STATISTICAL DOWNSCALING OF THE SIGNIFICANT WAVE HEIGHT

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OUTLINE

- Motivation
- Objectives and challenges
- Existing work
- The model
- Results
- Conclusion and perspectives

MOTIVATION

- ❑ Wave climate characterization is important for a wide number of marine activities
- ❑ GCMs (general circulation models) provide future projections for atmospheric variables with coarse spatial resolution
- ❑ GCMs simulate wind but not sea state parameters
- ❑ Statistical and dynamical downscaling models bridge the gap between GCM simulations and decision makers requirements

- Statistical downscaling models construct an empirical relationship between large scale and local scale variables using historical data
- Assuming that this relationship is stationary, future projections can be made using GCM simulations of the large scale variables
- This makes statistical downscaling models computationally efficient
- For a rigorous comparaison between statistical and dynamical methods we refer to the studies Wang et al. (2010)[1] and Laugel etal. (2014)[2]

➜ Before using climate model simulations for making projections with statistical downscaling models, bias correction methods are needed. And this is not the focus of this study

OBJECTIVES

- ❑Establish a statistical link function between the wind and the significant wave height
  - ❑ **Predictand**: the significant wave height (Hs) from the hindcast database Homere
  - ❑ **Predictors**: wind data from the ERA5 reanalysis dataset
  - ❑ **Method**: linear regression with a suitable penalization method
- ❑The relationship has to be physically interpretable

DATA

❑ Hindcast database Homere:

❖ Sea state hindcast database, based on WAVEWATCH III

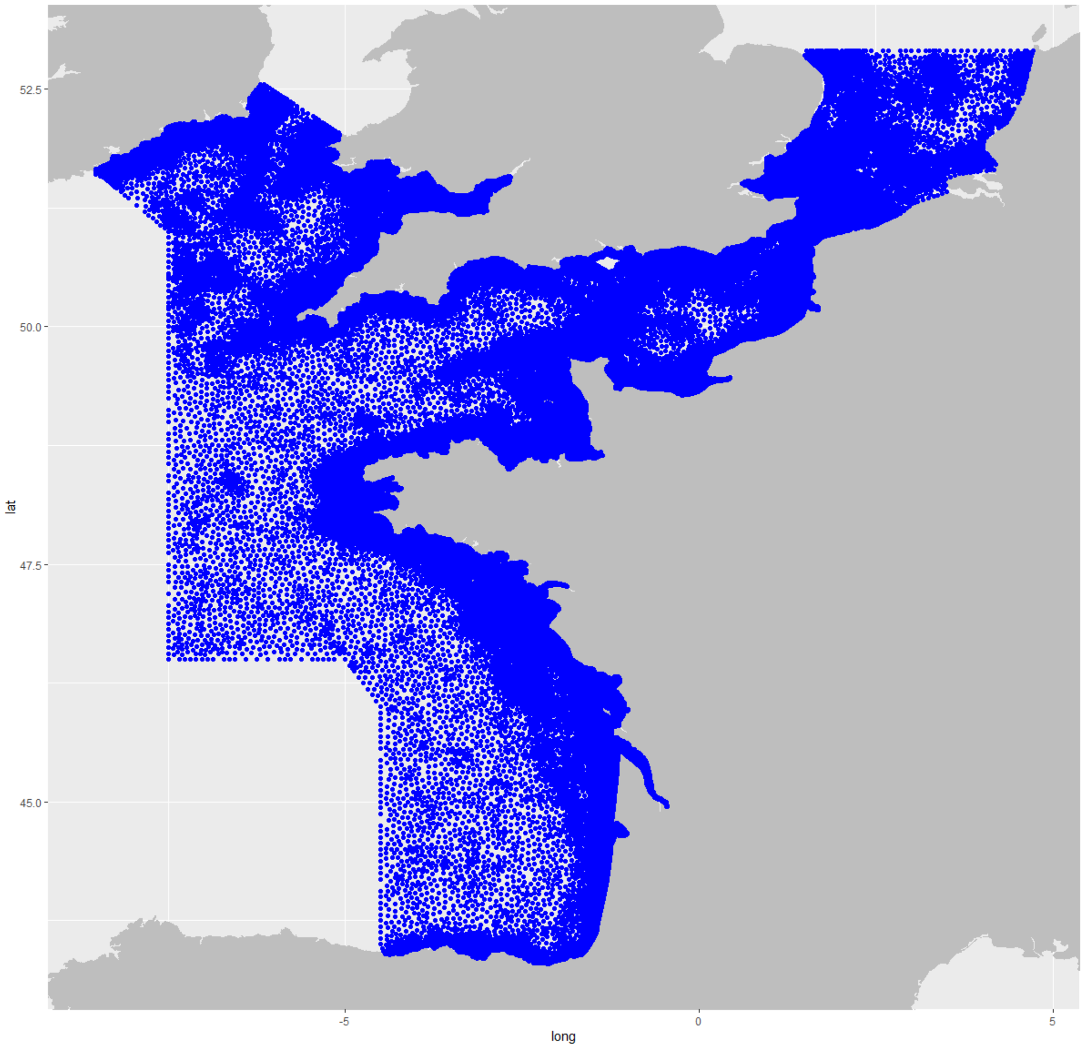
❖ High resolution grid with one hour time step

❖ From 1994 to 2019

❖ The wind forcing: CFSR

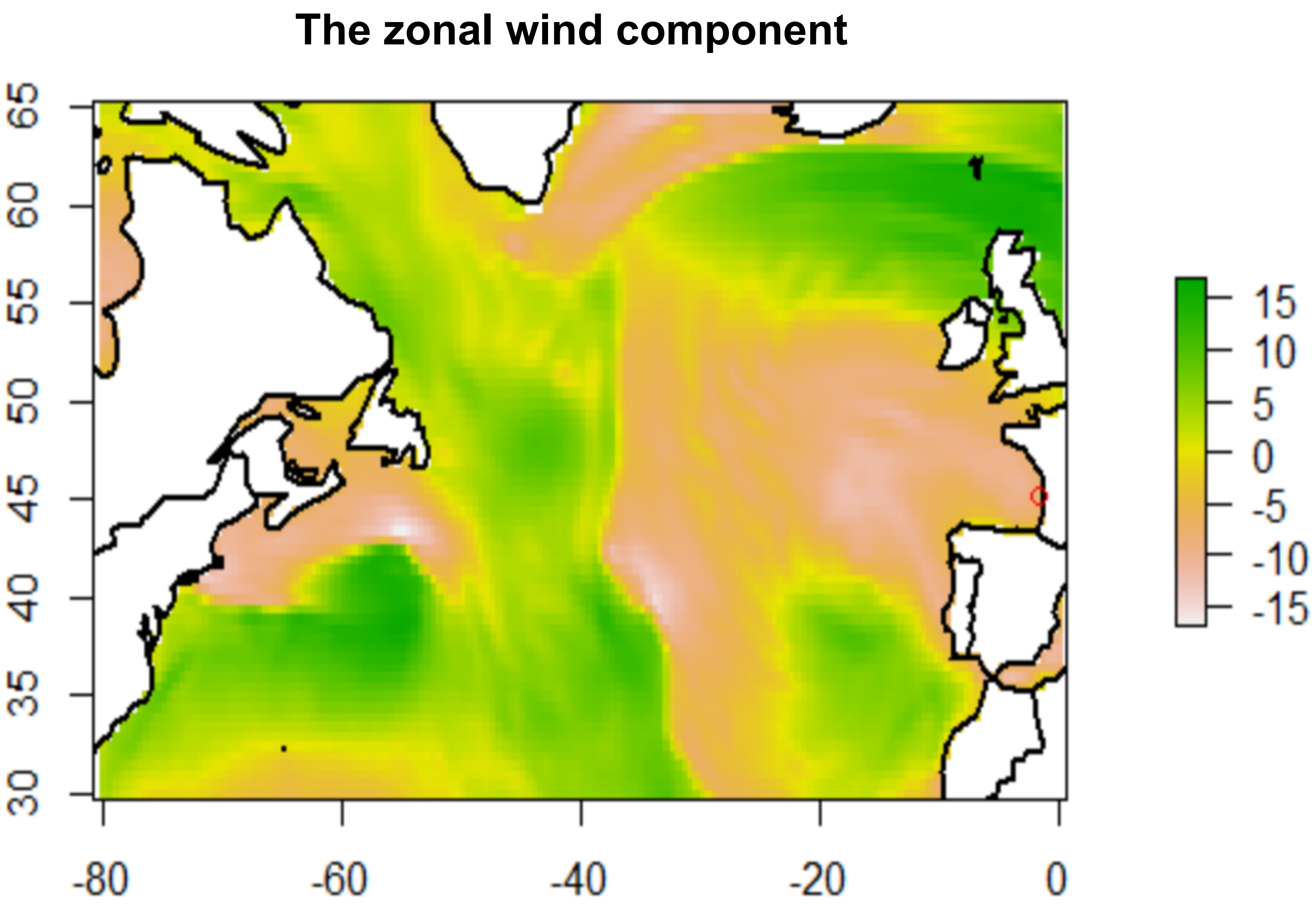
❑ ERA5 reanalysis database:

❖ Hourly wind components with $0.25° \times 0.25°$ spatial resolution



CHALLENGES

- High dimensionality of the input space
- Multicollinearity
- The statistical downscaling model has to take into consideration the sea state composition (wind sea – swells)
- Non-instantaneous and non-local relationship between wind and waves



The location of interest is situated at the Bay of Biscay at 45.2°N, 1.6°W

EXISTING WORK

- ❑ Camus et al. (2014b)[3] used a weather types model to downscale wave parameters in north-west of Spain. To account for the swell composition, the predictor was defined as the three-daily mean of sea level pressure and pressure gradients
- ❑ Perez et al. 2014[4] proposed a method, called ESTELA, that defines the wave generation area and wave travel time at any location worldwide
- ❑ Camus et al.(2014a)[5] and Herermiller et al. (2016)[6] used the ESTELA approach to define the predictors for their statistical downscaling approach

THE MODEL

$$Hs = X^{L}\beta^{L} + X^{G}\beta^{G} + \epsilon \qquad (1)$$

- ❑ Hs: significant wave height
- ❑ X^{L} *et* X^{G} : local and global predictors
- ❑ β^{L} et β^{G} : local and global coefficients
- ❑ ϵ: model error

THE PREDICTORS

- **The local predictor** X^{L} is defined based on the wind speed and the fetch at the local point

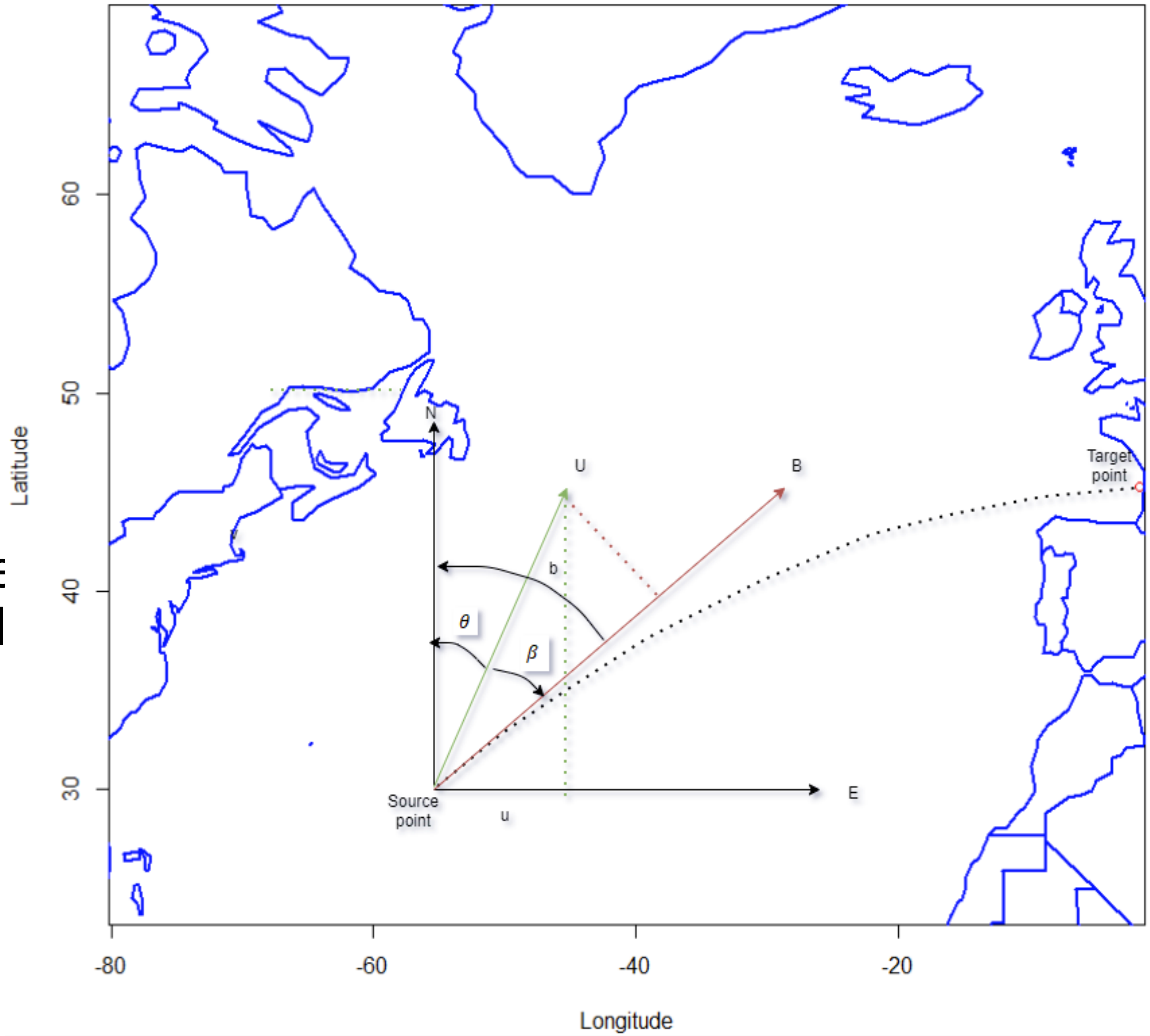
- **The global predictor** X^{G} is defined as the projected wind: the wind components at each grid point are projected into the bearing of the target point in a great circle path

$$W=\sqrt{u^2+v^2}\cos^2\left(\frac{1}{2}\beta\right)$$

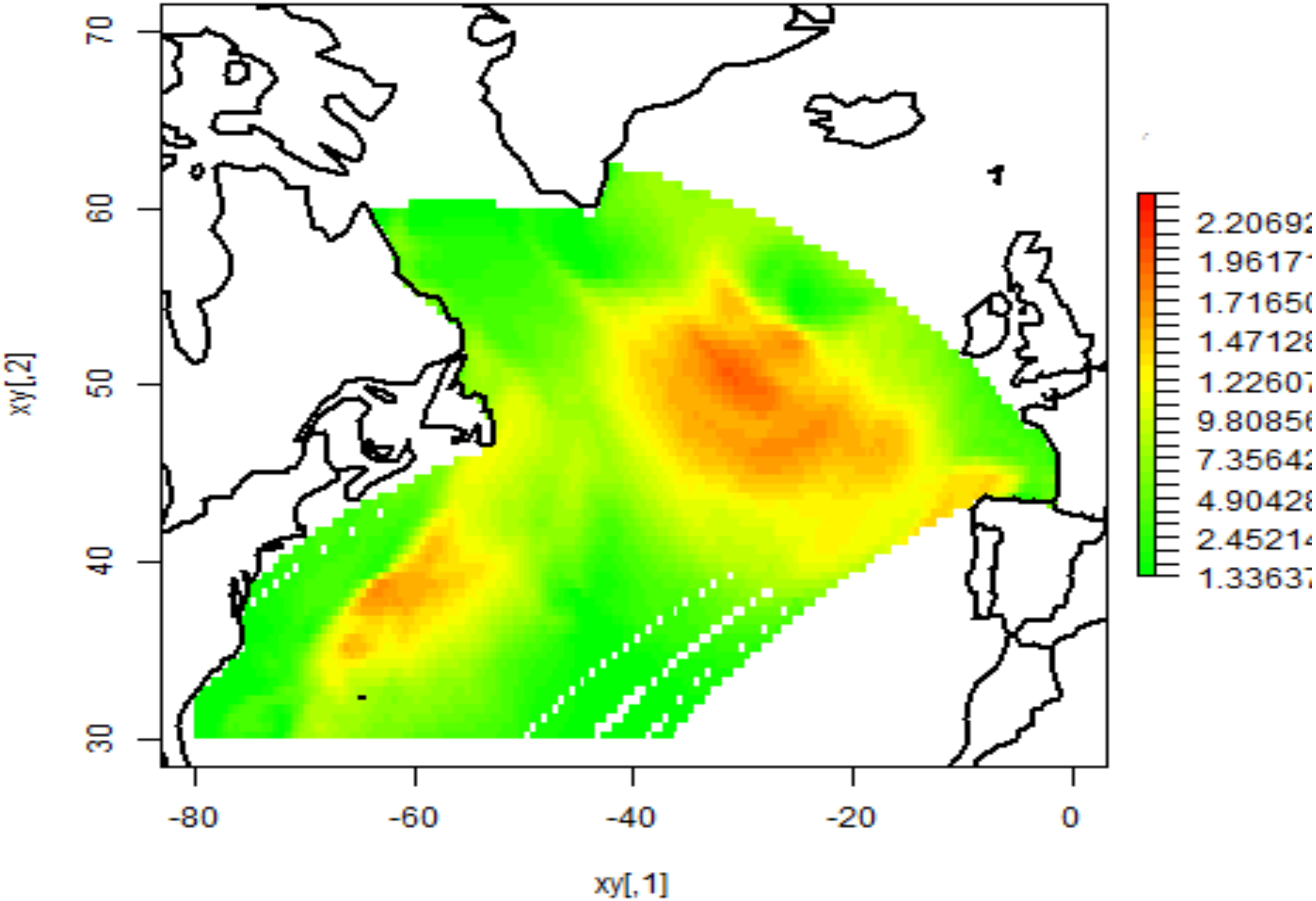
$$\beta=b-\theta$$

$$\theta=\mathrm{atan}(u/v)$$

- where W is the projected wind, u and v the wind components, b is the great circle bearing, and θ is the wind direction



The projected wind



- **The spatial coverage of X^G:** assuming that waves travel along a great circle path, grid points whose path is blocked by land are neglected
- **The temporal coverage of X^G** is defined by two parameters, called travel time of waves t_j and the temporal width α_j, using a fully data-driven approach

- At time t the global predictor X^G is defined as:

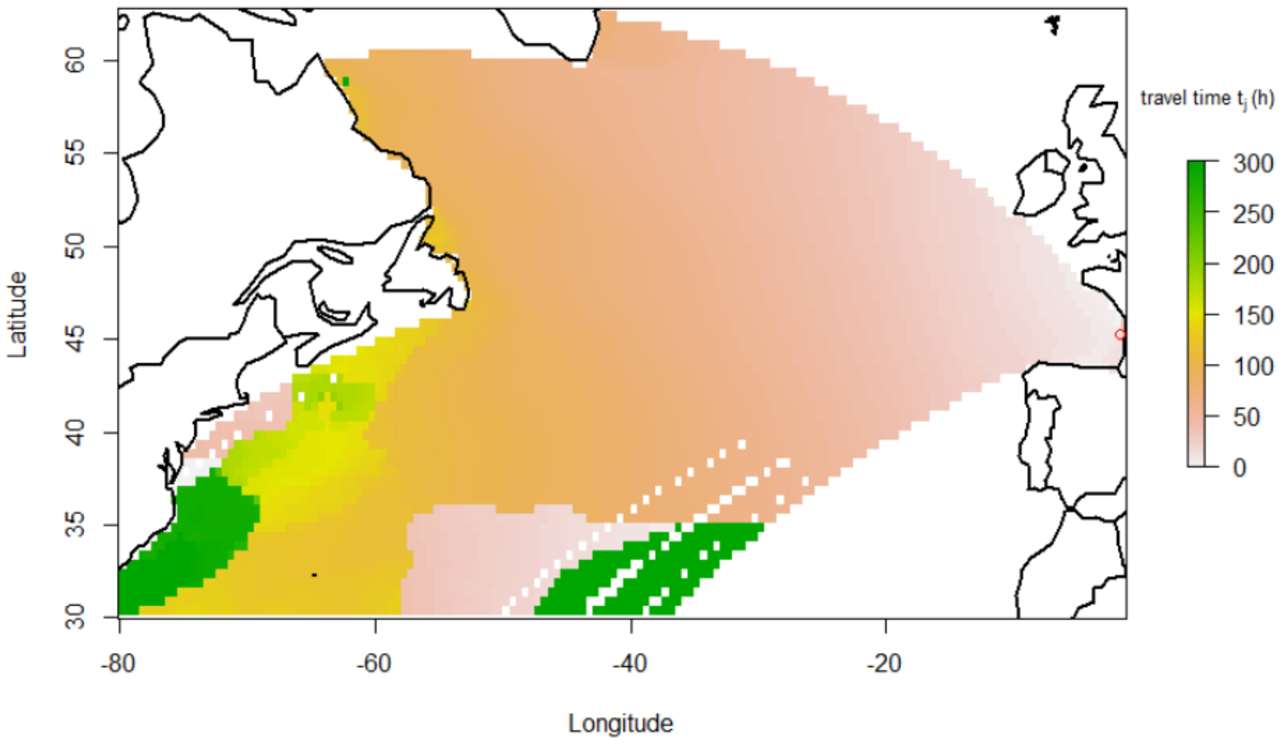
$$X^G(t) = \{\bar{W}_1^2(t - t_1 - \alpha_1 : t - t_1 + \alpha_1), \ldots, \bar{W}_j^2(t - t_j - \alpha_j : t - t_j + \alpha_j), \ldots, \bar{W}_m^2(t - t_m - \alpha_m : t - t_m + \alpha_m)\}$$

- Where $\bar{W}_j^2(t - t_j - \alpha_j : t - t_j + \alpha_j)$ is the mean of the squared projected wind at location j in a time window controlled by α_j and t_j

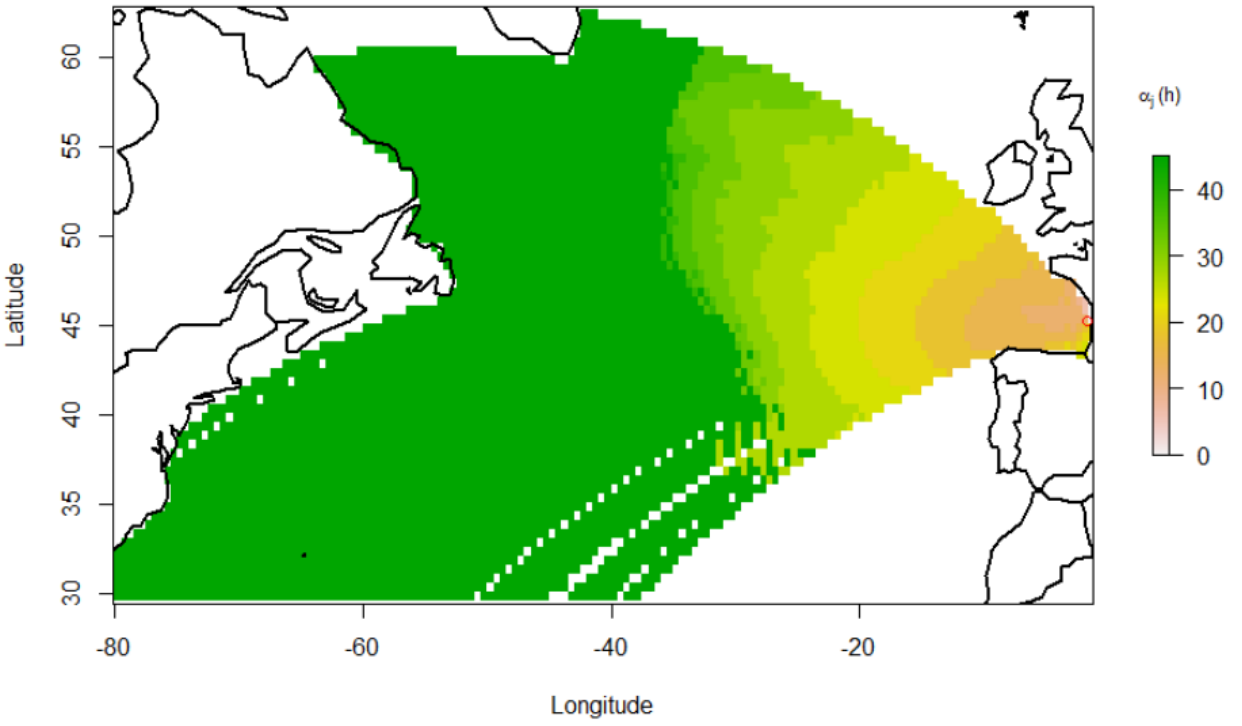
- α_j and t_j are estimated as follows :

$$(t_j, \alpha_j) = argmax\ cor(Hs, \bar{W}_j^2(t - t_j - \alpha_j : t - t_j + \alpha_j))$$

The estimated travel time t_{lj}



The estimated temporal width α_{lj}

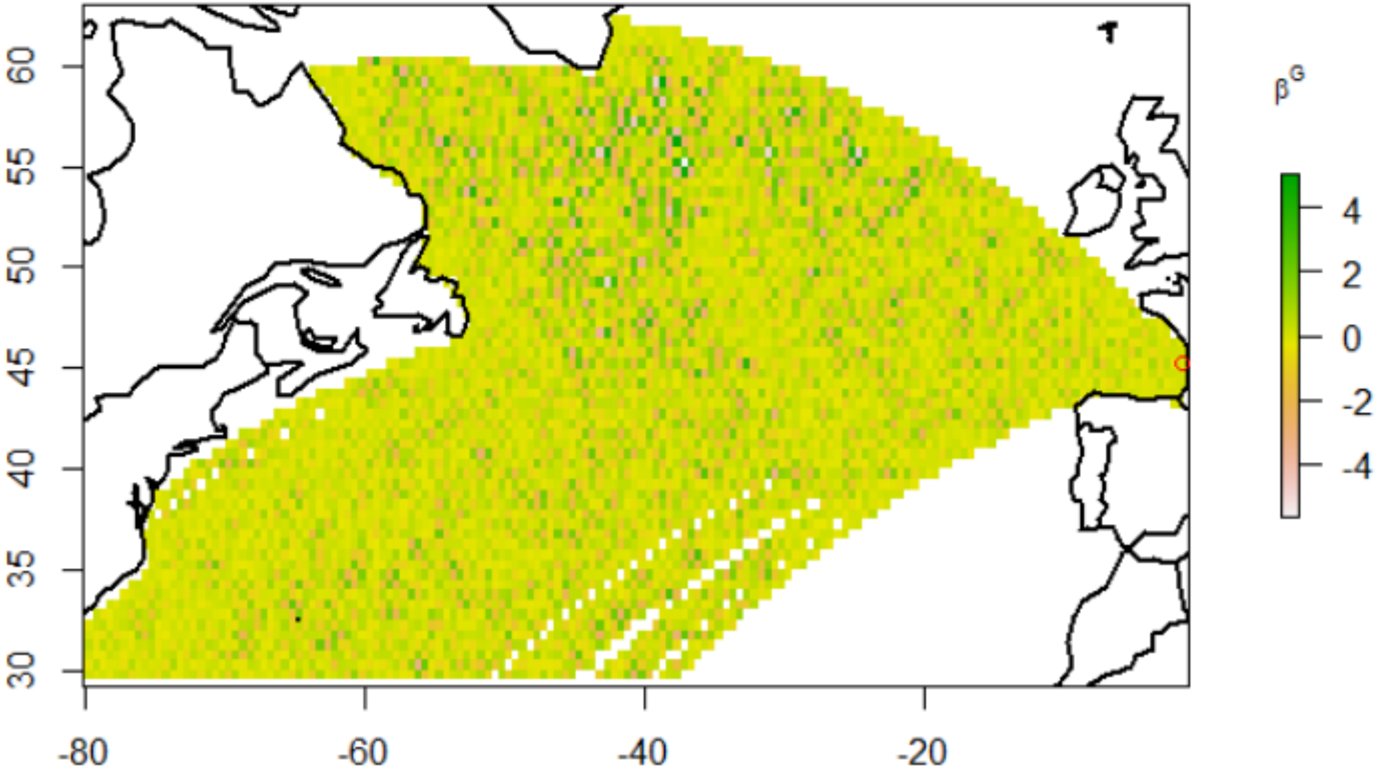


MODEL ESTIMATION

- The model $Y=X\beta+\epsilon$ can be estimated using least squares so that $\hat{\beta}^{ls} = (X^T X)^{-1} X^T Y$

- However, in the case of high multicollinearity, the matrix $X^T X$ may be ill-conditioned

- The least squares estimates have low bias and high variance which affects the prediction accuracy of the model



- To address this issue, Ridge regression shrinks the coefficients by imposing a penality on the residual sum of squares so that :

$$\beta^{ridge} = argmin\ ||X\beta - Y||_2^2 + \lambda||\beta||_2^2 \qquad (2)$$

- The solution of (2) is $\beta^{ridge} = (X^T X + \lambda I)^{-1} X^T Y$. Ridge thus, adds positive elements to the diagonal of $X^T X$ before inversion
- In fact Ridge shrinks all the EOFs of X and a high amount of shrinkage is applied to EOFs with small variance
- We extend this to the general case where $\beta^{Eridge} = (X^T X + \lambda \Delta)^{-1} X^T Y$ where Δ is the penality matrix. Δ can be interpreted as a prior on β
- LASSO is another shrinkage method. Instead of using the norm 2 in (2) it uses the norm 1 so that

$$\beta^{lasso} = argmin\ ||X\beta - Y||_2^2 + \lambda||\beta||_1$$

MODEL ESTIMATION

- The penalized version of the model (1) can be written as:

$$(\beta^L, \beta^G) = \text{argmin} \, ||X^L \beta^L + X^G \beta^G - Hs||^2 + \lambda \beta^{G^T} \Delta \beta^G$$

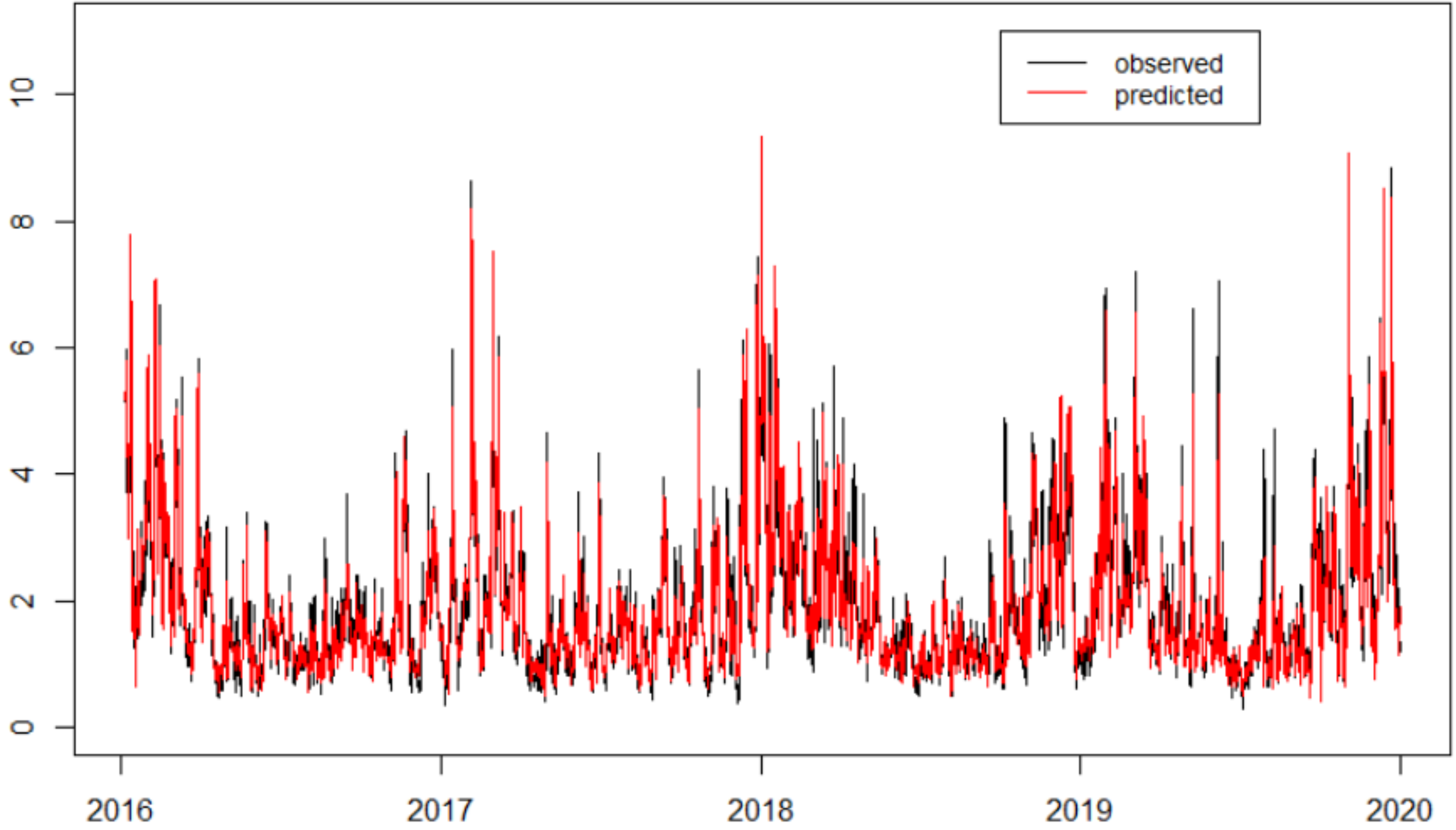
- In this study, we suppose that β^G is smooth and has the same EOFs as X^G and we choose $\Delta = (X^T X)^\alpha$ and λ and α are selected using cross validation

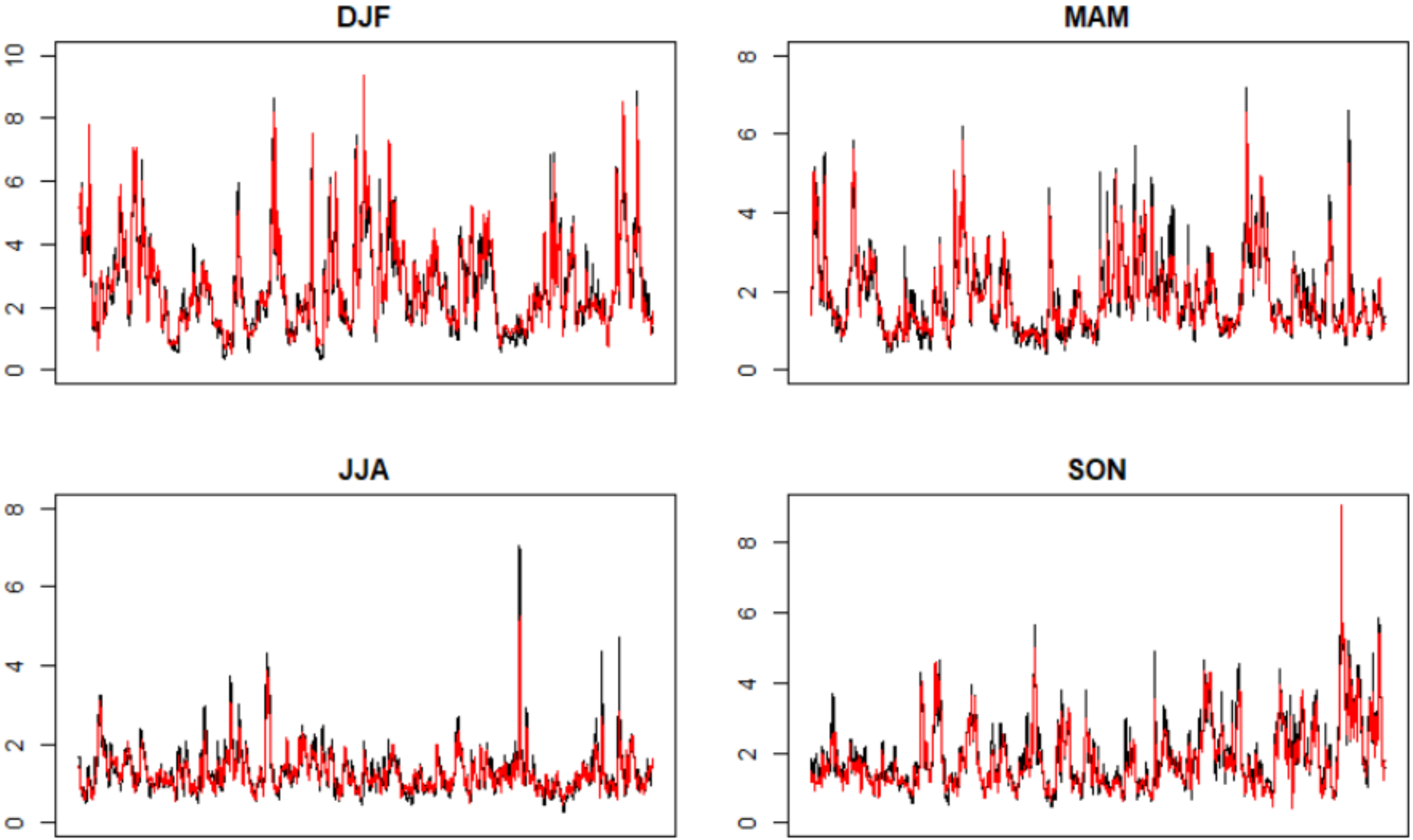
- The period from 1994 to 2012 is used to estimate the parameters β^{L} and β^{G}

- 2013 to 2016 is used to select the tuning parameters

- 2016 to 2019 is used as a validation period

RESULTS




DJF
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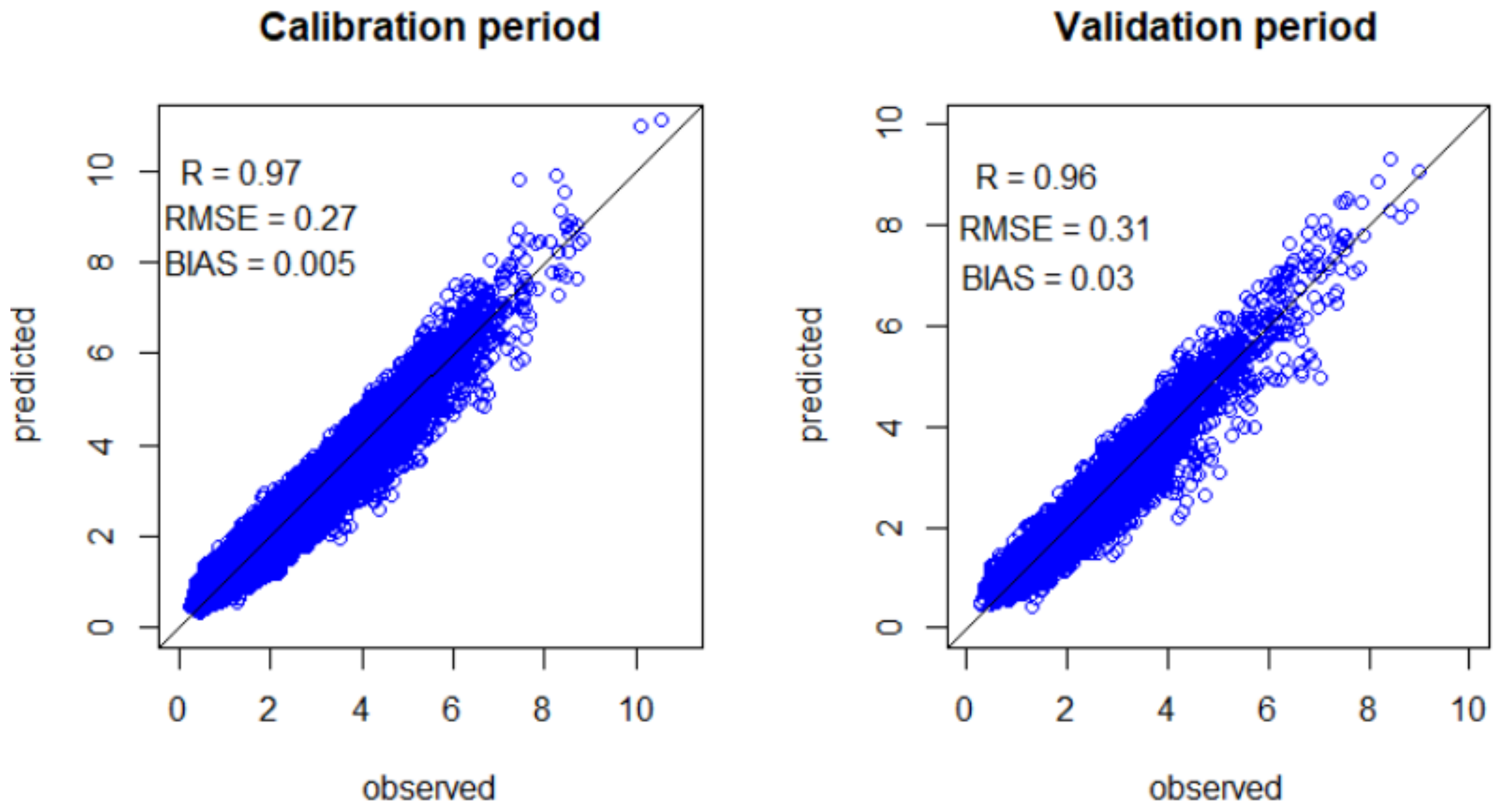
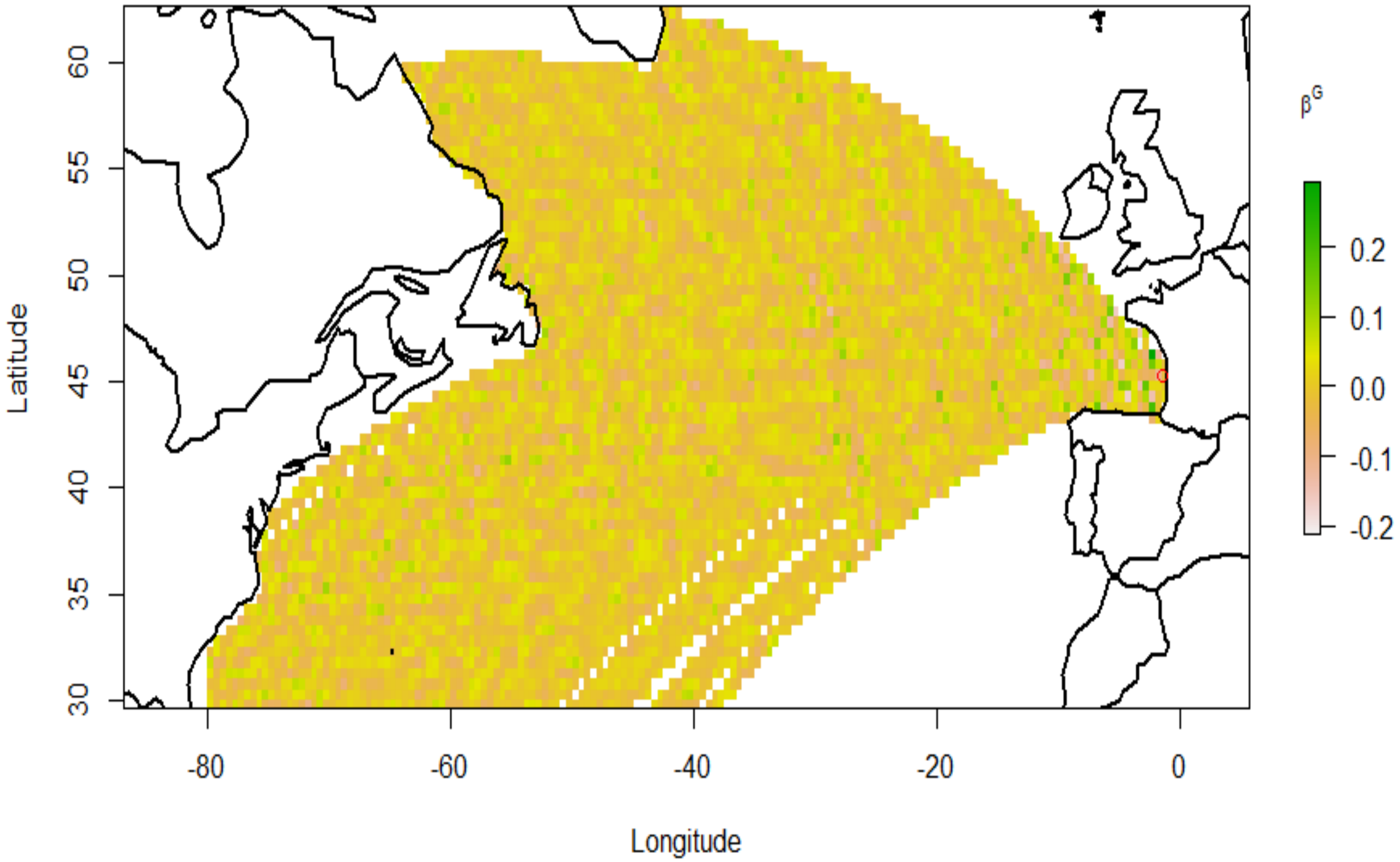


Calibration period
R = 0.97
RMSE = 0.27
BIAS = 0.005
predicted
observed
0
2
4
6
8
10
Validation period
R = 0.96
RMSE = 0.31
BIAS = 0.03
predicted
observed
0
2
4
6
8
10

COMPARAISON WITH OTHER METHODS

	R	RMSE	BIAS
Ridge	0.96	0.317	0.03
LASSO	0.96	0.318	0.03
Extended Ridge	0.961	0.313	0.03

THE ESTIMATED β^G USING LASSO

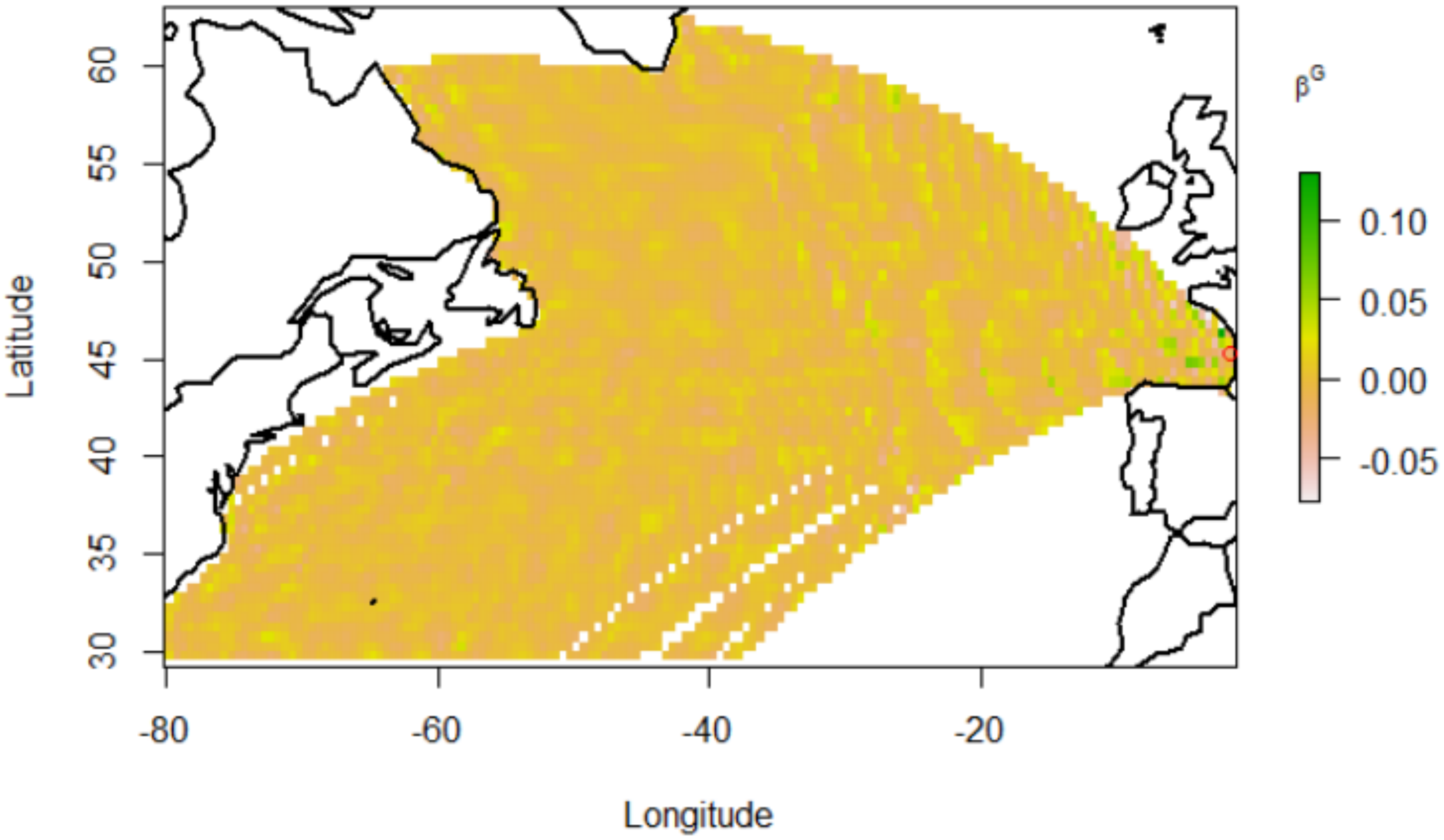


THE ESTIMATED $\beta \uparrow G$ USING THE EXTENDED RIDGE

❑ Endeed, the λ (the smoothness parameter) choosed by cross validation does not give the desired smoothness

❑ By using larger values of λ, the resulted coefficients are smooth however; the prediction accuracy get worse

❑ Trade off between model interpretability and model prediction accuracy?



CONCLUSION

- A statistical downscaling model that links the large-scale wind and the local-scale wave parameter (Hs) was proposed

- Predictors definition is a crucial step in the statistical downscaling framework

- The validation analysis proves the model's skill in predicting wave climate

- Working on the trade off between prediction accuracy and interpretability

REFERENCES

- [1] V. R. C. A. Wang, Xiaolan L.Swail, “Dynamical versus statistical downscaling methods for ocean wave heights” International Journal of Climatology, vol. 30, pp. 317–332,2010
- [2] A. Laugel, M. Menendez, M. Benoit, G. Mattarolo, and F. Mendez, “Wave climate projections along the French coastline: Dynamical versus statistical downscaling methods” Ocean Modelling, vol. 84, 112014.
- [3] P. Camus, M. Menendez, F. Mendez, C. Iza-guirre, A. Espejo, V. C´anovas, J. Perez, A. Rueda Zamora, I. Losada, and R. Med-ina, “A weather-type statistical downscaling framework for ocean wave climate,”Journal of Geophysical Research: Oceans, vol. 119,11 2014.
- [4] J. Perez, F. Mendez, M. Menendez, and I. Losada, “Estela: a method for evaluating the source and travel time of the wave energy reaching a local area” Ocean Dynamics, 08 2014.
- [5] P. Camus, F. Mendez, I. Losada, M. Menendez, A. Espejo, J. Perez, A. Rueda Zamora, and Y. Guanche, “A method for finding the optimal predictor indices for local wave cli-mate conditions ”Ocean Dynamics, vol. 64,07 2014
- [6] C. Hegermiller, J. Alvarez Antolinez, A. Rueda, P. Camus, J. Perez, L. Erikson, P. Barnard, and F. Mendez, “A multimodal wave spectrum-based approach for statis-tical downscaling of local wave climate” Journal of Physical Oceanography, vol. 47,12 2016
- [7] Hastie, Trevor, Trevor Hastie, Robert Tibshirani, and J H. Friedman. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. New York: Springer, 2001. Print
- [8] W. N. van Wieringen, “Lecture notes on ridge regression,” 2020

THANK YOU FOR YOUR ATTENTION