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Statistical downscaling of multivariate wave climate using a weather type approach

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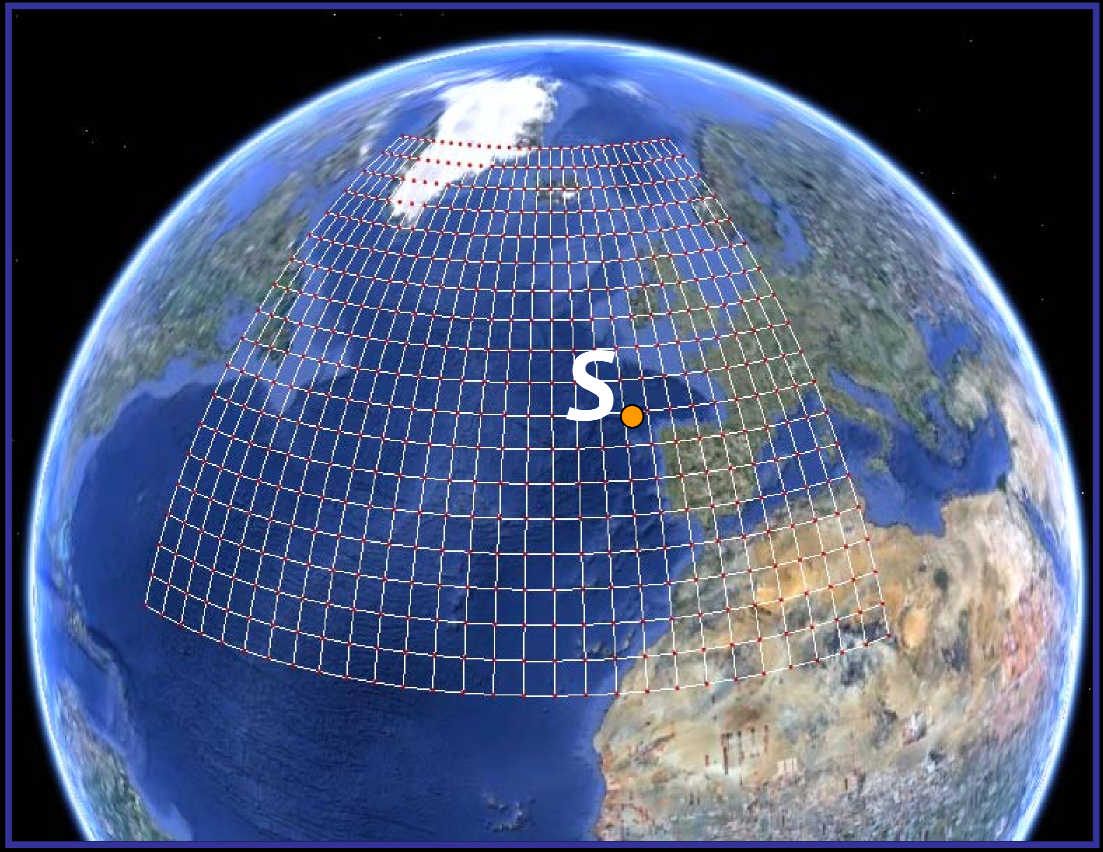
Environmental Hydraulics Institute, Universidad de Cantabria, SPAIN

❖ Objective #1

Predict multivariate wave climate (Y) at a particular location *S* as a function of synoptic atmospheric circulation (X)



❖ Objective #1

ATMOSPHERIC CIRCULATION
(predictor X: SLP)

→

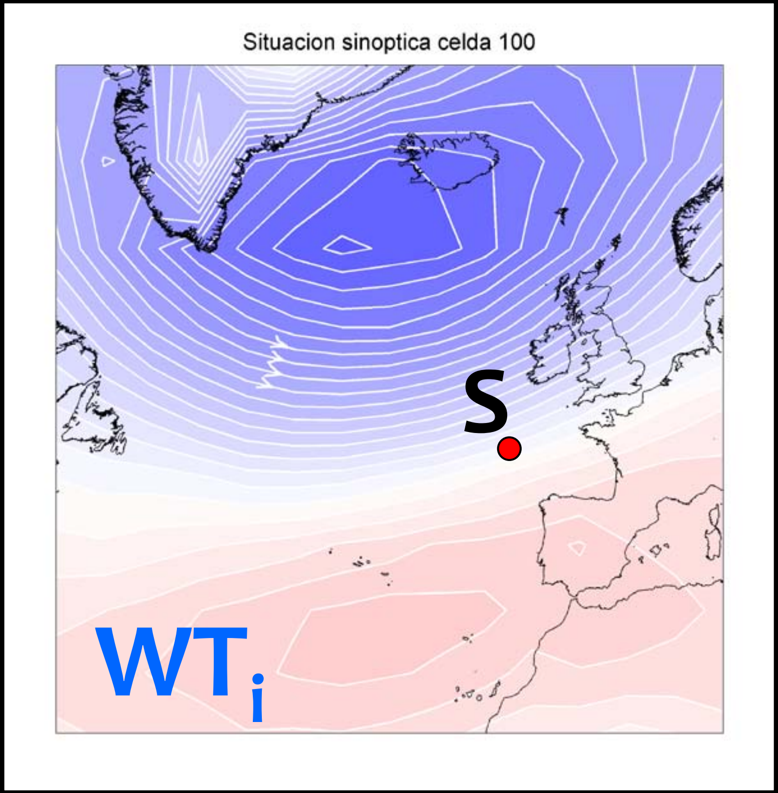
MULTIVARIATE WAVE CLIMATE
(predictand Y, H, T, Dir)

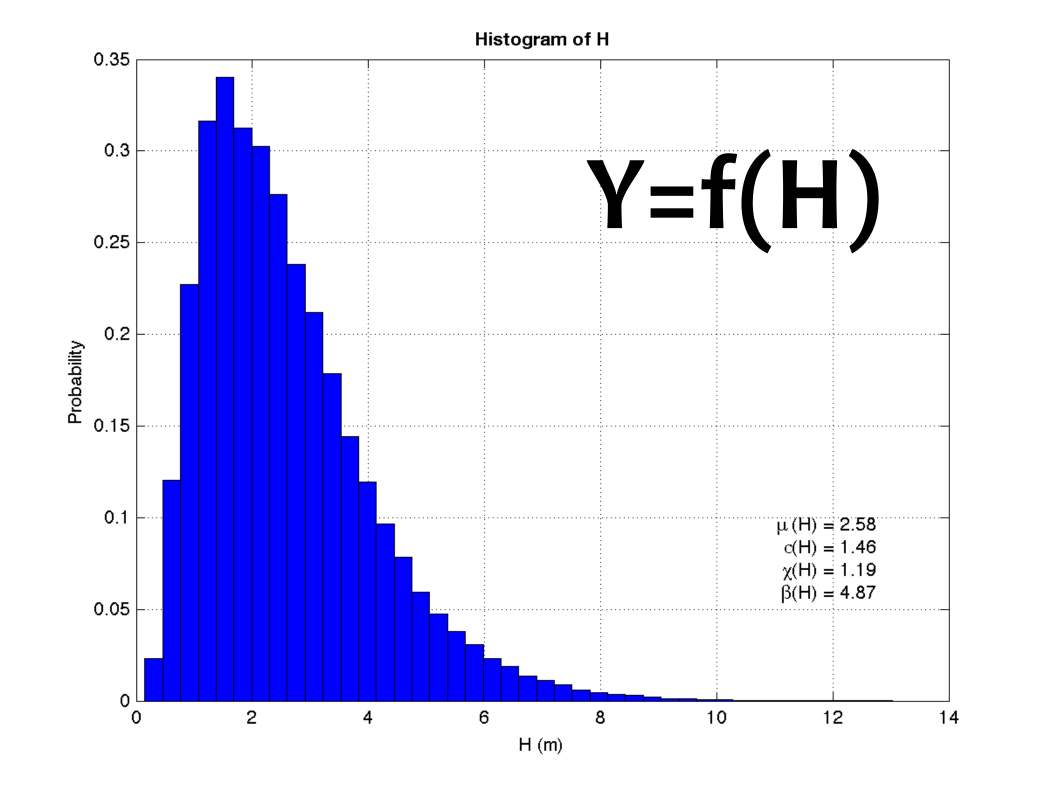
Regional atmospheric climatology (X)

Local wave climatology (Y)

❖ Objective 1

Predict multivariate wave climate (Y) at a particular location *S* as a function of **Synoptic Atmospheric Circulation patterns** (X)

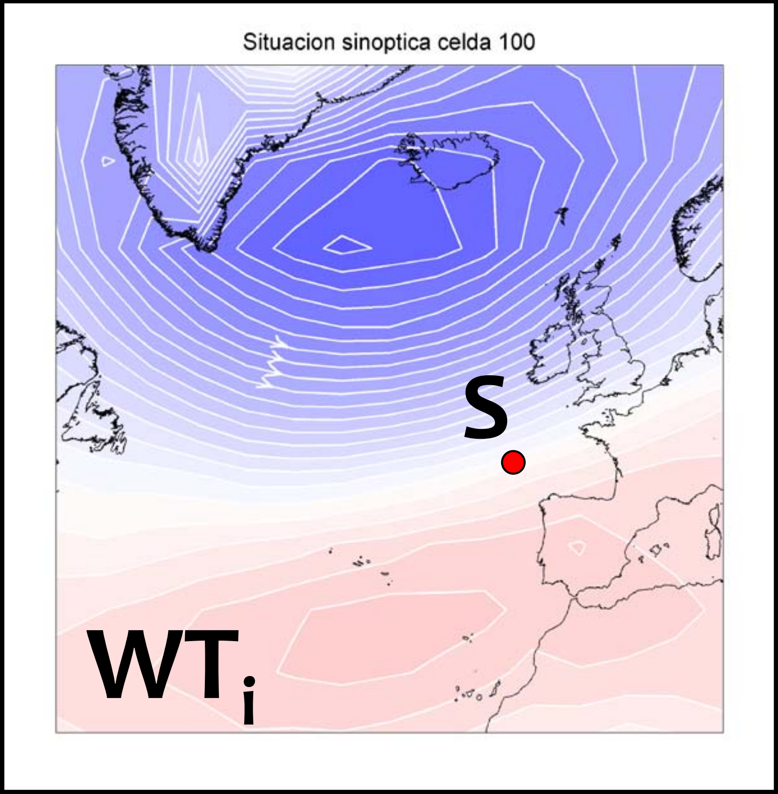


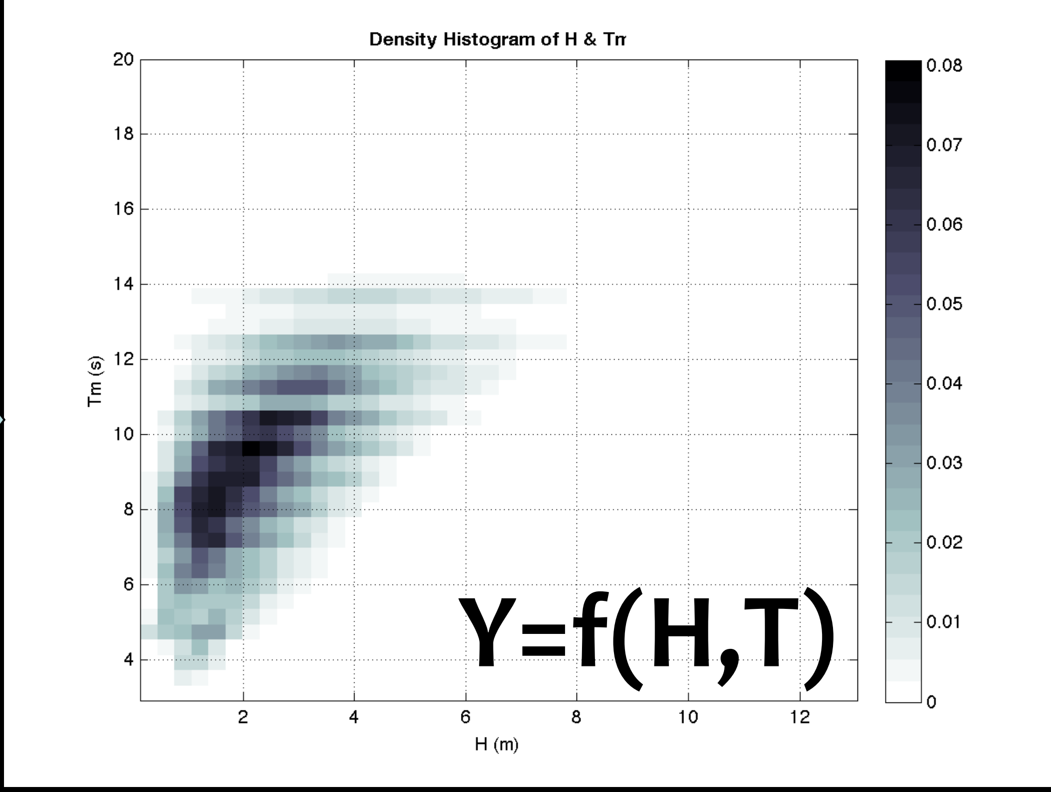


WT= Weather-type

❖ Objective 1

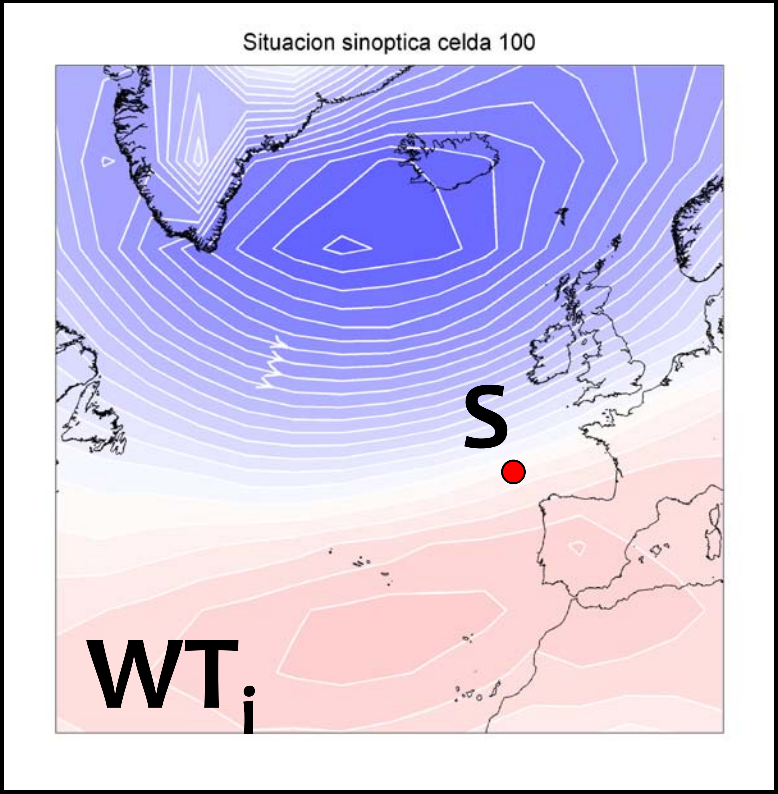
Predict multivariate wave climate (Y) at a particular location *S* as a function of synoptic atmospheric circulation patterns (X)

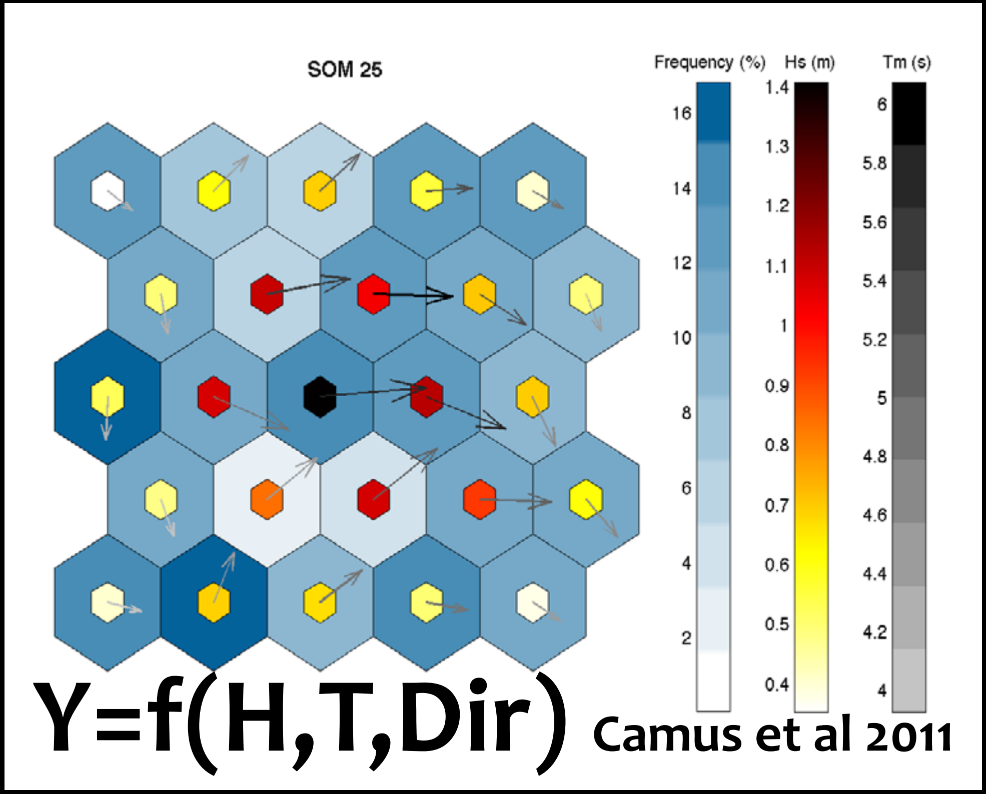




❖ Objective 1

Predict multivariate wave climate (Y) at a particular location *S* as a function of synoptic atmospheric circulation patterns (X)





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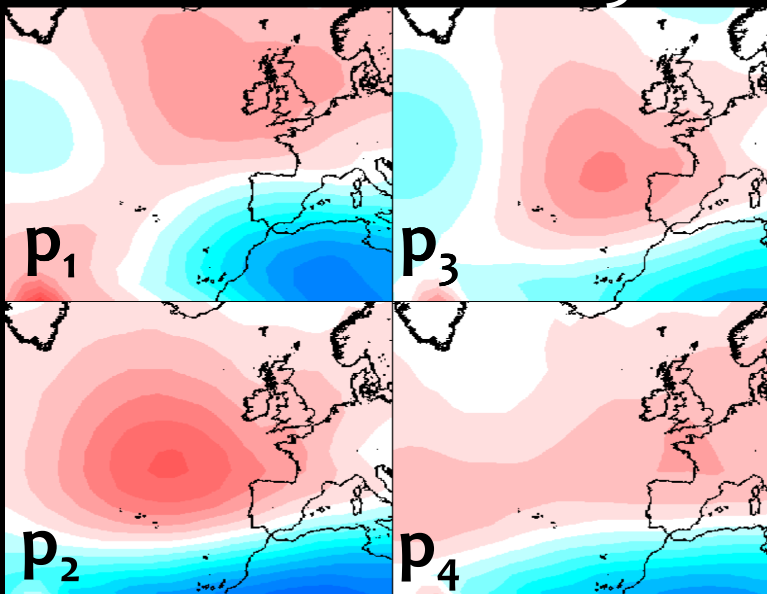
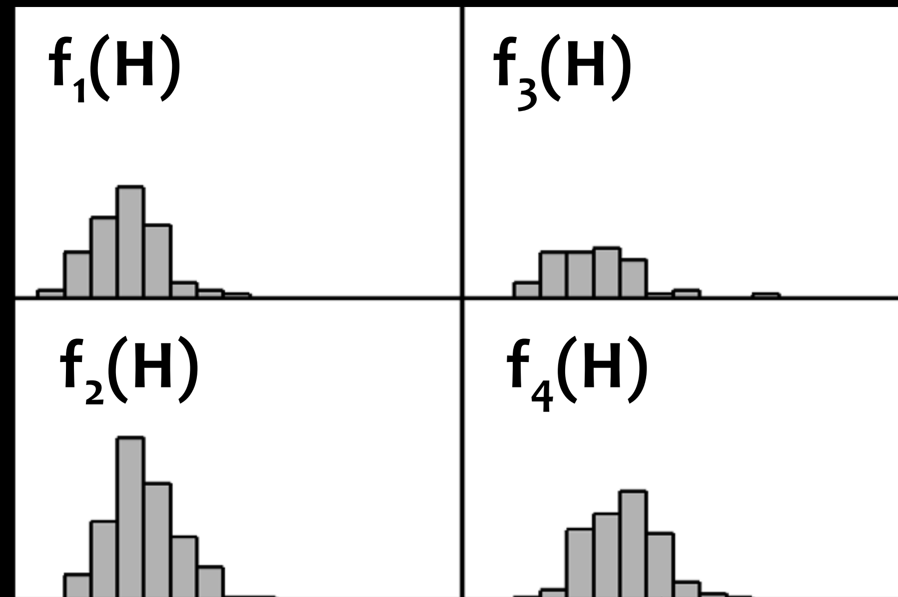
X = Predictor

$X=(WT_1,WT_2,WT_3,WT_4)$



Y = Predictand

Y

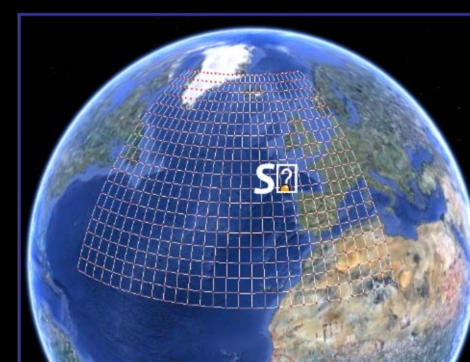


WT= Weather-type

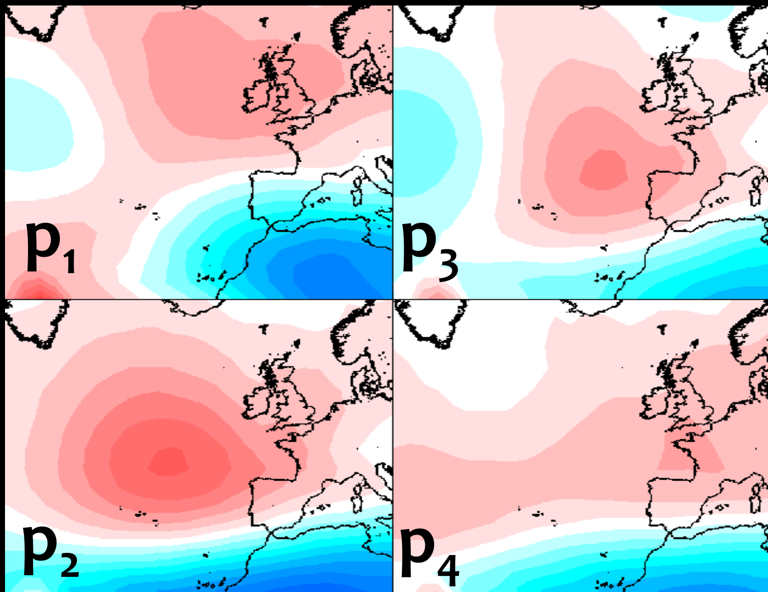
p_i=ocurrence probability of WT_i

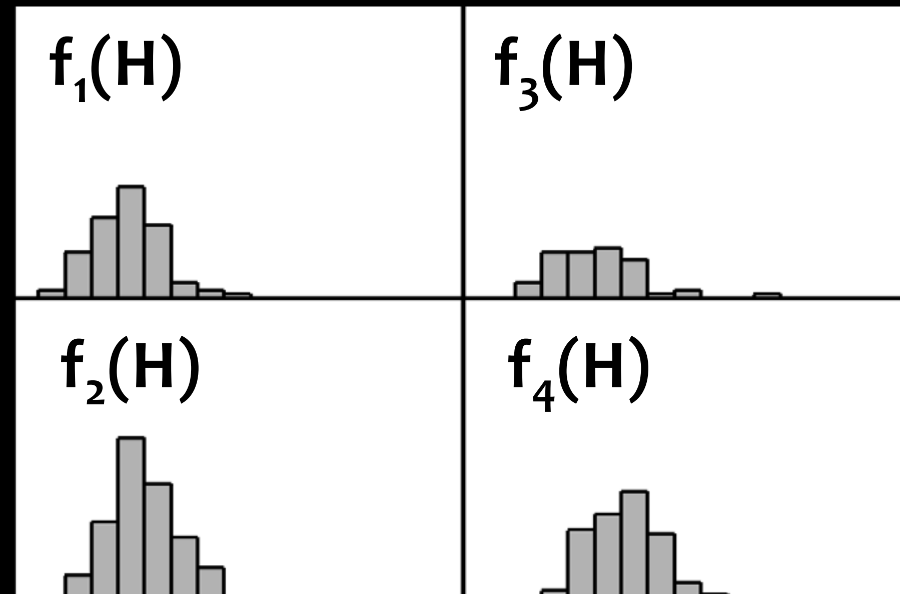
Regression model /Stat. Downscaling:

$Y=g(X)$



$X=(WT_1,WT_2,WT_3,WT_4)$ $\quad\quad$ Y





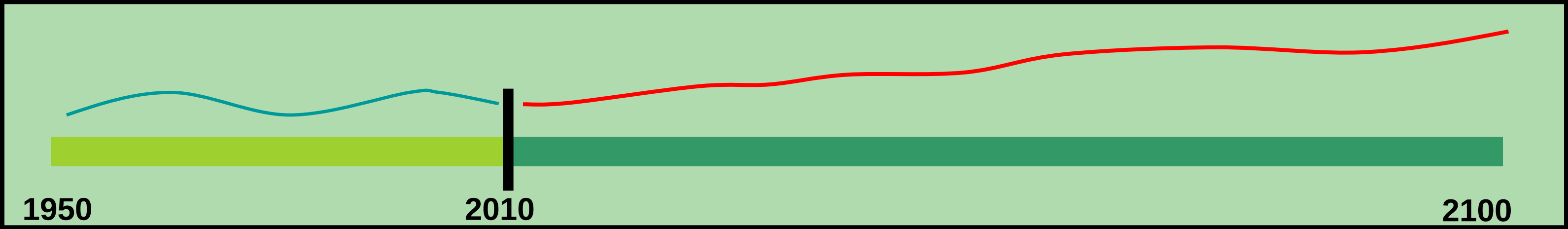
p_i=ocurrence probability of WT_i

$p_1+p_2+p_3+p_4=1$

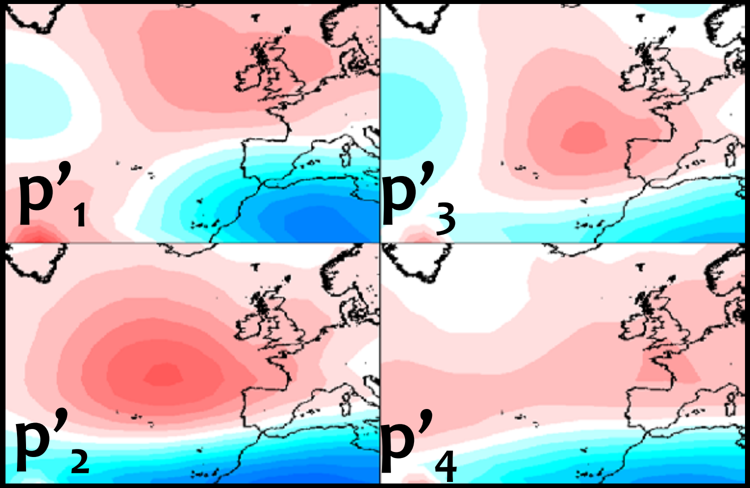
$f_S(H)=p_1f_1(H)+p_2f_2(H)+p_3f_3(H)+p_4f_4(H)$

❖ Objective #2

Project multivariate wave climate (Y) at a particular location *S* for a given GCM in a given time slice (X')



X'=new predictor



$$Y = g(X')$$

$$p'_1+p'_2+p'_3+p'_4=1$$

$$f'_S(H)=p'_1f_1(H)+p'_2f_2(H)+p'_3f_3(H)+p'_4f_4(H)$$

$$df(H)=f'_S(H)-f_S(H)$$

1. Synthesis of the work

2. **Choosing the predictand Y**

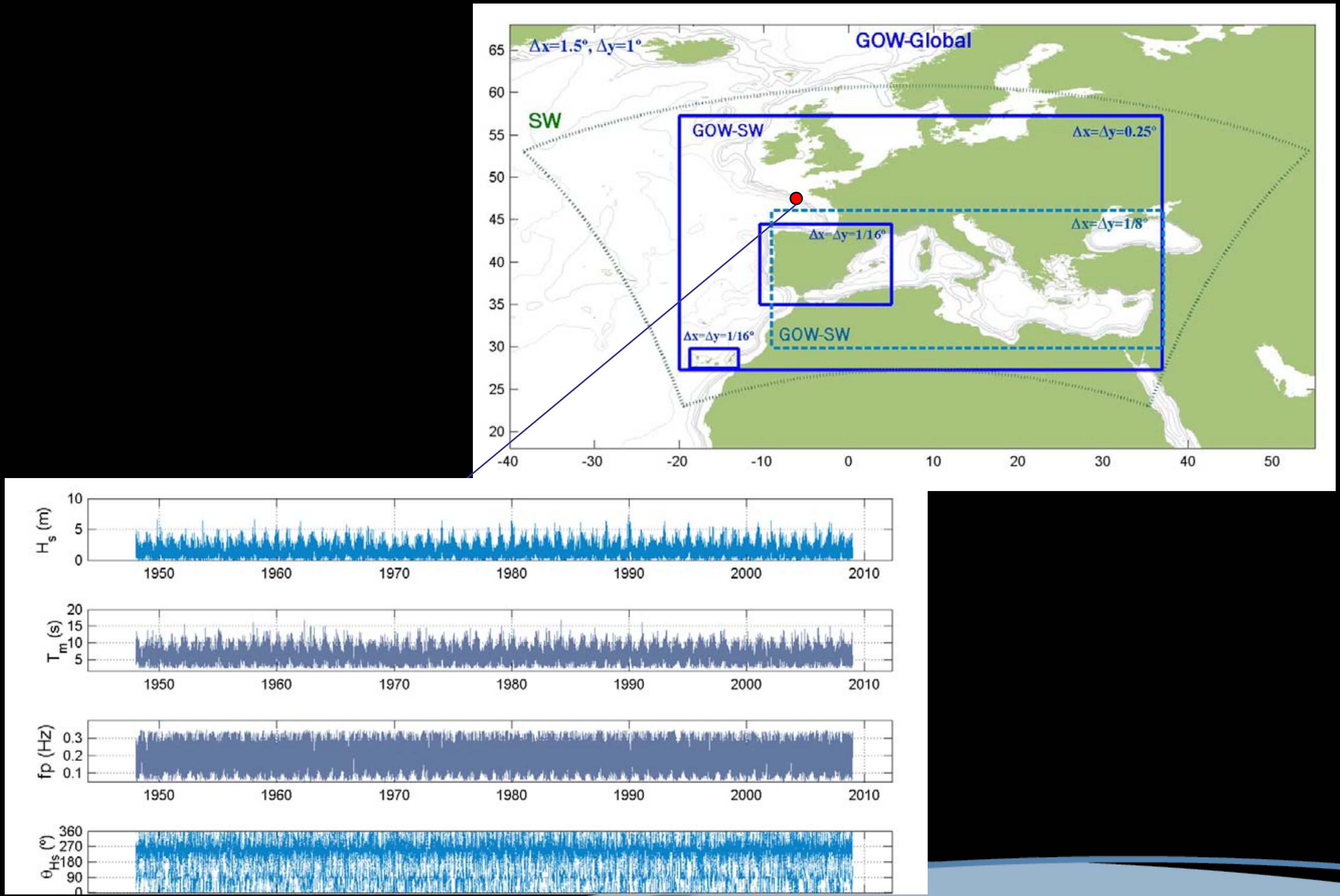
3. Choosing the predictor X

4. Statistical relationship: Y=g(X)

5. Wave climate projection

1. Conclusions

❖ GOW Wave reanalysis (IH Cantabria)



1. Synthesis of the work

2. Choosing the predictand Y

3. **Choosing the predictor X**

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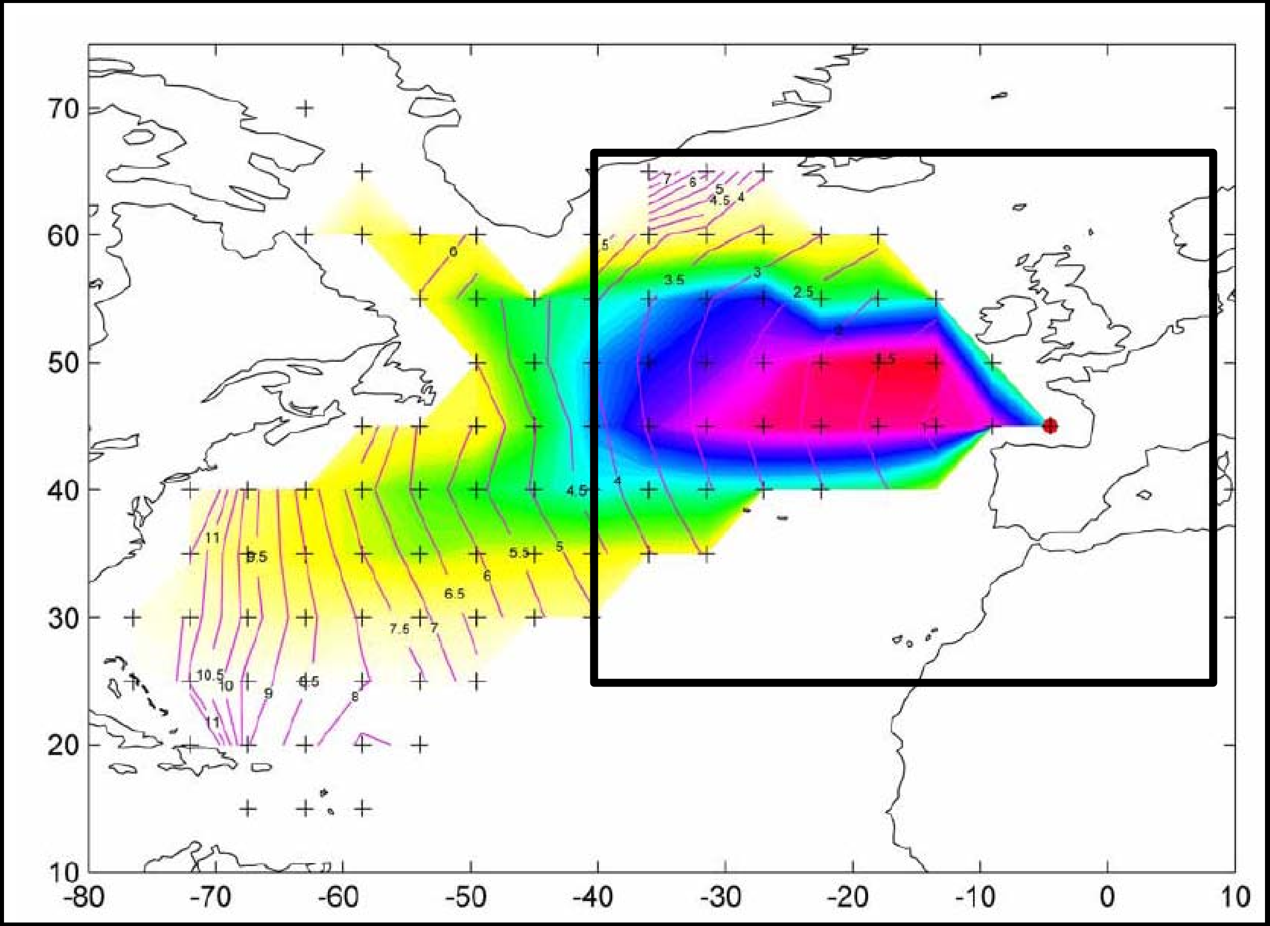
❖The predictor. Synoptic Atmospheric Circulation patterns

*Data: **Sea Level Pressure fields (SLP)***
(from NCEP-NCAR Atmospheric reanalysis)



SELECTION OF AREA

- Basin size
- Fetch

TEMPORAL SCALE

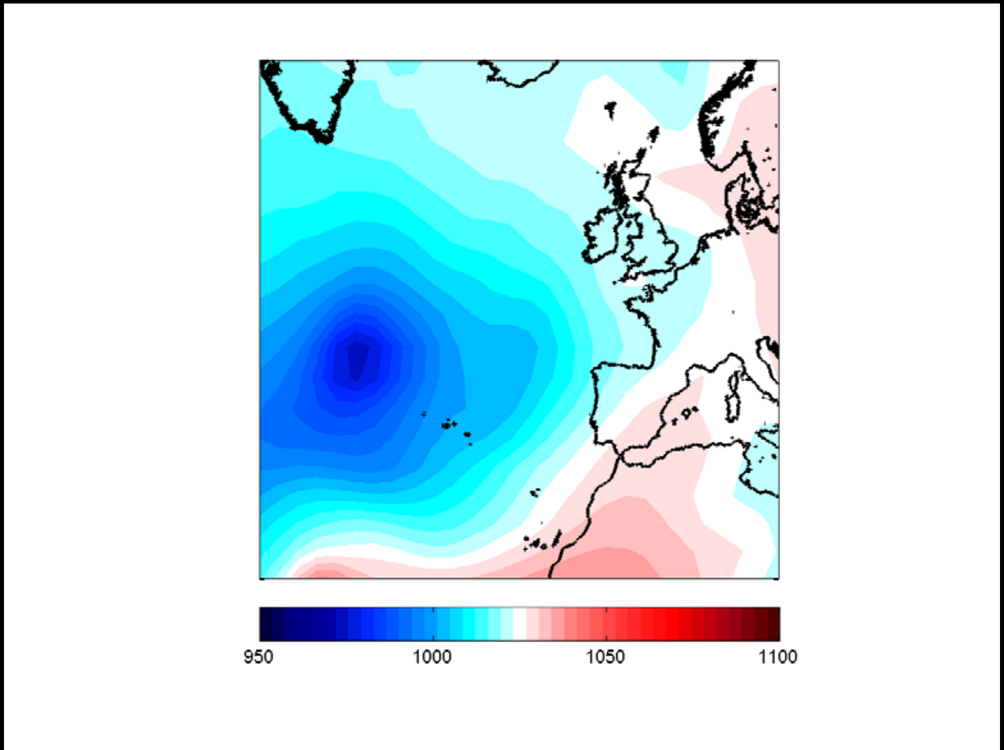
- Independence of cyclones
- Propagation time

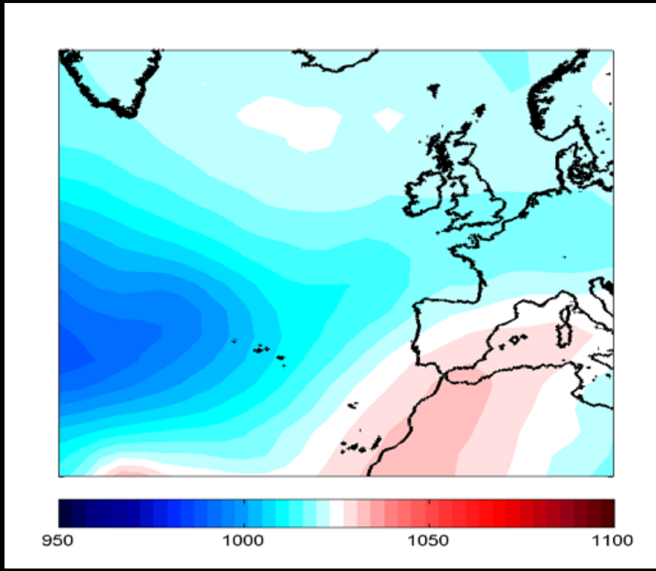
→ SLP_{3days}

❖The predictor. Synoptic Atmospheric Circulation patterns

*Data: **Sea Level Pressure fields (SLP)***
(from NCEP-NCAR Atmospheric reanalysis)

Averaged 3-daily SLP fields



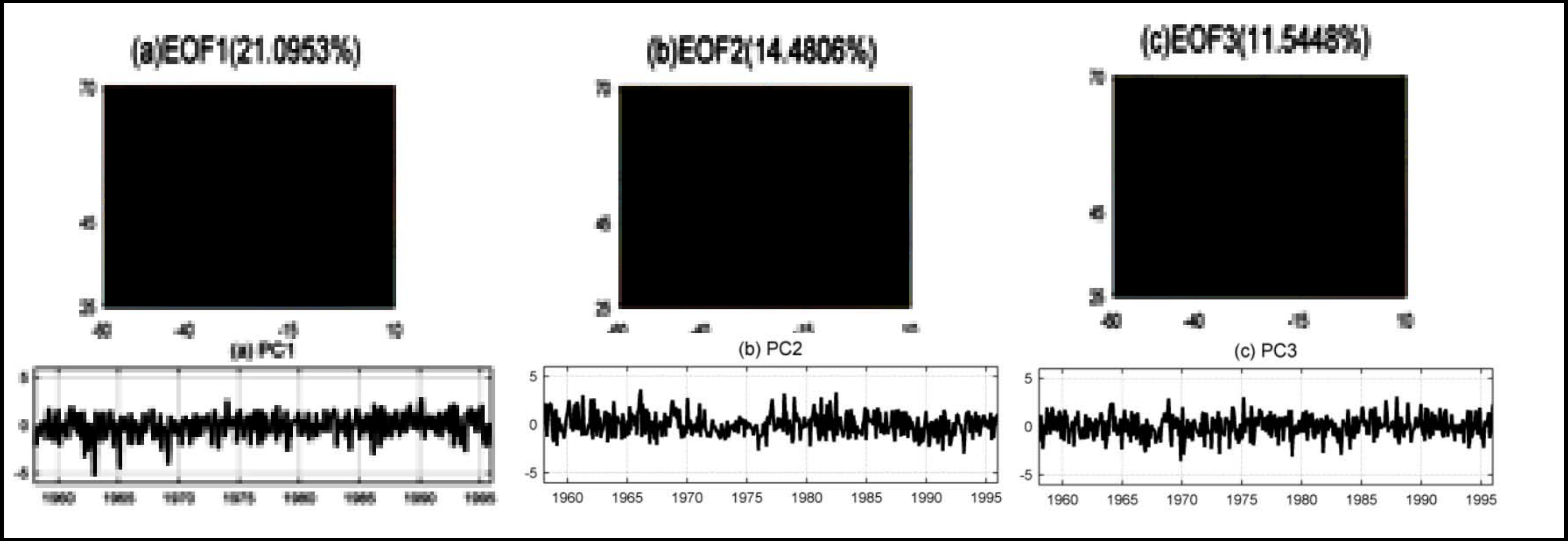


*From: **2009-Jan-1st 00:00** to **2009-Jan-3rd 18:00 p.m***

6 hourly SLP fields

❖The predictor. Synoptic Atmospheric Circulation patterns

Principal components analysis

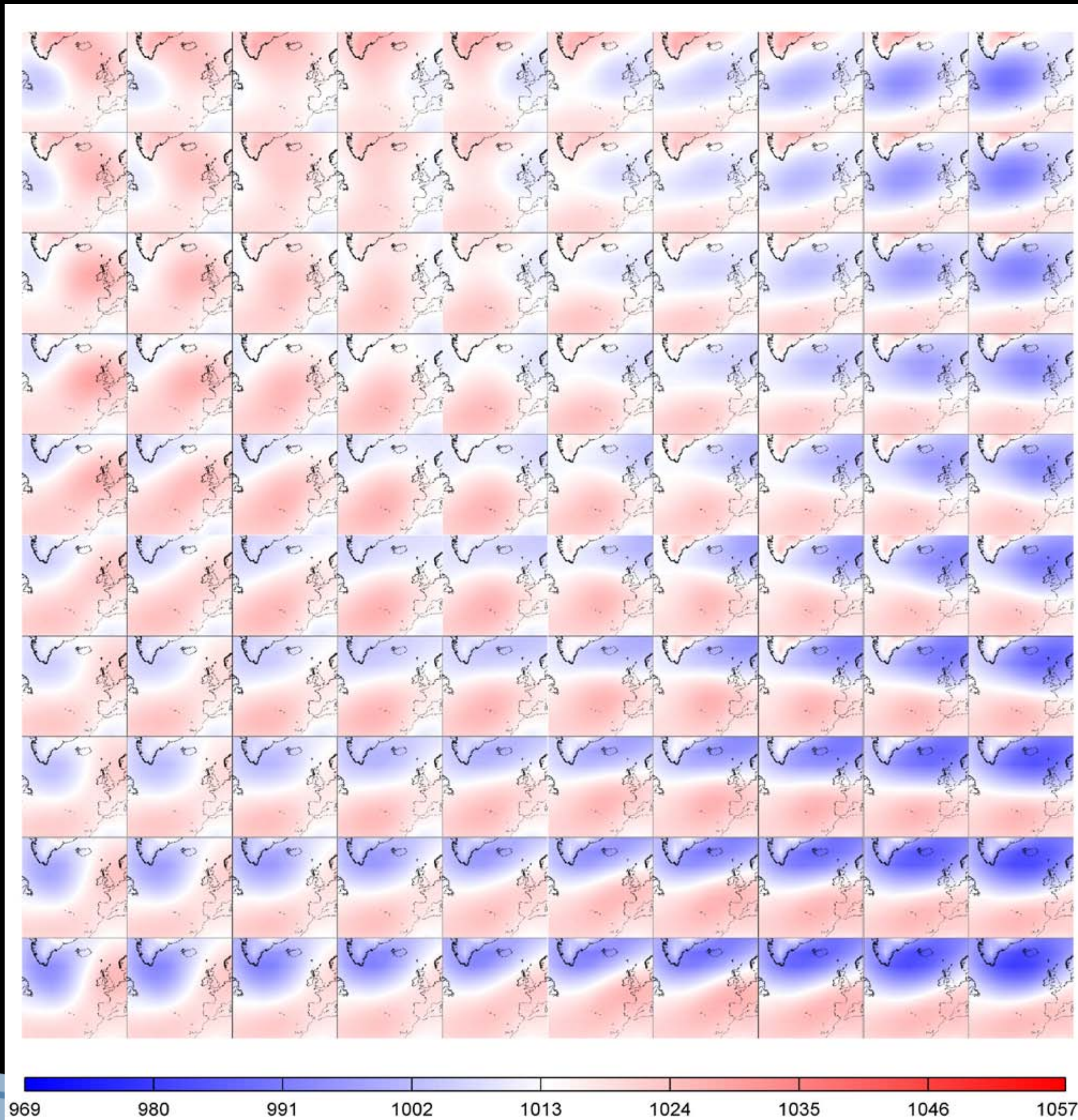


$$\{PC_1, PC_2, ..PC_M\}$$

Data mining algorithms

SELF ORGANIZING MAP (SOM)

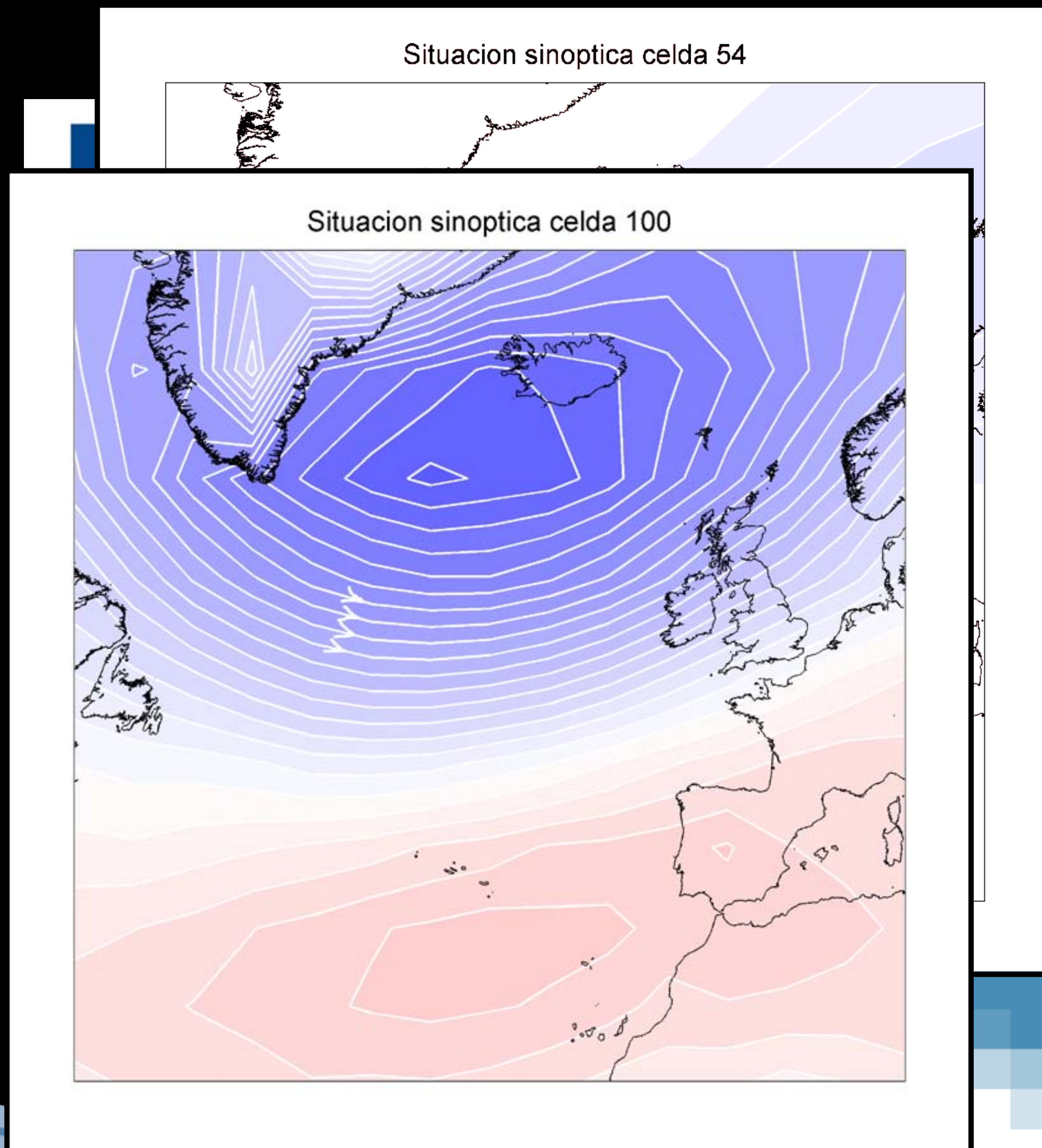
❖The predictor. Synoptic Atmospheric Circulation patterns



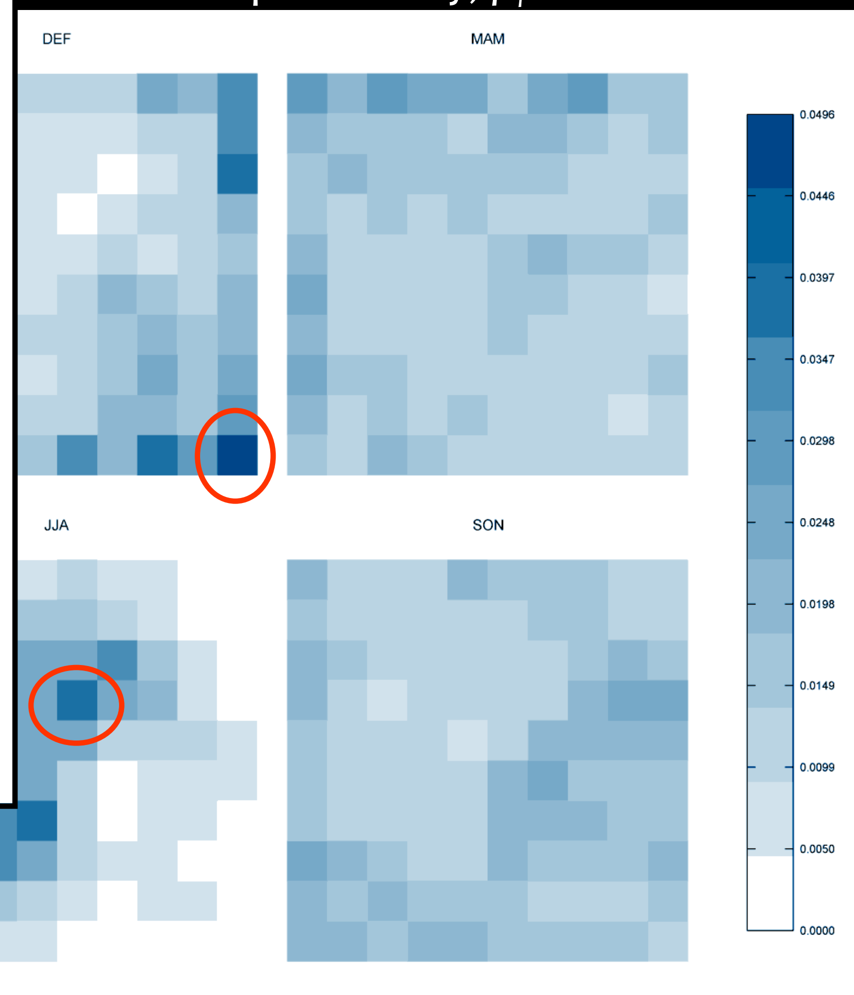
M=100 (10x10)

SELF ORGANIZING MAPS (SOM)

❖The predictor. Synoptic Atmospheric Circulation patterns



Occurrence probability, p_i



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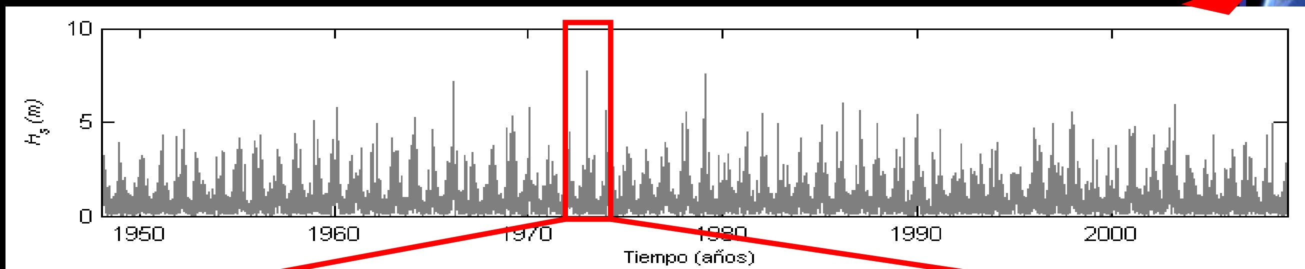
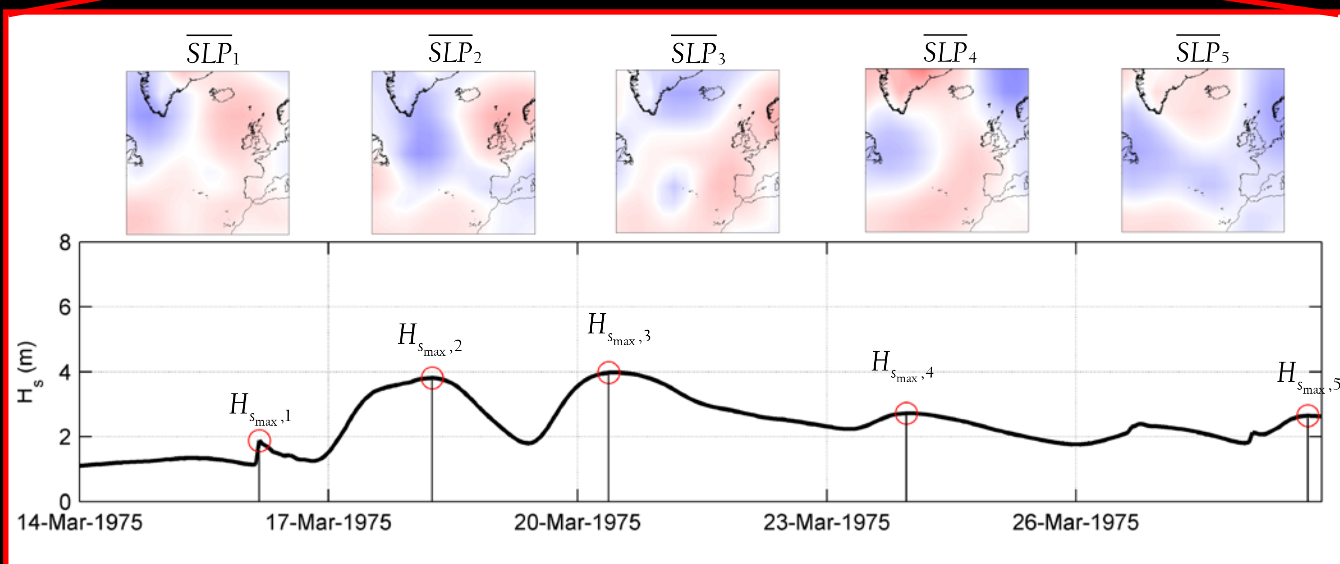
METHODOLOGY

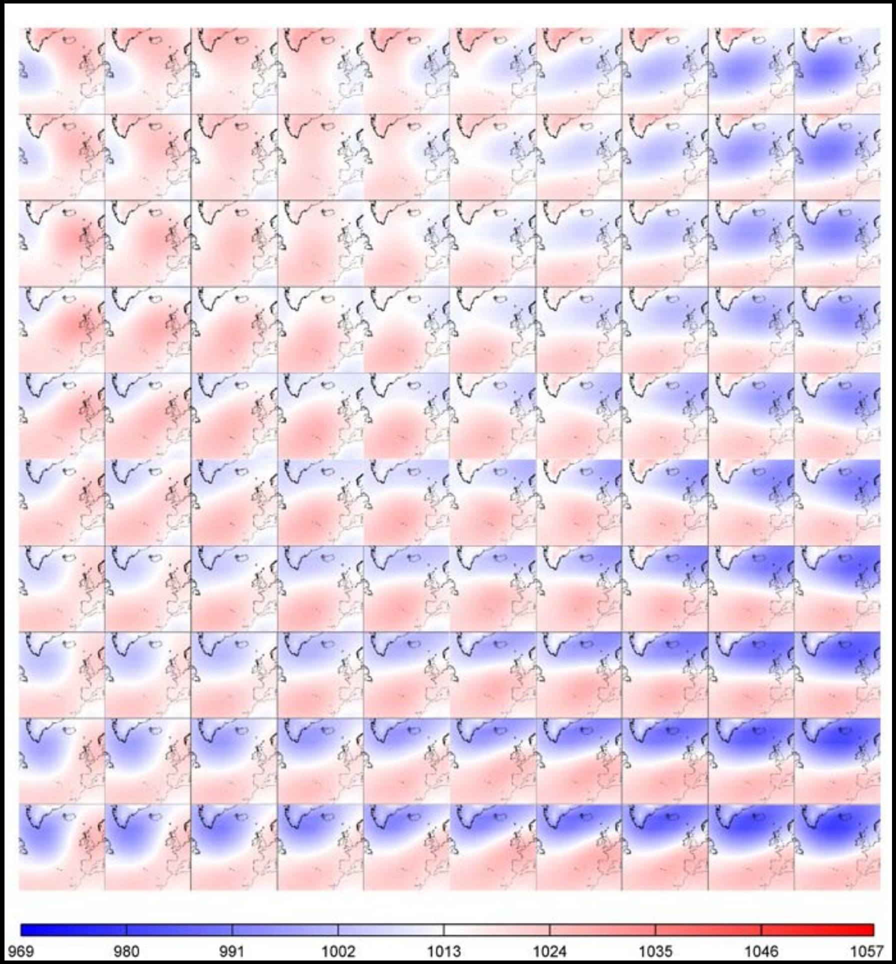
❖ Selection of (H,T,Dir). The predictand.

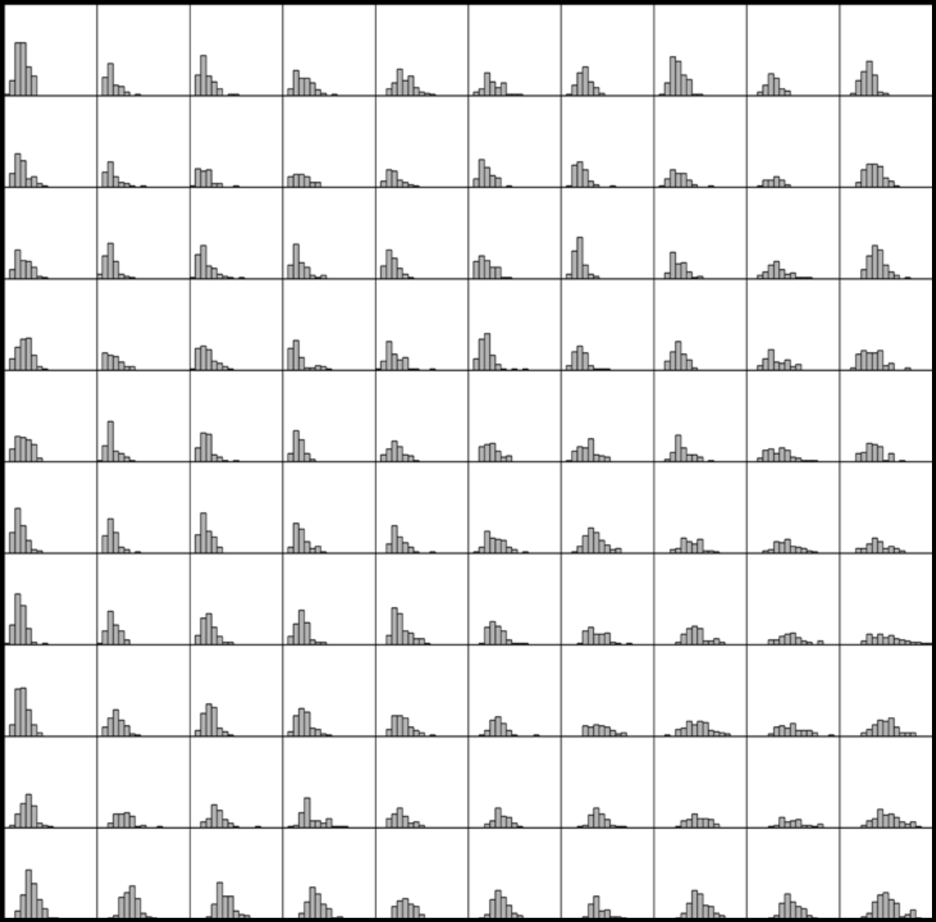




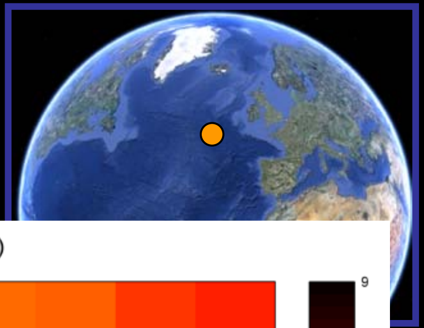
3-day Hs

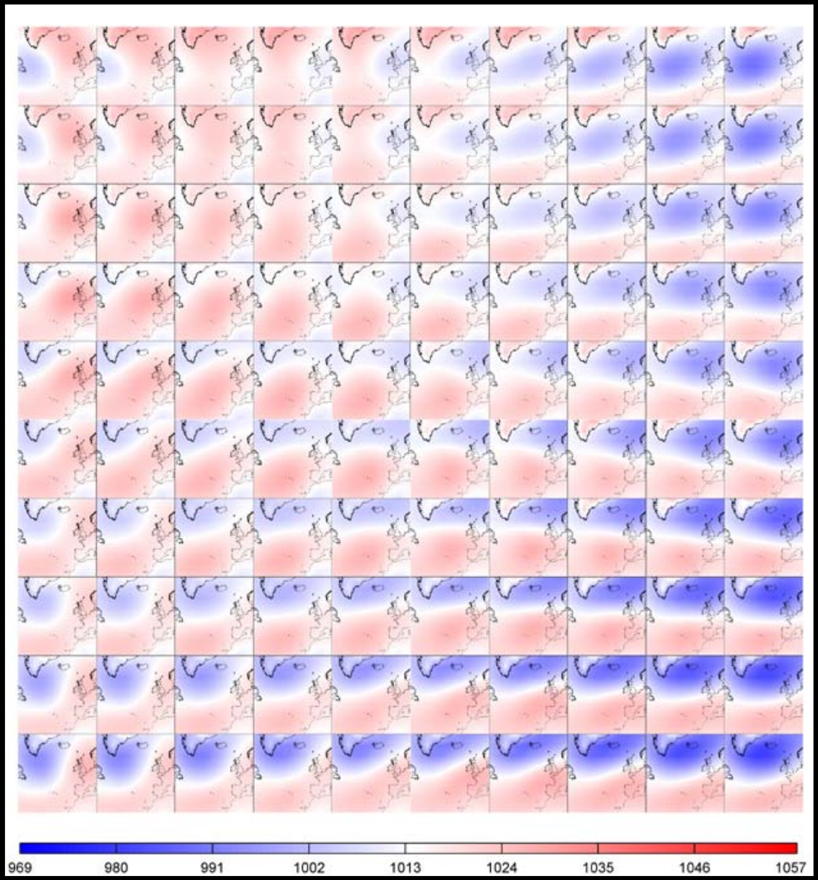
❖ Selection of (H,T,Dir). The predictand.

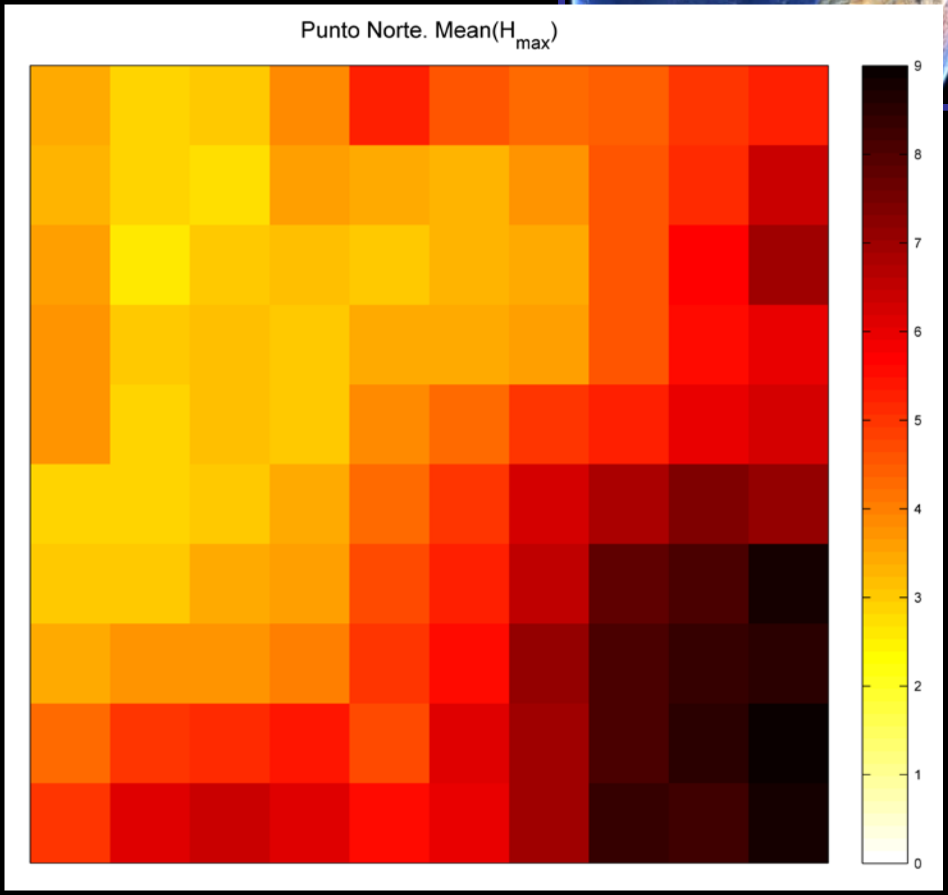




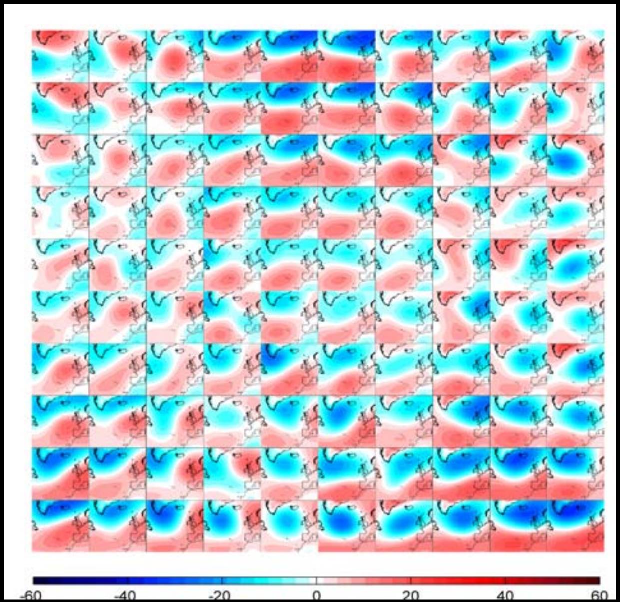
- Selection of (H,T,Dir). The predictand.

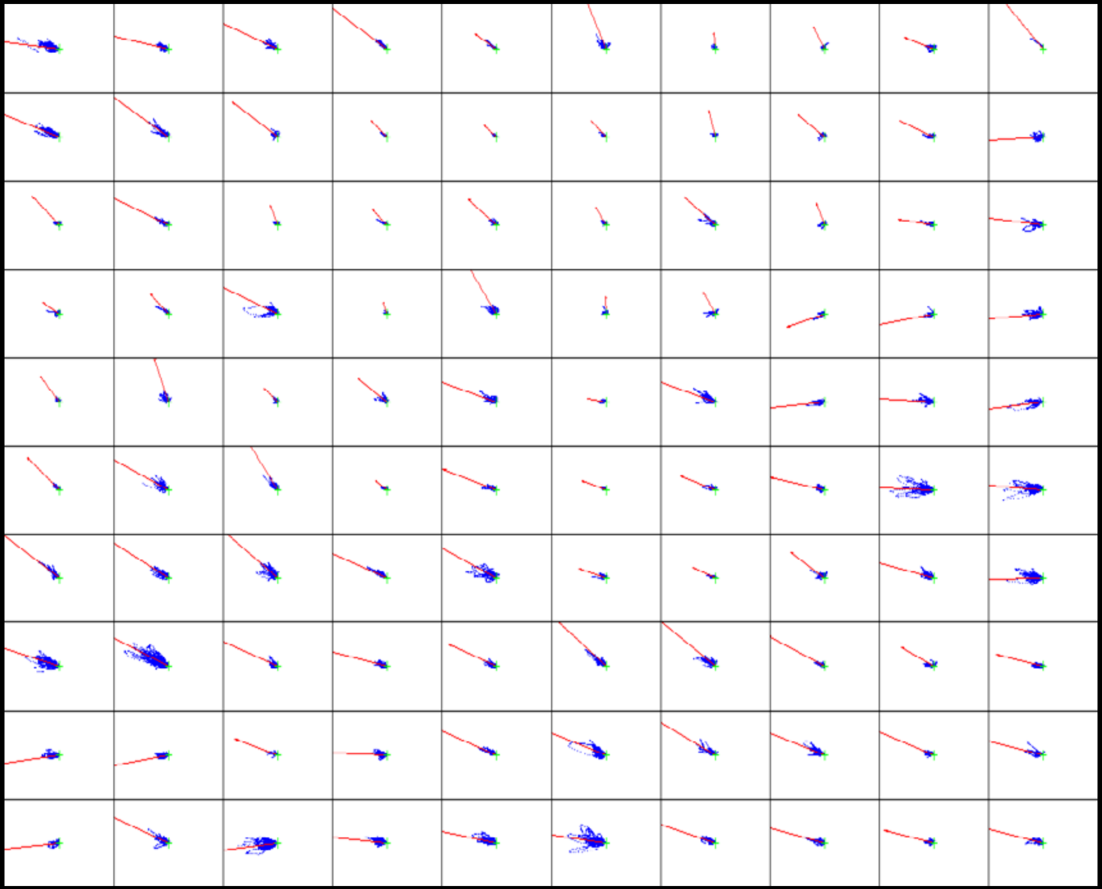






❖ 3-days directional energy flux (Fx, Fy)





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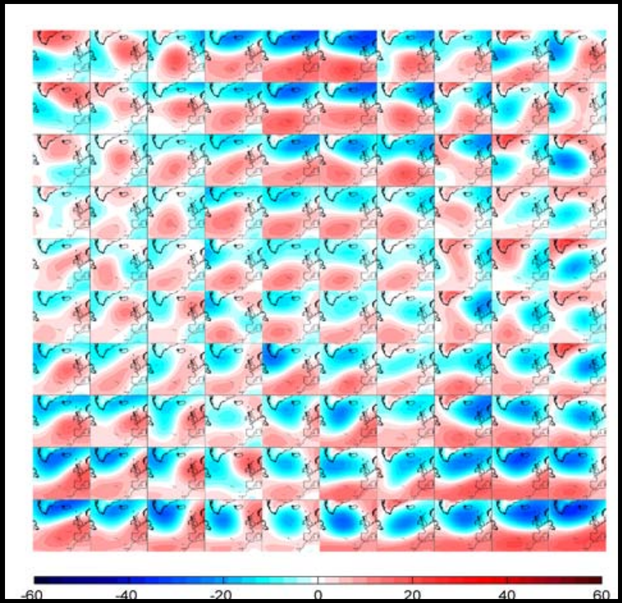
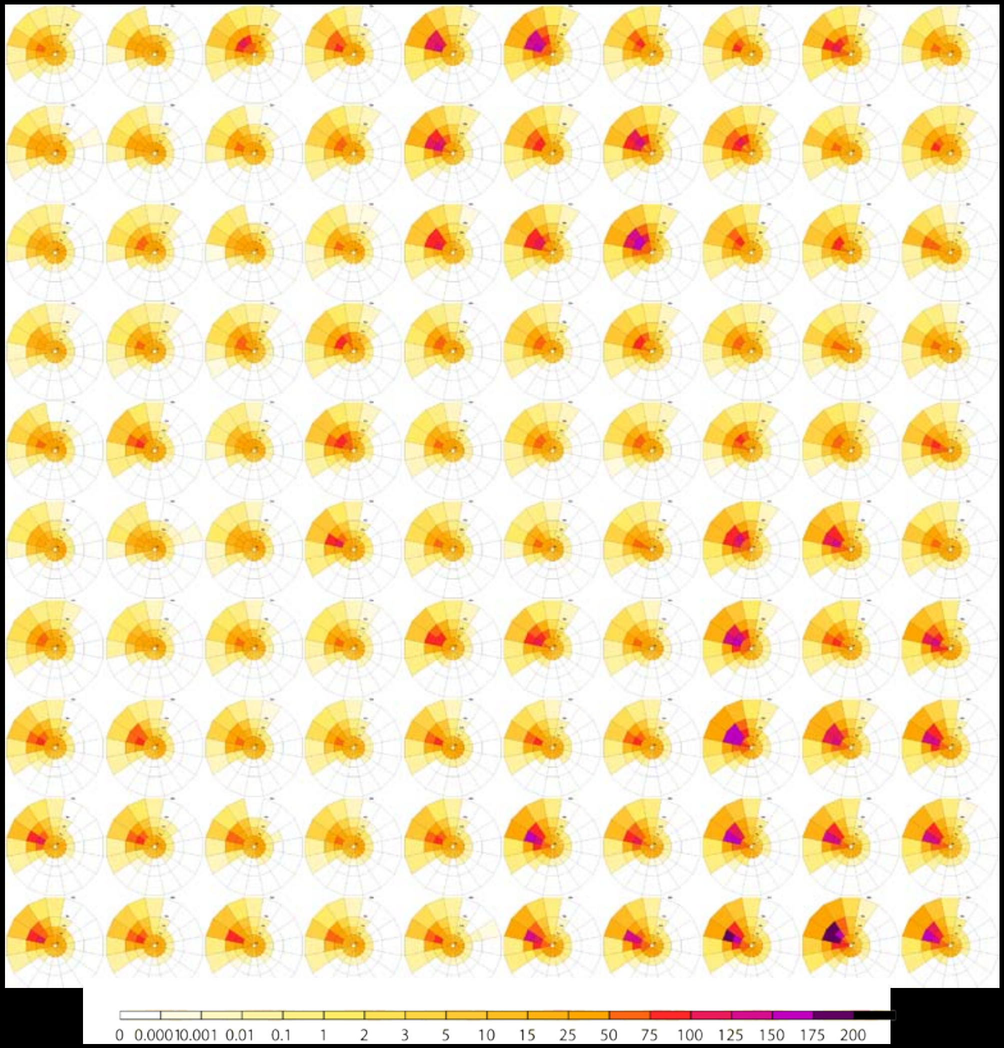
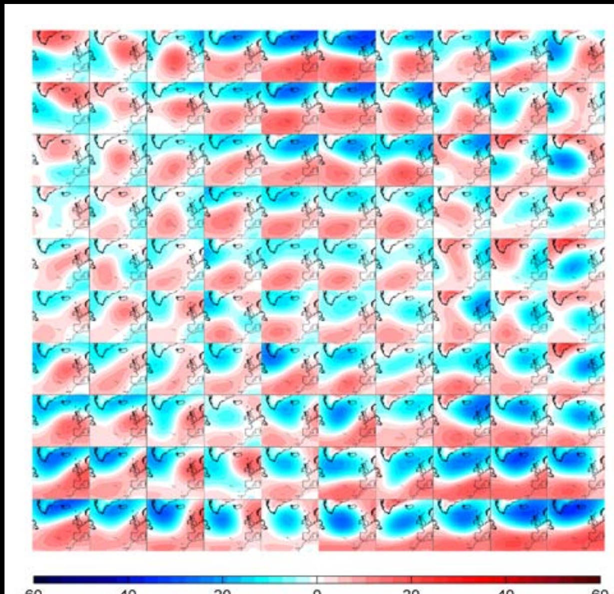
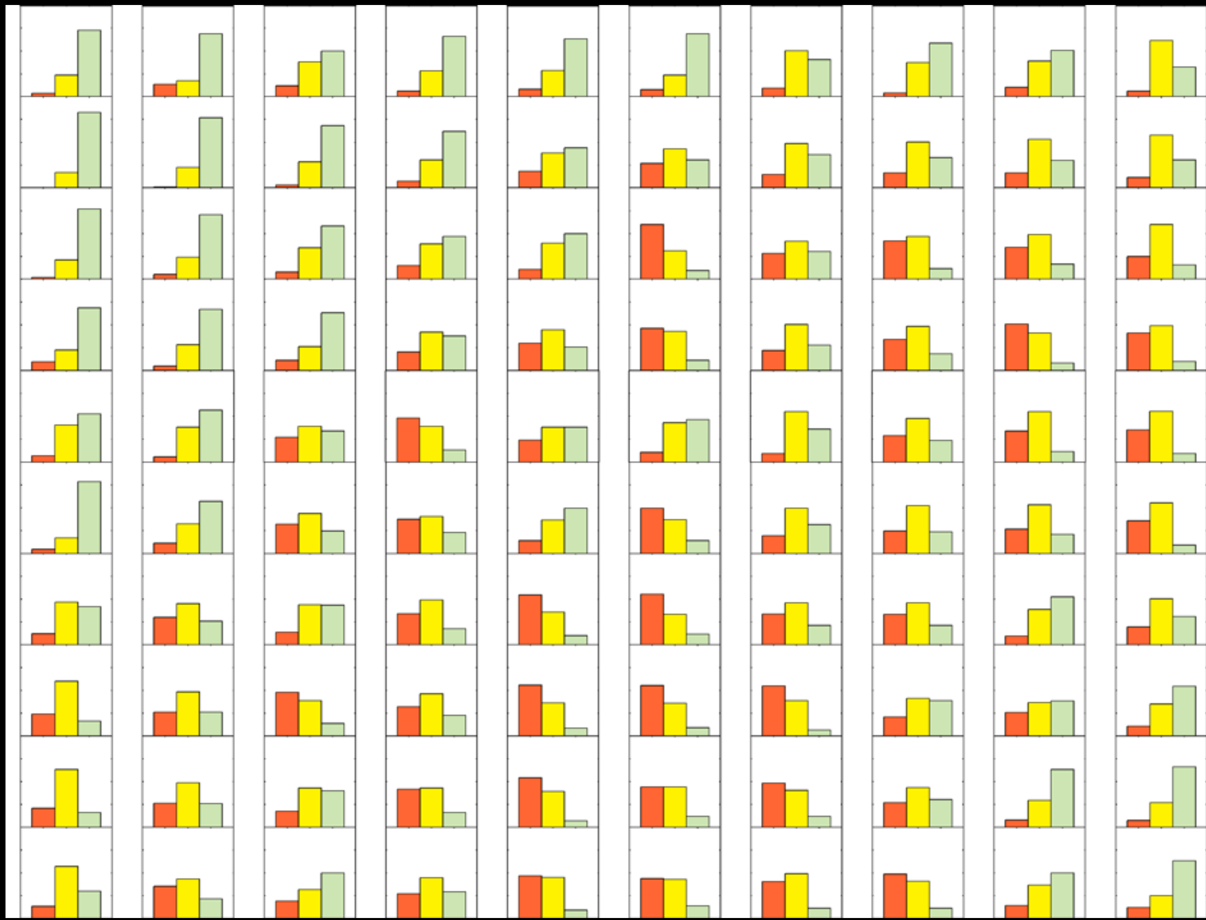
❖ 3-days wave spectra





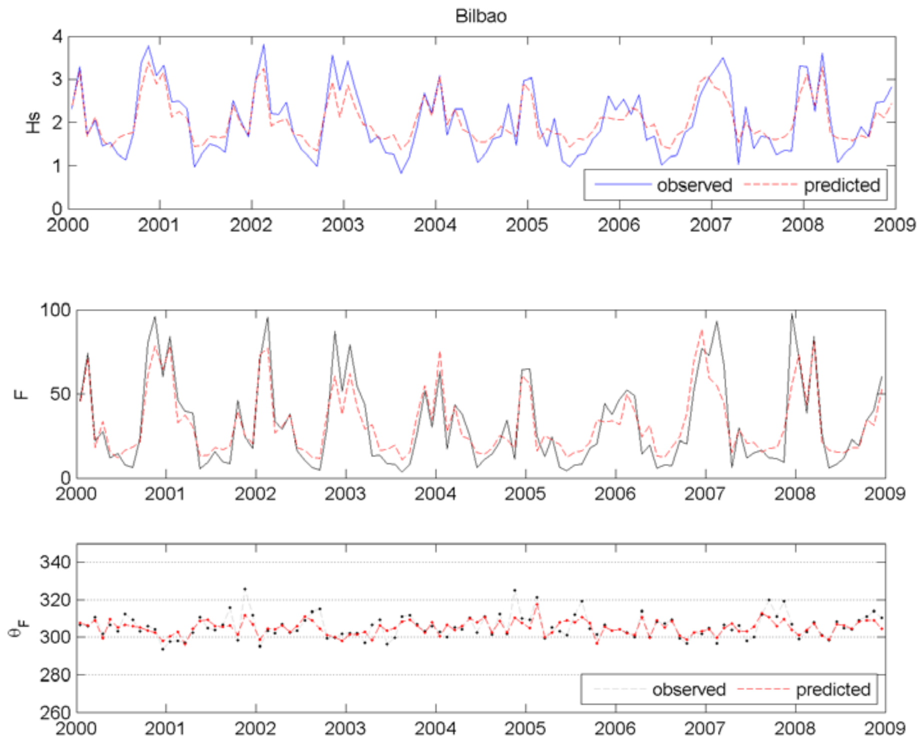
❖ Surfing conditions at Mundaka



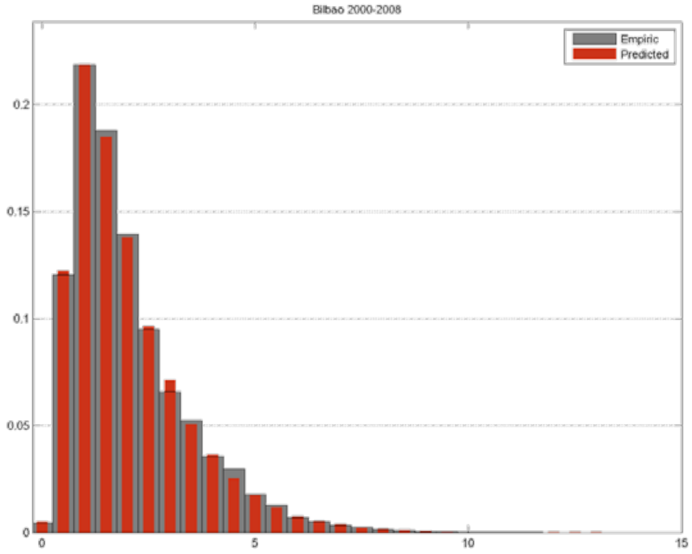


❖ Training (1948-1999), **Validation** (2000-2009)

Validation of monthly means



Validation of mean pdf of H



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❖ GCM models analyzed (from AR4)

	MODEL	Centre	Country	Runs
1	**BCM2**	Bjerknes Centre for Climate Research	Norway	1
2	**CCSM3**	National Center for Atmospheric Research	USA	4
3	**CGCM3.1(T47)**	Canadian Centre for Climate Modelling and Analysis	Canada	3
4	**CGCM3.1(T63)**	Canadian Centre for Climate Modelling and Analysis	Canada	1
5	**CNCM3**	Centre National de Recherches Meteorologiques	France	1
6	**CNCM33**	Centre National de Recherches Meteorologiques	France	1
7	**CSIRO-MK3.0**	Commonwealth Scientific and Industrial Research Organisation	Australia	1
8	**CSIRO-MK3.5**	Commonwealth Scientific and Industrial Research Organisation	Australia	1
9	**ECHAM5 MPI-OM**	Max-Planck-Institute for Meteorology	Germany	4
10	**ECHAM5C MPI-OM**	Max-Planck-Institute for Meteorology	Germany	3
11	**ECHOG**	University of Bonn	Germany	1
12	**EGMAM**	Freie Universitaet Berlin, Institute for Meteorology	Germany	3
13	**EGMAM2**	Freie Universitaet Berlin, Institute for Meteorology	Germany	1
14	**FGOALS-g1.0**	Institute of Atmospheric Physics	Chine	3
15	**GFDL-CM2.0**	Geophysical Fluid Dynamics Laboratory	USA	1
16	**GISS-AOM**	Goddard Institute for Space Studies	USA	1
17	**GISS-ER**	Goddard Institute for Space Studies	USA	1
18	**HADCM3C**	United Kingdom Met Office	United Kingdom	1
19	**HADGEM2**	United Kingdom Met Office	United Kingdom	1
20	**INGV-SXG**	Istituto Nazionale di Geofisica e Vulcanologia	Italy	1
21	**INM-CM3.0**	Institute of Numerical Mathematics	Russia	1
22	**IPSL-CM4**	Institut Pierre Simon Laplace	France	1
23	**MIROC3.2 (HIRES)**	Center for Climate System Research, NIES y RCGC.	Japan	1
24	**MRI-CGCM2.3.2**	Meteorological Research Institute	Japan	1
25	**PCM**	National Center for Atmospheric Research	USA	4

25 Models
42 runs

Ensemble (multi-model)

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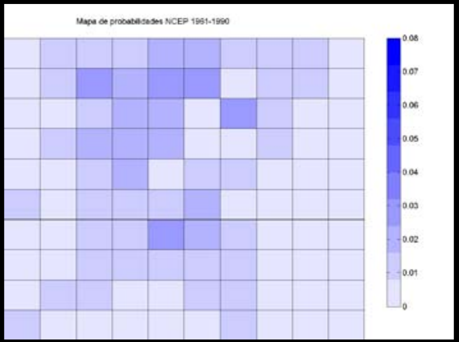
Are the GCMs able to forecast the climate of the past?

Reanalysis (1961-1990)

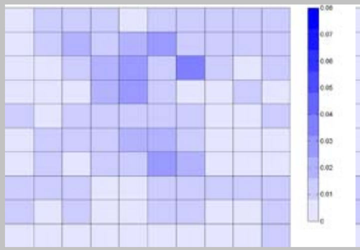
(reference pattern)



GCMs

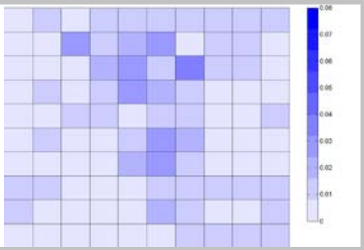
ECHAM5

run1



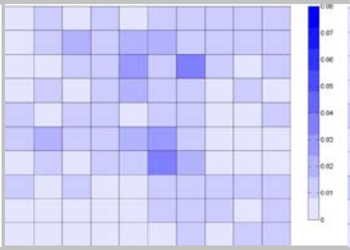
RE	0,33
SI	0,44

run2



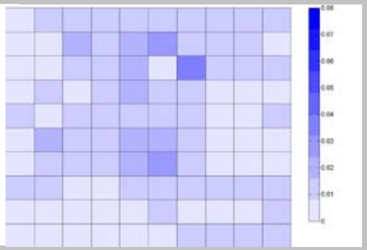
RE	0,35
SI	0,45

run3



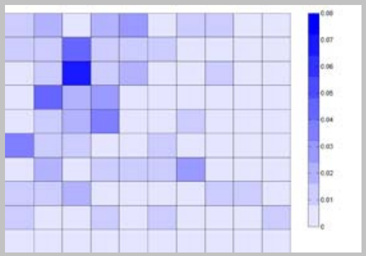
RE	0,37
SI	0,47

run4



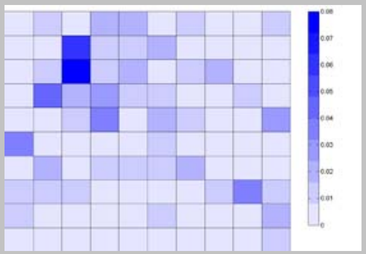
RE	0,35
SI	0,45

BCM2.0



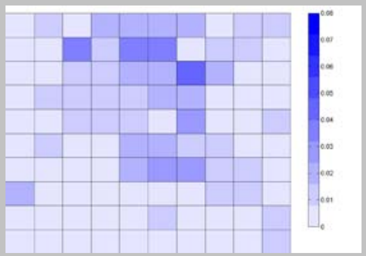
RE	0,67
SI	0,98

CNCM3



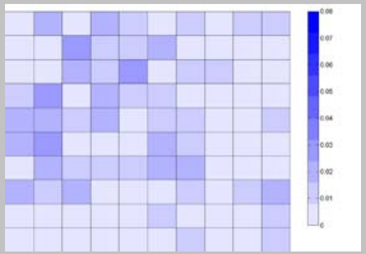
RE	0,85
SI	1,23

CSIROMK3.5



RE	0,50
SI	0,61

GFDLCM



RE	0,58
SI	0,70

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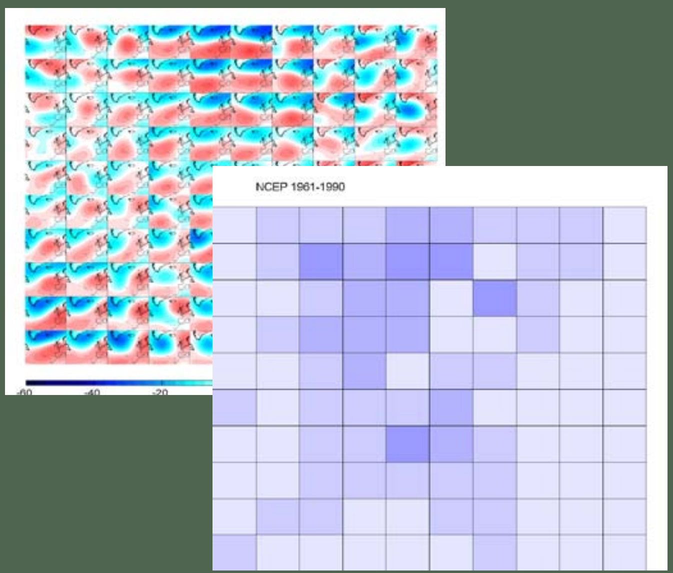
❖ Projection from GCM

Reanalysis/20C3M



Probability of occurrence

Predictand = X

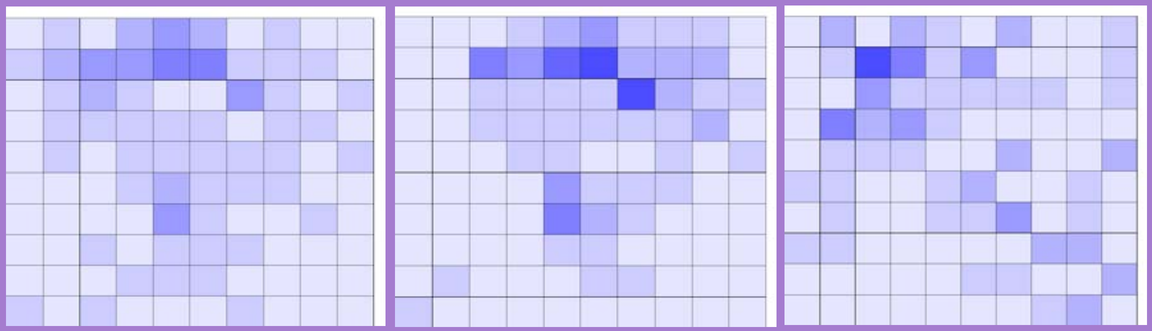
For a particular GCM..

$Y'=g(X')$

For a particular scenario …

Similar climate system (WT),

New Probability of occurrence !!



2010-2040 2040-2070 2070-2100

Predictand = X'

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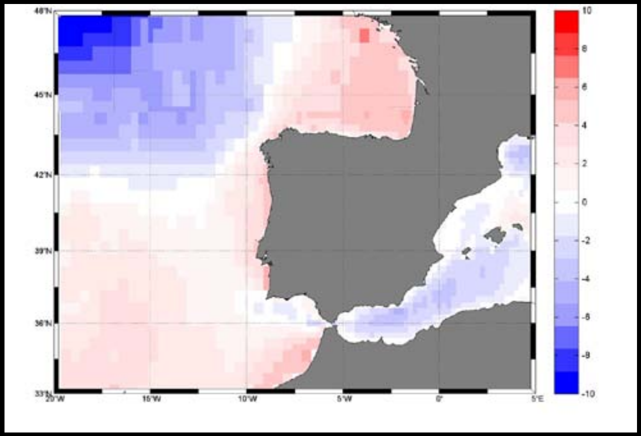
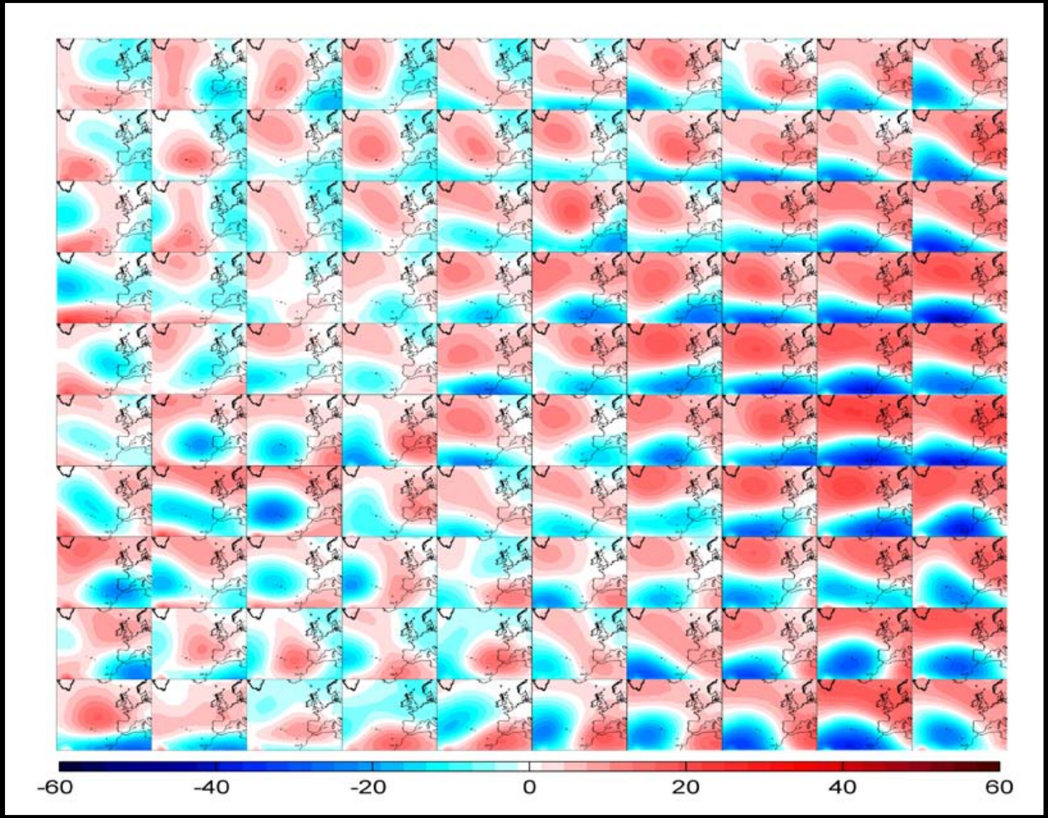


changes in downscaled wave climate



- Statistical Downscaling of Multivariate Wave Climate
- Based on Weather Types approach + Data Mining Techniques
- Easy visualization of WTs and associated wave climate
- The projection is based on the occurrence probability of each weather type
- Low computational cost for study of ocean wave climate projections.

12th International Workshop on Wave Hindcasting and Forecasting and 3rd Coastal Hazards Symposium

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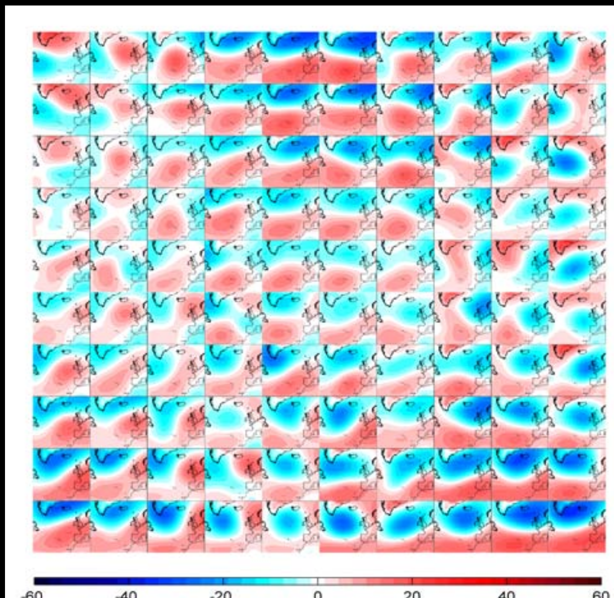
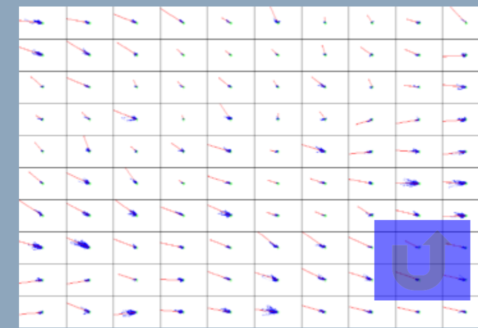
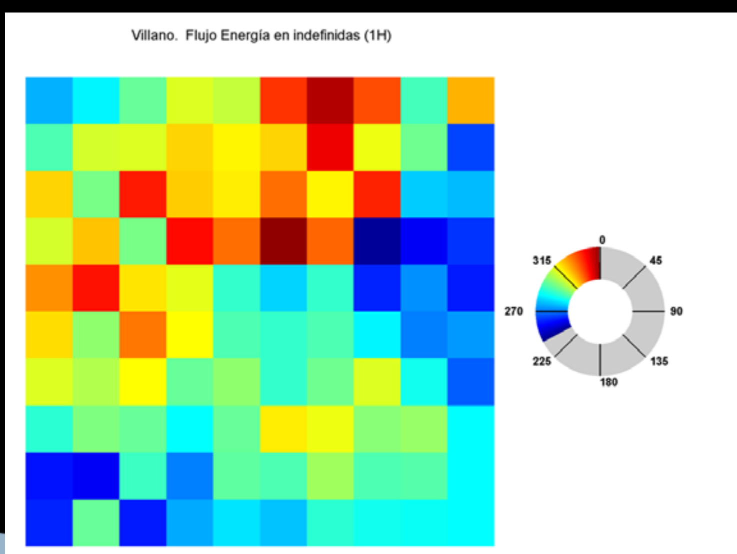
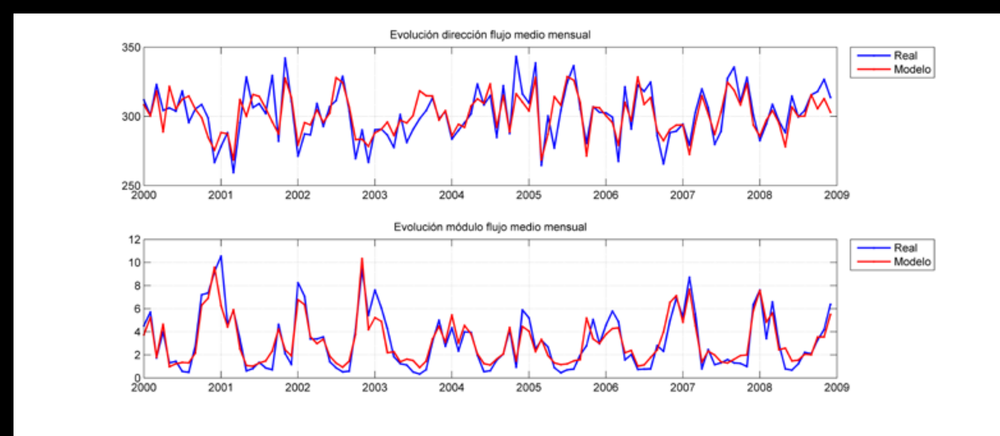
❖ Other applications..



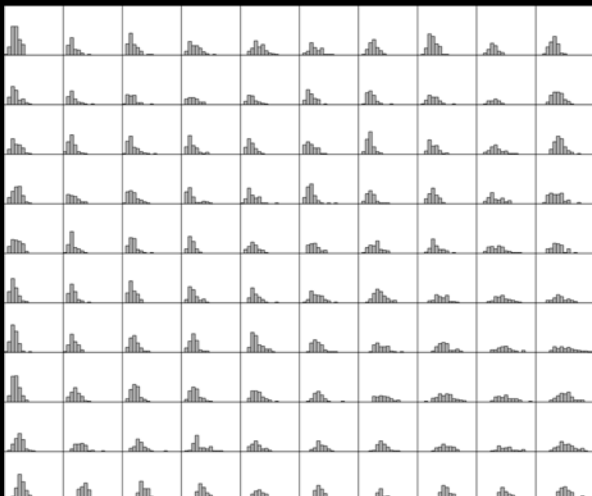
Wave energy flux







❖ Extreme value model



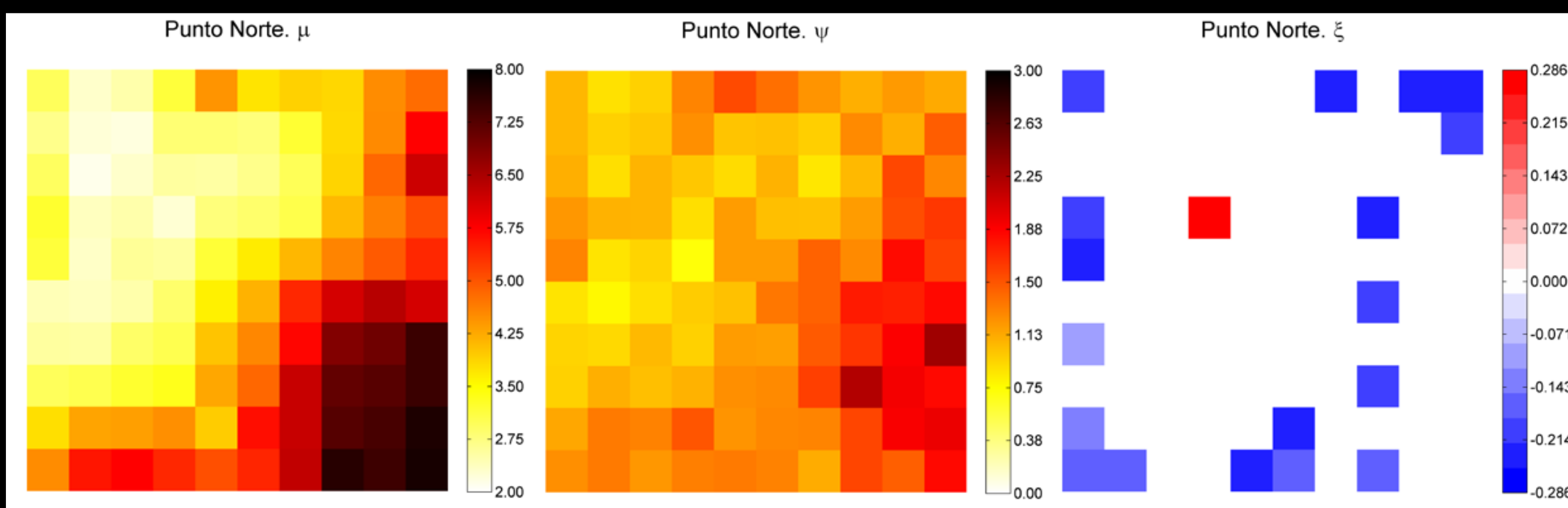
The HsMAX sample of each cell is fitted to a extreme value distribution.

Option a) **GEV**

$$F(x;\theta)=\exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\psi}\right)\right]^{-1/\xi}\right\}$$

Option b) **Pareto-poisson**

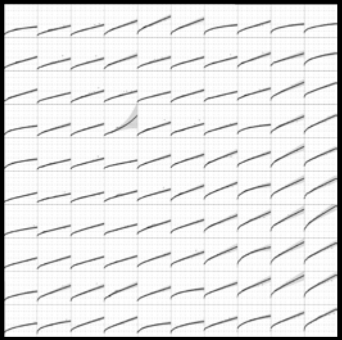
$$F(x;\theta)=1-\left(1+\xi\frac{x}{\sigma}\right)^{-1/\xi}, \qquad p(x;\theta)=e^{-\lambda}\frac{\lambda^{x}}{x!}$$



METHODOLOGY

❖ Extreme value model

Ndays maxima distribution → **Total annual maxima distribution**



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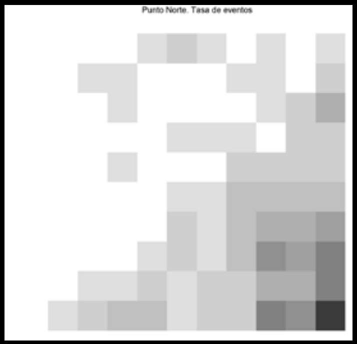

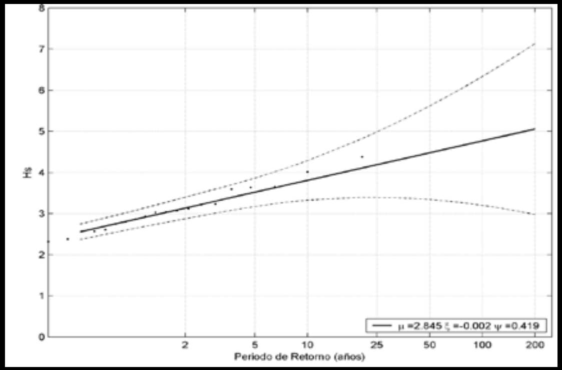

The composed extreme PDF can be obtained:

a) **GEV (annual maxima distribution)**

$$F(H;\mu,\psi,\xi) = \prod_{i=1}^{M} F_i\left(H;\mu_i,\psi_i,\xi_i\right)^{p_i \frac{365}{\Delta days}}$$

b) **Pareto-poisson**

$$F(H;\nu,\sigma,\xi) = \sum_{i=1}^{M} \nu_i F_i(H;\nu_i,\sigma_i,\xi_i)$$

Occurrence rate:

$$\nu = \nu_1 + \nu_2 + \ldots + \nu_n$$