Applied Energy 137 (2015) 435–444

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Seasonal climate forecasts for medium-term electricity demand forecasting

Matteo De Felice [a,*], Andrea Alessandri [a,b], Franco Catalano [a]

[a] Casaccia R.C., ENEA Energy and Environment Modelling Technical Unit, Rome, Italy
[b] International Pacific Research Center, University of Hawaii at Manoa, Honolulu, HI, USA

HIGHLIGHTS

- During the ten years, seasonal climate forecasts have improved their skill.
- We analyzed the link between summer average temperature and demand over Italy.
- Both deterministic and probabilistic forecasting approaches are here considered.
- Climate forecasts show a significant skill in predicting the demand in many regions.

ARTICLE INFO

Article history:
Received 19 June 2014
Received in revised form 5 October 2014
Accepted 6 October 2014

Keywords:
Seasonal climate forecasts
Medium-term load forecast
Electricity demand
Probabilistic forecast

ABSTRACT

Air temperature is an effective predictor for electricity demand, especially during hot periods where the need of electric air conditioning can be high. This paper presents for the first time an assessment of the use of seasonal climate forecasts of temperature for medium-term electricity demand prediction. The retrospective seasonal climate forecasts provided by ECWMF (European Centre for Medium-Range Weather Forecasts) are used to forecast the June–July Italian electricity demand for the period 1990–2007.

We find a relationship between summer (June–July) average temperature patterns over Europe and Italian electricity demand using both a linear and non-linear regression approach. With the aim to evaluate the potential usefulness of the information contained into the climate ensemble forecast, the analysis is extended considering a probabilistic approach.

Results show that, especially in the Center-South of Italy, seasonal forecasts of temperature issued in May lead to a significant correlation coefficient of electricity demand greater than 0.6 for the summer period. The average correlation obtained from seasonal forecasts is 0.53 for the temperature predicted in May and 0.19 for the predictions issued in April for the linear model, while the non-linear approach leads to the coefficients of 0.62 and 0.36 respectively. For the probabilistic approach, seasonal forecasts exhibit a positive and significant skill-score in predicting the demand above/below the upper/lower tercile in many regions.

This work is a significant progress in understanding the relationship between temperature and electricity demand. It is shown that much of the predictable electricity demand anomaly over Italy is connected with so-called heat-waves (i.e. long lasting positive temperature anomalies) over Europe.

1. Introduction

The main goal of this work is to investigate the use of seasonal climate forecasts for electricity demand over Italy, focusing on the summer period between 1990 and 2007. During the last decade, climate forecasts have significantly improved their skill on seasonal time-scales (from one month to six months) [27,5,22,4] but their application to decision-making processes are still rare on scientific literature. Considering also the challenges raised by the recent FP7 European Projects on Climate Services (CLIMRUN [1], SPECS [3], EUPORIAS [2]), this paper provides an initial assessment of the use of seasonal climate predictions for power systems management with the focus on electricity demand (load) forecast at lead times of one and two months.

* Corresponding author.
E-mail addresses: matteo.defelice@enea.it (M. De Felice), andrea.alessandri@enea.it (A. Alessandri), franco.catalano@enea.it (F. Catalano).

http://dx.doi.org/10.1016/j.apenergy.2014.10.030
0306-2619/

Given the necessity of ensuring the balance between electricity production and demand, an accurate estimation of future weather state could improve the efficiency and reliability of energy management at local and national scales. In fact, weather is a crucial element both for the generation and demand of electricity [25,16] The relationship between temperature and demand is well-known and it has been already investigated in many works focused on Europe. Valor et al. [28] and Pardo et al. [24] first recognized the strong coupling between electricity demand and temperature. Furthermore Bessec and Fouquau [9], analysing 15 European countries over twenty years, put the emphasis on the increasing sensitivity of electricity demand with respect to temperature during the recent years. On Italy, load forecasting has been analyzed by Bianco et al. [10] and De Felice et al. [17] at short time scales. However, the predictability of the medium-term load and the usefulness of seasonal climate forecasts at this time-scale need to be understood.

This paper focuses on Italian demand during summer. Due to the high temperatures that can be reached in many Italian regions, power grid can experience high demand peaks especially considering the increasing use of air conditioning, which have drastically increased the sensitivity of demand with respect to temperature in the last decade (an analysis of this phenomenon can be found in De Felice et al. [17]).

The effectiveness of seasonal climate forecasts for electricity demand forecasting is here analyzed both considering deterministic and probabilistic approaches. Probabilistic predictions allow for the reliable forecasting of future dichotomous events [19]. This information can be of particular value in situations where probabilities of different outcomes are needed in advance to make an optimal decision. To this end, instead of evaluating the difference of the ensemble mean from the target demand (deterministic approach), we evaluate the probability from the ensemble forecast in predicting a demand above/below normal (defined as the upper/lower tercile of the observed demand distribution).

After the description of the applied method in Section 2 we introduce and analyze the weather and climate data used in this paper in Sections 3.1 and 3.2 respectively. Section 4 provides a description of the probabilistic measures used in the rest of the paper. Then the results for the deterministic and probabilistic approaches are described respectively in Sections 5.1 and 5.2. All the results are discussed in Section 6 where we also provide an in-depth analysis on the relationship between heat-waves and electricity demand in Section 6.1. Finally, conclusions of this paper are reported in Section 6.2 outlining the future steps of this research.

2. Method

All the results shown in this paper have been obtained considering two regression approaches: a linear regression model and a Support Vector Machine, a well-established non-linear method.

2.1. Linear regression

Our linear approach has been inspired by Navarra and Tribbia [23] and it is based on the assumption of linearity between two fields, here denoted respectively with $\mathbf{Z}$ and $\mathbf{S}$.

Considering the equation $\mathbf{Z} = \mathbf{AS}$ we compute $\mathbf{A}$ matrix solving the least squares minimization problem:

$$\mathbf{A} = \mathbf{ZS}'(\mathbf{SS}')^{-1} \tag{1}$$

Finally we obtain the forced by field as:

$$\mathbf{Z}_{\mathbf{forced}} = \mathbf{AS} \tag{2}$$

It is worth noting that the residual $\mathbf{Z}_{\mathbf{free}} = \mathbf{Z}_{\mathbf{forced}} - \mathbf{AS}$ represents the variability of $\mathbf{Z}$ not connected with the variability of $\mathbf{S}$.

To reduce significantly the dimension of both data matrices, we applied Principal Component Analysis (PCA) using coefficients instead of original data, retaining the 99% of the total variance. Thus projecting $\mathbf{Z}$ and $\mathbf{S}$ into the principal component space we obtain respectively $\widetilde{\mathbf{Z}}$ and $\widetilde{\mathbf{S}}$, both with the selected modes as columns.

Using the PCA approach, Eq. (1) becomes:

$$\mathbf{A} = \widetilde{\mathbf{Z}}\widetilde{\mathbf{S}}'(\widetilde{\mathbf{S}}\widetilde{\mathbf{S}}')^{-1} \tag{3}$$

As suggested in Cherchi et al. [12] we can remove the least significant parts of $\mathbf{A}$ matrix (see Eqs. (1) and (3)) using a significance test. Here we put to zero all the coefficients of $\mathbf{A}$ that do not fit the confidence intervals of a 10% Student *t*-test for the correlation between $\mathbf{Z}$ and $\mathbf{S}$.

2.2. Support Vector Machine (SVM)

SVMs were developed by Cortes and Vapnik [13,29] for binary classification and then extended to regression problems (Support Vector Regression). The idea behind support vector-based methods is to use a non-linear mapping Φ to project the data into a higher dimensional space where solving the classification/regression task is easier than in the original space.

Following an approach similar to the linear method, we can think the SVM as a non-linear function $f(\cdot)$:

$$\mathbf{Z}_{\mathbf{forced}} = f(\mathbf{S}) \tag{4}$$

In our case, we used a Support Vector Regression method called ϵ-SVR [15], which tries to find a function $f(x) = \langle w, \Phi(x)\rangle + b$ that has at most ϵ deviation from the target values. A ϵ-SVR model has three parameters: the regularization parameter C, the ϵ value, and the width of the radial kernel γ.

The selection of the SVR model parameters has been carried out applying a grid search among 54 combinations of $C \in [10^{-1}, 10^{1}], \epsilon \in [10^{-2}, 1]$) and $\gamma \in [2^{-10}, 2^{2}]$. The parameters used through our work are the following: $C = 10, \epsilon = 10^{-2}, \gamma = 2^{-10}$.

As we did for the linear model, we use the PCA technique to reduce the dimensionality of $\mathbf{S}$ and $\mathbf{Z}$ spaces, considering pattern coefficients instead of the original data fields.

3. Data

3.1. Climate data

A seasonal climate forecast provides information about future climate conditions with a lead-time of one to six months. In this work, we use retrospective forecasts produced by the ECMWF[1] System 4 forecast system. This prediction system has been adopted as operational system since November 2011 [22]. For a detailed analysis of the seasonal prediction skills of System 4 forecasting system we refer to the works by Kim et al. [20] and Doblas-Reyes et al. [14].

Forecasts are issued monthly, here we consider two different starting months: April and May. For each starting month we used the predicted values of temperature fields for June and July, i.e. respectively with two and one month of lead time.

A way to deal with the complexity and uncertainties of the climate system is to use an ensemble of predictions, i.e. having at each starting date a set of forecasts each with slightly different initial conditions. System 4 has 51 ensemble members for the starting date in May 1st and 15 for April 1st. Fig. 1 shows an example of an

[1] ECMWF www.ecmwf.int. is an intergovernmental organisation which provides operational forecasts and super-computing facility for scientific research

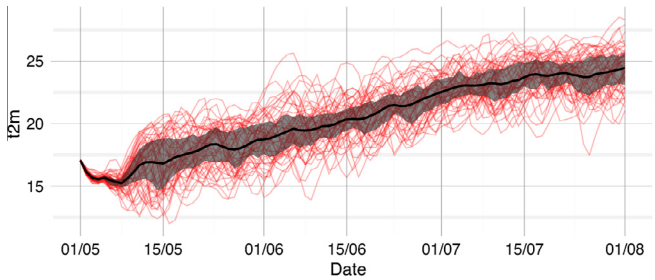


Fig. 1. An example of System 4 Seasonal Forecast issued in date 1/5/2012. The red lines represent the temperature predicted by each of the 51 members, the black line is the ensemble mean and the shaded area is the interval between the first and third quartile. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

ensemble temperature forecast starting the first day of May 2012. Given that this work is focused on Italy we selected a geographical domain centered on Europe, with the latitude between 20 N and 80 N, and the longitude between 40 W and 70 E. Data is on a gaussian grid with a resolution of about 80 km, with a total of 13,260 grid points.

To evaluate the System 4 prediction skill, we compare the predicted temperature with ERA-INTERIM reanalysis [8]. A reanalysis is an estimation of past weather states obtained by weather simulations assimilating observations (ground stations, satellites, etc.). We may consider the reanalysis as the best available estimation of temperature considering the entire domain. Fig. 2 reports the skill of 1-month lead (Fig. 2b) and 2-months lead (Fig. 2a) forecasts to predict seasonal anomalies of mean temperature (i.e. deviations from the average computed on 1990–2007).

A compact visualization of temperature data can be obtained using Principal Component Analysis (PCA) which allow us to decompose the temperature field into the most important components. Fig. 3 shows the three most informative patterns (i.e. with the highest variance) with the relative PC coefficients.

3.1.1. Application of regression methods to climate ensemble data

Temperature data field used in this work (here denoted as **S**) have $k \times n$ dimension with k the number of all the grid data points and n the number of yearly samples.

Given that the climate predictions we use in this paper are ensembles with 15/51 members we create a **S** matrix containing all the members data, in this way, unlike methods using ensemble mean, our approach allow us to exploit all the information contained into the ensemble members. The **S** of the entire ensemble has $r \times (nm)$ dimension with m the number of ensemble members. **S** is obtained concatenating for each grid points all the temperature values for each ensemble member. Having $t^m_{1,1990}$ as the first temperature grid point for year 1990 considering the m-th ensemble member, we can write **S** in the following way:

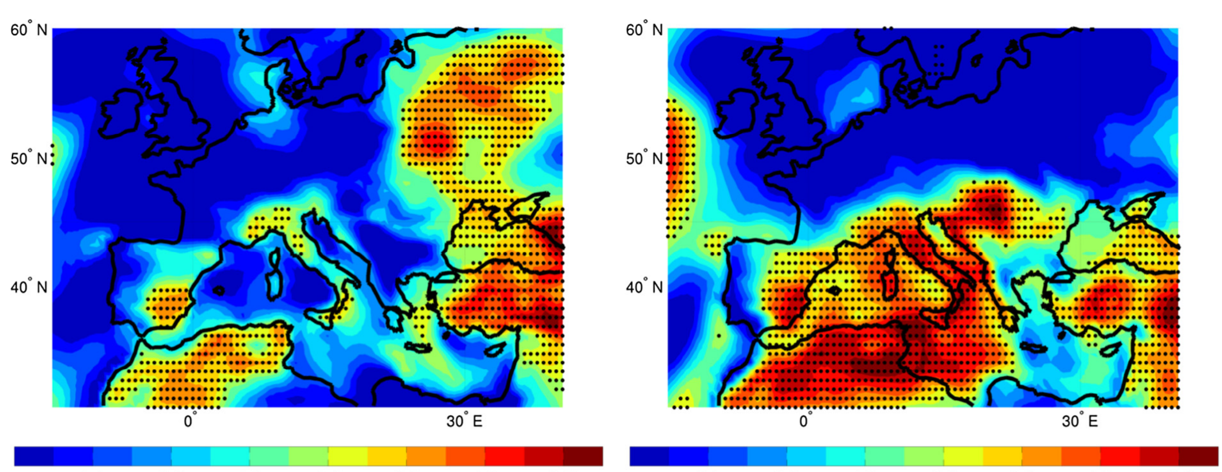
$$\mathbf{S} = \begin{bmatrix} t^1_{1,1990} & \dots & t^1_{1,2007} & t^2_{1,1990} & \dots & t^2_{1,2007} & \dots & t^m_{1,1990} & \dots & t^m_{1,2007} \\ \vdots & & & & & & & & & \\ t^1_{k,1990} & \dots & t^1_{k,2007} & t^2_{k,1990} & \dots & t^2_{k,2007} & \dots & t^m_{k,1990} & \dots & t^m_{k,2007} \end{bmatrix} \tag{5}$$

To make the dimension of the **Z** field (here electricity demand) consistent with **S**, the former has been manipulated replicating the temporal dimension for m times in order to increase the number of columns from n to nm. In this way, at the end of the procedure $\mathbf{Z}_{forced}$ (see Eq. (2)) will contain m different estimations of **Z**, one for each ensemble member.

3.2. Electricity data

Electricity demand data used in this paper have been provided by TERNA (Italian TSO, Transmission System Operator) and they refer to the period from the 1990 to 2007. Hourly data are subdivided by eight regions: North–West (NW), North (N), North–East (NE), North-Center (CN), Center (C), South (S), Sicily (I1) and Sardinia (I2). At first, given that this work focuses on summer demand, we calculated the monthly demand summing up all the hourly-loads for each month, then selecting only June and July. August data has not been included due to industrial closure, in fact during August industrial facilities usually close for one or two weeks reducing electricity demand independently of temperature.

Given that during 1990–2007 the electricity demand was steadily increasing, trend removal has been accomplished by fitting a second-order regression model $y = \alpha + \beta_1 x + \beta_2 x^2$ for each region and then computing the deviation from the fit (i.e. regression residuals). In Table 1 we provide the intercept, the two coefficients for each region, and some statistics about the deviations. Fig. 4 shows the eight normalized electricity demands time-series (black line) and the deviations obtained after removing the polynomial trend (red line).



(a) System 4 - April (b) System 4 - May

Fig. 2. Correlation coefficient between June–July temperature anomaly derived by ERA-INTERIM dataset on years 1990–2007 and climate forecast. Dots represents points with a 5% of significance calculated by bootstrapping.

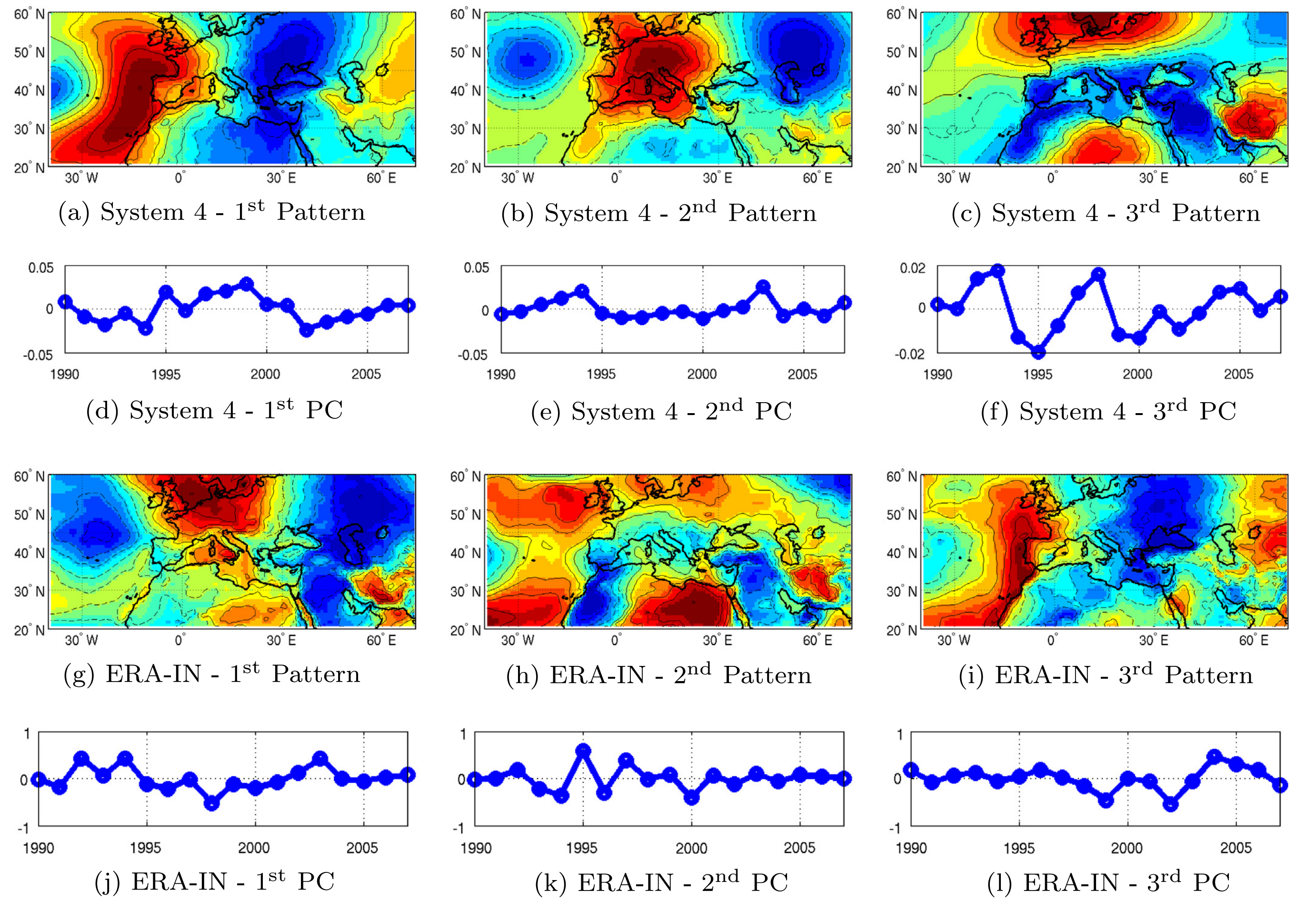


Fig. 3. First three patterns with relative coefficients obtained using Principal Component Analysis on System 4 and ERA-INTERIM temperature data. The three patterns represent for System 4 and ERA-INTERIM respectively the 37.4% and 49.4% of total variance.

Table 1
June–July summary statistics. All the unit measures are in GW h. For the maximum and minimum deviations in brackets we show the respective year.

	α	β_1	β_2	σ (deviations)	Max. Dev.	Min. Dev.
NW	3788	74	2.5	137	170 (2003)	−825 (2004)
N	7044	31	14.6	247	303 (2006)	−825 (2004)
NE	4552	23	10.9	227	450 (2006)	−657 (2004)
CN	4655	184	2.2	185	403 (2003)	−464 (2007)
C	4963	105	5.1	136	386 (2003)	−260 (2004)
S	4890	19	8.2	113	328 (2003)	−219 (1999)
I1	1969	37	2.4	57	153 (2003)	−87 (1996)
I2	1384	15	1.3	70	145 (2003)	−139 (2007)

All the datasets have been normalized dividing each time-series by its standard deviation.

In this paper we omitted region I2 because of the small demand associated to it (see Table 1).

4. Probabilistic metrics

To evaluate the performances with the deterministic approach, we use the Pearson correlation coefficient. For a more reliable estimation of correlation and to reduce the influence of outliers, we estimated the correlation coefficient through a bootstrap procedure with 1000 replications.

To assess the probabilistic quality of the forecasts we follow the approach and the skill measures described in Wilks [30]. The most common accuracy measure is the Brier Score (BS) [11], basically the mean squared error of the probability forecast. Being $y_i \in [0, 1]$ the probabilistic forecast for time i and $o_i \in \{0, 1\}$ the dichotomous event, the Brier Score is defined as follows:

$$BS = \frac{1}{N}\sum_{i=1}^{N}(y_i - o_i)^2 \tag{6}$$

We can observe that $0 \leqslant BS \leqslant 1$ and that better forecasts have a lower BS. The Brier Score can be transformed into a skill score considering the BS of a reference forecast, BS_{ref}. The Brier Skill Score (BSS) is consequently defined:

$$BSS = 1 - \frac{BS}{BS_{ref}} \tag{7}$$

As reference forecast is used the climatological relative frequency, i.e. the observed frequency of the event during the considered period.

We introduce here further quality measures: reliability and resolution.

Reliability (REL) summarizes the conditional bias of the forecast and it consists of a weighted average between forecast probabilities and relative frequencies of observed events. This measure can be defined as follows:

$$REL = \frac{1}{n}\sum_{i=1}^{I} N_i[y_i - p(o_1|y_i)]^2 \tag{8}$$

where n is the length of all the available observations, N the number of times that each forecast y is used, and I the number of distinct forecast values.

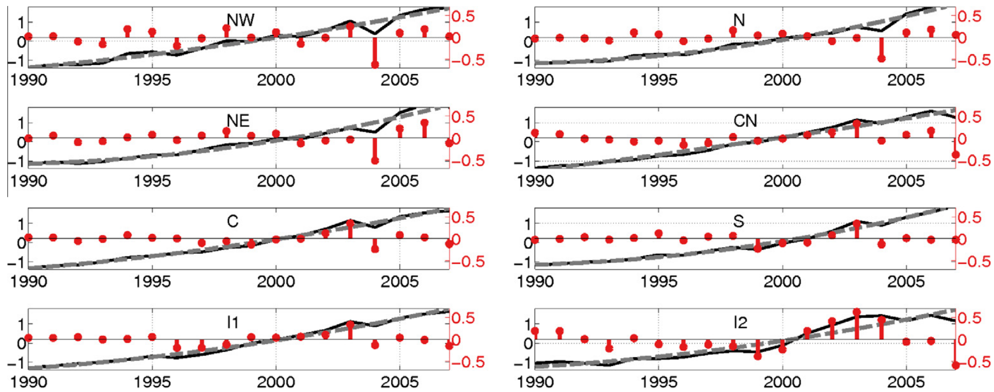


Fig. 4. Normalized electricity demand time-series for June/July for all the eight Italian regions are shown with the black line. Red dots describe the time-series obtained after the removal of the polynomial trend which is shown with the dashed gray line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Resolution (RES) represents the ability of the forecasts to separate situations into different types and differently from REL, for a good forecast we want RES to be as large as possible. The definition is the following:

$$RES = \frac{1}{n}\sum_{i=1}^{I} N_i[p(o_1|y_i) - \bar{o}]^2 \tag{9}$$

$$\bar{o} = \frac{1}{n}\sum_{i=1}^{I} N_i p(o_1|y_i) \tag{10}$$

Similarly to BSS, positively oriented RelSS and ResSS can be defined as:

$$RelSS = 1 - \frac{REL}{BS_{ref}} \tag{11}$$

$$ResSS = \frac{RES}{BS_{ref}} \tag{12}$$

A way to visually compare the probabilistic performances is through the use of reliability diagrams (see Wilks [30], Section 8.4.4). These diagrams, shown in Fig. 6, illustrate the observed frequency (conditional distribution of observation, $p(o_j|y_j)$) with respect to the forecast $p(y)$. The forecasts value have been discretized and then the bins are "centered" into the average of the samples they represent (see Wilks [30] for more details). Basically, the plot shows the probability that the event occurs when the forecast is within a specific range.

Another way to measure the capability of each probabilistic forecast to discriminate the events is called discrimination. Considering the two joint distributions $p(y_i|o_0)$ and $p(y_i|o_1)$, the discrimination (DISC) measures the difference between their means:

$$DISC = |\mu_{y|o_1} - \mu_{y|o_0}| \tag{13}$$

Larger is the distance between these two distributions and better is the capability of the forecast of detect the event. Discrimination diagrams provide a graphical display of joint distributions as functions of the forecast probability y. Better is the discrimination between two events and smaller is the overlap between the likelihoods. Perfect forecasts lead to $DISC = 1$ with $p(1|o_1) = 1$ and $p(0|o_0) = 1$.

5. Results

In this section we apply the methodology described in Section 2 for deterministic (Section 5.1) and probabilistic (Section 5.2) forecasting.

As stated in Section 2, to reduce the dimensionality of the involved spaces we apply a PCA on both the temperature and electricity demand fields. In this way, the dimensionality of temperature field will change from 8892 dimensions (spatial grid of 57×156 points) to 214 (the number of modes that explain the 99% of the observed variance) and the electricity demand goes from 7 (the regional data sets) to 6.

The quality measures described in Section 4 are applied to compare the two seasonal climate predictions for electricity demand forecasting considering the average electricity demand for June and July in the period 1990–2007. All the results shown below have been obtained through a leave-one-out cross-validation procedure (where each yearly sample is left out of the model calibration in turn and predicted once) in order to evaluate the model predictions for data it has not already seen.

5.1. Deterministic forecasting

The correlation coefficients between the predicted and the measured electricity demand are shown in Table 2. The R^2 obtained from the forecasts issued in May is $0.2, 0.36, 0.36, 0.14, 0.25, 0.38$ and 0.11 for the seven domains. Using the forecasts issued in April we instead obtain the following $R^2 : -0.2, -0.11, 0, 0.16, 0.06, 0.2$ $2, 0.08$.

The performance of SVM is generally better than the linear model, except for `C` and `S` where the linear regression leads to higher correlation coefficients.

Consistently with the results obtained with the short-term prediction [17], solid performances are obtained in south Italy for both the starting dates and the regression models. As already suggested by Fig. 2, the forecasts issued in May lead to a correlation consistently higher than in April, especially for the northern

Table 2
Correlation coefficient obtained by leave-one-out cross-validation for each data source and regression model considering June–July average electricity demand. Correlation values are computed applying a 1000 iterations bootstrapping procedure.

	June–July			Pearson correlation		
	Linear model			SVM		
	May	April	Difference	May	April	Difference
`NW`	0.54	−0.19	−0.73	0.55	0.32	−0.23
`N`	0.73	−0.04	−0.77	0.81	0.32	−0.49
`NE`	0.70	0.16	−0.54	0.71	0.31	−0.40
`CN`	0.35	0.39	0.04	0.63	0.17	−0.46
`C`	0.63	0.25	−0.38	0.49	0.50	0.01
`S`	0.70	0.48	−0.22	0.57	0.56	−0.01
`I1`	0.38	0.29	−0.09	0.43	−0.12	−0.56
`Avg.`	0.53	0.19	−0.34	0.62	0.36	−0.26

domains. Furthermore, the decrease of correlation due to the increase of lead-time is less marked for the center-southern regions evidencing a loss of predictability in the northern regions (especially NW and NE).

To better describe the characteristics of ensemble-based predictions, Fig. 5 illustrates the predicted load for S domain obtained by using the linear model, displaying the estimation provided by the ensemble and by each member.

A well-known error measure used to compare forecasting methods is the MAPE (Mean Absolute Percentage Error). Although percentage errors are scale-independent, they have the disadvantage of being undefined if the predictand is equal to zero and having excessively large values when the predictand is close to zero. Thus, we can not use MAPE on the load anomalies but we can apply it if we "denormalize" the forecasts adding back the trend that has been removed (as described in Section 3.2). In Table 3 we provide the MAPE for both the forecast methods and considering both the different starting dates.

5.2. Probabilistic approach

Differently from the deterministic forecast, where we have the aim to predict the absolute magnitude of electricity demand change, here we evaluate the probabilistic skill of predicting the dichotomous events of having the electricity demand above/below the normal. Estimating the probability of having such events is of potential relevance for the efficient economical management of an electric utility.

To quantify the "normal" demand we use the middle tercile (33th to 66th percentiles), i.e. a demand above/below normal is exceeding/falling below the 66th/33th percentile.

Thus, for each year i the predictand is a binary event that is $o_i = 1$ if the electricity demand is above/below the upper/lower tercile of the sample distribution and $o_i = 0$ otherwise. The predictand is built through a leave-one-out cross-validation procedure for each domain considering the entire period 1990–2007.

In Tables 4 and 5 the Brier Skill Score (BSS) of seasonal forecasts issued May 1st and April 1st are shown for both "above normal" (upper) and "below normal" (lower) events.

In Table 4 the skills shown are computed on the entire domain, obtained considering all the regional domains as a single one. As already observed in the previous section the difference in performances between forecasts issued in May and in April is very evident, the forecasts issued May 1st perform considerably better than those started in April. A better capability of predicting temperature leads to higher predictive skills of electricity demand. In general, the usefulness in using the seasonal forecasts issued in

Table 3
MAPE error obtained by leave-one-out cross-validation for each data source and regression model considering "denormalized" June–July average electricity demand.

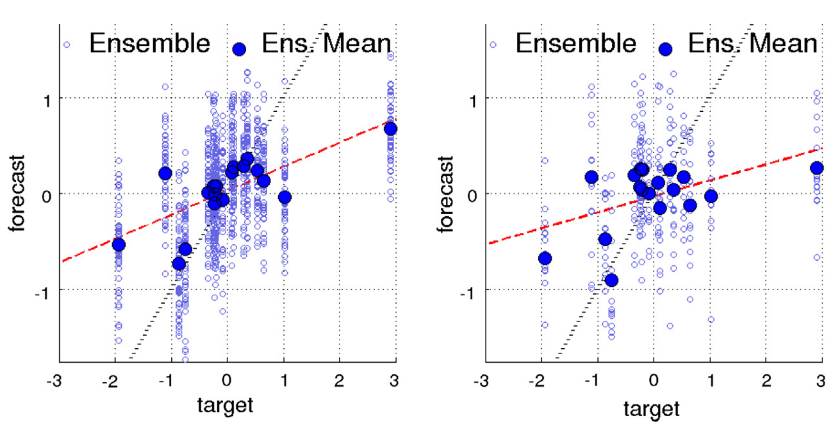
	June–July MAPE (%)			
	Linear model		SVM	
	May (%)	April (%)	May (%)	April (%)
NW	1.8	2.3	1.8	1.8
N	1.3	2	1.3	1.7
NE	2.1	2.7	2	2.4
CN	2	1.9	1.6	1.9
C	1.1	1.4	1.2	1.1
S	0.9	1.1	1	1
I1	1.5	1.5	1.4	1.7
Avg.	1.6	1.9	1.6	1.7

Table 4
Probabilistic measures for entire Italy considering June–July average electricity demand.

Linear Model	BSS	RelSS	ResSS	DISC
Upper – May	0.14	0.93	0.21	0.15
Upper – April	−0.07	0.90	0.03	0.03
Difference	0.21	0.03	0.18	0.12
Lower – May	0.13	0.97	0.17	0.16
Lower – April	−0.02	0.91	0.08	0.06
Difference	0.15	0.06	0.09	0.10
SVM				
Upper – May	0.21	0.99	0.21	0.21
Upper – April	0.01	0.94	0.07	0.09
Difference	0.20	0.05	0.14	0.12
Lower – May	0.13	0.97	0.17	0.18
Lower – April	−0.07	0.83	0.10	0.04
Difference	0.20	0.14	0.07	0.14

Table 5
Brier Skill Score (BSS) obtained by a leave-one-out cross-validation procedure considering June–July average electricity demand. Values that are significant at the 10% level using a bootstrap procedure are shown in **bold**.

	Above normal – BSS				Below normal – BSS			
	Linear model		SVM		Linear model		SVM	
	May	April	May	April	May	April	May	April
NW	**0.16**	−0.27	**0.14**	0	0.03	−0.25	0.06	−0.04
N	**0.20**	−0.18	**0.37**	0.05	**0.24**	−0.13	**0.19**	−0.16
NE	**0.22**	−0.14	**0.24**	0.03	**0.34**	−0.15	**0.29**	−0.09
CN	−0.07	0.00	**0.19**	0	−0.09	−0.05	0.09	−0.11
C	**0.40**	0.04	**0.30**	**0.26**	**0.15**	−0.03	0.06	0.06
S	**0.32**	0.02	**0.37**	**0.12**	**0.39**	**0.31**	**0.12**	**0.20**
I1	−0.03	−0.07	−0.09	−0.27	**0.21**	0.06	**0.17**	−0.24



(a) System 4 - May (b) System 4 - April

Fig. 5. Scatterplot of predicted June–July load anomaly on South Italy (S) by linear regression.

April (i.e. two months of lead time) is none for both the events, in both the cases the BSS is close to or smaller than zero. As explained previously in Section 4, a negative BSS means that using a climate forecast for electricity demand prediction is worse than not using it.

The overall good performances of May forecasts can be observed in Figs. 6 and 7, where reliability and discrimination diagrams of the forecasts provided by SVM are shown. The reliability diagram (Fig. 6) indicates a good agreement between the forecast issued in May and the observed frequency, especially for the above normal event. On the other side, the April forecast definitely shows a weak prediction, as shown in Table 4. The panels below the reliability diagrams show the distribution of the forecast values for both the starting dates.

The discrimination diagram (Fig. 7) shows how the separation between the likelihoods of both the events is greater when using May seasonal forecasts, although a clear overlap still exists. Moreover, at least for the May forecasts, the upper event seems to be

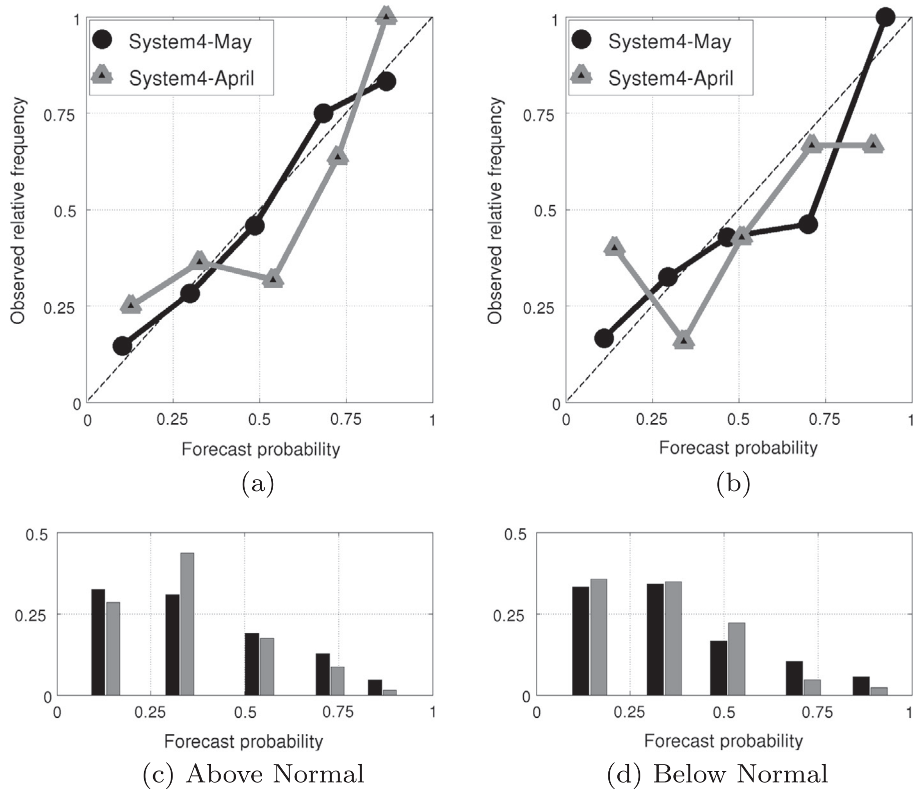


Fig. 6. Reliability diagrams of seasonal forecasts in predicting demand above (left) and below (right) normal using SVM. Lower panels show the distribution of samples for each bin.

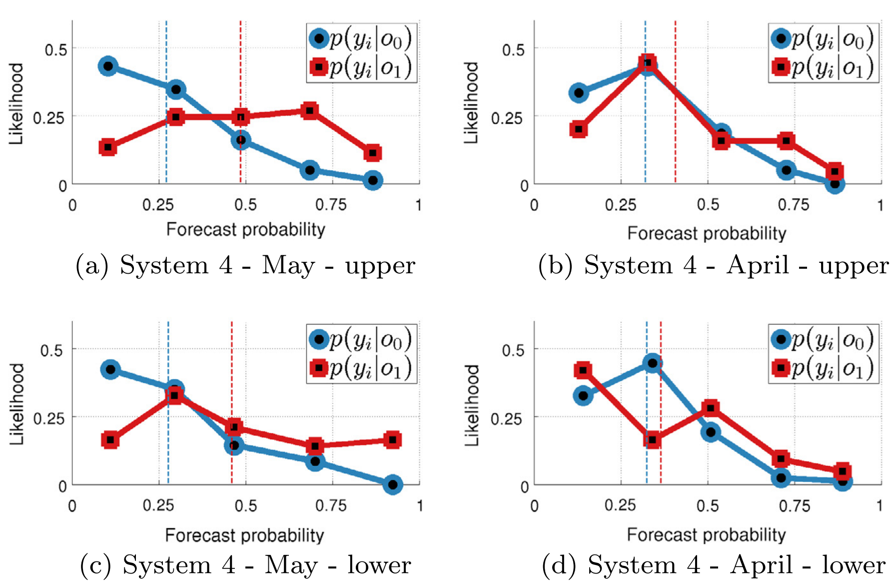


Fig. 7. Discrimination diagram of probabilistic forecasting (upper and lower events) of electricity demand using seasonal climate forecasts and SVM. Dashed line represents the average of the distribution.

Table 6
Probabilistic forecast of electricity demand for C and S domains related to the above normal event using linear model. The percentage value represents how many members inside the ensemble predict the event occurrence. The event occurrence has been highlighted by shaded grey.

	C			S		
Year	Event	May (%)	April (%)	Event	May (%)	April (%)
1990	Yes	37.3	33.3	no	31.4	33.3
1991	No	23.5	20	no	25.5	26.7
1992	No	43.1	46.7	yes	60.8	46.7
1993	No	13.7	46.7	no	35.3	46.7
1994	Yes	86.3	33.3	no	49	33.3
1995	No	29.4	53.3	yes	15.7	40
1996	No	29.4	40	no	25.5	46.7
1997	No	39.2	26.7	yes	60.8	33.3
1998	No	31.4	33.3	yes	52.9	46.7
1999	No	5.9	6.7	no	0	6.7
2000	No	29.4	6.7	no	2	0
2001	No	23.5	20	no	2	0
2002	Yes	52.9	26.7	yes	41.2	20
2003	Yes	68.6	46.7	yes	94.1	46.7
2004	No	15.7	53.3	no	47.1	46.7
2005	Yes	33.3	26.7	no	49	46.7
2006	Yes	41.2	73.3	no	7.8	53.3
2007	No	13.7	26.7	no	27.5	46.7

better discriminated with the two likelihood more separated than for the lower event.

Table 5 shows instead skill scores for all the regional domains. We can observe that the majority of the values (9 on 14 for the linear model and 10 on 14 for the SVM) for the May forecast are significantly different from zero while only few cases for April forecast (one for the linear model and three for the SVM). Moreover, only in few cases the climate forecasts with two months of lead-time lead to results better than using the climatology (i.e. positive BSS). However, for the South (S) and partially for the Center (C) domains we obtain significant positive scores for both the events and for the forecasts issued in May and in April. Again, as in the deterministic results, the electricity demand of South domain seems to be the most predictable using temperature forecasts.

To better understand the operational aspects of the results shown in Table 5 we show the probabilistic forecast for the above normal load for C and S domains in Table 6. For each season we indicate whether the above/below normal event has happened and the prediction provided by both the starting dates. It is worth noting that the BSS for the climate forecasts issued in April is 0.04 and 0.02 for the two datasets, this means that the prediction provided by seasonal forecasts is only slightly better than using a fixed value (observed frequency of 33%).

6. Discussion

This work investigates for the first time a potential application of seasonal climate forecasts to energy sector. During summer, power networks in Mediterranean countries, like Italy, experience a dramatic increase of demand and peak loads due to air conditioning and refrigeration. This means that having a reliable forecast of high/low demand events with one or two months of lead time could be useful for system operators and electric utilities.

For this analysis, we followed an approach inspired by the Coupled Manifold [23] that allowed us to deal with the high-dimensionality of the input involved and to exploit effectively all the information contained in the ensemble for forecast purposes. To widen our analysis, besides a linear model, we have also included a non-linear regression approach based on Support Vector Machines (SVM).

For an extensive analysis, we used temperature information provided by seasonal forecasts both for deterministic and probabilistic forecasting.

Both show consistent results, with better performances by using forecasts issued in May than in April both at national and regional level. On the national domain the results show the potential advantages in using seasonal predictions with one month of lead time for electricity demand forecasting. Climate forecasts issued in April tends to be ineffective in predicting national electricity demand, although they show positive skill scores in predicting demand for Center and South Italy.

The different performance between 1-month and 2-months lead-time could be anticipated by observing Fig. 2 where the higher accuracy of May's temperature forecasts over Italy is evident.

The probabilistic approach clearly shows the difference in performances with respect to the lead-time, with the predictions obtained with the use of April seasonal forecasts definitely worst than the use of the climate forecasts issued in May. We also observe a slight tendency of the forecasts to overestimate the occurrence of above normal events (see Fig. 6a). Observing regional domains, April forecasts are in few cases rarely better than using climatological information and leading to a significant skill score only in few cases (S dataset for below normal event using linear model and also S and C for above normal event using SVM). At one-month lead-time, the forecasts show significant performance for both the events (above and below normal) with a Brier Skill Score greater than 0.3 over C, S, N and NE domains.

To summarize, this work is the first step in assessing the application of seasonal forecasts for operational purposes. Results obtained using seasonal forecasts in predicting electricity demand over Italy are encouraging and thanks to the granularity provided by using regional electricity demand datasets we have improved our knowledge about the complex link between energy and climate. In the next section we want to examine in depth this link focusing on the heat-wave that affected Europe in the last twenty years.

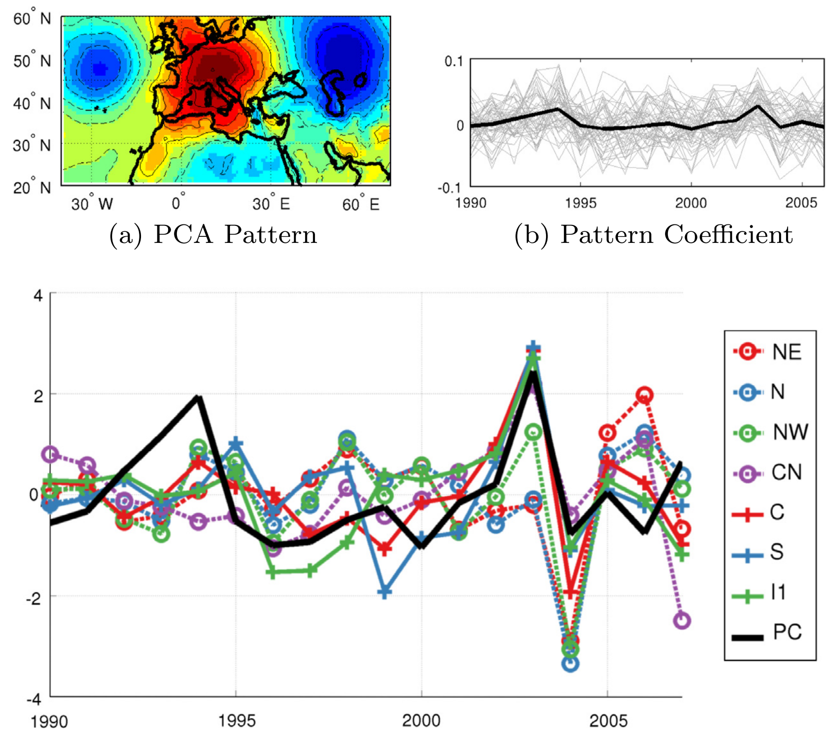
6.1. Heat-waves in Europe

In 2003 Europe experienced a record-breaking heat-wave that had dramatic health [21] and energy management impacts [16]. During the summer of 2003 temperature have exceeded by about 3 degrees the climatological mean (1961–1990) and the same year we observe a positive deviation in demand over most of Italy load domains (see Table 1).

To better examine this phenomenon, we take advantage of the possibility to analyze temperature pattern through the PCA technique. The temperature pattern that better describes the heat-wave phenomenon is the second pattern shown in Fig. 8a and b shows the PC related to this pattern, where we can clearly observe with two peaks in 1994 and 2003, i.e. in correspondence of the strongest heat-waves that affected central Europe during the last decade (see Fischer et al. [18] for an in-depth analysis on European heat-waves).

Then in Fig. 8c we compare the coefficient time-series with the electricity demand deviations of all the seven domains we considered. We can observe two important things: the peak related to 2003 leads to a peak demand for the center-south (i.e. the hotter) regions (C, S, and I1) and the peak related to 1994 does not correspond with evident demand peak for any domain. The absence of response of electricity demand with respect to temperature before 2003 can be explained with the minor use of air conditioning equipment in Italy. In support of this statement, we show in Fig. 9 some statistics provided by ANIMA/COAER[2] about the

[2] COAER is an association of national manufacturers of equipment and systems for air treatment. COAER is within the ANIMA Federation, an industry group with 7.250 employees and a total turnover of over 1.420 million euro.



(a) PCA Pattern (b) Pattern Coefficient

(c) Comparison of electricity demand anomalies

Fig. 8. 2nd Temperature pattern of climate forecasts issued in May (a). On the right (b) all the pattern coefficients for the ensemble members are shown in light gray with their mean marked as a thick black line. Panel (c) shows the comparison between the coefficient (normalized) shown in (b) with the electricity demand of all the datasets.

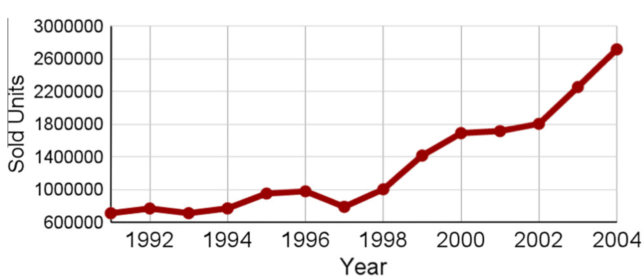


Fig. 9. Number of room conditioning units sold in Italy by year.

installed residential air conditioning equipment from 1991 to 2004. It is clear how during the years 2003–2004 the number of installed units increased drastically, while before 1999 the use of room air conditioning was less than half compared to 2003.

Considering that extreme hot periods normally lead to increasing electricity demand, especially in areas with a widespread use of air conditioning (see our previous work [17] and Apadula et al. [6] for further analysis related to Italy), the possibility to have an accurate forecast becomes more important, especially considering that extreme events will be more frequent in the future [7,26].

6.2. Future steps

As we stated before, this paper may be defined the first work that proposes an application of climate information for the energy sector at seasonal time-scales. The next step will be to extend the analysis to entire Europe, analysing the electricity demand provided by ENTSO-E.[3] This extension may help us to obtain more reliable and significant results. Furthermore the analysis will be extended to the winter period, given that in many northern Europe countries peak demands are observed during cold periods due to electric heating.

[3] ENTSO-E (https://www.entsoe.eu/) is the European Network of Transmission System Operators for Electricity.

Acknowledgments

We acknowledge TERNA for providing Italian regional demand data and we wish to thank Antonio Carrano and Martina Pede for their comments and insight about Italian power grid. This work was supported by the European Union Seventh Framework Programme (FP7/2007-13) under the grant agreement n. 303208 (CLIMITS project) and under the grant agreement n. 308378 (SPECS project).

References

[1] CLIM-RUN – Local Climate Informations to Respond to Users Needs. 2011, <http://www.climrun.eu/>.
[2] EUPORIAS – European Provision Of Regional Impacts Assessments on Seasonal and Decadal Timescales. 2012, <http://www.euporias.eu/>.
[3] SPECS – Seasonal-to-decadal climate Prediction for the improvement of European Climate Services. 2012, <http://www.specs-fp7.eu/>.
[4] Alessandri Andrea, Borrelli Andrea, Gualdi Silvio, Scoccimarro Enrico, Masina Simona. Tropical cyclone count forecasting using a dynamical seasonal prediction system: sensitivity to improved ocean initialization. J Climate 2011;24(12).
[5] Alessandri Andrea, Borrelli Andrea, Navarra Antonio, Arribas Alberto, Déqué Michel, Rogel Philippe, et al. Evaluation of probabilistic quality and value of the ENSEMBLES multimodel seasonal forecasts: comparison with DEMETER. Monthly Weather Rev 2011;139(2):581–607.
[6] Apadula Francesco, Bassini Alessandra, Elli Alberto, Scapin Simone. Relationships between meteorological variables and monthly electricity demand. Appl Energy 2012;98:346–56.
[7] Beniston Martin. The 2003 heat wave in Europe: a shape of things to come? An analysis based on Swiss climatological data and model simulations. Geophys Res Lett 2004;31(2).
[8] Berrisford P, Dee D, Fielding K, Fuentes M, Kallberg P, Kobayashi S, et al. The ERA-Interim archive. ERA Report Series 2009;1(1).

[9] Bessec Marie, Fouquau Julien. The non-linear link between electricity consumption and temperature in Europe: a threshold panel approach. Energy Econom 2008;30(5):2705–21.
[10] Bianco Vincenzo, Manca Oronzio, Nardini Sergio. Electricity consumption forecasting in Italy using linear regression models. Energy 2009;34(9):1413–21.
[11] Brier Glenn W. Verification of forecasts expressed in terms of probability. Monthly Weather Rev 1950;78(1):1–3.
[12] Cherchi Annalisa, Gualdi Silvio, Behera Swadhin, Luo Jing Jia, Masson Sebastien, Yamagata Toshio, et al. The influence of tropical indian ocean SST on the indian summer monsoon. J Climate 2007;20(13):3083–105.
[13] Cortes C, Vapnik V. Support-vector networks. Mach Learn 1995;20(3):273–97.
[14] Doblas-Reyes Francisco J, García-Serrano Javier, Lienert Fabian, Biescas Aida Pintó, Rodrigues Luis RL. Seasonal climate predictability and forecasting: status and prospects. Wiley Interdisciplinary Rev: Climate Change 2013;4(4):245–68.
[15] Drucker H, Burges CJC, Kaufman L, Smola A, Vapnik V. Support vector regression machines. Adv Neural Inform Process Syst 1997;9:155–61.
[16] Dubus Laurent. Practices, needs and impediments in the use of weather/climate information in the electricity sector. In: Management of weather and climate risk in the energy industry. Springer; 2010. p. 175–88.
[17] Felice Matteo De, Alessandri Andrea, Ruti Paolo M. Electricity demand forecasting over Italy: potential benefits using numerical weather prediction models. Electric Power Syst Res 2013;104(0):71–9.
[18] Fischer EM, Seneviratne SI, Lüthi D, Schär C. Contribution of land-atmosphere coupling to recent European summer heat waves. Geophys Res Lett 2007;34(6).
[19] Gneiting Tilmann, Katzfuss Matthias. Probabilistic forecasting. Ann Rev Stat Appl 2014;1:125–51.
[20] Kim Hye-Mi, Webster Peter J, Curry Judith A. Seasonal prediction skill of ECMWF system 4 and NCEP CFSv2 retrospective forecast for the Northern Hemisphere Winter. Climate Dynam 2012;39(12):2957–73.
[21] Kovats Sari, Wolf Tanja, Menne Bettina. Heatwave of august 2003 in europe: provisional estimates of the impact on mortality. Eurosurveillance Weekly 2004;8(11):11.
[22] Molteni F, Stockdale T, Balmaseda M, Balsamo G, Buizza R, Ferranti L, et al. The new ECMWF seasonal forecast system (System 4). ECMWF Techn Memorandum 2011;656.
[23] Navarra A, Tribbia J. The coupled manifold. J. Atmos Sci 2005;62(2):310–30.
[24] Pardo A, Meneu V, Valor E. Temperature and seasonality influences on spanish electricity load. Energy Econom 2002;24(1):55–70.
[25] Rothstein Benno, Halbig Guido. Weather sensitivity of electricity supply and data services of the german met office. In: Management of weather and climate risk in the energy industry. Springer; 2010. p. 253–66.
[26] Schär Christoph, Vidale Pier Luigi, Lüthi Daniel, Frei Christoph, Häberli Christian, Liniger Mark A, et al. The role of increasing temperature variability in european summer heatwaves. Nature 2004;427(6972):332–6.
[27] Stockdale Timothy N, Anderson David LT, Balmaseda Magdalena A, Doblas-Reyes Francisco, Ferranti Laura, Mogensen Kristian, et al. ECMWF seasonal forecast system 3 and its prediction of sea surface temperature. Climate Dynam 2011;37(3):455–71.
[28] Valor E, Meneu V, Caselles V. Daily air temperature and electricity load in spain. J Appl Meteorol 2001;40(8):1413–21.
[29] Vapnik V. The nature of statistical learning theory. springer; 2000.
[30] Wilks Daniel S. Statistical methods in the atmospheric sciences, vol. 100. Academic Press; 2011.