SEASONAL FORECASTS BASED ON STATISTICAL ALGORITHMS

Massimiliano Pasqui

Institute of Biometeorology National Research Council Rome, Italy.

m.pasqui@ibimet.cnr.it

with contributions from:

V. Pavan, F.J. Doblas-Reyes, J. Primicerio, S. Quaresima, E. Di Giuseppe, F. Guarnieri, L. Genesio, R. Benedetti, A. Crisci

REGIONAL TRAINING ON LONG-RANGE FORECASTS, CLIMATE WATCH RELATED ASPECTS AND CLIMATE SCENARIOS - LRF Training

13 - 16 November 2013, Belgrade, Serbia

BEST PRACTICES IN SEASONAL FORECASTING

The following requirements for producing, using, and assessing seasonal forecasts were agreed upon during and in discussions subsequent to the First WCRP Workshop on Seasonal Prediction.

- Forecast error must be addressed by appropriately quantifying dynamical model uncertainty;
- Model output should be recalibrated based on historical model performance;
- Probabilistic forecast information should be issued;
- A description of the forecast process should be made available;
- In retrospective forecast mode, no information about the future should be used;
- Forecast quality information should be provided, including several metrics of quality;
- Regional climate service providers need to work with both the forecasting and application communities to develop tailored downscaled products;
- Users must be encouraged to use all the ensemble members to quantify forecast uncertainty;
- Web-based tools need to be developed to allow users to tailor forecast information;
- Regional mechanisms like Regional Climate Outlook Forums (RCOFs) should be used to develop regional climate outlooks based on the consensus and objective scientific assessment of multiple-prediction outcomes;
- Liaison with users should be promoted to understand their climate information needs in decision making and also to raise their awareness of the uncertainty aspects of seasonal forecasting;
- Regional/national ownership of seasonal forecasts should be promoted through effective and sustained capacity building and infrastructural support.

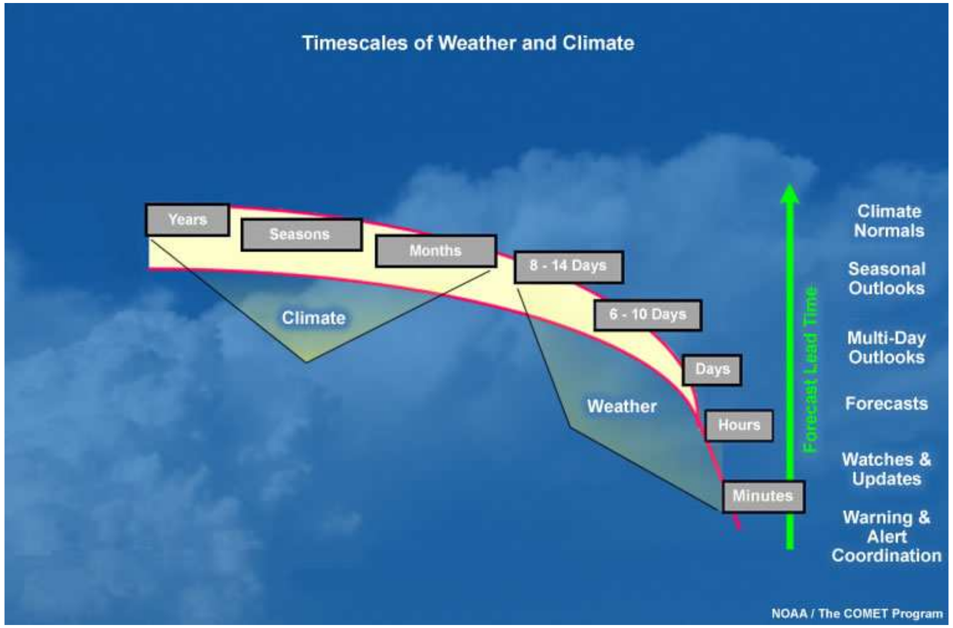
Kirtman, Ben, Anna Pirani, 2009: The State of the Art of Seasonal Prediction: Outcomes and Recommendations from the First World Climate Research Program Workshop on Seasonal Prediction. *Bull. Amer. Meteor. Soc.*, ***90*, *455–458.doi:* *http://dx.doi.org/10.1175/2008BAMS2707.1***

The State of the Art of Seasonal Prediction

Outcomes and Recommendations from the First World Climate Research Program Workshop on Seasonal Prediction

by Ben Kirtman and Anna Pirani

Interesting Timescales



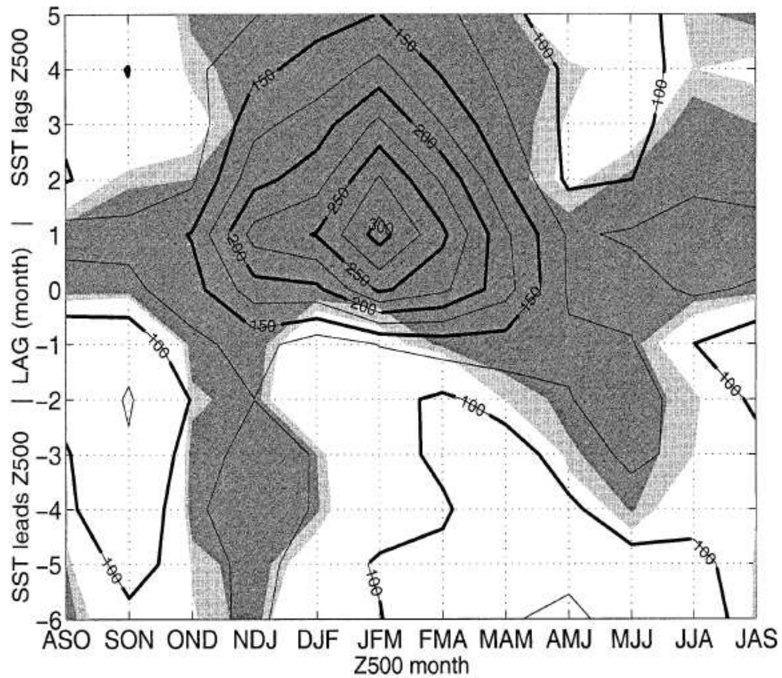
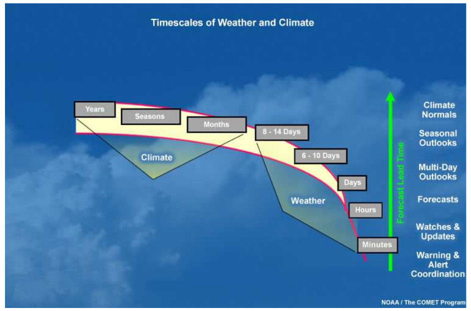


FIG. 1. The SC of the first MCA mode between Pan-Atlantic SST and Z_{500} anomalies (the SCs are dimensionless as the SST and height fields have been normalized—see section 2). SST leads Z_{500} at negative lags indicated (in months) on the y axis while the x axis denotes the months assigned to Z_{500}. The shaded area indicates where the covariance is statistically significant at the 5% and 10% level (dark and light shading, respectively).

Czaja and Frankignoul, 2002

Interesting Timescales #2



Days → Weeks → Month → Season → Decadal?

- Wind Storms
- Forest Fires
- Cold Air Outbreaks
- Dry/Wet Spells
- Drought Evolution
- Heat/Cold Waves
- Water Supply
- Energy Supply
- Normal Conditions (e.g. for Agri. Act. Planning)

- Seasonal forecasting represents the attempt to predict the spatial and temporal distribution of atmospheric anomalies few months in advance.

- Even though the detailed dynamical evolution of atmospheric system is not predictable on those time scales, some of its statistical features and behaviors can be forecasted.

- In particular it is possible to infer the mean behavior over a month or season and how much the PDFs of such values, or anomalies, differ from "climatology". Or in other words it can be highlighted a specific regimes.

- In the Mediterranean basin where a changing climate seems acting towards a remarkable footprint both for rainfall and more pronounced on heat wave related events, the water management should be adopted at seasonal time scale for critical scenario modelling.

- Nowadays seasonal forecast systems should still cover a dynamical scale gap to reach local scale and sub monthly climatic variability.

- E.g. drought is a composition of different physical mechanisms: *large scale climatic anomalies* and *local environmental factors* and it is of prime interest for civil, agricultural and industrial activities.

- Seasonal forecasting deals mainly with large scale climatic phenomena.

- Dynamical models become a major tool in seasonal prediction and have demonstrated a significant progress in tropical seasonal to inter-annual predictions (e.g., ENSO dynamic), but their direct outputs seem to be much less satisfactory for middle and higher latitudes;

- On the other side statistical models can give comparable and even higher skills for specific regions and for some variables, and their results can be easily applied for practical use without a full comprehension of physical mechanisms behind.

- Finally statistical models need little computational resources being much more simple to be used than dynamical ones.

- But they requires some careful attentions since reliability is obtained through a balance between goodness-of-fit and stability of the model.

IBIMET on SeaFor

Main Activities related:

- Early – Warnings
- Monitoring and Survey

Seasonal Forecasts Target Areas

- **Italy** — TEMPIO Project, Italian Ministry of Agriculture and Forest
- **Mediterranean Basin** — Internal funding
- **West African Mosoon** — Many different projects: AMMA, etc.

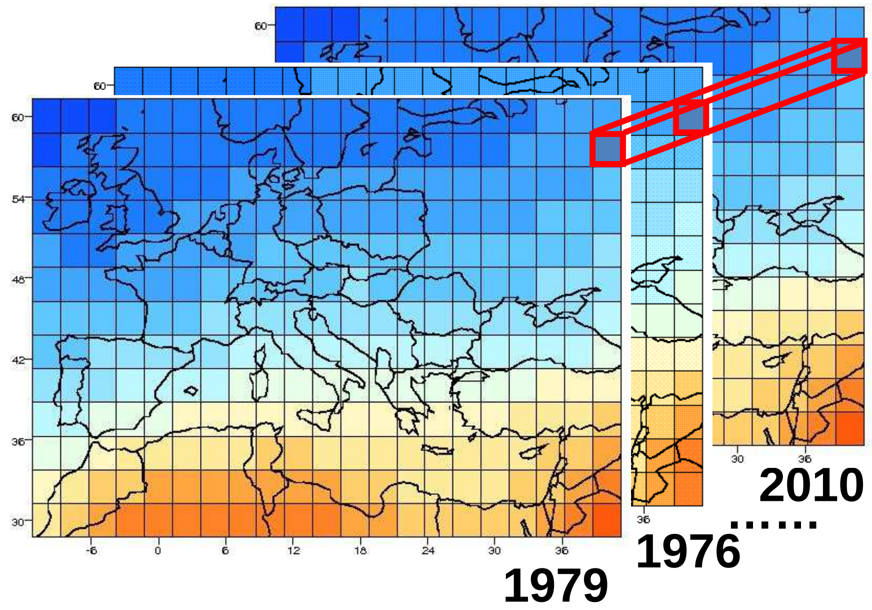
Institutional End Users

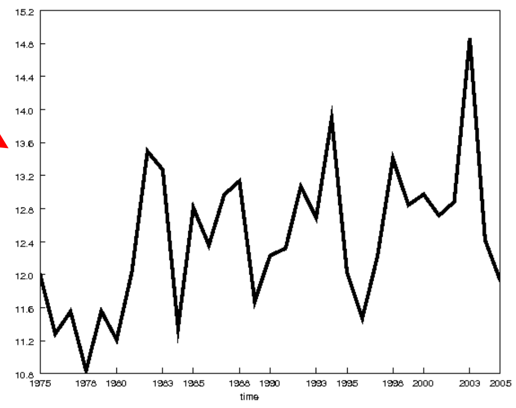
• National Civil Protection Department: Monthly and Seasonal forecast group. *It meets monthly, provides outlook for one to three months ahead mainly for the management of water scarcity crisis [it started in winter 2007]. It is composed by IBIMET, ARPA-SIM, CNMCA, CRA-CMA (ex UCEA), ISAC-CNR.*

• Arno river basin Water Safeguard Commission: *monthly meetings*

Seasonal Forecast Overview

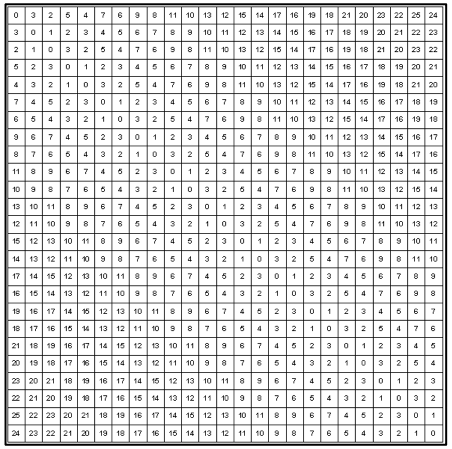
Observed Temperature Matrix





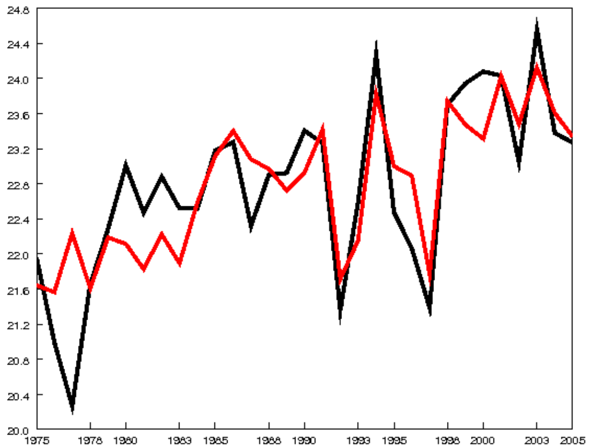
Temperature at location (x,y)

Predictors Matrix



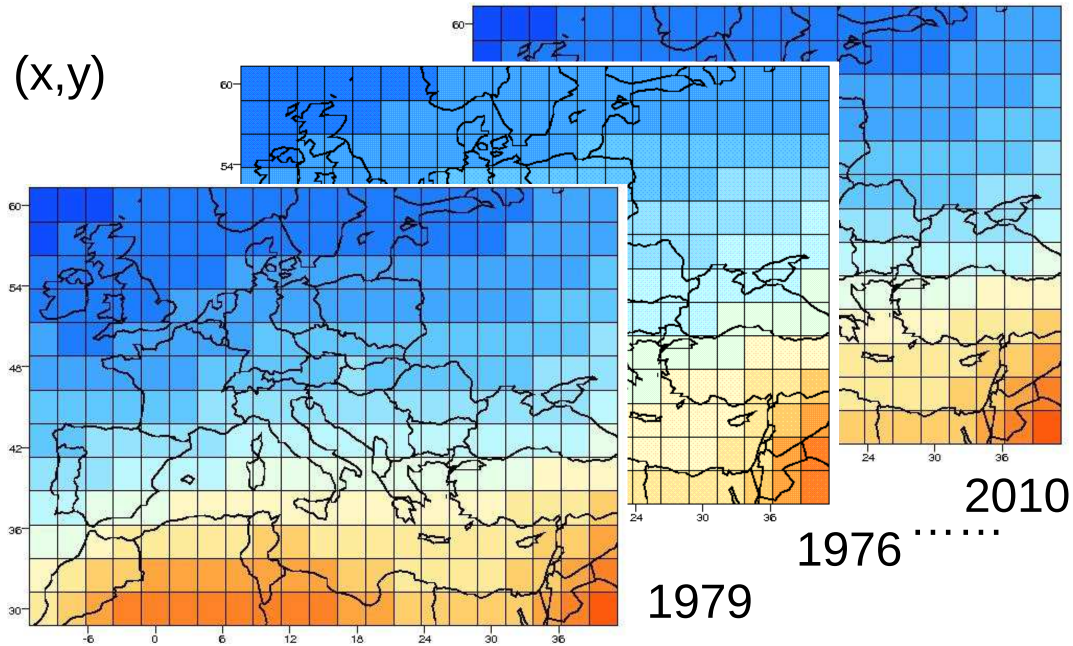
Multivariate Linear Regression algorithm

Forecasted Temperature at (x,y) for time (t) expressed as probability of occurrence



Hindcasted Temperature at location (x,y)

Hindcast Temperature Matrix



1979

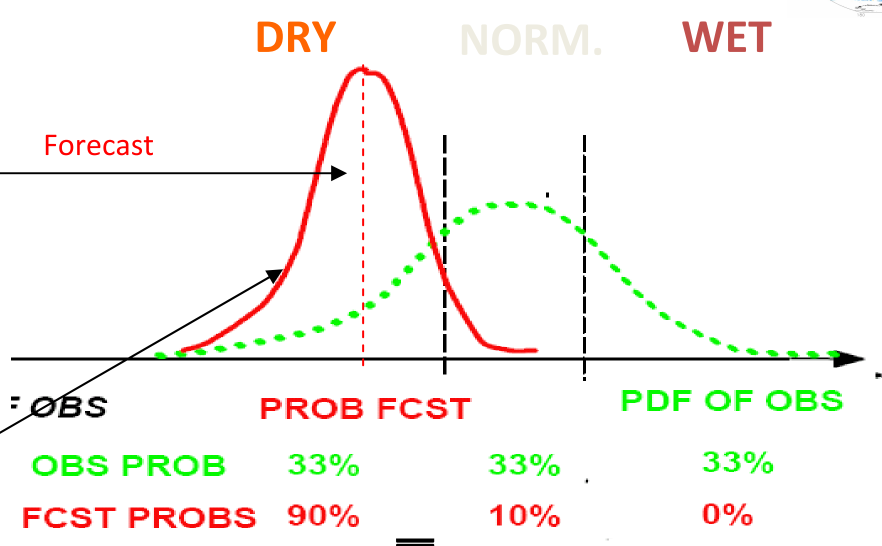
1976 ……

2010

Multiregressive

$$\hat{y}_i = b_0 + \sum_{k=1}^{K} b_k x_{ik}$$

$$\begin{Bmatrix} y_i & i = 1,\ldots n & \\ x_{i,k} & i = 1,\ldots n, & k = 1\ldots, K \end{Bmatrix}$$

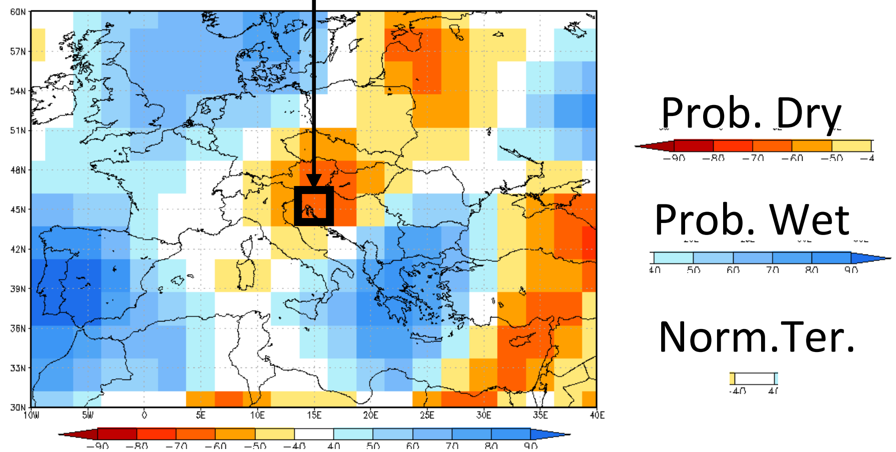


Multiregressive Errors

$$\boxed{s_\varepsilon^2 = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n - K - 1} = \frac{SSE}{n - K - 1}}$$

$$\boxed{P_{forecast(D,N,W)} \equiv PFcst \perp PObs_{D,N,W}}$$

s_ε^2 : Forecast Error Variance
SSE: Sum Square Errors
n : Sample amount
K : Predictors

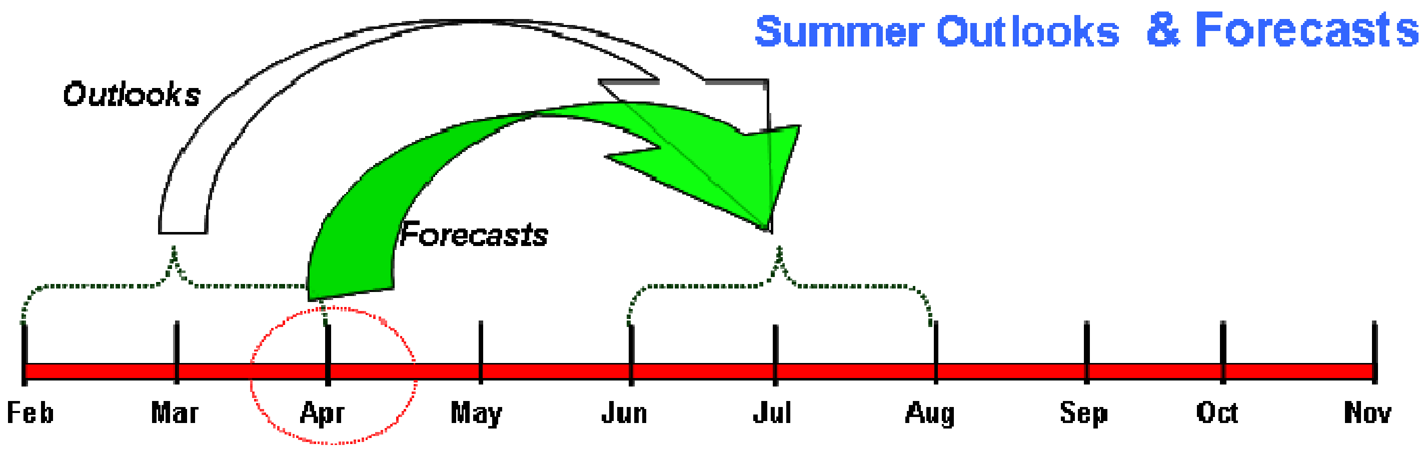


Dominant tercile maps

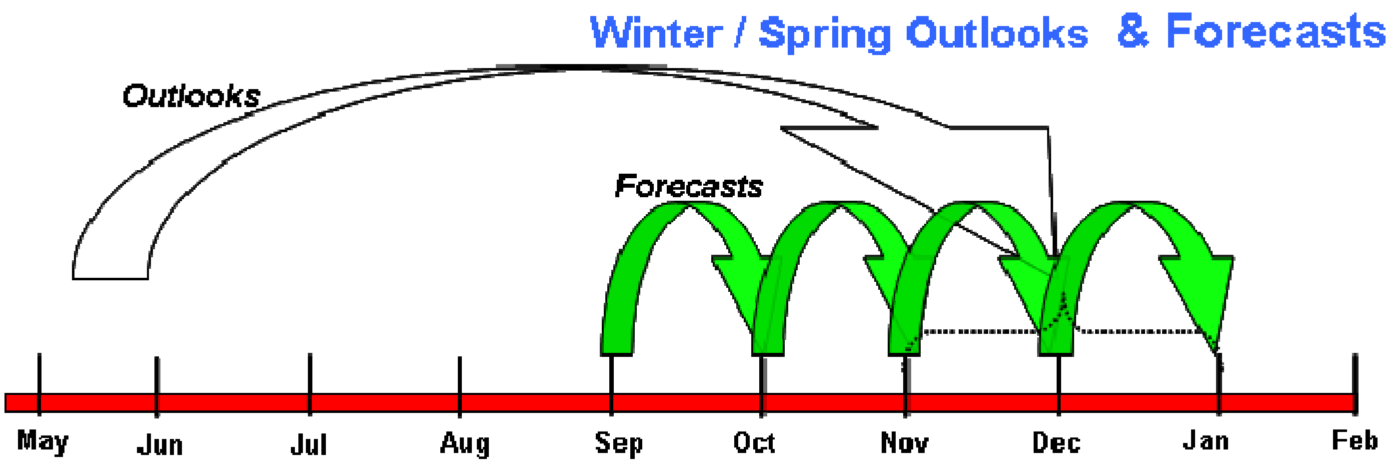
The multi-regressive method based on physical atmospheric indices and sea surface anomalies, at monthly time scale.

Lead – time choices are made on physical basis and on a maximization of the regression values between observed and forecasted field anomalies thus performing an "*adaptation*" for the best choice of predictors.

Short Name	Full Name	Source
MED	Mediterranean Sea 1ª EOF SST (JUNG ET AL., 2006)	CPC[6]
AMO	Atlantic Multidecadal Oscillation (Enfield et al., 2001)	CDC[7]
MEI	Multivariate ENSO Index (Wolter & Timlin, 1993)	CDC
NAO	North Atlantic Oscillation (Barnston and Livezey, 1987)	CPC
SV-NAM	Seasonally Varying Northern Hemisphere Annular Mode (Ogi et al., 2003, 2004)	HOK[8]
MZI	Modified Zonal Index (J. P. Li & Wang, 2003)	IRI[9]
TRI	Atlantic Tripole 1ª EOF SST (Deser & Timlin, 1997)	IRI
GUI	Guinea Gulf 1ª EOF SST[2]	IRI
IND	Indian Sea 1ª EOF SST[3]	IRI
NASCI	North American Snow Cover Index[4]	IRI
SISCI	Siberian Snow Cover Index[5]	IRI
PDO	Pacific Decadal Oscillation (Mantua et al., 1997)	JISAO



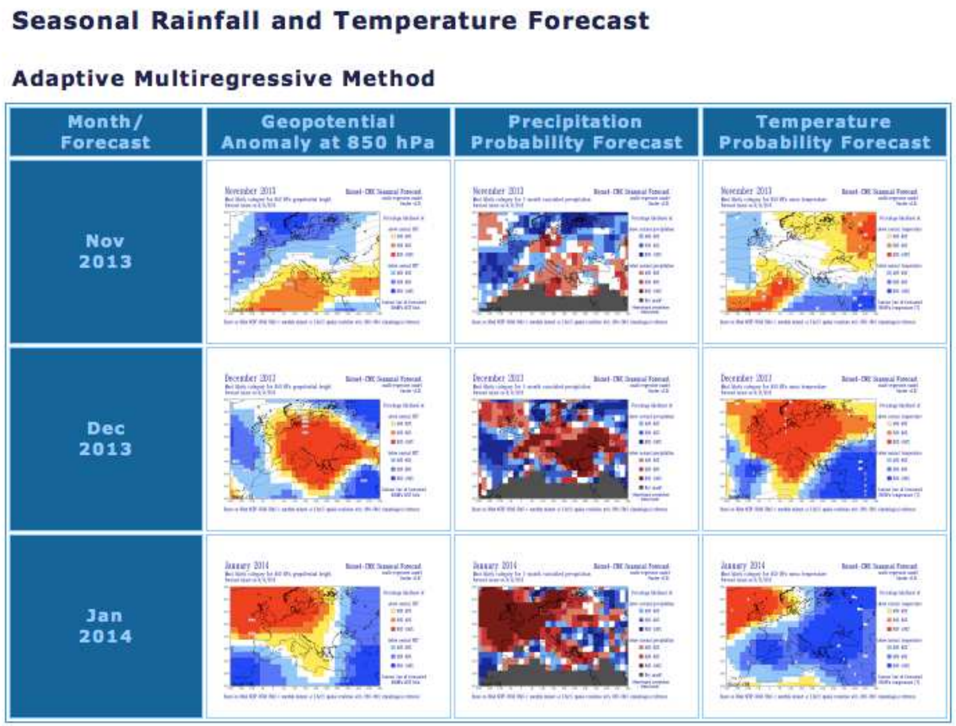
Summer variability could be associated to winter atmospheric variability (SV – NAM, snow cover, etc.) and to Atlantic SST anomalies (Tripole and 1st EOF Guinea).



Fall to Winter variability could be associated to Spring to SST anomalies through reemerging Atlantic SSTA mechanism (OUTLOOKS) plus the atmospheric fall – winter variability (MONTLY).

CNR - IBIMET

http://web.fi.ibimet.cnr.it/seasonal/

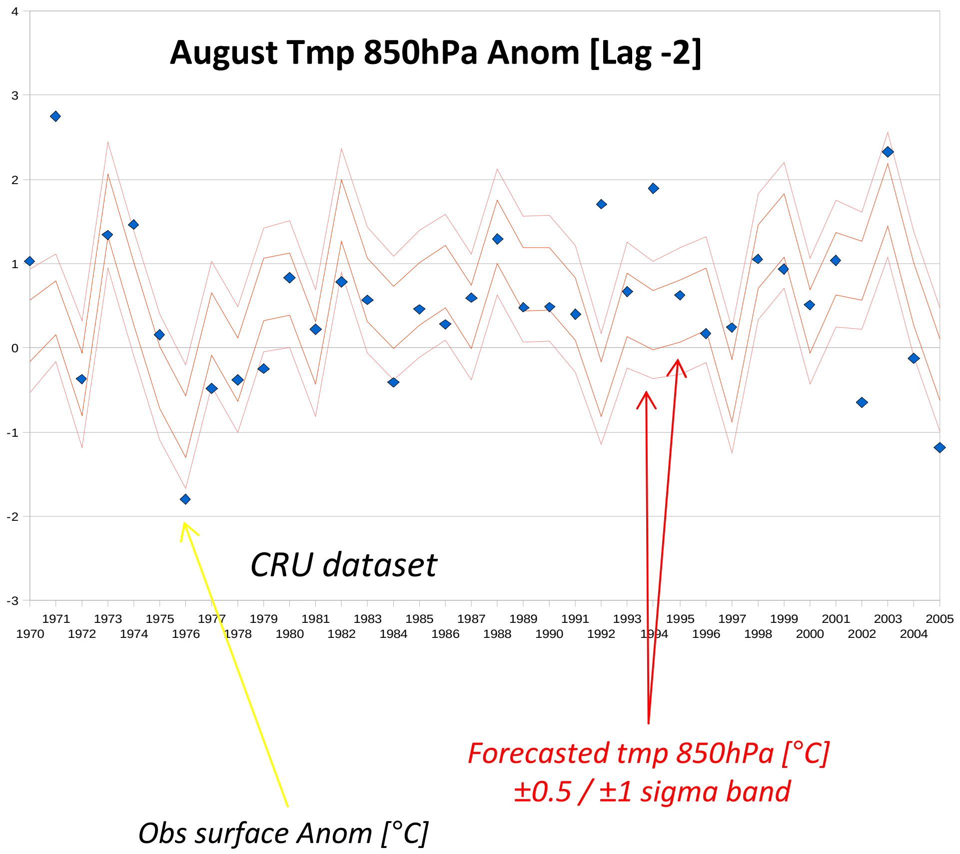


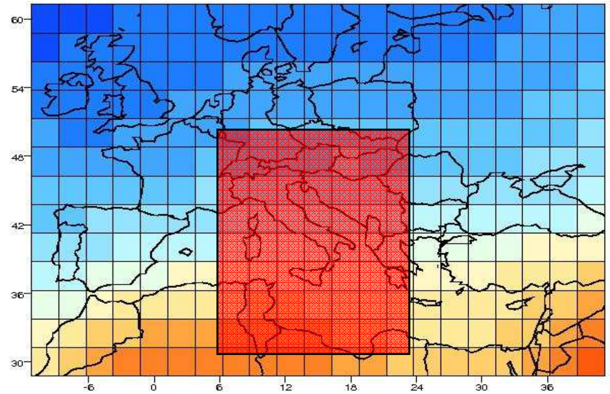
Seasonal Rainfall and Temperature Forecast

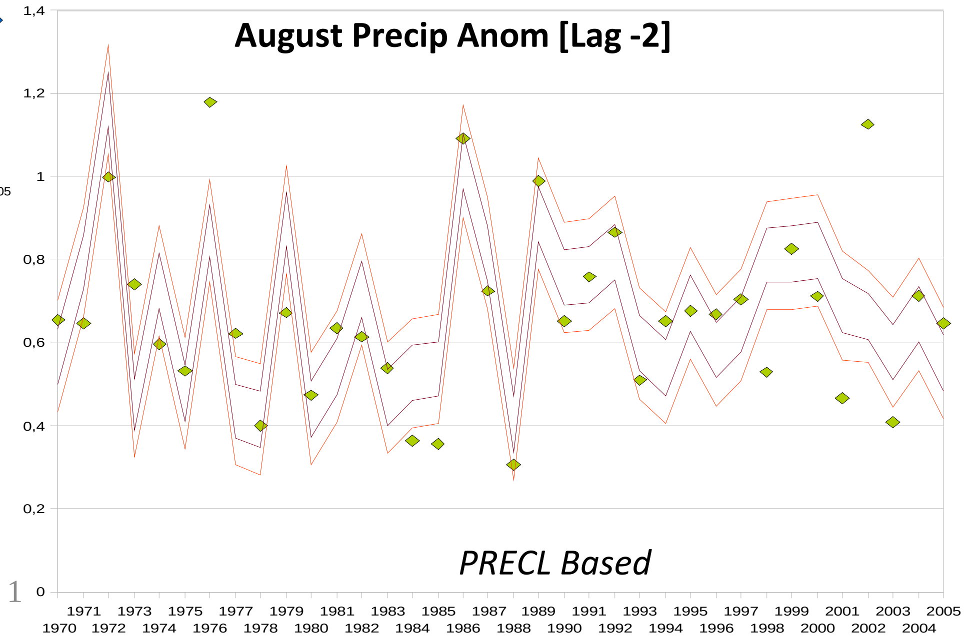
Adaptive Multiregressive Method

Month/ Forecast	Geopotential Anomaly at 850 hPa	Precipitation Probability Forecast	Temperature Probability Forecast
Nov 2013			
Dec 2013			
Jan 2014			

CNR - IBIMET

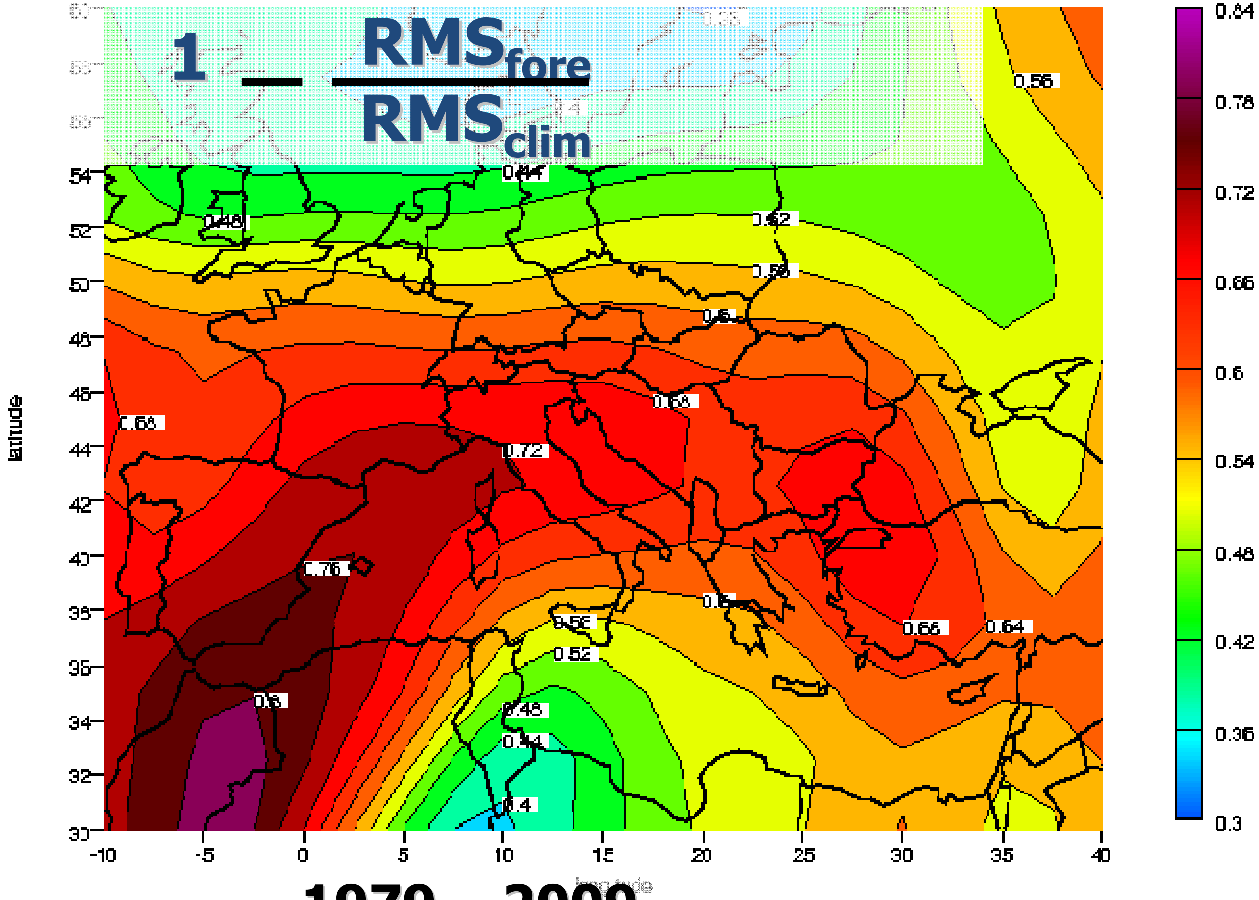

August Tmp 850hPa Anom [Lag -2]
CRU dataset
Obs surface Anom [°C]
Forecasted tmp 850hPa [°C]
±0.5 / ±1 sigma band




August Precip Anom [Lag -2]
PRECL Based

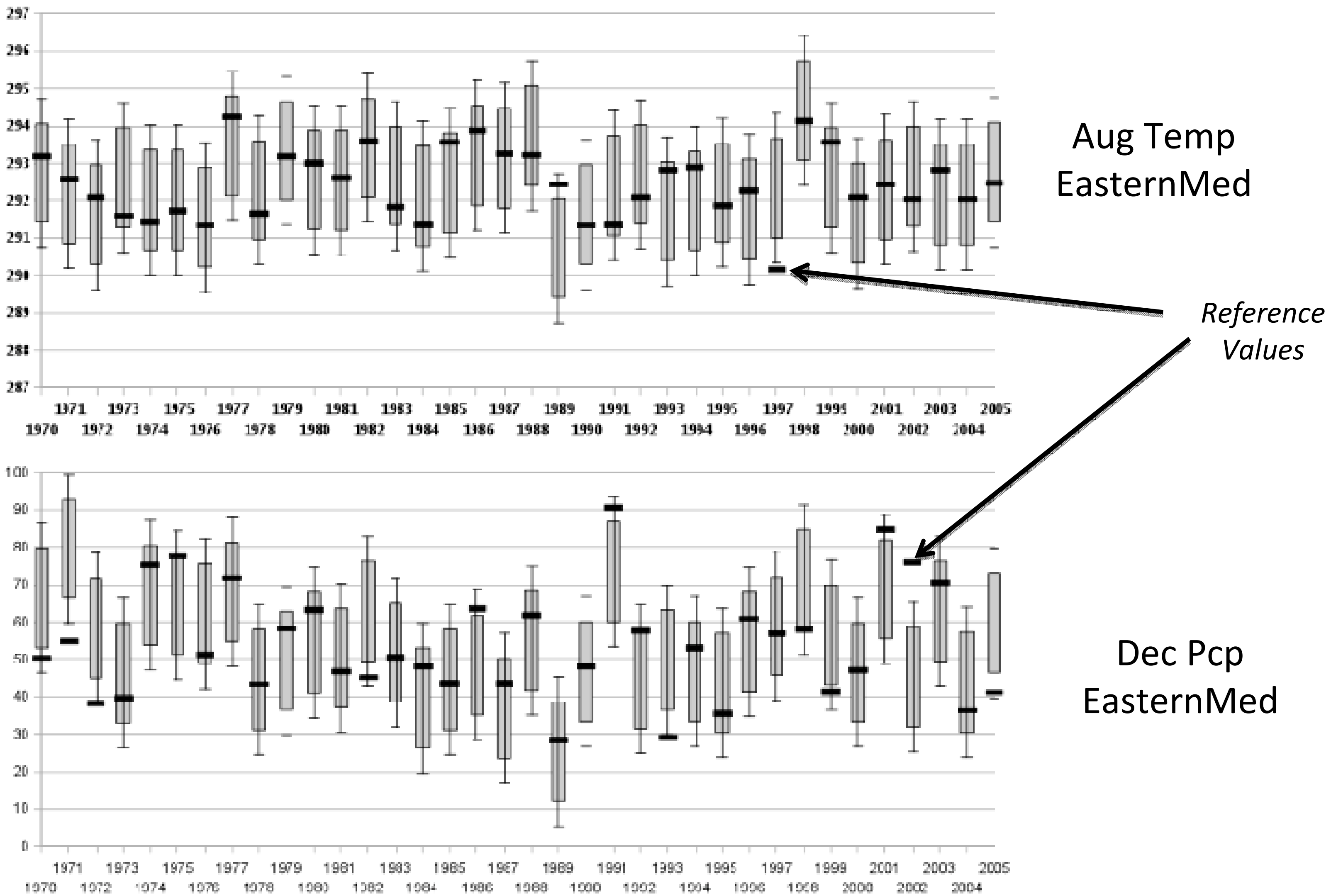
1

Es.: Temp 850hPa JJA issued in April



$$1 - \frac{RMS_{fore}}{RMS_{clim}}$$

1979 – 2009


297
296
295
294
293
292
291
290
289
288
287
1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005
Aug Temp
EasternMed
Reference
Values
100
90
80
70
60
50
40
30
20
10
0
1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005
Dec Pcp
EasternMed

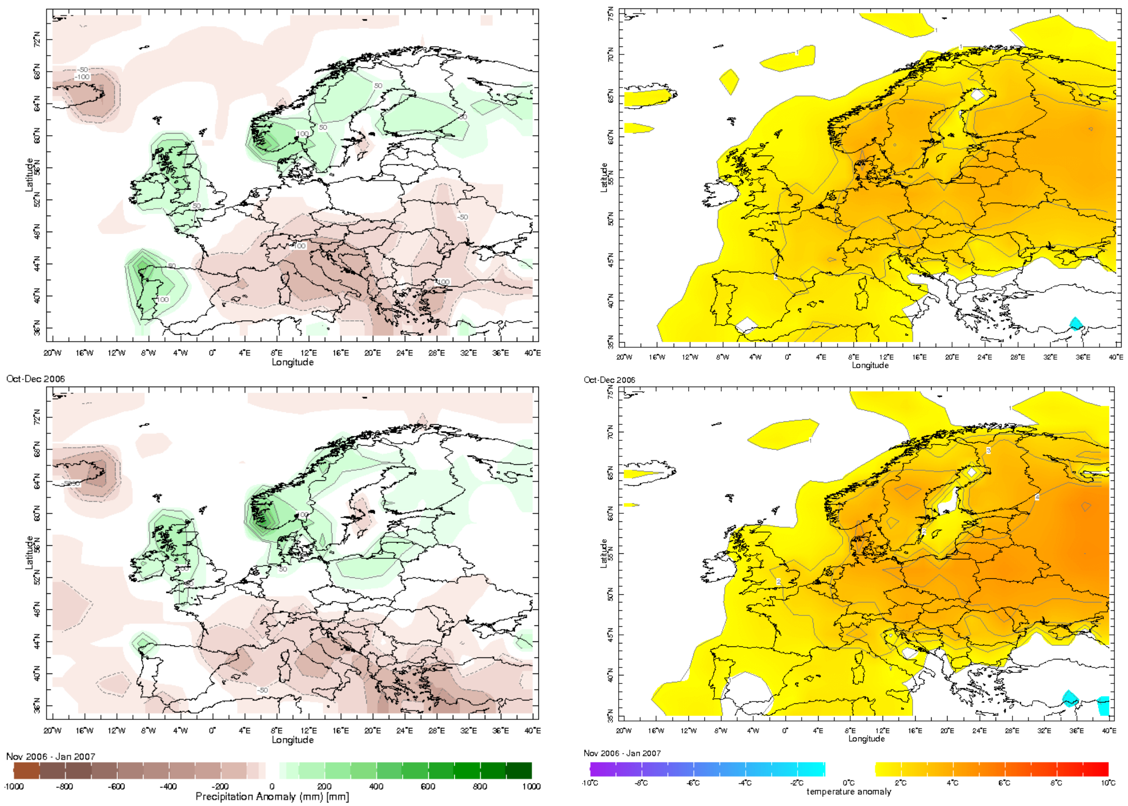
An exceptional (*) warm period in Europe and a long dry period in southern Europe.

In Jan 2007 Italian Civil Protection (DPC) established a technical working group for monthly to seasonal forecasts for drought emergency. It consist of 5 groups: ARPA-SIMC, AM, CRA-CMA, CNR-ISAC, CNR-IBIMET.

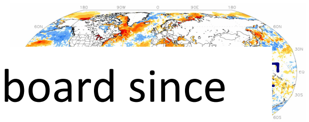
3-months seasonal forecast from ARPA-SIMC & CNR – IBIMET are shown here.

Oct – Dec 2006

Nov 2006 – Jan 2007



(*) Luterbacher J.; Liniger, M. A.*; Menzel, A.; Estrella, N.; Della-Marta, P. M.*; Pfister, C.; Rutishauser, T. ;Xoplaki, 2007Exceptional European warmth of autumn 2006 and winter 2007: Historical context, the underlying dynamics, and its phenological impactsGeophys. Res. Letter, 34, L12704

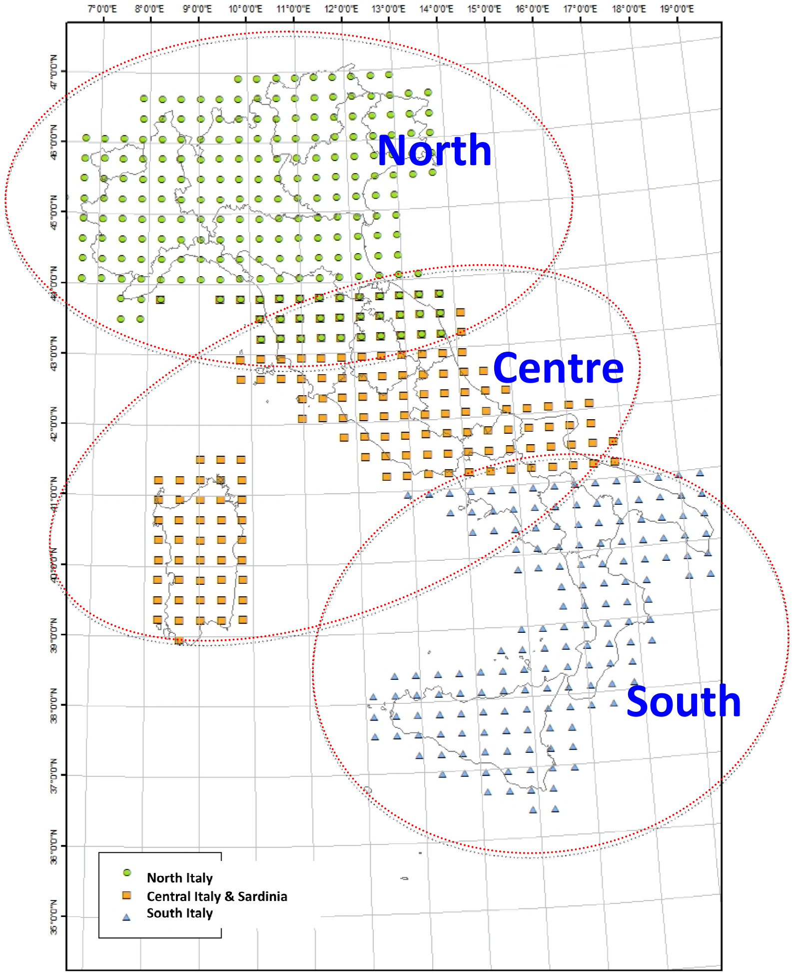


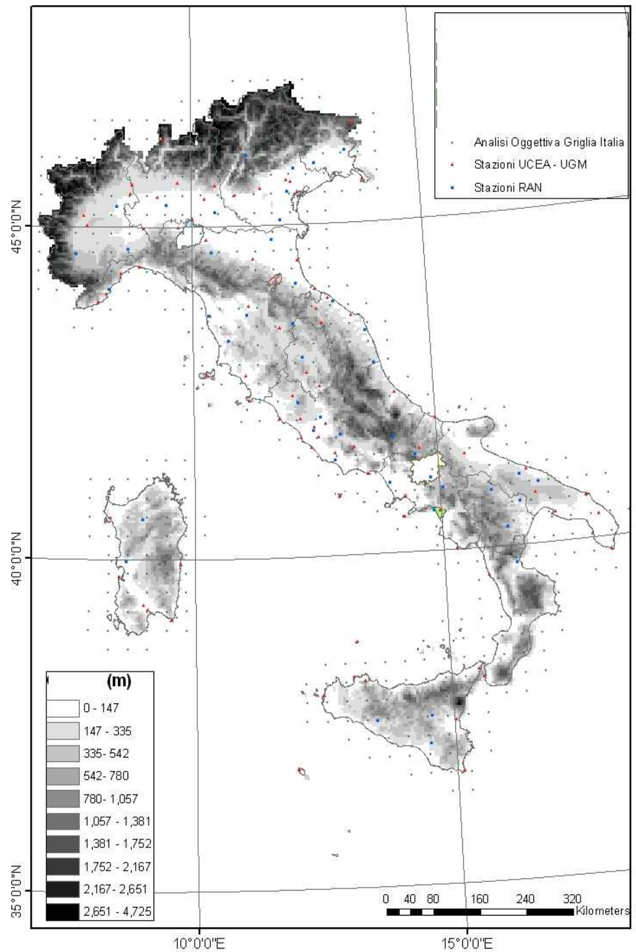
The Italian Civil Protection started a monthly to seasonal permanent forecast board since the (Extreme Dry/Warm) Winter 2006-2007 with monthly meeting regarding major critical environment and planning issue: *next three months along with a focus on the following month*.

Days → Weeks → Month → Season

	When?
Wind Storms	**All Season**
Forest Fires	**Summer**
Cold Air Outbreaks	**Winter/Summer**
Dry/Wet Spells	**All Season**
Drought Evolution	**All Season**
Heat/Cold Waves	**Winter/Summer**
Water Supply	**Winter/Summer**
Energy Supply	**Winter/Summer**
Normal Conditions (e.g. for Agri. Irrigation Planning)	**Extended Summer**

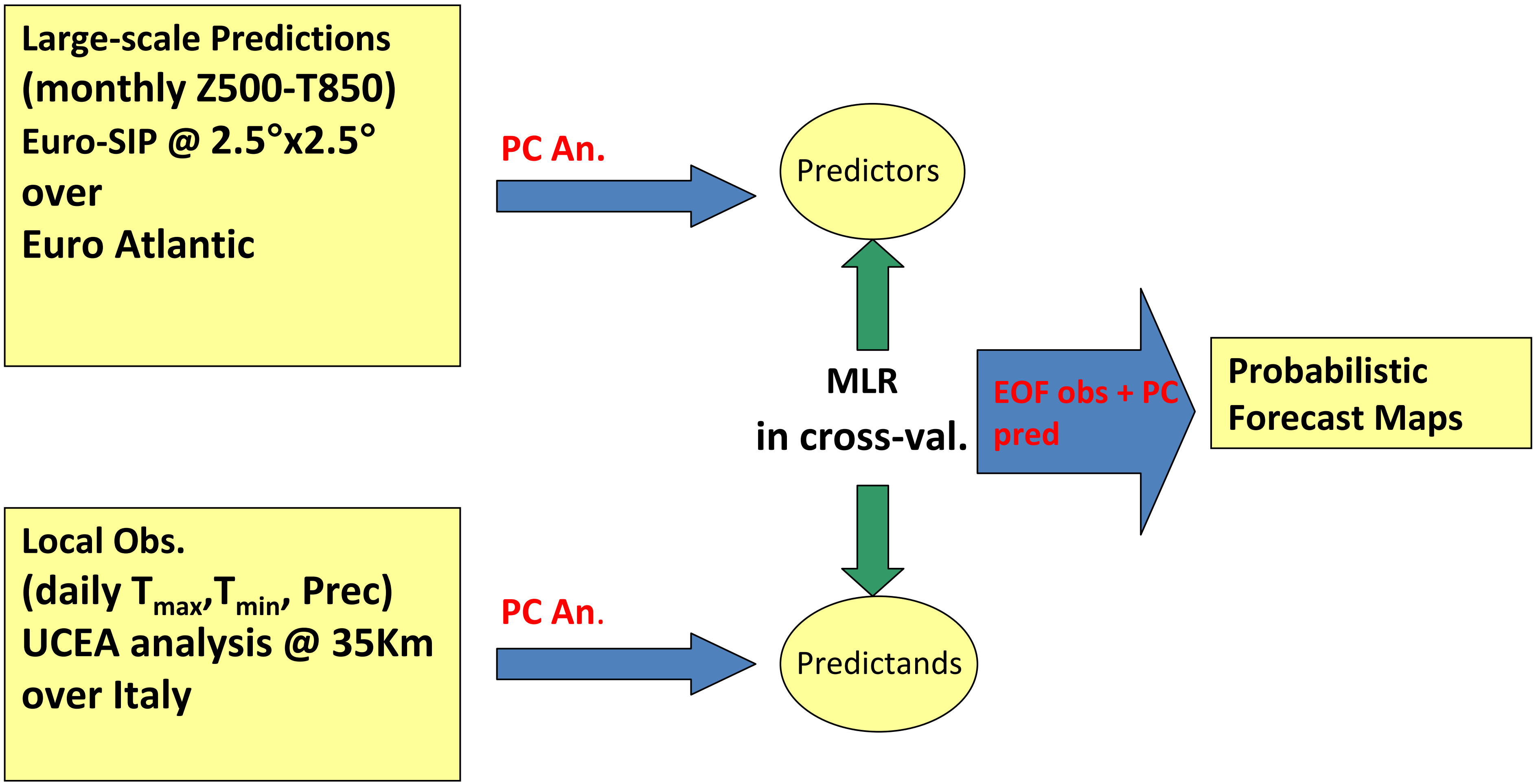
A reference “ground truth”





- Three reference areas were established according to the DPC needs of observation, long term forecast and a consensus basis, thus not purely climatic.
- The CRA-CMA Analysis data-set consists of an objective analysis of station data (AM & CRA-CMA) covering the whole Italian territory with a regular 35Km grid from 1951 to present and includes daily minimum, maximum temperature and precipitation.

ARPA-SIMC Calibration Scheme



Skill of T_{max} JJA predictions over Italy

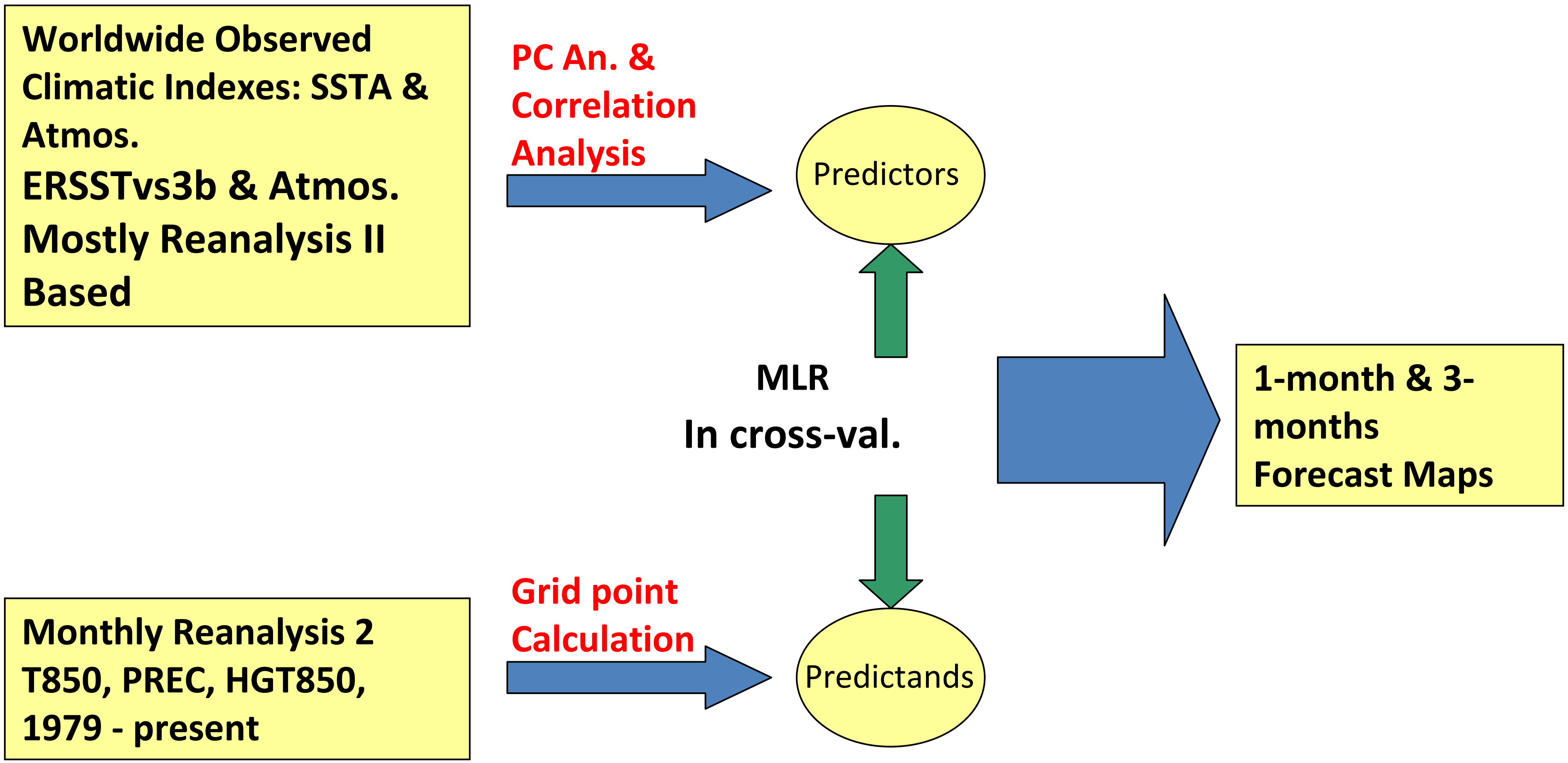
Results refere to ENSEMBLES-STREAMII multi-model seasonal forecasts (1971-2005)

Preprocessing	DMO		Calibrated	
	Cor	BSS	Cor	BSS
Full fields	0.38*	0.14	0.49**	0.21
Detrended	-0.01	0.004	0.27	0.11
Full fields - 2003	**0.45**	**-0.08**	**0.60****	**0.17**
(Full fields – 2003) detrended	**0.09**	-0.03	**0.49**	0.09

Pavan and Doblas-Reyes (2013)

- Calibrated seasonal multi-model seasonal predictions have better skills than DMO multi-model predictions
- Over Italy and in the summer season the DMO T_{max} predictions skill is mostly due to the correct representation of linear trends.
- Calibration can still produce skilful predictions even if trends are removed.
- The presence of extreme events in the data-set has a strong influence on the evaluation of the skill of the system and on the calibration process.

IBIMET – Statistical Forecast System



SeaFor Validation Results: ARPA-SIMC & IBIMET

Ranking primarily the BSS and considering POD & FAR:

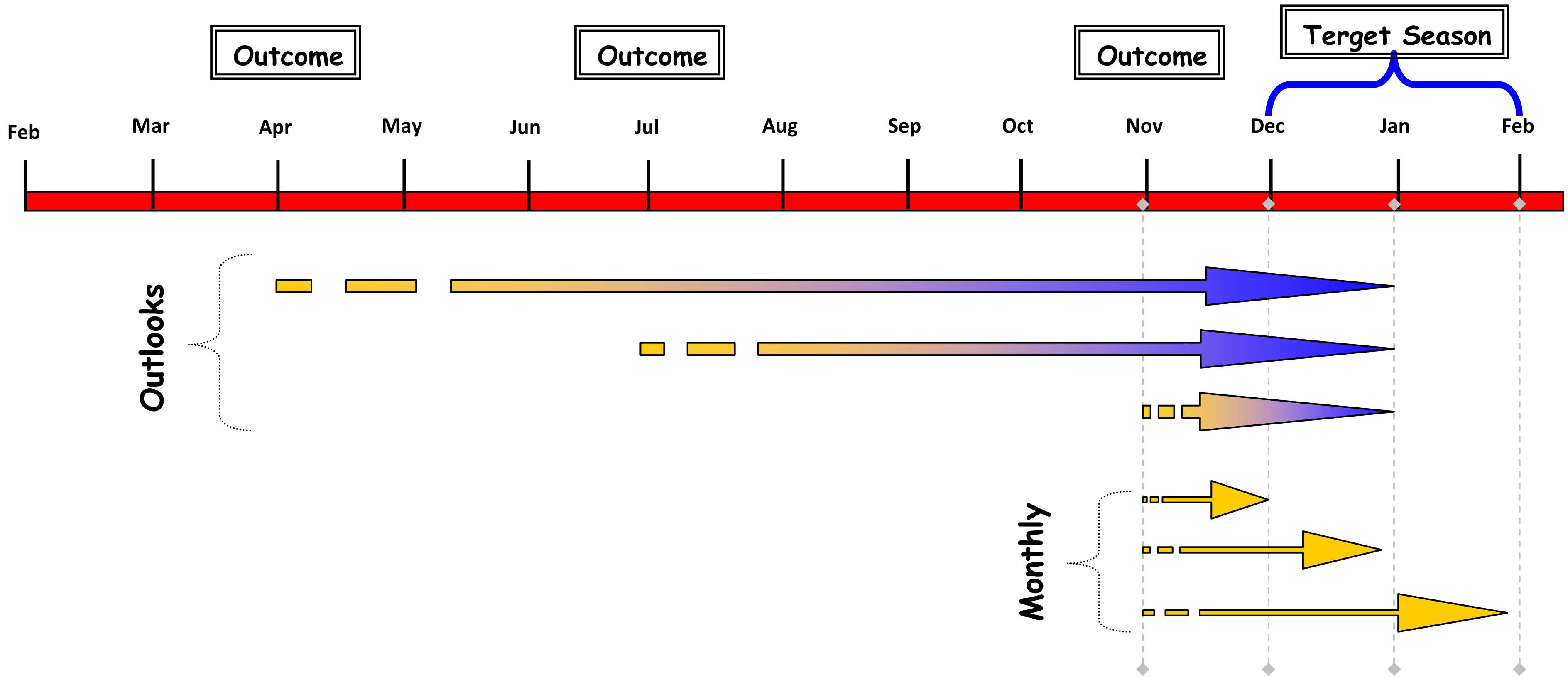
… general considerations:

- both 2-classes & 3-classes performances are similar good;
- JJA results are slightly better than DJF;
- T is slightly better than P;
- No major differences between P and T for same quarter year, areas;
- the southern area precipitation is the most critical;

… and specific considerations

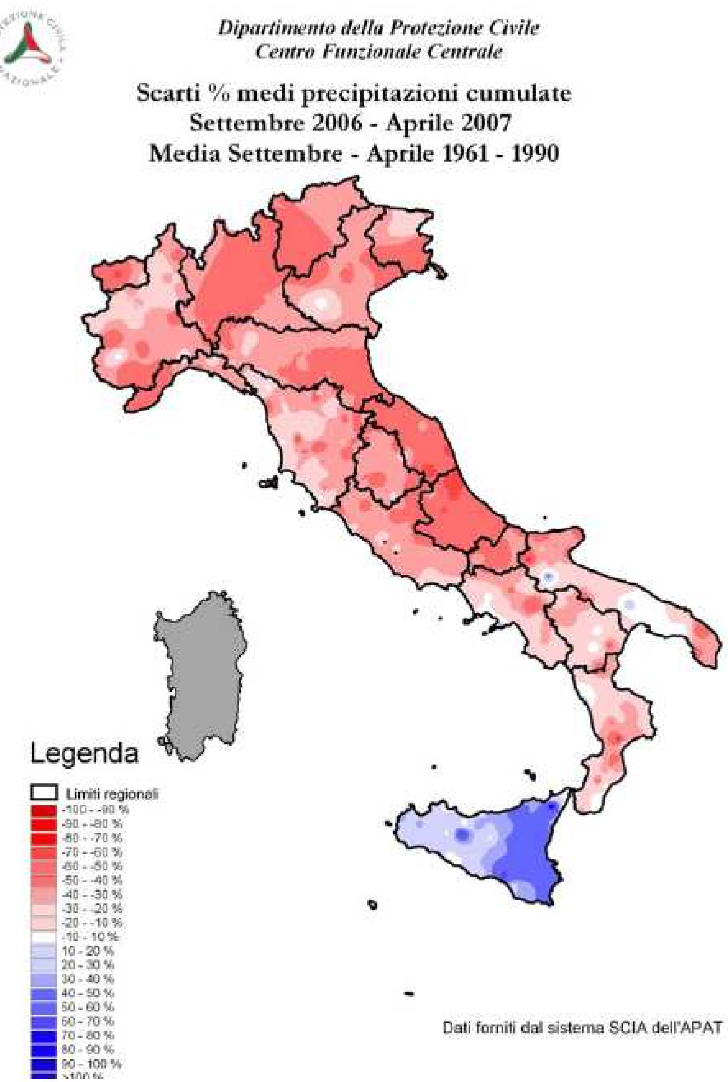
- overall ARPA-SIMC performances are clearly better than IBIMET;
- … it is clear in DJF, less evident in JJA;
- IBIMET forecasts are poor in DJF, especially for T (even at 850hPa);
- ARPA-SIMC T&P very good for both JJA and DJF in N-C areas;

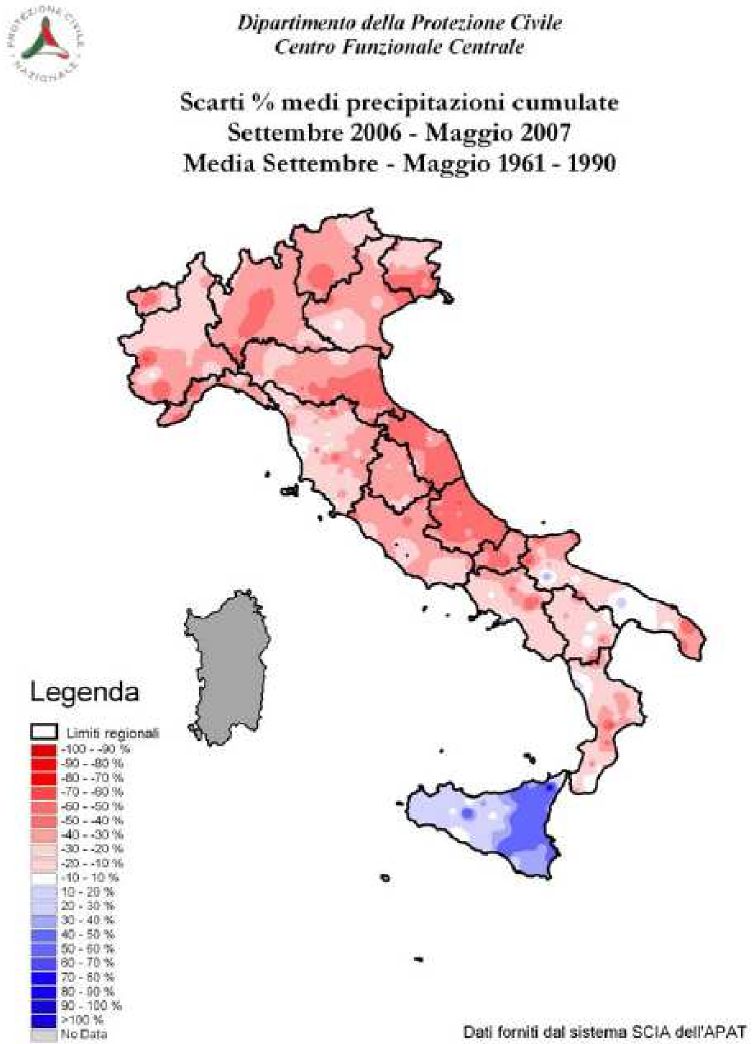
Winter 2006/2007 Case Study



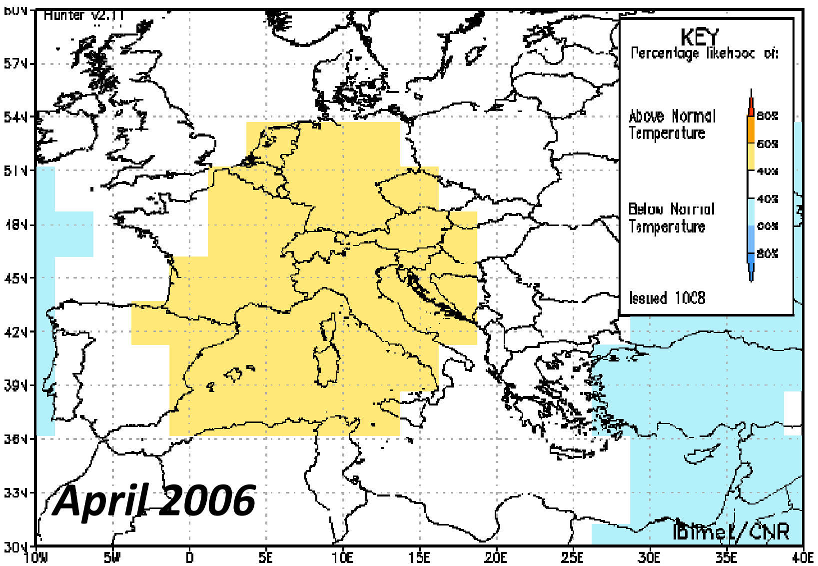
- **Outlooks:** Temp / Precip
- **Monthly:** Temp / Precip / SPI.3

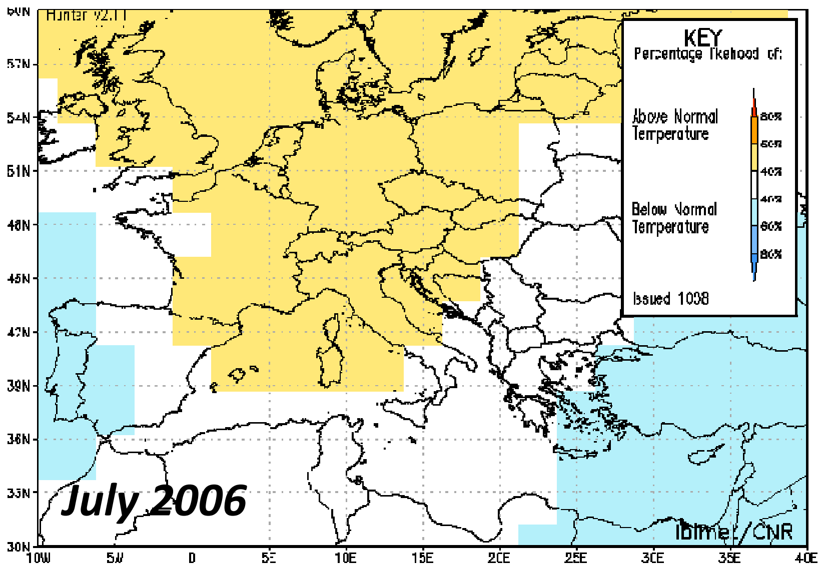
CNR - IBIMET

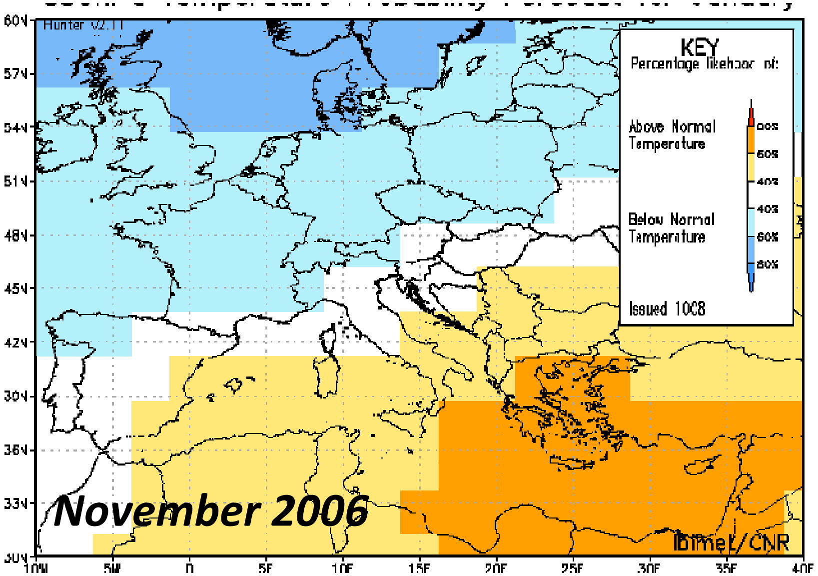


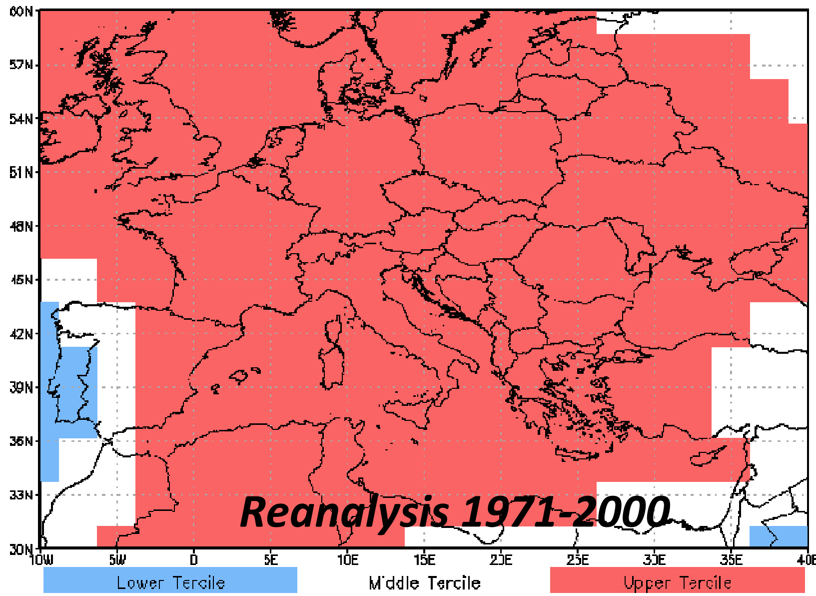


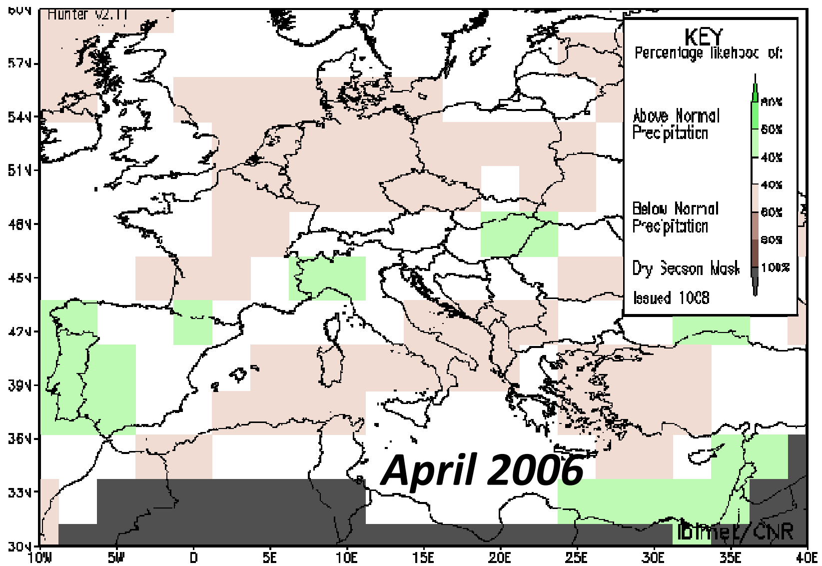
From: www.protezionecivile.gov.it

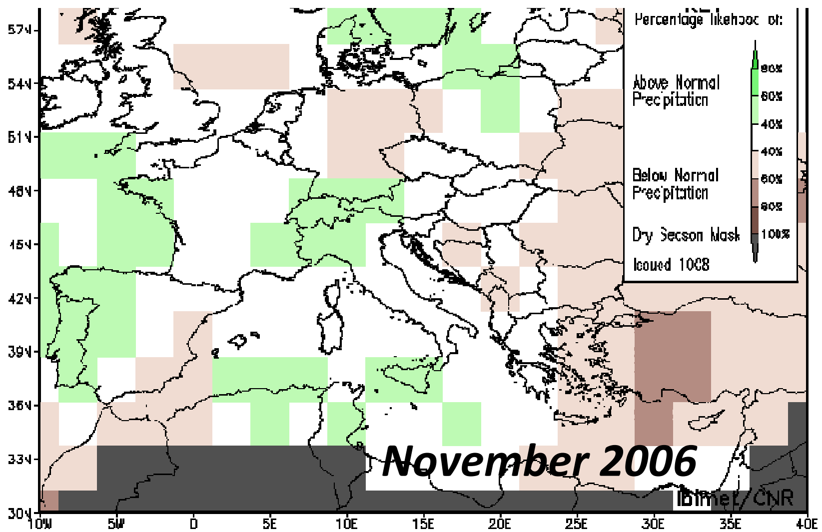

Hunter v2.11
KEY
Percentage likehood of:
Above Normal Temperature
Below Normal Temperature
Issued 1008
April 2006
Ibimet/CNR

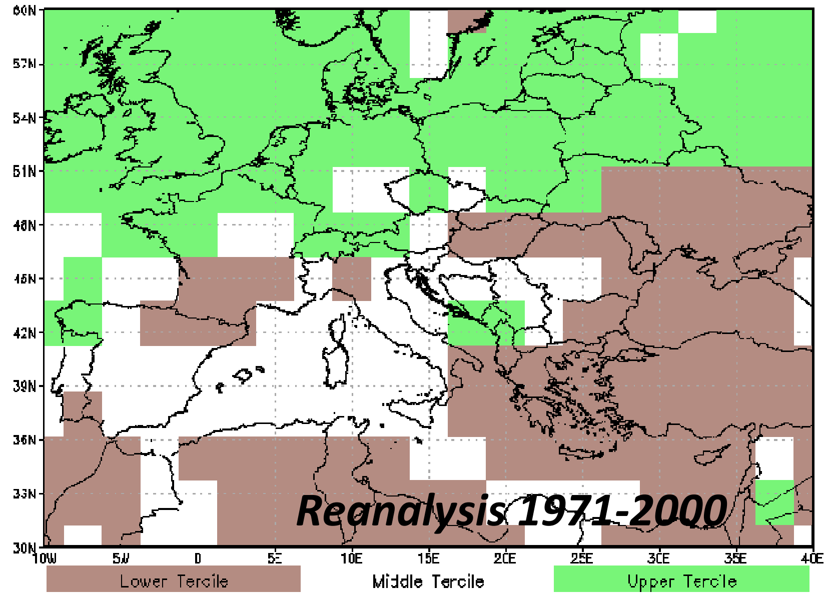

Hunter v2.11
KEY
Percentage likehood of:
Above Normal Temperature
Below Normal Temperature
Issued 1008
July 2006
Ibimet/CNR

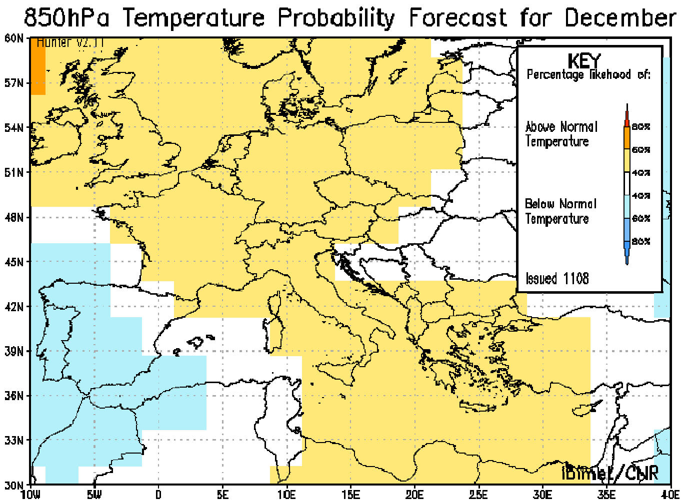

Hunter v2.11
KEY
Percentage likehood of:
Above Normal Temperature
Below Normal Temperature
Issued 1008
November 2006
Ibimet/CNR

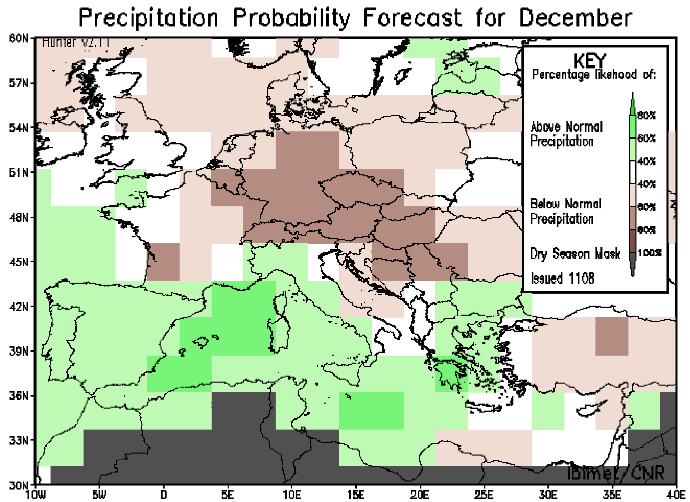

Reanalysis 1971-2000
Lower Tercile
Middle Tercile
Upper Tercile


Hunter v2.11
KEY
Percentage likelihood of:
Above Normal Precipitation
Below Normal Precipitation
Dry Season Mask
Issued 1008
80%
60%
40%
40%
60%
80%
100%
April 2006
Ibimet/CNR
57N
54N
51N
48N
45N
42N
39N
36N
33N
30N
10W
5W
0
5E
10E
15E
20E
25E
30E
35E
40E

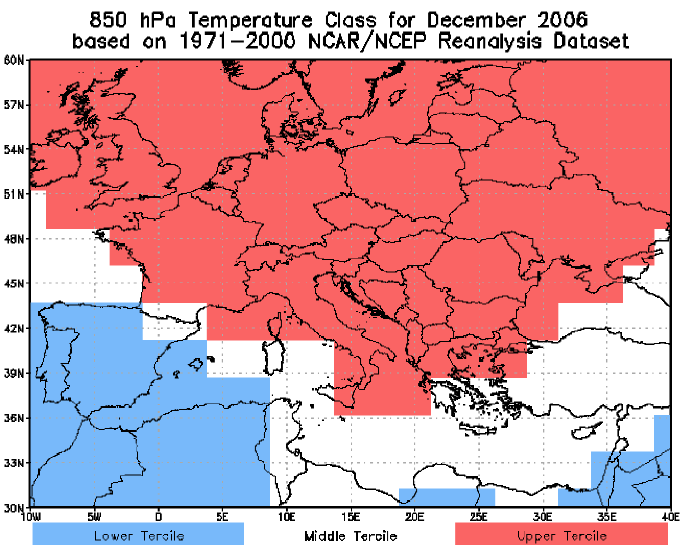

Percentage likelihood of:
Above Normal Precipitation
Below Normal Precipitation
Dry Season Mask
Issued 1008
80%
60%
40%
40%
60%
80%
100%
November 2006
Ibimet/CNR
57N
54N
51N
48N
45N
42N
39N
36N
33N
30N
10W
5W
0
5E
10E
15E
20E
25E
30E
35E
40E

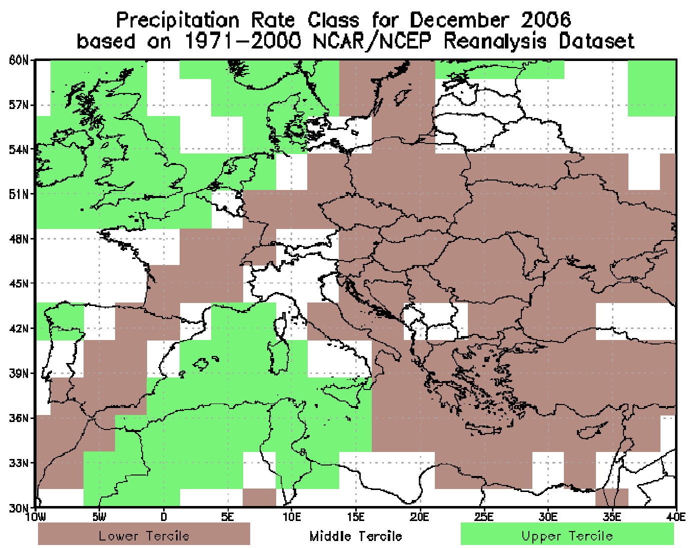

Reanalysis 1971-2000
Lower Tercile
Middle Tercile
Upper Tercile
60N
57N
54N
51N
48N
45N
42N
39N
36N
33N
30N
10W
5W
0
5E
10E
15E
20E
25E
30E
35E
40E



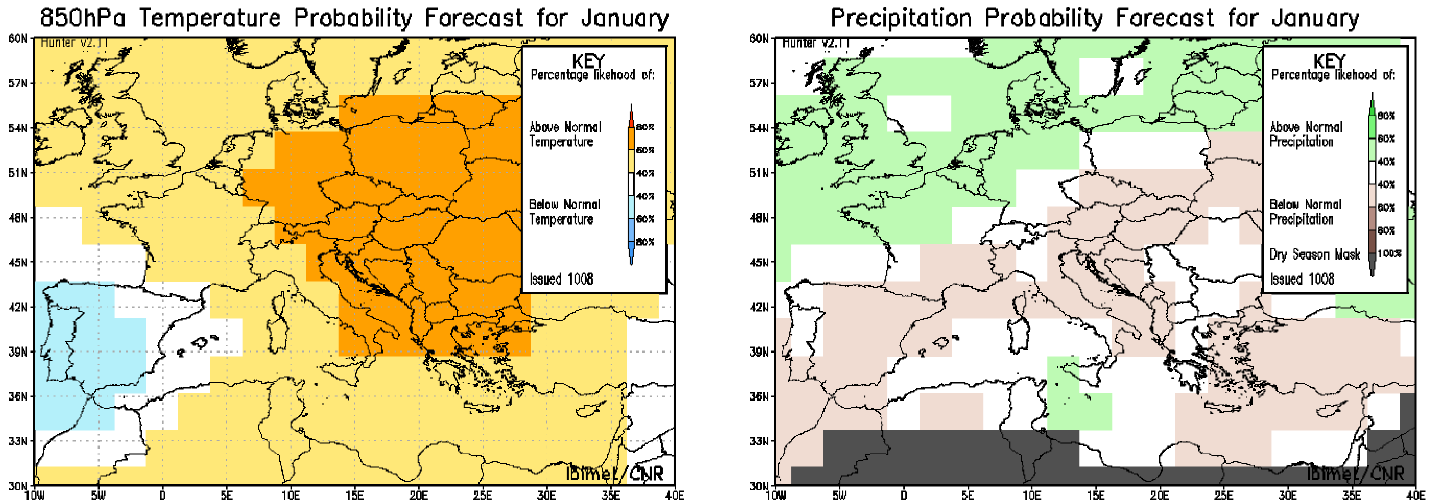


Data from Nov 2006

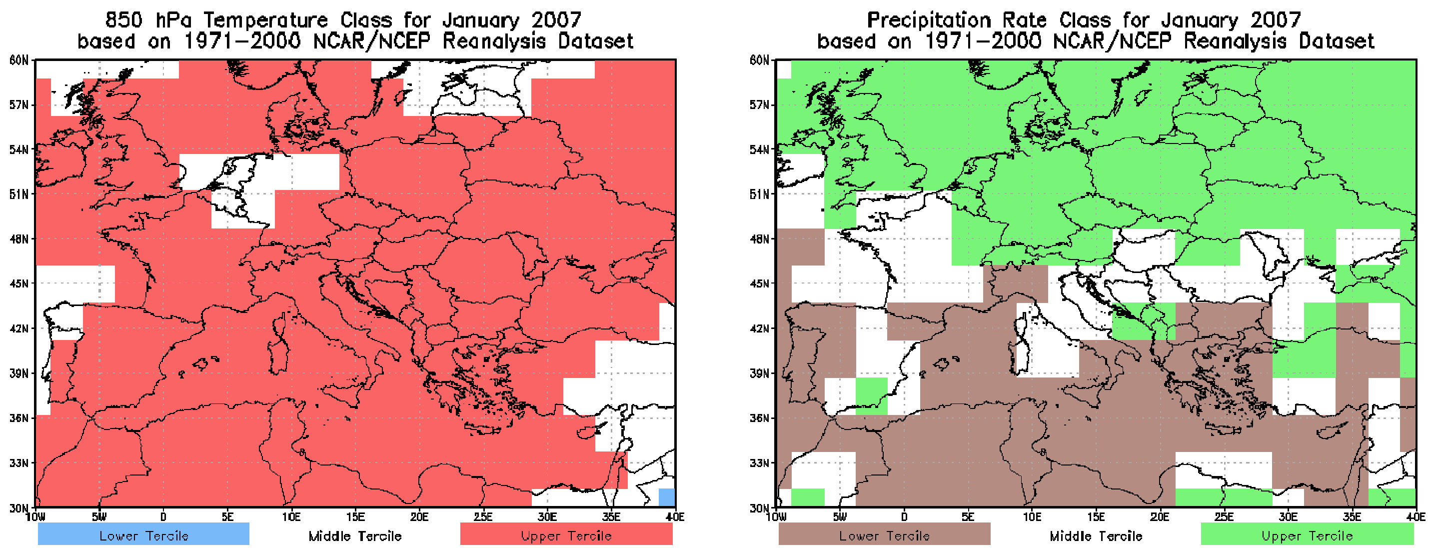




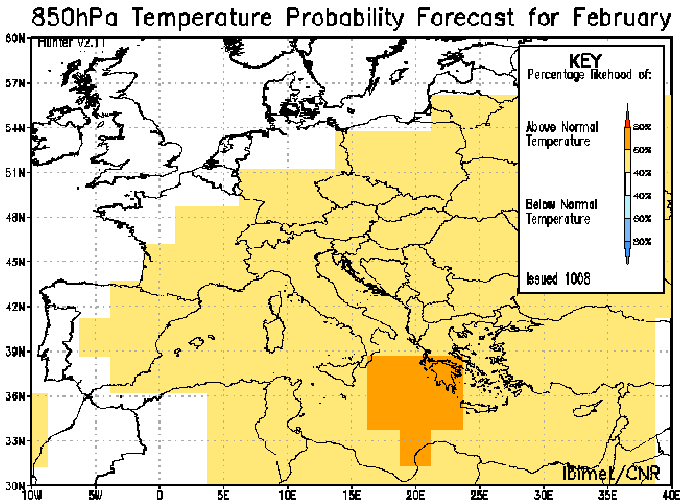
Reanalysis 1971-2000

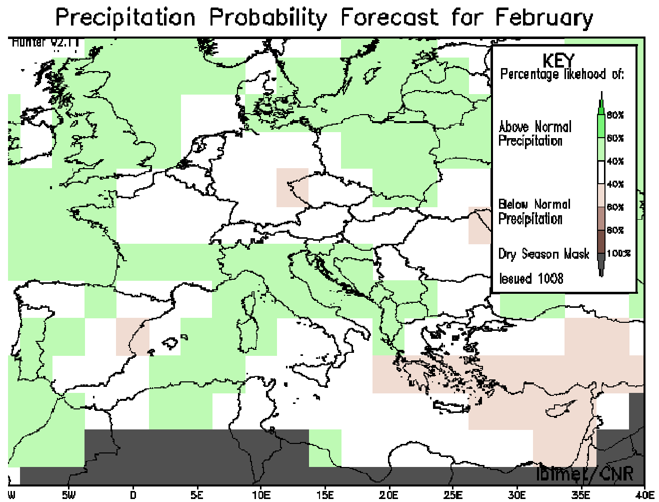


Data from Dec 2006

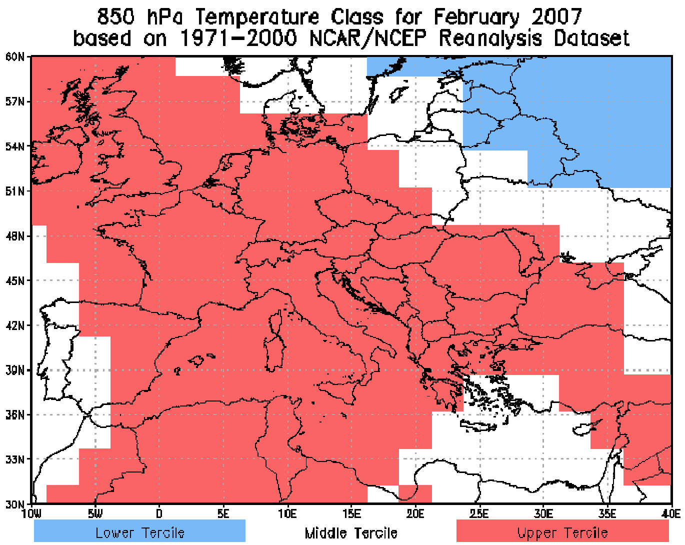


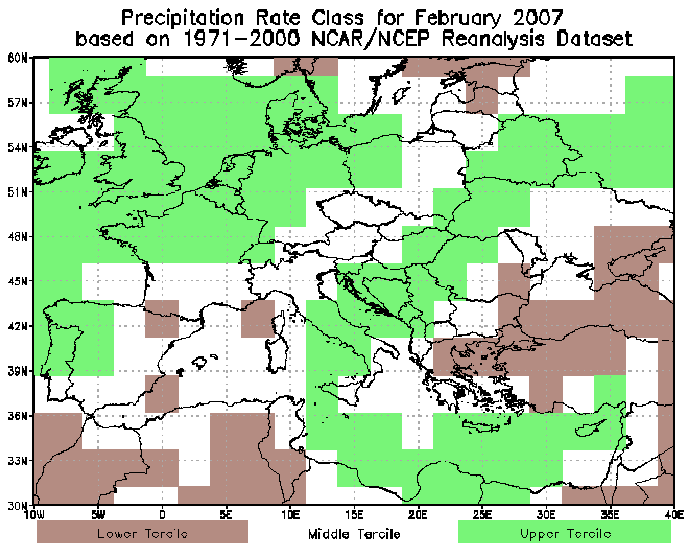
Reanalysis 1971-2000





Data from Jan 2006





Reanalysis 1971-2000

CNR - IBIMET

- This seasonal prediction method shows encouraging results over the Mediterranean area: large scale features and correspondent anomalies location have a reliable skill level.

- The successful key for summer season seems to be the choice of physical predictors and their long range memory which is linked to the Winter North Hemisphere Snow Cover extent and Spring melting.

- In particular winter SV-NAM and the Spring Atl. Tripole & 1st EOF Guinea, seem to produce the “core” Summer variability over that area.

- Even winter atmospheric anomalies present a reliable skill level.

- Further investigations will be focused on downscaling techniques based on statistical methods.

… some sub-seasonal (synoptic/regime) characterization …

Motivations

- Monthly and quarterly climate anomalies, issued by seasonal forecast systems, even if reliable, could be of marginal use without an associated synoptic regime characterization.
- Circulation classifications, along with a canonical correlation analysis, represent a promising and practical way to reduce the existing temporal gap, between monthly or quarterly climate anomalies and synoptic regime characterization.

Motivations

- Canonical (which means: reduced to the simplest or clearest possible scheme) Correlation Analysis approach is wide used in climatology and in particular it is applied, since late ’80s for extracting information among predictors. (e.g. Barnett and Preisendorfer, MWR, 1987)

- Two papers, Moron et al. (part I and part II, J.Climate, 2008), an inter – annual variability characterization of Sahel precipitation based on the WT inter – annual regime analysis from historical and forecast GCMs.

Basic Idea

- The basic idea is to find a (linear) relationship, at month or season time scale, between two daily datasets: **temperature anomalies** and a **WTC daily catalogue**.
- In order to move from daily to monthly or quarterly time scale, daily data could be classified. A possible choice is computing a class occurrence matrix.
- The seasonal forecasting goal is capability of capturing the inter and intra annual variability of atmospheric fields. Statistical methods are dealing with inter – annual variability, while global models approach mainly deal with intra – annual variability

Basic Idea

A very general hypothesis follows:

$$PDF(Temp.Anom)_{year} \Leftrightarrow PDF(WTC_{occc})_{year} \cdot PDF(WTC_{char})_{year}$$

A less general hypothesis follows:

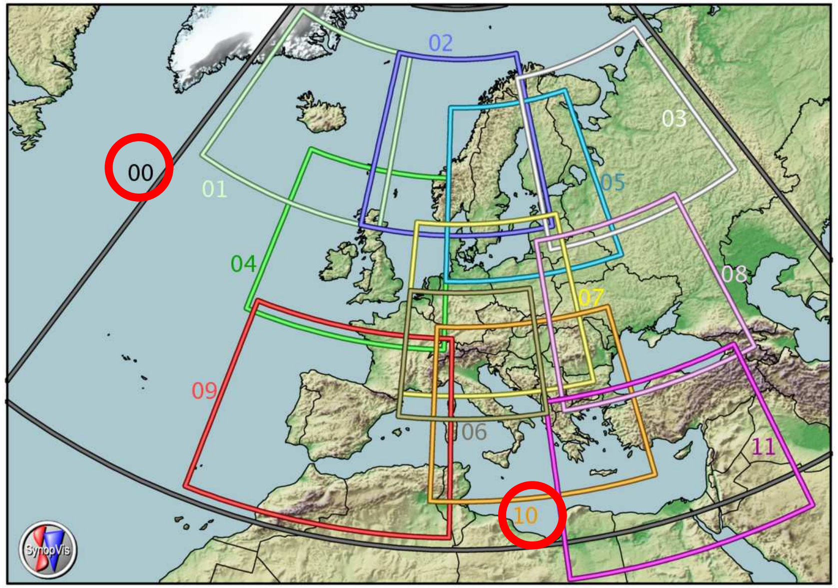
$$(Temp.Anom)_{year,class} = \sum_{type} (WTC_{occc})_{year,type} \cdot (WTC_{char})_{year,type,class}$$

2 ways:

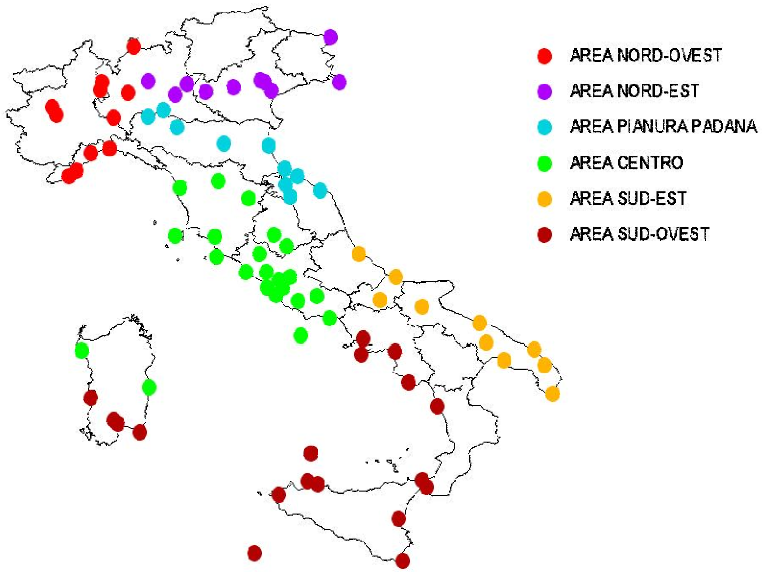
- CCA: $(Temp.Anom)_{year,class}$ & $(WTC_{occc})_{year,type}$
- CCA: $(Temp.Anom)_{year,class}$ & $(WTC_{occc})_{year,type,class}$

Data

Catalogue Candidate



Daily temp. anomalies



Among the large number of WTC catalogues available in the COST733 repository we select one "candidate" among circulation classifications: TPCA07 (Huth 2000); and 2 domains: D00 and D10.

86 station datasets were collected for the 1961 – 2001 period. After a PCA analysis, these datasets were grouped into 6 homogeneous areas, in the framework of a seasonal forecast research project: TEMPIO.

Canonical Correlation Analysis

Considering 2 datasets:

$Y_1, Y_2, \dots Y_p$ and $X_1, X_2, \dots X_q$

Construct a linear combination:

$U = u_1 Y_1 + u_2 Y_2 + \dots u_p Y_p$

$V = v_1 X_1 + v_2 X_2 + \dots v_q X_q$

with

$u' = [u_1, u_2, \dots, u_p]$

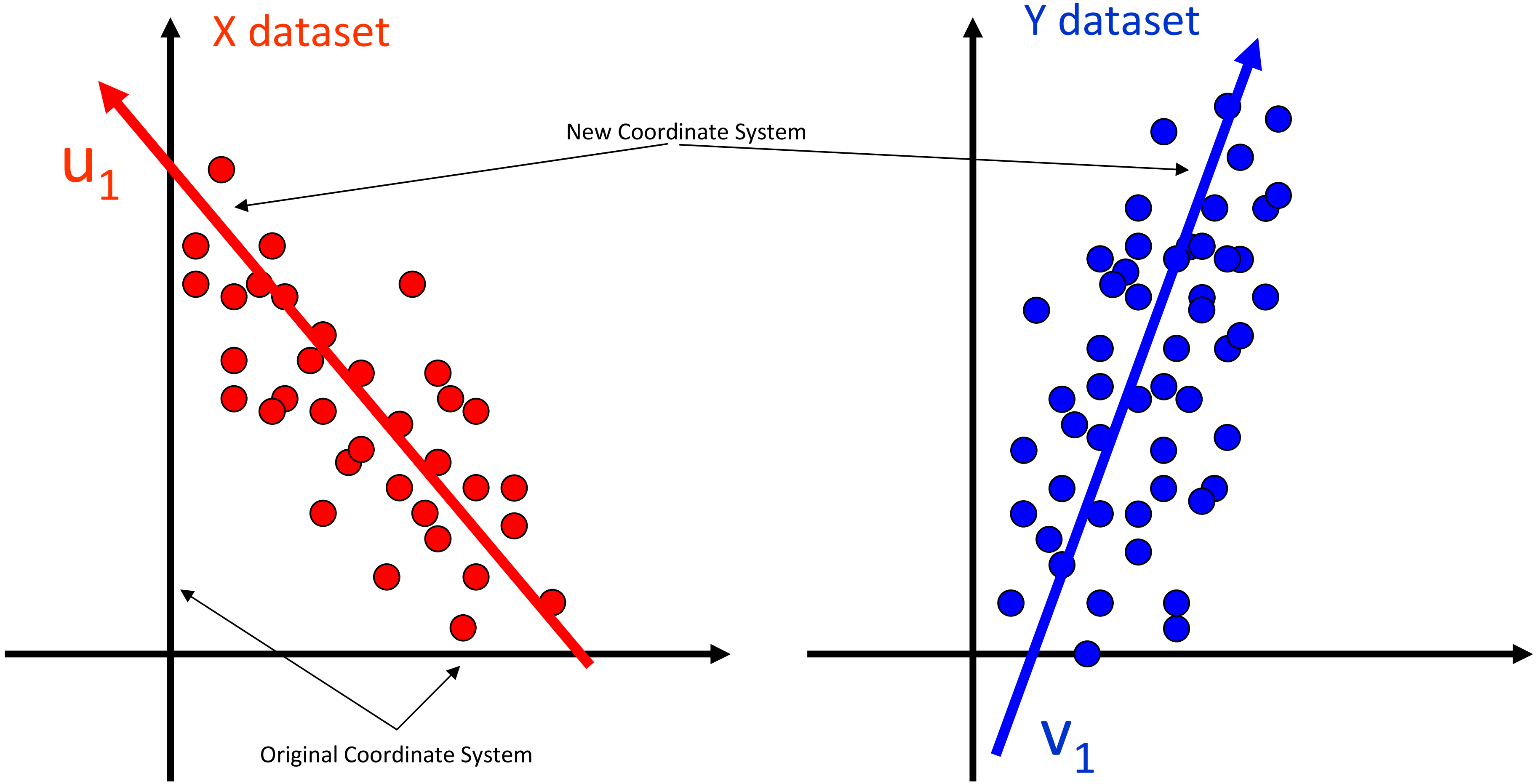
$v' = [v_1, v_2, \dots, v_q]$

such that correlation R(U,V) is a maximum

Let S be the variance – covariance matrix of X and Y datasets

$$\mathbf{S} = \begin{bmatrix} \mathbf{S}_{yy} & \mathbf{S}_{yx} \\ \mathbf{S}_{xy} & \mathbf{S}_{xx} \end{bmatrix}$$

Canonical Correlation Analysis



Finding two sets of basis (u, v) vectors such that the correlation between the projections of the variables onto these basis vectors is maximized

CCA overview scheme

Original Datasets
X and Y

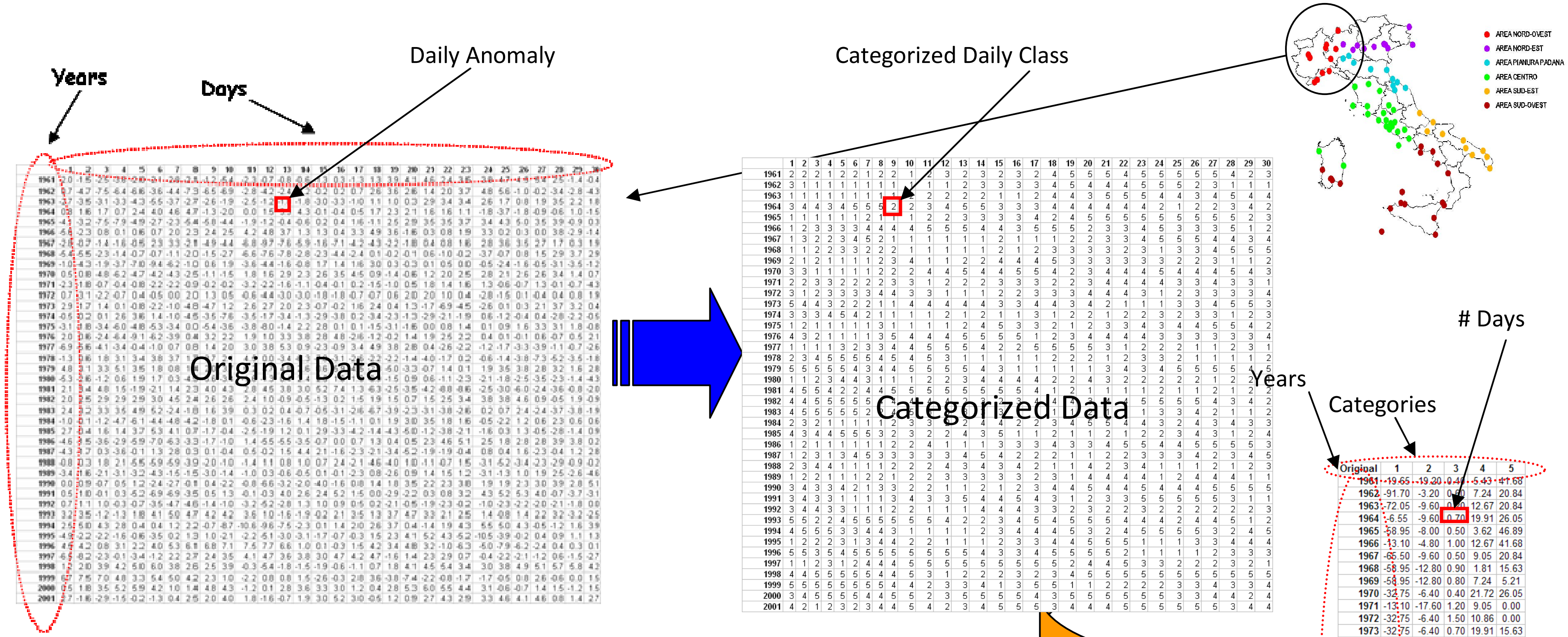
Find u and v with CCA and then
expressing original datasets in terms of the new
coordinate systems: U and V

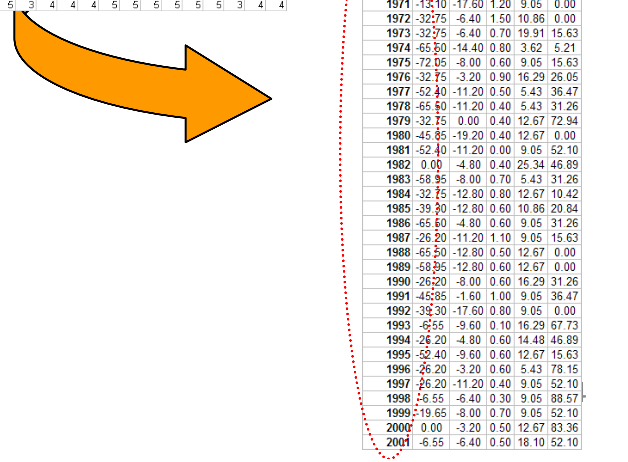
Express each V_i as a linear
function of correspondent U_i:
$V_i = \rho_i U_i$

Going back to the original coordinate system:
$Y^* = L(U_1)$

CNR - IBIMET

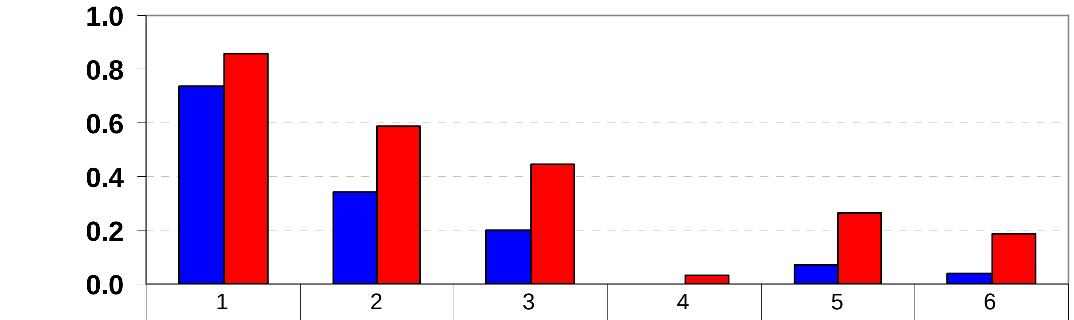
Data Preparation





1. A 5 – days smoothed daily time series anomaly (1971 – 2000 based climatology) for each area.
2. Time series is from 1961 – 2001.
3. Reference period is JJA and June, July, August.

CCA Results

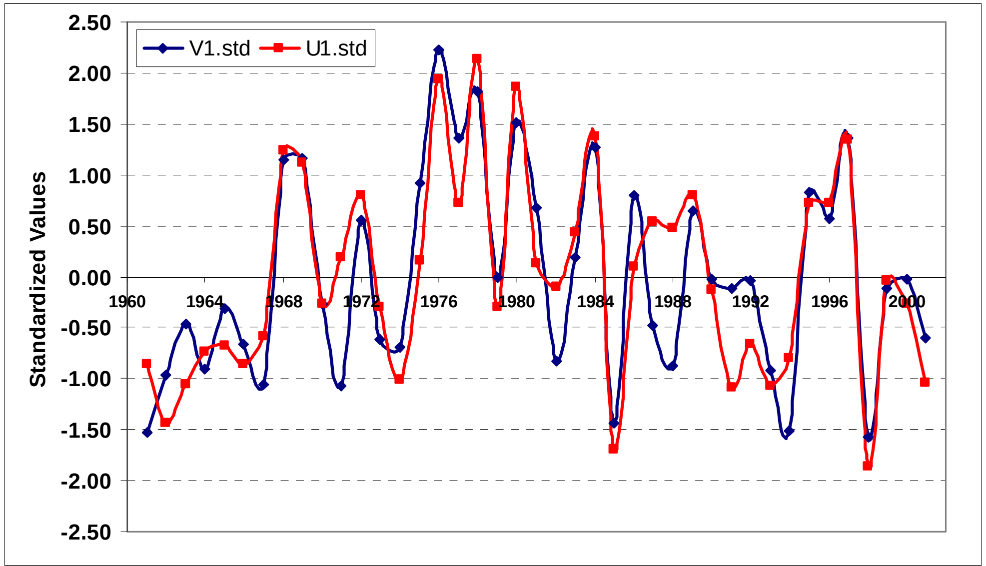


	1	2	3	4	5	6
Eigenvalue	0.738	0.342	0.198	0.001	0.071	0.036
Can. Corr.	0.859	0.585	0.445	0.030	0.266	0.190

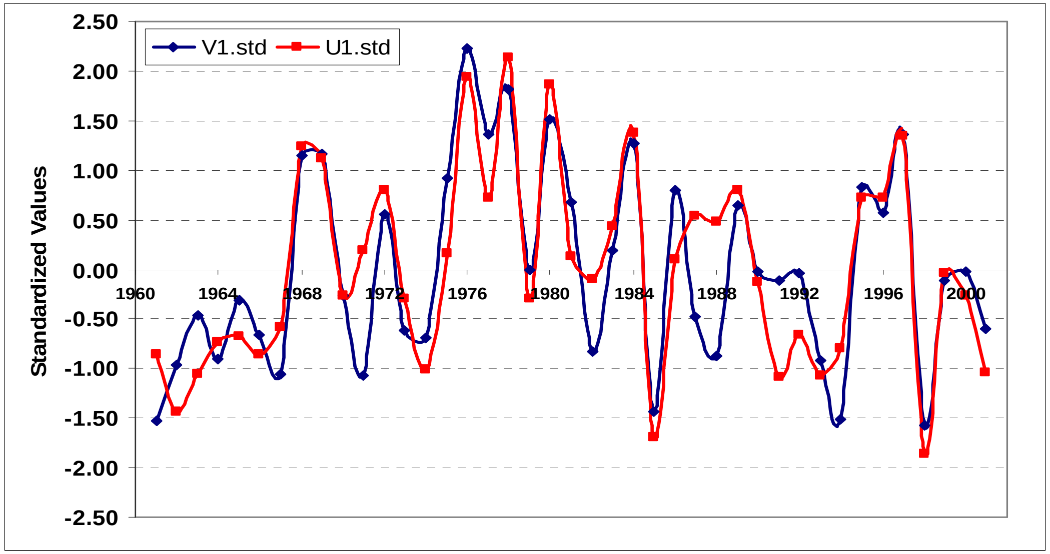
Canonica Variates

JJA – canonical variates

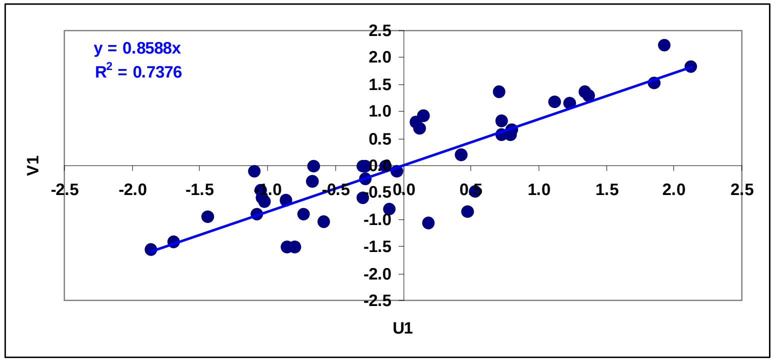
JJA – 1° pair

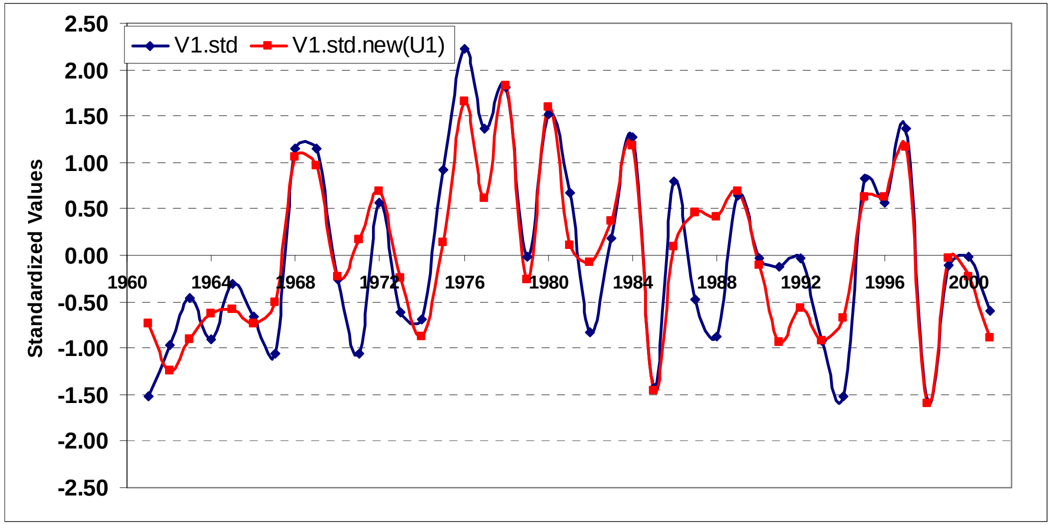


CCA Results



JJA – 1°





Expressing V_1 as a linear function of U_1

CCA Results

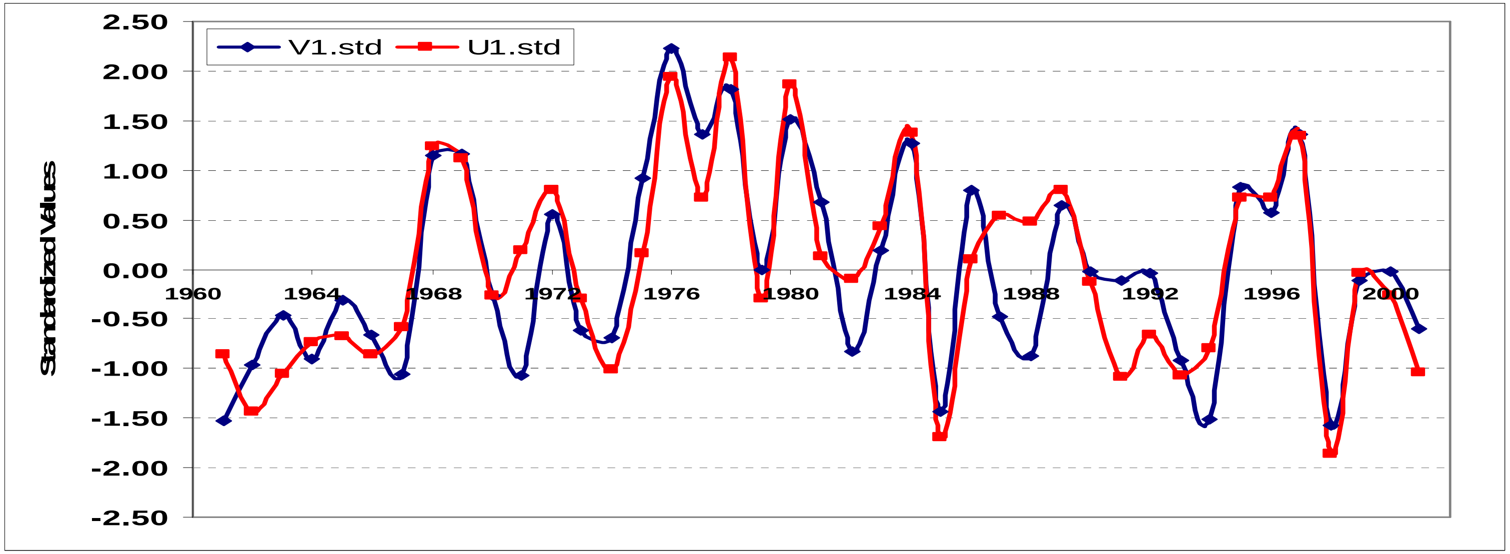
Finally, going back to the original coordinate system, we obtain the initial Y dataset in terms of the first canonical variate of X by means: $Y^* = L(U_1)$ where L is a linear operator.

$$\begin{pmatrix} y_{11} & \dots & y_{1p} \\ y_{21} & \dots & y_{2p} \\ \dots & \dots & \dots \\ y_{n1} & \dots & y_{np} \end{pmatrix} \qquad \begin{pmatrix} y^*_{11} & \dots & Y^*_{1p} \\ y^*_{21} & \dots & Y^*_{2p} \\ \dots & \dots & \dots \\ Y^*_{n1} & \dots & Y^*_{np} \end{pmatrix}$$

We can compare each column of Y with the correspondent column of Y*

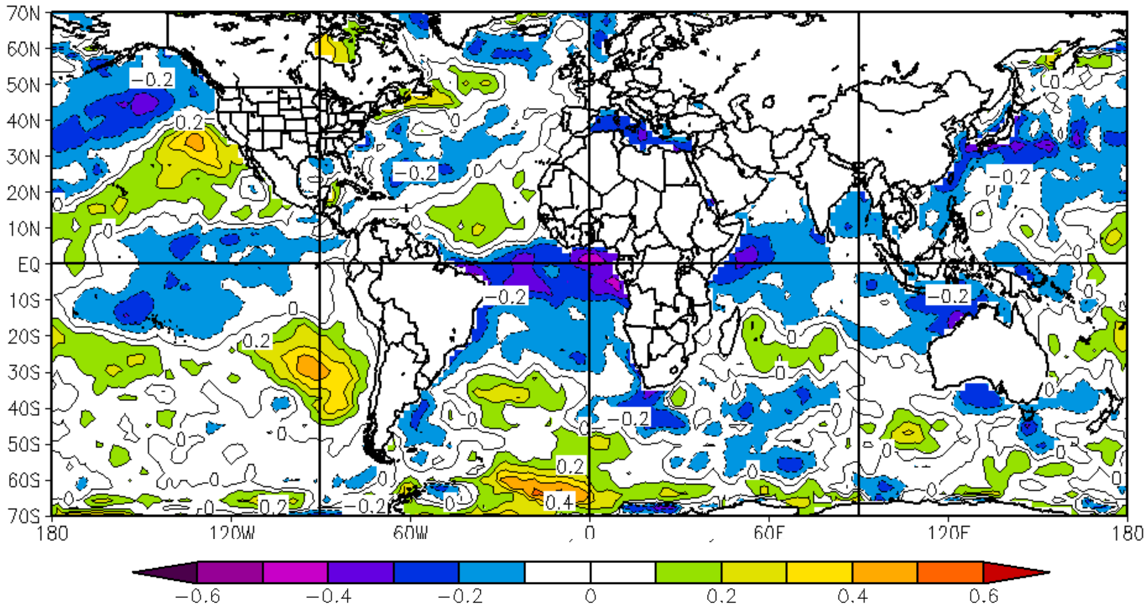
Physical Interpretation

We have now a canonical vectors pair which have the highest correlation between the two datasets. In other words we can express the inter-annual variability of Y (thermal categories) in terms of X (WTC occurrence).



Seasonal Applications

Since U_1 (WT occurrence) is the “essence” of such inter-annual variability correlated with V_1 (thermal categories) we can use it to explore its possible climatic sources. Some examples: SST (April) – WTC occurrence (JJA) relationship.



Thus we can forecast U_1 using SST predictors.

Seasonal Applications

1. It is possible to forecast U_1 , for example with a multi regressive approach, and then going back to V_1 to get the thermal distribution, instead of forecasting directly the thermal anomaly.

2. We can also reverse the strategy and associate a possible seasonal regime to an thermal seasonal forecast (coming from an independent system).

3. Since the CCA method is quite general, the Y dataset could be any classified inter – annual observables: e.g. number of rainy days of different thresholds, dry or wet spells of different duration, heat or cool waves of different duration.

Seasonal Applications

4. It could be applied to any climatic index after a simple phase classification in terms of strength or duration: Blocking, AO, NAO, etc.

5. Not only the inter – annual variability of WTC occurrence could be used, but also its climatological “character”, by means the thermal character of each WTC.

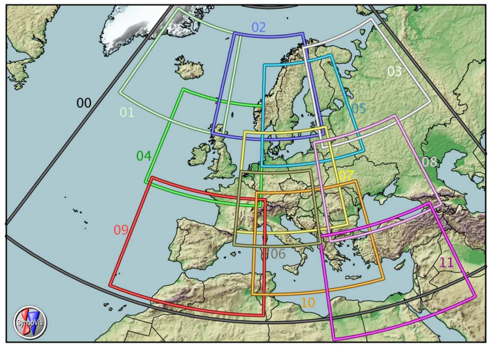
CCA and COST 733

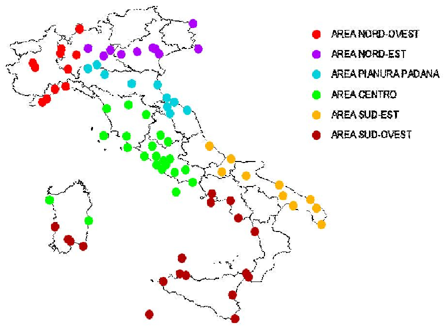
Is there any information, coming from the CCA, that could be used for “selecting” a WTC among the huge number of available catalogues? We think so! Let’s expand the previous example: for each WTC methods we have:

• different number of classes (original number plus some fixed amounts: 9, 18, 27);

• different domains (large, small, often superimposed);

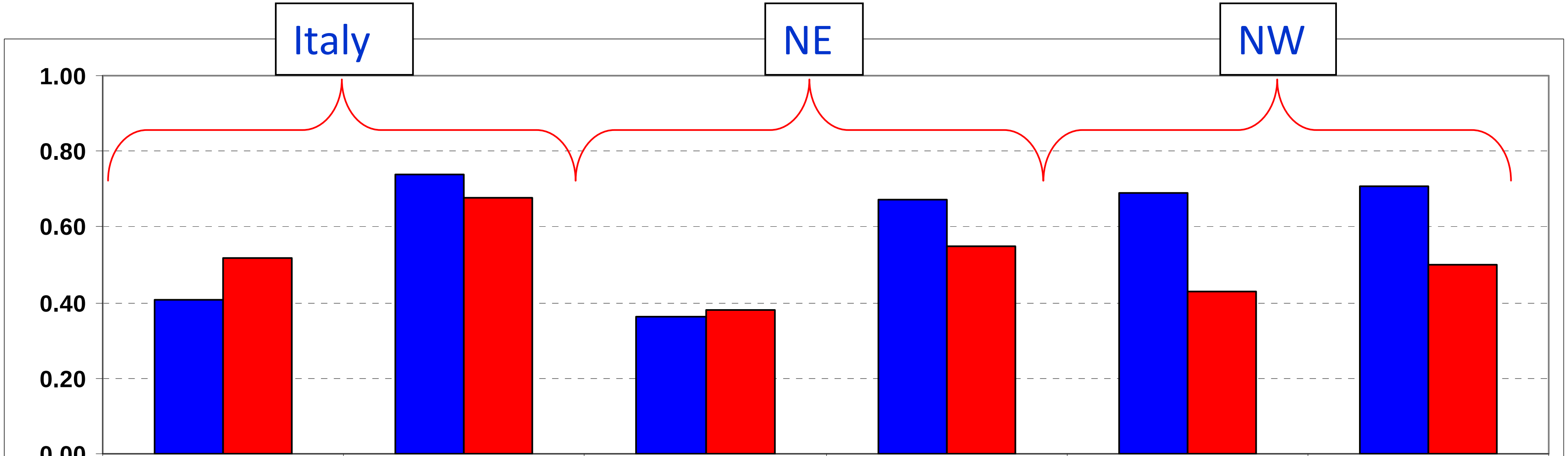
• different climatic areas: Italy, North – East, North – West, etc.





CCA and COST 733

For example applying the CCA to the same WTC, with 7 classes, but for: 2 domains D00 and D10; 3 climatic areas: Italy, N_EAST, N_WEST; WT occurrence and characters.



	ITA_7C_T-P	ITA_7C_T-WT	N_EAST_7C_T-P	N_EAST_7C_T-WT	N_WEST_7C_T-P	N_WEST_7C_T-WT
D00	0.405	0.738	0.362	0.672	0.689	0.709
D10	0.517	0.675	0.378	0.547	0.431	0.500

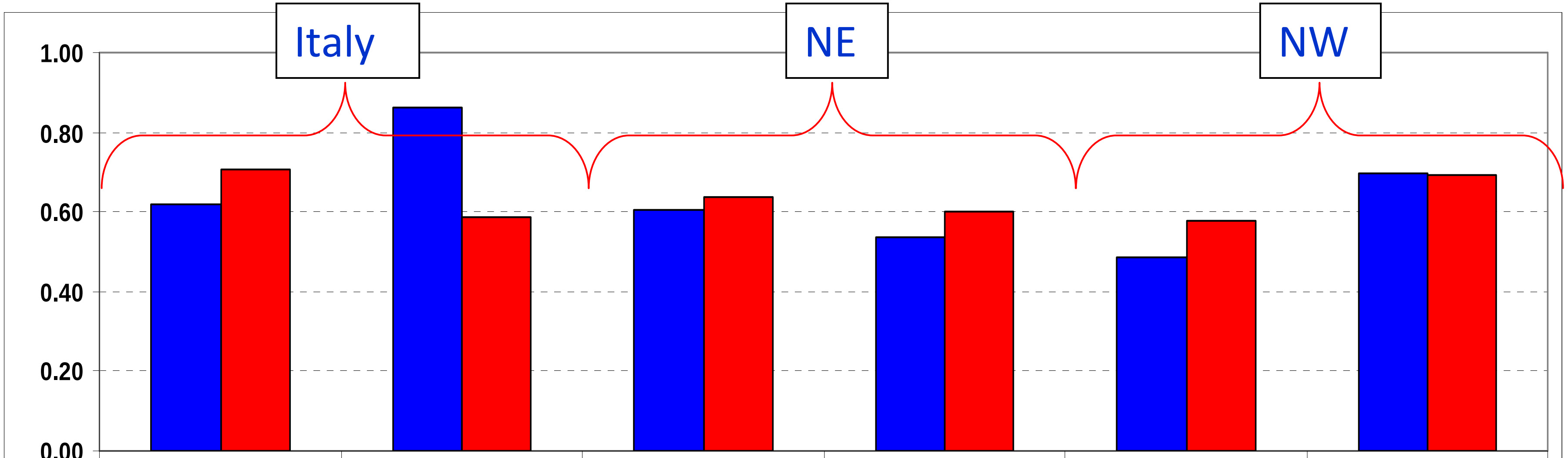
WTC_{char} vs. WTC_{occ}

Previous Example

JJA – 7 Classes

CCA and COST 733

As before, but for "9" classes:



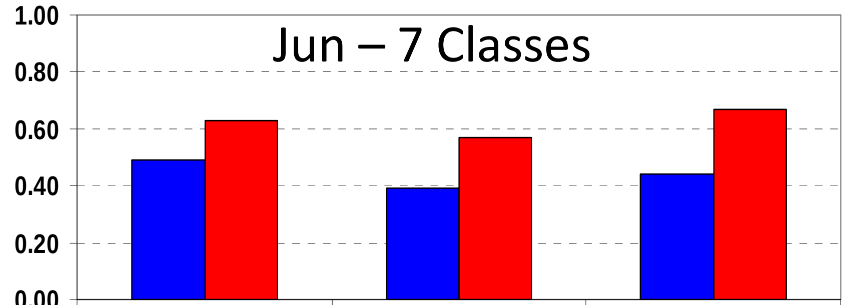
	ITA_9C_T-P	ITA_9C_T-WT	N_EAST_9C_T-P	N_EAST_9C_T-WT	N_WEST_9C_T-P	N_WEST_9C_T-WT
D00	0.62	0.86	0.61	0.54	0.49	0.70
D10	0.71	0.59	0.64	0.60	0.58	0.69

WTC_{char} vs. WTC_{occ}

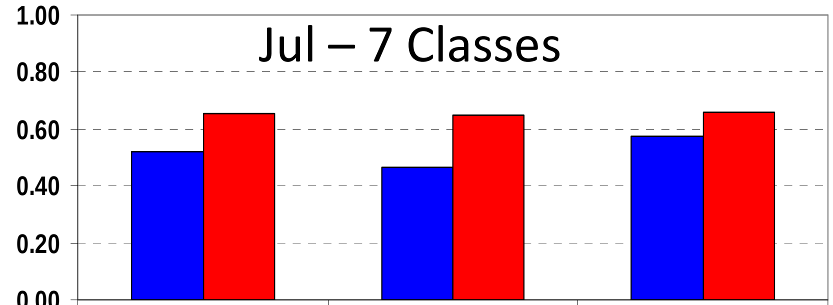
JJA ~ 9 Classes (D10=7 / D00=8)

CCA and COST 733

Going to the monthly time scale and using the WTC_{occ} to predict the temperature anomalies:

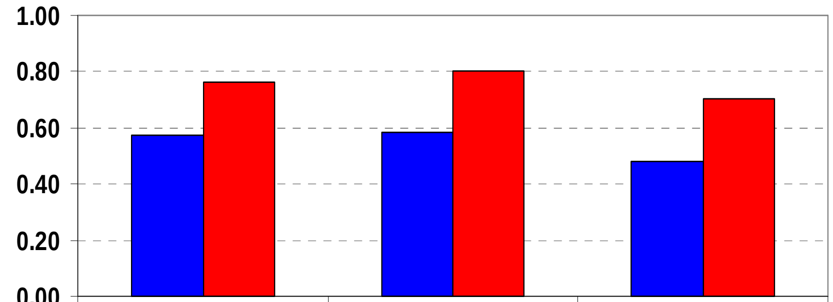


	ITA_WT-6	N_EAST_WT-6	N_WEST_WT-6
D00	0.49	0.39	0.44
D10	0.63	0.57	0.67



	ITA_WT-7	N_EAST_WT-7	N_WEST_WT-7
D00	0.52	0.47	0.58
D10	0.65	0.65	0.66

Aug – 7 Classes



	ITA_WT-8	N_EAST_WT-8	N_WEST_WT-8
D00	0.57	0.59	0.48
D10	0.76	0.80	0.70

1. The CCA method was applied to highlight linear correspondence between inter – annual variability of temperature anomalies and WTC occurrence/ WTC type character variability. Such correspondence exists and depends on number of classes/time scale/areas. Furthermore it is completely reversible, by means that we can linear predict one dataset in terms of the other.

2. Inter – annual WTC occurrence could be used as mid – level description tool between climatic anomalies and temperature or rainfall anomalies, in a seasonal forecast system.

CNR - IBIMET

3. From the eigenvalues analysis seems possible to describe both the seasonal and the monthly timescale inter – annual variability. This is quite important because the seasonal forecasting systems based on global models are not able to distinguish among different months in the target season.

4. More catalogues was analysed with CCA and will be available for interested people.

Thank you for your attention!

Some References and further reading:

Barnett, T., and R. Preisendorfer, 1987: Origins and Levels of Monthly and Seasonal Forecast Skill for United States Surface Air Temperatures Determined by Canonical Correlation Analysis. *Mon. Wea. Rev.*, 115, 1825–1850.
Moron, V., A.W. Robertson, M.N. Ward, and O. Ndiaye, 2008: Weather Types and Rainfall over Senegal. Part I: Observational Analysis. *J. Climate*, 21, 266–287.
Moron, V., A.W. Robertson, M.N. Ward, and O. Ndiaye, 2008: Weather Types and Rainfall over Senegal. Part II: Downscaling of GCM Simulations. *J. Climate*, 21, 288–307.
Kirtman, Ben, Anna Pirani, 2009: The State of the Art of Seasonal Prediction: Outcomes and Recommendations from the First World Climate Research Program Workshop on Seasonal Prediction. Bull. Amer. Meteor. Soc., 90, 455–458.
Benestad, Chen and Hanssen-Bauer: A compendium for statistical downscaling (version 0-9, updated on 16 June 2007): http://rcg.gvc.gu.se/edu/esd.pdf
Pavan, V. and F.J. Doblas-Reyes (2013). Calibrated multi-model ensemble summer temperature predictions over Italy. Climate Dynamics, 41, 2115-2132, doi:10.1007/s00382-013-1869-7.
Gaetani M. and M. Pasqui (2012), Synoptic patterns associated with extreme dust events in the Mediterranean Basin. Regional Environmental Change. 10.1007/s10113-012-0386-2
Di Giuseppe E., G. Jona Lasinio, S. Esposito, M. Pasqui, (2012) Functional clustering for Italian climate zones identification. Theoretical and Applied Climatology 10.1007/s00704-012-0801-0

http://cost733.geo.uni-augsburg.de/cost733wiki

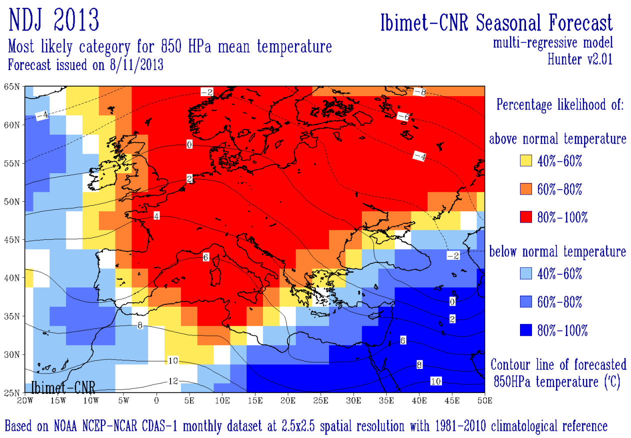
… and what about next NDJ ?

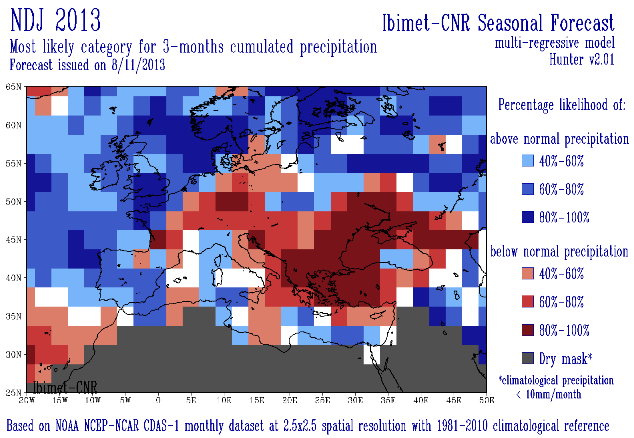
Bloomberg News

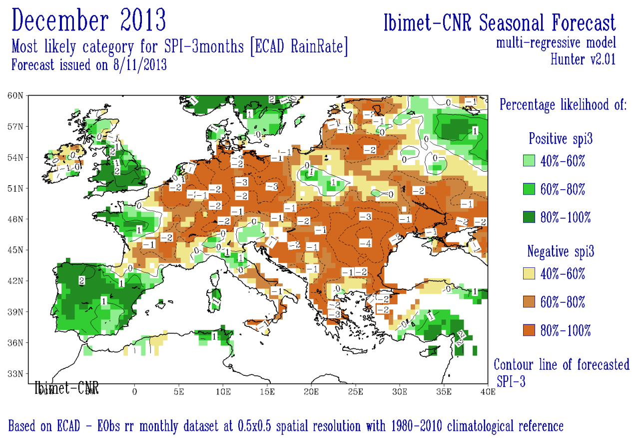
If New York Freezes in January Blame Siberian Snow Now

By Brian K. Sullivan | October 25, 2013

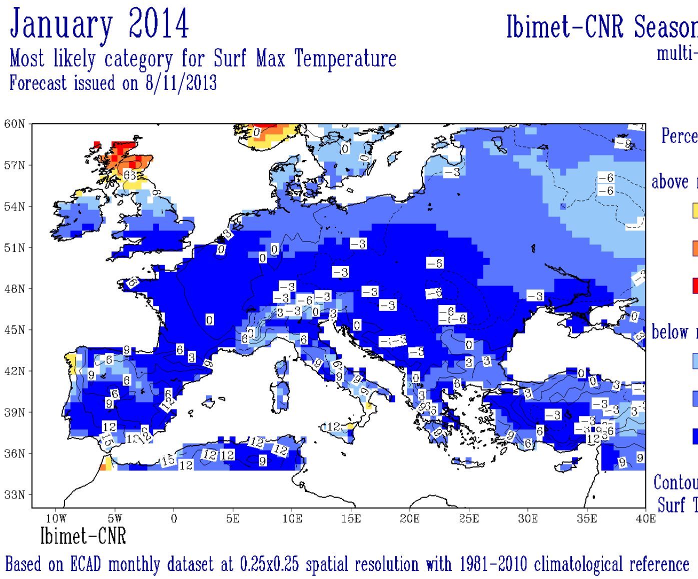
http://www.businessweek.com/news/2013-10-24/if-new-york-is-freezing-in-january-blame-today-s-siberian-snow#p1

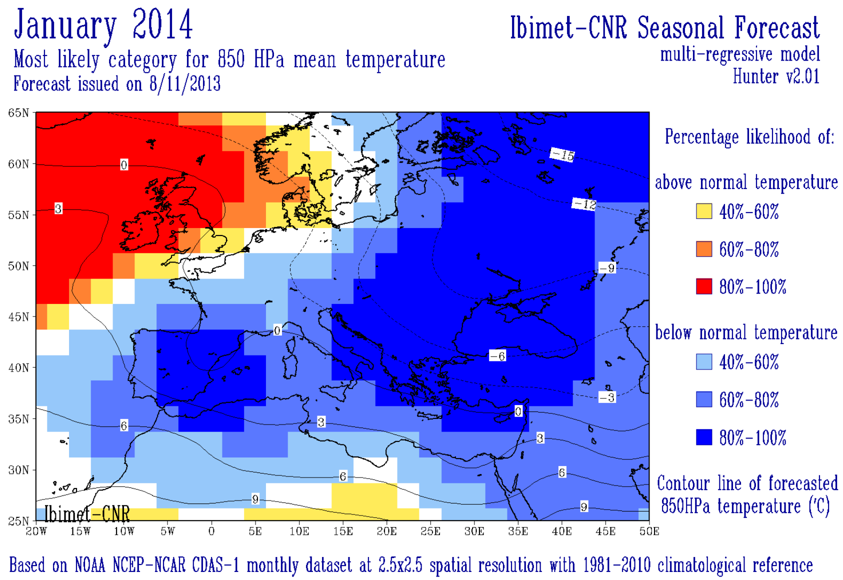






… but … in January 2014 …





… there is still room for a cold period!