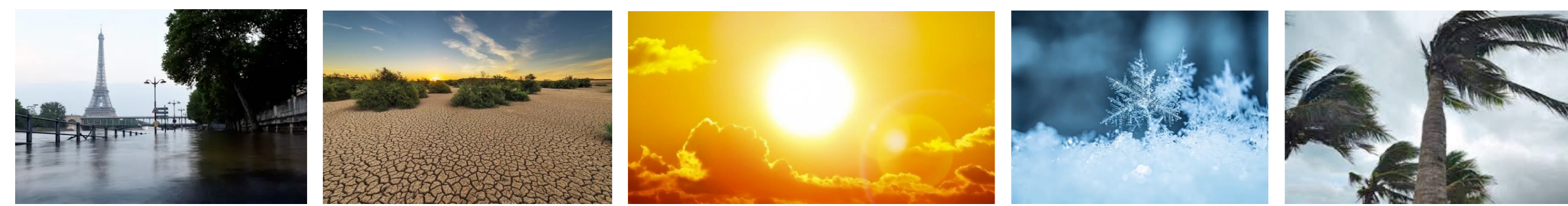




## 1. Introduction: Climate Extremes



- The effects of global warming are worsening
- Mostly due to extreme events
  - Droughts, floods, heat waves...
- Severe impacts on people and human activities
  - Health, buildings, agriculture...
- To face them: adaptation and mitigation
- Detect and characterize the evolution of extremes
  - Frequency, intensity, geographical extent, duration
- First focus on heat waves, with daily maximum temperature

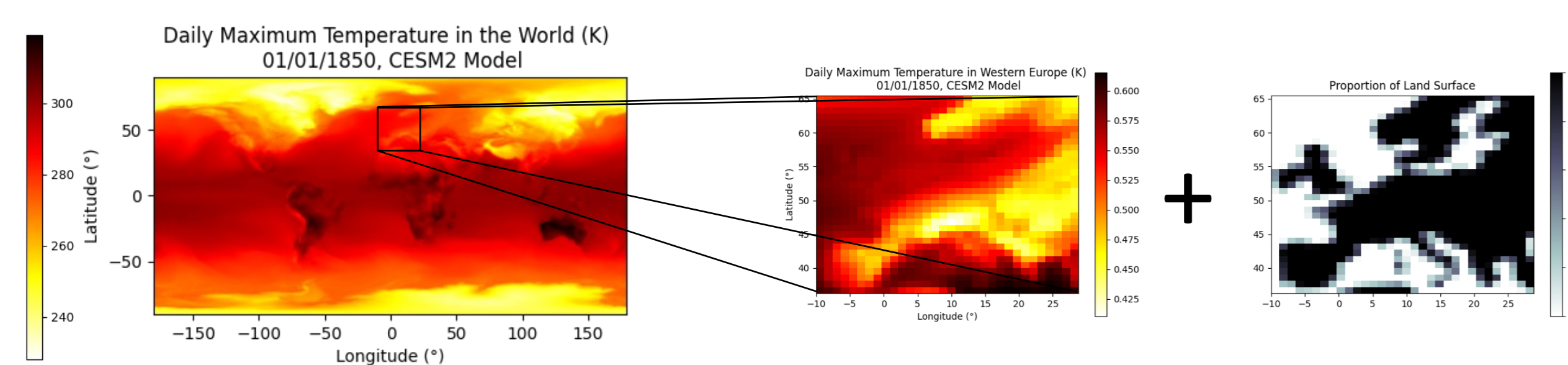
## 2. Future Climate Data

### Raw Data

- Coupled Model Intercomparison Project, phase 6 (CMIP6)
- General Circulation Models (e.g. CMCC-ESM2)
- 1°×1° resolution (~125km 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

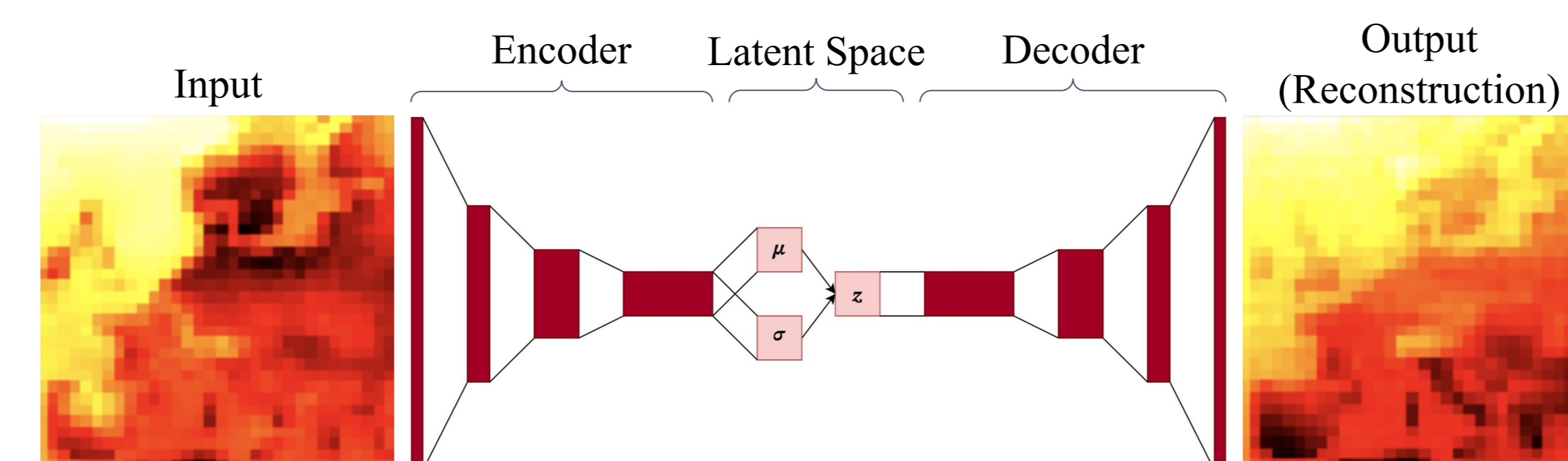
- From NetCDF files to numpy tables
- 32×32 square over Western Europe
- Season split
- Min-max normalization



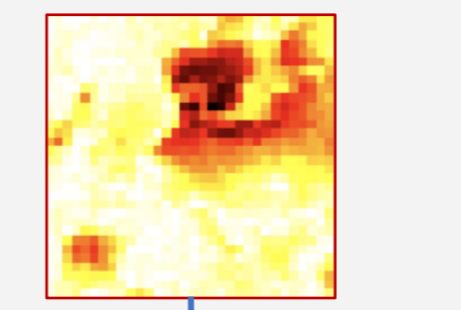
Preprocessing Steps: from World to Western Europe  
Normalized and Enhanced with Land-Sea Proportion

## 3. Deep Learning Method

### Convolutional Variational Auto-Encoder (CVAE)



### Reconstruction Error



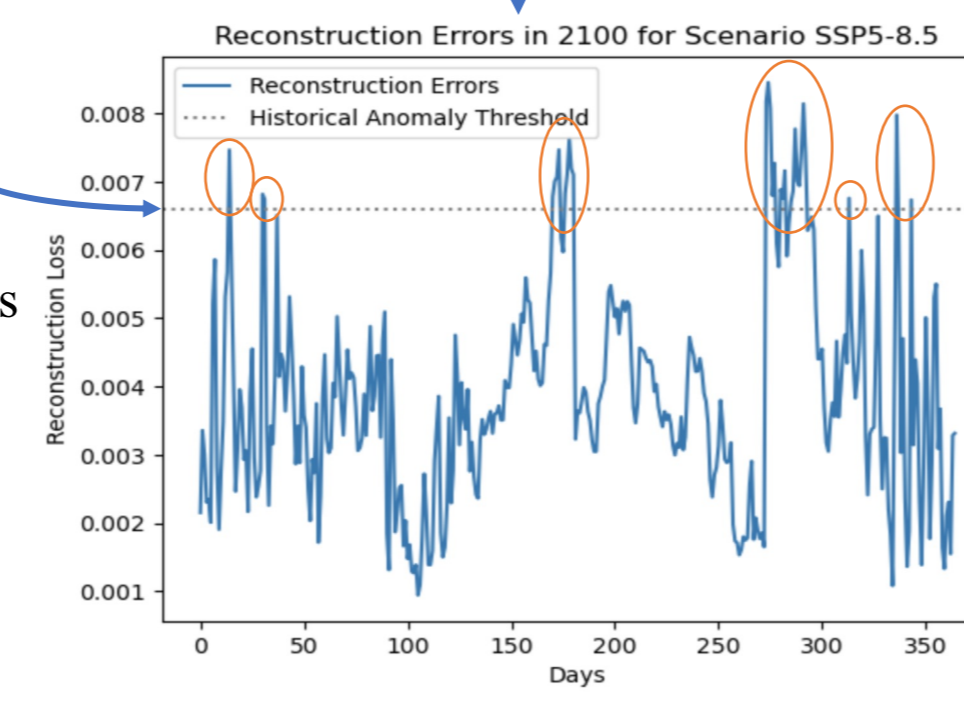
### Learning details:

- ~10<sup>5</sup> trainable parameters
- Latent space dimension: 64
- 5-minute training for 1 member over 1950-2000, 100 epochs
- 1-minute inference, all SSPs, 2015-2100

### 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.



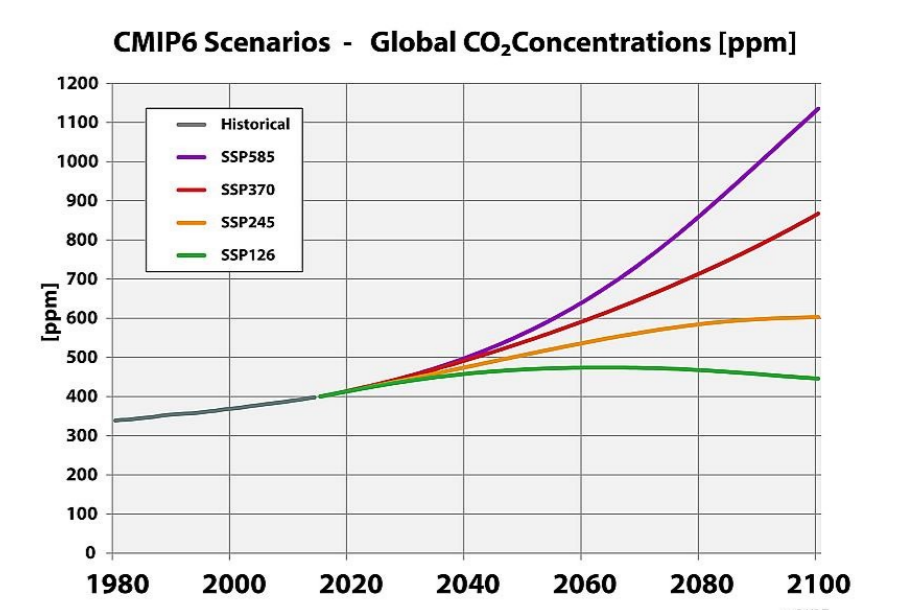
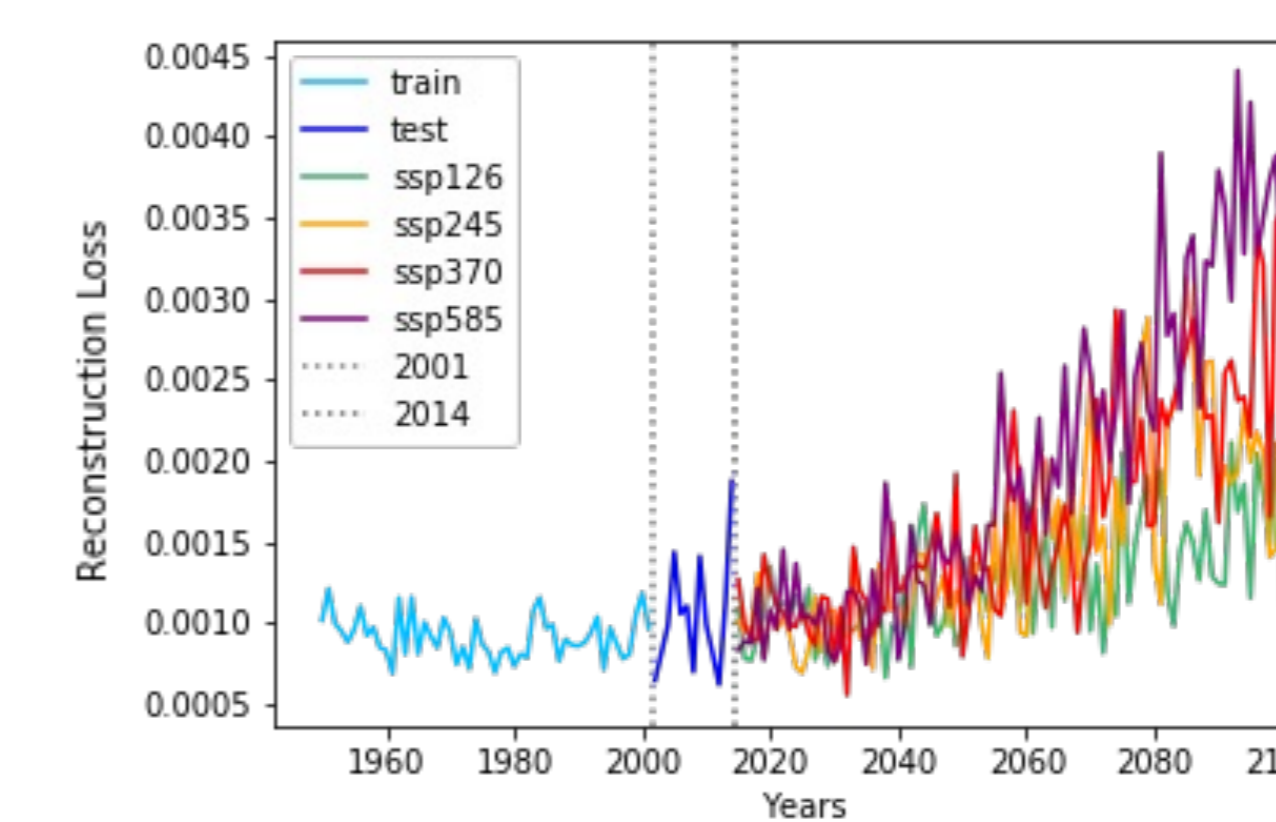
Extraction of event characteristics from time series:

- Frequency
- Duration
- Intensity

## 4. Results

### Comparison between IPCC Scenarios

Reconstruction Errors in CMCC-ESM2 Model Summers

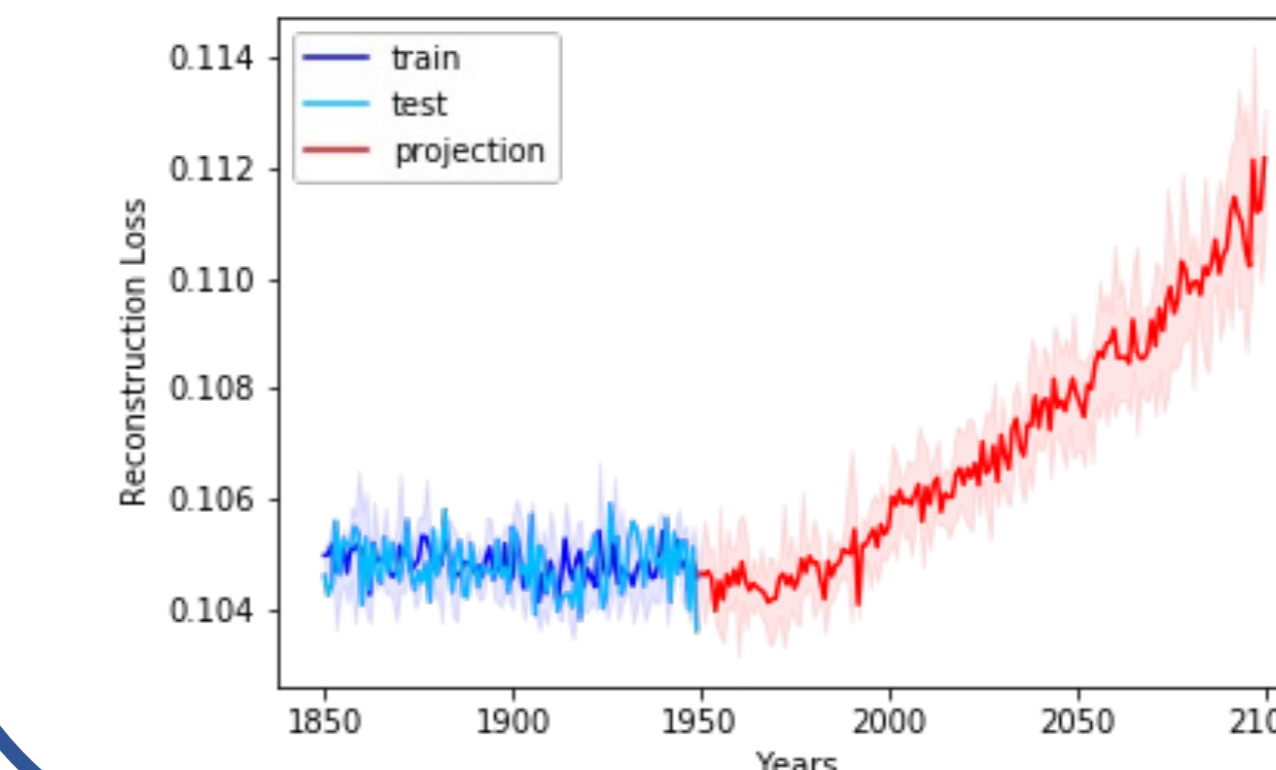


Anomaly Analysis in CMCC-ESM2 Model (Summers)  
Detection when the reconstruction error exceeds a threshold

Scenario	2001-2014		2015-2100			
	Test data	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5	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	

### 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

Member n°	1850-1950					1950-2100				
	Test Data	SSP3-7.0-1	SSP3-7.0-2	SSP3-7.0-3	SSP3-7.0-4	SSP3-7.0-5	SSP3-7.0-5	SSP3-7.0-5	SSP3-7.0-5	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				

## 5. Conclusion and Perspectives

### Perspectives

- Exploitation of **geospatial information**
- Implementation of a **severity index**, to better compare events
- Exploitation of the **latent space** of the neural network
- Validation with climate indices (analytical method: iclim<sup>1</sup>)
- **Integration** with the interTwin architecture and components
- Extension to **other climate variables** (e.g. precipitation)
- Paper preparation

### Take-Home Messages

- ✓ The Convolutional **Variational Auto-Encoder (CVAE)** achieves **Unsupervised Anomaly Detection**
- ✓ The model handles **big data** sets of **high complexity**
- ✓ Events are **characterized** with various indicators
- ✓ Results are **consistent**
- ✓ This model unlocks the ability to better quantify **climate impact uncertainties** (ensemble approach)

1. iclim indices: <https://github.com/cerfacs-globe/iclim>