Stochastic Models of Non-stationary Time Series of the Average Daily Heat Index

Nina Kargapolova[a]
Laboratory of Stochastic Problems, Institute of Computational Mathematics and Mathematical Geophysics SB RAS, Pr. Ak. Lavrent'eva 6, Novosibirsk, Russia
Department of Mathematics and Mechanics, Novosibirsk State University, Novosibirsk, Russia

Keywords: Stochastic Simulation, Non-stationary Random Process, Heat Index, Air Temperature, Relative Humidity, Model Validation.

Abstract: In this paper two numerical stochastic models of time series of the average daily heat index are considered. In the first model, time series of the heat index are constructed as a function of simulated joint nonstationary time series of air temperature and relative humidity. The second model is constructed under the assumption that time series of the heat index are non-stationary non-Gaussian random processes. Data from real observations at weather stations were used for estimating models' parameters. On the basis of the simulated trajectories, some statistical properties of rare meteorological events, like long periods of time with high heat index, are studied.

1 INTRODUCTION

It is known that of all the effects of the environment on human beings, one of the most significant for the human health and well-being are the factors determining the thermal state of a person. With adverse combinations of these factors, there is a threat of hypothermia or overheating of a body (Kobisheva et al., 2008; McGregor et al., 2015; Zare et al., 2018). Different bioclimatic indices (heat / cold stress index, heat index, weather severity index, etc.) are used to assess the combined heat effects on the human body of high temperature and relative humidity, cold humid air and wind speed, as well as other meteorological processes.

At present, to study the properties of the time series of bioclimatic indices two approaches are mainly used. In the framework of the statistical approach, data from real observations are analyzed, see, for example, (Kershaw and Millward, 2012; Revich and Shaposhnikov, 2018; Shartova et al., 2018). The second approach is a dynamical one – it is based on the use of hydrodynamic models of atmospheric processes (Gosling et al., 2009; Ohashi et al., 2014).

In 2018, the author of the paper together with colleagues at the Institute of Computational Mathematics and Mathematical Geophysics SB RAS (Novosibirsk, Russia) and the Voeikov Main Geophysical Observatory (St. Petersburg, Russia) began the development of a stochastic approach to studying and simulation of the time series of bioclimatic indices. For short time intervals (about 10–12 days), models of high-resolution time series of the heat index and the enthalpy of humid air were constructed and validated. These models take into account the daily variations of the real weather processes (Kargapolova et al., 2019).

The objective of this paper is to propose such a stochastic model of time series of the average daily heat index (ADHI) on a long intervals that would take into account the influence of a seasonal variation of air temperature and relative humidity on the time series of the ADHI. In this paper two stochastic models are considered. It is shown that the model based on simulation of the joint time series of air temperature and relative humidity does not reproduce properties of the ADHI time series as good as it reproduces properties of the high-resolution time series of the heat index. In contrast, a model based on simulation of the ADHI time series using the inverse

[a] https://orcid.org/0000-0002-1598-7675

Kargapolova, N.
Stochastic Models of Non-stationary Time Series of the Average Daily Heat Index.
DOI: 10.5220/0007788502090215
In *Proceedings of the 9th International Conference on Simulation and Modeling Methodologies, Technologies and Applications (SIMULTECH 2019)*, pages 209-215
ISBN: 978-989-758-381-0

distribution function method describes the real process precise enough.

2 THE HEAT INDEX

To describe the influence of high air temperature and relative humidity on a human being the so-called “heat index” is frequently used (Steadman,1979; Steadman, 1984). The overview and comparison of existing approaches to the definition of this index is provided in (Anderson et al., 2013). In this paper, the average daily heat index HI is defined using the approach, proposed in (Schoen, 2005):

$$HI = T - 1.0799e^{0.03755T}\left(1 - e^{0.0801(D-14)}\right),$$
$$D = \frac{237.3\alpha}{17.27 - \alpha},\ \alpha = \frac{17.27T}{237.3 + T} + lnH, \tag{1}$$

where T and H are the average daily air temperature and relative humidity, respectively, D is dew point temperature. Here unit of measurement of air temperature is a Celsius degree, and relative humidity is measured in fractions of unity; the heat is supposed to be dimensionless. It should be noted that the heat index is not measured at weather stations, but it could be calculated using the above-given formulas based on the observed values of air temperature and relative humidity.

Let $\overrightarrow{HI} = (HI_1, HI_2, \ldots, HI_N)$ denote time series of the average daily heat index (ADHI) on a N – day interval.

3 THE TH-MODEL

Since the heat index is a function of air temperature and relative humidity, a natural approach to the simulation of its time series is to simulate the joint time series of air temperature and relative humidity and then to calculate values of the heat index. Such an approach was proposed and validated in (Kargapolova et al., 2019) for the simulation of high-resolution time series of the heat index at short time intervals. The model proposed therein is based on the model of periodically correlated joint time series of air temperature and relative humidity detailed in (Kargapolova et al., 2018).

Let us apply the approach described to the simulation of time series of the ADHI at long time intervals. Statistical analysis of real meteorological data reveals that the joint time series $(\vec{T}, \vec{H}) = (T_1, T_2, \ldots, T_N, H_1, H_2, \ldots, H_N)$ of the average daily air temperature and relative humidity long time intervals are non-stationary.

One-dimensional distributions and a correlation structure of the joint time series of air temperature and relative humidity are used as the model input parameters.

In order to construct a stochastic model, the use of sample one-dimensional distributions is not reasonable, since the sample distributions do not have any tails, and therefore do not allow one to estimate the probability of occurrence of extreme values of the heat index. In this connection, it is necessary to approximate the sample distributions densities by certain analytic densities, which, on the one hand, do not greatly alter the form of a sample distribution and its moments, and on the other – possess tails.

It should be noted that for approximation of the empirical one-dimensional distribution $s_k(x)$ of the average daily temperature, the Gaussian distribution is often used (Ogorodnikov, 2013; Richardson, 1981; Richardson and Wright, 1984). However, the numerical experiments have shown that if, despite an increase in the complexity of simulation, one approximates the temperature distribution with a mixture

$$g_k(x) = \theta_k \frac{1}{b_{k1}\sqrt{2\pi}} \exp\left(-\frac{(x - a_{k1})^2}{2b_{k1}^2}\right) +$$
$$+(1 - \theta_k)\frac{1}{b_{k2}\sqrt{2\pi}} \exp\left(-\frac{(x - a_{k2})^2}{2b_{k2}^2}\right), \tag{2}$$
$$0 < \theta_k < 1,\ k = \overline{1, \mathrm{N}}$$

of the two Gaussian distributions, the quality of the model being significantly improved. In this paper, the parameters $\theta_k, a_{k1}, b_{k1}^2, a_{k2}, b_{k2}^2, k = \overline{1, \mathrm{N}}$ were chosen using the algorithm, proposed in (Marchenko and Minakova, 1980). This algorithm makes possible to choose such parameters of the density (2) (and the corresponding CDF $G_k(x)$) that mathematical expectation, variance and skewness of a random variable with the density $g_k(x)$ should be equal to the corresponding sample characteristics, and the function $g_k(x)$ minimizes the Pearson functional that describes the difference between $s_k(x)$ and $g_k(x)$.

For approximation of one-dimensional distributions of the average daily relative humidity densities that are mixtures $b_k(x)$ of the two Beta-distributions (with the corresponding CDF $B_k(x)$) are used.

In this paper, to construct a model of the time series $(\vec{T}, \vec{H})$ (and hence a model of time series $\overrightarrow{HI}$) the $2N \times 2N$ sample correlation matrix

$$R = \begin{pmatrix} R_T & R_{TH} \\ R_{HT} & R_H \end{pmatrix} \quad (3)$$

is used. Here R_T, R_H are the sample autocorrelation matrices of air temperature and relative humidity, respectively, and R_{TH}, R_{HT} are the sample cross-correlation matrices of these two weather elements.

For the simulation of $(\vec{T}, \vec{H})$ with given one-dimensional distributions (1) and a given correlation matrix (3), the method of inverse distribution function was used (Ogorodnikov and Prigarin, 1996). In the framework of this method, simulating the sequence $\overrightarrow{HI}$ comes down to an algorithm with four steps:

Step 1. Calculation of the matrix R' that is a correlation matrix of an auxiliary standard Gaussian process $(\vec{T'}, \vec{H'})$. The element $r'(\text{i}, \text{j})$ $i, j = \overline{1, 2N}$ of the matrix R' is the solution to the equation

$$r(\text{i}, \text{j}) =$$

$$= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} F_i^{-1}(\Phi(x)) F_j^{-1}(\Phi(y)) \varphi(x, y, r'(\text{i}, \text{j}))\, dxdy,$$

$$F_i = \begin{cases} G_i(x), \ i \le N, \\ B_{i-N}(x), i > N, \end{cases}$$

where $r(\text{i}, \text{j})$ is an element of the matrix R corresponding to $r'(\text{i}, \text{j})$, the function $\varphi(x, y, r'(\text{i}, \text{j}))$ is a distribution density of a bivariate Gaussian vector with zero mean, variance equal to 1 and the correlation coefficient $r'(\text{i}, \text{j})$ between components number i and j, $\Phi(\cdot)$ is a CDF of a standard normal distribution.

Step 2. Simulation of the standard Gaussian sequence $(\vec{T'}, \vec{H'})$ with the correlation matrix R'.

Step 3. Transformation of $(\vec{T'}, \vec{H'})$ into $(\vec{T}, \vec{H})$:

$$T_i = G_i^{-1}\left(\Phi\left(T_i'\right)\right), \ i = \overline{1, N},$$

$$H_j = B_j^{-1}\left(\Phi\left(H_j'\right)\right), \ j = \overline{1, N}$$

Step 4. Calculation of $\overrightarrow{HI}$ using its definition (1) given in the previous section.

If the matrix R', obtained at the first step, is not positive definite, it must be regularized. Several methods of regularization are described in (Ogorodnikov and Prigarin, 1996). In this paper, the method of regularization based on substitution of negative eigenvalues of the matrix R' with small positive numbers was used. At the second step, the simulation of the standard Gaussian sequence $(\vec{T'}, \vec{H'})$ with the correlation matrix R' could be done using the Cholesky or the spectral decomposition of the matrix R' (Ogorodnikov and Prigarin, 1996). The latter is used here. Steps 2-4 are repeated as many times as many trajectories are required.

Any stochastic model has to be verified before one starts to use simulated trajectories to study properties of a simulated process. For model verification, it is necessary to compare simulated and real data based estimations of such characteristics, which, on the one hand, are reliably estimated by real data, and on the other hand are not input parameters of the model.

In this paper, the long-term observations data from weather stations located in different climatic zones were used for verification. Although all examples in this paper are given only for the stations in the cities of Sochi (the Black Sea region, years of observation: 1993-2015) and Astrakhan (the Caspian Sea region, years of observation: 1966-2000), all the conclusions are valid for all considered weather stations.

The correlation coefficients $corr(HI_i, HI_k)$ of the ADHI time series are not input parameters of the TH-model, so they could be used for the verification of this model. Figure 1 shows the correlation coefficients $corr(HI_1, HI_{1+h})$, estimated with real data (with 2σ confidence interval) and with the 10^5 trajectories obtained with the TH-model. Numerical experiments show that for all considered weather stations and time intervals, the absolute difference of correlation coefficients estimated with real and simulated data does not exceed 2σ. Hereinafter, σ is a statistical estimate of the standard deviation of the characteristic under consideration when estimating with real data. Thus, the TH-model well reproduces the correlation structure of time series of the ADHI.

As a matter of fact, other properties of real time series of the ADHI are either not reproduced or poorly reproduced by the TH-model. As an illustration, Tables 1-3 show estimations of the average number $AN(lev)$ of the days in a considered time-interval with the ADHI above given level lev and estimations of the probability $p(l) = P(|HI_i - HI_{i+1}| > l)$ of a rapid change in the heat index. Simulated data bases estimations are given with significant digits only. This means that the TH-model, despite its soundness and applicability in cases of the high-resolution time series, should not be used for the simulation of the time series of the ADHI.

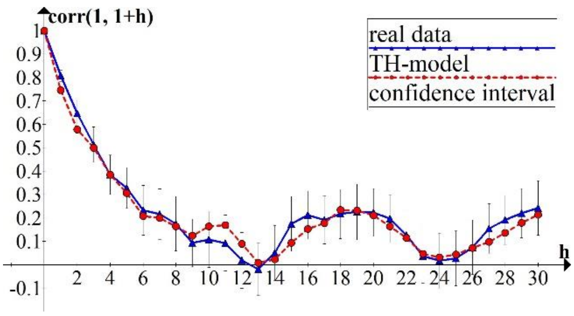

Figure 1: Correlation coefficients $corr(HI_1, HI_{1+h})$. Astrakhan. July, 1-31.

Table 1: Estimations of $AN(lev)$. Astrakhan. August, 1-31.

lev	Real data, $AN(lev) \pm 3\sigma$	TH-model
20	28.206 ± 1.630	27.193
24	21.088 ± 2.819	14.463
28	10.441 ± 0.887	1.032
32	2.853 ± 1.586	0.007
36	0.500 ± 0.640	0.000

Table 2: Estimations of the probability $p(l)$. Sochi. June, 1-30.

l	Real data, $p(l) \pm 3\sigma$	TH-model
1	0.585 ± 0.063	0.577
2	0.304 ± 0.037	0.275
3	0.150 ± 0.055	0.111
4	0.078 ± 0.039	0.040
5	0.039 ± 0.054	0.013

The most probable reason for the invalidity of the TH-model is related to the fact that the heat index is a nonlinear function of air temperature and relative humidity. It leads to the significant difference between the ADHI calculated with the average daily temperature and relative humidity (as in the TH-model) and the ADHI calculated as an average of the values of the heat index calculated with real meteorological high-resolution data. To avoid this problem, instead of the $(\vec{T}, \vec{H})$ one should simulate the high-resolution time series

$$\left(\overrightarrow{T^n}, \overrightarrow{H^n}\right) = \begin{pmatrix} T_1^1, T_1^2, \ldots, T_1^n, \ldots, T_N^1, \ldots, T_N^n, \\ H_1^1, \cdots, H_1^n, \ldots, H_N^1, \cdots, H_N^n \end{pmatrix},$$

Table 3: Estimations of the probability $p(l)$. Astrakhan. June, 1-30.

l	Real data, $p(l) \pm 3\sigma$	TH-model
1	0.685 ± 0.047	0.588
2	0.422 ± 0.055	0.283
3	0.223 ± 0.050	0.113
4	0.106 ± 0.040	0.038
5	0.055 ± 0.029	0.011

where T_i^k, H_i^k, $k = \overline{1,n}$, $i = \overline{1,N}$ are temperature and relative humidity measured n times per day in a day number i, respectively, then calculate the high-resolution time series of the heat index and average them to obtain the ADHI. It should be noted that this approach to the simulation is time-consuming (for instance, one has to solve n^2 times more equations to define the correlation matrix of an auxiliary Gaussian process than in case of the simulation of the $(\vec{T}, \vec{H})$ time series).

4 THE HI-MODEL

In this section, another approach to the simulation of the time series of the average daily heat index is considered. In the framework of this approach (denoted as the HI-model), at the first step, a sample of real time series of the ADHI is formed using the long-term observation data about the average daily temperature and relative humidity. Then sample histograms are approximated with some one-dimensional distribution densities $n_k(x)$, $k = \overline{1,N}$ and a sample $N \times N$ correlation matrix R_{HI} is estimated. In this paper, $n_k(x)$, $k = \overline{1,N}$ is a mixture of the two Gaussian distributions. Parameters of these mixtures were chosen just as parameters of the densities $g_k(x)$. To construct a completely parametric stochastic model of the time series, it is necessary to approximate the sample correlation function with some analytic parametric function (like was done with one-dimensional distributions). Such an approximation is in the course of development. The last step is the simulation of trajectories of the ADHI with the given densities $n_k(x),\ k=\overline{1,N}$ and the correlation matrix R_{HI} using the method of inverse distribution function (in a similar way to steps 1-3 in the TH-model).

Results of verification of the HI-model are provided below.

Tables 4 and 5 show the estimations of the average number $AN(lev)$, defined in the previous section. It is clearly seen that the HI-model well reproduces this characteristic of the ADHI time series both for harmless levels lev and for dangerous levels (the heat index between 32 and 41 is the extreme caution, between 41 and 54 is danger, above 54 is the extreme danger).

Table 4: Estimations of $AN(lev)$. Astrakhan. August, 1-31.

lev	Real data, $AN(lev)\pm\sigma$	HI-model
20	28.206 ± 0.451	28.120
24	21.088 ± 0.857	21.053
28	10.441 ± 0.946	10.323
32	2.853 ± 0.529	2.758
36	0.500 ± 0.213	0.566
40	0.118 ± 0.085	0.138
44	0.029 ± 0.048	0.056
48	0.000 ± 0.011	0.004

Table 5: Estimations of $AN(lev)$. Sochi. July, 1-31.

lev	Real data, $AN(lev)\pm\sigma$	HI-model
20	30.565 ± 0.234	30.515
24	27.652 ± 0.696	27.893
28	19.435 ± 1.323	19.753
32	10.261 ± 1.248	9.960
36	3.391 ± 0.768	3.564
40	1.044 ± 0.379	0.952
44	0.130 ± 0.115	0.108
48	0.000 ± 0.035	0.012
52	0.000 ± 0.010	0.001

Another characteristic that was used both for the verification of the HI-model and for the study of the heat index time series properties was the probability $p(l)$. Tables 6 and 7 show the estimations of $p(l)$ based on real data and simulated trajectories. For all the considered weather stations and time intervals, the absolute difference of $p(l)$ estimated on real and simulated data does not exceed 2σ. This means that this characteristic is well reproduced by the HI-model.

The verification of the HI-model has shown that this model with high accuracy reproduces many of the statistical characteristics of real ADHI time series. Accordingly, it is possible to use the HI-model to study those properties of the time series that cannot be studied using real data. Among other things, it is possible to investigate an impact of an increase in the average air temperature on the duration of periods with the extremely high ADHI, on probability of the occurrence of dangerous values of the ADHI and other properties of adverse weather phenomena. Below the results of one of the numerical experiments conducted using the HI-model are given.

Table 6: Estimations of the probability $p(l)$. Sochi. June 1-30.

l	Real data, $p(l)\pm\sigma$	HI-model
1	0.585 ± 0.021	0.638
2	0.304 ± 0.022	0.360
3	0.150 ± 0.018	0.183
4	0.078 ± 0.013	0.084
5	0.039 ± 0.008	0.035
6	0.021 ± 0.005	0.014
7	0.011 ± 0.003	0.005
8	0.006 ± 0.002	0.002
9	0.000 ± 0.001	0.001
10	0.000 ± 0.001	0.000

The main idea of the experiment was to increase the average daily temperature on condition that relative humidity does not change, to estimate the parameters of the distributions used in the HI-model using the simulated temperature data, real relative humidity data and real correlation coefficients, to simulate the time series of the ADHI and to access an average number $AN(lev)$ of the days with the ADHI above level lev. Simulation of air temperature non-stationary time series was based on the model proposed in (Kargapolova, 2018). Figure 2 shows the results of this experiment for the four cases: when the real average daily temperature was used and when the average daily temperature was increased by $0.1^oC, 0.5^oC, 1.0^oC$, respectively. The analysis shows that for $lev=32$ (recall that it is the extreme caution level) the number $AN(lev)$ increases by

$40-50\%$ depending on a weather station considered. For level *lev* above 41 values of the $AN(lev)$ almost double. This means that $1.0\,^{o}C$ rise in the average air temperature causes a hefty increase of days when people must be careful being outside. In this numerical experiment the simplest warming scenario was used.

Table 7: Estimations of the probability $p(l)$. Astrakhan. June 1-30.

l	Real data, $p(l)\pm\sigma$	HI-model
1	0.685 ± 0.016	0.698
3	0.223 ± 0.017	0.255
5	0.055 ± 0.010	0.069
7	0.018 ± 0.004	0.015
9	0.007 ± 0.002	0.003
11	0.003 ± 0.001	0.001
13	0.001 ± 0.001	0.000

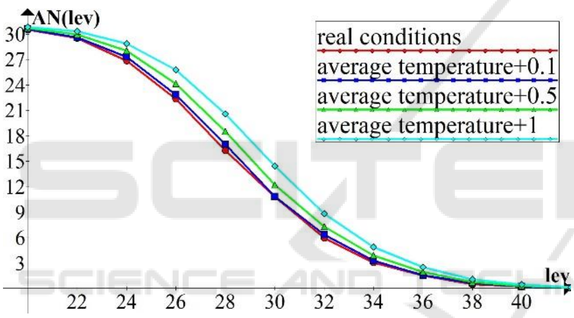

Figure 2: Average number $AN(lev)$ of days with the ADHI above level *lev*. Astrakhan. July, 1-31.

For a detailed study of the climate change influence it is necessary to use more complex scenarios. For example, dependence between changing temperature and relative humidity is meant to be taken into account. Study the possible alternation of the ADHI using complex climate change scenarios and stochastic models calls for further investigations.

5 CONCLUSIONS

In this paper, it is shown that the TH-model used to simulate high-resolution time series of the heat index cannot be used to simulate the ADHI series. Another approach (the HI-model) to the simulation of these time series is proposed. The results of verification of the HI-model and an example of its application for studying the ADHI properties, which cannot be studied from real data, are given.

In the future, it is intended to use the model constructed for solving a number of bioclimatological problems related to development of proper heat-/cold waves prediction systems and long-range forecasting of the climate regime alteration. To solve these problems, it is necessary to turn the proposed model into a fully parametric one and to add a capability to simulate conditional time series.

ACKNOWLEDGEMENTS

This work was partly financially supported by the Russian Foundation for Basic Research (grant No 18-01-00149-a), Russian Foundation for Basic Research and Government of Novosibirsk region (grant No 19-41-543001-r_mol_a).

REFERENCES

Anderson, G.B., Bell, M.L., Peng, R.D., 2013. Methods to calculate the heat index as an exposure metric in environmental health research. In *Env. Health Perspect.*, Vol. 121, No 10. P. 1111-1119.

Gosling, S.N., McGregor, G.R., Lowe, J.A., 2009. Climate change and heat-related mortality in six cities. Part 2: climate model evaluation and projected impacts from changes in the mean and variability of temperature with climate change. In *Int J Biometeorol*., Vol.53, No 1. P. 31-51.

Kargapolova, N. A., 2018. Monte Carlo Simulation of Non-stationary Air Temperature Time-Series. In *Proc. of 8th Int. Conf. on Simulation and Modeling Methodologies, Technologies and Applications “SIMULTECH-2018”*. P. 323-329.

Kargapolova, N. A., Khlebnikova, E. I., Ogorodnikov, V. A., 2018. Monte Carlo simulation of the joint non-Gaussian periodically correlated time-series of air temperature and relative humidity. In *Statistical papers*, Vol. 59. P.1471-1481.

Kargapolova, N. A., Khlebnikova, E. I., Ogorodnikov, V. A., 2019. Numerical study of properties of air heat content indicators based on the stochastic model of the meteorological processes. In *Russ. J. Num. Anal. Math. Modelling*, Vol. 34, No 2. P. 95-104.

Kershaw, S.E., Millward, A.A., 2012. A spatio-temporal index for heat vulnerability assessment. In *Environ. Monit. Assess.*, Vol. 184. P. 7329-7342.

Kobisheva, N.V., Stadnik, V.V., Klueva, M.V., Pigoltsina, G.B., Akentieva, E.M., Galuk, L.P., Razova, E.N., Semenov, U.A., 2008. *Guidance on specialized climatological service of the economy.* Asterion. St. Petersburg. (in Russian)

Marchenko, A.S., Minakova, L.A., 1980. Probabilistic model of air temperature time-series. In *Meteorology and Hydrology*, No 9. P. 39-47. (in Russian)

McGregor, G.R., Bessemoulin, P., Ebi, K., Menne, B., 2015. Heatwaves and Health: Guidance on Warning-System Development. WMO &WHO.

Ogorodnikov, V.A., 2013. *Stochastic models of meteorological processes: Teaching aid*. NSU. Novosibirsk.

Ogorodnikov, V.A., Prigarin, S.M., 1996. *Numerical Modelling of Random Processes and Fields: Algorithms and Applications*, VSP. Utrecht.

Ohashi, Y., Kikegawa, Y., Ihara, T., Sugiyama. N., 2014. Numerical Simulations of Outdoor Heat Stress Index and Heat Disorder Risk in the 23 Wards of Tokyo. In *J. Appl. Meteor. Climatol.*, Vol. 53. P. 583-597.

Revich, B., Shaposhnikov, D.A., 2016. Cold waves in the southern cities of the European part of Russia and premature mortality of the population. In *Problems of forecasting*, No 2. P. 125-131. (in Russian)

Richardson, C. W., 1981. Stochastic simulation of daily precipitation, temperature and solar radiation. In *Water Resour. Res.*, Vol. 17. P. 182-190.

Richardson, C. W., Wright, D.A., 1984. *WGEN: A Model for Generating Daily Weather Variables*. U. S. Department of Agriculture, Agricultural Research Service.

Schoen, C., 2005. A new empirical model of the temperature– humidity index. In *J Appl Meteorol.*, Vol 44. P. 1413-1420.

Shartova, N., Shaposhnikov, D., Konstantinov, P., Revich, B., 2018. Cardiovascular mortality during heat waves in temperate climate: an association with bioclimatic indices. In *Int. J. of Environmental Health Research*, Vol. 28, No. 5. P. 522-534.

Steadman, R.G., 1979. The Assessment of Sultriness, Part I: A Temperature-Humidity Index Based on Human Physiology and Clothing Science. In *J. Appl. Meteor.*, Vol. 18. P.861-873.

Steadman, R.G., 1984. A universal scale of apparent temperature. In *J Climate Appl Meteorol.*, Vol. 23. P. 1674-1687.

Zare, S., Hasheminejad, N., Shirvan, H.E., Hemmatjo, R., Sarebanzadeh, K., Ahmadi, S., 2018. Comparing Universal Thermal Climate Index (UTCI) with selected thermal indices/environmental parameters during 12 months of the year. In *Weather and Clim. Extremes*, Vol. 19. P. 49-57.