ERA4CS Joint Call on Researching and Advancing Climate Services Development – Topic B
(GRANT AGREEMENT 689029)

European Climate Observations, Monitoring and Services initiative (2)

Milestone M2.3

Preliminary version of empirical forecast systems available for comparison with dynamical forecasting systems

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Summary

In the frame of MEDSCOPE project, which mainly aims at improving predictability on seasonal timescales over the Mediterranean area, a seasonal forecast empirical model making use of new predictors based on a collection of targeted sensitivity experiments is being developed. Here, a first version of the model is presented. This version is based on multiple linear regression, using global climate indices (mainly global teleconnection patterns and indices based on sea surface temperatures, as well as sea-ice and snow cover) as predictors. The model is implemented in a way that allows easy modifications to include new information from other predictors that will come as result of the ongoing sensitivity experiments within the project.

Given the big extension of the region under study, its high complexity (both in terms of orography and land-sea distribution) and its location, different subregions are affected by different drivers at different times. The empirical model makes use of different sets of predictors for every season and every subregion. Starting from a collection of 25 global climate indices, a few predictors are selected for every season and every subregion, checking linear correlation between predictands (temperature and precipitation) and global indices up to one year in advance and using moving averages from two to six months. Special attention has also been payed to the selection of predictors in order to guaranty smooth transitions between neighbour subregions and consecutive seasons. The model runs a three-month forecast every month with a one-month lead time.

Comentado [ERC1]: Creo que habitualmente se escribe junto en inglés: subregions. También sub-regions. Separado lo he visto pocas veces.

1 Introduction

Dynamical models for seasonal forecasting have noticeably improved during the last decades mainly due to the advance both in the estimate of the atmospheric initial conditions as well as the model physics supported further by computing capabilities. However, they still show low skill over extratropical latitudes. The surroundings of the Mediterranean Sea are specially affected by this low skill, due either be to inherent lack of predictability or to errors in forecasting systems, being exacerbated by its complex orography and land-ocean distribution. Besides, the Mediterranean region is located in a transition zone between the arid belt of Northern Africa and the temperate zones over Europe. Another distinctive feature is the type of precipitation: over most of the domain, a high fraction of annual precipitation is convective, implying high spatial and temporal variability. It is not infrequent that average expected precipitation for a three months period can be reached in one single day for particularly intense events. In this context, the Mediterranean Services Chain based On Climate PrEdictions (MEDSCOPE) project (see https://www.medscope-project.eu) and others, developed under initiatives like the European Research Area for Climate Services (ERA4CS) (see http://www.jpi-climate.eu/ERA4CS) aim at improving Climate Services over this region, searching for new sources of predictability and developing different tools and products. In particular, one of the MEDSCOPE work packages consists of a collection of sensitivity experiments designed to explore new sources of predictability that may lead to improvements in our understanding of mechanisms and processes involved at seasonal timescales. As result of the sensitivity experiments conducted within the

MEDSCOPE project, new specific predictors will be proposed for the Mediterranean region. A by-product of this exploration will be the development of an empirical seasonal forecasting system bringing together predictors coming from new sources of predictability unveiled by the sensitivity experiments.

1.1 Choosing the model

Here we present a preliminary (beta) version of the empirical seasonal forecasting system specifically designed for the Mediterranean region. The purpose of this beta version is twofold: first, establish a reference version based on standard predictors making use of known sources of predictability and, second, compare its skill over the Mediterranean with the state-of-the-art dynamical systems. In this way, we can easily incorporate new predictors as they arise within the project and estimate the skill of future improvements with respect to this beta version. Eden et al. (2015) developed a global empirical seasonal forecasting system based on Multi Linear Regression (MLR), using a few global climate indices as predictors, and producing a probabilistic output using the residuals from regression. This system shows ability to produce skilful forecasts over several world regions, despite the reduced number of predictors used. Wang et al. (2017) showed, using MLR too, that a careful selection of predictors can produce skilful prediction of winter NAO.

The beta version of the empirical seasonal forecasting system here described will follow the same procedure based on MLR suggested by these two papers as this kind of models only requires very modest computing resources and has the additional advantage of being easy to modify. The second version of the empirical seasonal forecasting system, incorporating results from MEDSCOPE findings, will be developed and evaluated in the second part of the project.

2. Rationale

2.1. Definition of subregions

Given the extension of the Mediterranean domain, its great complexity (both orographic and land-ocean distribution), and location, subregions within the domain are affected by different factors at different times of the year. In order to improve the skill of the system, the empirical model will use different sets of predictors for every subregion and every season. However, one issue with this type of models is that they can be quite noisy showing very different results for neighbour grid points. So, as a compromise between selecting the best predictors for every point and forecasting synoptic scale anomaly patterns, the domain is divided in subregions. A different set of predictors will be selected for each subregion. Additionally, and to avoid abrupt transitions in space and time, predictors will be restricted to partially match among neighbour subregions and consecutive seasons (for example, January-March and February-April). To further smooth out transitions among subregions, they have been defined with a high amount of overlap. Those grid points belonging to more than one subregion will be assigned a weighted average from values from different subregions, based on distance to respective borders.

Subregions have been defined based on a principal components analysis of annual precipitation, taking the three first empirical orthogonal functions (EOFs) into account. Subregions have been defined seeking a compromise between encompassing main anomaly patterns from the three first precipitation

EOFs, and main land areas and countries. Figure 1 depicts the proposed subregions, showing the EOFs as background.

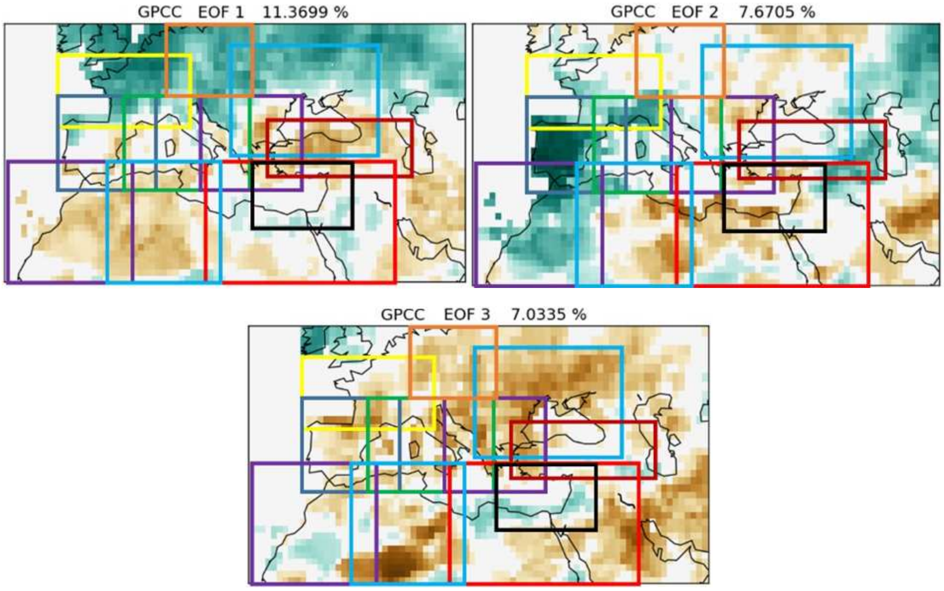


Figure 1: Domains proposed in this study. Plots of the first three Empirical Orthogonal Functions of annual precipitation (GPCCv7 data) over the selected zones or domains.

2.2 Choosing predictands

As we intend to deliver synoptic scale anomaly patterns, low- resolution predictands will be selected for this beta version of the system. Precipitation data from the Global Prediction Climate Centre (GPCC) dataset (Schneider et al. (2017)) will be used (2.5 degree version). Data will be a blend of GPCC v7 (until 2013) and its monitoring (v5) from 2014 onwards. Surface temperature will be obtained from the ERA-interim reanalysis (Dee et al. (2011)). In both cases, predictands will consist of the three months average for every season and grid point. The empirical model will be run every month with one- month lead time, i.e., computing a forecast for the following season (three months) and for both predictands. For example, in January, the forecast will be calculated for February-March-April.

2.3 Exploration of predictors

This beta version of the empirical model will exclusively make use of global climate indices provided by external sources. The initial proposal includes 25 monthly time series of indices associated to global teleconnection patterns, SST-based patterns (from Pacific, Atlantic and Indian oceans), ocean heat content, sea-ice and snow cover (table 1).

AAO	Antartic Oscillation	http://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/ aao/monthly.aao.index.b79.current.ascii
AO	Arctic Oscillation	http://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/ monthly.ao.index.b50.current.ascii
NAO	North Atlantic Oscillation	https://climexp.knmi.nl/data/icpc_nao.nc
EA	East Atlantic Pattern	http://climexp.knmi.nl/data/icpc_ea.nc
EA/WR	East Atlantic/Western Russia	http://climexp.knmi.nl/data/icpc_ea_wr.nc
SCAND	Scandinavia Pattern	ftp://ftp.cpc.ncep.noaa.gov/wd52dg/data/indices/scand_index.tim
SAM	Southern Annular Mode	http://www.nerc-bas.ac.uk/public/icd/gjma/newsam.1957.2007.txt
WP	West Pacific Pattern	ftp://ftp.cpc.ncep.noaa.gov/wd52dg/data/indices/wp_index.tim
PDO	Pacific Decadal Oscillation	https://www.ncdc.noaa.gov/teleconnections/pdo/data.csv
MEI	Multivariate ENSO Index	https://www.esrl.noaa.gov/psd/enso/mei/table.html
SOI	Southern Oscillation Index	http://www.cpc.ncep.noaa.gov/data/indices/soi
Niño12	El Niño Index, región 1+2	https://climexp.knmi.nl/data/iersst_nino12a.nc
Niño34	El Niño Index, región 3.4	https://climexp.knmi.nl/data/iersst_nino3.4a.nc
Niño3	El Niño Index, region 3	https://climexp.knmi.nl/data/iersst_nino3a.nc
Niño4	El Niño Index, región 4	https://climexp.knmi.nl/data/iersst_nino4a.nc
q300	Heat content over first 300m of the Pacific equatorial band	https://climexp.knmi.nl/data/icpc_eq_heat300.nc
Sn_EuA	Snow Cover Over Eurasia	https://climate.rutgers.edu/snowcover/files/moncov.eurasia.txt
Sn_NA	Snow Cover Over North America	https://climate.rutgers.edu/snowcover/files/moncov.namgnld.txt
Sn_NH	Snow Cover Over North Hemisphere	https://climate.rutgers.edu/snowcover/files/moncov.nhland.txt
DMI	Dipole Mode Index	https://climexp.knmi.nl/data/idmi_ersst.nc
SEIO	South Eastern Indian Ocean	https://climexp.knmi.nl/data/iseio_ersst.nc
TNA	Tropical North Atlantic	https://www.esrl.noaa.gov/psd/data/correlation/tna.data
TSA	Tropical South Atlantic	https://www.esrl.noaa.gov/psd/data/correlation/tsa.data
TASI	Calculated from ERSSTv5, NTA (average 20W-40W, 5N-20N) – SAT (average 15W-5E,20S-5S).	https://climexp.knmi.nl/NCDCData/ersstv4.nc
WHWP	Western Hemisphere warm Pool	https://www.esrl.noaa.gov/psd/data/correlation/whwp.data

Table 1. Climate indices tested as predictors.

Additionally, for each index, a new monthly time series is generated calculating the incremental value from the previous month (e.g., February value would be February minus January). The purpose of such incremental series is to try to find additional sources of predictability by analysing if a rapid change in the state of a certain indicator could be linked to anomalous atmospheric circulation. Before exploring these 50 indices (25 climate indices plus their 25 incremental series), moving averages from two to six months are applied, to better capture mechanisms from different time scales.

To check if one of these indices can be considered a predictor for a certain area, linear correlation between monthly values of the index and seasonal average of the predictand is calculated for every grid point of the area, checking the percentage of grid points that overpass certain threshold (significant correlation at 90%) for correlation. For one particular season, correlation between the predictand value and the index is computed applying different lead times (from one to twelve months). Correlation is also computed for six different options of moving average (from no moving average applied up to six months moving average). So, for a particular index and season, a table of predictors (see Table 2) will be obtained, having as many columns as lead time values and as many rows as moving average options.

GPCC		JFM									FMA								
	mv.avg \ lead	-2	-3	-4	-5	-6	-7	-8	-9	-10	-2	-3	-4	-5	-6	-7	-8	-9	-10
DMI	1M	12	18	12	24	3	3	6	0	12	0	15	18	18	27	18	6	9	0
	2M	0	18	18	18	24	6	6	0	3	0	9	18	15	30	21	15	3	0
	3M	0	0	24	24	24	15	9	0	0	0	0	15	15	18	21	21	9	0
	4M	0	0	0	24	27	18	12	3	0	0	0	0	15	18	21	21	15	3
	5M	0	0	0	0	30	18	18	9	0	0	0	0	0	18	18	21	24	18
	6M	0	0	0	0	0	27	21	18	6	0	0	0	0	0	18	18	18	21
incr_DMI	1M	9	9	0	15	12	0	12	9	9	18	0	12	3	9	0	21	6	3
	2M	0	6	0	0	27	3	6	21	6	0	18	0	15	3	24	15	3	15
	3M	0	0	12	3	0	12	6	12	18	0	0	15	3	0	12	42	0	3
	4M	0	0	0	0	15	3	18	18	9	0	0	0	24	0	3	21	15	6
	5M	0	0	0	0	12	9	9	33	15	0	0	0	0	6	0	12	3	12
	iberia	0	0	0	0	0	12	18	15	27	0	0	0	0	0	3	6	15	12

Table 2. Correlation table of Dipole Mode Index (DMI) and its incremental series and January-March and February-April seasons for precipitation.

Bearing in mind the known relative low predictability for the area studied, this procedure will try to unveil the best possible signal that a climate index can offer as a predictor playing with different lead times and moving averages. Considering correlation data from the different climate indices, and applying the restrictions proposed for continuity among regions, a set of predictors is selected for every region (see Table 3).

	Morocco	Iberia	France	Central Europe	Italy	Algeria Tunisia	Lybia	Balkans	East Europe	Turkey	East Mediterranean
JFM	I_AAO_S EA_ON TNA_July I_Sn_Na_SO DMI_SON	I_AAO_JJAS EA_JJAS EA_ON DMI_SON SOI_JJ	EA_SON I_AAO_JJAS EA_JJAS SOI_JJ I_Sn_EuA_Jun	AAO_Ag SOI_JJ I_AAO_S EA_ON I_SnNa_O I_SOI_O	EA_ON I_Sn_Na_O SOI_JJ I_Sn_EuA_O DMI_ASO I_AAO_S	NAO-N Sn_NA_O I_Sn_Na_SO SOI_JJ I_Niño4_N	NAO_JA I_Sn_Na_SO TNA_ON I_Niño4_N	SOI_JJ EA_SON AO_Jul I_Sn_EuA_SO Niño3_MJ	SOI_JJ EA_SON NAO_N DMI_May I_MEI_N	SOI_Jul EA_SON AO_Jul Niño34_Jul	SOI_JJ NAO_JA EA_SON I_MEI_N Niño12_Jun
FMA	I_AAO_S NAO-OND I_Niño4_N EA_OND TNA_July TNA_D I_Sn_Na_SO DMI_SON	I_AAO-JJAS NAO-OND EA_OND TNA_D DMI_SON SOI_JJ I_Niño4_N	I_AAO_JJAS NAO-OND I_Niño4_N TNA_D SOI_JJ I_Sn_EuA_Jun	SOI_JJ I_AAO_S I_SnNa_O I_SOI_O	I_Niño4_N I_Sn_Na_O SOI_JJ EA_ON DMI_ASO I_AAO_SON	NAO-ND Sn_NA_O I_Sn_Na_SO SOI_JJ I_Niño4_ND TNA_ND	NAO_JA I_Sn_Na_SO TNA_ON I_SOI_O I_Niño4_N EA/WR_O	EA_SON AO_Jul I_Sn_EuA_SO Niño3_MJ I_MEI_N	SOI_JJ EA_SON NAO_ND DMI_May I_MEI_N	SOI_Jul EA_SON I_Sn_EuA_S Niño34_Jul	NAO_JA EA_SON I_MEI_N Niño12_Jun
MAM	NAO-ONDE I_Niño4_N TNA_July TNA_DE I_Sn_Na_SO DMI_SON	NAO-ONDE I_Niño4_N TNA_July TNA_DE I_TNA_ND DMI_SON SOI_JJ	NAO-ONDE I_Niño4_N TNA_July TNA_DE SOI_JJ	SOI_JJ I_AAO_SON I_SnNa_O TNA_DE I_SOI_O	I_Niño4_N TNA_July TNA_DE SOI_JJ EA_ON DMI_ASO I_AAO_SON	NAO-ND Sn_NA_O I_Sn_Na_SO SOI_JJ I_Niño4_ND TNA_ND	NAO_JA I_Sn_Na_SO TNA_ON I_SOI_O DMI_E EA/WR_O	AO_Jul I_Sn_EuA_SO Niño3_MJ I_MEI_N I_SCAND_DE	EA_SON NAO_ND DMI_May I_MEI_N	NAO_JJA SOI_Jul EA_SON I_Sn_EuA_S Niño34_Jul	NAO_JA EA_SON I_MEI_N Niño12_Jun
AMJ	NAO-ONDE I_Niño4_N TNA_July TNA_DE DMI_SON I_NAO_EF	NAO-ONDE TNA_July TNA_DE DMI_SON I_TNA_ND I_NAO_EF SOI_JJ	NAO-ONDE I_Niño4_N TNA_July TNA_DE TSA_F I_NAO_EF SOI_JJ I_Sn_EuA_EF	SOI_JJ TNA_DE TNA_AS NAO_EF I_AAO_NDE	I_Niño4_N TNA_July TNA_DE EA_ON	NAO-ND Sn_NA_O I_NAO_EF I_SOI_F SOI_JJ I_Niño4_ND TNA_ND	I_Niño3_NDE I_Sn_Na_SO TNA_ON I_SOI_O DMI_E EA/WR_O	I_Niño3_NDE AO_Jul I_Sn_EuA_SO I_MEI_N I_AAO_NDE I_SCAND_DE	NAO_ND AO_EF I_MEI_N I_AAO_NDEF	NAO_JJA I_Sn_EuA_S Niño34_Jul I_Niño4_F	NAO_JAS I_MEI_N I_Niño4_F SAM_ONDE I_NAO_F
MJJ	TNA_July TNA_DE I_NAO_EF TSA_FM	TNA_July NAO-NDE i_EA/WR_FM TNA_DE I_TNA_NDE	TNA_July TSA_FM I_NAO_EF I_Sn_EuA_EF	TNA_E TNA_AS NAO_EF I_AAO_NDE SAM_O	TNA_July EA_ON I_AAO_NDE EA/WR_E SAM_O	Sn_NA_O I_NAO_EF I_SOI_F TNA_DEF TSA_FM	I_Niño3_NDE I_SOI_O DMI_E EA/WR_O PDO_N	I_Niño3_NDE I_MEI_N DMI_Mar I_AAO_NDE I_SCAND_DE	AO_EF I_MEI_N DMI_E I_AAO_NDEF	NAO_JJA Niño34_Jul DMI_Mar I_Niño4_F	NAO_JAS I_Niño4_F I_EA/WR_Marzo Sn_EuA_E DMI_E

		I_NAO_EF I_EA_O									SAM_ONDE I_NAO_F
JJA	TNA_DE I_NAO_EF I_SOI_EFMA TSA_FM	i_EA/WR_DEFMA TNA_DE I_NAO_EF I_SOI_F I_MEI_ASON i_q300_OND i_SAM_NDE	i_EA/WR_DEFMA i_q300_SONDE i_SAM_NDEF TSA_AS TSA_FM I_NAO_E I_Sn_EuA_EF	NAO_EF I_AAO_NDE SAM_O I_Sn_EuA_E	EA_ON I_AAO_NDE EA/WR_E SAM_O I_SnEuA_MA	I_NAO_EF I_SOI_F TNA_DEF TSA_FM	I_Niño3_NDE DMI_E EA/WR_O PDO_N	I_Sn_EuA_E I_Niño3_NDE I_MEI_N DMI_Mar I_AAO_NDE I_SCAND_DE I_Sn_NH_Mayo	AO_EF I_MEI_N DMI_E I_AAO_NDEF I_Sn_NH_Mayo	NAO_JJA DMI_Mar DMI_E I_Niño4_F I_EA/WR_MA	I_Niño4_F I_EA/WR_MA Sn_EuA_E DMI_E SAM_ONDE I_NAO_F
JAS	TNA_DE I_NAO_EF I_SOI_EFMA TSA_FM	EA/WR_DEFMAM AAO_DE I_SN_HN_E I_SAM_EFMA I_snow_NH_E i_whwp_ON i_niño3_ONDEFM i_q300_SON I_SOI_EF	i_EA/WR_NDEF i_q300_SOND i_AAO_NDE i_SAM_NDEFM iniño3_O i_whwp_SON I_Sn_EuA_E	NAO_EF I_AAO_NDE SAM_O I_Sn_EuA_E	I_AAO_NDE EA/WR_E SAM_O DMI_D I_SnEuA_EFM	I_NAO_EF I_SOI_F TSA_FM I_EA/WR_OND	I_NAO_EF I_EA/WR_OND EA/WR_O PDO_N I_niño3_FMA	I_Sn_EuA_E DMI_Mar I_SCAND_DE I_NAO_E PDO_N I_Sn_NH_Mayo	I_MEI_N DMI_E I_AAO_NDEF I_Sn_NH_Mayo	DMI_E I_Niño4_F I_EA/WR_MA I_NAO_FM EA_FM	I_Niño4_F I_EA/WR_MA DMI_D I_NAO_F PDO_N
ASO	PDO_EF I_niño_3_DEFM DMI_MJ TNA_DE I_SOI_EFMA TSA_FM	I_EA/WR_EFMAM SAM_D AAO_DE I_Sn_HN_E DMI_NDE i_q300_ON i_niño3_SONDEF i_MEI_FMA i_whwp_ON	I_AAO_EFMA DMI_NDE I_EA/WR_EFMAM i_q300_ON i_DMI_FMAMJ q300_Jun i_Sn_NH_E SEIO_J I_Sn_EuA_E	EA/WR_E EA_F I_Sn_EuA_E DMI_EF	EA/WR_E DMI_D I_SnEuA_EFM I_EA_M	I_SOI_F SEIO_J SAM_DE I_EA/WR_OND	TNA_MA I_TASI_FM I_EA/WR_OND PDO_N I_NAO_F SAM_D I_niño3_FMA	I_Sn_EuA_E I_SCAND_DE I_NAO_E PDO_N I_Sn_NH_Mayo DMI_D EA_FM I_niño3_FMA	I_MEI_N DMI_E I_Sn_NH_Mayo I_MEI_Mayo EA_FM DMI_D	DMI_D I_EA/WR_MA TNA_FM I_MEI_Mayo I_NAO_FM EA_FM	I_EA/WR_MA Sn_EuA_E DMI_D I_NAO_F PDO_N I_MEI_MJ I_niño3_FMA

		I_AAO_EFMA I_SOI_EF									
SON	PDO_EF I_niño_3_DEFMA DMI_MJ TNA_DE I_SOI_FMA	AAO_D I_AAO_EFMA DMI_NDE Q300_JJ I_DMI_FMAMJJ I_MEI_DEFMAM I_Sn_EuA_E I_TASI_Mar DMI_AMJ I_SOI_EF	AAO_D I_AAO_EFMA DMI_NDE Q300_JJ Niño3_MA I_DMI_FMAJJ I_niño3_Jun I_MEI_DEFMAM I_TASI_Mar I_Sn_EuA_E	EA/WR_E EA_F I_Sn_EuA_E DMI_EF	EA/WR_E DMI_D I_SnEuA_EFM I_EA_M	SEIO_J I_niño3_FMA SAM_DE I_TASI_FM	TNA_MA I_TASI_FM I_NAO_F SAM_D I_niño3_FMA	I_Sn_EuA_E I_Sn_NH_Mayo DMI_D EA_FM TNA_JJ I_niño3_FMA	I_MEI_N I_Sn_NH_Mayo I_MEI_Mayo EA_FM DMI_D	DMI_D TNA_FM I_MEI_Mayo I_NAO_FM EA_FM TNA_JJ I_niño3_FMA I_WP_F	I_EA/WR_MA Sn_EuA_E DMI_D I_NAO_F I_MEI_MJ TNA_JJ I_niño3_FMA I_SCAND_FMA
OND	I_EA_FMAMJJ PDO_EF I_niño_3_DEFMA DMI_AMJ TNA_DE I_SOI_FMA	AAO_D I_AAO_EFMA I_EA_AMJ Q300_J I_MEI_DEFMAM I_TASI_Marzo DMI_DE DMI_AMJJ	I_AAO_EFMA I_EA_MAMJ AAO_D Q300_J I_MEI_DEFMAM I_TASI_Marzo I_Sn_EuA_Jun	I_EA_MAMJJ EA/WR_E EA_F DMI_EF TSA_F EA/WR_MAMJ	EA/WR_E DMI_D TSA_F EA/WR_MAMJ	SEIO_J I_niño3_FMA SAM_DE I_TASI_FM	TNA_MA SAM_MAM I_TASI_FM I_NAO_F I_niño3_FMA	I_Sn_EuA_E DMI_D EA_FM EA/WR_MAMJ TNA_JJ I_niño3_FMA	I_MEI_Mayo EA_FM TNA_JJ DMI_D I_niño3_FMA EA_JA	DMI_D TNA_FM I_MEI_Mayo EA_FM TNA_JJ EA_JA I_niño3_FMA I_WP_F	I_EA/WR_MA Sn_EuA_E DMI_D I_NAO_F I_MEI_MJ TNA_JJ EA_JA I_niño3_FMA I_SCAND_FMA

NDJ	I_AAO_S I_EA_FMAMJ I_niño_3_DEFMAM DMI_AMJJ I_SOI_FMA	I_AAO_S I_AAO_EFMA I_EA_AMJJ i_SAM_JJAS Sn_EuA-A I_SN_HN_EF DMI_AMJ	I_AAO_EFMA I_EA_MAMJ DMI_AMJJA I_Sn_EuA_Jun	I_EA_MAMJ EA/WR_E EA_F DMI_EF TSA_F EA/WR_MAMJ I_SAM_AMJ	I_AAO_S EA/WR_E TSA_F I_SAM_AMJJ EA/WR_MAMJ	SEIO_J I_niño3_FMA I_AAO_S SAM_MA I_TASI_FM	TNA_MA SAM_MAM I_TASI_FM I_NAO_F I_niño3_FMA	I_Sn_EuA_E EA_FM EA/WR_MAMJ TNA_JJ I_niño3_FMA	I_MEI_Mayo EA_FM TNA_JJ I_niño3_FMA EA_JA	DMI_E TNA_FM I_MEI_Mayo TNA_JJ EA_JA I_niño3_FMA I_WP_F	I_EA/WR_MA Sn_EuA_E I_MEI_MJ TNA_JJ EA_JA I_niño3_FMA I_SCAND_FMA
DJF	I_AAO_S I_EA_FMAMJ I_niño_3_DEFMAM DMI_AMJJ I_SOI_FMA	I_AAO_S I_EA_AMJJ i_SAM_JJAS Sn_EuA-AS DMI_AMJ	I_EA_MAMJ I_AAO_EF I_EA_AMJ DMI_AMJJA I_Sn_EuA_Jun	I_EA_MAMJ TSA_F EA/WR_MAMJ I_SAM_AMJ	I_AAO_S TSA_F I_SAM_AM EA/WR_MAMJ i_SAM_AMJJ	SEIO_J I_niño3_FMA I_AAO_S SAM_MA I_TASI_FM	TNA_MA SAM_MAM I_TASI_FM I_niño3_FMA	EA_FM EA/WR_MAMJ TNA_JJ I_niño3_FMA	I_MEI_Mayo TNA_JJ I_niño3_FMA EA_JA	EA_JA I_niño3_FMA I_WP_FM I_SOI_AMJ	I_EA/WR_MAM EA_JA I_SCAND_FMA I_SOI_AMJ

Table 3. Predictors selected for the different areas and seasons.

2.4 Running the model

The model will use multiple linear regression (MLR), as described in Wilks (2006), over every grid point, using the set of predictors selected for that specific region of study. Trend is removed before calculating regression and then added to regression results. In order to express the forecast in probabilistic terms, first, terciles are calculated for predictands at every grid point. Then, probabilities are assigned to every tercile, using a normal distribution, centred in the deterministic output of the MLR and using information from residuals to adjust its width. This distribution represents the expected probability density function (pdf) for the forecasted predictand value. The computation of the area below this curve and between observed terciles provides the probability of the forecasted value to be in every one of them (Eden et al. (2015)).

This procedure requires predictands to adjust to a normal distribution. As this is not the case with precipitation, square root is previously applied over this predictand, to transform it into a normal-like distribution (Pasqui et al. (2007)). Besides, every time it runs, the system performs a series of checks to ensure assumptions required to run this type of models are true, among them: no collinearity among predictors, no overfitting, and residuals to be distributed in a way they have normal distribution, don't experience autocorrelation and are homoscedastic.

2.5 Verification of results

The first step on analysing how the empirical model is performing against dynamical models resides in the verification of model forecasts. For this purpose, a hindcast for the period 1983-2014 is calculated. Regression is trained for same period, using "*Leave-One-Out"* technique (Wilks (2006)), excluding a total of five years from the series (two before and two after the year we are forecasting), to avoid autocorrelation. In section 3.3 several verification indices are calculated for this version of the empirical system, comparing values of the same indices calculated from dynamical models.

3. Results.

3.1 Precipitation forecast.

Figure 2 shows a few examples of forecasts maps for precipitation. Although some noise can still be seen over certain areas, observed patterns are synoptic scale and continuous, generally speaking. Borders are not evident, either, so forecast maps are reasonably shaped, and defined subregions and proposed constraints for predictors seem to work well. This example was for 2018 JAS, and anomaly patterns resemble in terms of structures and spatial variability what dynamical models proposed for that same season.

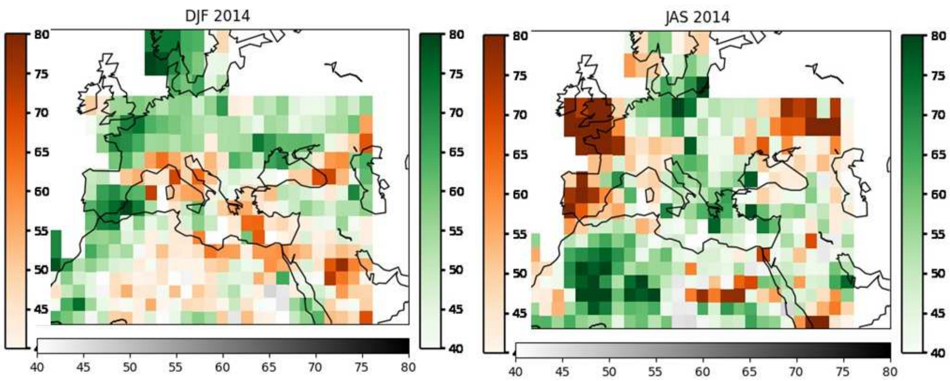


Figure 2: Example of precipitation forecasts. Probability for the most likely tercile is shown at every grid point. Green (orange) corresponds to upper (lower) tercile.

3.2 Temperature forecast.

In order to compare results, the empirical model is also run using temperature as predictand and the same predictors as for precipitation, under the assumption that same anomalous circulation captured by these predictors can affect to temperature as well. Results can be seen in Fig. 3. The same conclusions about the forecasts appearance also applies for temperature.

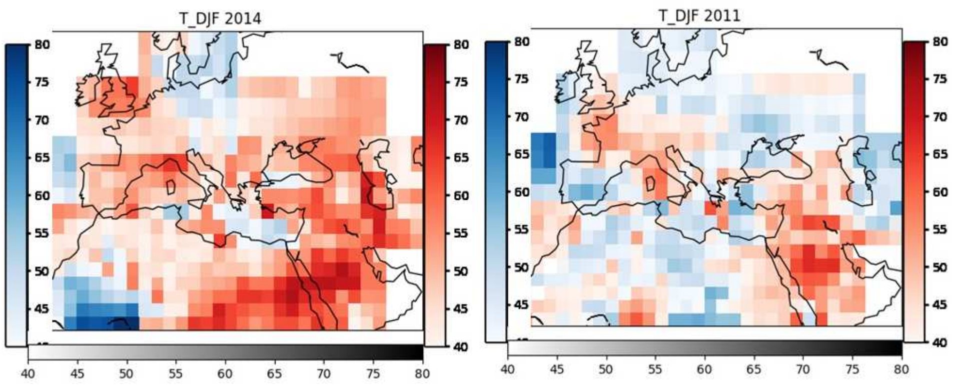


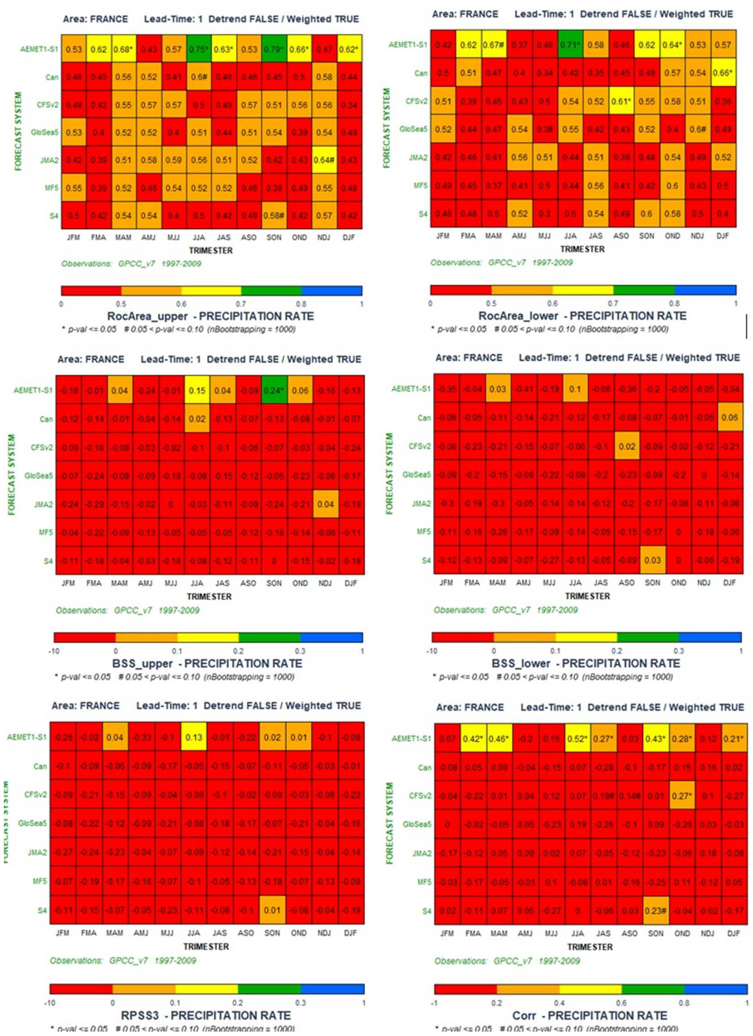
Figure 3: Example of temperature forecasts. Probability for the most likely tercile is shown at every grid point. Red (blue) corresponds to upper (lower) tercile.

3.3 Verification.

To compare the skill of this first version of the empirical model against state of the art dynamical models is necessary to select a period where hindcast data is available for all of them, to ensure differences in scores can't be explained by changes in predictability over the years. So, although hindcast is available for a longer period, skill is evaluated for period 1997-2009, using several verification indices: Ranked Probability Skill Score (RPSS) for terciles, Relative Operating Characteristic (ROC) and Brier Skill Score (BSS) for two events, as well as linear correlation for the deterministic output of MLR. Detailed definition of these scores can be found in Wilks (2006). Table 4 shows scores for several areas, as an example. Results from the empirical system are compared to the main dynamical models for seasonal forecasting at the time the system began to being developed: ECMWF system 4, Météo-France system 5, Met-Office system 9 (GloSea5), National Center for Enviromental Prediction (NCEP) system version 2, Canadian Seasonal to Inter-annual Prediction System (CanSIPS) and Japanese Seasonal Forecasting System 2.

Generally speaking, dynamical models show lower skill over the western part of the domain, and the empirical system seems to have better skill over some of those areas. For example over France empirical system shows very good results, better in average than dynamical models for precipitation, and at the same level for temperature. Over the eastern part of the domain, dynamical models tend to show better scores, although there are still some seasons where they show lower skill and empirical system seems to perform better.

Differences in scores among areas and seasons are better seen over spatial maps: Figures 4 and 5 show correlation coefficient maps for precipitation and temperature. Certain areas show very good correlation with observations, whereas others hardly show any. These maps show the potential of the model and at the same time, the big spatial differences in the correlation maps point out that there is room for improvement in the selection of predictors over many areas.



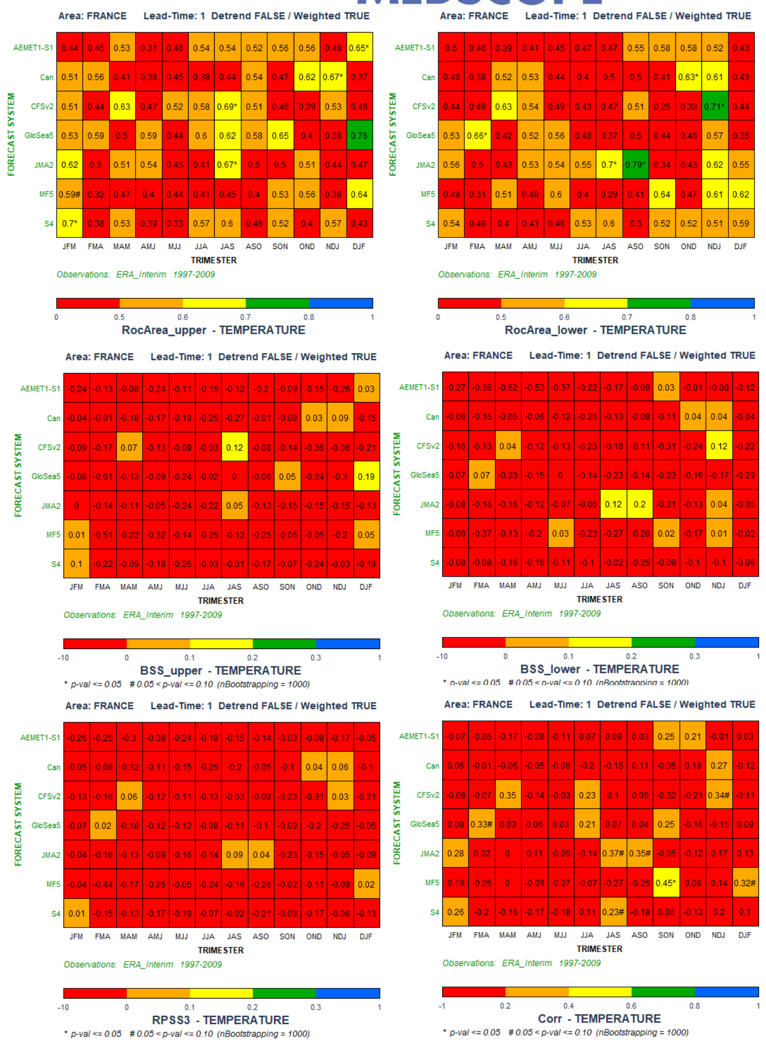
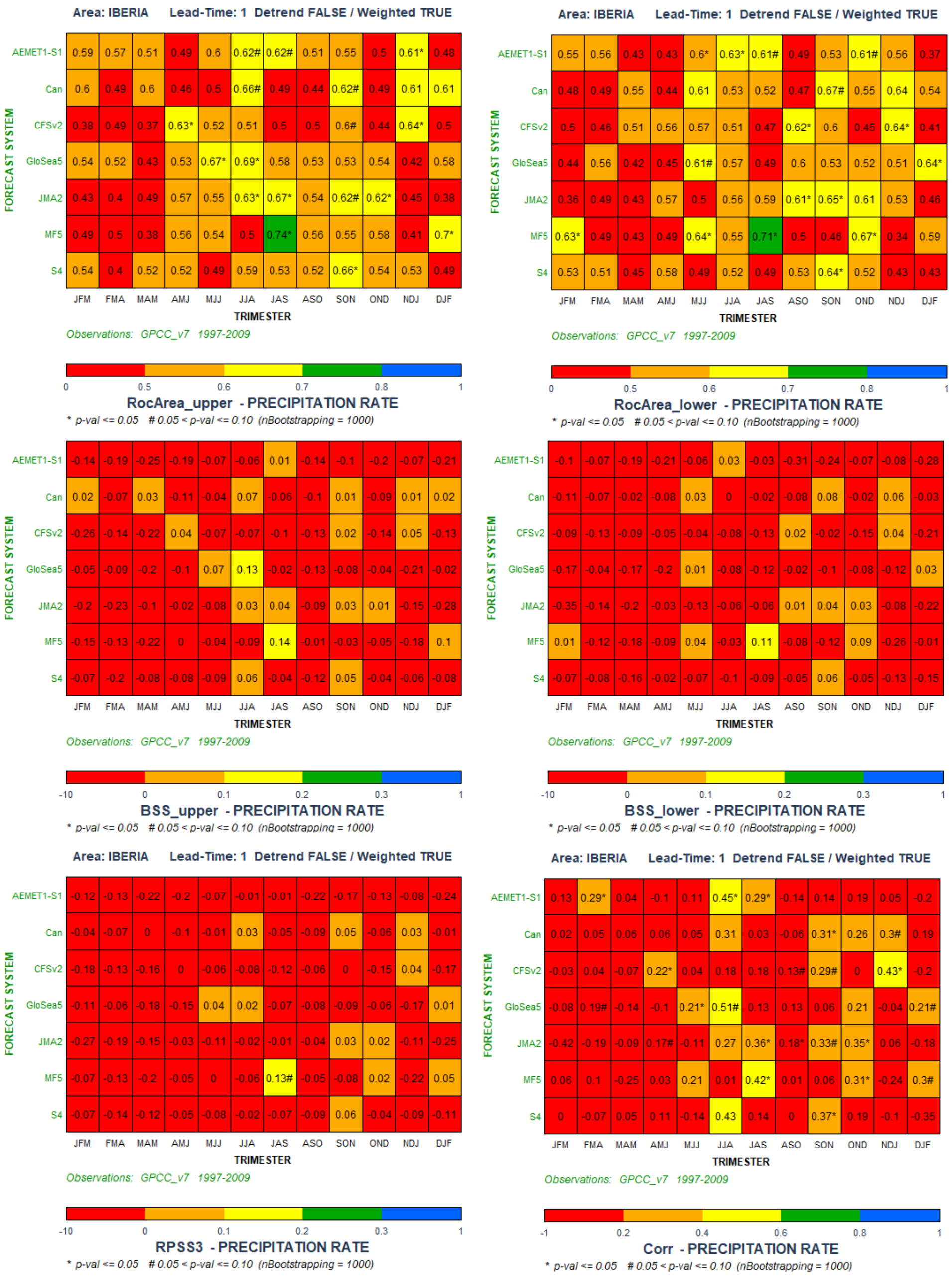


Table 4a. Verification scores for precipitation and for temperature, for France (41N-52N,6.4W-10E). Average of Roc area, Brier Skill Score, Ranked Probability Skill Score and Correlation for the area, calculated for 1997-2009 period. Every column stands for a different season. Every row stands for a different model. Upper row correspond to empirical system.

Results for precipitation are significantly better than average for models for the majority of months. For temperature, scores are on pair or slightly below values from the rest of models.


Area: IBERIA Lead-Time: 1 Detrend FALSE / Weighted TRUE
FORECAST SYSTEM
AEMET1-S1
Can
CFSv2
GloSea5
JMA2
MF5
S4
JFM FMA MAM AMJ MJJ JJA JAS ASO SON OND NDJ DJF
TRIMESTER
Observations: GPCC_v7 1997-2009
0 0.5 0.6 0.7 0.8 1
RocArea_upper - PRECIPITATION RATE
* p-val <= 0.05 # 0.05 < p-val <= 0.10 (nBootstrapping = 1000)
RocArea_lower - PRECIPITATION RATE
-10 0 0.1 0.2 0.3 1
BSS_upper - PRECIPITATION RATE
BSS_lower - PRECIPITATION RATE
RPSS3 - PRECIPITATION RATE
-1 0.2 0.4 0.6 0.8 1
Corr - PRECIPITATION RATE

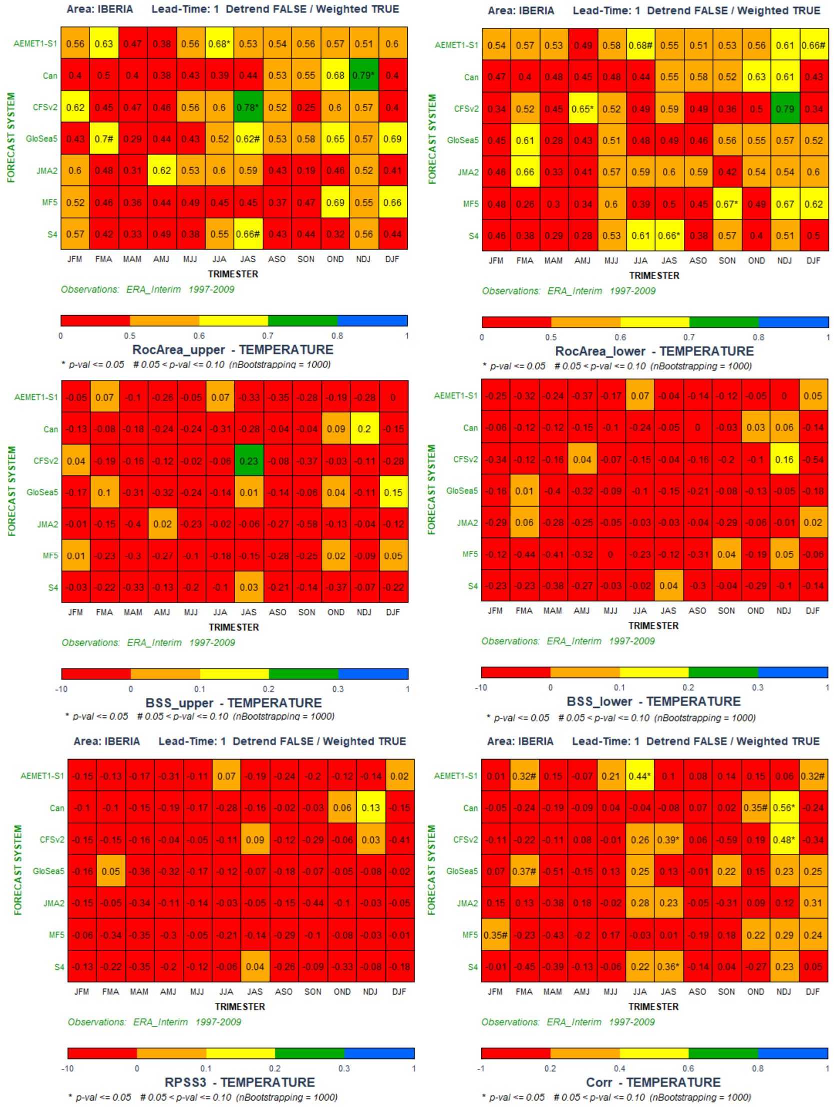
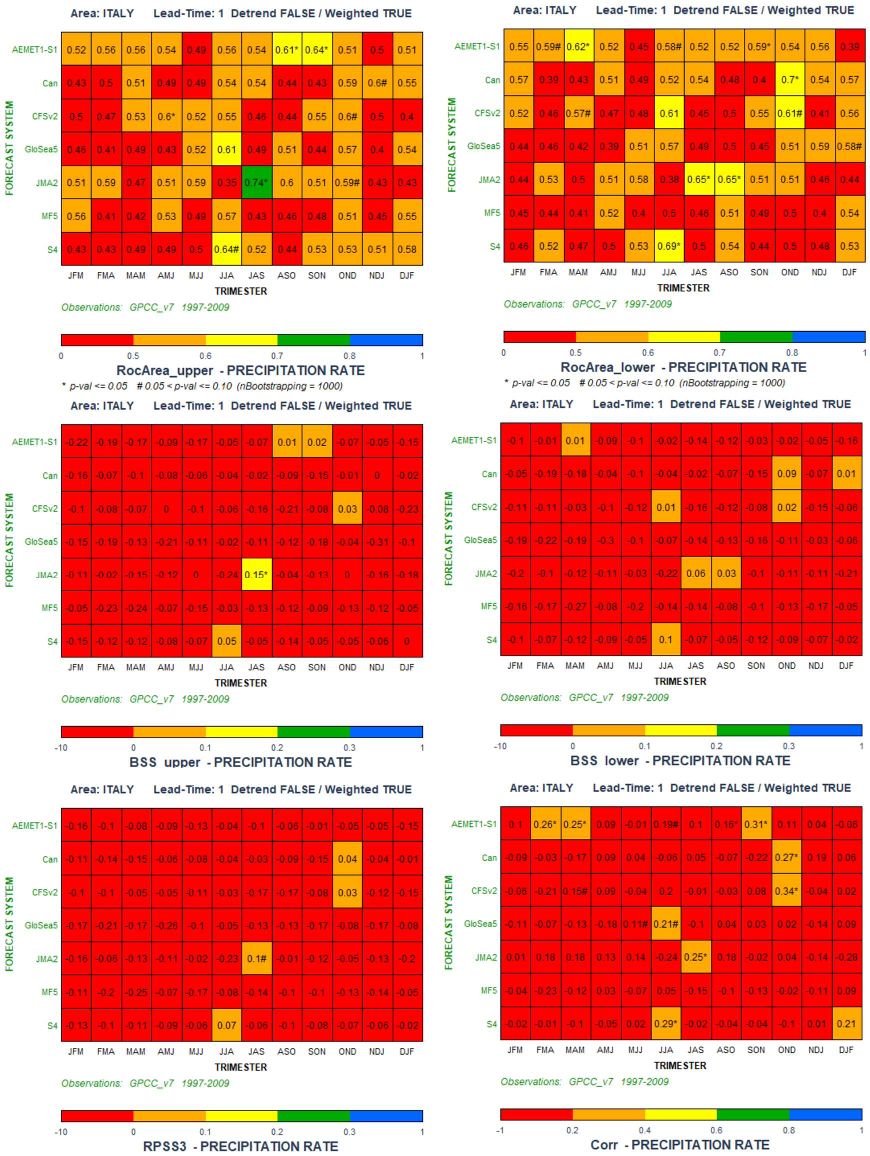


Table 4b. The same as table 4a, but for Iberia (32.5N-47.5N, 10W-7.5E)

Results for precipitation and temperature present similar values to dynamical models. Scores for spring have the lowest values.


Area: ITALY Lead-Time: 1 Detrend FALSE / Weighted TRUE
FORECAST SYSTEM
AEMET1-S1
Can
CFSv2
GloSea5
JMA2
MF5
S4
JFM FMA MAM AMJ MJJ JJA JAS ASO SON OND NDJ DJF
TRIMESTER
Observations: GPCC_v7 1997-2009
RocArea_upper - PRECIPITATION RATE
RocArea_lower - PRECIPITATION RATE
* p-val <= 0.05 # 0.05 < p-val <= 0.10 (nBootstrapping = 1000)
BSS upper - PRECIPITATION RATE
BSS lower - PRECIPITATION RATE
RPSS3 - PRECIPITATION RATE
Corr - PRECIPITATION RATE

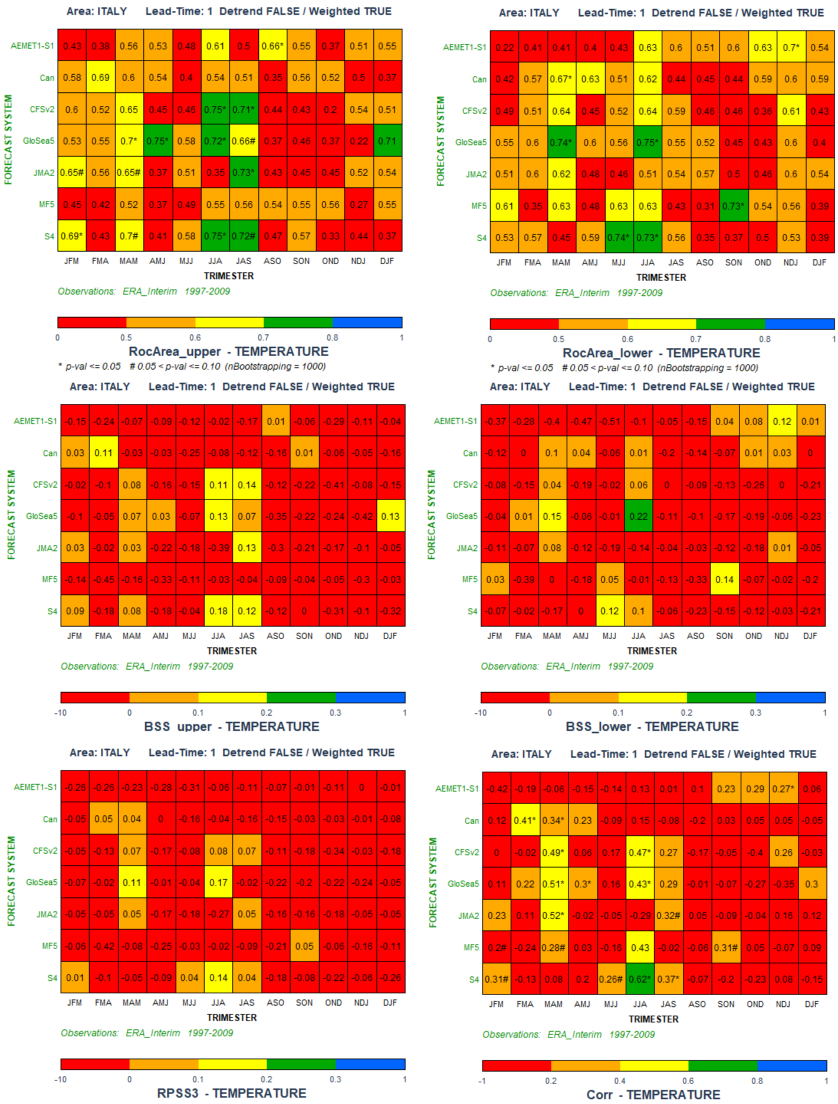
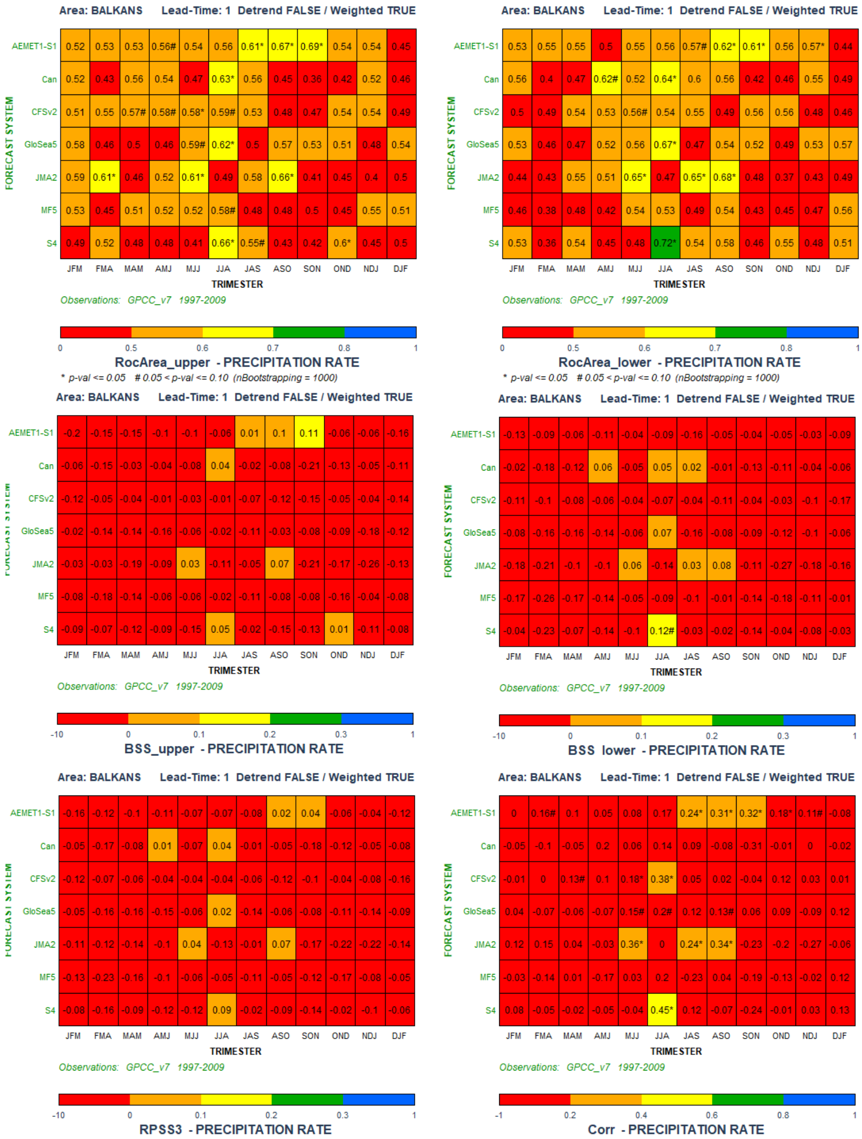


Table 4c. The same as table 4a, but for Italy(36N-47N,6.5E-18.5E)

Results for precipitation present similar or slightly better values compared to dynamical models. For temperature, skill seems lower than that of dynamical models, except for autumn/early winter.



Area: BALKANS Lead-Time: 1 Detrend FALSE / Weighted TRUE
FORECAST SYSTEM
AEMET1-S1
Can
CFSv2
GloSea5
JMA2
MF5
S4
JFM FMA MAM AMJ MJJ JJA JAS ASO SON OND NDJ DJF
TRIMESTER
Observations: GPCC_v7 1997-2009
RocArea_upper - PRECIPITATION RATE
RocArea_lower - PRECIPITATION RATE
* p-val <= 0.05 # 0.05 < p-val <= 0.10 (nBootstrapping = 1000)
BSS_upper - PRECIPITATION RATE
BSS lower - PRECIPITATION RATE
RPSS3 - PRECIPITATION RATE
Corr - PRECIPITATION RATE

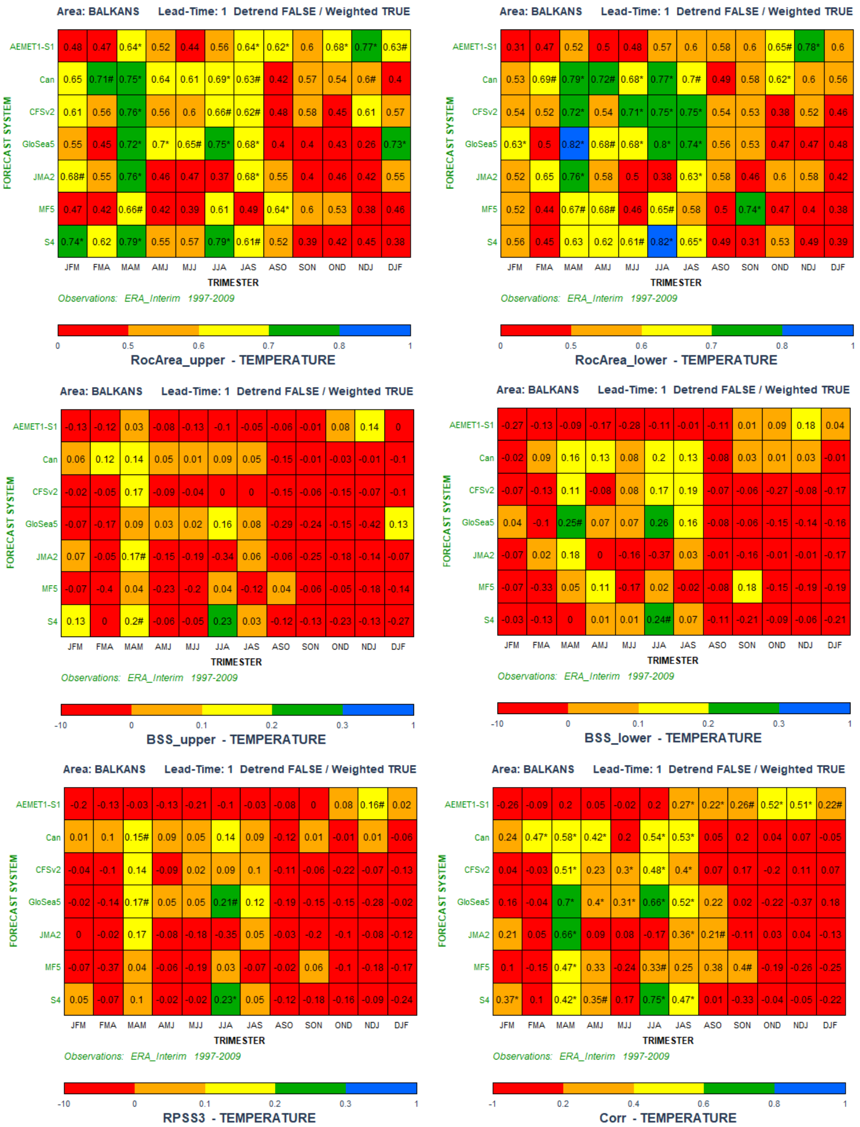
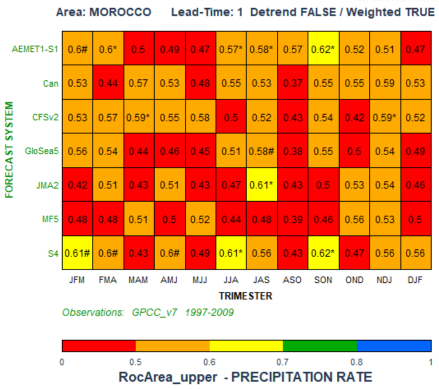
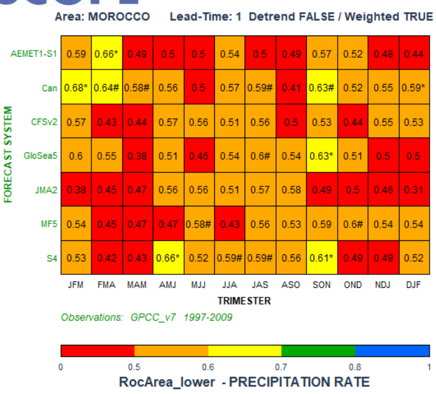
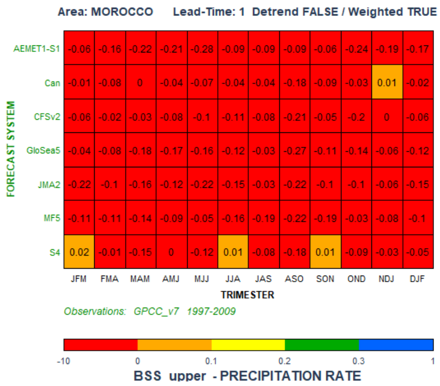


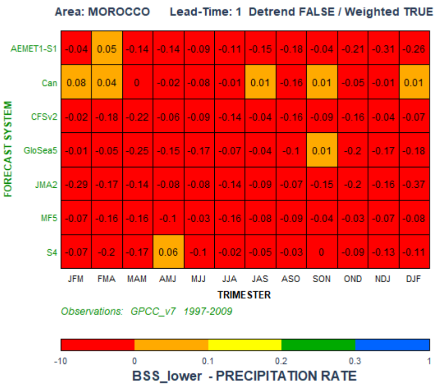
Table 4d. The same as table 4a, but for Balkans (34.5N-48.5N,13E-29E)

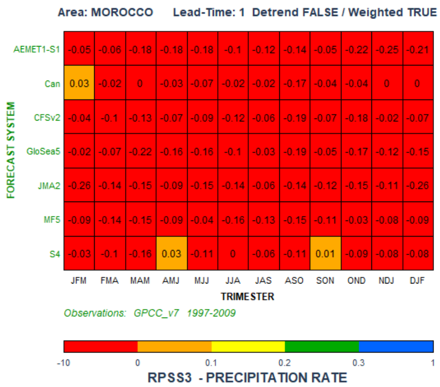
Results for precipitation present similar values compared to dynamical models. Late summer/early autumn has the highest skill. For temperature, skill seems clearly lower than that of dynamical models in late winter and spring, and higher from late summer to early winter.

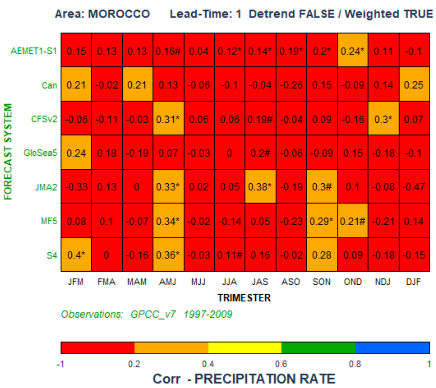

Area: MOROCCO Lead-Time: 1 Detrend FALSE / Weighted TRUE
FORECAST SYSTEM
AEMET1-S1
Can
CFSv2
GloSea5
JMA2
MF5
S4
JFM FMA MAM AMJ MJJ JJA JAS ASO SON OND NDJ DJF
TRIMESTER
Observations: GPCC_v7 1997-2009
0 0.5 0.6 0.7 0.8 1
RocArea_upper - PRECIPITATION RATE


Area: MOROCCO Lead-Time: 1 Detrend FALSE / Weighted TRUE
FORECAST SYSTEM
AEMET1-S1
Can
CFSv2
GloSea5
JMA2
MF5
S4
JFM FMA MAM AMJ MJJ JJA JAS ASO SON OND NDJ DJF
TRIMESTER
Observations: GPCC_v7 1997-2009
0 0.5 0.6 0.7 0.8 1
RocArea_lower - PRECIPITATION RATE


Area: MOROCCO Lead-Time: 1 Detrend FALSE / Weighted TRUE
FORECAST SYSTEM
AEMET1-S1
Can
CFSv2
GloSea5
JMA2
MF5
S4
JFM FMA MAM AMJ MJJ JJA JAS ASO SON OND NDJ DJF
TRIMESTER
Observations: GPCC_v7 1997-2009
-10 0 0.1 0.2 0.3 1
BSS_upper - PRECIPITATION RATE


Area: MOROCCO Lead-Time: 1 Detrend FALSE / Weighted TRUE
FORECAST SYSTEM
AEMET1-S1
Can
CFSv2
GloSea5
JMA2
MF5
S4
JFM FMA MAM AMJ MJJ JJA JAS ASO SON OND NDJ DJF
TRIMESTER
Observations: GPCC_v7 1997-2009
-10 0 0.1 0.2 0.3 1
BSS_lower - PRECIPITATION RATE


Area: MOROCCO Lead-Time: 1 Detrend FALSE / Weighted TRUE
FORECAST SYSTEM
AEMET1-S1
Can
CFSv2
GloSea5
JMA2
MF5
S4
JFM FMA MAM AMJ MJJ JJA JAS ASO SON OND NDJ DJF
TRIMESTER
Observations: GPCC_v7 1997-2009
-10 0 0.1 0.2 0.3 1
RPSS3 - PRECIPITATION RATE


Area: MOROCCO Lead-Time: 1 Detrend FALSE / Weighted TRUE
FORECAST SYSTEM
AEMET1-S1
Can
CFSv2
GloSea5
JMA2
MF5
S4
JFM FMA MAM AMJ MJJ JJA JAS ASO SON OND NDJ DJF
TRIMESTER
Observations: GPCC_v7 1997-2009
-1 0.2 0.4 0.6 0.8 1
Corr - PRECIPITATION RATE

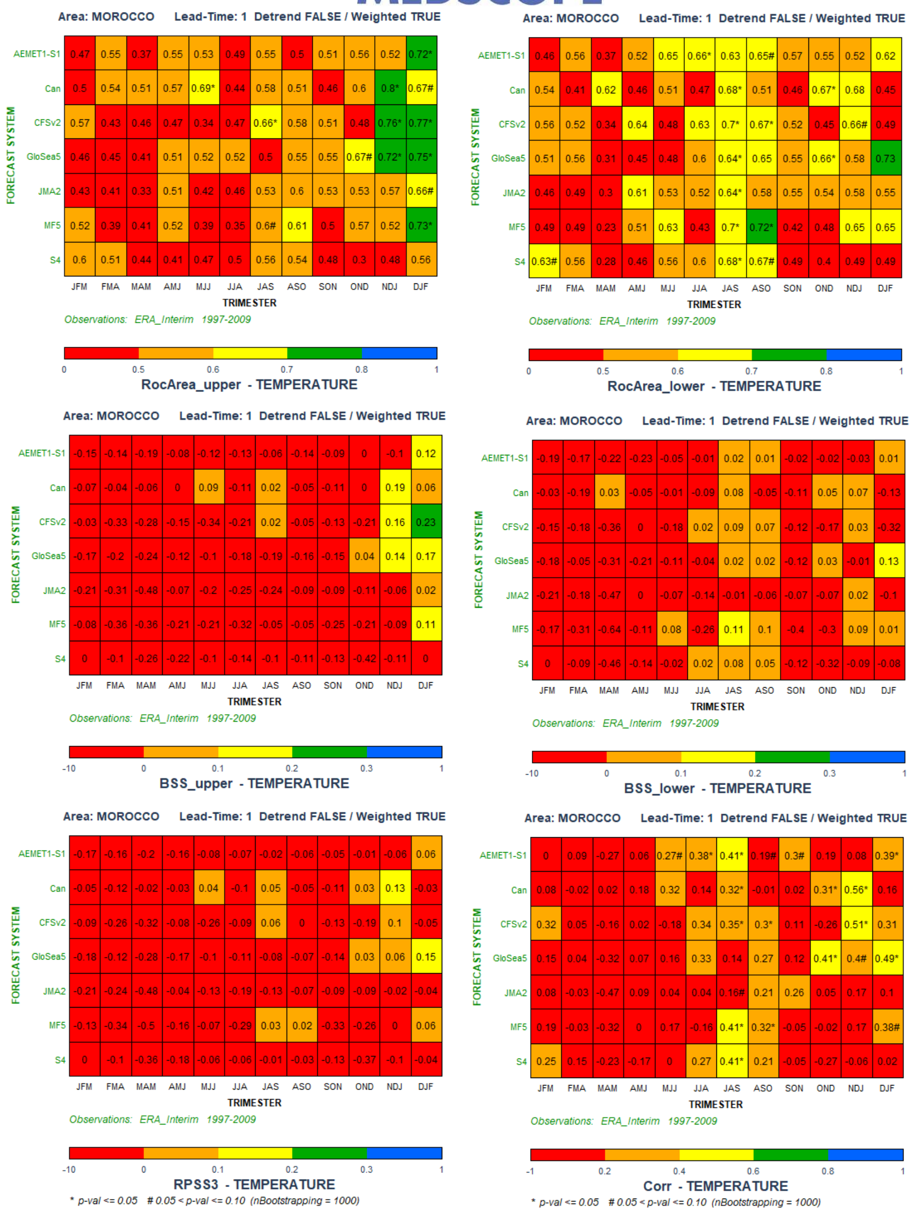
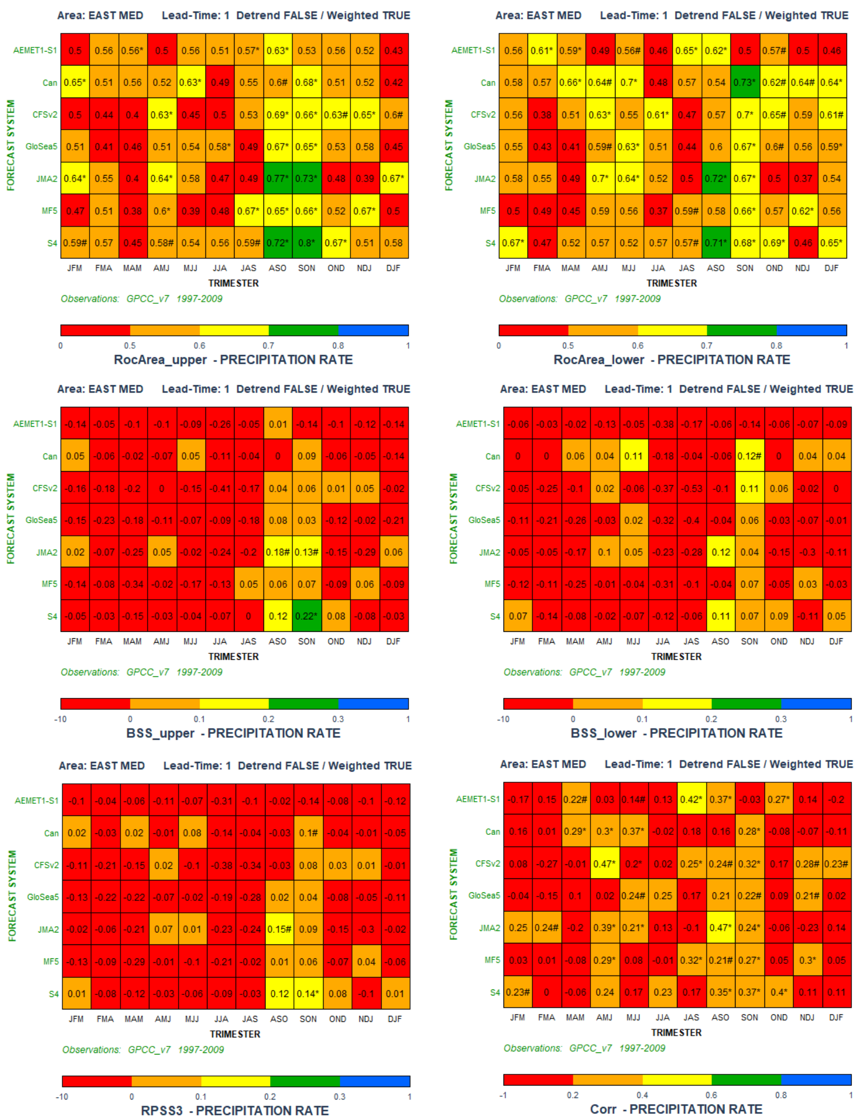


Table 4e. The same as table 4a, but for Morocco (21N-36N,17W-1W)

Results for precipitation and temperature present similar values and seasonal distribution of skill as that showed by dynamical models.


Area: EAST MED Lead-Time: 1 Detrend FALSE / Weighted TRUE
FORECAST SYSTEM
AEMET1-S1
Can
CFSv2
GloSea5
JMA2
MF5
S4
JFM FMA MAM AMJ MJJ JJA JAS ASO SON OND NDJ DJF
TRIMESTER
Observations: GPCC_v7 1997-2009
RocArea_upper - PRECIPITATION RATE
RocArea_lower - PRECIPITATION RATE
BSS_upper - PRECIPITATION RATE
BSS_lower - PRECIPITATION RATE
RPSS3 - PRECIPITATION RATE
Corr - PRECIPITATION RATE

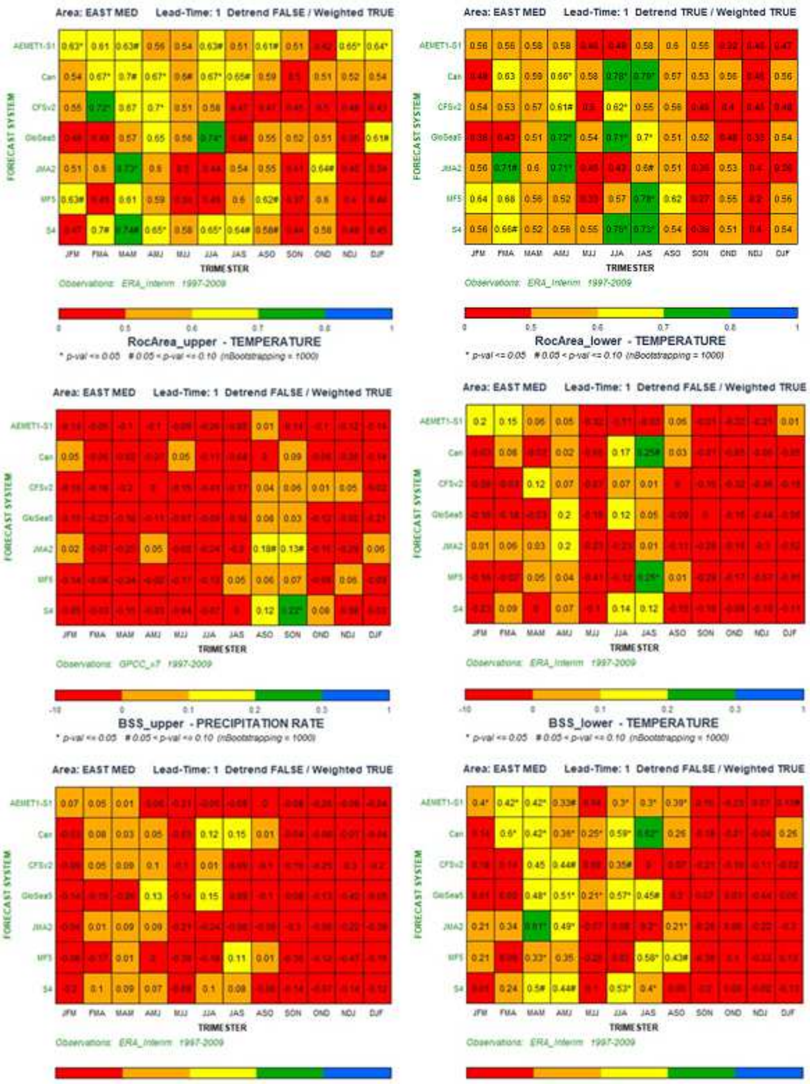


Table 4f. The same as table 4a, but for East Mediterranean (20 N-40N, 27.5 E-62.5 E). Results for precipitation show slightly lower skill than dynamical models. Results for temperature present similar values for skill as that showed by dynamical models.

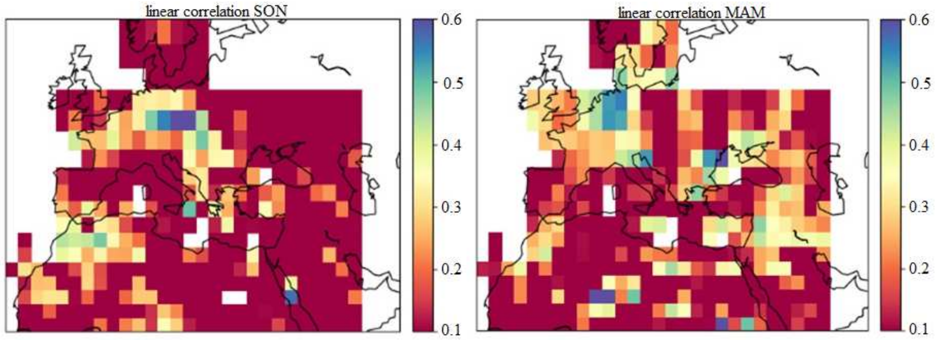


Figure 4: Linear correlation between model forecast and observed precipitation for September-November and March-May, for 1983-2014 period.

Figure 4 represent the spatial (and season-dependant) differences of skill over the domain. There is still work to do in the exploration of predictors to try to reduce the areas of low skill.

4. Conclusions

Major research and climate services initiatives support advances in seasonal forecasting. In the frame of MEDSCOPE project, we present here a first version of a seasonal forecast empirical system that uses new predictors based on a collection of targeted sensitivity experiments. As these experiments are still ongoing, the purpose of this first version is just to develop a system capable of producing coherent seasonal forecasts. We believe that the proposed system is valuable as a starting point, so that when the results of next experiments are available; their implementation will be rather straightforward. Bearing this in mind, the code has been designed in such a way to facilitate both either modification or incorporation of new predictors.

As indicated earlier, the nature and appearance of spatial patterns observed on the forecasts seems to fulfil the original aim of producing both synoptic scale structures and continuity among regions. Furthermore, when comparing verification scores from the empirical system with six state-of-the-art dynamical models, the empirical system shows higher skill over some regions for precipitation while comparable results for temperature. Nevertheless, as regards other regions, skill is poor and comparable or below dynamical models. Plausible causes for this result may be attributed to the fact that selection of predictors was made subjectively and only for precipitation. Besides, selection was based in linear correlation between predictors and accumulated precipitation, whereas the model uses its square root. Another possible cause related with the procedure for selection of predictors could be that it checks the percentage of points showing some signal within a region, but does not take into account where that signal is: it may be possible that all predictors show signal over the same part of the region, and at the same time, it may not exist any good predictor for other parts. Next version of the system will implement an automatic procedure for selection of predictors, and efforts will focus on developing an objective procedure that cover the issues above described.

On the other hand, the fact that selected predictors for temperature are the same than for precipitation is a serious limitation of the empirical model. We expect better results when making an independent selection of proper predictors for this predictand. Nevertheless, present results are encouraging, with scores being roughly at the same level as for dynamical models. In any case, using the same predictors for temperature and precipitation makes easier to analyse circulation anomalies for the incoming season and its physical interpretation.

Therefore, this first version of the model shows encouraging results and at least similar skill as dynamical models. Improvements currently being developed in the empirical system and the expected new specific predictors from MEDSCOPE will be implemented in the next version of the system. The new version is expected to be an additional and reliable source of information to be used in combination with dynamical models and aiming at improving the skill of seasonal forecasts over the Mediterranean region.

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Tables and Figures