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Copernicus

European Commission

AI for risk assessment:

Supporting Drought Risk Management in Agriculture

Arthur Hrast Essenfelder

European Commission - Joint Research Centre

Coventry University

Disaster Risk Management online training series

2024 31/10, 10:00 - 11:00 (U.K. Time)

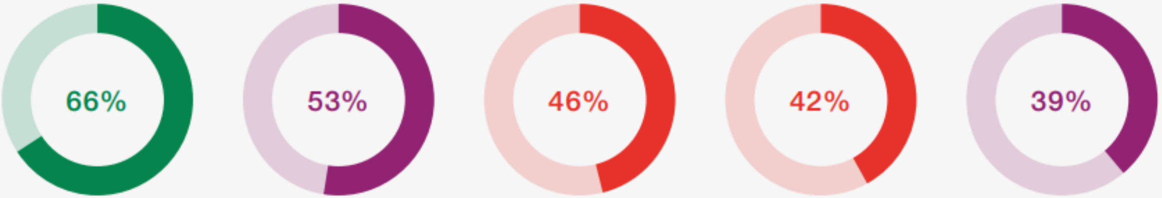
COPERNICUS EMERGENCY MANAGEMENT SERVICE

WORLD ECONOMIC FORUM

Risk categories

- Economic
- Environmental
- Geopolitical
- Societal
- Technological

	2 years	10 years
1st	Misinformation and disinformation	Extreme weather events
2nd	Extreme weather events	Critical change to Earth systems
3rd	Societal polarization	Biodiversity loss and ecosystem collapse
4th	Cyber insecurity	Natural resource shortages
5th	Interstate armed conflict	Misinformation and disinformation
6th	Lack of economic opportunity	Adverse outcomes of AI technologies
7th	Inflation	Involuntary migration
8th	Involuntary migration	Cyber insecurity
9th	Economic downturn	Societal polarization
10th	Pollution	Pollution



1st Extreme weather

2nd AI-generated misinformation and disinformation

3rd Societal and/or political polarization

4th Cost-of-living crisis

5th Cyberattacks

Source: The Global Risks Report 2024, 19th Edition, published by the World Economic Forum.

Environmental risks could hit the point of no return

Environmental risks continue to dominate the risks landscape over all three time frames. Two-thirds of GRPS respondents rank **Extreme weather** as the top risk most likely to present a material crisis on a global scale in 2024 (Figure B), with the warming phase of the El Niño-Southern Oscillation (ENSO) cycle projected to intensify and persist until May this year. It is also seen as the second-most severe risk over the two-year time frame and similar to last year's rankings, nearly all environmental risks feature among the top 10 over the longer term (Figure C).

However, GRPS respondents disagree about the urgency of environmental risks, in particular **Biodiversity loss and ecosystem collapse** and **Critical change to Earth systems**. Younger respondents tend to rank these risks far more highly over the two-year period compared to older age groups, with both risks featuring in their top 10 rankings in the short term.

GREEN DEAL

Sendai Framework for Disaster Risk Reduction 2015 - 2030

Paris Climate Agreement

COP28 UAE

EARLY WARNINGS FOR ALL

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Initiatives and Research in AI/ML for supporting Disaster Risk Management

Source: arXiv:2202.11214 [physics.ao-ph]

CLINT
CLIMATE INTELLIGENCE
EXTREME EVENTS
HOTSPOTS
MACHINE LEARNING

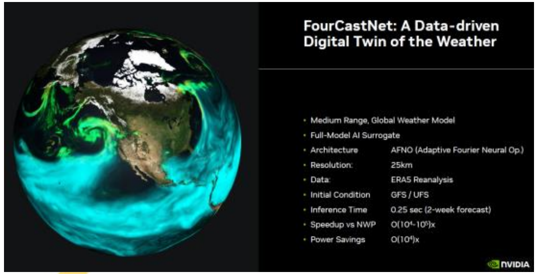
https://climateintelligence.eu/

XAIDA

https://xaida.eu/

AI for Natural Disaster Management
ITU Focus Group

NOAA AI
CENTER FOR ARTIFICIAL INTELLIGENCE

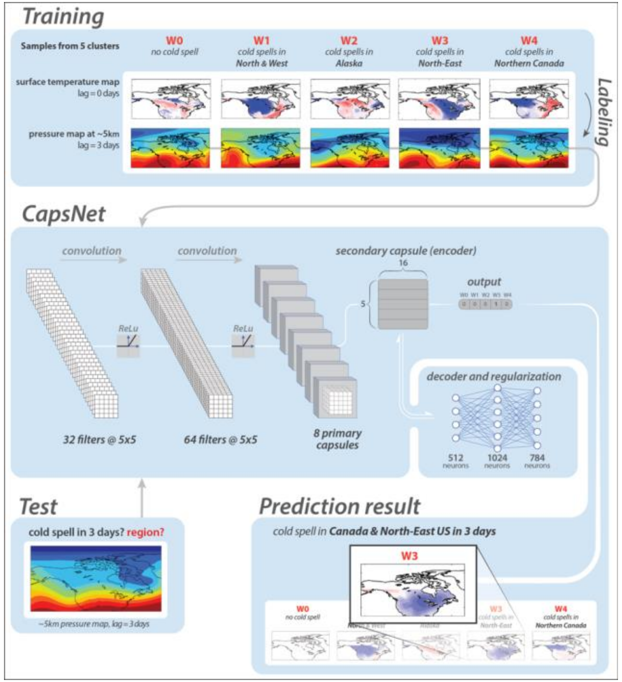


Source: arXiv:2202.11214 [physics.ao-ph]

https://arxiv.org/abs/2212.12794

MedEWSa

https://www.medewsa.eu/



Source: Chattopadhyay et al., 2020, https://doi.org/10.1029/2019MS001958, CC BY 4.0

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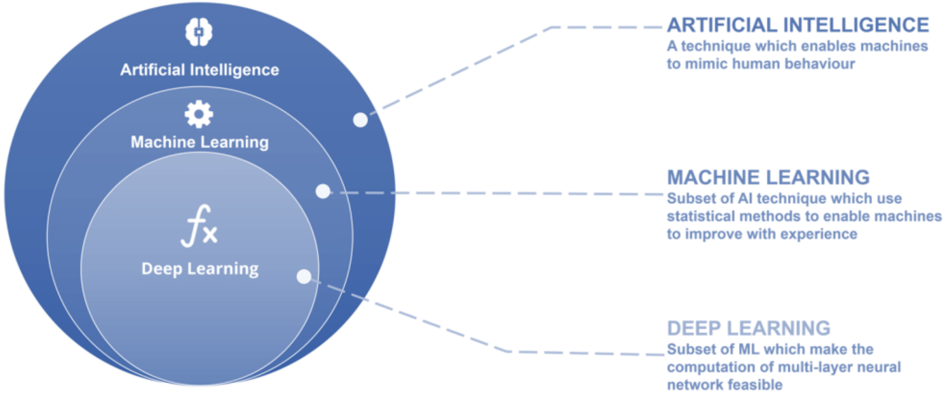
What is Machine-Learning?

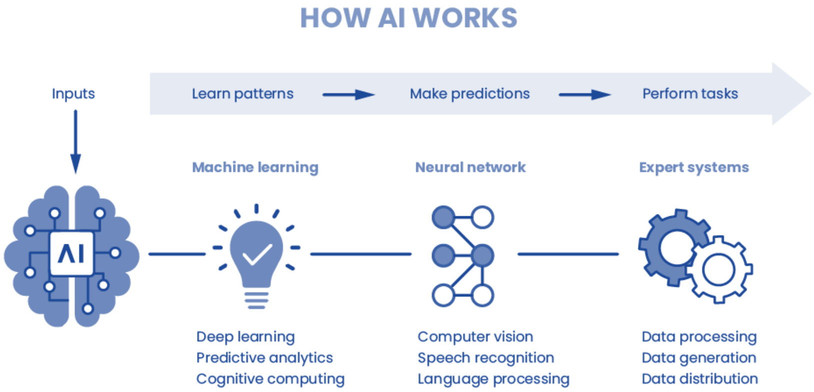
Definition

- Machine Learning (ML) is a subset of Artificial Intelligence (AI) that enables computers to learn from data and improve their performance over time without being explicitly programmed



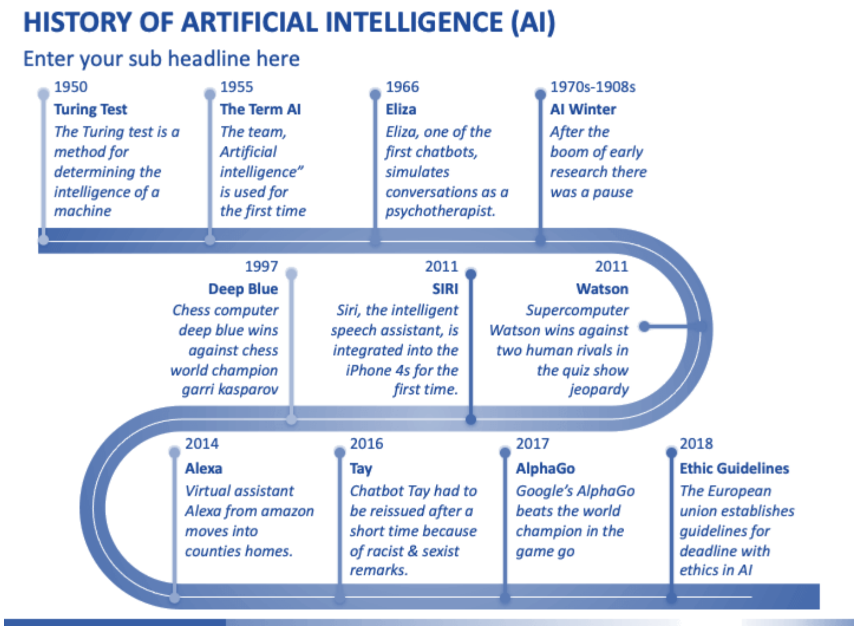
Key Components

- Data
- Algorithms
- Models



A bit of history…

- AI technology draws inspiration from the human brain, evolving as our understanding of brain functions and computational capabilities advance.
- The inception of AI began in the mid-20th century:
  - Alan Turing and John von Neumann introduced ideas of machines simulating human thought.
  - The 1956 Dartmouth Conference formalized AI as a research field, aiming to create machines that emulate human intelligence.
- Development phases in AI:
  - 1950s-60s: Symbolic reasoning and problem-solving through logical rules.
  - 1970s: Emergence of knowledge-based systems, using rules for reasoning.
  - 1980s-90s: Shift to machine learning, with neural networks and expert systems learning from data patterns.
  - 2000s onward: Deep learning advancements in computer vision, NLP, and speech recognition powered by big data and computational advances.
- Recent innovations in machine learning and generative AI have expanded AI applications across fields like healthcare, finance, disaster risk, and autonomous systems, solidifying AI's impact on daily life.



GUIDELINES FOR DEVELOPER

Ethics Guidelines for Trustworthy AI

Trustworthy AI has three components:

- it should be lawful, complying with all applicable laws and regulations
- it should be ethical, ensuring adherence to ethical principles and values and
- it should be robust, both from a technical and social perspective since, even with good intentions, AI systems can cause unintentional harm

EU AI Act: first regulation on artificial intelligence

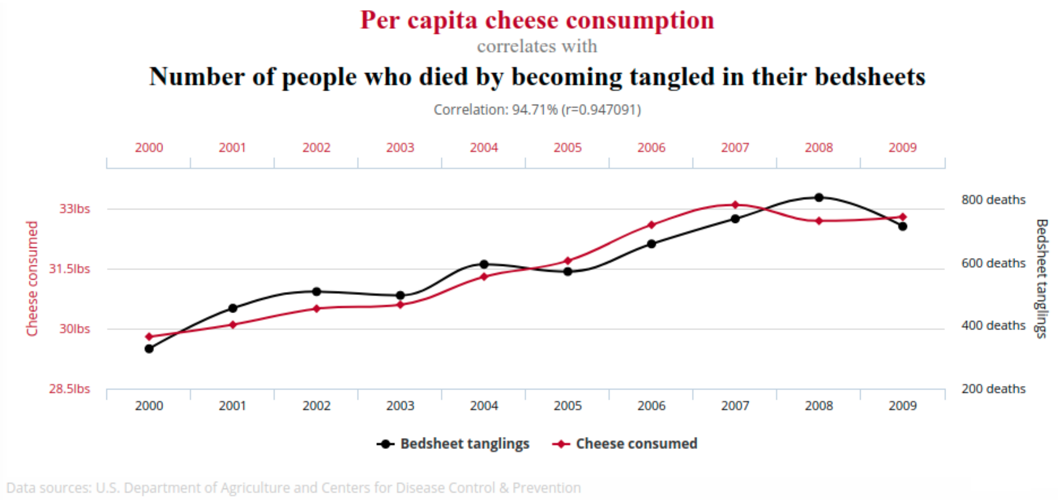
The use of artificial intelligence in the EU will be regulated by the AI Act, the world's first comprehensive AI law. Find out how it will protect you.

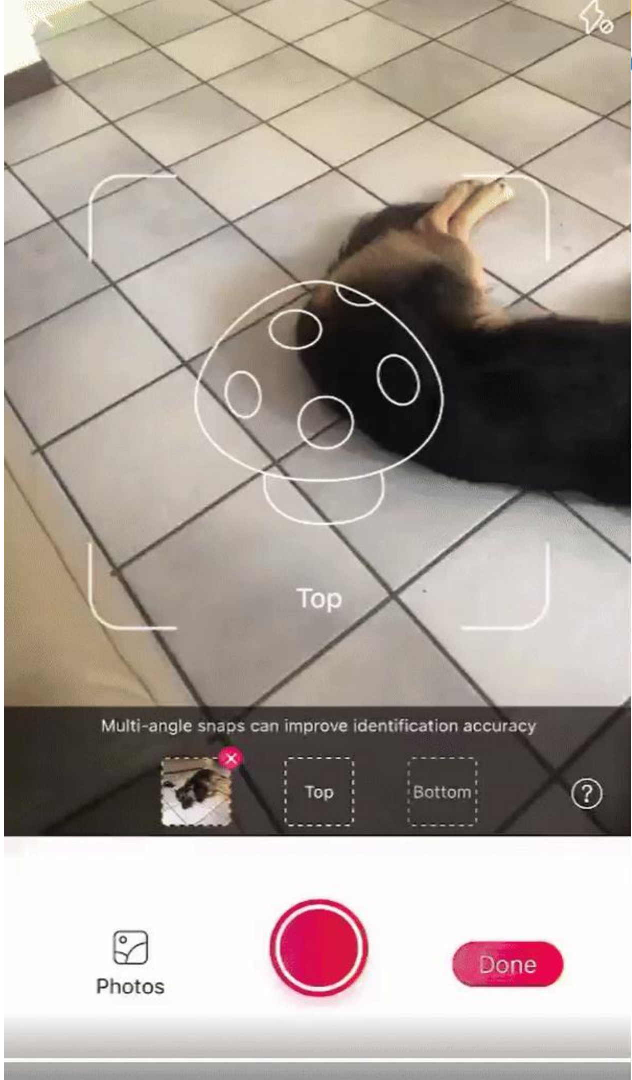
Published: 08-06-2023

https://www.europarl.europa.eu/topics/en/article/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence

A robust model is important…

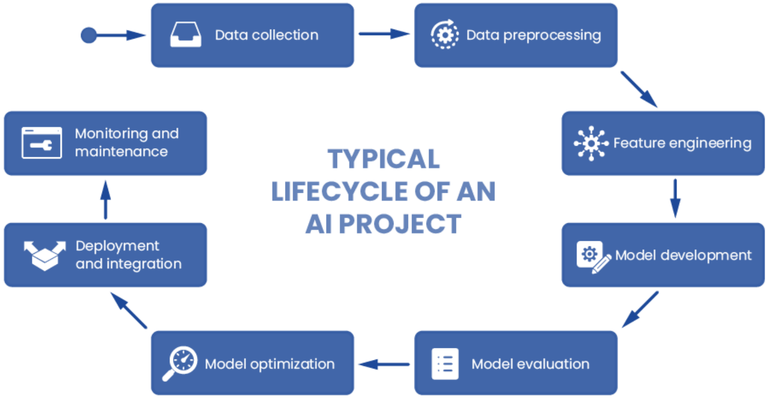
- Two highly correlation variables do not necessarily mean we know whether one variable causes the other to occur.
- This is why "correlation does not imply causation."
- A strong correlation might indicate causality, but there could be other explanations:
  - It may be the result of random chance, where the variables appear to be related, but there is no true underlying relationship.





Key components of Machine-Learning

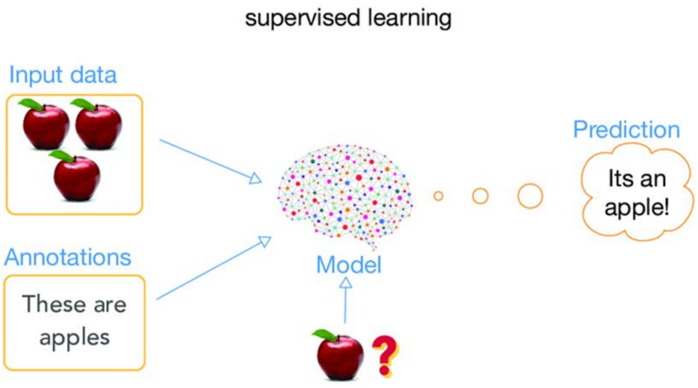
- **Data preparation**:
  - Obtain data, check data source, check data consistency, data cleaning
- **Feature selection & Dimensionality Reduction**:
  - In case of high-dimensional input data, techniques such as Principal Component Analysis (PCA) and AutoEncoder Neural Networks can be used to reduce the number of input variables
- **Normalisation & Standardisation**:
  - In case of input variables with different units of measurement, normalisation/standardisation is required
- **Specify assumption**:
  - Based on domain and problem knowledge, assumptions are made in order to integrate expert-knowledge into the model (e.g. algorithm for minimisation of errors in machine-learning training).
  - *As for instance physics informed machine learning.*
- **Model development**:
  - Based on the assumptions, the model is set-up and calibrated/trained
- **Model evaluation**:
  - A loss function is applied in order to identify how well the model is performing against a set of unbiased data.
  - *E.g. Root mean squared error (RMSE)*



Main types of Machine Learning

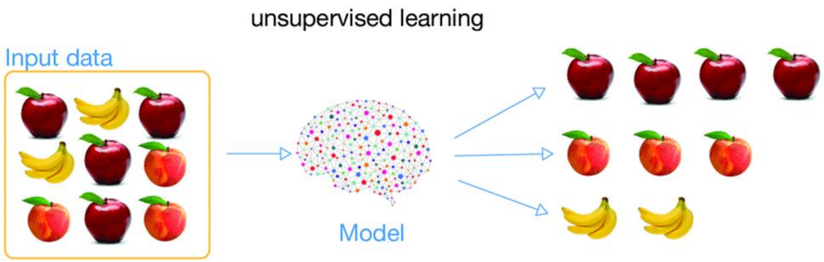
Supervised Learning

- Guided by a reference model using pre-labelled training data, the aim is to classify inputs into distinct categories or to perform regression to predict continuous variable values.

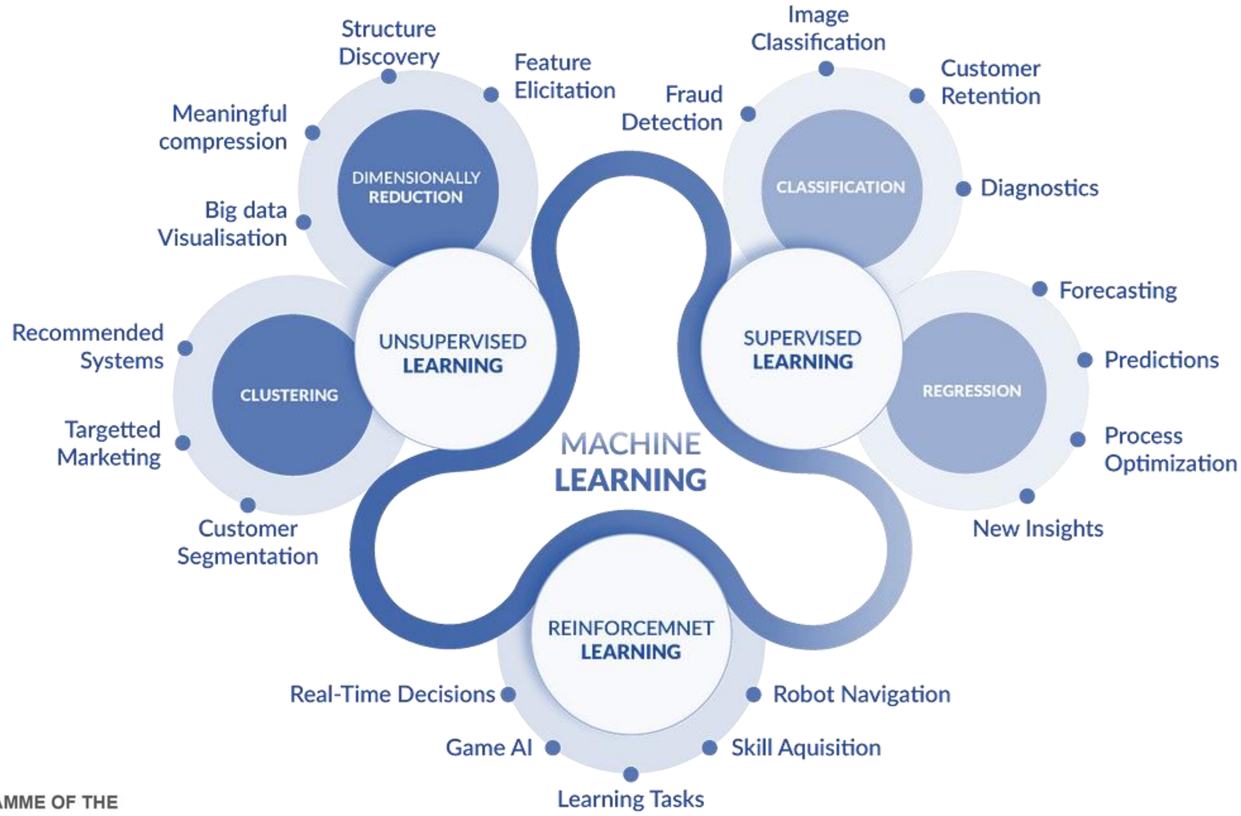


Unsupervised Learning

- Algorithms learn from unlabelled data to discover hidden patterns via clustering and simplify data while retaining key features through dimensionality reduction



Not only supervised or unsupervised learning



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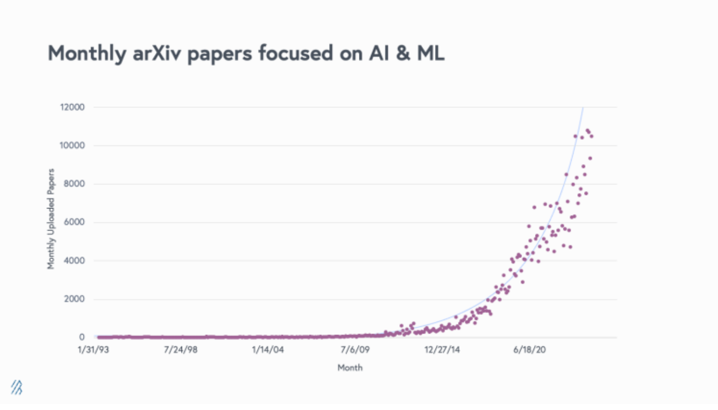
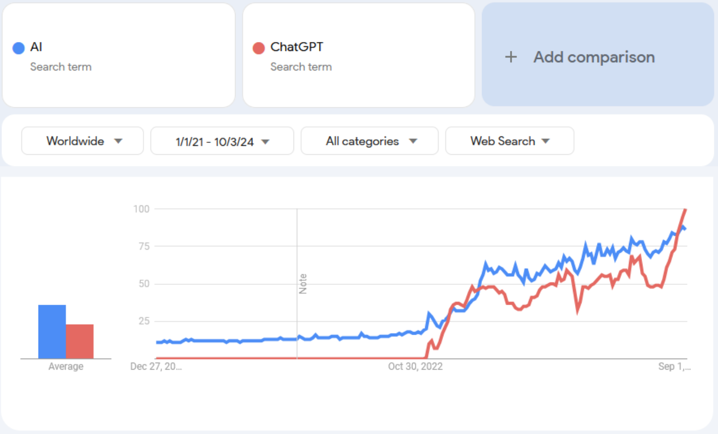
Growing interest in different areas

- **Data availability**: The explosion of structured and unstructured data enables ML models to achieve high accuracy and reliability.
- **Advancements in computing power**: Specialized hardware like GPUs and TPUs allows for efficient processing of large datasets and complex ML models.
- **Enhanced ML techniques**: Improved algorithms and training methods, such as deep learning, have boosted ML model performance and accuracy.
- **Cloud computing**: Scalable and cost-effective infrastructure makes ML adoption easier and more accessible without significant upfront investment.





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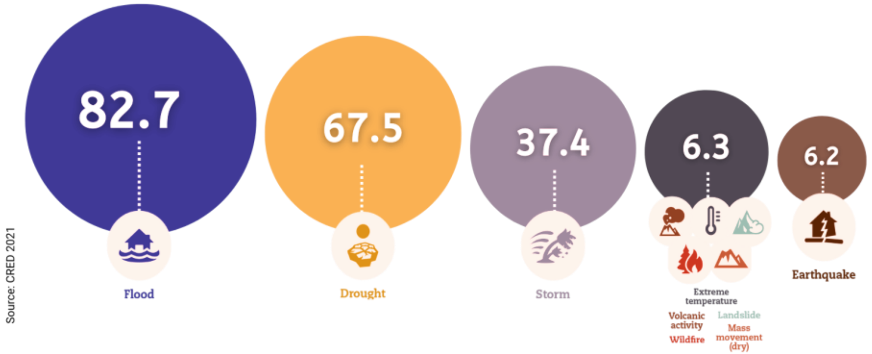
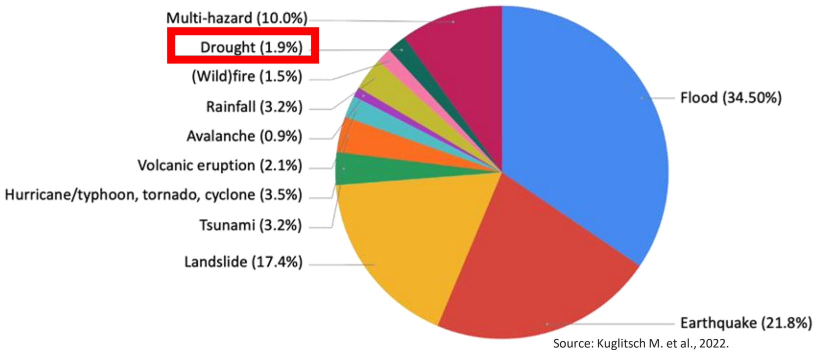
Annual average number of (millions) affected by disaster type (2001 - 2020)

UNDRR
UN Office for Disaster Risk Reduction



Applications



Source: Kuglitsch M. et al., 2022.

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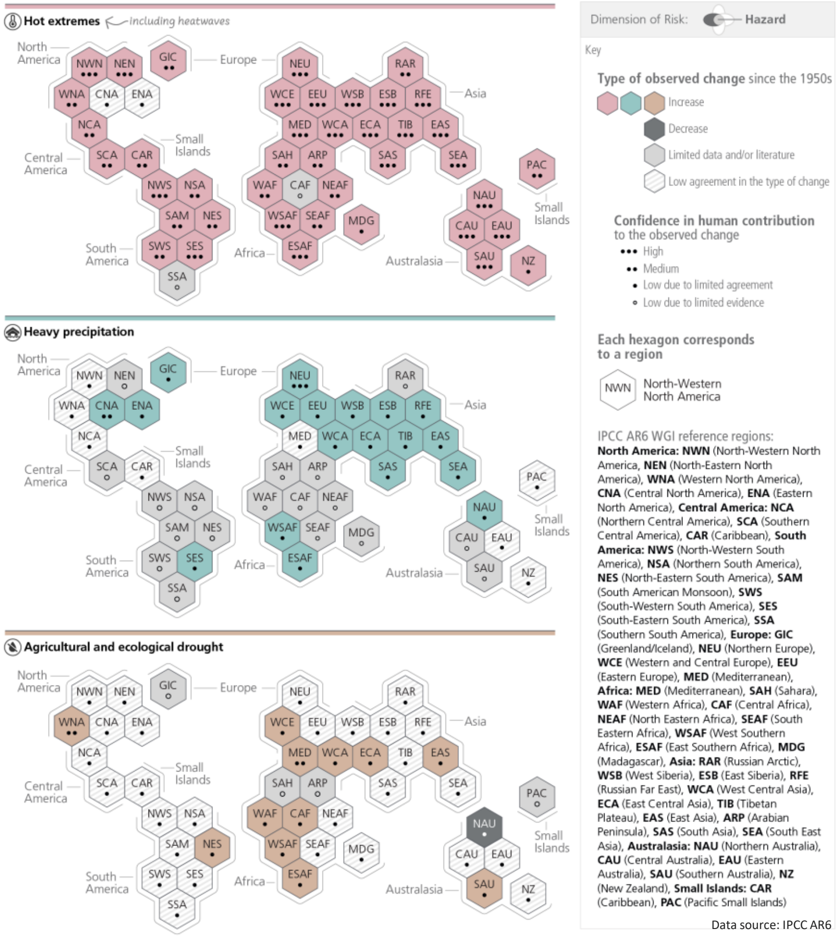
Climate change has impacted human and natural systems across the world with those who have generally least contributed to climate change being most vulnerable

a) **Synthesis of assessment of observed change in hot extremes, heavy precipitation and drought, and confidence in human contribution to the observed changes in the world's regions**

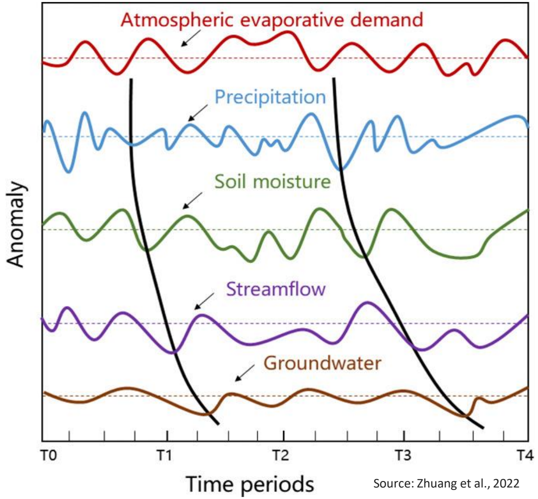


Data source: IPCC AR6

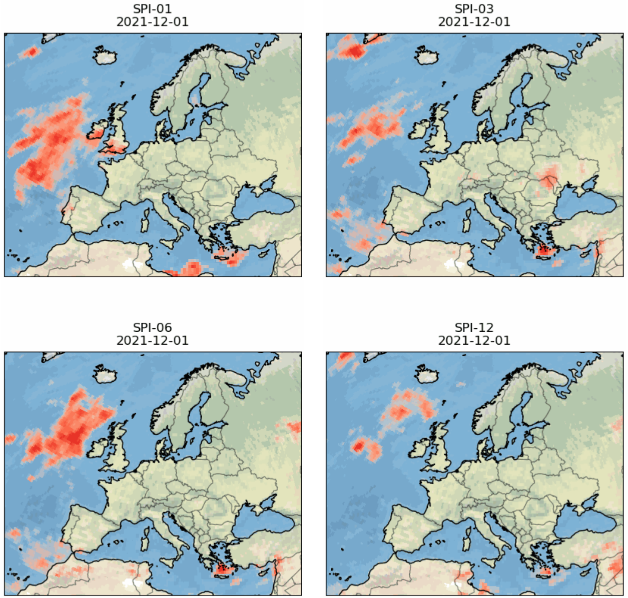
Challenges in Drought Risk Management

Drought Characterisation and Forecasting

- Why extreme events, such as droughts, matter?
  - ‘High-impact, low-probability' (HILP) events (e.g. Summer of 2022)
- To prepare for such events, one must:
  1. Observe trends;
  2. Forecast outcomes, and
  3. Evaluate scenarios for better mitigating any potential threat
- Yet, droughts are not trivial to define in time and space



Source: Zhuang et al., 2022



Data source: ERA5 reanalysis

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AI-enhanced Agro-Climate Service - AIACS

- To tackle such issues and buildings from the expert knowledge on extreme weather events at the JRC, initiatives such as the development of new weather/climate services and early warning systems can help on building resilience to extreme events:

AI-enhanced Climate Services

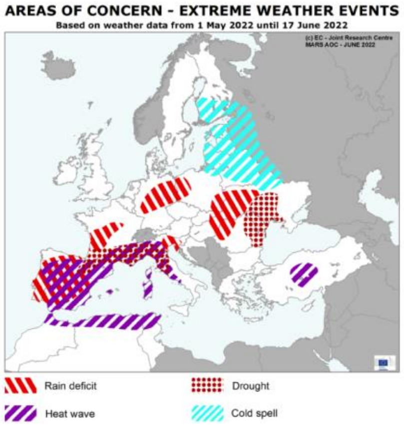
AIACS (AI-enhanced Agro-Climate Service) is an exploratory research project that aims at developing an innovative AI-enhanced climate service prototype capable of digesting, analyzing and interpreting data and information from various sources to monitor and forecast unfavorable climate conditions and climate extremes.

Global Framework for Climate Services: GFCS

Expertise from the JRC

Areas of Concern

- Each month the JRC issues the MARS Bulletin on the assessment of European crops’ status and yield forecasts.
- Synthetic maps called **Areas of Concern (AOC)** are produced in each Bulletin depicting extreme weather events and their impact during the analysis period.
- AOC are defined based on a range of quantitative and qualitative agro-meteorological data and heavily relying on expert analysis.



Source: JRC MARS Bulletin Vol. 30, no 6, June 2022

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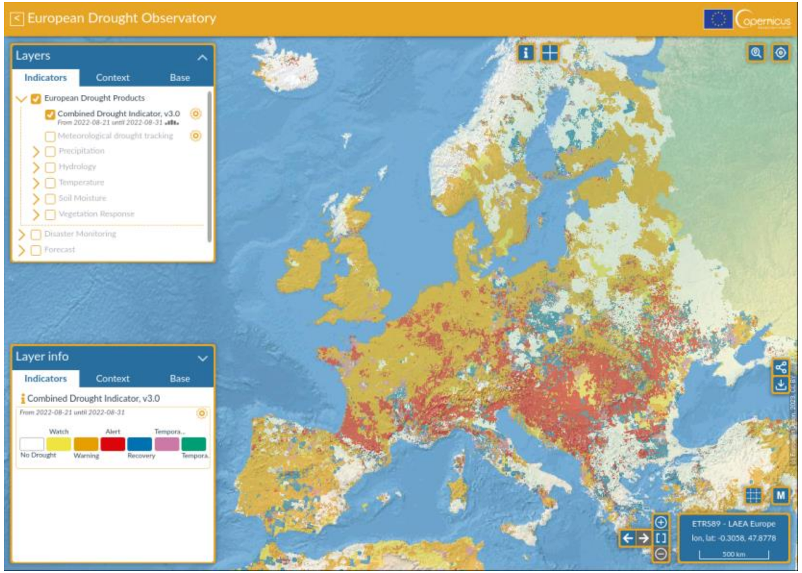
European (EDO) and Global (GDO) Drought Observatories



Climate Change
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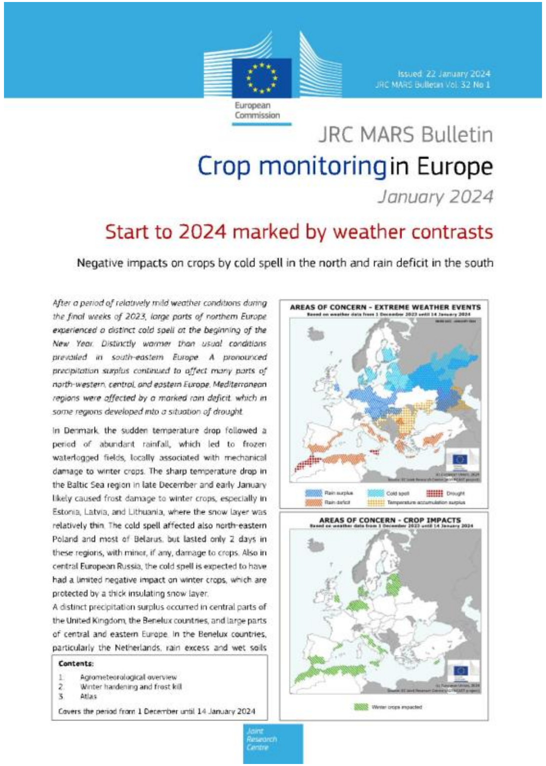
Areas of Concern – JRC MARS Bulletins

Meteorological event	Definition
Rain excess or rain deficit	*Cumulated rainfall* *RA: ± 25% observed in two or more analysis period* *RA: ± 50% over the analysis period* *One or more days with daily precipitation > 50 mm*
Radiation deficit	*Cumulated radiation* *RA: ± 25% observed in two or more analysis* *RA: ± 50% over the analysis period*
Heat wave	*Three or more days with Tmax > 30 °C and no precipitation*
Cold spell	*One day with Tmin < −18 °C or* *Two or more days with Tmin < −10°C or* *Three or more days with Tmin < 0 °C* *Average Tmin has RA < −50%*
Hot and dry conditions	*Three or more days with 25 °C < Tmax < 30 °C and no precipitation* *Average Tmax has RA > 0%*
Drought	*Rain deficit event observed for at least two or more analysis* *Evidence of effect on crops from remote sensing observation*
Temperature accumulation surplus or deficit	*Sum of average temperatures (Tsum)* *RA: ± 50% over the analysis period*


Issued: 22 January 2024
JRC MARS Bulletin Vol. 32 No 1

European Commission

JRC MARS Bulletin
Crop monitoring in Europe
January 2024

Start to 2024 marked by weather contrasts

Negative impacts on crops by cold spell in the north and rain deficit in the south

After a period of relatively mild weather conditions during the final weeks of 2023, large parts of northern Europe experienced a distinct cold spell at the beginning of the New Year. Distinctly warmer than usual conditions prevailed in south-eastern Europe. A pronounced precipitation surplus continued to affect many parts of north-western, central, and eastern Europe. Mediterranean regions were affected by a marked rain deficit, which in some regions developed into a situation of drought.

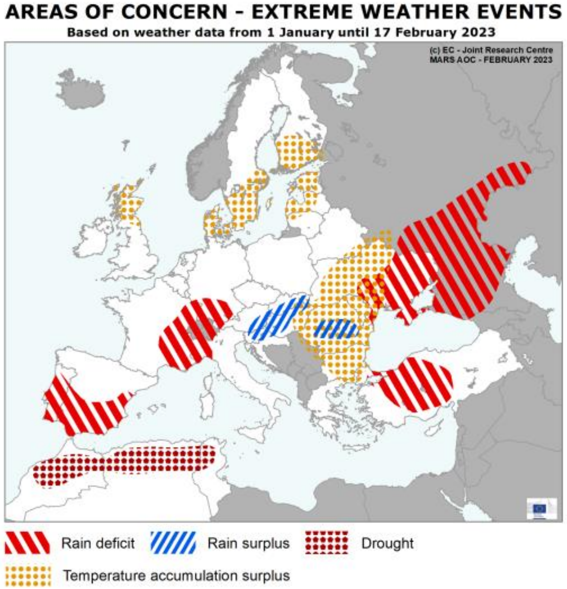
In Denmark, the sudden temperature drop followed a period of abundant rainfall, which led to frozen waterlogged fields, locally associated with mechanical damage to winter crops. The sharp temperature drop in the Baltic Sea region in late December and early January likely caused frost damage to winter crops, especially in Estonia, Latvia, and Lithuania, where the snow layer was relatively thin. The cold spell affected also north-eastern Poland and most of Belarus, but lasted only 2 days in these regions, with minor, if any, damage to crops. Also in central European Russia, the cold spell is expected to have had a limited negative impact on winter crops, which are protected by a thick insulating snow layer.

A distinct precipitation surplus occurred in central parts of the United Kingdom, the Benelux countries, and large parts of central and eastern Europe. In the Benelux countries, particularly the Netherlands, rain excess and wet soils

Contents:

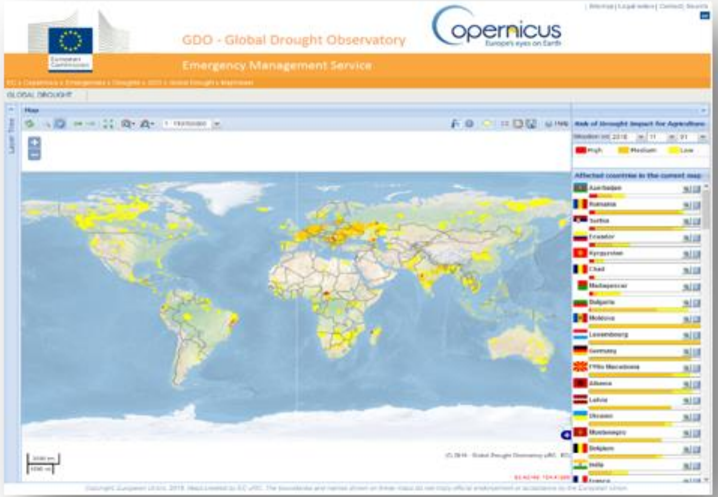
Covers the period from 1 December until 14 January 2024

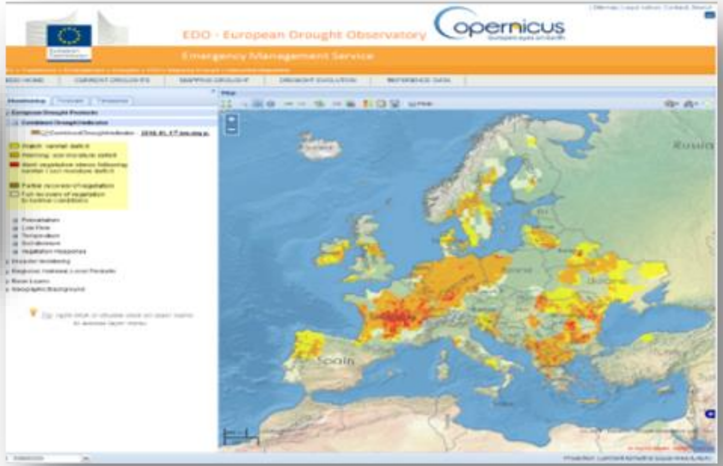
Joint Research Centre



https://joint-research-centre.ec.europa.eu/monitoring-agricultural-resources-mars/jrc-mars-bulletin_en

European and global drought observatories





https://drought.emergency.copernicus.eu/tumbo/gdo/map/

https://drought.emergency.copernicus.eu/tumbo/edo/map/

European (EDO) and Global (GDO) Drought Observatories - Indicators

Standardized Precipitation Index (SPI)

- SPI at SYNOP stations from the MARS database
- SPI ERA5 at 0.25° grid
- Monthly precipitation (GPCC and MARSMet)

Soil Moisture Anomaly (SMA)

- Last Daily Soil Moisture Index (SMI) & Anomaly
- Ten-daily Soil Moisture Index (SMI) & Anomaly

Vegetation Productivity (fAPAR) Anomaly

- fAPAR values & anomalies

Low-Flow Index

- Observed flows
- LISFLOOD model output

Heat and Cold Wave Index (HCWI)

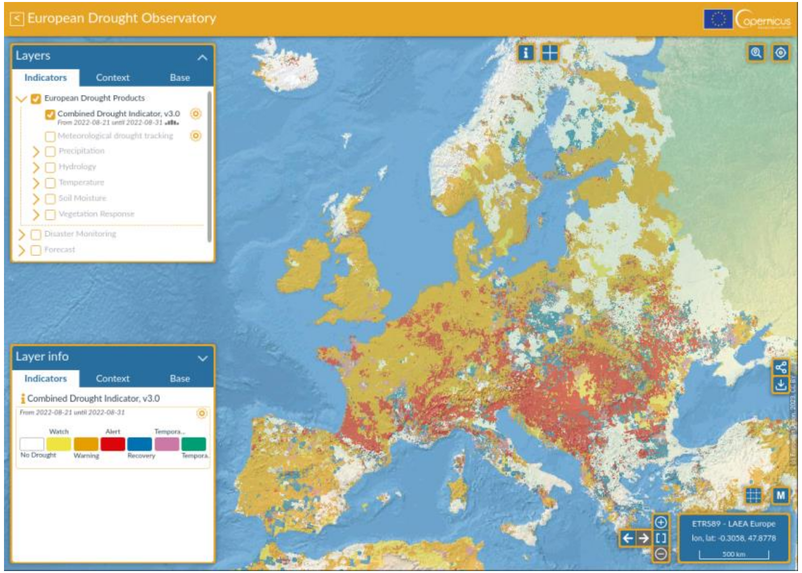
- Daily minimum and maximum temperatures (Tmin and Tmax)
- Daily temperature amplitude (Tmax minus Tmin)
- Daily maximum temperature anomaly
- Calendar day thresholds used to detect heat and cold waves
- Strongest yearly heatwaves, and most recent in current year

Indicator for Forecasting Unusually Wet and Dry Conditions

GRACE Total Water Storage (TWS) Anomaly

Combined Drought Indicator

Meteorological Drought Event Tracking



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AI-based first guess of Areas of Concerns

Gradient Boosted Trees Model

- Expert-based approaches that require the combination of big quantitative and qualitative data are often time consuming and laborious.

- We build a collection of Gradient Boosted Decision Tree model using the TensorFlow Decision Forests (TF-DF) library to train, run and interpret a decision model capable of producing a **first-guess of AOC**, which can then be more easily digested by an expert.

- A Gradient Boosted (Decision) Tree (GBT) is a set of shallow decision trees trained sequentially, where each tree is trained to predict and then "correct" for the errors of the previously trained trees.

- Individual models are trained at classifying areas as of concern for different extreme meteorological AOC events

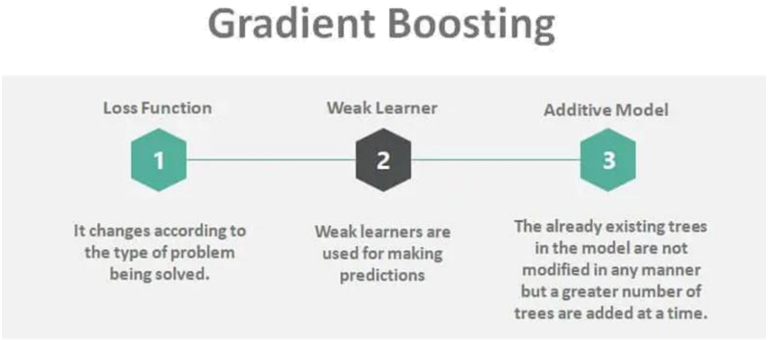

Image source: Gradient Boosting (wallstreetmojo.com)

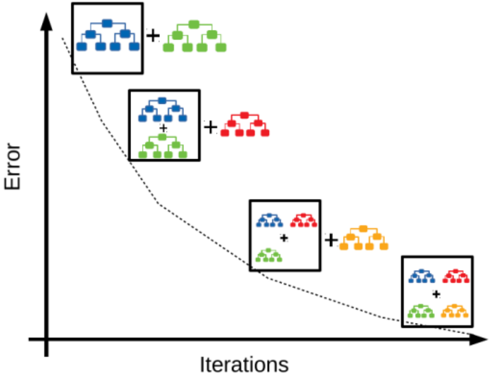

Image source: medium.com/

AI-based first guess of Areas of Concerns

Gradient Boosted Trees Model

- The objective is to develop a model that is both **interpretable** and **transferrable**
- We use both ERA5 and CEMS data for detecting and analysing various meteorological AOC
- Data is passed as mean, anomalies and standardized-anomalies (where applicable) for the specific period of analysis
- A class-balanced approach based on a simple proportion between the positive and negative classes is implemented to adjust for the importance of each class during training
- The model uses a logistic regression objective function for the binary classification of a cell as an AOC or not
- A collection of 1,000-folded individually-trained models for each AOC type is implemented.

Meteorological event	Definition
Rain excess or rain deficit	*Cumulated rainfall* *RA: ± 25% observed in two or more analysis period* *RA: ± 50% over the analysis period* *One or more days with daily precipitation > 50 mm*
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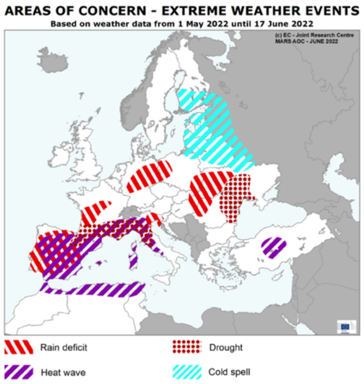

DATASET	Dataset Description	VARIABLE	Variable Description	SI Unit
CEMS	Copernicus Emergency Management Service (CEMS) European Drought Observatory (EDO)	spi01	SPI (1-month accumulation)	-
		spi03	SPI (3-months accumulation)	-
		spi06	SPI (6-months accumulation)	-
		spi09	SPI (9-months accumulation)	-
		spi12	SPI (12-months accumulation)	-
		sma	ensemble soil moisture anomaly	-
		fapar	fAPAR anomaly	-
ERA5-derived	Variables derived from the ERA5 database (frequency of days)	daystmax25a30C	number of days when tmax is between 25 and 30°C	days
		daystmax30C	number of days when tmax is larger than 30°C	days
		daystmin0C	number of days when tmin is lower than 0°C	days
		daystminm10C	number of days when tmin is lower than 10°C	days
		daystminm18C	number of days when tmin is lower than 18°C	days
		daystp01mm	number of days when tp is over 1mm	days
		daystp30mm	number of days when tp is over 30mm	days
	Variables derived from the ERA5 database (mean and anomalies)	msla	air pressure at sea level	Pa
		spa	surface air pressure	Pa
		t2ma	near-surface air temperature	K
		tmaxa	maximum near-surface temperature in period	K
		tmina	minimum near-surface temperature in period	K
		z500a	geopotential height	$m^2 s^{-2}$

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AI-based first guess of Areas of Concerns

Gradient Boosted Trees Model - Methods

- The expert-driven xAI model is built on an XGBoost (eXtreme Gradient Boosting) algorithm, known for high performance in regression and classification by using sequential decision trees that refine the model through gradient boosting to minimize errors.
- XGBoost enhances model interpretability by ranking feature importance, allowing experts to understand the factors driving model predictions. This helps increase transparency and trust in the model's output.
- The input data for the model is structured in a tabular format, split into training, validation, and test datasets to prevent temporal and spatial data leakage. The last year is reserved as a test set to evaluate model performance on unseen data, while class-balancing techniques address the imbalanced nature of AOC classes.
- The model is trained with up to 200 decision trees, with early-stopping if no improvement is observed after 12 rounds. The training process includes subsampling and an ensemble of 1,000 models using diverse hyperparameters to mitigate bias and randomness.
- Evaluation metrics include Accuracy, Recall, Precision, and F1-Score, with a focus on F1-Score for balanced performance assessment. Logistic regression output is used to classify AOC regions, with a probability threshold of 0.5 for binary classification.
- Feature importance is evaluated per model using SHAP values along with gain, cover, and frequency. Aggregated metrics (mean, standard deviation, etc.) from the ensemble of 1,000 models provide insights into the consistency and reliability of the predictions for AOC detection.

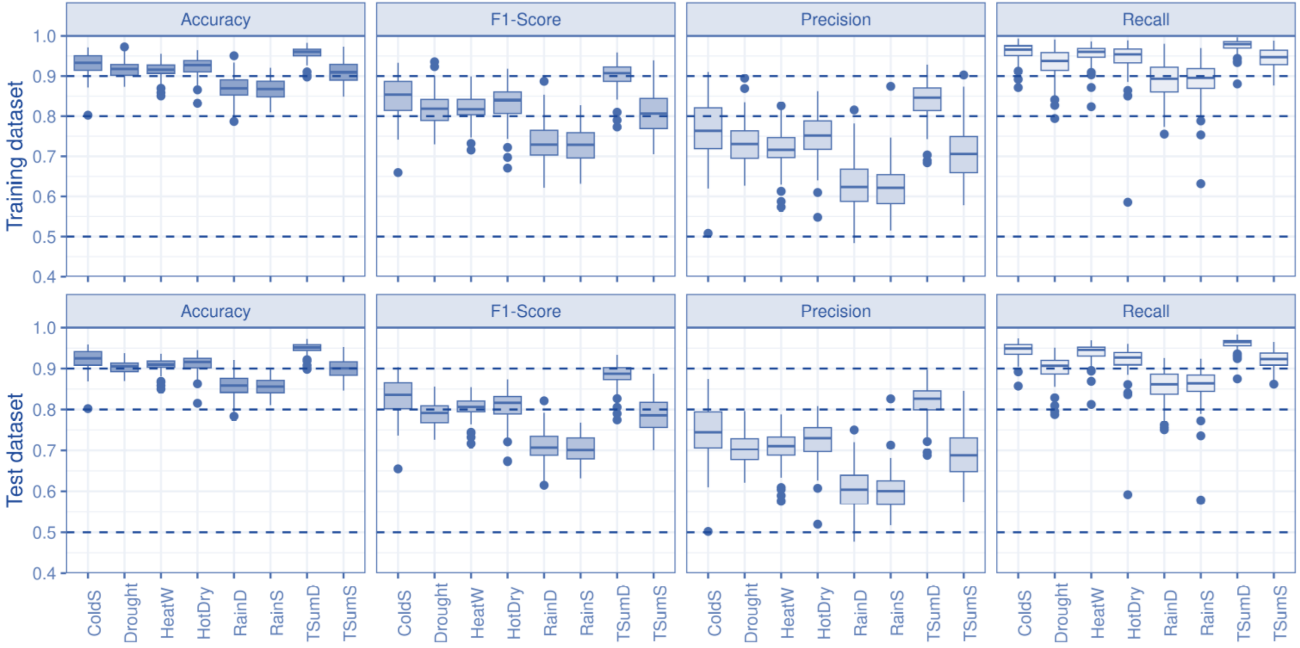
Results – Training Metrics and Results

$$precision = \frac{TP}{TP + FP}$$

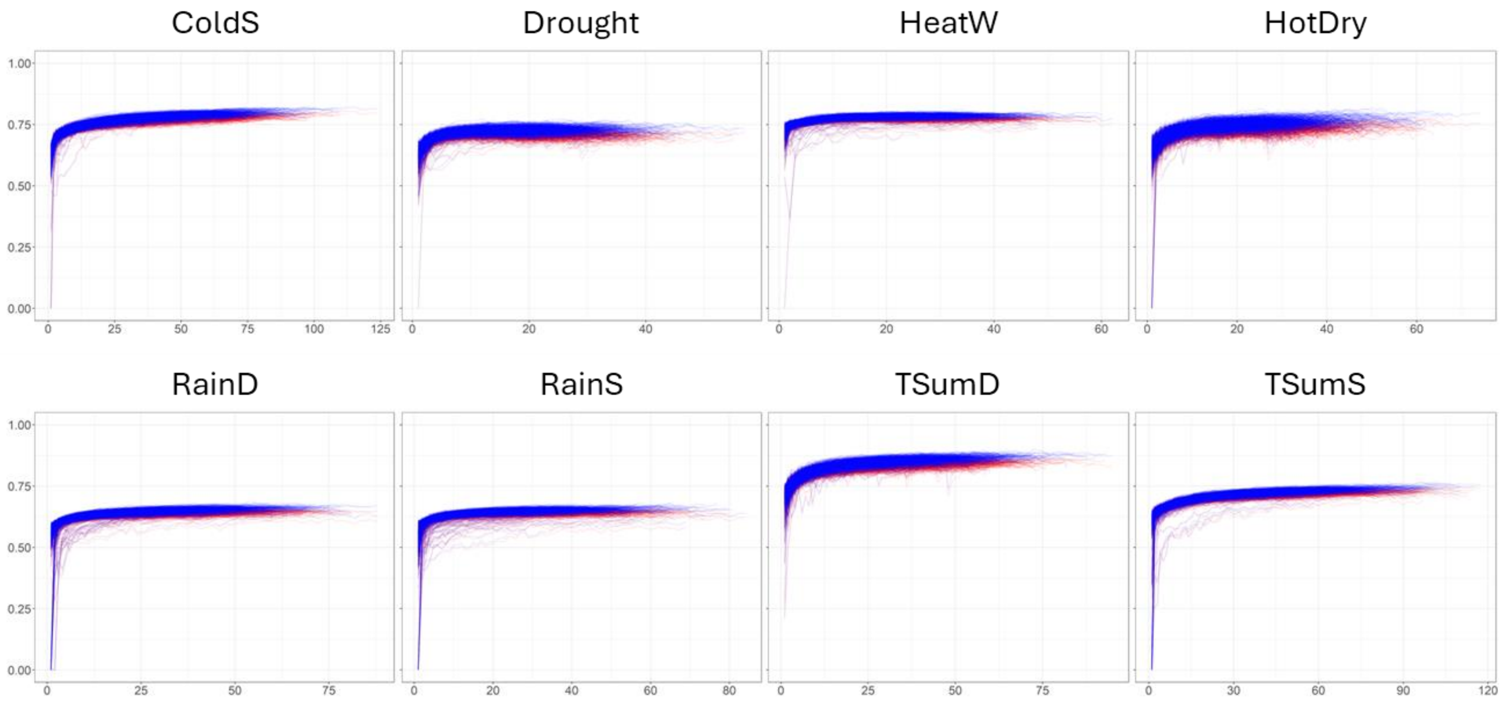
$$recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall}$$

$$accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$



Results – Evolution Log (boosting rounds)



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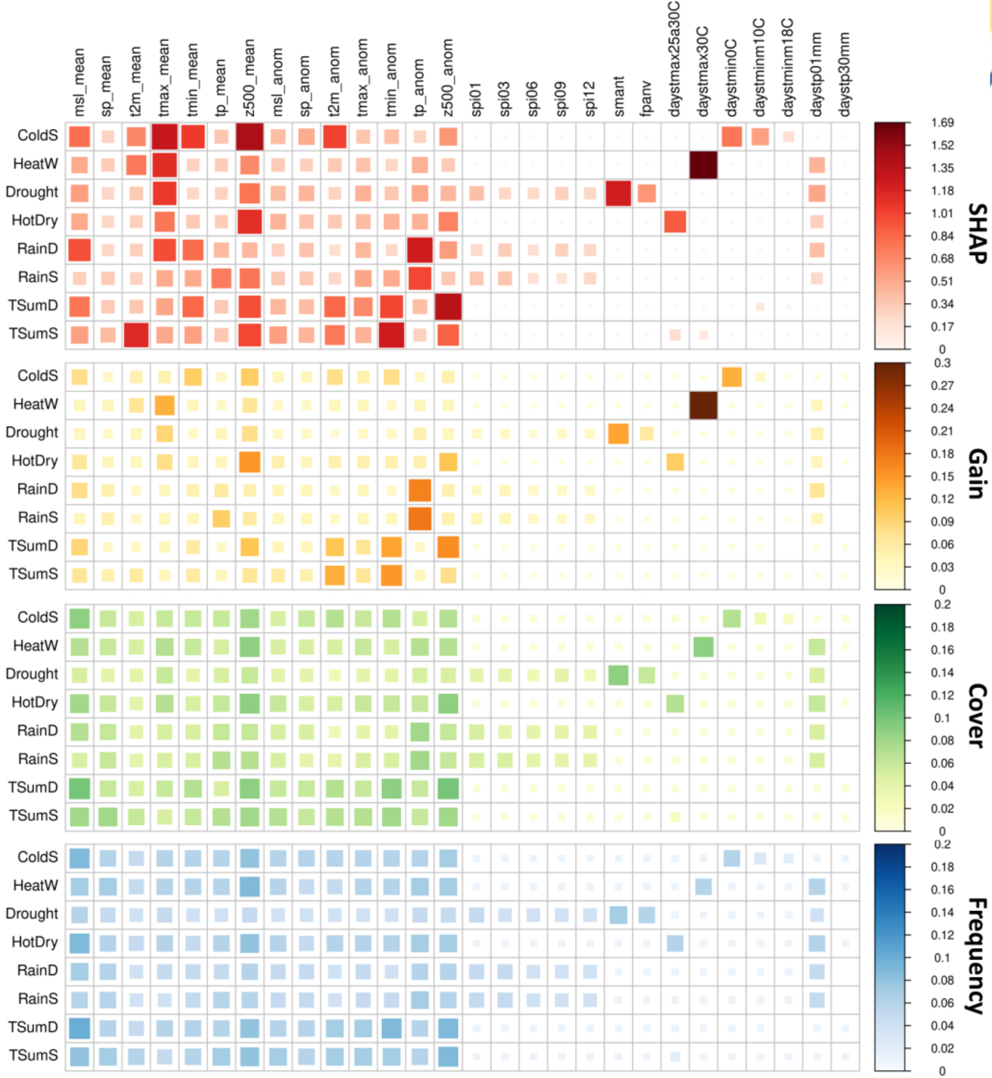
Results – Variable Importance Matrix

- **SHAP:** The mean absolute SHAP (SHapley Additive exPlanations) value is the average of the absolute SHAP values for a given feature across all the instances in the dataset and it measures the average magnitude of a feature's contribution to the model's predictions

- **Gain**: higher values indicate that a variable is more important for generating a prediction. Gain reflects the increase in accuracy brought by each single feature.

- **Cover**: measures the relative number of observations related to this feature. It is related to the second order derivative (or Hessian) of the loss function with respect to a particular variable.

- **Frequency**: relative number of times a particular feature occurs in the trees of the model. Frequency is associated with the number of times a feature is used and to its overall utility



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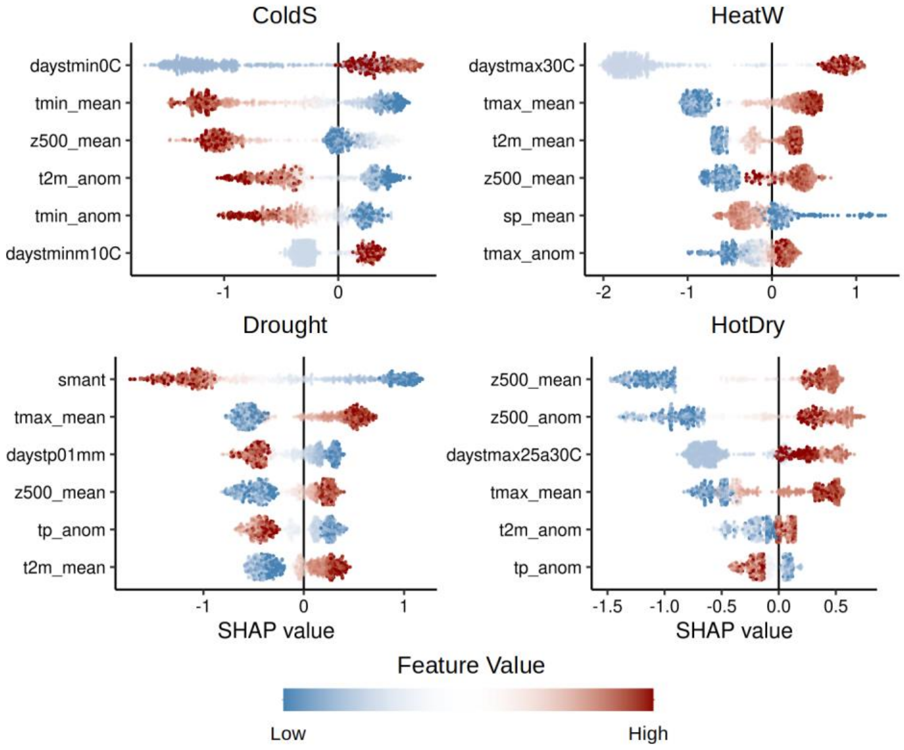
Results – SHAP

- **SHAP:** The results from the SHAP analysis allow for the understanding of how a certain input feature contributes, both positively and negatively, to the detection of AOC regions.

- As shown, higher values of geopotential height at 500 hPa are associated with the detection of heatwaves and of regions not classified as under cold spells, a pattern that is coherent with large-scale climate dynamics.

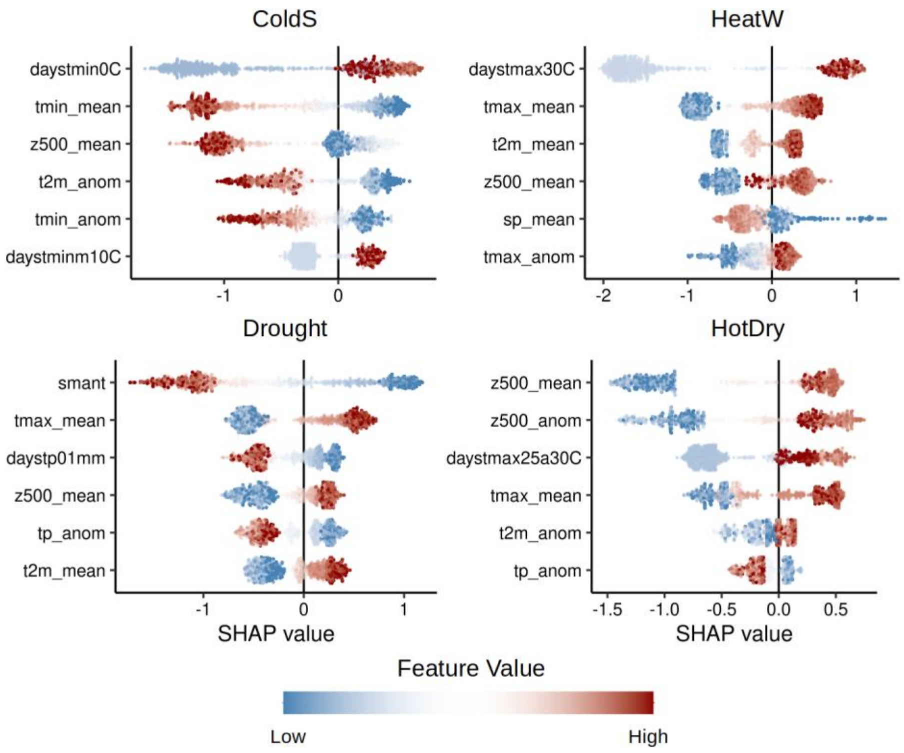
- These results enhance explainability and make possible to evaluate the adherence of the model to the physical understanding of processes behind the detection of AOC regions.

- With respect to the other AOC classes, for instance, the anomalies and mean values of geopotential height at 500 hPa significantly contribute to the detection of hot-and-dry AOC, while also contributing to drought AOC detection.



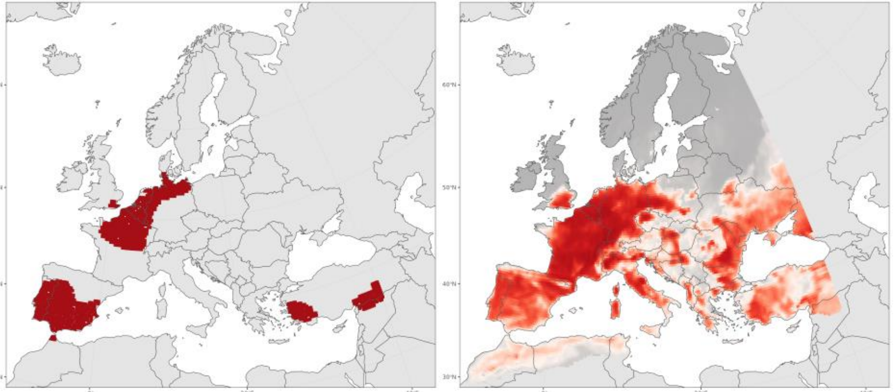
Results – SHAP

- **<u>Droughts:</u>** input features such as the ones based on the SPI and SMANT seem to be relevant for droughts detection.
- Indeed, complex spatio-temporal hazards such as droughts necessitate the use of more advanced indicators, such as SPI and SMANT, rather than relying solely on total precipitation data, as droughts are anomalies that manifest over extended periods of time and over varying spatial areas.
- Moreover, the potential impacts of droughts are linked to the hydrological cycle dynamics and the potential response of the vegetation, meaning that precipitation alone may often be insufficient to fully describe them.
- Indeed, the multi-dimensional nature of drought and rain deficit impacts, usually resulting from a combination of temperature, soil moisture, and precipitation anomalies, requires the integration of a range of variables into a comprehensive assessment, a complexity that seems to be captured well by the ensemble XGboost models.
- In general, the variable soil moisture anomaly achieves the highest scores in all four measures for drought detection, a pattern that is coherent with agricultural drought detection and that is the focus of AOC when detecting droughts.

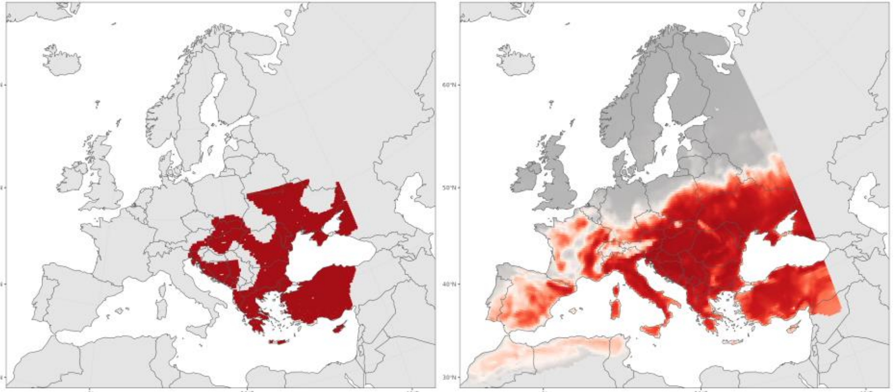


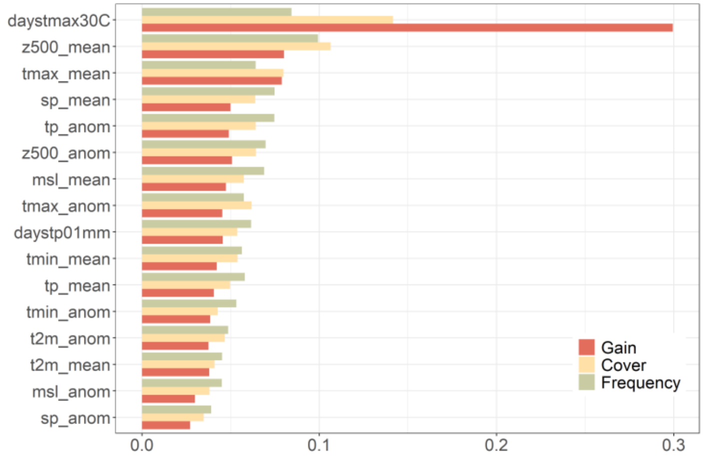
AI-based first guess of Areas of Concerns – Heat waves

Training dataset



Test dataset



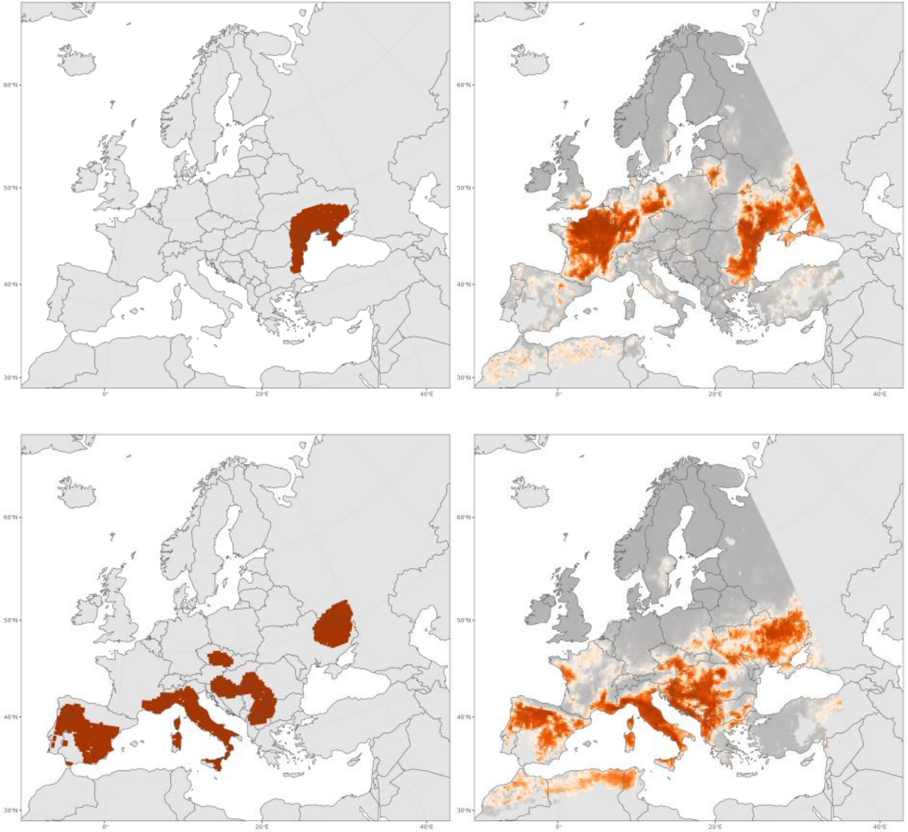


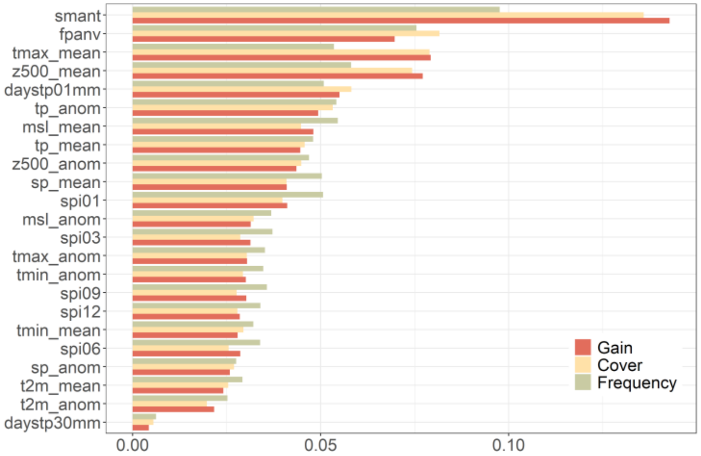
- **Gain**: higher values indicate that a variable is more important for generating a prediction.
- **Cover**: measures the relative number of observations related to this feature.
- **Frequency**: relative number of times a particular feature occurs in the trees of the model.

AI-based first guess of Areas of Concerns – Droughts

Training dataset

Test dataset



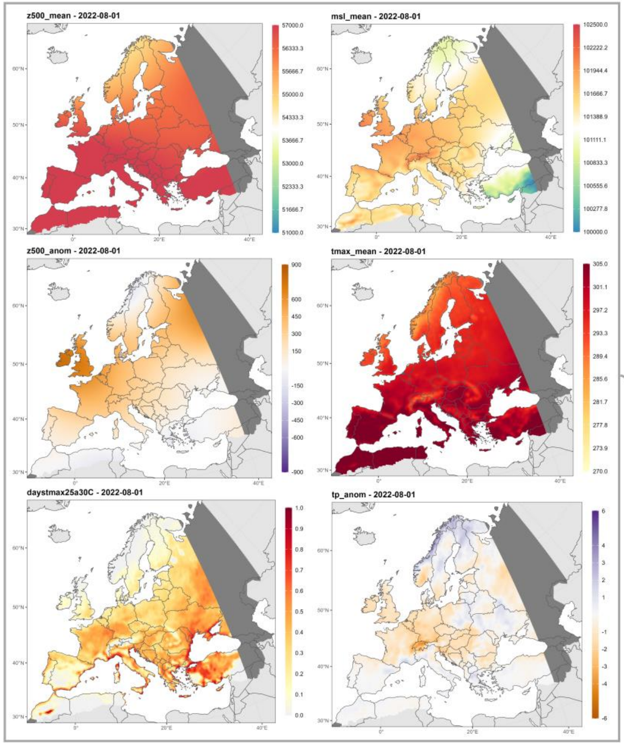


- **Gain**: higher values indicate that a variable is more important for generating a prediction.
- **Cover**: measures the relative number of observations related to this feature.
- **Frequency**: relative number of times a particular feature occurs in the trees of the model.

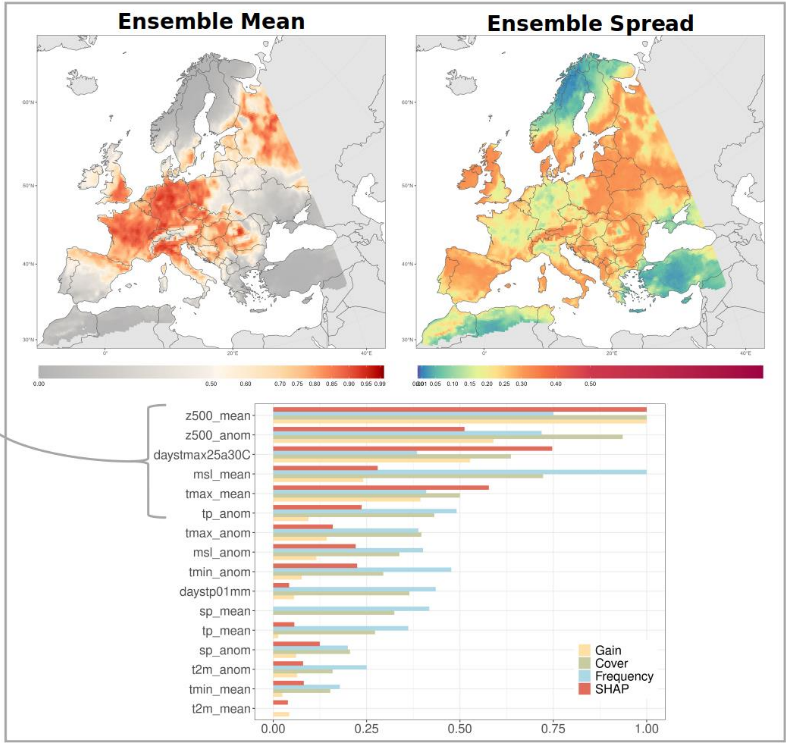
Probabilistic Nature of the System

- The ensemble-based approach reduces the final impacts of potential errors from individual models by smoothing out outlying results when considering a large-enough ensemble.
- Areas where hazard and impacts are almost certain (e.g. the Po valley in Italy during the summer of 2022) are characterised by lower spread and higher probability in detecting hot-and-dry conditions, highlighting the overall coherency and the strong signal.
- In contrast, in areas such as the Iberian Peninsula where the combined probabilities of hazard and expected impacts are lower, higher differences are observed in the models' response, indicated by a higher spread.

INPUT FEATURES



OUTPUTS



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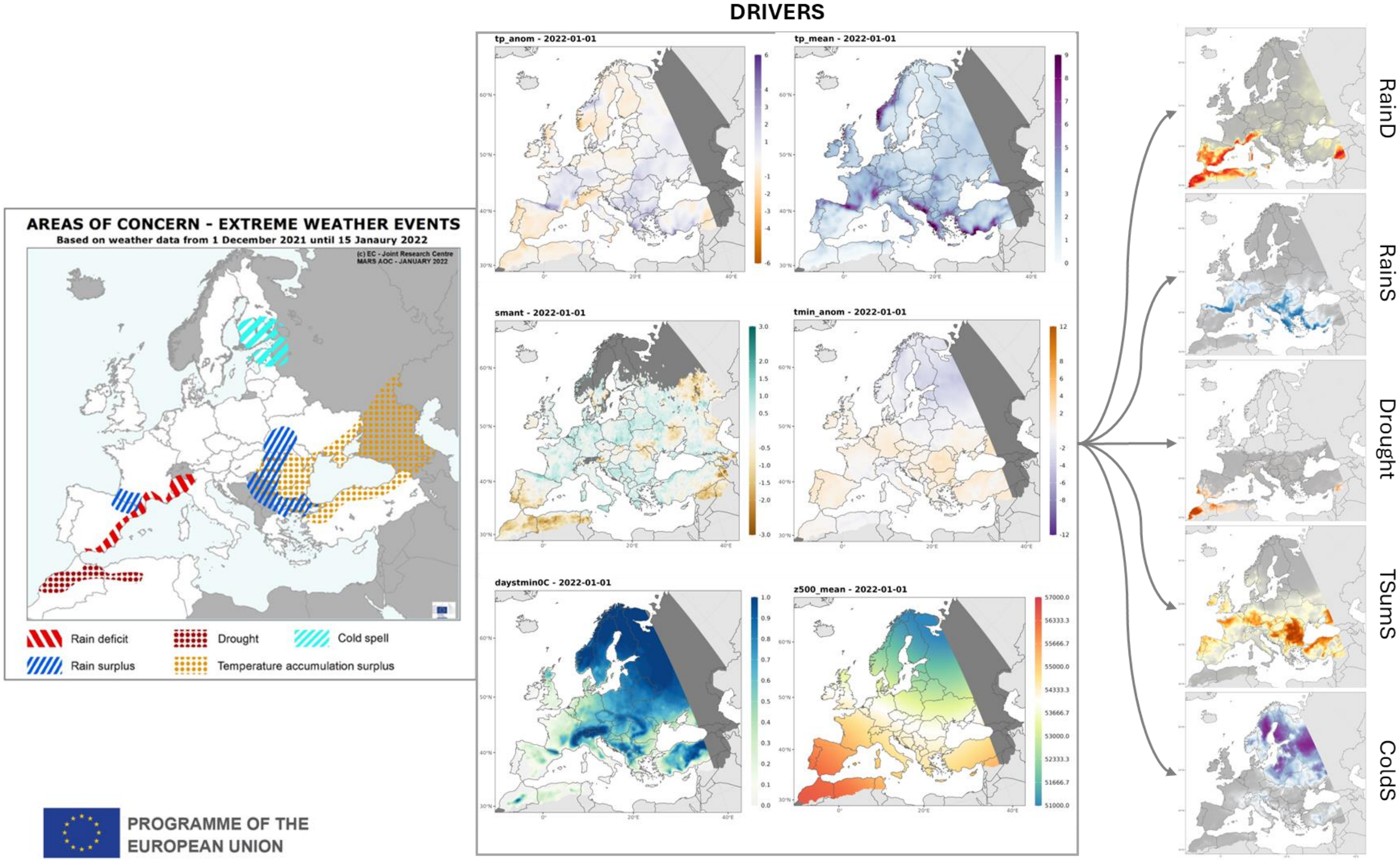
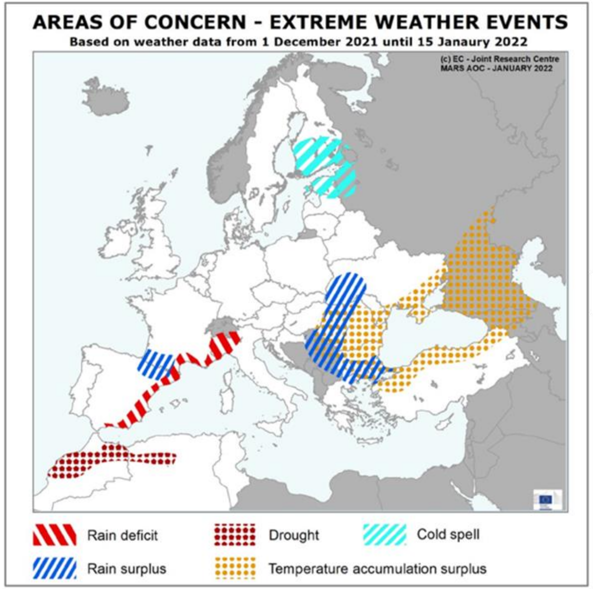
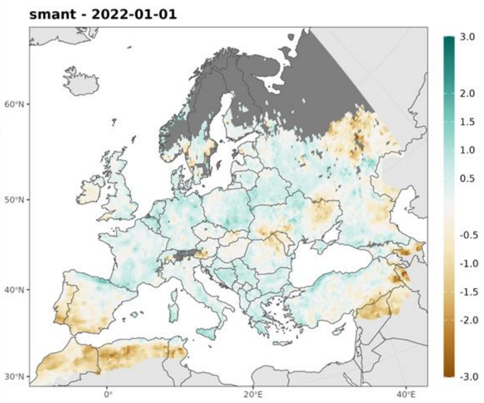
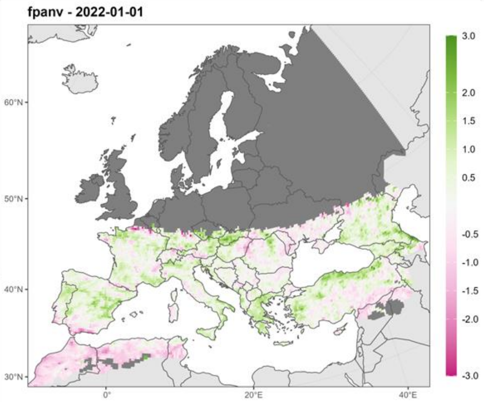
ERA5 Drivers of 2022 First-Guess

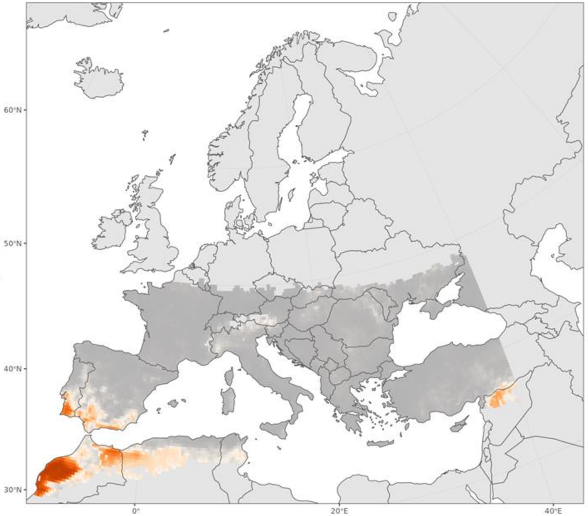


ERA5 Drivers of 2022 First-Guess – Droughts

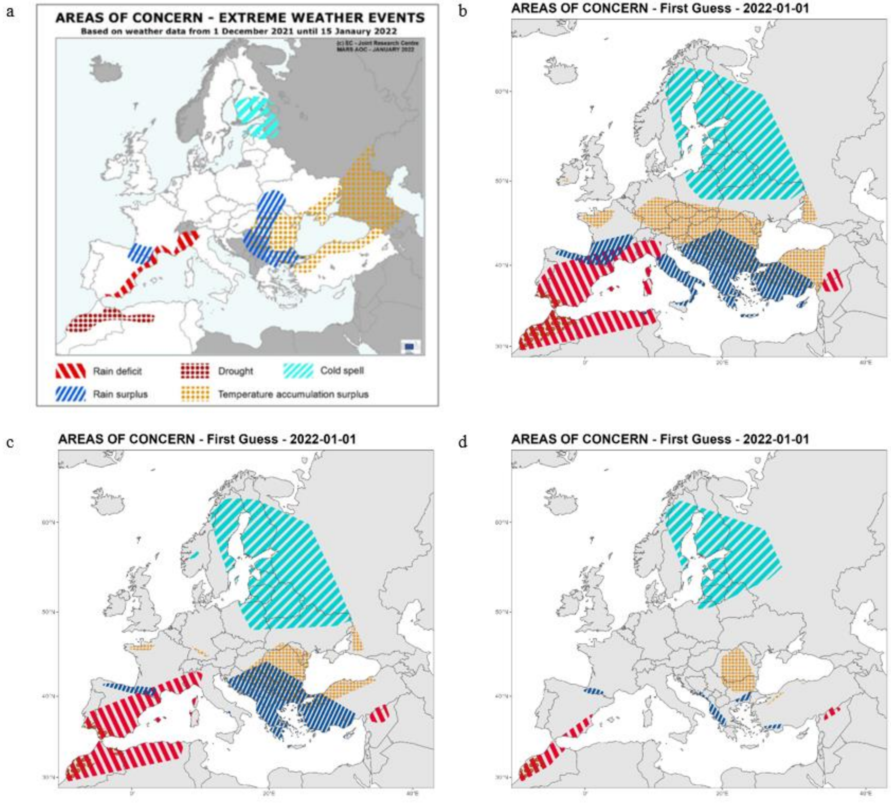








ERA5 Drivers of 2022 First-Guess – AOCs



Example of the first-guess identification of AOC over Europe during the period of analysis covered in the MARS Bulletin of January 2022; a) Actual meteorological AOC in the MARS Bulletin. The AOC first-guess when about: b) two-thirds; c) 90%, and d) 95% of the XGBoost models agree on the detection of a certain AOC type.

Conclusions

- We have developed a **<u>hydbrid xAI-based model</u>** that results from the combination of **data-driven AI methods** with the **expert-based knowledge** produced in JRC to provide a first-guess of meteorological extremes as AOCs in Europe

- The proposed solution tackles two currently frontiers in science:

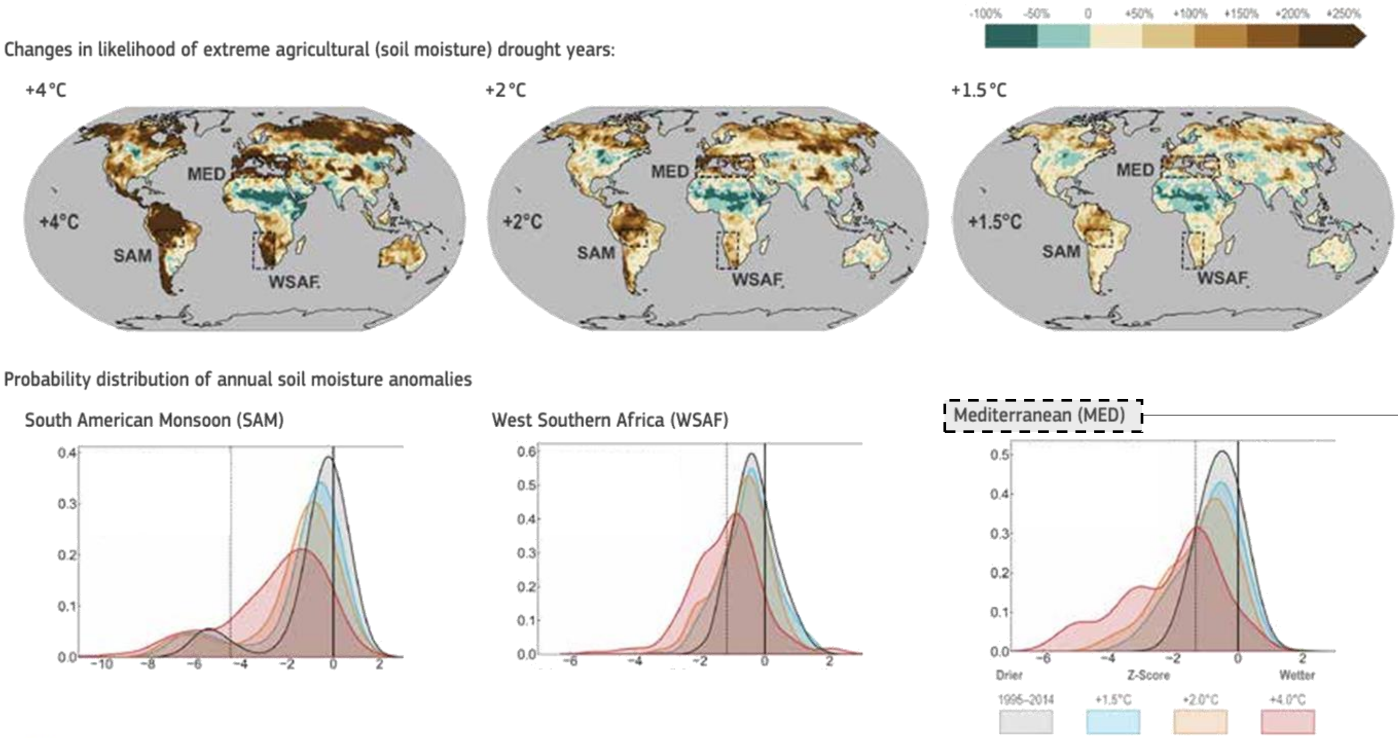
    1. A system for the detection, in space and time, of multi-hazard extreme events
    2. The application of (x)AI-based methods in a context of DRR for droughts

- The developed model/solution is **<u>xAI-based</u>** as it is both **<u>interpretable</u>** (i.e. the results given and decision taken by the AI system are understandable) and **<u>transparent</u>** (i.e. capable of understanding which kind of data it uses, how the system works, and how it takes decisions).

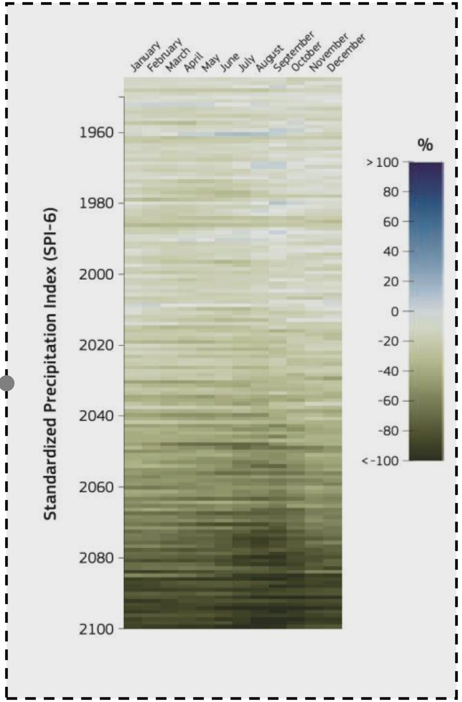
Policy Relevance

- With respect to potential future policy relevance:
  - **Water Resilience Initiative**: during the State of the Union address on 13 September 2023, the main priorities and flagship initiatives for the year to come have been outlined, one being the _Initiative for Water Resilience as part of the European Green Deal_. Increasing water resilience includes a holistic perspective of water resources, and the provision of spatio-temporal information on extreme events such as droughts is fundamental, an area where AIACS can provide support.
  - **Climate Adaptation Strategy**: The Strategy of the European Union aims to adapt to the unavoidable _impacts of climate change and become climate resilient by 2050_. Impact assessment and management of extreme events requires the detection and forecasting of those, an area where AIACS can provide support.
  - **EU Civil Protection Mechanism**: Aims to strengthen cooperation between the EU countries and participating states on civil protection to _improve prevention, preparedness, and response to disasters_. AIACS can help in boosting prevention and preparedness to disasters by providing information on the detection and forecasting of extreme events
  - Other future policy relevance may include the future **Common Agriculture Policy (CAP)** and the **Early Warning for All** initiative promoted by the WMO

Future Risks – Droughts



Fonte: IPCC AR6, WGII



Fonte: IPCC Atlas, online

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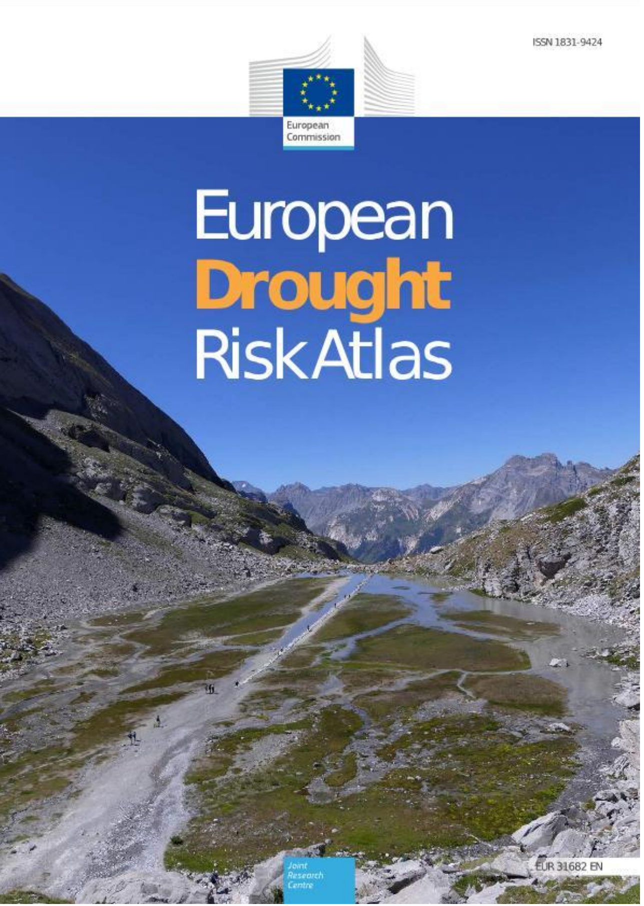
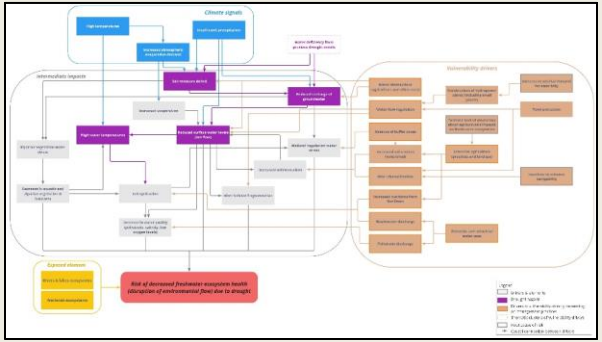
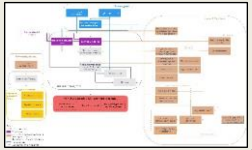


European Drought Observatory for Resilience and Adaptation

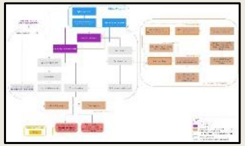
Freshwater ecosystems



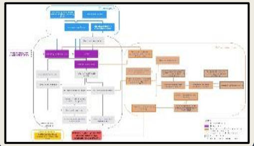
Forest Ecosystems



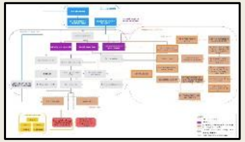
Agriculture (rain-fed)



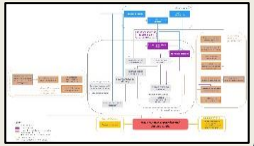
Inland water transport



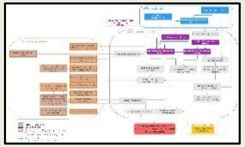
Agriculture (irrigated)



Energy



Public water supply



- The EDORA impact chains* explore **drivers of drought risks** for different sectors and systems, informing the risk assessment
- The conceptual models explain **how impacts manifest**, pointing at possible **entry points** for risk reduction and adaptation

** Developed through literature review and experts' consultations*

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Meteorological Drought Event Tracking

MARCH 2023 CAMMALLERI AND TORETI 537

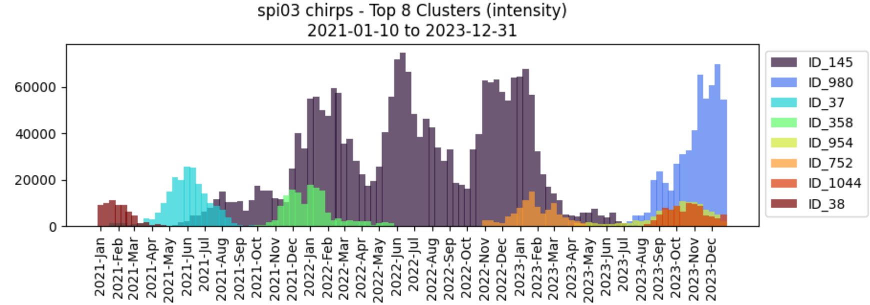
A Generalized Density-Based Algorithm for the Spatiotemporal Tracking of Drought Events

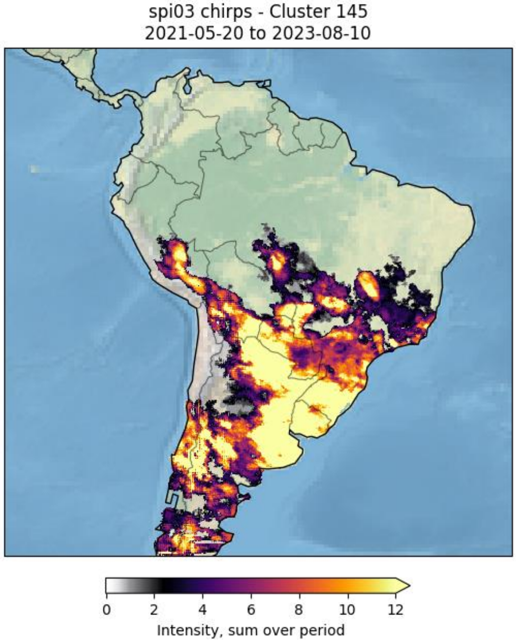
C. CAMMALLERI[a] AND A. TORETI[a]
[a] Joint Research Centre, European Commission, Ispra, Italy

(Manuscript received 6 June 2022, in final form 10 November 2022)

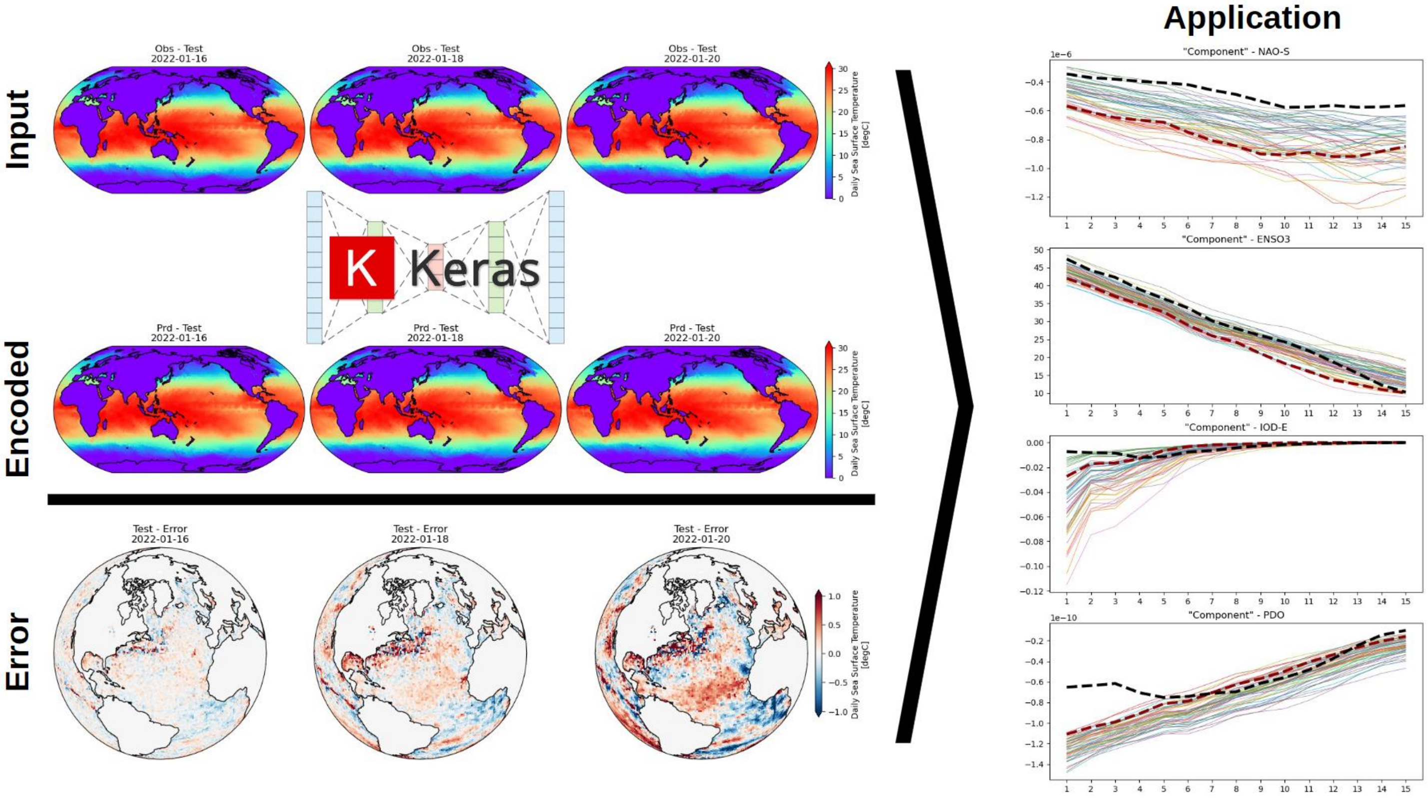
ABSTRACT: Drought events evolve simultaneously in space and time; hence, a proper characterization of an event requires the tracking of its full spatiotemporal evolution. Here we present a generalized algorithm for the tracking of drought events based on a three-dimensional application of the DBSCAN (density-based spatial clustering of applications with noise) clustering approach. The need for a generalized and flexible algorithm is dictated by the absence of a unanimous consensus on the definition of a drought event, which often depends on the target of the study. The proposed methodology introduces a set of six parameters that control both the spatial and the temporal connectivity between cells under drought conditions, also accounting for the local intensity of the drought itself. The capability of the algorithm to adapt to different drought definitions is tested successfully over a study case in Australia in the period 2017–20 using a set of standardized precipitation index (SPI) data derived from the ERA5 precipitation reanalysis. Insights on the possible range of variability of the model parameters, as well as on their effects on the delineation of drought events, are provided for the case of meteorological droughts in order to incentivize further applications of the methodology.

KEYWORDS: Drought; Precipitation; Clustering





AI-Enhanced Drought Forecasting?



(Efficient-)CapsNet for Drought Forecasting?

> J Adv Model Earth Syst. 2020 Feb;12(2):e2019MS001958. doi: 10.1029/2019MS001958. Epub 2020 Feb 23.

Analog Forecasting of Extreme-Causing Weather Patterns Using Deep Learning

Ashesh Chattopadhyay [1], Ebrahim Nabizadeh [1], Pedram Hassanzadeh [1 2]

Affiliations — collapse

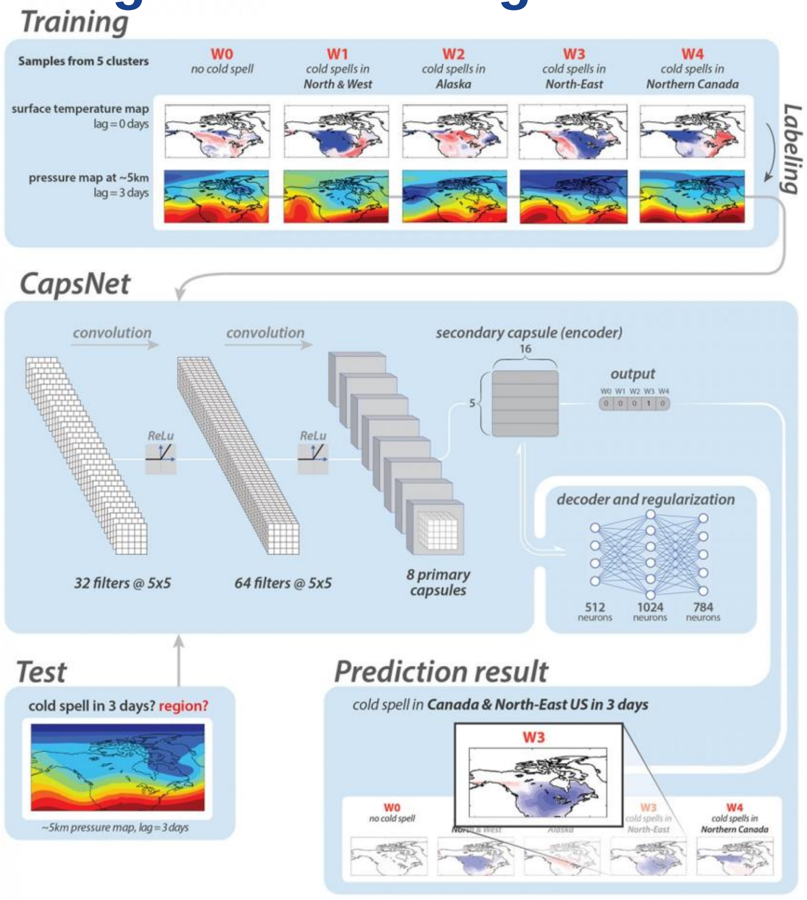
Affiliations

1 Department of Mechanical Engineering Rice University Houston TX USA.
2 Department of Earth, Environmental and Planetary Sciences Rice University Houston TX USA.

PMID: 32714491 PMCID: PMC7375135 DOI: 10.1029/2019MS001958

"Authors found that because the relative position of weather patterns play a key role in their evolution, using a more advanced deep learning method that tracks the relative position of features improves the accuracy and is also more robust when we don't have a large amount of data for training."

Could the same be true for drought forecasting at seasonal scales?



(Efficient-)CapsNet for Drought Forecasting?

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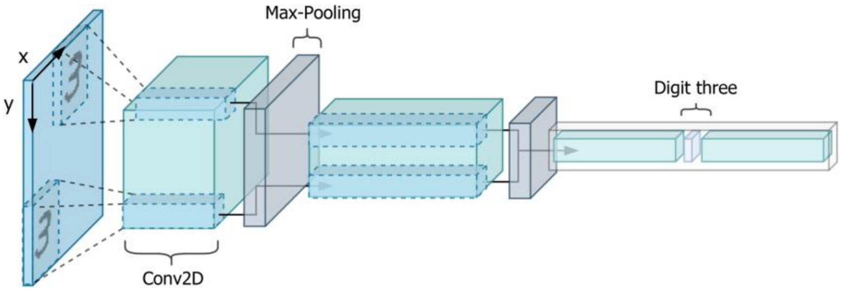

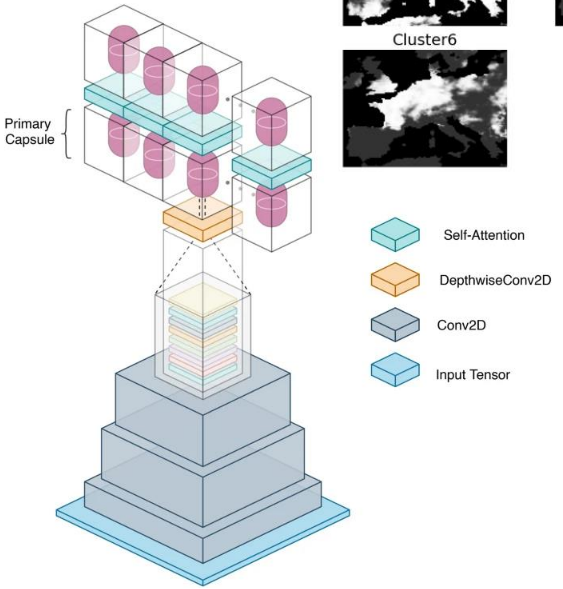

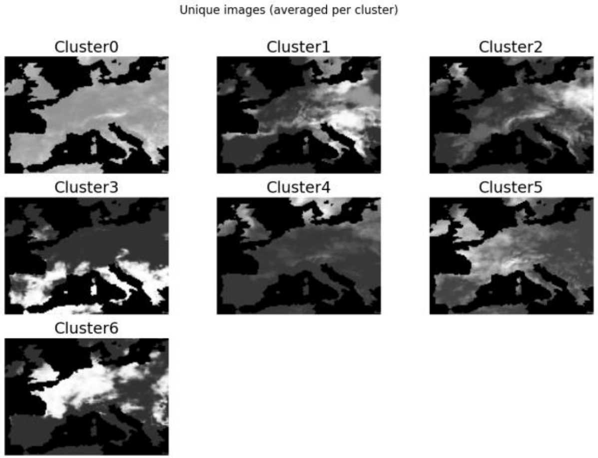

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