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AI applications to extreme climate events

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The what:
(their thesis)

Ebenezer

”Spatial and compound dependencies in drought and heatwaves in the climate of South-Western Europe”

The what:
(their thesis)

Marte

”Analyzing heatwaves, droughts, and wildfires on the Iberian Peninsula”

Ebenezer

”Spatial and compound dependencies in drought and heatwaves in the climate of South-Western Europe”

The what:
(research questions)

Ebenezer

- What is the nature of the **statistical relationship between droughts and heatwaves** in the Iberian Peninsula, and how has this relationship changed **over time**?
- How do different seasons influence the climate system in the Iberian Peninsula, particularly in terms of affecting the likelihood and severity of droughts and heatwaves?
- **What are the probabilities or likelihood of transitioning from one climatic condition to another, for example; from normal conditions to extreme events or vice versa?**

The what:
(research questions)

Marte

- **How do threshold based methods compare to the isolation forest method when identifying hot and dry extremes on the Iberian Peninsula?**
- **What role does dry and hot weather play in driving wildfires on the Iberian Peninsula?**
- How does the conditions in previous months influence fire occurrences?
- What identification method is best suited for wildfire prediction?

Ebenezer

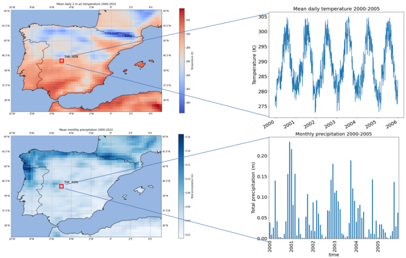
- What is the nature of the **statistical relationship between droughts and heatwaves** in the Iberian Peninsula, and how has this relationship changed **over time**?
- How do different seasons influence the climate system in the Iberian Peninsula, particularly in terms of affecting the likelihood and severity of droughts and heatwaves?
- **What are the probabilities or likelihood of transitioning from one climatic condition to another, for example; from normal conditions to extreme events or vice versa?**

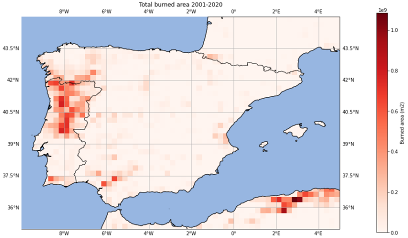
The how:
(Methodology)

The how:
(Methodology)

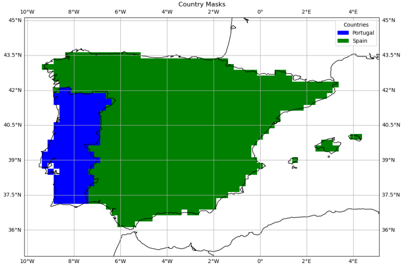
Data → Processing → Identifying extremes → Models → Model evaluation

(Data)





The how:
(Data processing)



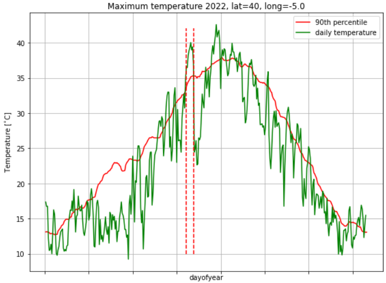
- **Regional Masking:** See figure

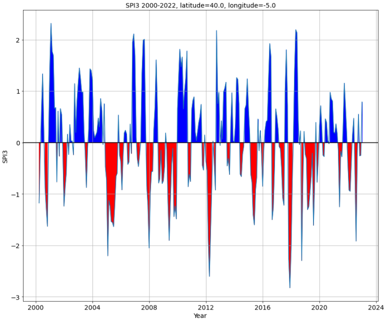
- **Aggregation to Daily and Monthly Values:** The hourly temperature and precipitation data was aggregated to daily and monthly values
- **Regridding Fire Data:** Fire data has 0.125 degrees between the the grids in both the longitudinal and latitudinal direction. The ERA5 data was used for the reference grid, and the fire data was regridded using the nearest neighbor method.

The how:
(Data processing)

Temperature	→	Heatwave
Precipitation	→	Drought
Burned area	→	Wildfire

The how:
(Data processing)





Temperature → Heatwave

Precipitation → Drought

Burned area → Wildfire

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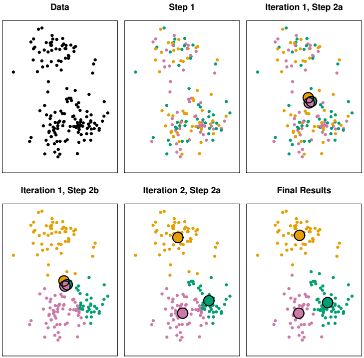
The how:
(Methods)

- **Clustering** methods: K-means and hierarchical clustering
- Isolation forest and **outliers** classification
- For **prediction**:
  - Markov-chains
  - Neural networks

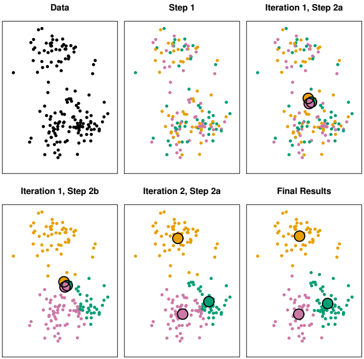
Methods:
Clustering methods

K-means

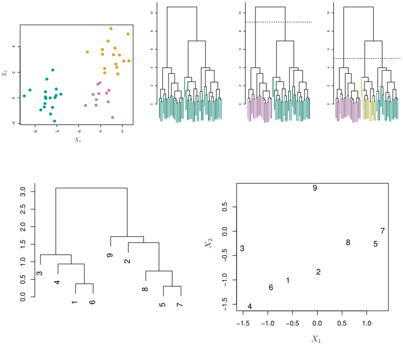


Methods:
Clustering methods

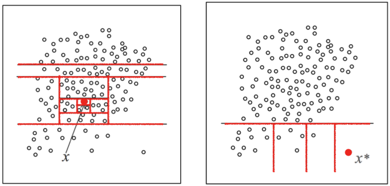
K-means



Hierarchical clustering

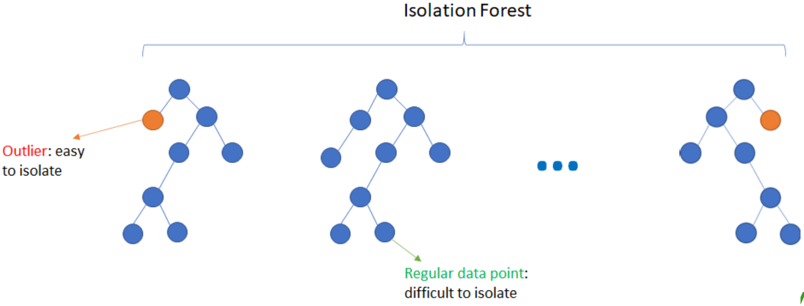


Methods:
Isolation forest

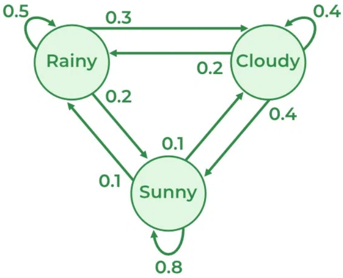


normal point:
10 cuts

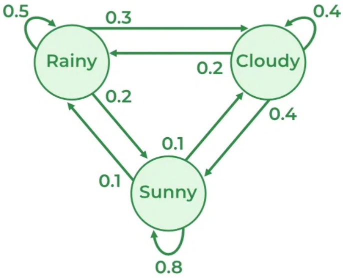
anomalous point:
4 cuts



Methods:
Markov chains



Methods:
Markov chains



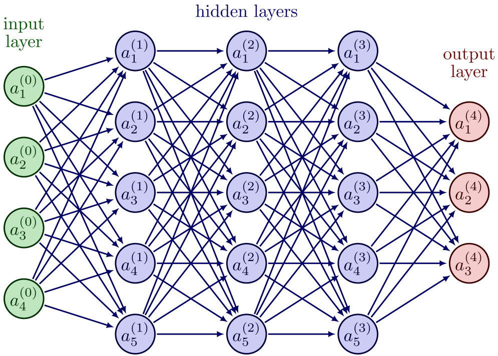
$(0,0) =$**(NO Heatwave, No Drought)**

$(1,0) =$**(Heatwave, No Drought)**

$(0,1) =$**(NO Heatwave, Drought)**

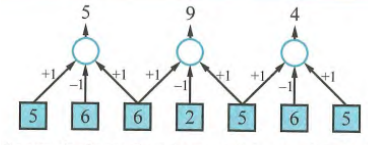
$(1,1) =$**(Heatwave, Drought)**

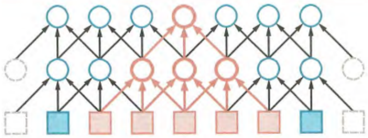
Methods:
Neural networks



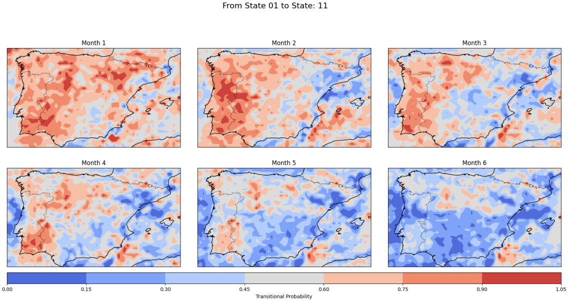
Methods:
Convolutional neural networks

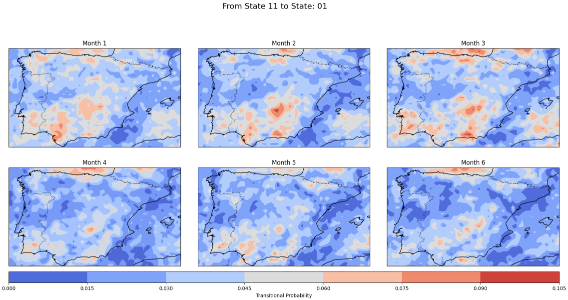
- **Convolutional Neural Networks**: Construct the hidden layers so that each hidden units receives input from only a small local region of the image.
- Two degrees of freedom:
  - Length of the kernel
  - Stride (similar to dimension reduction)





Results:
Markov chain models





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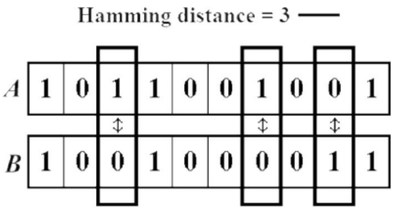
Results:
Similar regions from the perspective of extreme events

Hamming distance



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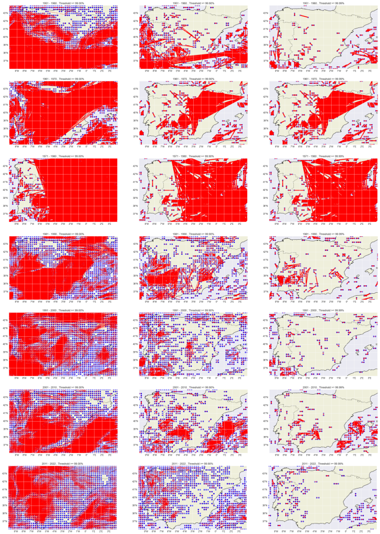
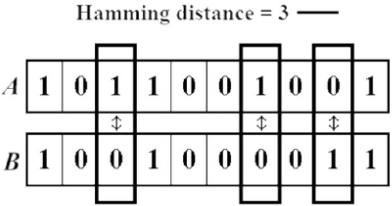
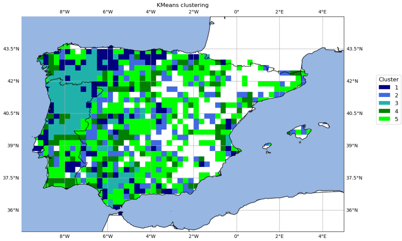


Hamming distance

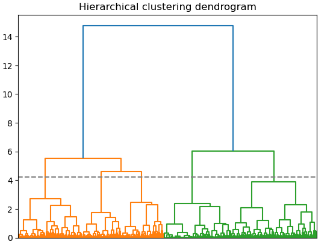


Results:
Clustering wildfire regions

K-means



Hierarchical clustering



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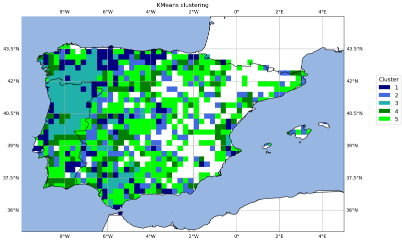

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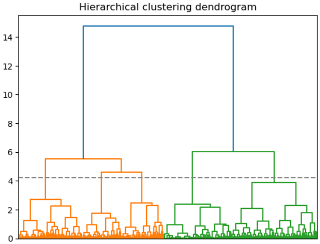
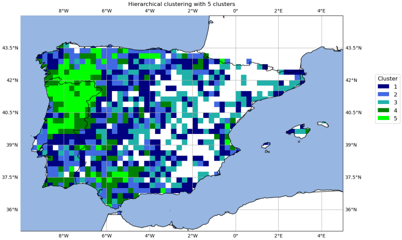
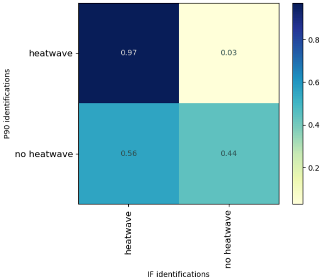




Results:
On the definition of extreme event: Why 90 percentile?

Heatwaves



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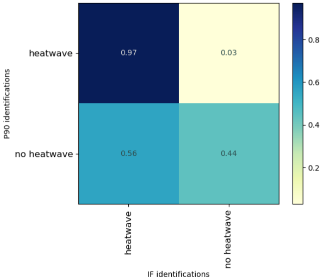
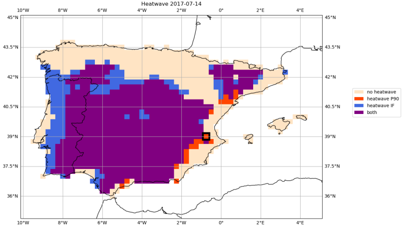
Heatwaves





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Results:

On the definition of extreme event: Why 90 percentile?

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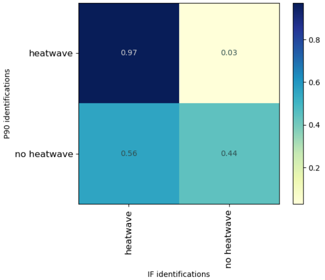
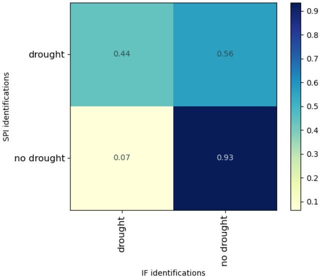
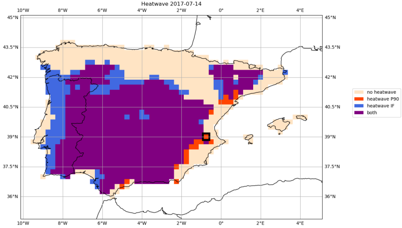
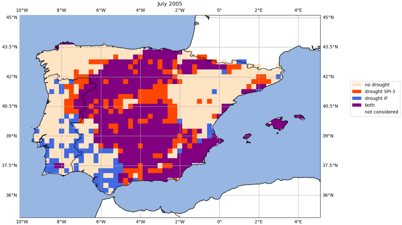


Droughts



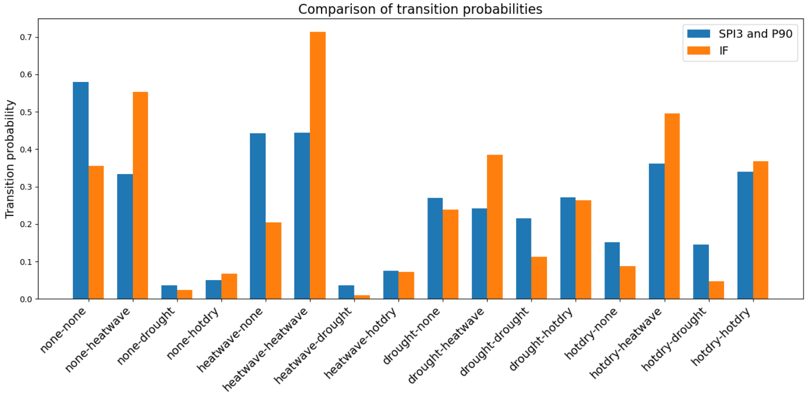




Results:

On the definition of extreme event: Markov chain models discrepancies

	none	heatwave	drought	hot-dry
none	0.580/0.356	0.333/0.553	0.036/0.024	0.050/0.068
heatwave	0.443/0.204	0.444/0.713	0.037/0.010	0.076/0.072
drought	0.271/0.239	0.242/0.384	0.215/0.112	0.272/0.264
hot-dry	0.152/0.088	0.363/0.495	0.146/0.048	0.399/0.369



Results:

Predicting wildfires using CNN model 1/2

	P90 and SPI-3	Isolation forest
Accuracy	0.89	0.88
Precision	0.16	0.15
Recall	0.85	0.84
Specificity	0.89	0.88

Results:

Predicting wildfires using CNN model 2/2

	Accuracy	Precision	Recall	F1-score	Specificity
P90 and SPI-3					
1 month	0.867	0.157	0.884	0.267	0.867
2 month	0.890	0.236	0.856	0.370	0.892
3 month	0.878	0.269	0.865	0.411	0.878
4 month	0.904	0.323	0.820	0.463	0.909
5 month	0.879	0.307	0.828	0.448	0.882
6 month	0.887	0.355	0.808	0.493	0.893
Isolation forest					
1 month	0.867	0.156	0.880	0.266	0.867
2 month	0.888	0.232	0.860	0.366	0.889
3 month	0.879	0.271	0.864	0.413	0.880
4 month	0.899	0.313	0.829	0.454	0.903
5 month	0.886	0.318	0.808	0.457	0.890
6 month	0.893	0.366	0.785	0.499	0.901

Conclusions

- Hamming distance to characterize similar drought/heatwave regions
- Markov-chain: transition probability between extreme (binary) ”states”
- Prediction of wildfire
  - ”Conservative” predictor
  - (Seemingly) independent of outlier definition

Conclusions

- Hamming distance to characterize similar drought/heatwave regions
- Markov-chain: transition probability between extreme (binary) ”states”
- Prediction of wildfire
  - ”Conservative” predictor
  - (Seemingly) independent of outlier definition

Next steps?

- Comparison Norway/Portugal as a prototype of North/South Europe ”connections”.
- Other definitions of outliers?
- Combination with public health data (contacts soon with NIPH; and Portugal?)