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NEWTON'S SECOND LAW IN THE SERVICE OF CLIMATE CHANGE – TEMPERATURE TREND ANALYSIS

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Abstract: New approach of using Newton's Second Low in the analysis of a non-mechanical system is presented. A force that satisfies Newton's second law is introduced, where real time series of average monthly temperatures are transformed into time-dependent force parameters. The force acts on a point in data space. This method of data analysis can be considered as a type of information filtering. Extreme values of certain force parameters were analyzed as potential predictors of temperature trend emergence. Specific force parameters were calculated based on the average monthly temperature values for several cities in Bosnia and Herzegovina. A review and discussion of possible changes in average monthly temperatures in the future are provided, based on the values of the obtained force parameters.

Keywords: Newton's Second Low, Climate changes, Temperature.

1. INTRODUCTION

We are witnessing many climate changes happening today. The interest of the scientific community has long been focused on the analysis and modeling of climate systems, as well as possible predictions of future climate changes [1 - 4]. The climate system is a complex system that can be viewed as a synthesis of weather conditions, including mean values and variability of atmospheric variables such as temperature, precipitation, and wind. According to the recommendations of the World Meteorological Organization, data collected for an area over a 30-year interval are adequate for performing statistics used to define the climate. Additionally, data characteristic of ancient periods are also very interesting for analysis and comparison [6]. In general, complex systems are hardly predictable because a combination of chaos and stochasticity. Climate system is also complex system which is affected by internal and external forces, and its behavior is conditioned by natural and anthropogenic factors. Here we present a possible way of using Newton's second law in the rough prediction of temperature trends without entering into the real complexity of the climate system. Rough predictions of the increase in temperature uncertainty are given, which we associate with extremely large values of the force parameters. Our main assumption is that the exceptional instability in a short time interval makes possible the rough prediction of future oscillations [7].

2. METHOD

In this method we observe artificial and real time series that describe chaotic-stochastic oscillations and subsequently convert these series into time-depending force parameters [8]. The force components, conforming to Newton's second law, encompass contributions from elastic forces, nonlinear effects, damping forces, and coercive forces. That is certain form of the nonconventional force that satisfying the Newton's second law (1):

$$v_k - v_{k-1} = a(x_k - S_j) + a_2(x_k - S_j)^2 + a_3(x_k - S_j)^3 + bv_k + w + \sum_{i=2}^{6} c_i cos\frac{6.28k}{i} \quad (1)$$

For a measured time series $x_1, x_2, x_3, \dots x_n$, velocity is given with (2):

$$v_k = x_k - x_{k-1} \quad (2)$$

where

$$k = n + j, \quad n = 2,3,4, \dots ,12; \quad j = 0,1,2, \dots \quad (3)$$

In equation (1), S_j is represented as (4):

$$S_j = \frac{1}{12}\sum_{n=1}^{12} x_{n+j} \; . \quad (4)$$

The oscillations of the system considered here are nonlinear and occasionally damped, amplified and unstable. The nonconventional force is acting on a point in the space of data. Solving ten equations (1), for $3 \le n \le 12$, it could be found ten force parameters (5):

$$a = a(j),\ a_2 = a_2(j),\ a_3 = a_3(j), b = b(j), w = w(j),\ c_i = c_i(j);\ i = 2,3,4,5,6 \quad (5)$$

The time interval $[j + 1, j + 12]$ is assigned to each of these force parameters. Analyzing these parameters yields significant insights into the behavior of the system.

In equation (1), the initial term represents the elastic force. The negative sign of force signifies the elastic force's tendency to act opposite to the applied force direction. When $a < 0$, the force acts as an elastic force, working to restore the system to its equilibrium position. However, when $a > 0$, the amplitude increases, causing the system to move further away from equilibrium (where equilibrium in 'S' is not stable).

The second and third terms in equation (1) represent nonlinearity. In nonlinear systems, the system's response to an applied force is not directly proportional to the force's magnitude, and these systems exhibit chaotic properties. In this research, particular attention is directed towards the parameter a_3 and its influence on the system's behavior at a certain delayed moment.

The fourth term represents a damping force when $b < 0$, while if $b > 0$, it becomes an amplifying force. The force parameter w is assumed to be constant within a short time interval. The sixth term corresponds to the driving force. In this approach, we have introduced certain assumptions: 1) A large positive value of the parameter a is related to an increase in unpredictability due to stochastic processes, but large values of parameters a_2 and a_3 are related to an increase in unpredictability due to chaotic behavior; 2) Large positive value of the parameter b is related to an increase in the amplitude of the oscillations and large values of parameters w and c_i are related to a significant driving force. Certainly, analyzing different pairs of force parameters is a possibility. However, for our present discussion, we will focus on parameter a_3 and its impact on the future behavior of the system.

3. RESULTS

3.1. Artificial time series

To enhance comprehension of the results obtained from real system data, we have generated artificial time series. Below, we provide several examples of these artificial time series (Figure 1). Artificial time series are generated from equation:

$$\frac{dx(t)}{dt} = 672 \sin\frac{(3.1\, y(t) + 5.9f(t))}{10},$$

$$\frac{dy(t)}{dt} = 671 \cos(3.6x + 5.7f(t))\,; \quad (6)$$

$$x(0) = 0.8384760001, 0.8384760002, \dots 0.8384760009,$$

$$y(0) = -0.60364300001, -0.60364300002, \dots, -0.60364300009, f(t) \in [-1,1].$$

$$\frac{dx(t)}{dt} = 375\sin(2.8y(t) + 1.0f(t))$$
$$\frac{dy(t)}{dt} = 376\cos(2.4x(t) + 1.0f(t)). \quad (7)$$

$$x(0) = 0.25974100001, 0.25974100002 \ldots 0.25974100009,$$

$$y(0) \ = -0.36784100001, -0.36784100002, \ldots, -0.36784100009, f(t) \in [-1,1].$$

$$\frac{dx(t)}{dt} = 472\text{sin}\ (1.1y(t) + 2.9f(t))$$

$$\frac{dy(t)}{dt} = 471\text{cos}\ (1.6x(t) + 2.7f(t)); \quad (8)$$

$$x(0) = 0.8384760001, 0.8384760002, \ldots 0.8384760009,$$

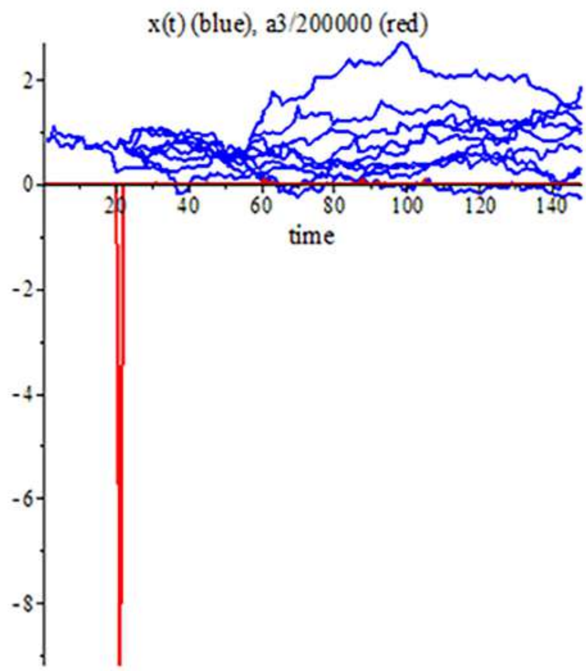
$$y(0) \ = -0.60364300001, -0.60364300002, \ldots, -0.60364300009, f(t) \in [-1,1].$$

$$\frac{dx(t)}{dt} = 462\sin\big(2.1y(t) + 0.9f(t)\big),$$

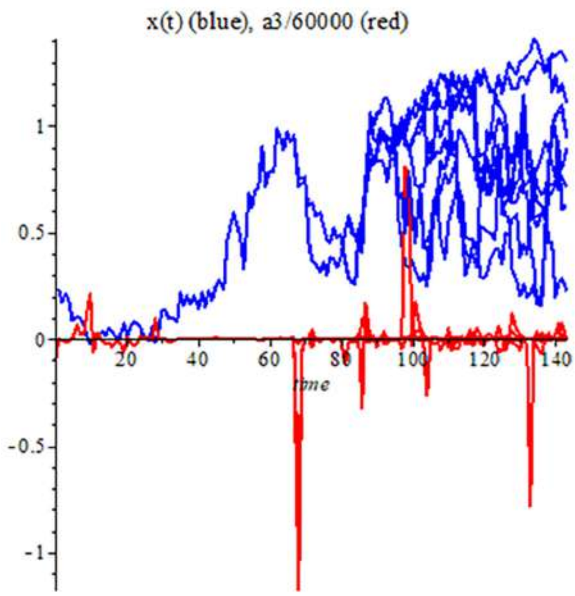
$$\frac{dy(t)}{dt} = 461\cos\big(2.6x(t) + 1.2f(t)\big); \quad (9)$$

$$x(0) = 0.3245660001, 0.3245660002, \ldots 0.32456660009,$$

$$y(0) \ = -0.60364300001, -0.60364300002, \ldots, -0.60364300009, f(t) \in [-1,1]$$



a)



b)

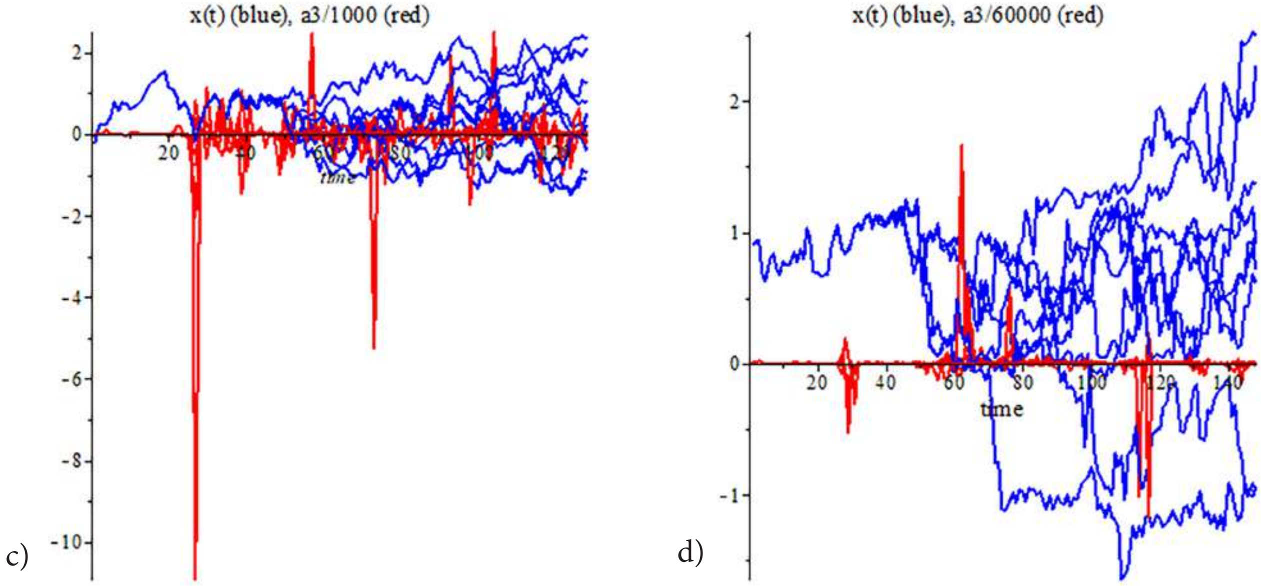


Figure 1. *Force parameter a_3 (red) and $x(t)$ (blue); a) Time series generated by equations (6): b) Time series generated by equations (7): c) Time series generated by equations (8): d) Time series generated by equations (9).*

The previous examples have highlighted the connection between a high value of force parameter a_3 and the amplification of uncertainty in the system's behavior represented by (t). Now, let us consider examples where there are no pronounced peaks or high maxima in the value of parameter a_3 (Figure 2).

Artificial time series are generated from equations (10):

$$\frac{dx(t)}{dt} = 162\sin\big(2.3y(t) + 2.9f(t)\big),$$

$$\frac{dy(t)}{dt} = 163\cos\big(2.6x(t) + 2.2f(t)\big)\,; \tag{10}$$

$$x(0) = 0.27567800001, 0.27567800002, \ldots 0.27567800009,$$

$$y(0) = 0.875201300001, 0.875201300002, \ldots, 0.875201300009, f(t).\,201126$$

and

$$\frac{dx(t)}{dt} = 101\sin\big(0.3y(t) + 1.9f(t)\big),$$

$$\frac{dy(t)}{dt} = 103\cos\big(0.6x(t) + 2.1f(t)\big)\,; \tag{11}$$

$$x(0) = 0.27567800001, 0.27567800002, \ldots 0.27567800009,$$

$$y(0) = 0.367841300001, 0.367841300002, \ldots, 0.367841300009, f(t).\,201126$$

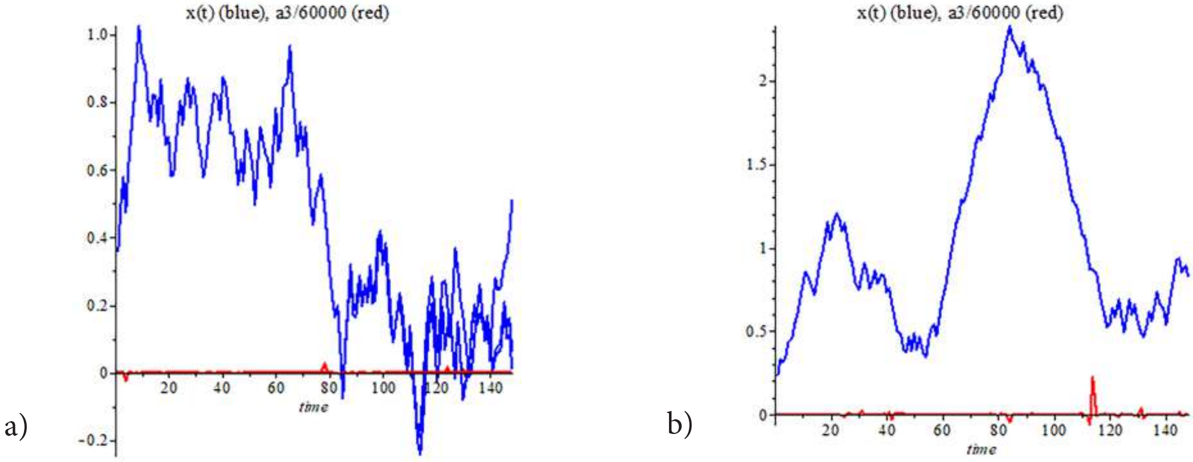


Figure 2. *Force parameter* a_3 *(red) and* (*t*) *(blue); a) Time series generated by equations (10): b) Time series generated from equations (11).*

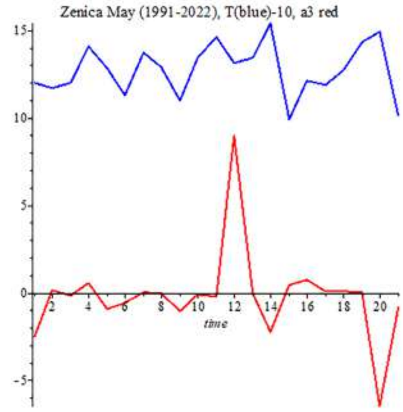
Approximate predictability emerges as an outcome of the interplay between chaos and stochastic processes. The combination of these two factors contributes to the complex behavior observed in many natural and engineered systems. Chaotic dynamics introduce sensitivity to initial conditions, leading to divergence of trajectories over time, which can hinder long-term predictions. On the other hand, stochastic processes introduce random fluctuations, further complicating the predictability of the system's evolution. As a consequence, systems exhibiting both chaotic and stochastic features often demonstrate a delicate balance between short-term predictability, limited by the chaotic nature, and long-term unpredictability due to the influence of stochastic elements. Understanding and quantifying this interplay is crucial for various fields, including climate science, financial modeling, and biological systems, where approximate predictability plays a central role in forecasting and decision-making processes.

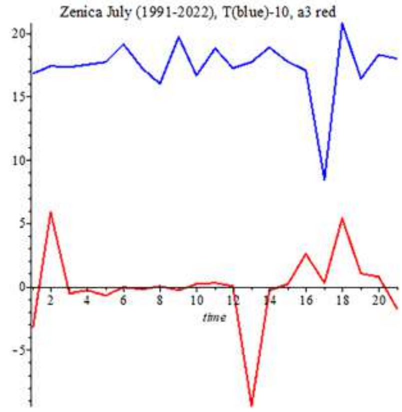
3.2. Real time series

In the context of real time series, we continue to apply the same principle as described in the previous paragraph for artificial time series. In this case, the real time series comprises values of average montly temperatures for several cities in Bosnia and Herzegovina. Our focus remains on observing the parameter a_3 and its relationship with the corresponding temperature values over time. By analyzing the behavior of parameter a_3 alongside the temperature data, we can gain insights into the relationship of parameter a_3 and the temperature fluctuations and patterns exhibited by the real system.

Similar to the artificial time series analysis, we investigate whether high values of force parameter a_3 in the real system result in increased temperature uncertainty and variability, leading to chaotic or unpredictable temperature trends. Conversely, when a_3 takes on moderate or low values, the temperature data are expected to show less dramatic changes over time.

The dataset utilized in this study was procured from two sources: the Federal Hydrometeorological Institute of Bosnia and Herzegovina [9], and the Republic Hydrometeorological Institute of the Republic of Srpska, [10]. Calculations related to temperature measurements within cities in the region were conducted. In the Federation of Bosnia and Herzegovina, average monthly temperature measurements at 2 p.m. were utilized. For the Republic of Srpska, data on average daily temperatures were utilized, subsequently undergoing averaging for each specific month. However, this aspect does not hold significance for the final conclusion, as the study primarily addresses the temperature trend, rendering the methodology of measurement inconsequential. When we examine the original data, we can conclude that, for example, the average temperature for the month of May in Mostar was 25.2 °C in 1994, and it had already decreased to 22.1 °C by 1996. Notably, in the year 2003, there was a substantial increase with the average May temperature reaching 28.3 °C, while in 2004, it dropped significantly to 20.8 °C. Nevertheless, the average temperature in September 2003 was


Zenica May (1991-2022), T(blue)-10, a3 red
time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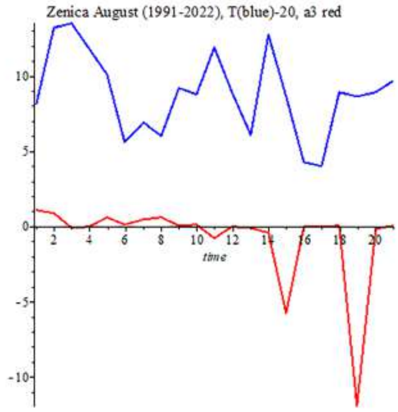
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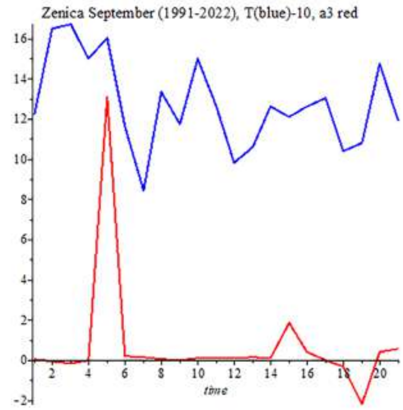
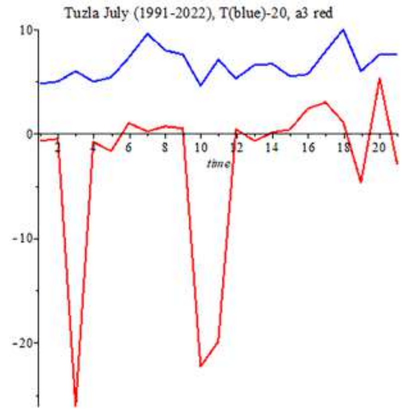

Zenica September (1991-2022), T(blue)-10, a3 red
time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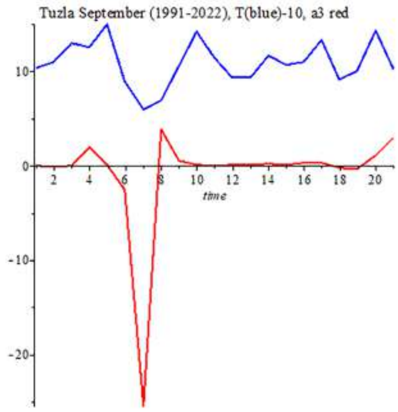
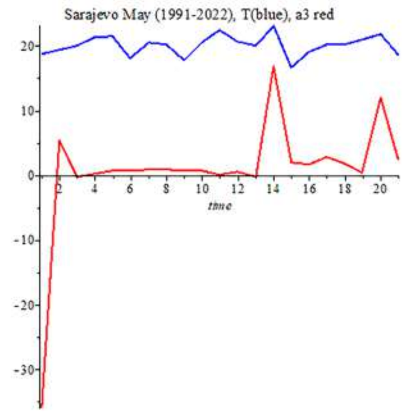
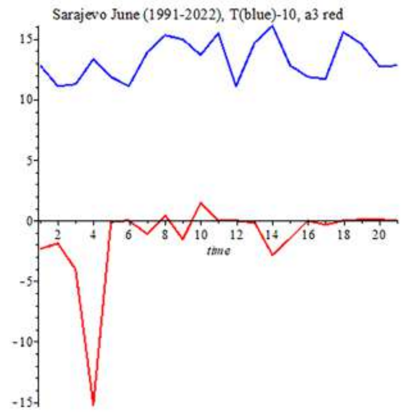
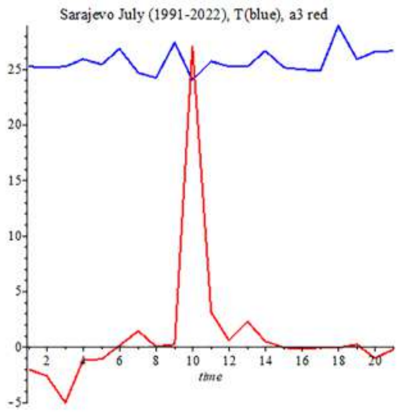
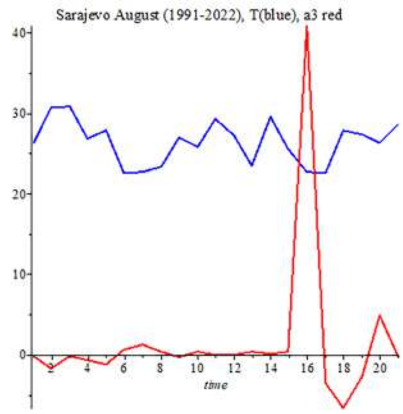
time

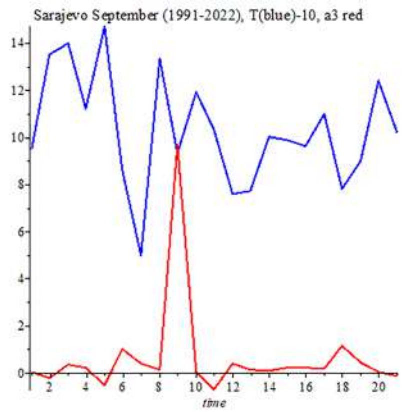

Tuzla September (1991-2022), T(blue)-10, a3 red
time

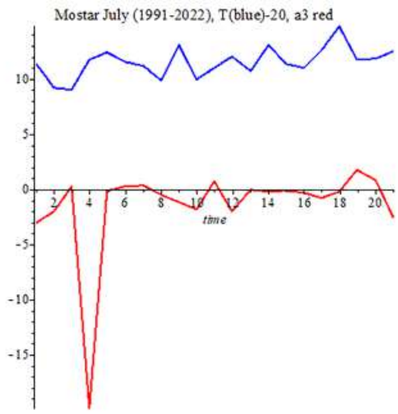

Sarajevo May (1991-2022), T(blue), a3 red
time


Sarajevo June (1991-2022), T(blue)-10, a3 red
time


Sarajevo July (1991-2022), T(blue), a3 red
time


Sarajevo August (1991-2022), T(blue), a3 red
time


Sarajevo September (1991-2022), T(blue)-10, a3 red
time


Mostar July (1991-2022), T(blue)-20, a3 red
time

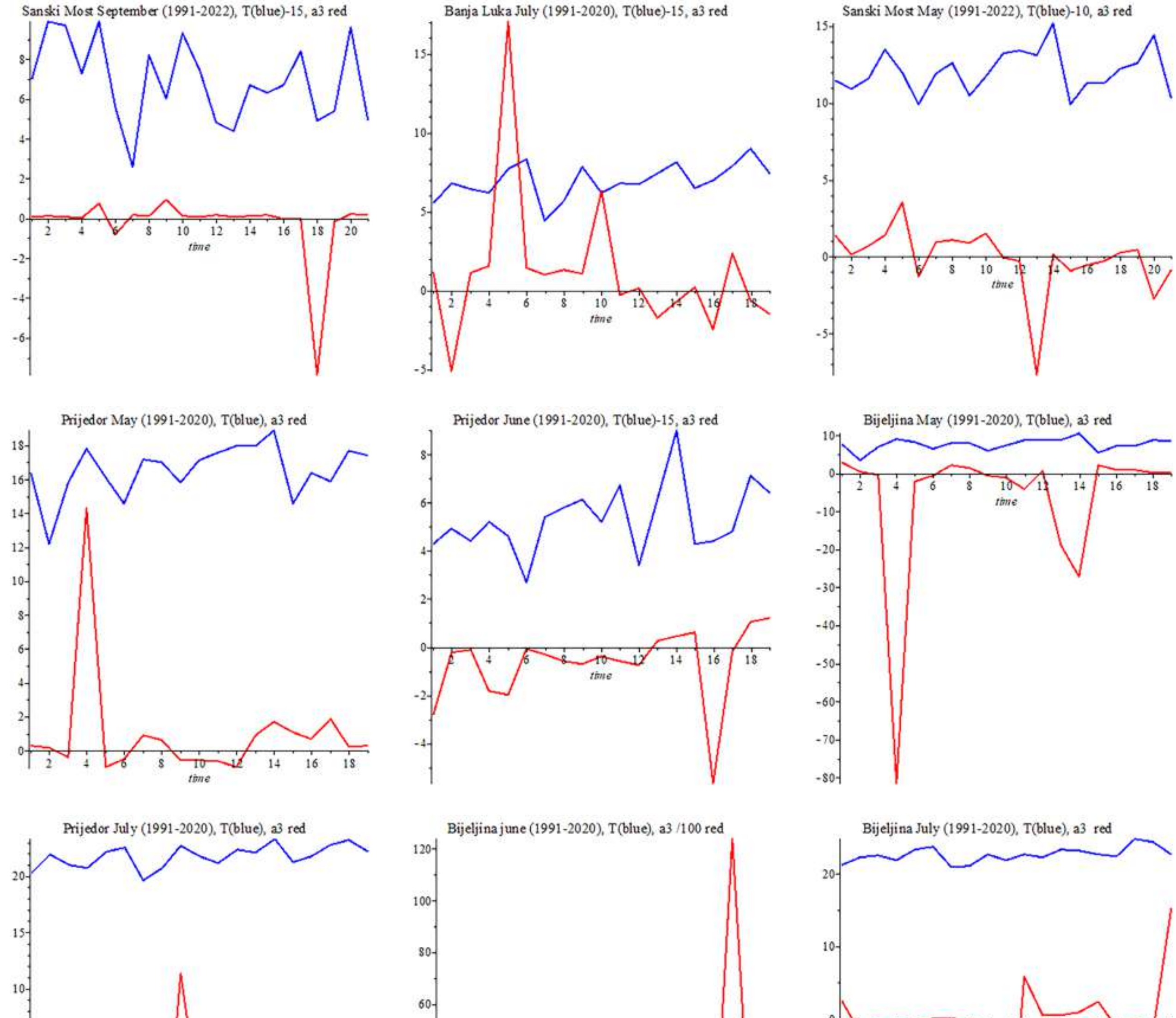


Figure 3. *Graphical representations of results for specific cities: Average temperature blue, parameter* a_3 *red*

0.3 degrees lower than that of September 2004. Upon reviewing the additional data, it can be confirmed that it aligns with the results obtained through this method. There is a strong likelihood that the average temperature for a specific month will be higher, corresponding to the peak of the a_3 parameter, while the subsequent month's temperature may fall below the monthly average. Consequently, we might experience above-average temperatures in May in the future for Sarajevo, with June being colder than the average. Similarly, in the case of Bijeljina, a warmer June but a cooler July could be anticipated.

4. CONCLUSION

The paper provides calculated values for the temperature trend for several cities in Bosnia and Herzegovina. When examining the original temperature data, it becomes evident that substantial fluctuations in average monthly temperatures for specific cities occurred even in preceding periods. Concluding a consistent trend of constant temperature increase is unwarranted, as revealed by the outcomes of this analysis. It is quite plausible that in the near future, the average temperature for a particular month could be below average, while the subsequent month might experience temperatures higher than the average. At the end, it should be noted that importance of this approach lies not in providing a detailed prediction of the temperature trend and the climate system, but in the fact that it allows the application of the laws of physics to a non-mechanical system. This enables us to gain a better understanding of the system itself.

5. REFERENCES

[1] Chanh Kieu, Richard Rotunno, Characteristics of Tropical-Cyclone Turbulence and Intensity Predictability, Geophysical Research Letter, 49,8, 2022

[2] Goldhirsch, I., Sulem, P. L., & Orszag, S. A. (1987). Stability and Lyapunov stability of dynamical systems: A differential approach and a numerical method. *Physica*, 27D, 311– 337

[3] Durran, D. R., Reinecke, P. A., & Doyle, J. D. (2013). Large-scale errors and mesoscale predictability in Pacific northwest snow-storms. *Journal of the Atmospheric Sciences*, 70, 1470– 1487.

[4] Judt, F. (2018). Insights into atmospheric predictability through global convection-permitting model simulations. *Journal of the Atmospheric Sciences*, 75(5), 1477– 1497.

[5] Plamer T., Stevens B., 2019, The scientific challenge of understanding and estimating climate change, *PNAS*, Vol. 116, 49, 24390-24395

[6] Goosse H., P.Y. Barriat, W. Lefebvre, M.F. Loutre, and V. Zunz (2010). Introduction to climate dynamics and climate modeling. Online textbook available at http://www.climate.be/textbook.

[7] Z. Rajilić, N. Stupar, T. Vujičić and S. Lekić, *Emergence of ordered motion of the oscillator driven by fluctuating force*, Contemporary Materials, Vol. 11 (2020) 122–127

[8] Rajilić Z., Stupar N., Malivuk Gak D., 2021, Mechanical Analysis of the S&P 500 Index Time Series, Journal of Physics: Conference Series, 1814 01204

[9] https://www.fhmzbih.gov.ba/latinica/index.php

[10] https://rhmzrs.com

ДРУГИ ЊУТНОВ ЗАКОН У СЛУЖБИ КЛИМАТСКИХ ПРОМЈЕНА – АНАЛИЗА ТЕМПЕРАТУРСКИХ ТРЕНДОВА

Сажетак: Представљен је нови приступ коришћења Другог Њутновог закона у анализи немеханичког система. Уведена је сила која задовољава Други Њутнов закон, гдје се реалне временске серије просјечних мјесечних температура трансформишу у временски зависне параметре силе. Сила дјелује на тачку у простору података. Овај начин анализе података може се сматрати једном врстом филтрирања података. Екстремне вриједности појединих параметара силе анализиране су као могући предиктори настанка температурског тренда. Параметри силе израчунати су на основу вриједности просјечних мјесечних температура за поједине градове на територији Босне и Херцеговине. Дат је преглед и дискусија о могућим промјенама вриједности просјечних температура за одређене мјесеце у будућности, на основу вриједности добијених параметара силе.

Кључне ријечи: Други Њутнов закон, климатске промјене, температура.

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