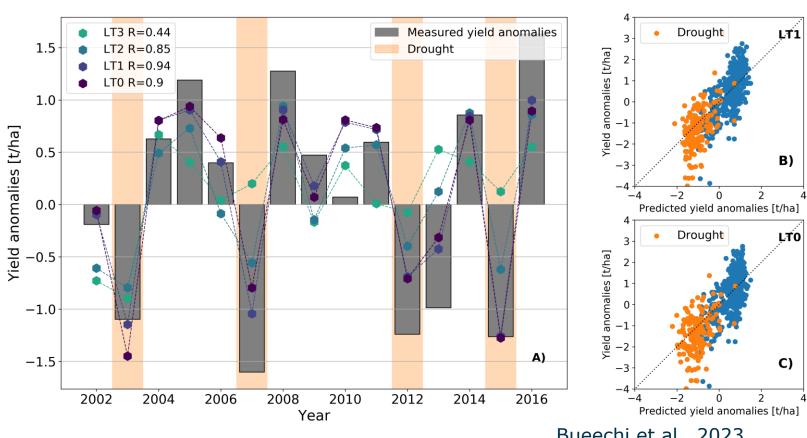
Regional forecasts

Monthly updated crop yield
forecasts for different crops

Reliable forecasts from 2 months
before harvest

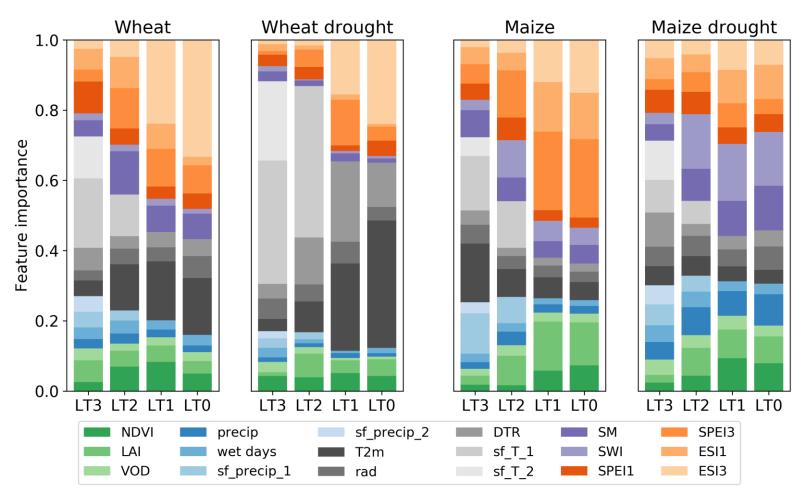Losses in drought years early
detected, but..

...extremes are underestimated

Bueechi et al., 2023

Understanding the models

ML models usually too complicated to understand

- Regression weights can be analysed
- Decision trees have weights, but usually to complex to understand
- Neural Networks are usually black boxes (too complex)

Feature importance shows impact of features on model performance

Bueechi et al., 2023

Machine learning for crop yield forecasting

Works well with sufficient data for training

What can we do when we do not have much data from a certain region / scale?

Transfer learning

Trains and applies the model in different domains

Reduces need of specific input data
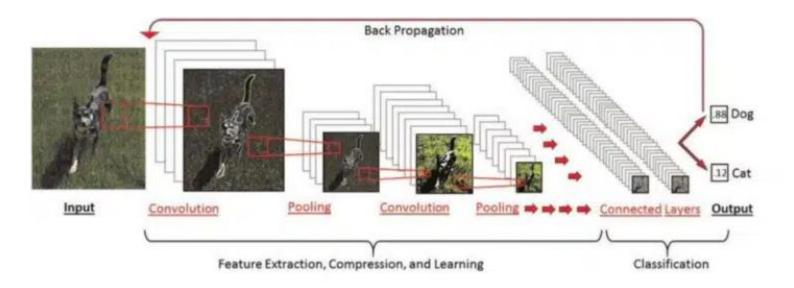
Improves models in data scarce scenarios

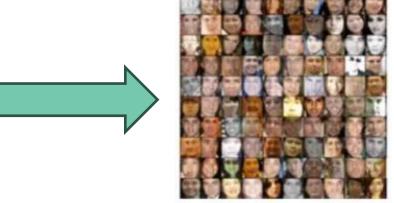

Pexels.com

Comes from image classification

Model learns to make sense of pictures

    Detect structures, edges that make image characteristic

From animal classification to face recognition

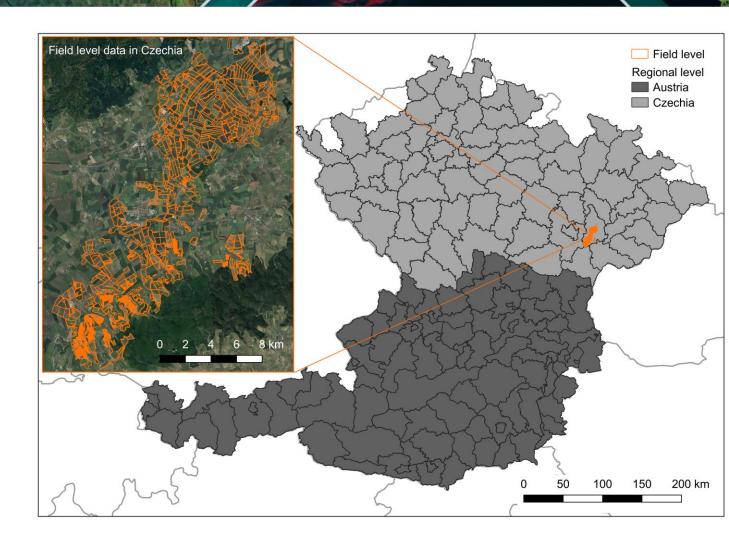   Needs only some fine-tune data

From regional to field level

Crop yield data in Europe often available at regional level

Field-level data harder to obtain

In this study, we trained the model at regional scale and tested it at field scale

Data from Czechia and Austria

From regional to field level

From regional to field level
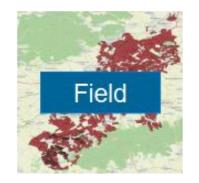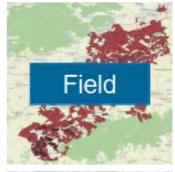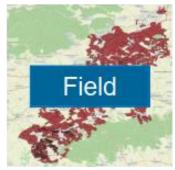
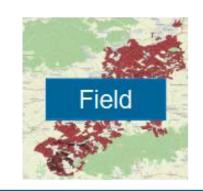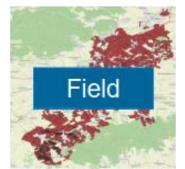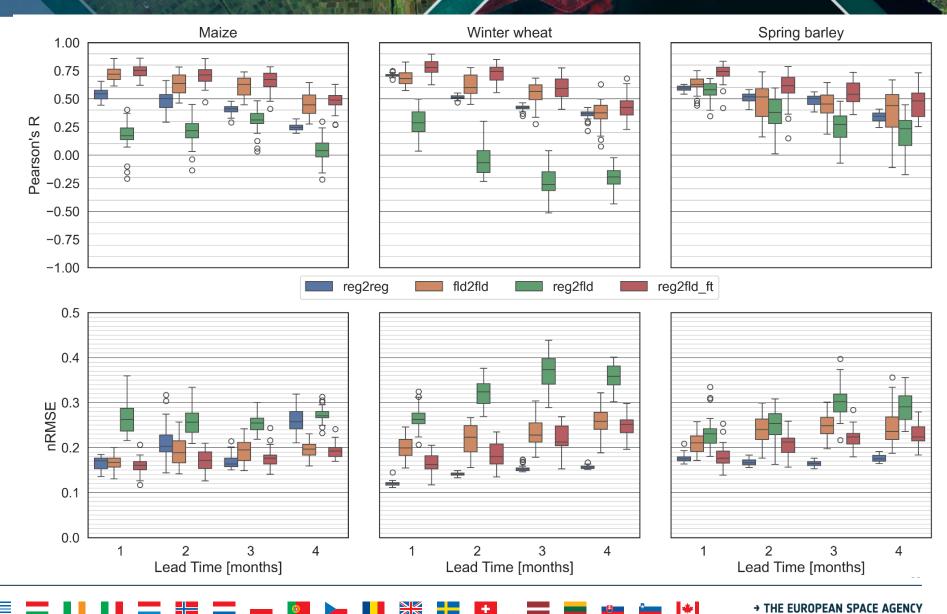Highest performance by finetuned model

Good performance from 3 months before harvest
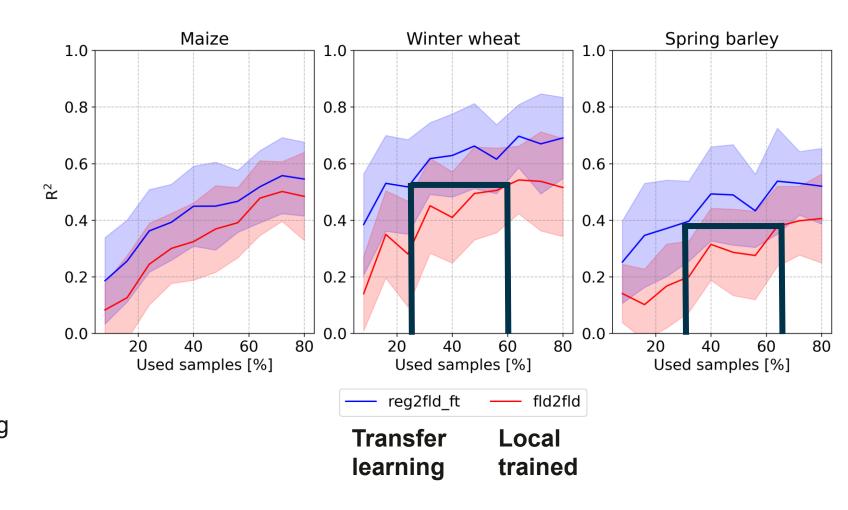
Without finetuning no useful results

Transfer learning outperforms field-trained model

Significantly higher performance for all setups

Needs >50% less data for same performance

Performance gain dependent on samples of original training (maize ~300, winter wheat~1000)

Maize | Winter wheat | Spring barley

— reg2fld_ft   — fld2fld

Transfer learning   **Local trained**

Field-scale forecast conclusion

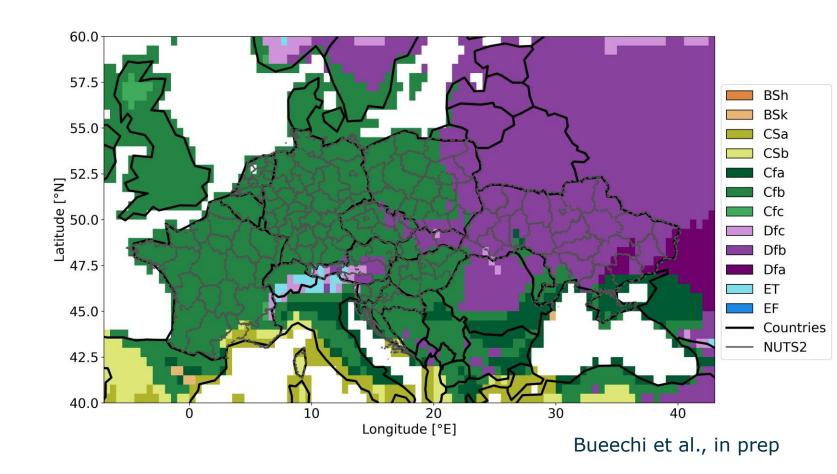Good results achieved for field-scale crop yield forecasts 3 months before harvest

Transfer learning outperforms purely field-trained models for crop yield forecasting

Transfer learning needs <50% field data to achieve skill of field-trained model

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Ukraine crop yield modelling

Crop yield modelling in Ukraine as major crop producer impacted by war
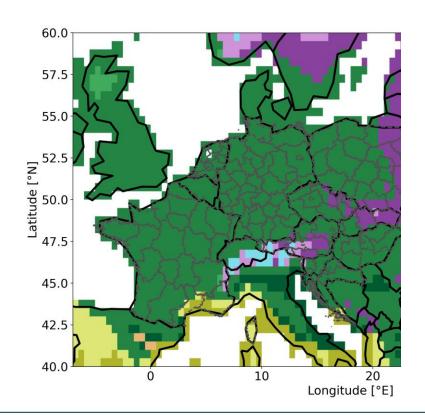
Problem: not much data in Ukraine itself, but much from central Europe

o !Different climate!

Bueechi et al., in prep
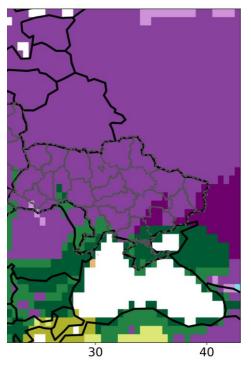
Transfer learning Ukraine yields

Transfer learning for crop yield modelling in Ukraine

Train in central Europe, fine-tune and test in Ukraine

Crop models implemented for 3 crops

Different model setups tested

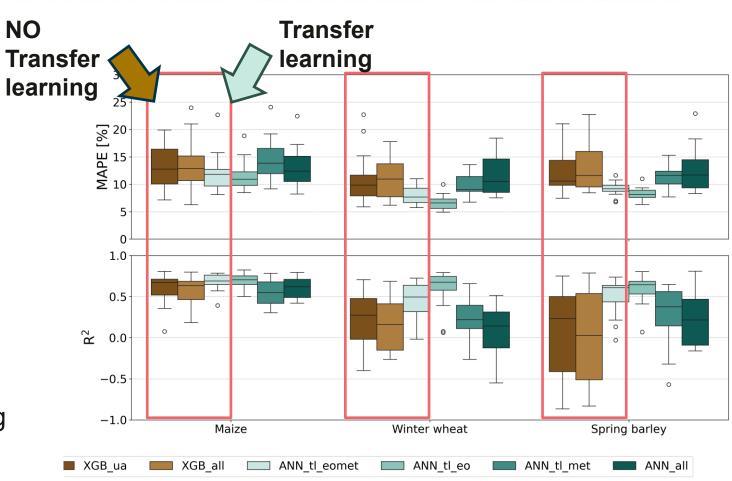   XGB -> Extreme Gradient Boosting

        - only UA data

        - incl. Central European (CE) data

    ANN with transfer learning

        trained in CE - finetuned in Ukraine

Best results obtained with transfer learning

XGB performance decreases with CE data

Conclusion

Crop yield forecasting helps to ensure food security in a changing climate

EO and ML are a perfect fit to establish such forecasts

  Optimally use vast amount of EO data

  Learn complex relationships between predictors and target

Issues with crop yield data scarcity can be diminished with transfer learning

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Questions?

esa

Thank you for your attention!