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# The 3-Hour-Interval Prediction of Ground-Level Temperature in South Korea Using Dynamic Linear Models

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**ABSTRACT**

The 3-hour-interval prediction of ground-level temperature from +00 h out to +45 h in South Korea (38 stations) is performed using the DLM (dynamic linear model) in order to eliminate the systematic error of numerical model forecasts. Numerical model forecasts and observations are used as input values of the DLM. According to the comparison of the DLM forecasts to the KFM (Kalman filter model) forecasts with RMSE and bias, the DLM is useful to improve the accuracy of prediction.

**Key words:** temperature forecasting, systematic error, dynamic linear model

## 1. Introduction

Nowadays many numerical models for generating meteorological and climate factors, due in large part to advances in related theories and digital computing, are much improved. The improvement of their accuracy is the most important target of extensive research and application. Numerical model forecasts however still have some systematic errors like bias. The elimination of their systematic errors is needed in order to improve their accuracy of prediction. For this purpose, two statistical methods which use numerical model forecasts as inputs, (1) MOS (Model Output Statistics) and (2) KF (Kalman filtering), are usually considered as physical-statistical models. MOS is applied to remove the systematic error by finding the statistical relationship between predictand and numerical model forecasts of predictors. Glahn and Lowry (1972) considered the characteristics of numerical models and developed the forecast model using numerical outputs. Many authors have considered MOS for the prediction of temperature and precipitation (Lemcke and Kruizinga, 1988; Ross, 1989; Kok and Kruizinga, 1992). MOS however has some disadvantages; the MOS models need long period data and should be reestimated when the numerical model is changed.

KF, proposed by Kalman (1960), needs short period data and maintains the dynamic and nonlinear aspects through a set of statistical equations that provides an efficient solution of the least-squares method. KF is very powerful to estimate past, present, and future states even when the precise nature of the modeled system is unknown. So KF has been the subject of extensive application. Since 1980, KF has been applied for the analysis and the prediction of meteorological and climatological data. Ghil and Malanotte-Rizzoli (1991), Simonsen (1991), Persson (1991), Kilpinen (1992), Ross and Strudwicke (1994), and Homleid (1995) applied KF for the prediction of temperature and probability of precipitation. Verron et al. (1999) considered the extended Kalman filter for the purpose of assimilating observations into a high-resolution nonlinear numerical model of the tropical Pacific Ocean. Many meteo-statisticians predicted that KF will be a useful skill for working with physical-statistical models at the 8th international meeting on statistical climatology held in March 2001.

Since early 2002, the Korea Meteorological Administration (KMA) began to provide the 3-hour-interval forecasts for ground-level temperature and precipitation at 38 stations in South Korea out to +45 hours for every 00 UTC and 12 UTC run using a numerical model (Regional Data Assimilation and Prediction System; RDAPS) and a Kalman filter model (KFM). Though the KF reduces the bias of RDAPS forecasts, the two plots in Fig. 1 show that the KFM inclines to generate more or less under estimated forecasts. Therefore a more accurate forecast model is needed.

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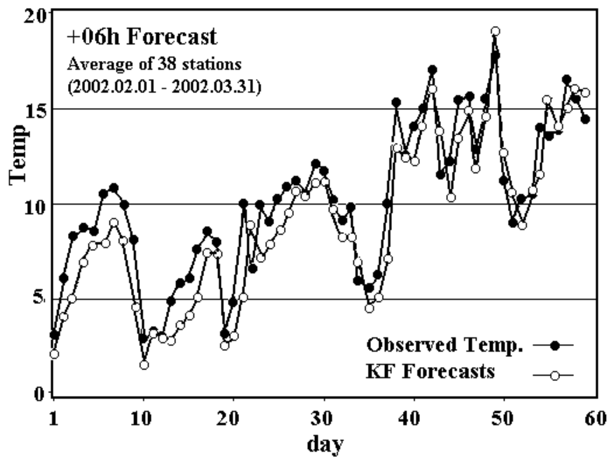


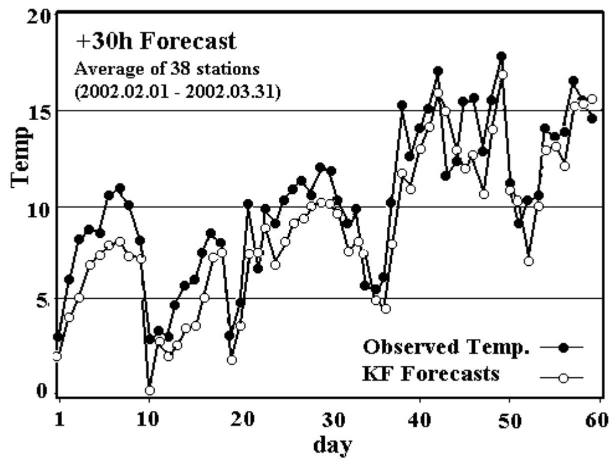


**Fig. 1.** Time series plots of KF forecasts and observations of averaged temperature of 38 stations in South Korea: Left: +06 h forecast case, Right: +30 h forecast case.

This paper concentrates on the Bayesian KFM, called the dynamic linear model (DLM), for the improvement of the prediction of ground-level temperature. In the classical KFM, the modeler would take constant values for the components of the output error variance $V(t)$ and the evolution error variance-covariance matrix $\boldsymbol{W}(t)$ under the empirical sense. However in the DLM, $V(t)$ and $\boldsymbol{W}(t)$ can be estimated dynamically by the updating equations and the latest observations. This is the difference between the KFM and the DLM. Therefore the optimal DLM is better than the optimal KFM. The DLM has been studied by many statisticians, including West and Harrison (1997). However there are few studies of the DLM in meteorological applications. Sohn et al. (2001) and Sohn and Kim (2001) applied the DLM to typhoon track forecasting and the mid-term prediction of max/min temperature. According to the results of those papers, the DLM, as a physical-statistical model, is useful to reduce the systematic error and robust to the initial values. The structure of the DLM is same as the KFM except the output error variance in the DLM changes dynamically.

In this paper, the DLM is applied to remove the systematic errors of RDAPS forecasts for improving the predictability. The dataset for our study is presented in section 2. A brief introduction to the DLM and the forecast strategy is presented in section 3, and the comparison of RDAPS, KFM, and DLM forecasts are made in section 4.

## 2. Data used

The three datasets of the 3-hour-interval ground-level temperature on 38 stations in South Korea are used for our study: (1) 3-hour-interval observations, (2) 3-hour-interval RDAPS forecasts out to +45 hours for every 00 UTC and 12 UTC run and (3) 3-hour-interval KFM forecasts out to 45 hours for every 00 UTC and 12 UTC. These data are obtained from KMA. Each dataset is divided into two groups: one is for the model training (1 February to 20 April 2001) and the other is for the model validation (1 February to 31 March 2002).

## 3. Dynamic linear model and forecast strategy

### 3.1 *Structure and updating procedure of DLM*

The considered DLM consists of two equations, the state equation and the output equation, and initial distributions given by

(1) (output equation) $Y(t) = \boldsymbol{F}(t)^{\mathrm{T}}\boldsymbol{\theta}(t) + v(t)$,

$v(t) \sim N(0, V(t))\ ,\ \ V(t) \sim IG(n(t)/2, n(t)s(t)/2)\ ,$

(2) (state equation) $\boldsymbol{\theta}(t) = \boldsymbol{\theta}(t-1) + \boldsymbol{w}(t)\ ,$

$\boldsymbol{\theta}(t) \sim T(n(t);\ \boldsymbol{m}(t),\ \ \boldsymbol{C}(t))\ ,$

$\boldsymbol{w}(t) \sim T(n(t)-1; 0,\ \ \boldsymbol{W}(t))\ ,$

(initial distributions) $\boldsymbol{\theta}(0) \sim T(n(0);\ \boldsymbol{m}(0), \boldsymbol{C}(0))\ ,$

$V(0) \sim IG(n(0)/2\ , n(0)s(0)/2)\ ,$

where $Y(t)$ is a univariate observation at time $t; \boldsymbol{F}(t)$ is an input vector which consists of 1 for the intercept, RDAPS forecasts, the previous observations, and the previous DLM forecasts; $\boldsymbol{\theta}(t)$ means a state vector (dynamic coefficient vector) at time $t; v(t)$ is an output error which has a univariate normal distribution with mean 0 and variance $V(t)$ which has an inverse gamma distribution $IG(n(t)/2, n(t)s(t)/2)$ with two parameters $n(t)$ and $s(t)$; an evolution error $\boldsymbol{w}(t)$

has the multivariate $T$ distribution with mean vector 0 and covariance matrix $\boldsymbol{W}(t); v(t)$ is independent of $\boldsymbol{w}(t)$; and $\boldsymbol{m}(t)$ and $\boldsymbol{C}(t)$ are the mean vector and covariance matrix of $\boldsymbol{\theta}(t)$ respectively.

The DLM needs initial values and the states are dynamically determined by the given state equation and then the observation is generated from the inputs and states by the given output equation. When a new observation is collected, the DLM is dynamically updated. To learn about the DLM in detail, see West and Harrison (1997).

In order to generate the forecasts using the above DLM, parameters $\{\boldsymbol{m}(t), \boldsymbol{C}(t), n(t), s(t)\}$ should be determined dynamically via the recursive updating procedure below.

Repeat the following steps with varying $t = 1, 2, \ldots$ .

[**Step 1**] Posterior distribution of $\boldsymbol{\theta}(t-1)$ (the results of the previous procedure):

$$\boldsymbol{\theta}(t-1) \mid \boldsymbol{D}(t-1) \sim$$
$$T(n(t-1);\ \boldsymbol{m}\ (t-1),\quad \boldsymbol{C}\ (t-1))\ ,$$
$$V(t-1) \mid \boldsymbol{D}(t-1) \sim$$
$$IG(n(t-1)/2,\ n(t-1)s(t-1)/2)\ ,$$

where $\boldsymbol{D}(t)$ means the total information up to time $t$.

[**Step 2**] Prior distribution of $\boldsymbol{\theta}(t)$ and the one-step-ahead-forecast $f(t)$:

$$\boldsymbol{\theta}(t) \mid \boldsymbol{D}(t-1) \sim T(n(t-1)\ ; \boldsymbol{a}(t)\ ,\ \boldsymbol{R}(t))\ ,$$
$$Y(t) \mid \boldsymbol{D}(t-1) \sim T(n(t-1)\ ; f(t)\ ,\ Q(t))\ ,$$

where

$$\boldsymbol{a}(t) = \boldsymbol{m}(t-1)\ , \boldsymbol{R}(t) = \boldsymbol{C}(t-1) + \boldsymbol{W}(t)\ ,$$
$$f(t) = \boldsymbol{F}(t)^{\mathrm{T}}\boldsymbol{m}(t-1)\ ,$$
$$\text{and}\ \ Q(t) = \boldsymbol{F}(t)^{\mathrm{T}}\boldsymbol{R}(t)\boldsymbol{F}(t) + s(t-1)\ .$$

[**Step 3**] Posterior distribution of $\boldsymbol{\theta}(t)$, given $Y(t)$:

$$\boldsymbol{\theta}(t) \mid \boldsymbol{D}(t) \sim T(n(t)\ ;\ \ \boldsymbol{m}(t)\ , \boldsymbol{C}(t))\ ,$$
$$V(t) \mid \boldsymbol{D}(t) \sim IG(n(t)/2\ , n(t)s(t)/2)\ ,$$

where

$$\boldsymbol{A}(t) = \boldsymbol{F}(t)^{\mathrm{T}}\boldsymbol{R}(t)/Q(t)\ , e(t) = Y(t) - f(t)\ ,$$
$$n(t) = n(t-1) + 1,\ s(t) = s(t-1)$$
$$+ (e(t)^2/Q(t) - 1)s(t-1)/n(t)\ ,$$
$$\boldsymbol{m}(t) = \boldsymbol{m}(t-1) + \boldsymbol{A}(t)\boldsymbol{e}(t)\ ,$$
$$\boldsymbol{C}(t) = (\boldsymbol{R}(t) - \boldsymbol{A}(t)\boldsymbol{A}^{\mathrm{T}}(t)Q(t))s(t)/s(t-1)\ ,$$
$$\text{and}\ \boldsymbol{D}(t) = \{\boldsymbol{D}(t-1)\ , Y(t)\}\ .$$

The recursive procedure for updating and forecasting in the DLM is shown in Fig. 2. In the first step, some initial values are randomly selected. For 00 UTC forecasting, the DLM generates their forecasts using the RDAPS forecasts (from the 00 UTC run) and the latest observation by [step 2] in the above updating procedure. When a new observation at 00 UTC is collected, the DLM is updated by [step 3] in the above updating procedure. This updated DLM is used for 12 UTC forecasting. The same processing is then repeated.

### 3.2 *Model training and forecast strategy using DLM*

In order to generate the DLM forecasts, the following forecast strategy is considered.

(1) The DLM is applied to each duration time (out to +45 hours) separately.

(2) The optimal components of input vector $\boldsymbol{F}(t)$, which minimize the RMSE (root mean square error), are determined by the model training dataset. The RMSE is the square root of averaged sum of squared forecast errors, $e(t)^2$.

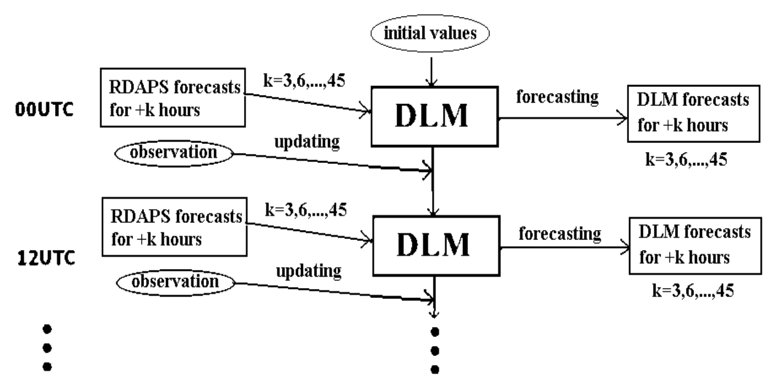


**Fig. 2.** Updating and forecasting in the DLM.

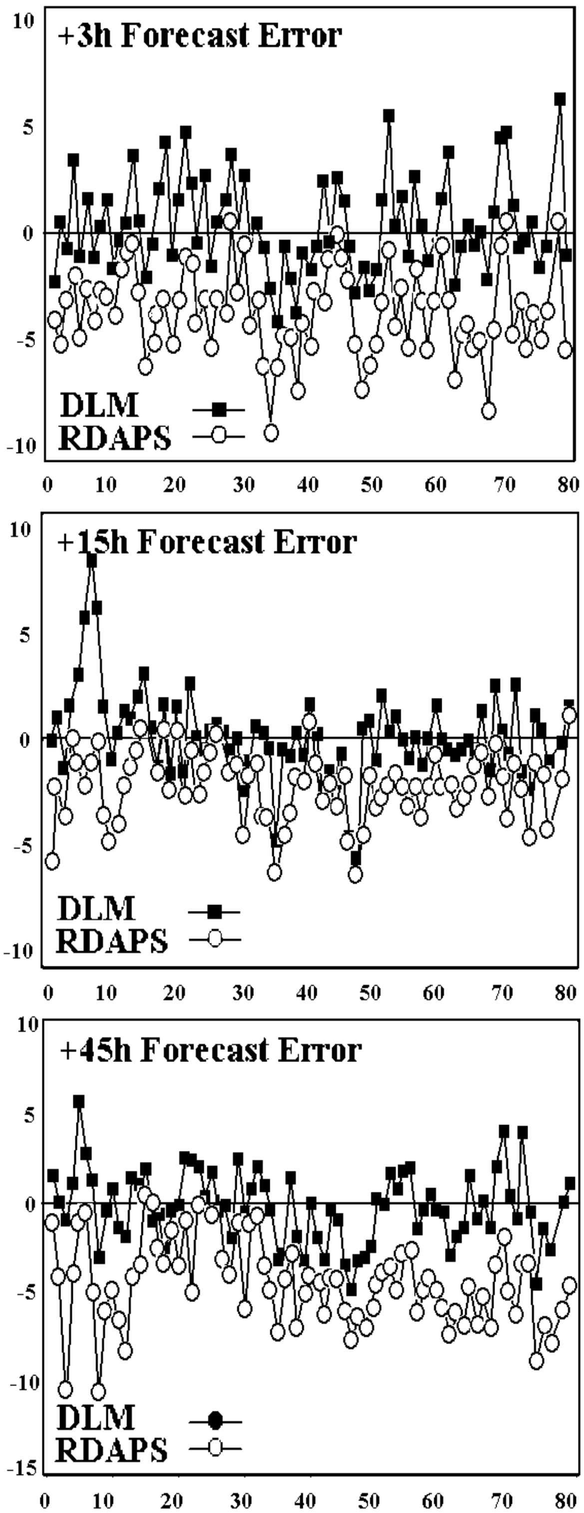


**Fig. 3.** Time series plots of forecast errors for +3h forecast, +15h forecast and, +45h forecast for Seoul ($y$-axis: relative temperature (°C), $x$-axis: time.

(3) The discount factor $\delta, 0 < \delta \leqslant 1$, is considered in order to determine $\boldsymbol{W}(t)$. Varying $\delta$ from 0.01 to 1, we generate the forecasts from the DLM with $\boldsymbol{W}(t) = \boldsymbol{C}(t-1)(1-\delta)/\delta$ and calculate the RMSE for each $\delta$. Among them, we determine the optimal $\delta$ that minimizes RMSE.

(4) The model validation is performed using the validation dataset and compared with the results of the model training.

## 4. Results

Using observations and RDAPS forecasts in the training period, the components and parameters in the DLM are estimated. And then, using the validation data, we generate DLM forecasts and compare the three model forecasts to each other. In this section we focus on the comparison of the three models (RDAPS, KFM, and DLM). The parameters of the KFM and the DLM are estimated by the training dataset (observations and RDAPS forecasts) separately and then the comparison of the DLM and the KFM is made by the validation data (RDAPS forecasts, KFM forecasts, and DLM forecasts) for each forecast duration time.

### 4.1 *Estimated DLM using training data*

Using the updating procedure in the previous section, the optimal discount factor in DLM is estimated for each time (out to +45 hours) and each station (38 stations) separately. Table 1 shows the comparison of the DLM and the RDAPS in Seoul, Korea. The RMSEs of the DLM forecasts are generally smaller than those of the RDAPS forecasts. The error reduction rate is defined by Error reduction rate=1–RMSE(DLM)/RMSE(RDAPS).

For +03 hours forecasting, the value of the optimal discount factor is 0.94, the RMSE of the DLM forecast is 2.28 and that of RDAPS is 4.61 and the error reduction rate is 50.5%. Table 1 says that DLM improves the RDAPS forecasts except for the +33 hours forecasting. Three time series plots in Fig. 3 show that the RDAPS inclines to generate under estimated (negatively biased) forecasts and the DLM removes those biases. According to the sensitivity analysis in Sohn and Kim (2001), the DLM for forecasting temperatures is robust to the initial values $\{\boldsymbol{m}(0), \boldsymbol{C}\ (0), n(0), s(0)\}$. That is, the effect of bad guessing the initial values is short-lived.

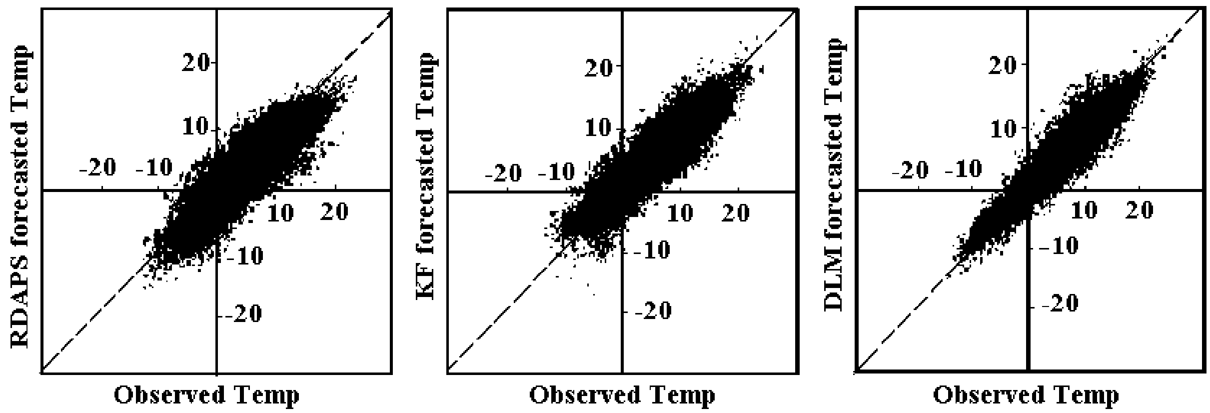


**Fig. 4.** Scatter diagrams for RDAPS (left), KFM (center), and DLM (right) forecasts with observations at 38 stations ($y$-axis: model forecasts, $x$-axis: observations)

**Table 1.** Comparison of DLM and RDAPS in seoul

| Forecast duration time (hours) | Estimated $\delta$ | RMSE (unit: °C) | | Errorr reduction rate (%) |
|---|---|---|---|---|
| | | RDAPS | DLM | |
| +30 | 0.94 | 4.61 | 2.28 | 50.5 |
| +06 | 0.91 | 2.00 | 1.87 | 6.5 |
| +09 | 0.99 | 1.51 | 1.45 | 4.0 |
| +12 | 0.98 | 2.16 | 1.26 | 32.9 |
| +15 | 0.94 | 2.63 | 1.55 | 41.1 |
| +18 | 0.99 | 2.82 | 1.52 | 46.1 |
| +21 | 0.92 | 5.68 | 1.54 | 72.9 |
| +24 | 0.93 | 7.81 | 3.74 | 52.1 |
| +27 | 0.94 | 5.80 | 3.39 | 41.6 |
| +30 | 0.91 | 2.69 | 2.46 | 8.6 |
| +33 | 0.99 | 1.66 | 1.79 | –7.8 |
| +36 | 0.98 | 2.62 | 1.62 | 38.2 |
| +39 | 0.94 | 2.88 | 1.84 | 36.1 |
| +42 | 0.99 | 2.82 | 1.55 | 45.0 |
| +45 | 0.92 | 5.81 | 1.87 | 67.8 |

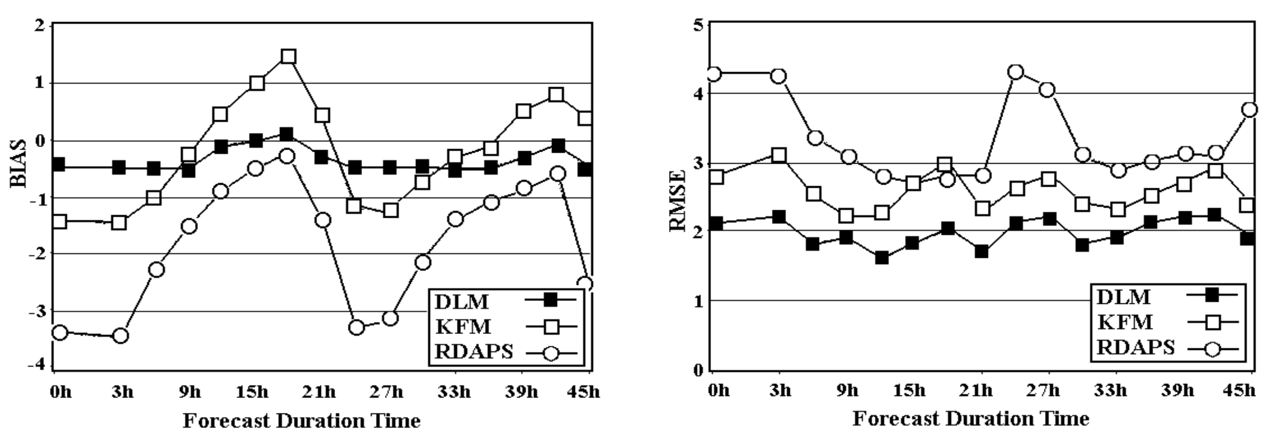


**Fig. 5.** Comparison of RDAPS, KFM, and DLM for each forecast duration time: Bias (left) and RMSE (right) for 38 stations (unit: °C).

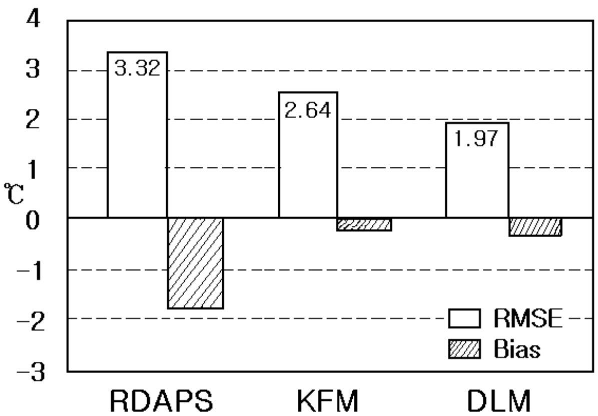


**Fig. 6.** Comparison of RDAPS, KFM, and DLM : RMSE and Bias for 38 stations.

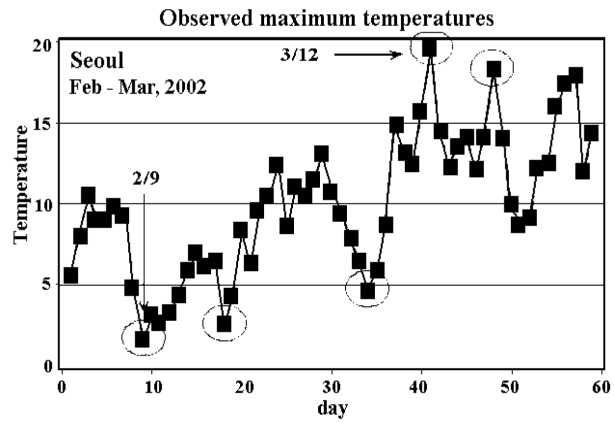


**Fig. 7.** Examples of Peak points in validation period for Seoul.

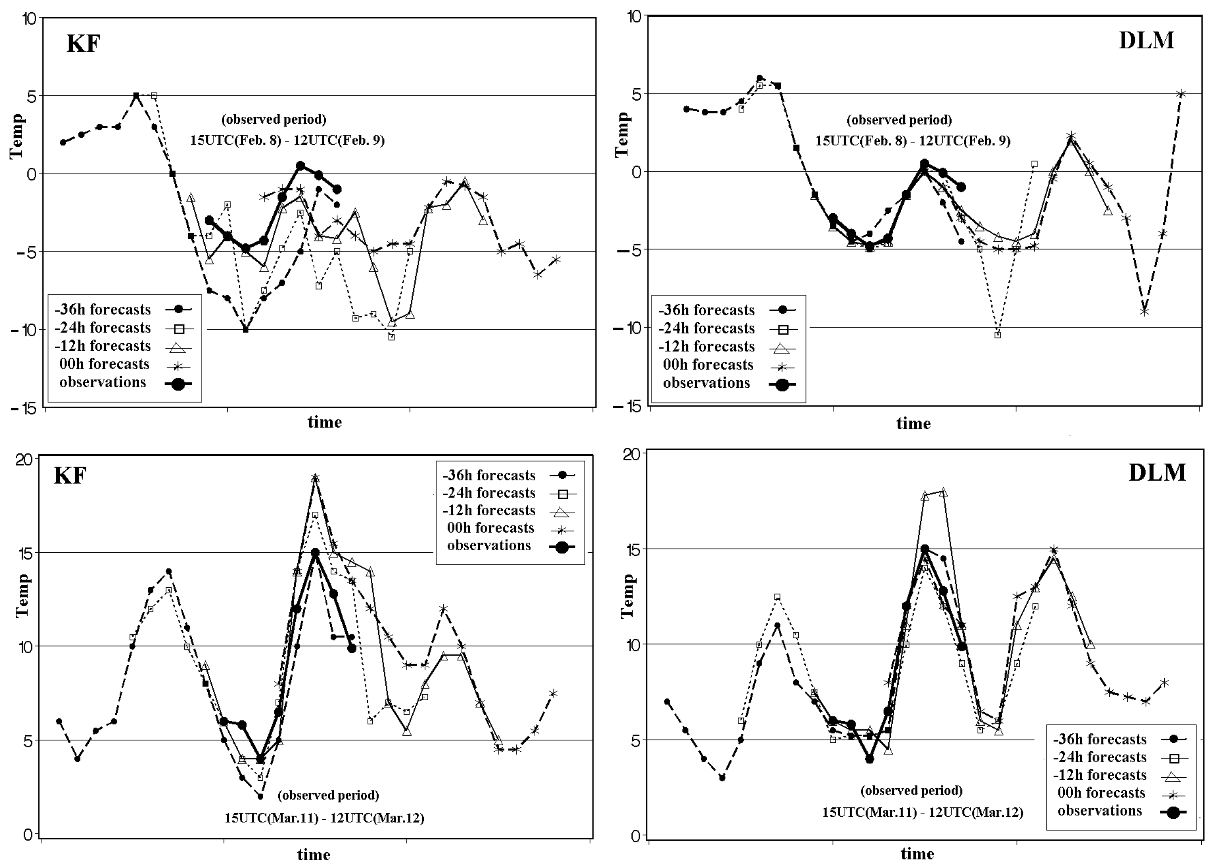


**Fig. 8.** Flow of DLM forecasts (right) and KFM forecasts (left) around two peak points (9 Feb. and 12 Mar.) for Seoul.

### 4.2 *Comparison of KFM and DLM forecasts*

Using the data of the validation period, we compare the RDAPS forecasts with the KFM and DLM forecasts. Figure 4 shows three scatter diagrams between model forecasts and observations of 38 stations. The diagonal line means the exact forecast case. We can see that the DLM forecasts have the narrowest and nearest shape to the diagonal line than the others. Figure 5 shows the biases and the RMSE of the three model forecasts for each forecast duration time. We can see that DLM forecasts have the smallest RMSE among the three models. Figure 6 gives a summary of the overall biases and overall RMSE. The RMSE of the RDAPS is 3.32, 2.64, for the KFM and 1.97 for the DLM. The DLM forecasts have the smallest RMSE. In short, the plots in Figs. 4–6 say that the DLM is better than the KFM.

### 4.3 *Special case study*

Many forecasters are interested in the forecast patterns of special cases like the peak points in Fig. 7. We select two cases, Feb. 9 and Mar. 12, for which the daily maximum temperatures are change points. Daily maximum temperatures are obtained from the 3-hour-interval forecasts. Figure 8 consists of the plots of the KFM and DLM forecasts for each case. For the case of Feb. 9, the plots contains 5 time series; (1) 12 UTC run forecasts on 7 February (-36h forecasts), (2) 00 UTC run forecasts on 8 February (-24h forecasts), (3) 12 UTC run forecasts on 8 February (-12 h forecasts), (4) 00 UTC run forecasts on 9 February (00 h forecasts), and (5) observations from 12 UTC 8 February to 12 UTC 9 February. Comparing the DLM forecasts with the KFM forecasts in Fig. 7, we can see that the DLM forecasts follow the corresponding observations more accurately than the KFM forecasts.

## 5. Concluding remarks

The statistical correction of numerical model forecasts is considered using the DLM, as a Bayesian Kalman filter model and a physical-statistical model, in order to forecast the 3-hour-interval ground-level temperature out to +45 hours at 38 stations in South Korea for every 00 UTC and 12 UTC event. According to the comparison of the DLM with the RDAPS and the KFM, the DLM is a useful model for the prediction of temperature which reduces the systematic error of numerical models and reduces the RMSE. Since the DLM uses only the RDAPS forecasts and the latest observation about the ground-level temperature, the structure and components of the DLM are very simple. The updating and forecasting algorithms are easy to program.

Like the KFM, the DLM also has advanced versions: the extended DLM, the nonlinear DLM, and the multivariate DLM. The DLM can use several model forecasts together as a super-ensemble model. These various versions of the DLM may be useful to forecast the other climate factors having some persistency: the wind speed and direction, the short-term precipitation, the air pressure, TC track and intensity, and data assimilation.

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