Average Daily Air Temperature's Long-Range Forecast Using Inductive Modeling and Satellite Datasets

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Abstract. *In this paper, long-range forecasting average daily air temperature using inductive method was proposed. Principle of high-impact weather events substantiates the different places' interaction by atmosphere, hydrosphere, landmass, biosphere, etc. Forecasting model reasoning's first stage is selection of three most data-related places using Pearson product-moment correlation coefficient, which has to be greater than 0.8 in absolute value. 66 datasets were acquired from NOAA Satellite and Information Service. Second stage is finding weighting coefficients of forecasting model and criterion "minimum of regularity plus maximum of conjunctions" by combinatorial algorithm. This concept is illustrated by Skopje Airport's forecasting model and criterion reasoning, which include datasets from Beijing (China), Ulaanbaatar (Mongolia), and Paphos Airport (Cyprus). Results (conjunctions' percent is 74.8 %, mean absolute error (MAE) is up to 5.7 °F, 166 days lead-time) showed an efficiency of proposed approach. Similar results were achieved for Kiev (MAE is up to 7.2 °F, 167 days lead-time) and Washington National Airport (MAE is up to 6.07 °F, 173 days lead-time). Web-site prototype www.weatherforecast.tk was developed using Ms Windows Azure public cloud computing technology. Proposed approach is characterized by high accuracy, final linear difference equations' simplicity, low computational complexity, and user-friendly interface, which is very suitable for meteorological services.*

Keywords

Long-range forecast, inductive modeling, average daily air temperature.

1 Introduction

Weather data mining methods and forecasting algorithms have been of long standing interest because of high importance for noosphere. E.g., the air temperature has great influence on power service's load (Robinson, Peter J., 1997), and one's direct application is for estimating future fuel needs. More critically, the arid weather with heat waves may produce significant disruptions to agricultural industries (Hudson D. et al., 2011), freezing rains and snowstorms (Jianhua Sun, and Sixiong Zhao, 2010) have similar extreme impact on environment. Sometimes, weather forecast allows predicting possible natural disasters (e.g., Rocheva E.V., 2012), and do appropriate preventives if necessary.

Nowadays, several meteorological factors (e.g., air temperature, precipitation, wind, pressure, visibility, snow depth) are analyzed and predicted for the climate's description (Kattsov V.M., 2010). In a fact, they interact constantly, and every factor is evaluated approximately using other parameters. However, first two are used for long-range forecast mostly. Precipitation has close relation to air temperature and vice versa (Van Den Dool H. M., and Nap J. L., 1985). Precipitation's forecast is effective mostly during two weeks, air temperature – much longer (greater than a year; Zubov D.A., and Vlasov Y.N., 2004). In addition to the ground-based observations, satellite monitoring appends and corrects existing datasets (e.g., Kleshchenko A.D. et al., 2012). Hence, this paper emphasizes importance of the average daily air temperature's long-range forecast. Further, daily values may be used as very good basis for week, month, and season forecasts.

2 Previous results' analysis

Average daily air temperature's long-range forecast has been of long standing interest (e.g., Kolobkov N.V., 1950). Weather impact of the ocean nearby lands (Drozdov V.V., and Smirnov N.P., 2011; Van Den Dool H. M., and Nap J. L., 1985) showed useful skill values (lead-time is up to 60 days, score is up to 70 %). Usually, short-range (up to 48 hours; e.g., Romeo Steve Tanessong et al., 2012) and medium-range (up to two weeks; McCollor, Doug, and Roland Stull, 2009) weather forecasts are discussed. Nowadays, a wide spectrum of the forecasting models was developed (Vilfand R.M. et al., 2003). They are usually classified into synoptic (e.g., Vorobiov V.I., 1991), hydrodynamic (e.g., Belov P.I. et al., 1989), and statistical (e.g., Onwubolu G.C. et al., 2007) models. First two are used for short and medium-range forecast mostly because of significant errors at long-range period (more than 20 % in the mean) and equations' high complexity. In a fact, heterogeneous mathematics is used for weather forecast, e.g.: seasonal time series (Qiang Song, 2011), neural networks (Gyanesh Shrivastava et al., 2012), probability theory (Sadokov V.P. et al., 2011), ensemble forecast (Astahova E.D., and Alferov Y.V., 2008), scenarios (Bardin M.Y., 2011), ENSO cycle (Higgins R. W. et al., 2004). In addition, forecast's nonlinearity and sensitivity, possible small errors in initial conditions (dust, sand, pollution), random observation errors, background states, and high impact datasets finding's complexity disturb the forecast accuracy and complicate the forecasting models' design (Douglas, Arthur V., Phillip J. Englehart, 2007; Fathalla A. Rihan, and Chris G. Collier, 2010; Tyndall Daniel P. et al., 2010).

Recent research based on the inductive methods showed possibility of the long-range (half-year lead-time) forecast with mean absolute error (MAE) up to 8 ^{0}F. Particularly, the average daily air temperature forecast's MAE is up to 6.02 ^{0}F for Skopje Airport, Macedonia (half-year lead-time; Zubov D., 2012). Main stages of the forecasting model's reasoning are selection of the data-related places using correlation analysis, identification of the structure and parameters of the linear regression model with criterion "minimum of the regularity plus displacement" on the basis of self-organisation. This approach is characterized by final linear difference equations' simplicity (this feature is very suitable for meteorological services) and high computational complexity of the forecasting model reasoning. High forecast accuracy is based on the significant correlation among places. The principle of high-impact weather events like El Niño-Southern Oscillation (e.g., Hoskins B., 2012) substantiates the different places' interaction by atmosphere, hydrosphere, landmass, biosphere, etc. Cloud computing web-site's prototype www.weatherforecast.tk was developed. It is well known that trend is used for the long-range weather forecast fuzzy comparison; unfortunately, this question stayed out of discussion.

Three main requirements to the average daily air temperature's long-range forecasting system were formulated now:

1. Lead-time is half-year approximately.
2. MAE is up to 8 0F.
3. Software's user-friendly web-interface.

3 Datasets and Forecasting Model

The datasets' acquisition is not trivial task. Next sources were chosen subjectively. 66 places (www7.ncdc.noaa.gov; daily data): Nwso Agana (Guam; 1), Aarhus Lufthavn (Denmark; 2), Abbeville (France; 3), Aeropuerto Pettiros (Paraguay; 4), Amman Airport (Jordan; 5), Amsterdam AP Schiph (Netherlands; 6), Annaba (Algeria; 7), Ashgabat Keshi (Turkmenistan; 8), Auckland Airport (New Zealand; 9), Bangkok Metropolis (Thailand; 10), Beijing (China; 11), Ben-Guron Int. Airport (Israel; 12), Beograd-Surcin (Serbia; 13), Bogota-Eldorado (Colombia; 14), Brasilia-Aeroporto (Brazil; 15), Bratislava-Letisko (Slovakia; 16), Bruxelles National (Belgium; 17), Bucuresti INMH-Bane (Romania; 18), Budapest-Ferihegy (Hungary; 19), Busan (Southern Korea; 20), Cairo Airport (Egypt; 21), Canberra Airport (Australia; 22), Caracas-Maiquetia (Venezuela; 23), Damascus Int. Airport (Syria; 24), Geneve-Cointrin (Switzerland; 25), Gibraltar (Gibraltar; 26), Guernsey Airport (Guernsey; 27), Helsinki-Vantaa (Finland; 28), Hengchun (Taiwan; 29), Jersey Airport (Jersey; 30), Kiev (Ukraine, 31), Kingston-Norman Man (Jamaica, 32), Kisinev (Moldavia; 33), Kwajalein-Bucholza (Marshall Islands; 34), La Paz-Alto (Bolivia; 35), Lima-Callao Airport (Peru; 36), Lisboa/Portela (Portugal; 37), London/Heathrow Airport (Great Britain; 38), Luqa (Malta; 39), Luxembourg (Luxembourg; 40), Minsk (Belorussia; 41), Moscow (Russia; 42), Nassau Airport New (Bahamas; 43), New Delhi-Safdarjun (India; 44), Noumea-Nlle-Calledo (New Caledonia; 45), Nuuk (Greenland, 46), Oslo-Gardermoen (Norway; 47), Paphos Airport (Cyprus; 48), Praha-Libus (Czech Republic; 49), Rabat-Sale (Morocco; 50), Rarotonga (Cook Islands; 51), Reykjavik (Iceland; 52), Riga (Latvia; 53), Roma-Ciampino (Italy; 54), Skopje Airport (55), Tallin-Harku (Estonia; 56), Tashkent (Uzbekistan; 57), Tokyo (Japan; 58), Torshavn (Faroe Islands; 59), Tripoli (Libya; 60), Tunis-Carthage (Tunisia; 61), Ulaanbaatar (Mongolia; 62), Vaduz (Liechtenstein; 63), Warszawa-Okecie (Poland; 64), Washington National (USA; 65), Wien-Hohe Warte (Austria; 66). In addition, sea level (Aburatsu, Japan; http://ilikai.soest.hawaii.edu/woce/wocesta.html; daily), Darwing and Tahiti sea level pressures, southern oscillation index (SOI), equatorial SOI, sea surface temperature (www.cpc.ncep.noaa.gov/data/indices; monthly), multivariate ENSO index (www.esrl.noaa.gov/psd/enso/mei/table.html; monthly) data took part in the correlation analysis.

Correlation analysis showing related datasets allows decreasing the computational complexity in several times for the forecasting model's reasoning. Some places dominate: 52 correlation results (out of 66) are highly related to Beijing and Ulaanbaatar (1st, 2nd, 3rd, and/or 4th rank). 42 of them have Pearson product-moment correlation coefficients

(PPMCC) greater than 0.8 in absolute value. It was found that non-temperature parameters have lower PPMCCs. Some PPMCCs are less than 0.1 in absolute value.

Proposed average daily air temperature's long-range forecasting model has next linear structure:

$$\frac{X_F[i]}{\max\{X_R[p]\}} = k_0 + \frac{k_1 X^*_{j_1}[i-d_1]}{\max\{X^*_{j_1}[p-d_1]\}} + \frac{k_2 X^*_{j_2}[i-d_2]}{\max\{X^*_{j_2}[p-d_2]\}} + \frac{k_3 X^*_{j_3}[i-d_3]}{\max\{X^*_{j_3}[p-d_3]\}}, \quad (1)$$
$$p = 1,\ 2,\ \ldots,\ l,\ \ j_1 \neq j_2 \neq j_3,$$

where $X_F[i]$, $X_R[i]$ – prediction and true air temperature in the forecasted point; i – data position's number in time series, i = 1,2,3, ..., 14521 (19 July 1973 – 20 April 2013); l = 14045 – training sequence's length; k_0, k_1, k_2, k_3 – weighting coefficients; $X^*_{j_1}[i-d_1], X^*_{j_2}[i-d_2], X^*_{j_3}[i-d_3]$ – biased by lead-times d_1, d_2, d_3 and three days averaged true air temperature time series for the appropriate places j_1, j_2, j_3 = 0,1,2, ..., 66 (number of the place from the above list; plus additional parameters optionally; 0 means the same place in the right and left sides). Equation (1) reflects an idea of cross-covariance matrices plus predictor/predictand fields (Sánchez Gómez E., Ortiz Beviá M. J., 2003) and regression-based schemes (Zheng, Xiaogu, James A. Renwick, 2003).

Combinatorial inductive method (step is 0.01) uses next criterion "minimum of regularity plus maximum of conjunctions" for the parametric optimisation of model (1):

$$\alpha \frac{\sum_{i=1}^{l} |X_R[i] - X_F[i]|}{l \cdot \max\{X_R[p]\}\big|_{p=\overline{1,l}}} + \frac{l-c}{l} \to \min, \quad (2)$$

where |.| – absolute value; α – weighting coefficient; c – number of conjunctions (quantity of pairs ($X_R[i]$, $X_F[i]$) which are located on the one side of trend; trend is considered equal to mathematical expectation). In a fact, first summand in (2) represents MAE if $\alpha = \max\{\cdot\} = 1$.

In a fact, time series $X^*_{j_1}, X^*_{j_2}, X^*_{j_3}$ are not centered at trend. Nevertheless, trend is taken into consideration in the criterion (2). Moreover, additional research showed an inapplicability of the model (1) and criterion (2) for the average daily air temperature's long-range forecast because of low accuracy if time series $X^*_{j_1}, X^*_{j_2}, X^*_{j_3}$ are centered at trend. In last case, PPMCCs have slightly less but similar high values (0.8 in absolute approximately) at half-year lead-time.

The main task is finding weighting coefficients α, k_0, k_1, k_2, and k_3.

The forecasting model and criterion's reasoning is not trivial task (Ferro, Christopher A.T., David B. Stephenson, 2011) which is solved using following assumptions:

1. Inductive criterion (2) includes two polar parts – minimum of regularity plus maximum of conjunctions. Hence, two training sequences' usage (classical self-organising approach) is not necessary.
2. Forecasting model (1) describes the air temperature time series adequately.
3. Coefficients k_1, k_2, and k_3 use to have the same sign as appropriate PPMCCs. E.g., Skopje Airport's PPMCCs have negative values, and, hence, $k_1, k_2, k_3 \leq 0$.
4. Three days data averaging is optimal. That is confirmed by Skopje Airport average daily air temperature's correlation analysis: 0, 3, 5, 7, and 30 days data averaging were considered. It was found that just first two (0 and 3) have the same set of most related places.
5. Data from 1 January 1973 to 20 April 2013 represent air temperature adequately because 35-year period is within this interval (Sidorenkov N.S., and Sumerova K.A., 2012).

4 Skopje Airport Average Daily Air Temperature's Long-Range Forecast

Skopje Airport's three most related places are Beijing (PPMCC = -0.88518, d_1=186), Ulaanbaatar (PPMCC = -0.87464, d_2=189), and Paphos Airport (PPMCC = -0.87247, d_3=166). Lead-time varied from 150 to 200 days. Just for comparison, last three points according to correlation are the followings: Noumea-Nlle-Calledo (PPMCC = 0.81092, d_1=165), Rabat-Sale (PPMCC = -0.80839, d_1=164), Guernsey Airport (PPMCC = -0.8014, d_1=162).

It was found using inductive method, that forecasting model (1) has next view for Skopje Airport (temperature measures Fahrenheit degrees; α=4; k_1, k_2, k_3=[-0.75; 0]):

$$X_F[i] = 92.6\left(1.16 - 0.25\frac{X_{11}^{*}[i-186]}{90.1} - 0.17\frac{X_{62}^{*}[i-189]}{85.37} - 0.46\frac{X_{48}^{*}[i-166]}{86.87}\right). \quad (3)$$

A criterion (2) has next view on the training sequence (MAE = 92.6 · 0.06065 ≈ 5.7 °F):

$$4 \cdot 0.06065 + (14045 - 7159) / 14045 = 0.73288$$

A criterion (2) has next view on the validation sequence (MAE = 92.6 · 0.05679 ≈ 5.26 °F; MAE for trend is 5.3 °F):

$$4 \cdot 0.05679 + (476 - 322) / 476 = 0.55066$$

In a fact, number of conjunctions is higher if we consider the adjacency of forecasted and true values. Discussing one-year interval (from 21 April 2012 to 20 April 2013), we have the following:

$$100 \cdot 273 / 365 = 74.8\ \%$$

Furthermore, MAE is 5.03 °F and MAE for trend is 5.13 °F (one-year interval is discussed).

Thus, forecasting model (3) has slightly better quality than trend, but conjunctions' percent is quite sufficient – 74.8 %, MAE is up to 5.7 °F. True and forecasted data from 21 April 2012 to 20 April 2013 plus trend at Skopje Airport are shown in Fig. 1. This line chart analysis shows that we have gotten quantitative (e.g., from June to August when true and forecasted values greater than trend) and qualitative accuracy (e.g., from mid-February to mid-March when true and forecasted extremums are equal). Skopje Airport average daily air temperature (166 days lead-time) trend plus third-order polynomial approximation of true and forecasted data are presented in Fig. 2. Draft visual analysis shows the same tendency in true and forecasted datasets that is considered as confirmation of the proposed approach's efficiency.

Similar results were achieved for Kiev (MAE is up to 7.2 °F, 167 days lead-time) and Washington National Airport (MAE is up to 6.07 °F, 173 days lead-time).

5 Cloud Computing Web-Site Development

Nowadays, weather forecasting software is developed in many ways. Ms Windows Azure public cloud computing technology (Baun C., 2011) was chosen because of high performance, maintenance's low cost, and web-based technologies. As additional benefit, cloud computing application can do different tasks in parallel (thin client concept). Web-site's www.weatherforecast.tk screenshot is shown in Fig. 3. User chooses place, date, and degree regime (Fahrenheit or Celsius) optionally.

6 Summary and Conclusion

In this paper, long-range forecasting average daily air temperature using inductive method was proposed. The principle of high-impact weather events substantiates the different places' interaction by atmosphere, hydrosphere, landmass, biosphere, etc. The main assumptions are:

1. Forecasting model (1) describes the air temperature time series adequately; coefficients k_1, k_2, and k_3 use to have the same sign as appropriate PPMCCs.
2. Inductive criterion (2) includes two polar parts – minimum of regularity plus maximum of conjunctions; hence, two training sequences' usage (classical self-organising approach) is not necessary.
3. Three days data averaging is optimal.

Forecasting model reasoning's first stage is selection of three most data-related places using PPMCCs. 66 datasets were acquired from NOAA Satellite and Information Service. Second stage is finding weighting coefficients α, k_0, k_1, k_2, and k_3 by combinatorial algorithm (step is 0.01). E.g., Skopje Airport's forecasting model includes datasets from Beijing, Ulaanbaatar, and Paphos Airport, and shows high accuracy – conjunctions' percent is 74.8 %, MAE is up to 5.7 °F at 166 days lead-time. Similar results were achieved for Kiev (MAE is up to 7.2 °F, 167 days lead-time) and Washington National Airport (MAE is up to 6.07 °F, 173 days lead-time). Web-site prototype www.weatherforecast.tk was developed using Ms Windows Azure public cloud computing technology.

Correlation analysis showed that some places dominate: 52 correlation results (out of 66) are highly related to Beijing and Ulaanbaatar (1st, 2nd, 3rd, and/or 4th rank). 42 of them have the PPMCCs greater than 0.8 in absolute value.

In a fact, Darwing and Tahiti sea level pressures, SOI, equatorial SOI, sea surface temperature, multivariate ENSO index were taken into consideration using the month data averaging. So, more detailed (e.g., daily) and/or different data's usage are the main prospects for the future research.

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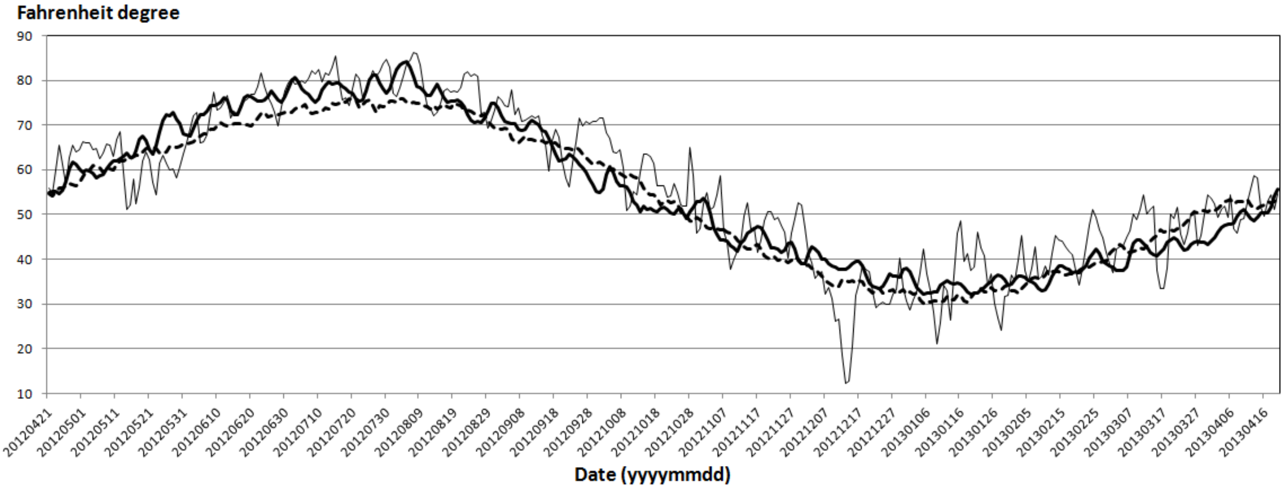

Fig. 1. True (thin solid line) and forecasted (bold solid) data plus trend (dashed) at Skopje Airport

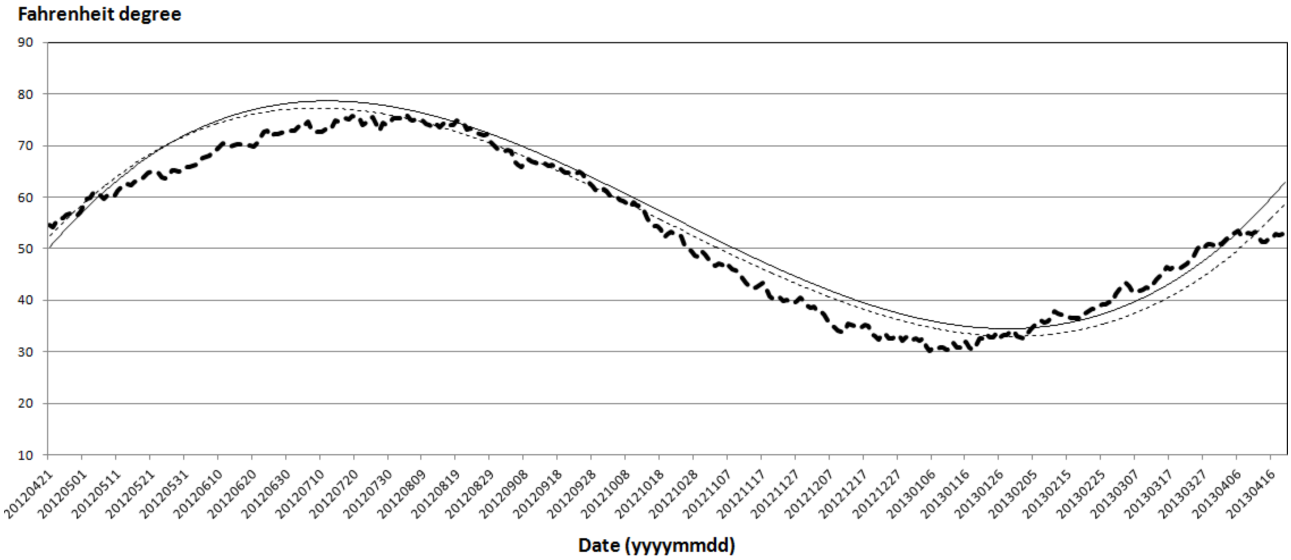

Fig. 2. Trend (bold dashed line) plus third-order polynomial approximation of true (thin solid) and forecasted (thin dashed) data at Skopje Airport (166 days lead-time)

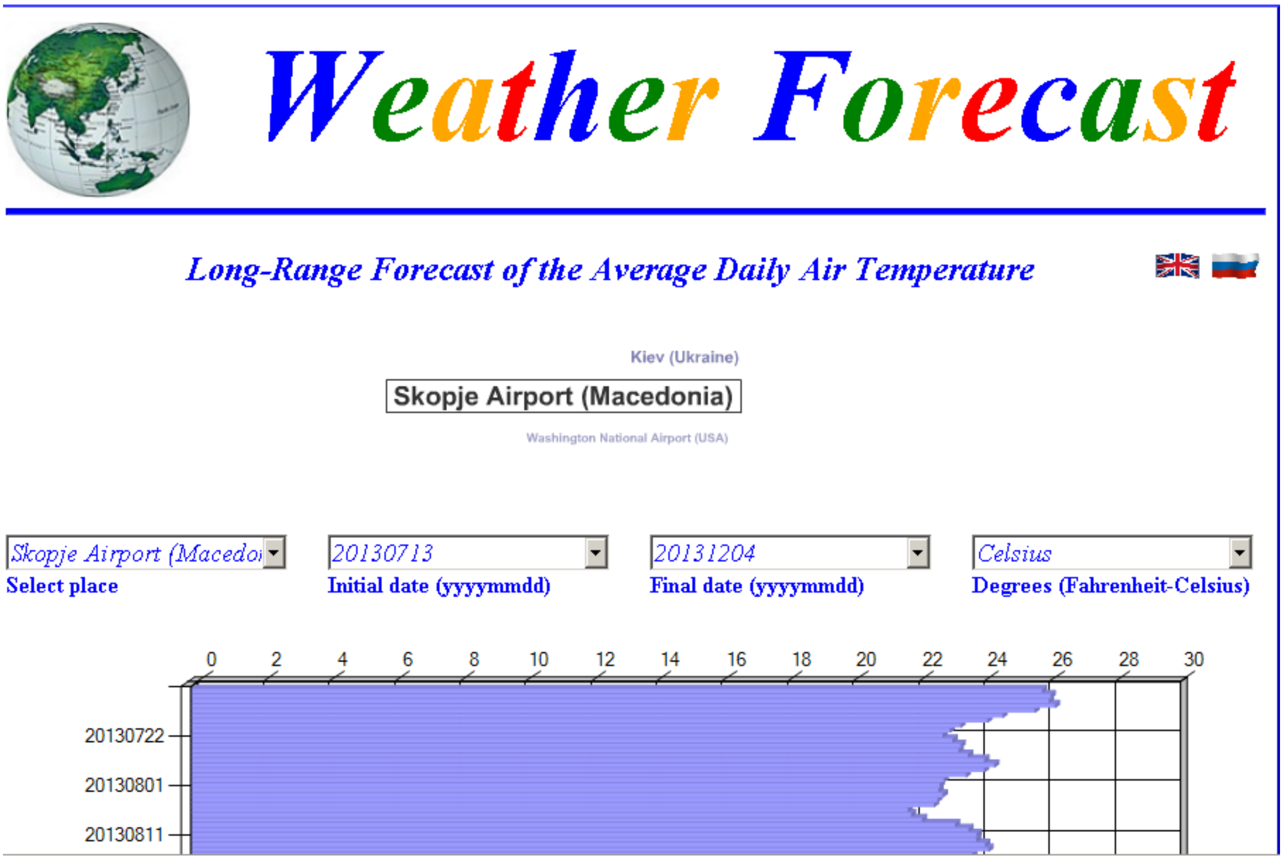

Fig. 3. Screenshot of the web-site www.weatherforecast.tk (Skopje Airport forecast's illustration)