PREDICTABILITY OF TELECONNECTION INDEXES AND THEIR APPLICABILITY IN SEASONAL AND DECADAL PREDICTION

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RESUMEN
Hasta hace poco, las salidas de modelos dinámicos han sido la principal fuente de información para obtener proyecciones climáticas a escalas de tiempo cortas. Sin embargo, en los últimos 10 años ha habido un progreso considerable en lo que se conoce como predicción decadal. Es decir, simulaciones multianuales hasta 30 años que se inician cada 5 años. Estas simulaciones se realizan normalmente a partir de modelos dinámicos, con los consiguientes problemas de inicialización. En este sentido, los índices de teleconexión, calculados a partir de patrones espaciales y temporales de variables atmosféricas u oceánicas, representan las interacciones del sistema océano-atmósfera y su evolución temporal. Su incorporación como predictores en modelos estadísticos para la meteorología estacional y climatología decadal representa una oportunidad para mejorar la previsibilidad de la atmósfera y el océano. En este trabajo, la predictibilidad de las diferentes índices de teleconexión se analizó mediante validación cruzada de la periodicidad obtenida con las técnicas de Transformada rápida de Fourier (FFT) y los filtros de rachas de Monjo.

ABSTRACT
Until recently, dynamical outputs have been the main source of information available for climate prediction at seasonal timescales. However, in the last 10 years there has been considerable progress in the so-called decadal prediction. That is, multi-annual simulations up to 30 years that are usually initiated every 5 years. These simulations are made usually from dynamical models, with the consequent initialization problems. In this sense, teleconnection indices - calculated from spatial and temporal patterns of atmospheric or oceanic variables - represent the interactions of the ocean-atmosphere system and its temporal evolution. Their incorporation as predictors of seasonal meteorology and decadal climatology from statistical models represents an opportunity in improving the predictability of the atmosphere and the ocean. In this work, the predictability of different teleconnection indices was analyzed by cross-validation the periodicity obtained with Fast Fourier Transform (FFT) techniques and Monjo's spell filters.

1. INTRODUCTION

The goal of this study is to improve seasonal and decadal prediction – a discipline halfway between weather forecast and climate projections – in order to anticipate the needs of the population, services and agencies, and to increase resilience to adverse weather and climatic events.

Until recently, dynamical projections have been the main source of information available for climate predictions at short time scales (Eden et al., 2015, Suckling et al., 2017). However, in the last 10 years there has been considerable progress in the so-called decadal prediction (Doblas-Reyes et al., 2012). That is, simulations of more than 10 years that are initiated every 5 years from initial states (Kim et al., 2012). These simulations are made traditionally from dynamical models, with the consequent initialization problems (Kirtman et al., 2013). Among others, the main problems presented by the dynamical models are:

1. Highly dependent variables: Since the climatic system is a non-linear dynamic system, the modelling depends on a high number of equations (equation of state, equation of energy, equation of continuity, etc).
2. Computational problems: Misconditioning of equations, imprecise definition of initial state, the need of parameterizations, truncation and related computational processes.
3. Lack of data effects on numerical initialization. Some regions of the world, such as Africa, oceans and polar regions, present a low density of surface stations.

Regarding the empirical prediction methods, some authors used linear regression-based models to forecast seasonal anomalies using surface or deep ocean temperatures (Doblas-Reyes et al., 2013). To improve the seasonal and decadal predictability, we propose to use of supplemental statistical models based on nonlinear techniques to predict teleconnection indexes. Teleconnection indexes are the physical links between different anomalies obtained from temporal and spatial patterns of variables such as sea level pressure, geopotential height or even precipitation (Hurrell 1995; López-Bustins et al. 2008). Different teleconnection indexes can be identify according to point/area differences or measures of climatic anomaly or climatic variability (e.g. main components). Some examples of most outstanding indexes are defined from the Atlantic Multidecadal Oscillation (AMO), El Niño Sourthern Oscillation (ENSO), or Artic Oscillation (AO). For Europe, the most commonly used are the Mediterranean Oscillation index (MOi), the Western Mediterranean Oscillation index (WEMOi), and SCAND (Barnston and Livezey, 1987). However, a new index is required to better understand the climatic variability of this region (because of its geographical complexity and size), that is the Upper Level Mediterranean Oscillation index (ULMOi). ULMOi is defined as the normalized difference of geopotential height at 500 hPa between a Balearic Sea window at west and northern Lybia at east (Redolat et al. 2018).
This technique was tested in a European project named RESilience to cope with Climate Change in Urban arEas (RESCCUE). The project aims to improve the seasonal-to-decadal prediction in order to assess climate-related impacts in three cities: Barcelona, Lisbon and Bristol.

2. STUDY AREA AND DATA

According to the RESCCUE project, a total of 817 weather stations were selected for three studied areas around Barcelona, Lisbon and Bristol. Observed data were collected for both atmospheric and oceanic variables from the Spanish State

Meteorology Agency (AEMet), the Portuguese Institute for Sea and Atmosphere (IPMA), the British MetOffice and the National Oceanic and Atmospheric Administration (NOAA). For the observed variables, the database consisted of temperature, precipitation, snowfall, wind, wave height and sea level. In order to apply the chosen statistical downscaling, it was enough to use at least 5 years of observed data (Ribalaygua et al., 2013). A set of tests were applied over all-time series: general consistency, outliers and inhomogeneities (Monjo 2016).

To analyse the main teleconnection and climate variability modes, 17 indexes were chosen for this study (Table 1). All of them were detrended and normalized with the standard deviation.

3. METHODOLOGY

3.1. Quasi-oscillation hypotheses

From a conceptual view, two hypotheses are assumed: (1) The climate system is a coupled dynamic system with small perturbations close to equilibrium. (2) The coupling factor between the variables is small and almost constant. Thus, temporal (t) variation of each index x_i can be considered as a quasi-oscillation, i.e. a perturbation term plus a coupling term,

$$dx_i = \frac{\partial x_i}{\partial t} dt + \frac{\partial x_i}{\partial x_j} dx_j = \underbrace{i\,\omega_i x_i dt}_{perturbation} + \underbrace{f_i^j dx_j}_{coupling\ term}$$

where ω_i is the proper oscillation frequency and $f_i^j = \partial x_i / \partial x_j$ is the factor coupling of x_i with respect to x_j.

3.2. Harmonic fitting

In order to model the temporal evolution of each teleconnection index, simple harmonic functions are obtained from three stages corresponding to the fitting parameters: oscillation frequency, initial phase/time and amplitude.

In the first stage, periodogram was taken from Fast Fourier Transform (FFT) and filtered using Monjo's spell function (Monjo, 2016). Specifically, a factor of 2 was considered to determine dry/wet spells in the periodogram. Once the main oscillation frequencies are found, the initial phase was fitted according to nonlinear Newton algorithm applied to the sum of simple harmonic functions (normalized to the unity). In the third stage, significant amplitudes are fitted from a backward stepwise regression.

3.2. Temporal cross-validation

Each teleconnection index is simulated using the corresponding harmonic model according to the above section. Then, two time periods were considered: the training and the validation windows (cross-validation). Both time windows were backward moving to cross-validate each harmonic model (hindcast). Several window sizes were tested to find the optimal window size for training the harmonic model of each teleconnection index.

Index	Start	End	Used variable	Used region	Reference
ENSOi	1870	2015	SST	El Niño 3.4 (170ºW to 120º W-EQ)	NOAA (2017)
NAOi	1950	2015	P	Ponta Delgada–Reykjavik	NOAA (2017)
AOi	1950	2015	P	Atlantic 20ºN to North Pole	NOAA (2017)
AMOi	1870	2015	SST	Atlantic 0º–60ºN and 7.5ºW–7.5ºE	NOAA (2017)
MOi	1948	2015	P	Algiers–Cairo	CRU (2017)
WeMOi	1821	2013	P	Padua–San Fernando	UB (2017)
PDOi	1854	2016	SST	Pacific 20ºN	JISAO (2017)
SAHEL-Pi	1901	2016	R	Africa 8º to 20ºN – 20ºW to 10ºE	Mitchell (2016)
GSNWi	1966	2010	SST	Atlantic 55º to 75ºW - 35ºN	Taylor (2011)
GJSL	1871	2015	WS	45ºN to North Pole	Redolat et al. (2018)
AJSL	1871	2015	WS	Atlantic 4º to 53ºW – 45ºN to North Pole	Redolat et al. (2018)
ULMO	1979	2015	GH	Balearic window - Libyan window	Redolat et al. (2018)
EAWR	1950	2017	GH	North Atlantic-North Caspian Sea 60°W–60°E, 20– 80°N	NOAA (2017)
SCAND	1950	2017	GH	Scandinavia-Northwest Mongolia	NOAA (2017)
EA	1950	2017	GH	55ºN, 20-35ºW | 25-35ºN - 0-10ºW	NOAA (2017)
QBO	1948	2017	WS	Equator at 30 mb	NOAA (2017)
NHIE	1978	2017	I	Ice sea in North Hemisphere	NSIDC (2017)

Table 1. Indexes used in this study, with period data, variable and area that define them and reference.

On the other hand, the temperature and precipitation variances of each station were separately analysed to be explained by the best set of teleconnection indexes (predictors). To this purpose, a backward stepwise regression was applied.

Finally, temperature and precipitation hindcasts were performed to validate their predictability according the several time horizon and time resolution of prediction.

The cross-validation provided performance statistics such as Standardized Absolute Error (SAE) and Standardized Square Error (SSE), which correspond to the Explained Anomaly (EA), and Explained Variance (EV) respectively.

4. RESULTS AND DISCUSSION

From the harmonic fitting an expected result was found: The greater the amplitude, the greater the predictability. AMO and WEMO are some examples of great amplitudes for great periods (Figure 1).

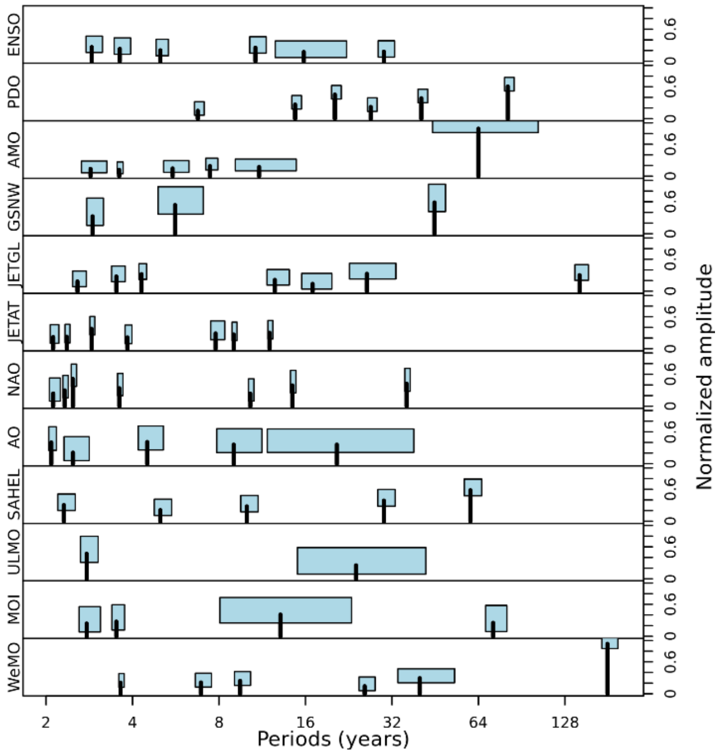

Figure 1. Filtered periodogram: normalized amplitude boxplot for periods of several indexes.

Regarding to the cross-validation applied to each index, important differences were found depending on the origin of variable used: On the one hand for oceanic indexes, the greater training window, the greater is the explained variance. In contrast for atmospheric indexes, the smaller moving window, the greater explained variance.

The selection of the best indexes also leaded interesting results. According to the *p*-value of the multi-model, the greatest skill for explaining temperature was obtained by the AMOi, followed by ULMOi. While ULMOi obtained the best result for precipitation in the Mediterranean basin.

According to the SAE obtained from precipitation and temperature hindcasts, results depend on the temporal resolution of prediction. For example, the greatest variance explained for temperature is achieved for decadal resolution (Figure 2), as opposed to precipitation, where the highest explained variance in seasonal than decadal projections (Figure 3). This is due to the great natural variability of rainfall over short time periods. Since teleconnection indexes represent physical predictors, their ability is to explain greater variance and thus they can be used to find the influence or contribution of the natural variability modes on current climate change.

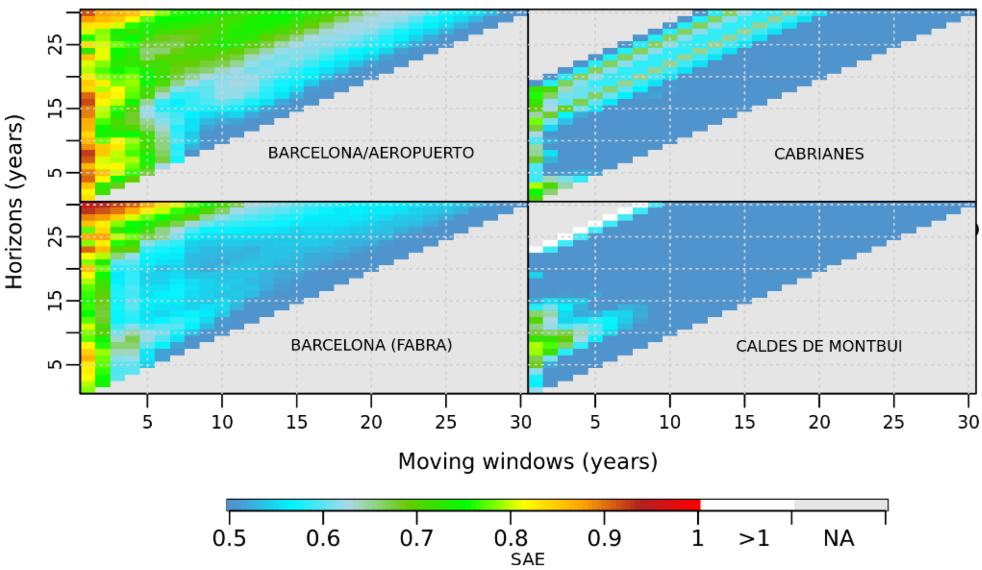

Figure 2. SAE for control stations in Catalonia for the temperature variable in decadal prediction

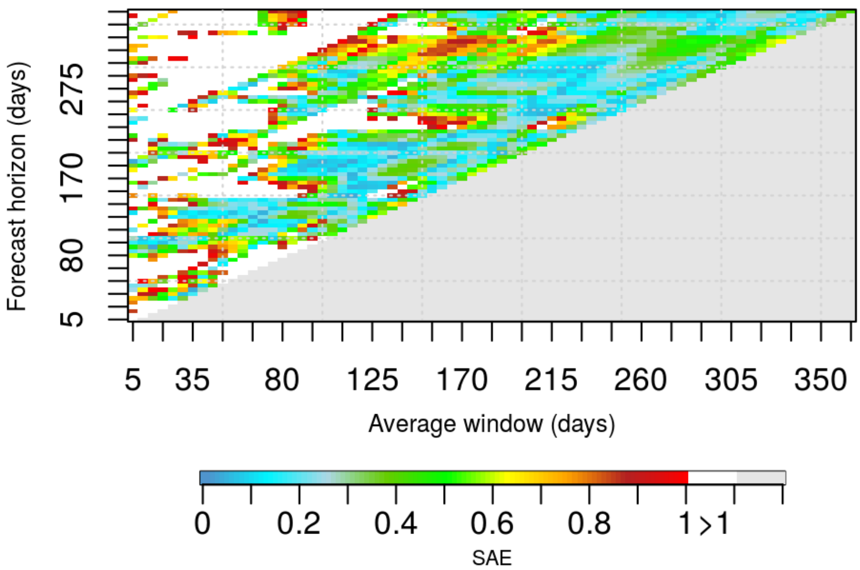

Figure 3. SAE for Barcelona Airport observatory, for precipitation variable in seasonal prediction.

In terms of statistical significance for temperature between indexes and observations across the seasons of the year, a great number of significant cases was found for ULMO following forward by MOi can be seen. This high significant cases is more remarkable during the equinoxes, being weaker in winter and especially in summer

(Figure 4). In the case of precipitation (not shown), the statistical significant cases is drastically reduced, although good results were obtained for certain Mediterranean observatories, and mainly for two indices, firstly "MOi" followed closely by "ULMO". The other indices performed significantly worse.

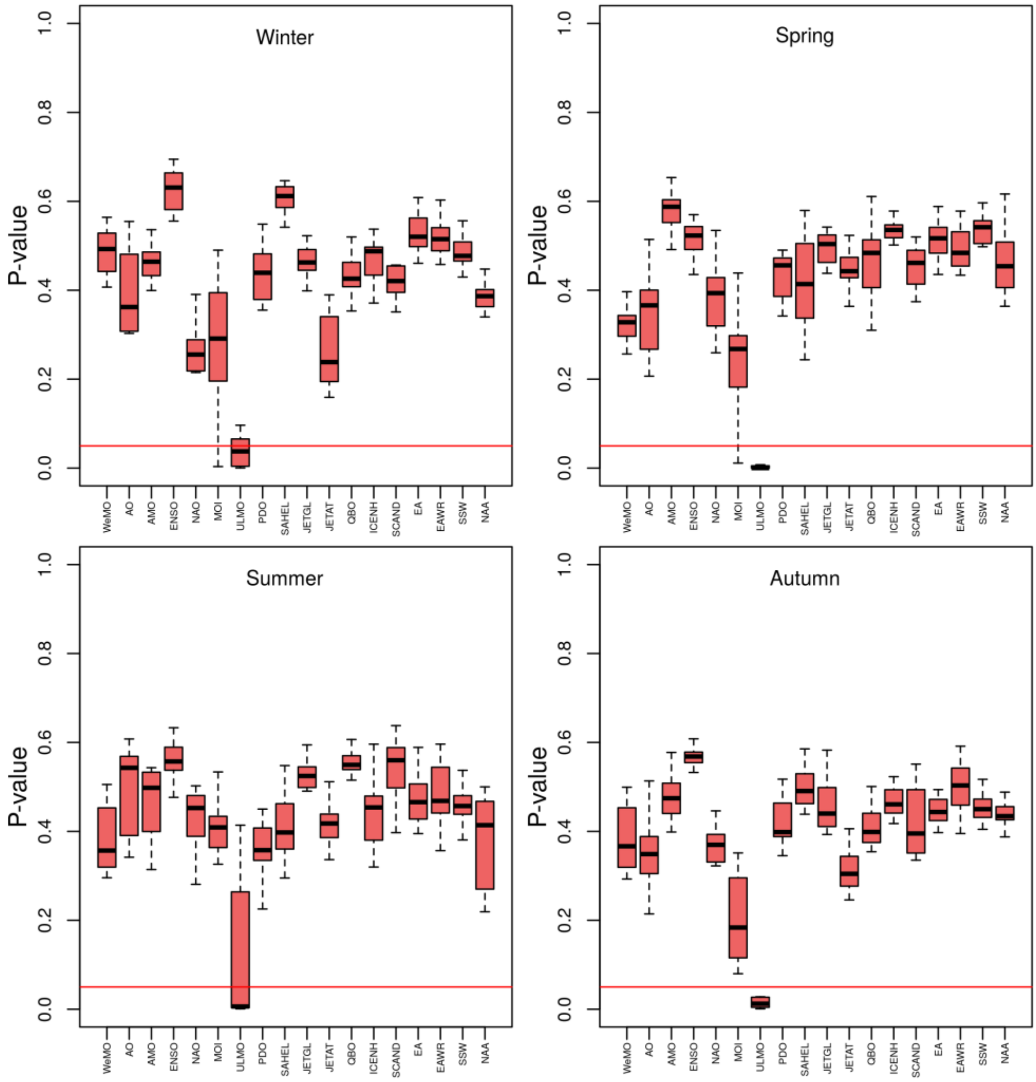

Figure 4.Pearson correlation p-value of the predictions of temperature according to each season of the year.

5. SUMMARY

As preliminary conclusions, it can be summarized that:

1. Dynamical models present difficulty for simulating oceanic oscillations (data scarcity) (Kim et al. 2012, Doblas-Reyes et al. 2013). It is suggest to be complemented with teleconnection-based statistical models. However, modelers are working in some improvements in the internal variability simulation by dynamical techniques for the CMIP6 (Boer, G et al 2016).
2. The climate is a dynamical system self-coupled with small perturbations: The quasi-oscillation approach can be considered.
3. Oscillations with large amplitudes and slow transitions are more predictable: the oceanic oscillations.
4. Double application of the study: seasonal/decadal prediction and attribution of climate variability at multi-annual timescales; could be useful to distinguish between natural and anthropogenic contribution to climate change.

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REFERENCES

Barnston A.G. and Livezey R.E. (1987). Classification, Seasonality and Persistence of Low-Frequency Atmospheric Circulation Patterns. Monthly Weather Review 115(6):1083-1126 DOI: 10.1175/1520-0493(1987)115.

Boer, G. J., Smith, D. M., Cassou, C., Doblas-Reyes, F., Danabasoglu, G., Kirtman, B., Kushnir, Y., Kimoto, M., Meehl, G. A., Msadek, R., Mueller, W. A., Taylor, K. E., Zwiers, F., Rixen, M., Ruprich-Robert, Y., and Eade, R.: The Decadal Climate Prediction Project (DCPP) contribution to CMIP6, Geosci. Model Dev., 9, 3751-3777, https://doi.org/10.5194/gmd-9-3751-2016, 2016.CRU (2018). Mediterranean Oscillation Index (MOI) data. Climate Research Unit. Link: https://crudata.uea.ac.uk/cru/data/moi/ (accessed on 31 May 2018).

Doblas-Reyes, F.J.; Andreu-Burillo, I.; Chikamoto, Y.; García-Serrano, J.; Guemas, V.; Kimoto, M.; Mochizuki, T.; Rodrigues, L.R.L.; van Oldenborgh, G.J. (2012). Initializednear-term regional climatechangeprediction. NatureCommunications 4.

Doblas-Reyes, F. J., García-Serrano, J. , Lienert, F. , Biescas, A. P. and Rodrigues, L. R. (2013), Seasonal climate predictability and forecasting: status and prospects. WIREs Clim Change, 4: 245-268. doi:10.1002/wcc.217

ECA (2018) European Climate Assessment & Dataset. Link: http://www.ecad.eu/dailydata/index.php (accessed on 10 June 2018).

Eden, J., van Oldenborgh, G. J., Hawkins, E., & Suckling, E. B. (2015). A global empirical system for probabilistic seasonal climate prediction. Geoscientific Model Development, 8(12), 3947-3973

JISAO (2018) Joint Institute for the Study of Atmosphere and Ocean http://jisao.washington.edu/data_landing (accessed on 31 May 2018).

Kim, H.M.; Webster, P.J.; Curry, J.A. (2012). Evaluation of short-termclimate change prediction in multi-model CMIP5 decadal hindcasts. Geophys. Res. Lett. 39 L10701.

Kimoto, M.; Meehl, G.A. (2013). Near-term Climate Change: Projections and Predictability. IPCC.

Kirtman, S.B.; Power, S.B.; Adedoyin, J.A.; Boer, G.J.; Bojariu, R.; Camilloni, I.; Doblas-Reyes, F.J., Fiore, A.M.; Kimoto, M.; Meehl, G.A.; Prather, M.; Sarr, A.; Schär, C.; Sutton, R.; van Oldenborgh, G.J.; Vecchi G.; Wang, H.J. (2013). Near-term Climate Change: Projections and Predictability. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 953–1028, doi:10.1017/CBO9781107415324.023.

Mitchell, T. (2016) Sahel precipitation index, Joint Institute for the Study of the Atmosphere and Ocean, Univ. of Washington, doi:10.6069/H5MW2F2Q. Link: http://research.jisao.washington.edu/data_sets/sahel/ (accessed on 10 June 2018).

Monjo, R. (2016). Measure of rainfall time structure using the dimensionless n-index. Climate Research, 67: 71-86. doi: 10.3354/cr01359.

NOAA (2018) Climate Indices. Enlace: http://www.esrl.noaa.gov/psd/data/climateindices/list/ (accessed on 31 May 2018).

Redolat, D.; Monjo, R.; Lopez-Bustins, J.A.; Martin-Vide, J. (2018). Upper-Level Mediterranean Oscillation index and seasonal variability of rainfall and temperature. Theoretical and Applied Climatology. doi: 10.1007/s00704-018-2424-6.

Ribalaygua J., et al. (2013). Description and validation of a two-step analogue/regression downscaling method. Theoretical and Applied Climatology 114: 253-269. doi:10.1007/s00704-013-0836-x

Suckling, E. B., van Oldenborgh, G. J., Eden, J. M., & Hawkins, E. (2017). An empirical model for probabilistic decadal prediction: global attribution and regional hindcasts. Climate Dynamics, 48(9-10), 3115-3138.

Taylor, A.H. (2011). The Dance of Air and Sea: How Oceans, Weather and Life Link Together. Oxford University Press, 288 pp.

UB. (2017). Western Mediterranean Oscillation indes. University of Barcelona. Link: http://www.ub.edu/gc/2016/06/08/wemo/ (accessed on 10 June 2018).

Zhang, Y.; Wallace, J.M.; Battis, D. S. (1997). ENSO interdecadalvariability. J Climate 10:1004-1020.