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Correcting temperature and humidity forecasts using Kalman filtering: potential for agricultural protection in Northern Greece

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Abstract

A correction method for the provision of accurate near-surface temperature and humidity forecasts is developed, based on the combination of a Kalman theory filtering technique and an empirical method with exponential smoothing. The combined method is applied on high-resolution weather forecasts provided by an operational model in Greece, over a basin in the northern part of the country, where agricultural protection is of great importance, especially due to mildew in potatoes, which represents a constant threat for farmers. The application of the method has shown that it can substantially reduce errors of the near-surface temperature and humidity forecasts provided for 2–3 days ahead in time. Based on these corrected forecasts, farmers can then schedule their fungicide spraying programs according to the expected weather, thus reducing the cost and the ecological impact of frequent preventive spraying interventions.

Keywords: Weather forecasts; Kalman filtering; Agricultural protection

1. Introduction

Weather conditions are of paramount importance for the growth but also for the development of diseases in agricultural cultivations. Accurate weather forecasts can

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have an important impact on the activities related to agriculture. This work has been motivated by the importance of meteorological conditions for the protection of potato cultivation from mildew. Namely, mildew (caused by the fungus *Peronospora parasitica*) is a common disease in potato cultivation that can cause destruction of an important part of yearly production. The occurrence and spread of the disease is highly correlated with temperature and humidity and the disease thrives in environments with moderate temperatures, high humidity and frequent precipitation. The only way to prevent cultivations from being infected is the frequent use of fungicides. In many places around the world farmers follow intensive preventive programs of spraying with fungicides, with obvious negative economical and ecological impacts.

Accurate forecasts of temperature and humidity conditions prone for the occurrence of the disease could be used as a decision-making tool for the application of specific preventive programs of spraying with fungicides. It is however well known that specific forecasts of near-surface temperature and humidity, especially over complex terrain, are rather inaccurate as their diurnal cycle is controlled by a number of both dynamical and physical processes. Systematic errors to the prediction of near-surface weather parameters may not only be due to shortcomings of the model dynamics or of the implemented physical parameterizations, but also to the subgrid phenomena (induced by terrain complexity, local micrometeorology, etc.), which may not be resolved by the meteorological model.

The Kalman filter theory (Kalman, 1960; Priestley, 1981) has been proved an efficient tool to correct systematic forecast errors, combining observations with model forecasts. Applications of the Kalman filter theory for the correction of surface temperature forecasts are based either only on temperature information (Homleid, 1995) or on the adaptive correction of surface temperature forecasts (Kilpinen, 1992), where other parameters such as relative humidity and surface winds are used. In the frame of this paper, a high-resolution meteorological model is used and a Kalman-based correction technique is applied in order to correct the forecasts of near-surface temperature and humidity. Moreover, the Kalman filter technique is combined with an empirical method in order to provide corrected forecasts of 2-m temperature and humidity, based only on temperature and humidity observations, respectively.

The method is applied at the Nevrokopi basin, which is located in the northern part of Greece, very close to the Greek–Bulgarian borders. A major part of the basin is cultivated with potatoes and mildew is one of the most threatening diseases for the agricultural production. High-resolution weather forecasts provided by the Bologna limited area model (BOLAM) are used in this study for a time period spanning throughout 2002. BOLAM forecasts of 2-m temperature and humidity are corrected through a combination of the Kalman filter and the empirical method, based on hourly observations provided by an automatic weather station operating within the basin. The automatic station consists of a thermometer by Vector Instruments with an accuracy ± 0.1 °C and a hygrometer by Rotronic with an accuracy of $\pm 5\%$. The station is located in an agricultural area 800 m from a neighbouring village.

Section 2 is devoted to the presentation of the area and provides some information about the mildew problem. Section 3 gives a short description of the methodology used, while Section 4 is devoted to the presentation of results. Finally in Section 5, the results of the work are summarised and future prospects are discussed.

2. The potato mildew at Nevrokopi basin

The Nevrokopi basin is located near the Greek–Bulgarian border, centred at 41°20′N, 23°50′E, with a mean elevation of 600 m above sea level. The basin surface is around 9000 ha and it is almost totally devoted to agricultural cultivation. The basin is surrounded by mountains from the east (1600 m high), from the south (1800 m high) and from the west (1800 m high). Coniferous and deciduous trees cover the surrounding mountains. The basin is notorious for the occurrence of very low temperatures during the winter, with significant inversions, which are more pronounced when the basin is covered by snow. During the transient periods of the year, fog is frequent, especially after rain events.

Potato mildew is the most important agricultural disease in the area. The growing season for potatoes is from April up to July while the period of high risk for mildew is June and July. The yearly cost for crop insurance reimbursements only at Nevrokopi basin varies between 2 (in years with mild seasons) and 12 (in years with wet winter, as in 1995 and 2002) million Euros. Preventive interventions per farmer reach a number of 12 per year for years where weather conditions favour the disease, while the local Agronomy Advisory Office expects that this number could be decreased to 4–5 per year, if accurate weather forecasts could be used as a decision tool for preventive interventions.

As it was already mentioned, mildew in potato cultivation is highly related with high values of relative humidity, combined with relatively high temperatures. Namely, when for a period of at least 18 h the relative humidity exceeds 80% and the mean temperature is 17 °C, there is a great chance for mildew to develop on potatoes (indeed the epidemiological algorithm gives a danger of the fungus that peaks at 17 °C while it is smaller for both smaller and larger values). The fungus attacks rapidly and fungicides can be effective only during the first 48 h of the infection. Therefore, the risk for epidemiological spread of the disease can be estimated, if accurate temperature and humidity forecasts are available 1 or 2 days in advance. Early and accurate warning would help to reduce the number of preventive interventions with fungicides with obvious positive economic and ecological results.

3. Description of the method

In the frame of this paper, a combination of a Kalman filtering technique with an empirical correction is applied for the correction of 2-m temperature and humidity forecasts. A brief description of the methodology is given in the following.

3.1. The Kalman filter technique

The Kalman filter theory has been proved an efficient tool to correct systematic forecast errors, combining observations with meteorological models forecasts. Many researchers applied this theory for the correction of 2-m temperature forecasts (e.g. Simonsen, 1991; Homleid, 1995; Anadranistakis et al., 2002; Galanis and Anadranistakis, 2002). A complete description of Kalman filter can be found in Kalman (1960), Gelb (1974), and Priestley (1981). For the convenience of the reader, some basic notions of the general Kalman filter theory are presented in the following paragraphs.

Let $\mathbf{x}_t$ be a vector (the *state vector*) describing the state of an unknown process at time t. The change of the process from time $(t-1)$ to t is given by the *system equation*:

$$\mathbf{x}_t = \mathbf{\Phi}_t \mathbf{x}_{t-1} + \mathbf{w}_t \tag{1}$$

where $\mathbf{\Phi}_t$ is the state transition matrix at time t which determines the subsequent states and can be time-varying, and $\mathbf{w}_t$ represents the disturbance matrix giving the random change from time $t-1$ to time t (assumed to be a Gaussian zero-mean, white noise process).

The state $\mathbf{x}_t$ is not observable but is related to observations $\mathbf{z}_t$ through the *observation equation*:

$$\mathbf{z}_t = \mathbf{M}_t \mathbf{x}_t + \mathbf{v}_t \tag{2}$$

where $\mathbf{z}_t$ represents the observation measurement vector at time t, $\mathbf{M}_t$ is the observation matrix at time t relating the state of the system to the measurements, and $\mathbf{v}_t$ represents the corrupting measuring noise (also assumed to be a Gaussian zero-mean, white noise process). Kalman filter theory gives a method for the recursive estimation of the unknown state vector $\mathbf{x}_t$ utilizing all the observation values $\mathbf{z}_t$ up to time t; $\mathbf{z}_1$, $\mathbf{z}_2$, $\ldots \mathbf{z}_t$.

The dynamical system is supposed to express the systematic deviation/error between the observed and the forecasted temperatures or humidity. The changes of the systematic deviations are supposed to be random, and as a matter of fact the state transition matrix, $\mathbf{\Phi}_t$, is an identity matrix. The forecasted temperature or humidity at each time t (TH_{ft}) is assumed to be linearly related to the observed temperature or humidity at the same time (TH_{ot}) as follows:

$$TH_{\mathrm{ot}} = a + dTH_{\mathrm{ft}} + v_t, \tag{3}$$

where $\mathrm{v_t}$ is a random error. If we let $\mathrm{b = d - 1}$ then we have:

$$TH_{\mathrm{ot}} - TH_{\mathrm{ft}} = a + bTH_{\mathrm{ft}} + v_t, \tag{4}$$

which can be also expressed as:

$$TH_{\mathrm{ot}} - TH_{\mathrm{ft}} = [1 TH_{\mathrm{ft}}][ab]^T + v_t, \tag{5}$$

For a realistic correction procedure the parameters a and b should dynamically evolve with time. So let:

$$a_t = a_{t-1} + w_{1t} \tag{6}$$

$$b_t = b_{t-1} + w_{2t} \tag{7}$$

where w_{1t}, w_{2t} represent random changes. If we let $\mathbf{x}_t=[a_t\ b_t]^{\mathrm{T}}$ and $z_t=TH_{\mathrm{ot}}-TH_{\mathrm{ft}}$, then the process and measurement equations (Eqs. (1) and (2)) are given by:

$$\mathbf{x}_t = \mathbf{x}_{t-1} + \mathbf{w}_t \text{ and } z_t = \mathbf{M}_t\mathbf{x}_t + \mathbf{v}_t \tag{8}$$

where the observation matrix $\mathbf{M}_t$ equals $[1\ TH_{\mathrm{ft}}]$.

3.2. Empirical method

For the correction of 2-m temperature and humidity, in addition to the Kalman filtering technique, an empirical method of forecasting time-series with exponential smoothing has been also applied. The exponential smoothing weighted average (Harvey, 1993) provides estimate of the current level of a time series, but instead of using the sample mean (i.e. equal weights for all observations), it uses a weighting scheme which puts more weight on the most recent observations.

Let us suppose that we have a series of observed values of temperature or humidity TH_{o1}, TH_{o2}, $\ldots TH_{\mathrm{ot}}$. Then we suppose that the forecast values TH_{f2}, TH_{f3}, $\ldots TH_{\mathrm{ft+1}}$ are given as follows:

$$TH_{\mathrm{f2}} = TH_{\mathrm{o1}}, \tag{9}$$

$$TH_{\mathrm{f3}} = cTH_{\mathrm{o2}} + (1-c)TH_{\mathrm{f2}}, \tag{10}$$

…,

$$TH_{\mathrm{f(t+1)}} = cTH_{\mathrm{ot}} + (1-c)TH_{\mathrm{ft}} \tag{11}$$

or even

$$TH_{\mathrm{ft}} = TH_{\mathrm{f(t-1)}} + c(TH_{\mathrm{o(t-1)}} - TH_{\mathrm{f(t-1)}}) \tag{12}$$

where c is an empirically defined constant value, between 0 and 1. Following this procedure, it is supposed that the forecasted values at t equals the forecasted values at the previous timestep corrected by the forecast error at time $(t-1)$. A general formulation can then be given as follows:

$$TH_{\mathrm{ft}} = cTH_{\mathrm{o(t-1)}} + c(1-c)TH_{\mathrm{o(t-2)}} + c(1-c)^2TH_{\mathrm{o(t-3)}} + \ldots + c(1-c)^{t-2}TH_{\mathrm{o1}} \tag{13}$$

Recent application of the method (Anadranistakis et al., 2002) has shown that an optimum value for the constant value c is around 0.6.

3.3. Combined correction method

As follows from the previous subsections, two corrected temperature or humidity values are provided at each timestep. Therefore, the final forecast value for temperature or humidity at time t (TH_t) can be produced as a combination of the two corrected values from the two methods ($TH_{j,t}$, $j=1,2$), with weights (R_j) applied on each method, that is:

$$TH_t = \sum_{j=1}^{2} TH_{j,t} R_j \tag{14}$$

The estimation of weights R_j is based on the forecast errors of each method during the last n times. For each method, the total forecast error (S_j) of the last n times is estimated by: $S_j = \sum_{i=n}^{1} [E_{j,i}(i/n)]$, where $E_{j,i}$ is the absolute forecast error of method j for time i. The weights R_j are given by: $R_j = \sum_{j=1}^{2} [1/S_j]/S_j$. It can be easily deduced that $\sum_{j=1}^{2} R_j = 1$ while the larger contribution on the estimate of the weights R_j results from the forecast error of the most recent timestep. For our application, n has been set equal to 25. This period has been selected empirically as it has been found that increase of this number does not produce any improvement on the results and it only increases the computation time.

It should be noted that eight observational time series are used, namely the observations at 00, 03, 06, 09, . . ., 21 UTC. Each time series is used for the correction of the respective forecast; for example, the 00 UTC observational time series is used for the correction of the 24, 48 and 72-h forecasts since all three of them are valid at 00 UTC. For the statistical measures that are discussed in the following section, the first 10 days of application are discarded as this is a period of adjustment of the method (both for the Kalman filtering and for the empirical method and as a matter of fact for the combined method).

Anadranistakis et al. (2002) have shown that the combined correction method almost always provides better results for the correction of 2-m temperature compared to the results obtained by the independent application of the Kalman filter correction, or of the empirical method correction.

4. Application of the method—results

The methodology described in Section 3 has been applied to the forecasts of BOLAM meteorological model that is running operationally at the National Observatory of Athens (NOA). BOLAM is a hydrostatic model described by Buzzi et al. (1997, 1998). The model has the ability to perform one-way nested simulations. For that purpose, a first simulation is performed with a coarse grid interval and then the outputs of this coarse simulation are used as initial and boundary conditions on a subsequent run with finer grid resolution. In the operational chain of BOLAM at NOA, two one-way nested grids have been used:

– the coarse nest with 0.21° horizontal grid interval covering the major part of Europe and the Mediterranean,
– the fine nest with 0.06° horizontal grid interval, covering the entire Greek peninsula.

The Medium-Range Forecast (Aviation run-AVN, provided by the National Centers for Environmental Predictions-NCEP, USA) gridded analysis fields and 6-h interval forecasts, at 1.25° lat/lon horizontal grid increment, are used to initialise the model and to nudge the boundaries of the coarse nest during the simulation period. These fields are interpolated by BOLAM on sigma levels from which they are then interpolated on the model grid points.

For the purpose of this study, only forecasts from the fine nest are used. The method is applied to the 2-m temperature and relative humidity forecasts provided by the model every 3 h, from 12:00 UTC of the first day of simulation ($t+12$) up to 00:00 UTC of the third day of simulation ($t+72$). Overall, 21 distinct forecast times are available within this time frame. The period of application of the correction method spans from January to December 2002.

The mean error (ME), the mean absolute error (MAE), the root mean square error (RMSE) and the standard deviation of the error (SDE) have been estimated for the forecasted and the corrected temperature and humidity values. The statistical scores for temperature are presented in Fig. 1 and Table 1.

As shown in Fig. 1, the MAE of forecasted temperatures (solid bars) exceeds 2.8 °C for all forecast times, with the larger errors (approaching 3.6 °C) during the night hours, when the model overestimates the minimum temperatures (see also ME in Table 1). Positive values of the ME show that the model systematically overestimates temperature and this behaviour is less pronounced during the day hours (Table 1). Large RMSE are also evident, especially during night hours. The application of the combined correction method is able to reduce considerably the forecast errors, as it can be seen in both Fig. 1 (open bars) and Table 1. MAE reduces down to 1.3–1.8 °C for all forecast times and the reduction of errors is larger during the night hours. The success of the application of the correction method even for forecasts with large MAE supports the idea that a large part of the forecast error presents a systematic character. This systematic character can be related to the specific topography of the basin (as described in Section 2), which is not accurately represented by the currently available resolution of the model fine grid (6.5 × 6.5 km).

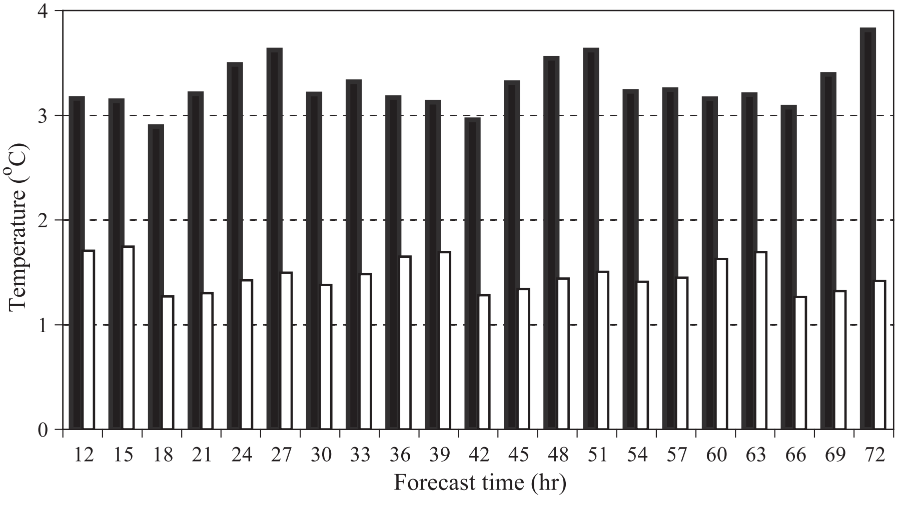

Fig. 1. Variation of 2-m temperature mean absolute error (MAE) with respect to forecast lead time (from $t+12$ to $t+72$). Solid bars denote model forecast values and open bars corrected values.

Table1
Statistical scores for forecasted and corrected 2-m temperatures. MAE, mean absolute error; RMSE, root mean square error; ME, mean error; STD, standard deviation of errors. Forecast times corresponding to night hours are in bold

Forecast time	Forecasted				Corrected			
	MAE	RMSE	ME	STD	MAE	RMSE	ME	STD
12	3.16	4.29	0.41	4.27	1.71	2.26	0.09	2.26
15	3.14	4.12	0.40	4.10	1.75	2.24	0.03	2.24
18	2.89	3.73	1.55	3.39	1.27	1.64	− 0.01	1.64
21	3.21	3.99	2.28	3.27	1.30	1.65	− 0.05	1.65
24	3.49	4.37	2.59	3.52	1.42	1.79	− 0.05	1.79
27	3.62	4.57	2.68	3.70	1.50	1.89	− 0.04	1.89
30	3.20	4.17	2.25	3.51	1.38	1.74	− 0.02	1.74
33	3.32	4.30	1.61	3.98	1.48	1.93	0.02	1.93
36	3.17	4.29	0.50	4.26	1.65	2.21	0.05	2.21
39	3.12	4.13	0.50	4.09	1.69	2.19	0.02	2.19
42	2.96	3.84	1.57	3.50	1.28	1.65	− 0.04	1.65
45	3.31	4.09	2.27	3.40	1.34	1.69	− 0.07	1.69
48	3.54	4.45	2.60	3.61	1.44	1.82	− 0.07	1.81
51	3.62	4.62	2.69	3.76	1.51	1.89	− 0.07	1.89
54	3.23	4.26	2.28	3.60	1.41	1.75	− 0.04	1.75
57	3.24	4.27	1.66	3.94	1.45	1.91	− 0.02	1.91
60	3.16	4.27	0.60	4.23	1.63	2.15	0.02	2.15
63	3.20	4.17	0.74	4.11	1.69	2.17	0.00	2.17
66	3.08	3.89	1.79	3.45	1.27	1.61	− 0.04	1.61
69	3.39	4.17	2.41	3.41	1.32	1.64	− 0.07	1.64
72	3.82	4.81	2.67	4.00	1.42	1.85	− 0.05	1.84

Moreover, during wintertime when the basin is covered by snow, this information is not taken into account in the model initial conditions, thus resulting in an overestimation of 2-m temperature.

The deficiency of the model to correctly represent 2-m temperature during the winter season is also evident in Fig. 2, where the time evolution of the 36-h forecast as well as the observed and corrected values are shown. During the first 50 days (January and February 2002), when the basin was covered by snow for a long period, the model (solid line) overpredicts 2-m temperature at 12:00 UTC by about 7–10° (observations in bold line). From day 60 and beyond (March–June 2003) the model forecast values fit very well with the observations, following also the day-to-day temperature variability. It is encouraging however, that the correction method (grey line) is able to significantly reduce the errors during wintertime.

The success of the method is also supported by the resulting almost unbiased corrected forecasts. Indeed, the ME of the corrected forecasts fluctuates around zero for all forecast times (Table 1). Moreover, the standard deviation of the errors is reduced for all forecast hours, by at least a factor of 2.

As for relative humidity forecasts, there is a net improvement after application of the correction method (Fig. 3 and Table 2). Before correction, MAE ranges between 16% and 21% for all forecast hours (solid bars in Fig. 2), while after application of the method it reduces down to 5% and 8%. As seen in Table 1, the ME of the corrected forecasts is

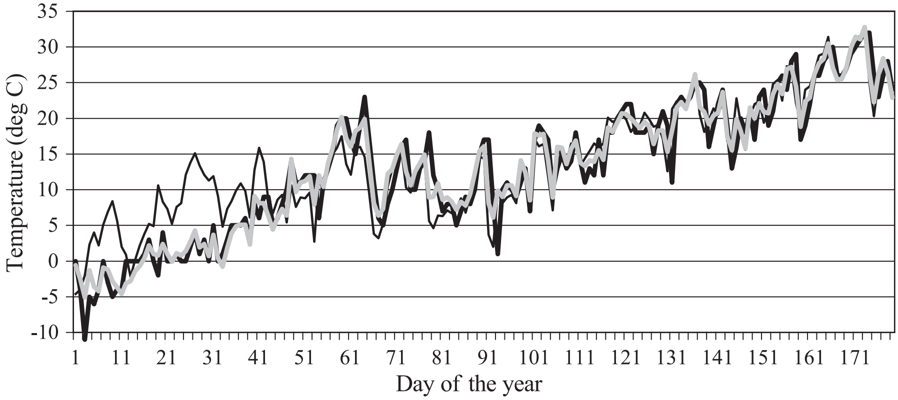

Fig. 2. Time evolution of 12:00 UTC 2-m temperature during the first 180 days of year 2002 (January–June). Observations are shown in bold line, 36-h BOLAM forecasts with solid line and corrected forecasts with bold grey line.

around 0, while again the standard deviation of error is considerably suppressed after the application of the method.

5. Discussion and prospects

This work presents the application of a method for the correction of 2-m temperature and relative humidity forecasts in the Nevrokopi basin in Northern Greece, an area devoted to potato cultivation where the meteorological conditions often favour the development of

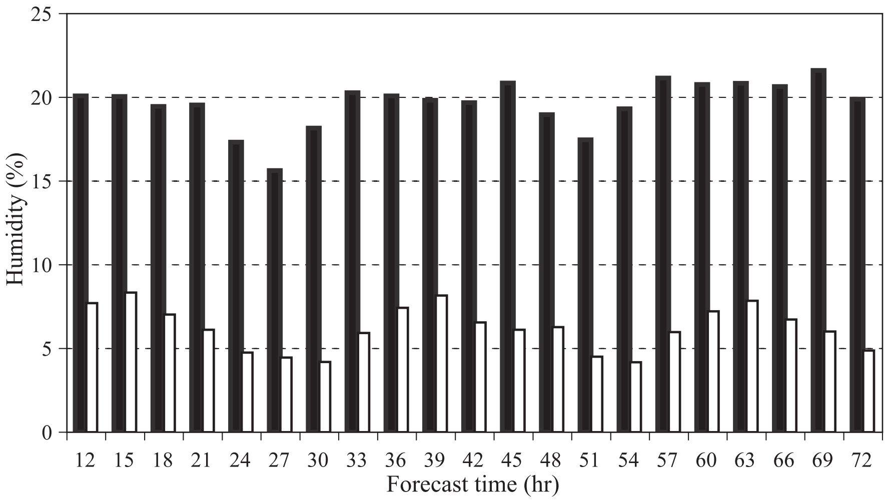

Fig. 3. Variation of 2-m relative humidity mean absolute error (MAE) with respect to forecast lead time (from $t+12$ to $t+72$). Solid bars denote model forecast values and open bars corrected values.

Table 2
Statistical scores for forecasted and corrected 2-m relative humidity. MAE, mean absolute error; RMSE, root mean square error; ME, mean error; STD, standard deviation of errors. Forecast times corresponding to night hours are in bold

Forecast time	Forecasted				Corrected			
	MAE	RMSE	ME	STD	MAE	RMSE	ME	STD
12	20.09	24.72	13.75	20.54	7.71	10.19	0.09	10.19
15	20.05	24.30	12.42	20.89	8.34	10.83	0.03	10.83
18	19.46	23.09	11.41	20.08	7.03	9.02	− 0.01	9.02
21	19.55	23.51	9.63	21.45	6.12	7.88	− 0.05	7.87
24	17.33	20.75	7.08	19.51	4.76	6.14	− 0.05	6.13
27	15.63	19.20	5.20	18.48	4.46	6.00	− 0.04	5.99
30	18.16	21.42	7.61	20.02	4.20	5.52	− 0.02	5.50
33	20.27	23.86	13.78	19.48	5.93	7.85	0.02	7.84
36	20.09	24.43	13.01	20.67	7.43	9.69	0.05	9.68
39	19.83	24.28	12.00	21.11	8.16	10.43	0.02	10.43
42	19.68	23.42	11.16	20.59	6.55	8.37	− 0.04	8.36
45	20.86	24.92	9.65	22.98	6.11	7.93	− 0.07	7.91
48	18.97	22.25	7.26	21.03	6.28	8.45	− 0.07	8.44
51	17.46	20.78	5.91	19.92	4.50	6.03	− 0.07	6.02
54	19.32	22.68	8.30	21.11	4.18	5.52	− 0.04	5.51
57	21.15	24.56	13.63	20.43	5.98	7.94	− 0.02	7.92
60	20.77	25.02	12.77	21.52	7.22	9.48	0.02	9.48
63	20.84	25.16	12.24	21.98	7.85	10.20	0.00	10.19
66	20.65	24.56	11.44	21.74	6.73	8.54	− 0.04	8.54
69	21.60	25.68	9.89	23.70	6.02	7.83	− 0.07	7.81
72	19.90	23.49	7.92	22.11	4.88	6.25	− 0.05	6.24

mildew disease. The correction method is based on the combination of two different filters: one based on the Kalman filter theory and a second one based on an empirical method for forecasting time-series with exponential smoothing. The final corrected forecasts are produced by the combination of the two corrected forecasts resulting from the application of each of the two filters with a weight assigned to each of them. The method has been applied to the forecasts provided by a high-resolution operational model during the whole year of 2002.

The application of the combined correction method for the 2-m temperature forecasts resulted in a significant improvement of all statistical measures. Namely, the mean absolute errors have decreased from a range of 2.8–3.6 °C to a range of 1.3–1.8 °C for all forecast hours. Following the same line, the MAE of the relative humidity forecasts that ranged between 16% and 21% before correction for all forecast hours have decreased to a range of 5% and 8% after correction. The success of the method is also supported by the fact that after correction and for both parameters, the mean error decreases to values close to zero, showing that the method is able to provide almost unbiased corrected forecasts, while the standard deviation of the error also decreases by 50%.

The analysis of 1-year temperature and relative humidity forecasts at Nevrokopi showed that the application of the combined correction method would allow provision of reliable forecasts of near-surface parameters 2–3 days in advance. These corrected forecasts could be used as a decision support tool for preventive interventions with fungicides for the protection of the potato cultivations. Such a procedure is expected to reduce the number of prevention only when these are necessary, with obvious positive economic results for the farmers and the insurance companies and positive ecological results for the local ecosystem.

The encouraging results of this work support the real-time application of the method in the Nevrokopi basin. Indeed, it is in the authors' immediate plans, in collaboration with the local authorities, to start the application of the method on a pilot basis from autumn 2003.

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