



# interTwin

**A novel approach for a Digital Twin to explore future  
climate extremes to assess impacts**



**EGI2024 Conference, Sep 30 – Oct 2, 2024  
Lecce, Italia**

**Christian Pagé, CERFACS  
Use Case Lead  
Anne Durif, CERFACS  
Research Engineer**



Funded by the  
European Union

The interTwin project is funded by the European Union - Grant Agreement Number 101058386



# The Challenge: Climate Extremes

## Generic detection algorithm:

- Intense rainfall
- Drought
- Heatwave
- Cold spell
- High wind

Different methods for one-time events (intense rainfall, high wind) vs. longer-term events (droughts,...)

## Characterization (What-if Scenarios):

- Frequency of occurrence
- Spatial extent
- Intensity (if relevant)
- Duration





# The Challenge: Climate Extremes



*2021 Germany Ertstadt,  
southwest of Cologne*

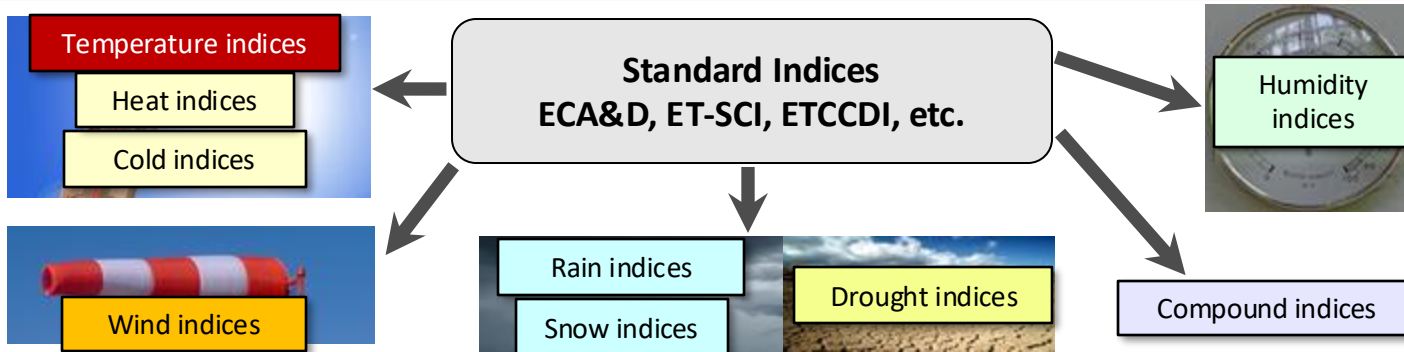


*2020 Hurricane Delta causes damage to  
Louisiana's Gulf Coast*

- Urgent needs of impact assessments
- Identify mitigation solutions
- Extreme events attribution
- Multiple domains: infrastructures, urban, agriculture, transportation, etc.
- Flexible tools needed for very diverse users



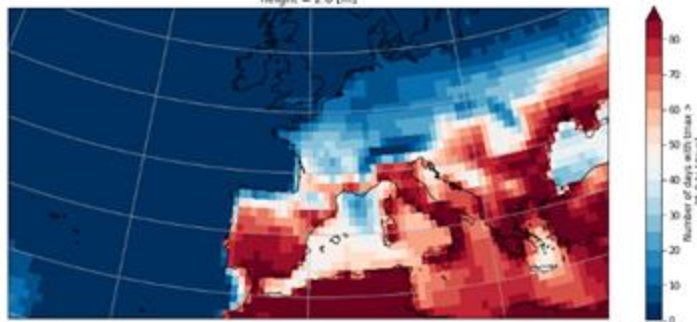
# Climate Indices and Indicators



- Intra-period extreme temperature range [°C] - **ETR**
- Warm days (days with mean temperature > 90th percentile of daily mean temperature) - **TG90p**
- Summer days (days with max temperature > 25 °C) - **SU**
- ...

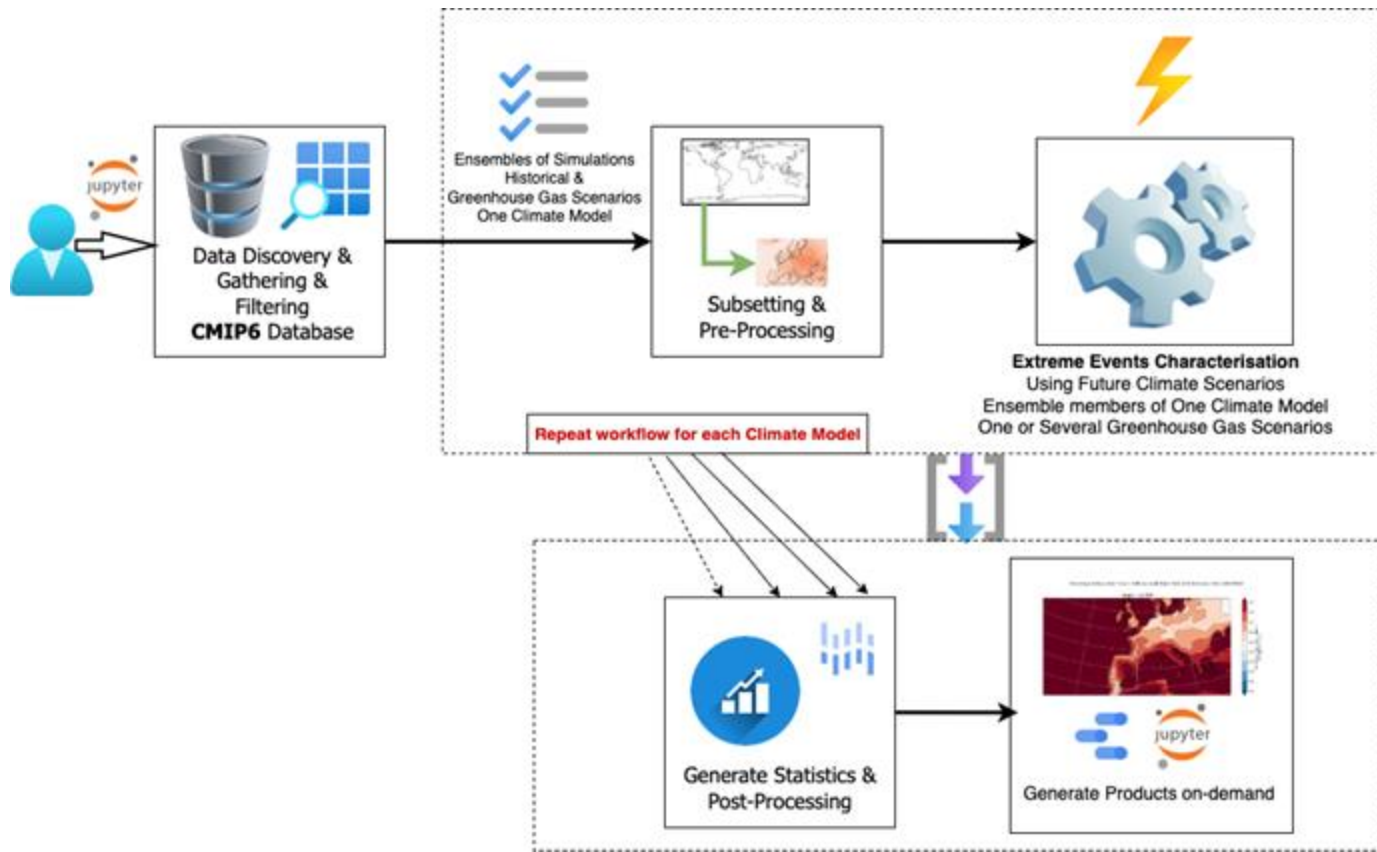
*iclim* python package

<https://github.com/cerfacs-globc/iclim>





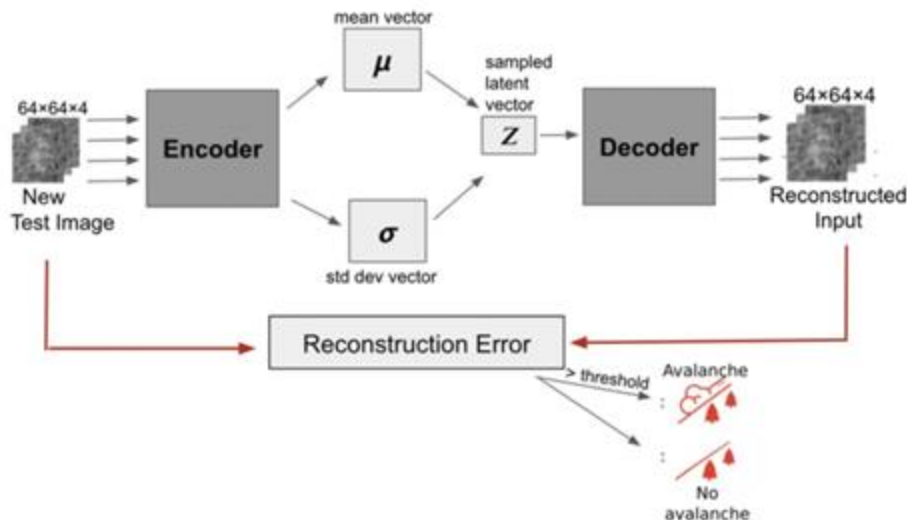
# Extreme Workflow: the User Perspective





# Why use a AI based method?

- To analyze a very large database of climate scenarios with a good performance
- Use efficiently new architectures (GPUs)
- Scalability in cloud-based environments
- Extreme Events spatial structures are similar to avalanches
  - Variational Autoencoder: Deep Learning Technique

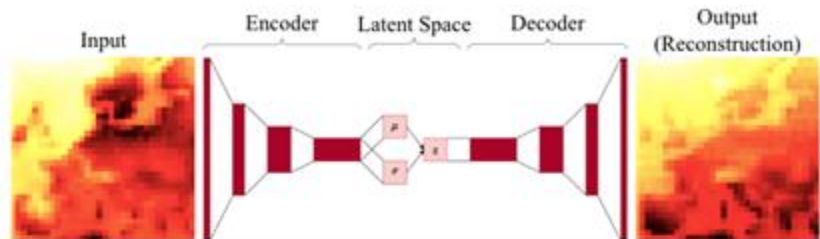


Sinha, Saumya & Giffard-Roisin, Sophie & Karbou, Fatima & Deschatres, Michael & Karas, Anna & Eckert, Nicolas & Coléou, Cécile & Monteleoni, Claire. (2020). Variational Autoencoder Anomaly-Detection of Avalanche Deposits in Satellite SAR Imagery. 113-119. 10.1145/3429309.3429326.



# Deep Learning Method

## Convolutional Variational Auto-Encoder (CVAE)



- Learning details:**
- $\sim 10^5$  trainable parameters
  - Latent space dimension: 64
  - 5-minute training for 1 member over 1950-2000, 100 epochs
  - 1-minute inference, all SSPs, 2015-2100

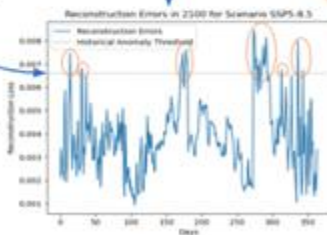
xtclim python package

<https://github.com/cerfacs-globc/xtclim>

## Characterization

**Anomaly threshold**  
*defined over a reference period*

- Compute the reconstruction errors (time series) of this period.
- Keep the 1%-most-extreme events of the period.
- Compute the corresponding anomaly threshold.
- Compare the number of events with a greater reconstruction error on projection data.



Extraction of event characteristics from time series:

- Frequency
- Duration
- Intensity



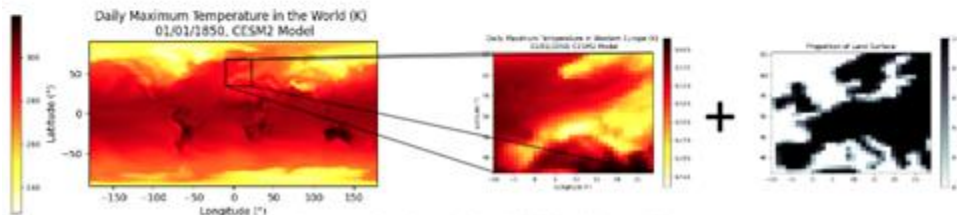
# Data...

## Raw Data

- Coupled Model Intercomparison Project, phase 6 (CMIP6)
- General Circulation Models (e.g. CMCC-ESM2)
- $1^\circ \times 1^\circ$  resolution ( $\sim 125\text{km}$  spatial grid)
- Daily data from 1850 to 2100
- Climate variables: temperature, precipitations, wind...
- Various carbon emission scenarios (IPCC):
  - SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5

## Preprocessing

- From NetCDF files to numpy tables
- $32 \times 32$  square over Western Europe
- Season split
- Min-max normalization



Preprocessing Steps: from World to Western Europe  
*Normalized and Enhanced with Land-Sea Proportion*

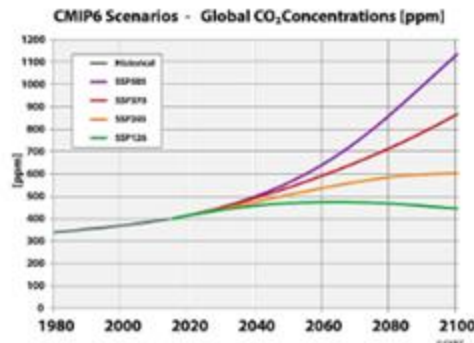
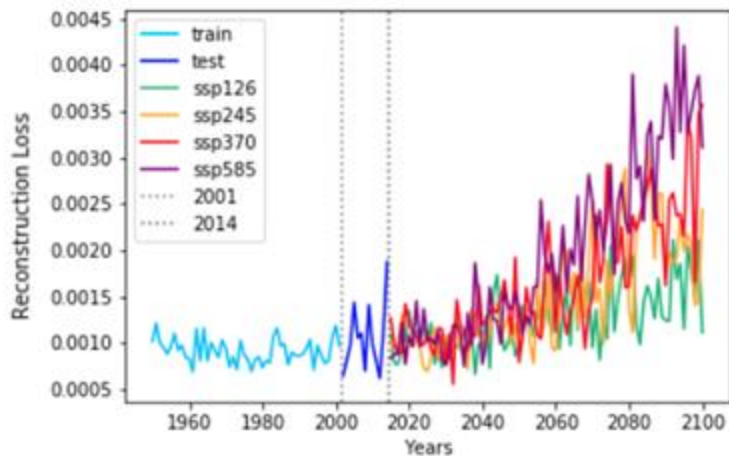




# Fast comparison between GES

## Comparison between IPCC Scenarios

Reconstruction Errors in CMCC-ESM2 Model  
Summers



### Anomaly Analysis in CMCC-ESM2 Model (Summers)

*Detection when the reconstruction error exceeds a threshold*

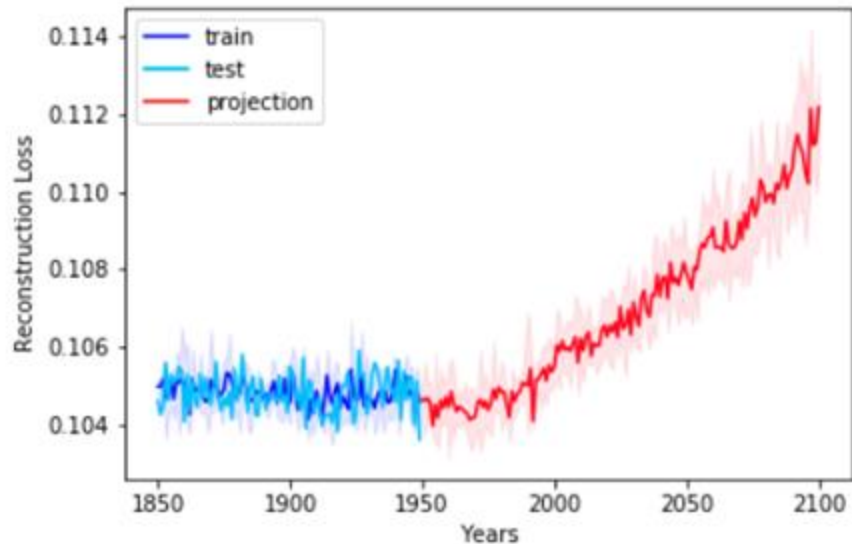
| Scenario                   | 2001-2014 |          | 2015-2100 |          |          |
|----------------------------|-----------|----------|-----------|----------|----------|
|                            | Test data | SSP1-2.6 | SSP2-4.5  | SSP3-7.0 | SSP5-8.5 |
| Proportion of unusual days | 1,00%     | 3,78%    | 8,09%     | 11,07%   | 17,83%   |
| Maximum spike              | 0,0051    | 0,0053   | 0,0089    | 0,0087   | 0,0095   |
| Maximum duration (days)    | 5         | 22       | 27        | 53       | 55       |
| Average duration (days)    | 2         | 3,44     | 5,66      | 6,17     | 7,51     |



# Large Ensemble Data Analysis

## Comparison between ensemble members

Reconstruction Errors in CESM2 Model  
*Summers, Members 1-5, Scenario SSP3-7.0*



Anomaly Analysis in CESM2 Model  
*Member Comparison for Scenario SSP3-7.0*




|                            | 1850-1950     | 1950-2100    |              |              |              |              |
|----------------------------|---------------|--------------|--------------|--------------|--------------|--------------|
| Member n°                  | Test Data - 5 | SSP3-7.0 - 1 | SSP3-7.0 - 2 | SSP3-7.0 - 3 | SSP3-7.0 - 4 | SSP3-7.0 - 5 |
| Unusual days               | 92            | 3530         | 3614         | 3931         | 3455         | 3798         |
| Proportion of unusual days | 1,00%         | 25,41%       | 26,02%       | 28,30%       | 24,87%       | 27,34%       |
| Maximum spike              | 0,112         | 0,123        | 0,119        | 0,120        | 0,119        | 0,121        |
| Average maximum            | 0,1094        | 0,1108       | 0,1108       | 0,1110       | 0,1109       | 0,1110       |
| Maximum duration (days)    | 7             | 83           | 77           | 81           | 81           | 78           |
| Average duration (days)    | 2,4           | 9,7          | 9,9          | 10,4         | 9,7          | 10,5         |
| Proportion of spikes       | 39            | 91           | 91           | 94,25        | 88,75        | 90,25        |



# Integration with interTwin DTE

- Integration with itwinai and DTE Core Components (unlocks additional functionalities)
  - Extensive Logging
  - Hyper-Parameters' Optimization
- Containerization



```
itwinai / use-cases / xtclim / pipeline.yaml   
  
r-sarma Bug fixes and addition of CERFACS use-case (#151)    
  
Code Blame 31 lines (29 loc) · 922 Bytes  
  
1 # General configuration  
2 dataset_root: '/p/scratch/intertwin/datasets/cerfacs/'  
3 epochs: 3  
4 batch_size: 10  
5 lr: 0.001  
6 scenario: '245'  
7 strategy: 'ddp'  
8  
9 # Workflows  
10 pipeline:  
11   class_path: itwinai.pipeline.Pipeline  
12   init_args:  
13     steps:  
14       preprocessing-step:  
15         class_path: preprocessing.preprocess_functions_2d_ssp.PreprocessData  
16         init_args:  
17           dataset_root: ${dataset_root}  
18           scenario: ${scenario}  
19       preprocessing-split-step:  
20         class_path: preprocessing.preprocess_2d_seasons.SplitPreprocessedData  
21         init_args:  
22           scenario: ${scenario}  
23       training-step:  
24         #class_path: src.trainer_dist.XTClimTrainer  
25         class_path: src.trainer.TorchTrainer  
26         init_args:  
27           epochs: ${epochs}  
28           batch_size: ${batch_size}  
29           lr: ${lr}  
30         #strategy: ${strategy}  
31
```



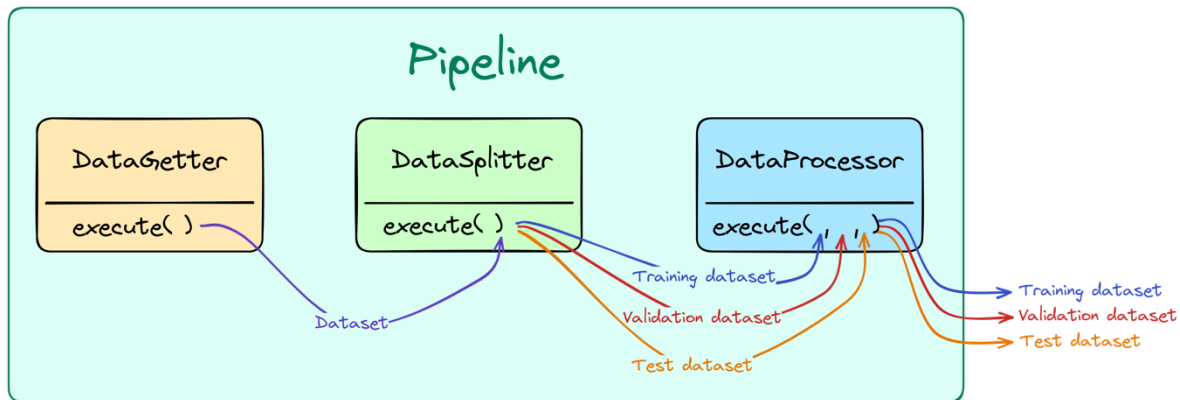
# Integration with interTwin DTE

- Advanced workflow composition (CWL)

- Integration with the interTwin

## Data Lake

- Rucio
- STAC Catalog
- ENES Data Lake



**Source:** itwinai Documentation

[https://itwinai.readthedocs.io/latest/how-it-works/workflows/explain\\_workflows.html](https://itwinai.readthedocs.io/latest/how-it-works/workflows/explain_workflows.html)



# Integration with interTwin DTE

## Perspectives

- Exploitation of **geospatial information**
- Implementation of a **severity index**
- Exploitation of the **latent space** of the Neural Network
- **Validation** against analytical method for robustness assessment (icclim)
- **Extensions** to other climate variables



# Next Steps

## Take-Home Messages

- interTwin DTE enables fast Digital Twin Application Development and Exploitation
- The Convolutional **Variational** Auto-Encoder (CVAE) achieves **Unsupervised Anomaly Detection**
- Events can be **characterized** with various indicators
- Results are **consistent**
- Performance of this approach unlocks the ability to better **quantify climate change impact uncertainties**

# Thank you!

# Questions?

Christian Pagé  
christian.page@cerfacs.fr



LI @pagechristian



[www.intertwin.eu](http://www.intertwin.eu)



[info@intertwin.eu](mailto:info@intertwin.eu)



[intertwin\\_eu](https://twitter.com/intertwin_eu)



[intertwin](https://www.linkedin.com/company/intertwin)