Artificial Intelligence for Modeling and Understanding Extreme Weather and Climate Events

Jordi Cortés-Andrés, **Maria** Gonzalez-Calabuig, **Mengxue** Zhang, **Miguel-Ángel** Fernández-Torres, **Gustau** Camps-Valls

@ migferna@ing.uc3m.es, miguel.a.fernandez@uv.es

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Destination Earth 4th DestinE User eXchange

Tasks

Detection
- Spatio-temporal extreme maps
- Discover underlying patterns

Forecasting
Anticipate future extremes

Impact assessment
- Predict and analyze consequences
- Social, economic, environmental

Explainable AI
- Expert-comprehensive representations
- Deployment in real scenarios

Challenges

1) Lack of spatio-temporal databases
2) Data quality, gap filling, weak labels
3) Model design and receptive field
4) Evaluation procedures and metrics
5) A more scientifically valuable XAI
6) Compound events
7) Extreme event impact assessment
8) Generic vs. location-aware models
9) Integration of expert knowledge
10) Generic framework for all extremes

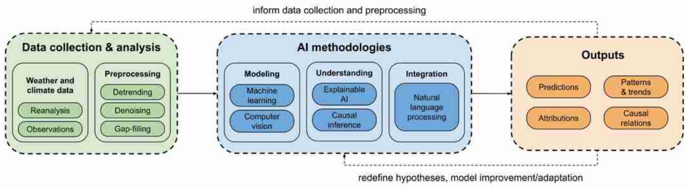
Drought Detection

- Better understanding of their generating process and facilitates their anticipation

- Drought indices
  - Often defined for one drought type
  - No spatio-temporal dependencies
  - Specific PDFs or simple TH ratios
  - Limited to particular time scales

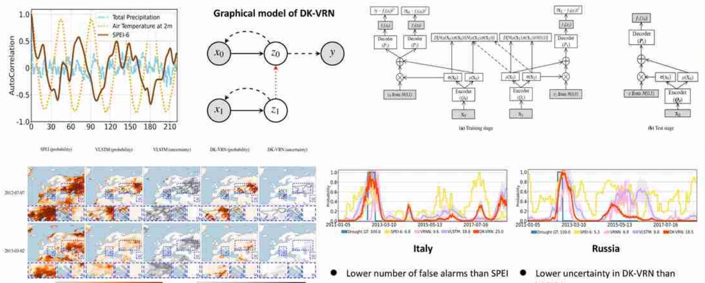
- Machine learning models
  - Directly learn from historical data
  - Input: Climate variables and/or indices
  - Output: Intensity, relevant variables

A General AI-Driven Extreme Event Analysis Pipeline



Domain Knowledge-Driven Models

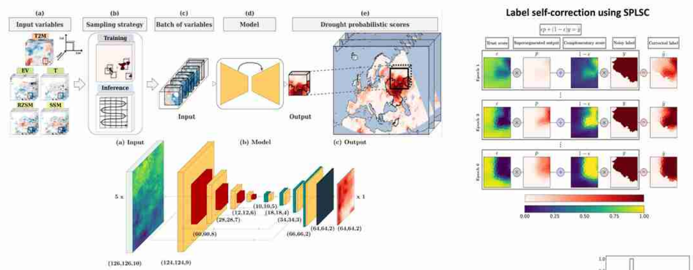
A novel hybrid variational recurrent neural network (LSTM-based) for drought detection. Estimated expectation and uncertainty by means of importance sampling (K outputs).

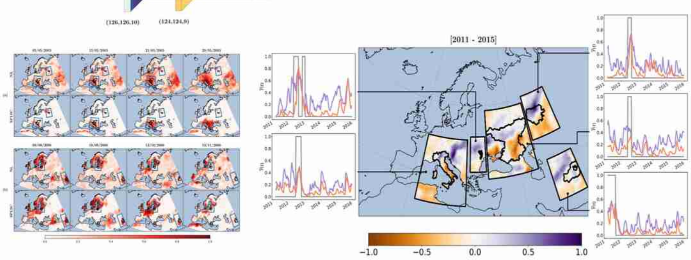


- Lower number of false alarms than SPEI
- Lower uncertainty in DK-VRN than VLSTM

Deep Learning with Noisy Labels

Spatio-temporal (3D CNN) convolutional encoder-decoder for drought detection. Robust learning with noisy labels, including a superpixel-based self-correction method.



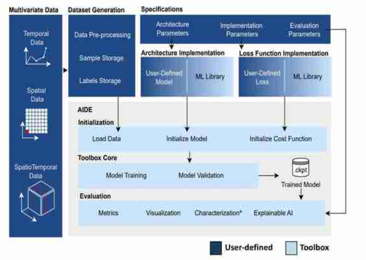


Drought detection in Europe. Historical drought events in 2003-2018 due to 10 deaths or 100 affected, or an emergency declaration.

The AIDE Toolbox

A generic framework to simplify ML workflows
- Detection and characterization
- Impact assessment

https://github.com/IPL-UV/AIDE



Category	Examples	♯ Methods	Dimension	Module
Probabilistic	KDE	10	P	ML
Linear Models	PCA, Hotelling	6	P	ML
Proximity-Based	k-NN	11	P	ML
Combination	Majority-vote	7	P	ML
Ensembles	XGBOD	13	P	ML
Fully-connected	MLP	9	P, T, S	DL
CNN	ResNet	30	S	DL
RNN	LSTM	8	T	DL
Transformers	Mix-ViT	8	T, S	DL
Graphs	LUNAR	2	P	DL
Classification metrics	F1, AUROC	27	T, S, ST	EVAL
Detection metrics	mAP, IoU	7	T, S, ST	EVAL
Regression metrics	MSE, R^2	18	T, S, ST	EVAL
Other metrics	Mean, SSIM	92	T, S, ST	EVAL
Visualization	Maps, time series	2	T, S	EVAL
Characterization	Area, perimeter	7	T, S	EVAL
Gradients	Saliency, IG	20	T, S, ST	XAI
Perturbation	SHAP	7	T, S, ST	XAI

Spatial (S) — Machine Learning (ML)
Temporal (T) — Deep Learning (DL)
Spatiotemporal (ST) — Visualization/Characterization (EVAL)
Pointwise (P) — Explainable AI (XAI)

Current and Future Work

- Spatio-temporal databases: in-situ measurements, remote sensing data, crowdsourcing geospatial data
- Forecasting under extreme climate conditions
- Location-aware models
- Unsupervised/semi-supervised approaches
- Uncertainty analysis
- Intrinsically interpretable models

References and Acknowledgments

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