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Correction of 2 m-temperature forecasts using Kalman Filtering technique

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Abstract

Numerical weather prediction (NWP) models generally exhibit systematic errors in the forecast of near-surface weather parameters due to a wide number of factors, including poor resolution of model topography, or deficient physical parameterizations. In this work, deviations between 2 m-temperature observations and forecasts provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) are analysed at 12 synoptic stations located in Portugal. Systematic errors vary considerably with geographical location and time of day as well as throughout the year. The Kalman Filter theory provides a suitable tool to correct systematic errors of this type and therefore improve model forecasts. Accordingly, a Kalman Filter is applied to 2 m-temperature forecasts issued in 2003, a year marked by one of the most severe heat waves in Europe. It is shown that the developed methodology is versatile in adapting its coefficients to different seasons and weather conditions. The proposed Kalman Filter allows an objective forecast correction for 2 m-temperature, reducing the bias of the forecasts at each station to values close to zero, and improving the root mean square error from 10% up to over 70%, with respect to the raw ECMWF forecasts.

Keywords: Kalman filter; Statistical forecast correction

1. Introduction

Reliable forecasts of surface temperature together with an adequate characterization of its diurnal cycle have a wide range of applications in Portugal, such as in tourism planning and organization of sport events, monitoring of wildfire risk and forest fire control, agriculture and hydrology, amongst others. However, numerical weather prediction (NWP) models usually produce errors for forecast of near-surface weather parameters, which are, to a great extent, due to the poor resolution of model topography, deficient physical parameterizations, and uncertainties in cloud fields. Forecasts provided by NWP models, generally present both systematic (bias) and non-systematic (random) errors. In contrast to systematic errors, random errors are more difficult to quantify because of the complexity of separating model inaccuracy from initial state error (e.g., Jung et al., 2005). Systematic errors may be quantified more easily and are in general related to the resolution of the NWP model that is unable to resolve sub-grid phenomena, or represent sub-grid topography or small water bodies. Inaccuracies in the physical/dynamical equations of the model may introduce biases in the forecasts. In this respect, an accurate prediction of near-surface parameters (e.g., surface temperature and

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humidity, winds and precipitation) has been especially challenging since it is determined to a large extent by the physical realism of model representation of surface-atmosphere interactions (e.g. Viterbo and Beljaars, 2002). Statistical correction of model errors may therefore reveal to be extremely useful either to recover estimations of parameters that are not model output variables, or to improve parameters, describing e.g. phenomena at scales not resolved by the model in an adequate way. Furthermore, such techniques may be used to customise forecasts by providing more accurate values to specific locations. In this respect the Portuguese Civil Protection Service (SNBPC) is worth being mentioned as an end user greatly benefiting from improvements on very short-range forecasts (of the order of 3 h) of temperature at specific places, in particular of its maximum and minimum values. Such benefits mainly relate to the heat health warning system and the defence system against wildfires. The dramatic impacts on mortality and morbidity of the heat waves of June 1981 and July 1991 led to the development in Portugal of the first European health warning system. Lisbon's ICARO's surveillance system (Nogueira, 2005) has started in 1999 as a result of the co-operation between the Portuguese Health Observatory (ONSA) and the Portuguese Weather Service (IM). ICARO's surveillance system is operational from May, 15 to September 30 and has proven to be extremely useful in mitigating the impacts on population health of the severe heat waves of August 2003 and August 2005 (Díaz et al., 2006). The system is composed by three main components; (i) 3-day forecasts of maximum temperature; (ii) forecasts of associated excess mortality; and (iii) computation of ICARO index which is an indicator of the severity of the situation. ICARO index is available to decision makers every morning and an accurate 3-hour forecast of maximum temperature at the local and regional levels is of invaluable assistance to those that are responsible for issuing warnings and alerts. Since 1988, the Portuguese Weather Service (IM) has been involved in building up meteorological indices of wildfire risk. A modified Nesterov index was used until 1998 and from then on IM has relied on the Canadian Fire Weather Index (FWI) System (van Wagner, 1987), which consists of six components that account for the effects of fuel moisture and wind on fire behaviour. Temperature is one of the input parameters of the first three components, i.e. the Fine Fuel Moisture Code (FFMC), the Duff Moisture Code (DMC) and the Drought Code (DC) that rate the average moisture content of litter and organic layers of the soil. Two of the fuel moisture codes (DMC and DC) are then combined to produce the so-called Buildup Index (BUI) that is a rating of the total amount of fuel available for combustion. BUI is finally combined with the Initial Spread Index (ISI) to produce the Fire Weather Index (FWI) that has proven to be a suitable general index of fire danger. The Portuguese defence system against wildfires is operational from July 1 to September 30 and improved very short-range forecasts of temperature for critical locations would help decision makers in assessing local risks and planning specific actions for fire prevention.

The perfect prog approach (short for perfect prognosis) was the first technique to take advantage of the dynamical forecasts from NWP models (Klein et al., 1959). Development of perfect prog regression equations is identical to the development of classical regression equations in the sense that only observed variables are used to predict observed predictands, i.e., only historical climatological data are used in the development of the perfect prog technique (Wilks, 1995). The MOS technique (short for Model Output Statistics) is the second, and most used approach to incorporate NWP model outputs into statistical weather forecasting (Glahn and Lowry, 1972). Unlike the perfect prog case, MOS uses NWP forecasts as predictors for both the development and the implementation phases.

Adaptative techniques, such as the KF (e.g. Kalman, 1960, 1963; Kalman and Bucy, 1961) present an alternative solution to the standard regression models and do not suffer from the two main drawbacks of the above-mentioned methodologies, i.e. (i) the perfect prog is unable to correct for NWP model biases; (ii) MOS requires frequent updating of the statistical relationship between the predictand variable and NWP output, due to modifications in the NWP model itself (generally updated twice a year). In fact, the KF has been widely used in the last years as a useful tool to provide objective corrections of NWP model forecasts at specific locations. Unlike MOS, adaptative regression is sequential, and puts more weight to recent data than to older observations (Kalnay, 2003). Persson (1991) used the KF technique to correct 2 m-temperature forecasts in Sweden, while Simonsen (1991) applied the KF to improve wind and temperature prediction in Denmark. Kilpinen (1992) has also applied the KF for statistical interpretation of NWP forecasts and Homleid (1995) has relied on the same adaptative technique to correct the diurnal cycle of surface temperature forecasts in Norway. Recent applications of the KF to the forecast of near-surface parameters may be found in Galanis and Anadranistakis (2002), Anadranistakis et al. (2004), Boi (2004) and Crochet (2004).

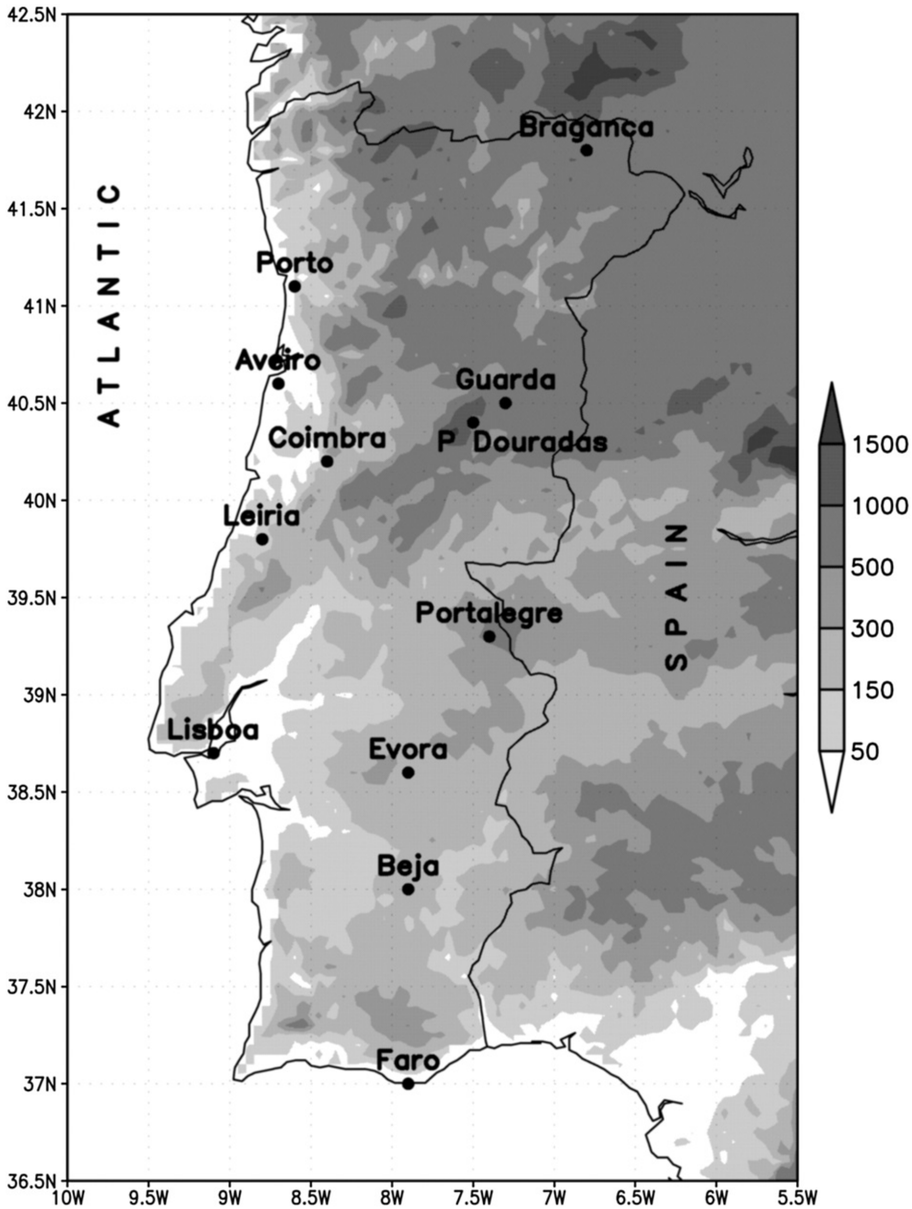

Fig. 1. Map of Portugal showing the orography (m) and the location of the 12 meteorological stations studied.

In this paper, we analyze the performance of the European Centre for Medium-Range Weather Forecasts (ECMWF) surface temperature forecasts over 12 ground stations in Portugal (Fig. 1). The aim is (i) to evaluate the performance of ECMWF forecasts over regions with different characteristics, and under a range of weather conditions; and (ii) to develop an objective correction procedure, appropriate for use in Portugal. A simple KF is then developed in order to correct systematic errors present in surface temperature forecasts, the performance of the technique being then assessed by comparing KF-corrected values against the raw ECMWF output. Moreover, the KF is applied to 2 m-temperature forecasts issued in 2003, a year marked by one of the warmest summer seasons in Europe during the last 500 years (e.g., Luterbacher et al., 2004). The meteorological conditions associated with the heat wave of 2003 were also associated to the most devastating sequence of large wildfires ever recorded in Portugal (Trigo et al., 2006). It is shown that the KF is versatile in adapting its coefficients to different seasons and weather conditions. Its performance in correcting biases as well as in predicting the extreme 2 m-temperatures during the heat wave is put into evidence. The statistical enhancement of NWP forecasts, despite the huge improvement of NWP models during the last decades, is proved to be a useful tool for weather forecasters as well as to a wide range of end-users, in particular those involved in the health and wildfire warning systems.

2. The Kalman filter

The KF model basically consists of a set of two equations, the observation and the system equations. The observation equation is well known from traditional multiple linear regression methods and adjusts to the best relationship between predictors and predictands. In contrast to traditional methods, e.g., MOS, the coefficients of the KF system equations vary in time (Simonsen, 1991). This allows for a recursive updating of regression coefficients, which may then adapt to changes in NWP model and/or in meteorological conditions. Homleid (2004) has pointed out that a large database of forecasts and observations is very useful when defining the KF model, but this is not a prerequisite for applying the correction procedure.

In the KF approach measurements (i.e., new information) subject to noise (errors) are used to update the *a priori* understanding or expectation about the state of a given system (or update the system parameters). In the absence of measurements, the estimate is fully determined by the imposed *a priori* knowledge. Thus, the KF updates our knowledge about the state of the system if we assume an *a priori* knowledge about this state and are able to describe it by means of a probability distribution function (Kirsch, 1996). In the current application, recent observations of 2 m-temperature are used to update the first guess given by a NWP model.

The filter equations may be split into two groups, the time update and the measurement update equations. The time update equations are responsible for the time projection of the system state and of its covariance matrix in order to generate an *a priori* estimate to the next time step. The latter group provides the new information (as obtained from the most recent observations available) into the *a priori* estimation in order to obtain the best *a posteriori* estimation of the state and of its covariance matrix (Welch et al., 2001). Essentially, the KF is a prediction–correction algorithm, where the time update equations are called prediction (or system) equations, and the measurement update equations are known as correction (or observation) equations.

The most important characteristic of the KF is its recursive nature. The process is repeated at each time step using the last *a posteriori* covariance matrix in order to generate new *a priori* estimations. A brief description of the adaptive procedure is given in Annex I; a complete description of the KF model and the derivation of equations may be found, e.g., in Gelb (1974) or Priestley (1981).

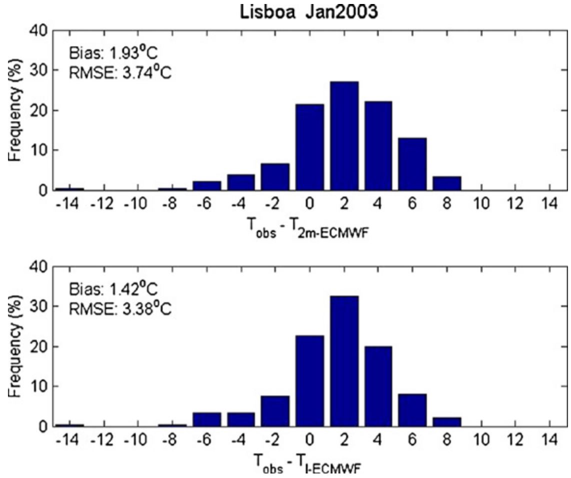

Fig. 2. Histograms of the difference between 2 m temperature observations taken in Lisboa during January 2003, and the corresponding 3-hourly forecasts of 2 m temperature ($T_{2\ \mathrm{m}}$; upper panel) and of the temperature at the lowest model level (T_l; lower panel).

3. Data and methodology

3.1. Data

The purpose of this work is the estimation of unbiased forecasts of 2 m-temperature ($T_{2\ \mathrm{m}}$) for synoptic stations in Portugal. In the current exercise we use ECMWF temperature forecasts at the lowest model level (T_l), as obtained from 12UTC analysis. The forecast steps range from 12 to 33 h, and the study focus on the period from 1 January to 31 December 2003. For each synoptic station, forecasts of $T_{2\ \mathrm{m}}$ are obtained by applying a KF to T_l values, corresponding to the nearest inland point of the ECMWF reduced Gaussian grid (N256), and without any correction for location or topographic errors. ECMWF forecasts of $T_{2\ \mathrm{m}}$ at the nearest inland ECMWF grid point are also used, but only for purposes of comparison of error statistics of the different forecasts available at the same location.

T_l is a prognostic model variable at the lowest model level — about 10 m above the surface in the ECMWF operational model for the one-year study period. Besides ECMWF $T_{2\ \mathrm{m}}$ forecasts result from the interpolation between the lowest level of the model

($\sim$10 m) to 2 m above the model topography. Estimations of $T_{2\text{ m}}$ depend on stability profile functions and surface parameters such as roughness length for heat, which are difficult to estimate (e.g., Malhi, 1996; Trigo, 2002). The error statistics for Portuguese synoptic stations are very similar for both T_1 and $T_{2\text{ m}}$. As an example, Fig. 2 shows the histograms of the differences between 2 m temperature observations, taken in Lisboa during January 2003, and corresponding 3-hourly forecasts of T_1 and $T_{2\text{ m}}$; the mean discrepancies between observations and the two model outputs differ by less than 0.5 °C.

The KF approach has been applied to 12 synoptic stations located in Portugal, namely, Aveiro, Beja, Bragança, Coimbra, Évora, Faro, Guarda, Leiria, Lisboa, Penhas Douradas, Portalegre and Porto (Fig. 1). When applied in an operational mode, the KF, and thus the forecasts, are updated at the arrival of new observations. For each time-slot, we will have updated forecasts every 3 h (since only 3-hourly observations are used), with lead times ranging from 3 to 21 h. Taking into account the above-described specific needs related to the health and wildfire warning systems, results presented here correspond to very short-range forecasts of 2 m-temperature, with lead times of 3 h. Observations of 2 m-temperature at these stations are regularly submitted to quality control, a prerequisite for reliable estimation of verification scores (e.g., Jolliffe and Stephenson, 2003).

3.2. Application of KF to ECMWF 2 m-temperature forecasts

The aim of the current exercise is to correct 2 m-temperature forecast errors. For this purpose, we define our predictand y_t, at a given time t, as the difference between the model forecast T_{ECMWF} (i.e., the temperature at the lowest model level, T_1, at the nearest model grid point to the station) and the observation T_{OBS}:

$$y_t = (T_{\text{ECMWF}} - T_{\text{OBS}})_t \tag{1}$$

We consider y_t to be a function of the ECMWF forecast error at the previous time $t-1$, i.e., $(T_{\text{ECMWF}} - T_{\text{OBS}})_{t-1}$. Denoting by y_t the vector of corrections to 2 m-temperature forecasts for the whole diurnal cycle (00, 03, 06, 09, 12, 15, 18 and 21UTC) estimated at time t, we have the following regression equation:

$$\mathbf{y}_t = \mathbf{K}_t \mathbf{x}_t + \varepsilon_t \tag{2}$$

where x_t represents the regression coefficients updated by the KF, ε_t denotes the observation noise, and K_t the predictors, which are here assumed to be given by:

$$\mathbf{K}_t = \left[1 \; (T_{\text{ECMWF}} - T_{\text{OBS}})_{t-1}\right] = [1 \; y_{t-1}] \tag{3}$$

It is also assumed that the *a priori* estimation of coefficients ($\mathbf{x}'_t$) valid for time t is given by the last KF update $\hat{x}_{t-1}$.

In the KF formulation used here, the coefficients in Eq. (2) are given by the following system equation:

$$\mathbf{x}_t = \mathbf{x}_{t-1} + \zeta_t \tag{4}$$

where the state error, $\boldsymbol{\zeta}_t$, and the measurement error ε_t, are Gaussian zero mean white noise processes, i.e., with covariance matrices (their dimension in the current application is indicated in brackets):

$$E\left(\varepsilon_t \varepsilon_t^T\right) = \mathbf{R}_t \; (8 \times 8) \tag{5}$$

$$E\left(\zeta_t \zeta_t^T\right) = \mathbf{W}_t \; (2 \times 2) \tag{6}$$

The algorithm operates sequentially in time in such a way that at $t-1$ the KF produces an estimate $\hat{\mathbf{x}}_{t-1}$ of $\mathbf{x}_{t-1}$ with associated error covariance $\widehat{\mathbf{P}}_{t-1}$. Eq. (4) is then applied at time t in order to provide an *a priori* estimate of x'_t and its associated covariance Q'_t:

$$x'_t = \hat{\mathbf{x}}_{t-1} \tag{7}$$

$$Q'_t = \widehat{P}_{t-1} + W_t \tag{8}$$

Eqs. (7) and (8) are then combined with the observation Eq. (2), at time t, in order to produce an updated estimate $\hat{\mathbf{x}}_t$ and of its covariance $\widehat{\mathbf{P}}_t$:

$$\mathbf{G}_t = Q'_t \mathbf{K}_t^T \left(\mathbf{K}_t Q'_t \mathbf{K}_t^T + \mathbf{R}_t\right)^{-1} \tag{9}$$

$$\hat{\mathbf{x}}_t = x'_t + \mathbf{G}_t[\mathbf{y}_t - \mathbf{K}_t x'_t] \tag{10}$$

$$\widehat{\mathbf{P}}_t = Q'_t - \mathbf{G}_t \mathbf{K}_t Q'_t \tag{11}$$

The first estimation of the regression coefficients, or initial state vector, $\mathbf{x}'_{t=0}$, was performed by fitting a linear regression applied to a subset (1 month long) of the available forecasts and respective observations. The initial state vector $\mathbf{x}'_{t=0}$ was estimated both at each location (in a total of 12 stations) and for each of the 8 forecast times (00, 03, 06, 09, 12, 15, 18 and 21UTC), resulting in $12 \times 8 = 96$ regression analyses.

One of the major difficulties in KF applications concerns the estimation of the observation error

Table 1
Real height (m) of the 12 meteorological stations studied and ECMWF model surface orography (m) at the respective nearest point

Station	$H_{STATION}$ (m)	H_{ECMWF} (m)
Aveiro	5	119
Beja	246	153
Bragança	691	964
Coimbra	171	219
Évora	245	211
Faro	8	45
Guarda	1020	662
Leiria	24	148
Lisboa	104	81
P. Douradas	1380	662
Portalegre	597	287
Porto	93	197

covariance matrix and the system error covariance matrix, respectively, $\mathbf{R}_t$ (Eq. (5)) and $\mathbf{W}_t$ (Eq. (6)). Here, we have assumed (i) that both matrices are constant in time, and (ii) that correlations of observation and system errors between different forecast times are negligible, meaning that **R** and **W** may be reduced to diagonal matrices.

The observation error covariance matrix **R** was estimated as a by-product of the linear regressions that were used for the first estimation of regression coefficients $\mathbf{x'}_{t=0}$, the diagonal of **R** corresponding to the mean square error of each of those linear regressions. The analysis of the regression coefficients $\mathbf{x'}_{t=0}$ also provided the first estimation of their covariance matrix, $\mathbf{Q'}_{t=0}$ (Eq. (8)).

The system covariance matrix, **W**, may be estimated either by means of a statistical estimation procedure, e.g. the Expectation Maximization algorithm (Dempster et al., 1977), or by "tuning" it to make the KF behave as requested (Homleid, 1995). In our case, the form of **W** (with constant diagonal elements equal to 10^{-3}) was found empirically. Once an initial value for **W** was chosen subjectively, the KF was implemented and the results have been studied. The system covariance matrix was tuned until the KF works as expected, i.e., allowing the KF to react quickly to new conditions, but minimising the errors in 2 m-temperature on the long run.

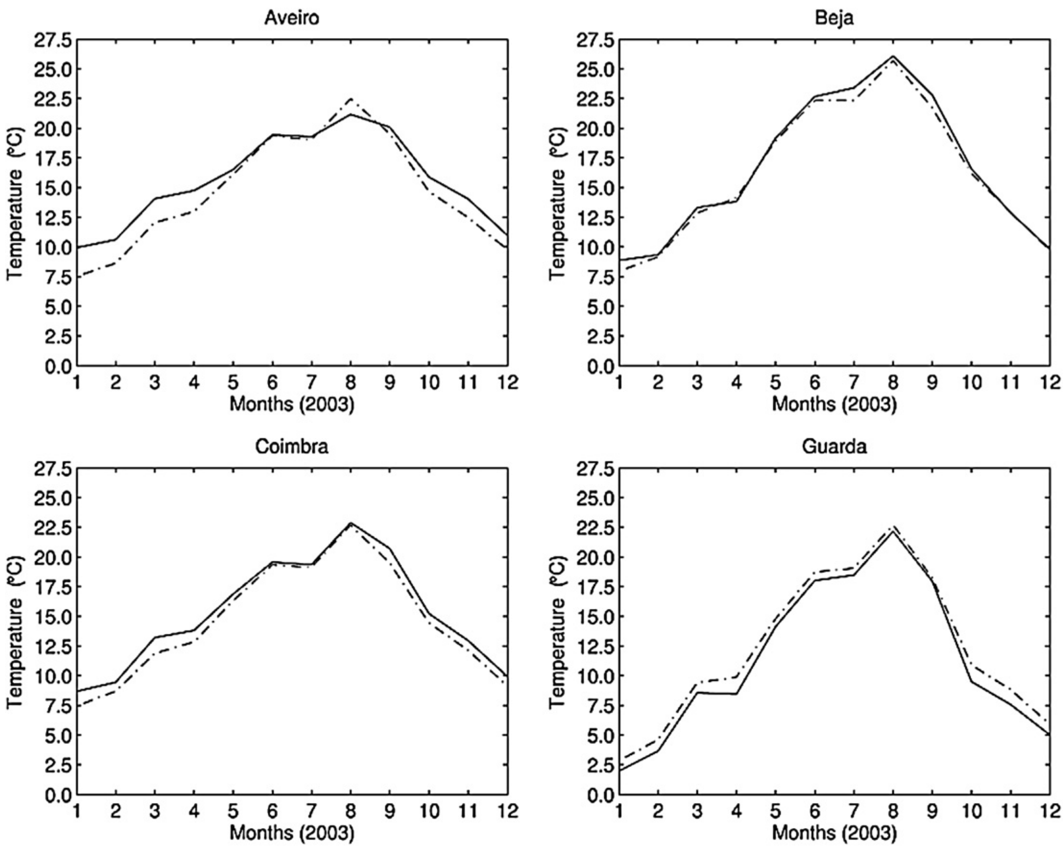

Fig. 3. Monthly mean values of 2 m-temperature observations (solid line) and forecasts (dashed line) at four locations in Portugal.

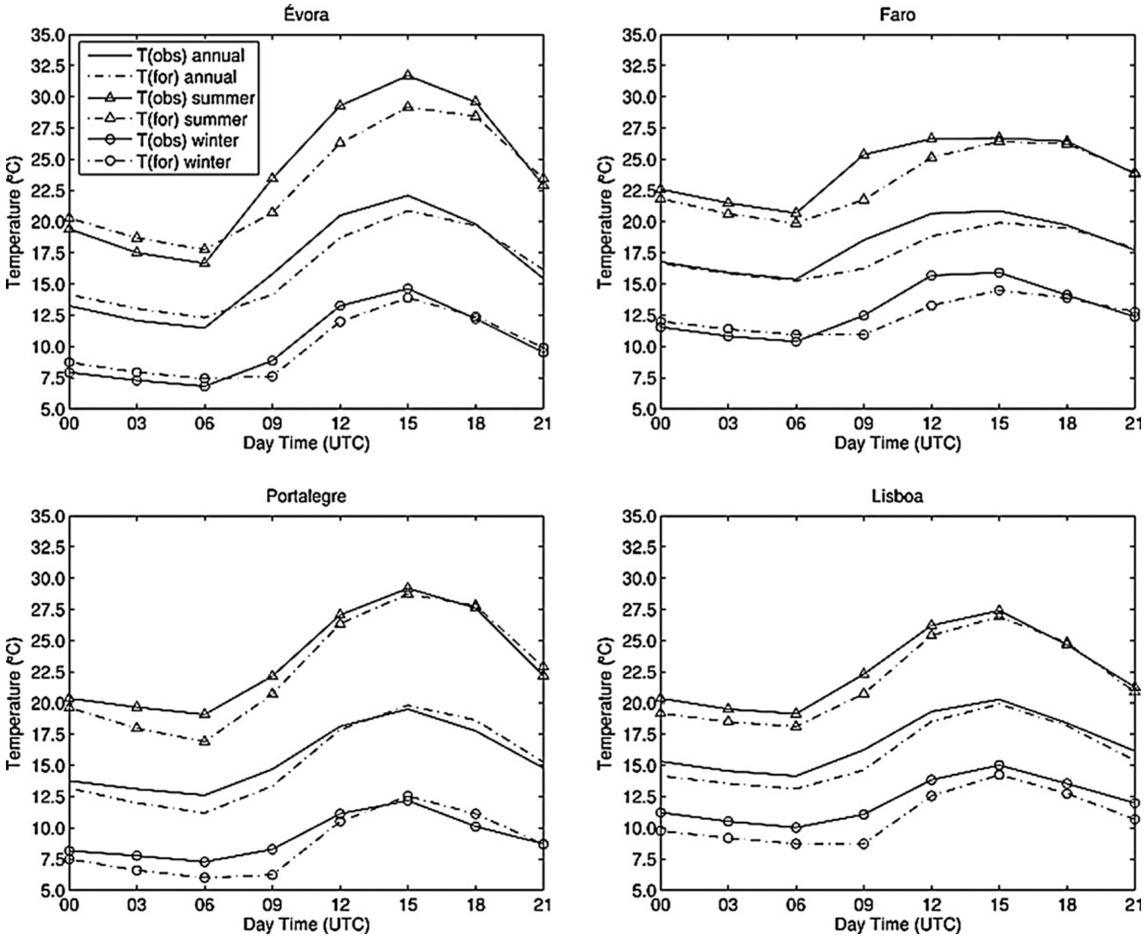

Fig. 4. Hourly values of 2 m-temperature observations (full line) and forecasts (dashed line) at four locations in Portugal. Curves represent averages for winter, summer, and the whole year.

3.3. Forecast error characteristics

The comparison between ECMWF raw forecasts of 2 m-temperature and observations at synoptic stations during the year 2003 allows identifying both systematic and random deviations. The systematic errors may be related as follows to several shortcomings of the NWP model:

a) Differences between topography heights in the ECMWF NWP model and real station heights may reach several hundred meters (Table 1), implying large systematic errors in the temperature forecasts;
b) The spatial resolution of the NWP model (~40 km) may introduce systematic errors at coastal stations. It was noted that temperature forecasts are either too close to typical diurnal cycles over sea, or to inland ones with overestimation of daily amplitudes.
c) Surface parameters or variables in the NWP model (e.g. land cover, soil moisture, surface temperature) may also induce systematic errors in temperature forecasts, as they are directly related to the surface radiative budget.

As shown below, the relative importance of different error sources often depends on weather conditions and may also vary widely by location, season, and time of day.

Monthly mean values of 3-hourly $T_{2\ m}$ observations (solid line) and forecasts (dotted line) for 2003 are shown in Fig. 3 at 4 meteorological stations — Aveiro, Guarda, Beja and Coimbra. Forecast monthly mean values correspond to +12, +15, +18, +21, +24, +27, +30 and +33 h forecast steps, as generated from 1200UTC analyses. Differences between mean observations and forecasts may vary significantly from station to station and throughout the year. For all 12 synoptic

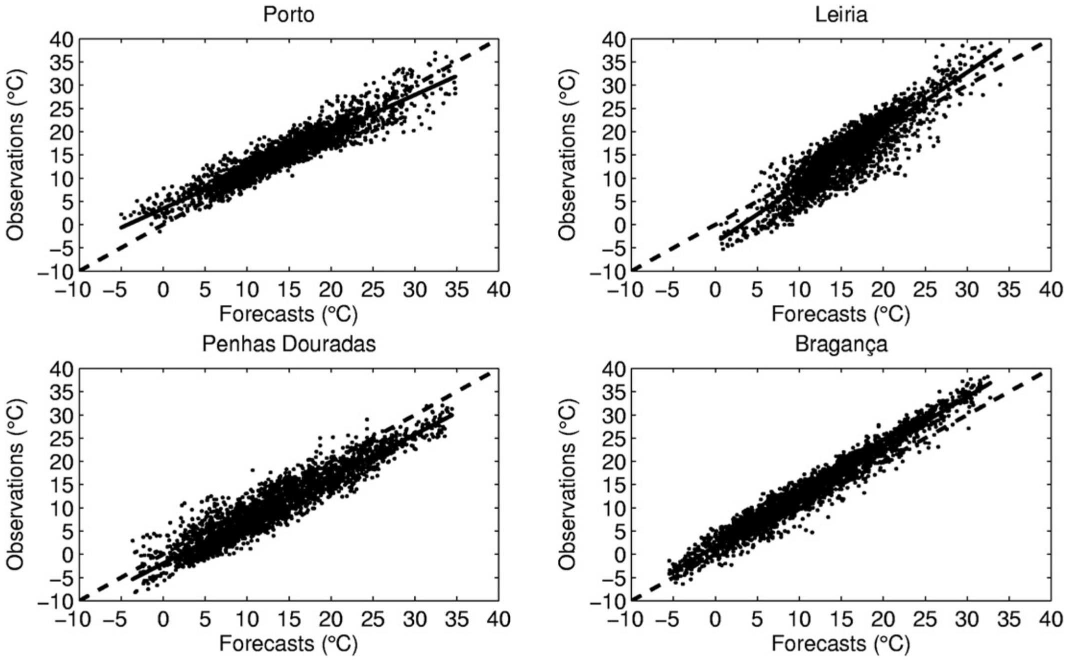

Fig. 5. Scatter plot of observations vs. forecasts for Porto, Leiria, Penhas Douradas and Bragança. The 1:1 line (dashed line) and the best linear fit (solid line) between forecasts and observations are also plotted.

stations analysed in this study, ECMWF model tends to underestimate 2 m-temperature, except for Guarda (Fig. 3) and Penhas Douradas (not shown), these two stations being located over the mountainous region in Central Portugal, where model topography is respectively about 400 m and 700 m below the real station heights.

Fig. 4 shows 3-hourly observations and forecasts, averaged over winter, summer, and the whole year, respectively, at 4 of the 12 studied locations. For most of the studied stations, forecasted daytime temperatures are generally cooler than observations (e.g., Lisboa in Fig. 4), often leading to modelled diurnal amplitudes lower than observations (e.g., Faro in Fig. 4). Daily amplitudes are particularly underestimated for Évora (Fig. 4), where the minimum (maximum) temperature tends to be overestimated (underestimated). In the case of Portalegre, an inland city like Évora (Fig. 1), forecasted minimum temperatures are generally cooler than observations, which, in this case, result in an overestimation of the modelled daily amplitude.

Fig. 5 shows scatter-plots of observations versus forecasts of $T_{2\ \mathrm{m}}$ at 4 locations. Results reveal a conditional bias for Porto (Leiria), corresponding to model temperatures warmer than observations during daytime (night-time), and cooler during night-time (daytime). At the remaining 2 locations shown in Fig. 5 (Bragança and Penhas Douradas), forecasts are systematically overestimated at Bragança and underestimated at Penhas Douradas. These steady discrepancies in temperature essentially result from the mismatch between model and real station height; model orography is about 300 (700) meters above (below) real station height at Bragança (Penhas Douradas).

It is worth noting that the year of 2003 was characterised in Europe by extremely warm weather during the summer. Europe was exceptionally warm and dry from May to the end of August (Luterbacher et al., 2004) with persistent anticyclone conditions leading to consecutive heat waves and drought (Fink et al., 2004; Black et al., 2004). Fig. 6 shows the daily evolution of observed (upper panel) and ECMWF forecasted (lower panel) values of maximum and minimum 2 m-temperatures at Lisboa during 2003 in comparison with the respective daily values of the percentiles 10 and 90 of observed 2 m-temperature for the period 1961–1990. Differences between the time series of observed and forecasted values are well apparent along the year, being especially conspicuous when observed temperatures are close to the climatological extremes. This is especially true during the period between July and August, especially during the first two weeks of August, when the absolutes records of maximum and minimum temperatures were exceeded. Arrows in the panels indicate

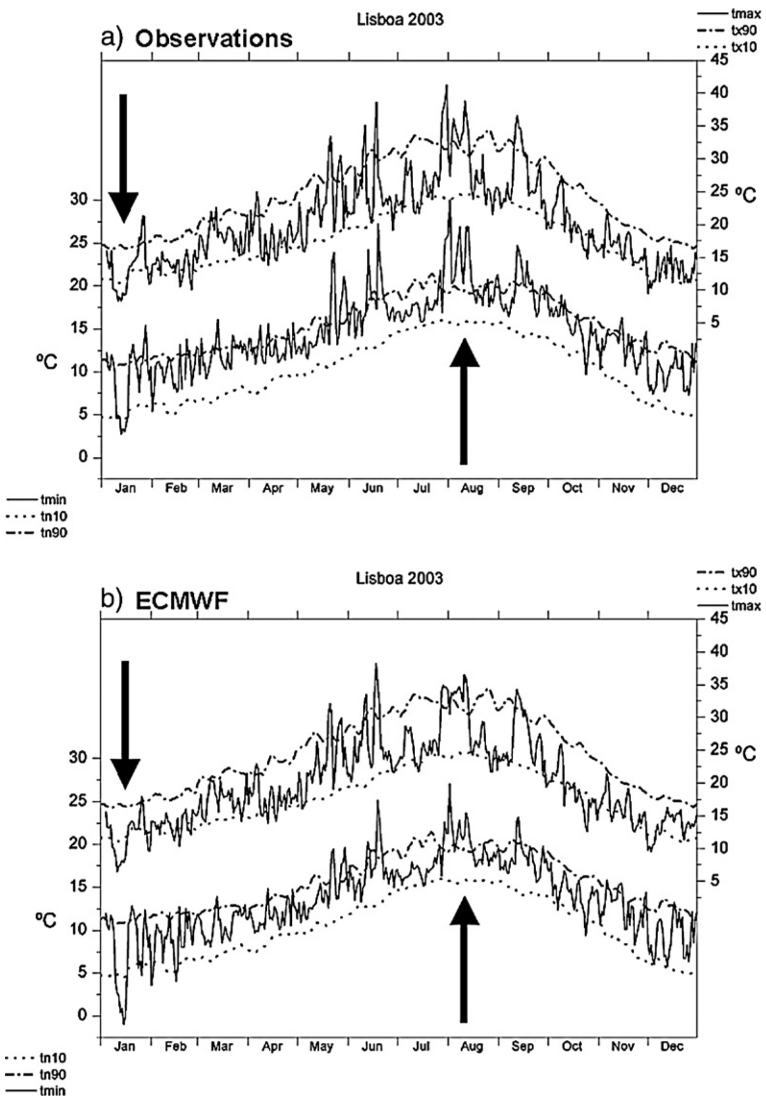

Fig. 6. Daily evolution of observed (upper panel) and ECMWF forecasted (lower panel) values of maximum and minimum 2 m temperature (°C; solid lines) at Lisboa during 2003. For comparison purposes, daily values of the percentiles 10 (dotted lines) and 90 (dashed–dotted lines) of observed 2 m-temperature for the period 1961–1990 period are also shown in both panels.

two extreme events, namely a cold wave and a hot wave that occurred in mid-January and in the beginning of August. In both cases the tendency of the model to underestimate both maximum and minimum temperatures is well apparent. In particular it is clear that ECMWF was not able to reproduce the observed heat wave in Portugal.

Results shown in this section put into evidence the existence of systematic errors and conditional bias in ECMWF $T_{2\,m}$ forecasts for Portuguese synoptic stations. We will make use of the KF theory to adjust ECMWF model output, in particular with the aim of improving temperature forecasts for the whole daily cycle.

4. Results and discussion

Fig. 7 allows comparing "raw" and KF-corrected ECWMF 2 m-temperature forecasts with observations at Lisboa at 03UTC during the 2003 winter (January to March) period and at 15UTC during the 2003 summer (July and August) period, that respectively represent the times of the day of minimum and maximum temperatures. Overall, Fig. 7 puts into evidence the obtained improvements in the KF-corrected temperature forecasts, which follow the observations quite well during this anomalous heat year, according to Fig. 6. It is worth noting in particular, the marked drop in temperature observed on 12

January, which was overestimated by the “raw” ECMWF forecasts, and was reasonably well corrected by the KF technique. A similar situation occurs on 15 February, when ECMWF forecasts errors are greater than 7 °C. During the summer period, ECMWF model seems to be very conservative, being unable to forecast large variations from day to day. On the other hand the KF technique is capable to adapt itself and correct the systematic errors.

Histograms of forecast errors ($T_{\mathrm{FORECAST}}-T_{\mathrm{OBSERVATION}}$) for “raw” ECMWF and KF outputs are shown in Figs. 8 and 9, respectively for Portalegre and Lisboa at 03, 09, 15 and 21UTC. It is worth noting that the KF error distributions are much closer to the normal than the respective ECMWF histograms, and present considerably smaller distribution tails, suggesting that the KF is removing systematic errors in an effective way. Moreover, KF forecast errors concentrate within the range of ±1 °C at each location, and for the whole diurnal cycle.

The Skill Score (SS) of the KF outputs with respect to ECMWF raw model output provides a measure of the improvement of corrected forecasts (e.g., Wilks, 1995):

$$SS = \frac{\mathrm{RMSE_{ECMWF}} - \mathrm{RMSE_{KALMAN}}}{\mathrm{RMSE_{ECMWF}}} \times 100\% \qquad (12)$$

In the above expression, $\mathrm{RMSE_{ECMWF}}$ and $\mathrm{RMSE_{KALMAN}}$ are the root mean square error (RMSE) of ECMWF and KF 2 m-temperature forecasts, respectively. Positive (negative) values of SS indicate that the KF provides better (worse) forecasts than ECMWF. Fig. 10 presents SS values at four locations, by time of the day. Improvements in RMSE range between 10% and 80%, staying around 50% for most cases. Meteorological stations with best relative performances, i.e. with SS values reaching over 70%, include Bragança and Penhas Douradas, which presented high ECMWF model errors associated to topography. Lower values of SS are obtained at Beja, Évora and Faro, where KF results in improvements of the order of 30–40% in the RMSE.

Tables 2–5 present the RMSE, bias and the standard deviation of the errors (STD) of corrected (Kalman) and uncorrected (ECMWF) forecasts at each station and at verification times 00, 06, 12 and 18UTC, respectively. As pointed out by the histograms in Figs. 8 and 9, the removal of systematic errors results in values of bias close to zero, while improvements in forecast accuracy are mirrored in the reduction of RMSE, to values within the range of 1 to 1.5 °C. As in other statistical methods for forecast correction, the goal of the KF is the reduction of systematic errors of the model. However, it should be stressed that the KF technique as applied to the 12 Portuguese synoptic stations studied is also able of reducing conditional bias, with consequent improvement of forecast accuracy.

As expected, the best SS were obtained for times or at locations where ECMWF forecasts presented the

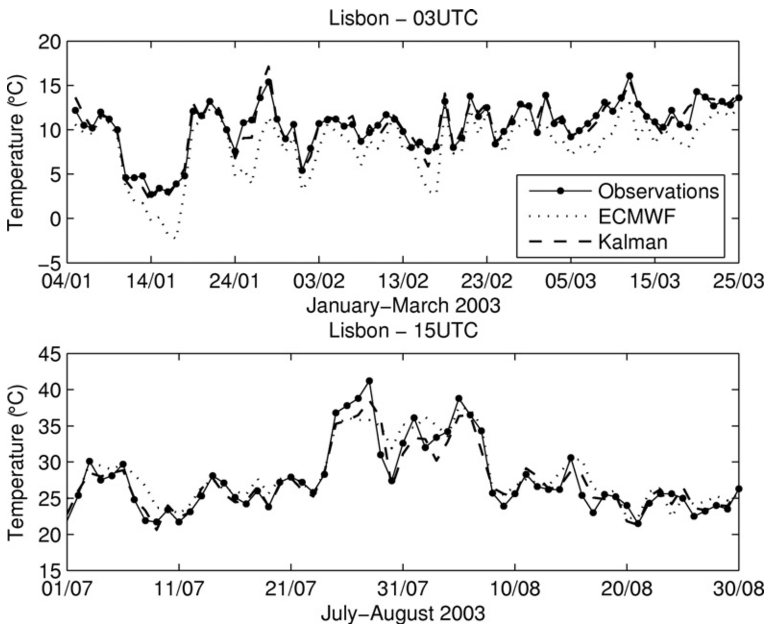

Fig. 7. Temperature observations (black dots full line), ECMWF 2 m-temperature forecasts (pointed line) and temperature forecasts corrected by the KF (dashed line) for (a) Lisboa during 2003 winter period (January to March) at 03UTC; and (b) during 2003 summer period (July and August) at 15UTC.

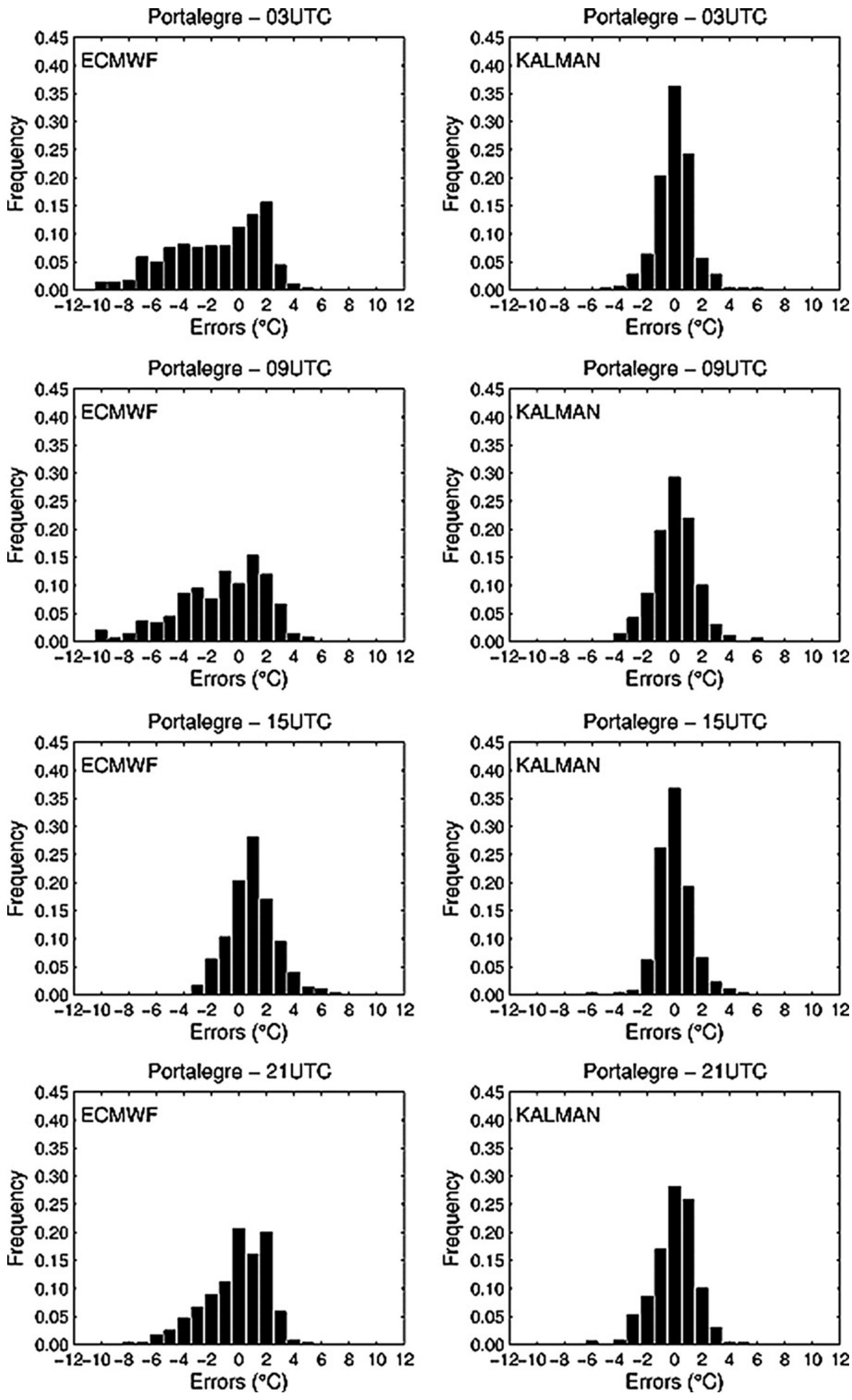

Fig. 8. Histograms of forecast errors (model minus observations) for raw ECMWF 2 m-temperature (left) and for KF output (right), at Portalegre for verification times 03, 09, 15 and 21UTC.

highest systematic errors. This is the case of Porto, where the bias of ECMWF raw forecast for 00UTC (12UTC) is −2.0 °C (−0.2 °C), and where SS reaches 53% (36%).

As mentioned before, one of the main advantages of the KF is its capability to adapt itself to singular meteorological situations or to modifications in NWP model characteristics. Fig. 11 shows an example of estimated

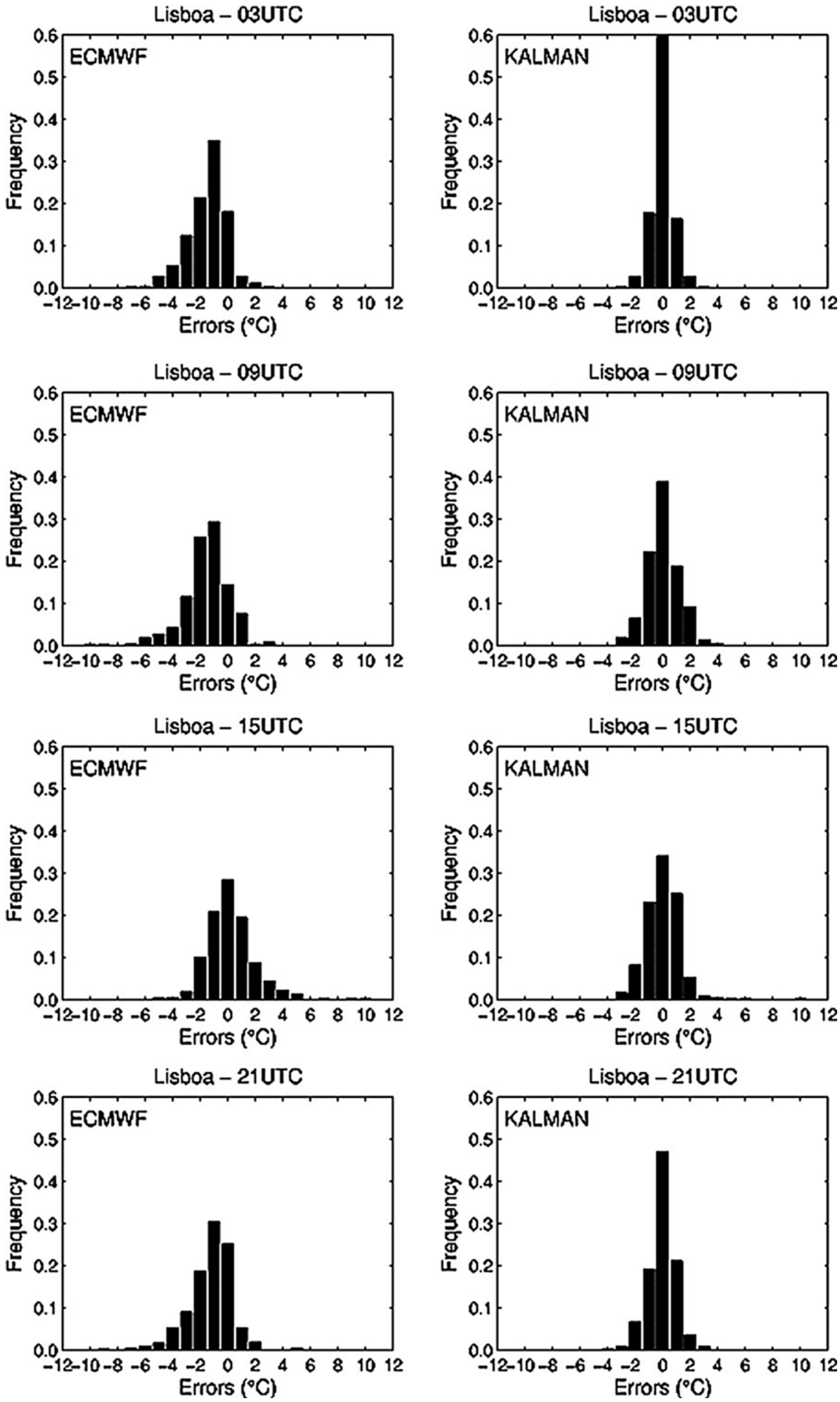

Fig. 9. As in Fig. 8, but at Lisboa.

KF coefficients, for the whole 2003-year. The significant changes in the KF coefficients during season transitions – e.g., beginning of June, October, and December – are worth noting. It is worth pointing out that the behaviour of the KF coefficients is particularly related with the anomalous period of temperature described in Fig. 6.

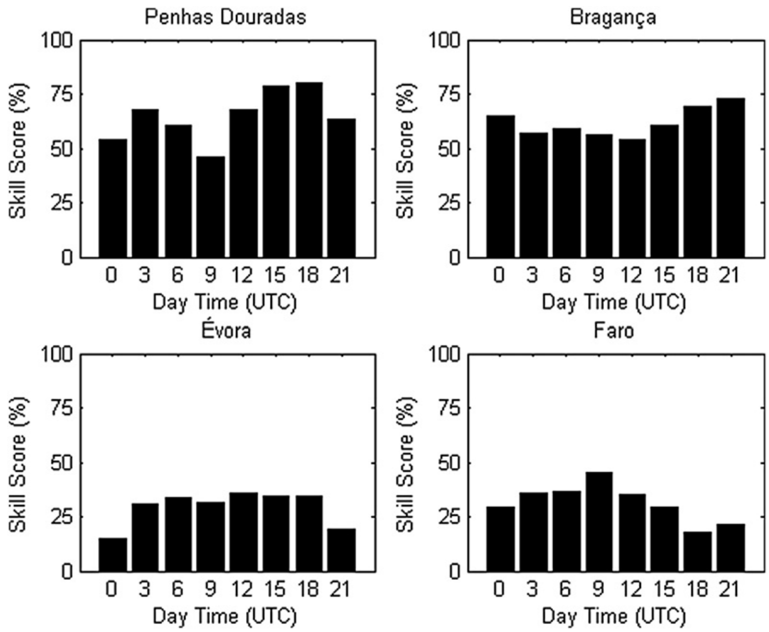

Fig. 10. Skill Score values (based on the RMSE) of the KF with respect to ECMWF raw model output, for each forecast verification time, and for the indicated stations.

This fact emphasizes the advantage of using the KF technique in extreme weather conditions, both in winter and summer situations.

5. Conclusions

The KF technique has been widely used to correct NWP model forecasts (Homleid, 1995; Galanis and Anadranistakis, 2002; Anadranistakis et al., 2004; Boi, 2004; Crochet, 2004). In Portugal, the complex orography and local effects such as sea breezes that are not adequately resolved by NWP models, together with the misrepresentation of model surface variables result in (conditionally) biased forecasts of 2 m-temperature. It was shown here that the KF designed for 12 Portuguese synoptic stations, is able to significantly improve 2 m-temperature forecasts, including a more accurate reproduction of the forecasted diurnal cycle. The KF is an extremely versatile technique, able to adapt to different seasons/weather conditions, including extreme events, such as the summer 2003 heat wave.

Over most locations and time of the day, the RMSE of adjusted 2 m-temperature forecasts shows improvements of 30 to 50%, reaching over 70% for areas where

Table 2
RMSE, bias and error STD of the corrected (Kalman) and uncorrected (ECMWF) forecasts for each station at 00UTC

00UTC	RMSE (°C)		BIAS (°C)		STD (°C)	
	ECMWF	KF	ECMWF	KF	ECMWF	KF
Aveiro	3.13	1.22	−2.30	0.13	3.88	1.21
Beja	1.48	1.08	0.29	0.02	1.45	1.07
Bragança	3.31	1.16	−2.86	0.03	4.37	1.15
Coimbra	2.19	1.25	−1.22	0.00	2.50	1.25
Évora	1.36	1.16	0.37	−0.05	1.30	1.16
Faro	1.53	1.08	0.18	−0.01	1.51	1.08
Guarda	2.09	1.23	0.55	0.02	2.01	1.22
Leiria	3.16	1.73	1.93	0.01	2.50	1.73
Lisboa	2.18	0.97	−1.62	−0.01	2.71	0.97
PDouradas	3.34	1.53	2.19	0.00	2.52	1.53
Portalegre	3.10	1.65	−1.14	0.02	3.30	1.64
Porto	2.91	1.35	−2.02	0.13	3.54	1.34

Table 3
As in Table 2 but at 06UTC

06UTC	RMSE (°C)		BIAS (°C)		STD (°C)	
	ECMWF	KF	ECMWF	KF	ECMWF	KF
Aveiro	3.19	1.10	−2.31	0.03	3.93	1.09
Beja	1.60	0.98	0.13	−0.01	1.59	0.98
Bragança	2.80	1.15	−2.00	−0.01	3.44	1.15
Coimbra	2.22	1.04	−1.23	0.02	2.53	1.03
Évora	1.50	0.99	0.42	−0.01	1.44	0.99
Faro	1.70	1.08	0.40	0.00	1.65	1.08
Guarda	2.46	1.03	0.07	−0.05	2.45	1.03
Leiria	3.29	1.34	1.81	0.01	2.74	1.34
Lisboa	2.03	0.79	−1.51	0.01	2.53	0.78
PDouradas	3.30	1.30	1.38	−0.02	2.99	1.30
Portalegre	4.02	1.21	−1.87	−0.01	4.43	1.21
Porto	3.09	1.11	−2.25	0.01	3.82	1.11

Table 4
As in Table 2 but at 12UTC

12UTC	RMSE (°C)		BIAS (°C)		STD (°C)	
	ECMWF	KF	ECMWF	KF	ECMWF	KF
Aveiro	2.86	1.63	−0.01	0.15	2.86	1.62
Beja	2.04	1.48	−0.92	0.05	2.23	1.47
Bragança	3.65	1.69	−3.06	0.07	4.76	1.68
Coimbra	2.00	1.40	−0.62	0.02	2.09	1.39
Évora	2.14	1.37	−1.28	0.05	2.49	1.36
Faro	2.24	1.46	−1.56	0.01	2.72	1.46
Guarda	2.94	1.21	2.57	0.04	1.42	1.20
Leiria	2.97	1.89	−2.22	0.02	3.70	1.88
Lisboa	1.54	1.27	−0.14	0.05	1.54	1.26
PDouradas	5.04	1.63	4.48	0.06	2.30	1.62
Portalegre	2.09	1.37	0.42	0.00	2.04	1.37
Porto	2.79	1.78	−0.24	0.10	2.80	1.77

the representation of local topography in the model is the poorest, and where model biases are the highest. Over all studied locations and periods of the day, the KF was able to provide unbiased forecasts, with reduced STD (Tables 2–5). The decrease in the standard deviation, generally associated to random errors (e.g., Murphy, 1995) is likely to be due to the elimination of conditional bias, e.g., corresponding to systematic errors associated to specific weather types, or seasons. The good results obtained with the application of the KF technique are clearly associated to its flexibility in adapting to different synoptic situations. It is worth mentioning, in particular, the quick changes of the filter coefficients during transition periods between seasons.

Since the beginning of 2006, the ECMWF operational NWP model has undergone significant changes (e.g., Miller and Untch, 2005), particularly in what concerns its spatial resolution (T799 corresponding to about 25 km horizontal resolution, and 91 vertical levels between the surface and 0.1 hPa). The consequent improvement of the

Table 5
As in Table 2 but at 18UTC

18UTC	RMSE (°C)		BIAS (°C)		STD (°C)	
	ECMWF	KF	ECMWF	KF	ECMWF	KF
Aveiro	2.71	1.27	−0.08	0.05	2.71	1.26
Beja	1.60	1.07	−0.28	−0.01	1.62	1.07
Bragança	3.65	1.13	−3.25	−0.01	4.88	1.13
Coimbra	1.94	1.21	−0.85	0.00	2.11	1.21
Évora	1.68	1.10	−0.59	0.00	1.78	1.10
Faro	1.72	1.41	−0.41	0.02	1.76	1.40
Guarda	2.37	0.97	1.91	0.00	1.40	0.97
Leiria	1.65	1.51	−0.15	0.07	1.65	1.50
Lisboa	1.80	1.03	−0.38	−0.01	1.83	1.03
PDouradas	5.70	1.12	5.36	0.00	1.93	1.12
Portalegre	1.80	1.13	0.65	0.01	1.67	1.13
Porto	2.36	1.17	0.11	0.04	2.35	1.16

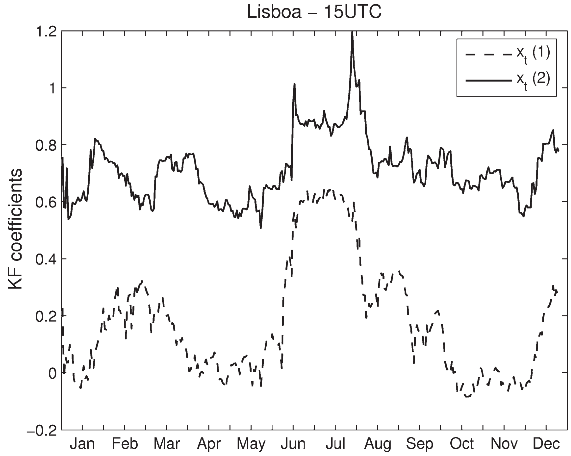

Fig. 11. Evolution of the KF coefficients estimated for Lisboa (15UTC verification time) throughout the whole year.

represented surface orography is likely to reduce model biases associated to mismatches between station and model height; the performance of the new model version over Portugal is currently under study. Nevertheless results of the current study are very encouraging, and support the following lines of future work: (i) the use of KF to provide maximum and minimum temperatures, as suggested by the improvement of the adjusted temperature daily cycle; (ii) the application of the KF technique to higher forecast steps; (iii) the extension to other variables of interest, particularly near-surface wind forecasts, which present significant biases along the Portuguese coastal areas. Further work will also focus on new methodologies to estimate KF parameters, such as the system and observation noise statistics.

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