Post-Processing of the WRF Output for 10-meter Wind Speed and 2-meter Temperature Using Nonlinear Kalman Filtering Method

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Extended Abstract

1 Introduction

The Numerical Weather Prediction (NWP) models usually surface systematic errors in the forecasts of certain meteorological parameters. This drawback is a result not only of the shortcoming in the physical parameterization, but also of the inability of these models to handle successfully sub-grid scale phenomena.

In order to reduce the influence of the above mentioned drawbacks in the final output of a NWP model, a variety of approaches based on statistical methods has been used. Most of them are derived from Model Output Statistics (MOS), which are able to account for local effects and seasonal changes. The limitation of this method and the similar ones is the necessity of access to long term data which are not always available. Among the methods that doesn't need to long term data, Kalman filter is one of the most successful methods to this problem (post-processing) [Azadi et al, 2007; Chochet, 2004; Galanis and Anadranistakis, 2002; Homleid, 1995; Kalman and Bucy, 1961]. In this method, observations are recursively combined with recent forecast using weights that minimize the corresponding biases. The structure of Kalman filter algorithms is more suitable to describe linear procedures. For this reason, their application on meteorological parameters following a non-linear discontinuous behavior is always dubious.

The method presented in this study, called, "non-linear Kalman filter" is based on the paper of Galanis et al (2006). Using this method, they investigated the use of non-linear functions in classical Kalman filter algorithms on the improvement of regional weather forecasts. After, application of the non-linear Kalman filter on the WRF model outputs, has been described for obtained an optimum polynomial for improving

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(WRF) model forecasts. The results are based on NWPs and observations of temperature and wind speed obtained for time period 15 October 2008 to 5 July 2009.

2 Materials and methods

The main goal is the simulation of evolution in time of an unknown process (state vector), whose "True" value at time t_i is denoted here by $x^t(t_i)$. A relevant known array y_i^O at the same time is also utilized. The change of X in time is described by:

$$x^t(t_{i+1}) = M_i[x^t(t_i)] + \eta(t_i) \qquad (1)$$

and the relation between the observation vector and the unknown one is:

$$y_i^O = H_i[x^t(t_i)] + \varepsilon_i \qquad (2)$$

A first (forecast) step of the state vector X and its error covariance matrix P, based only on the previous time step analysis values, is given by:

$$x^f(t_i) = M_{i-1}[x^a(t_{i-1})] \ ; \ \ p^f(t_i) = M_{i-1}p^a(t_{i-1})M_{i-1}^T + Q(t_{i-1}) \qquad (3)$$

This is followed up by an update (analysis) step in which the observation available at time t_i is blended with the previous information:

$$x^a(t_i) = x^f(t_i) + K_i(y_i^o - H_i[x^f(t_i)]) \ ; \ \ p^a(t_i) = (I - K_iH_i)p^f(t_i) \qquad (4)$$

Where

$$K_i = p^f(t_i)H_i^T[H_i p^f(t_i)H_i^T + R_i]^{-1} \qquad (5)$$

is the Kalman gain that arranges how easily the filter adjusts to possible new conditions. Equations (1)-(5) update the Kalman algorithm from time t_{i-1} to t_i.

In the above equations, as observation matrix $H_i = \begin{bmatrix} 1 & m_i & m_i^2 & \ldots & m_i^{n-1} \end{bmatrix}$ and as system matrix $M_i = I_n$. Specifically m_i denoting the direct output of model at time t_i referring on one parameter (temperature or wind speed) the we estimate at each case.

The initial values are $X_0 = 0$, $P_0 = \begin{pmatrix} 4 & 0 & \cdots & 0 \\ 0 & 4 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & 4 \end{pmatrix}$, $Q(t_0) = I_n$, and $R(t_0) = 6$. Our statistical analysis was based on the:

- Bias of forecasted (filtered or not) values: $\text{Bias} = \frac{1}{k}\sum_{i=1}^{k}\left(for(i) - obs(i)\right)$

- Absolute Bias or Mean Absolute Error (MAE) values: $MAE = \frac{1}{k}\sum_{i=1}^{k}\left|for(i) - obs(i)\right|$

- $Score\ Skill = 1 - \dfrac{MAE\ of\ Kalman\ \ filter}{MAE\ of\ WRF\ \mathrm{mod}\,el\ output}$

Where $obs(i)$ denotes the recorded (observed) value at time i, $for(i)$ the respective forecasted value (direct model output or improved forecast via the proposed filter) and k the size of our sample.

4 Results and discussion

Fig. 1 present the overall performance of the Kalman filter based on the bias and MAE using polynomial of first to tenth (sixth) order against the model direct output for wind speed (temperature). The biases values (Y-axis at the left side of fig.1) show that Kalman filter of order of one to four (five) for wind speed (temperature) is optimal choice for all forecasting periods. In all cases the corresponding bias is close to zero suggesting that the systematic error is eliminated regardless its type (underestimation or overestimation) and the main goal of a Kalman-type filter is fulfilled. Additionally, this is supported by the results of MAE (absolute bias) presented in fig.1 (Y-axis at right side) for (a) wind speed and (b) air temperature.

Fig. 2 focus on the score skill of different Kalman filters outputs for (a) wind speed and (b) air temperature. It is obvious that any polynomial of degree greater than 4 (5) for wind speed (temperature) leads to a large percentage of instabilities.

(a)

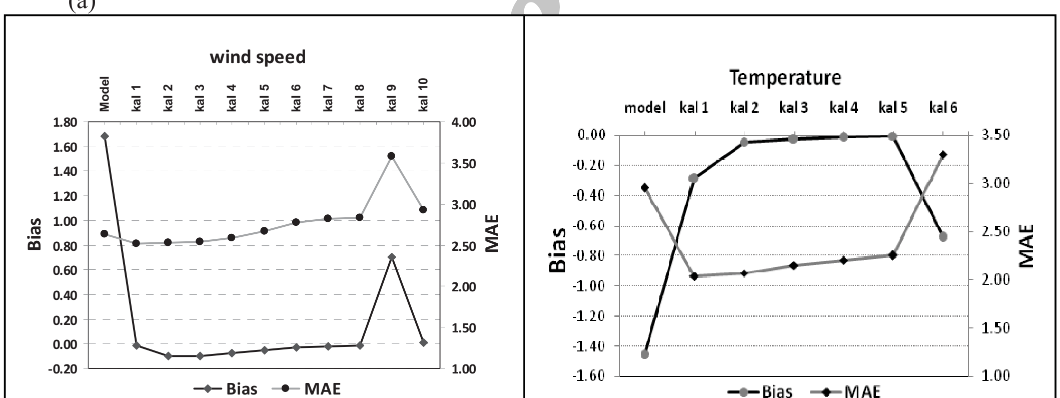

Fig. 1. Bias and absolute bias (MAE) of (a) wind speed and (b) temperature for model and different Kalman filters outputs.

(b) (a)

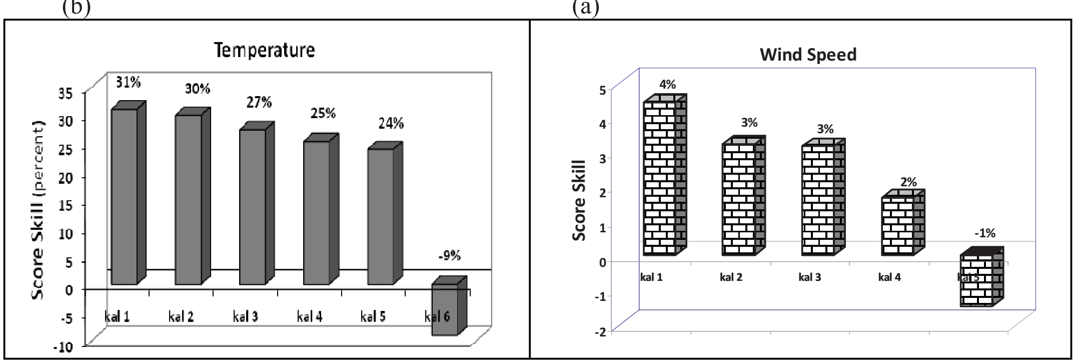

Fig. 2. score skill of different Kalman filters outputs for (a) wind speed and (b) temperature

5 Conclusions

A new methodology of implementing non-linear polynomial functions in the classical linear Kalman flter algorithms is proposed. Different order polynomials were examined, based on time series of two meteorological parameters with different type of behavior, namely the air temperature and the wind speed. This methodology showed high performance for air temperature and low performance for wind speed. This study suggests that:

- A low order polynomial, of first to fourth (fifth) order for wind speed (temperature), seems to be the optimal choice that guarantees the successful elimination of any type of standard bias (linear or not) strongly contributing, in this way, to a successful final forecast.
- Higher order polynomials do not increase the sensitivity of the Kalman filter in use, while they require increased CPU time.

Keywords: WRF model- NWP- Post-processing- Polynomial- Kalman filter