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Research article

Analysis and numerical simulation of temperature measurements made on earth and from space

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A R T I C L E I N F O

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A B S T R A C T

The sum of all currently known facts confirms the existence of a global warming process. The development models of this process are statistical in nature and often do not take into account the specifics of local conditions. This fact confirms our analysis of measurements of the average annual surface air temperature during the period 1980–2019 in the city of Krasnodar (Russia). We used data from ground based (World Data Center) and space based (POWER project) measurements. A comparison of the data showed that the discrepancies in ground and space based measurements of surface air temperatures until 1990 do not exceed the data error ($s = \pm 0.7$ °C). After 1990, the most significant short-term discrepancies were observed in 2014 (−1.12°C) and 2016 (1.33°C). An analysis of the forecast model of the Earth's surface air average annual temperature for 1918–2020 indicates a gradual decrease in the average annual temperature even in the presence of short-term impulses of its increase. The rate of decrease in the average annual temperature from ground based observations is slightly higher than from space based observations, which is probably due to a more complete consideration of local conditions in ground based observations.

1. Introduction

All life on Earth and its future conditions directly depend on the intensity of the incoming integrated flow of energy emitted by the Sun - the so-called astronomical solar constant [1]. Possible changes in climatic parameters are predicted using appropriate models, that, due to unresolved issues in the study of the causes of changes in the rotation speed of the Earth, the mechanism of solar terrestrial interactions, the ocean, atmosphere, and processes inside the Earth, are statistical in nature and need to be refined using ground and space based observations. In this regard, the task of measuring and preparing high quality local data arrays necessary for studying climatic conditions, as well as developing methods for analyzing them and interpreting trends in their changes over long periods of time, is of paramount importance.

The sum of all currently known facts confirming the existence of the global warming process and the prospects for the development of this process are the subject of numerous publications summarized in regular reports of the inter-governmental group of experts on climate change - IPCC [2, https://www.ipcc.ch]. Nevertheless, in order to speak confidently about global warming, it is necessary to follow global changes in the temperature of surface air, since the temperature on our planet has experienced and is experiencing significant fluctuations, both in time and in space [3]. And in order to confidently record the warming, such measurements must be carried out continuously for several hundred years.

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There are a number of works suggesting the existence of mechanisms that enhance the effect of solar activity, that are not taken into account in modern models, or that the importance of solar activity in comparison with other factors is underestimated. The work by Laut Pete [4] provides arguments in favor of the relationship between changes in the rotation speed of the Sun, bursts of X-ray energy and momentum in the irregular motion of the Sun around the barycenter of the planetary system. It is assumed that these pulses are associated with the secular cycle of solar activity and deviations such as the Maunder minimum plus pulses in geomagnetic activity [5]. Currently, the Sun is experiencing one of the deepest solar lows of the space age. There were no sunspots for most of 2018, and solar ultraviolet output fell sharply. New studies show that the Earth's upper atmosphere responds to these changes [6].

Climate changes occur gradually over millennia and are accompanied by cyclical temperature fluctuations at individual intervals, the intensity of which increases with the manifestation of extreme endogenous and exogenous activity in the Earth system [7,8,9]. Currently, there is no strict theory of the generation and interaction of cycles in the solar system [10,11]. At the same time, solar cycles affect energy changes in global heliogeodynamic cycles [10,12–14]. Stable fluctuations of heliogeophysical and other natural processes are formed inside the solar system during the interaction of gravitational fields of celestial bodies [10,15]. To understand the influence of stellar activity on (exo) planetary systems, we can consider the Sun and the planetary system as the closest and most studied space laboratory and investigate the solar-planetary relationships in it.

The authors of this article previously investigated changes in insolation and temperature in various places in Crimea: coherent fluctuations between individual variations in the data on insolation and surface air temperature, magnetic field parameters, Earth rotation parameters and solar cycles were discovered and established [16,17]. For analysis, space based observations of insolation and air temperature at a height of 2 m were used. The differences we found in the local trends in the increase in insolation and temperature in Crimea, and their differences from global trends prompt us to continue these studies [18]. For analysis, we selected Krasnodar because of the homogeneity and high quality of the time series of ground based observations at this point [19].

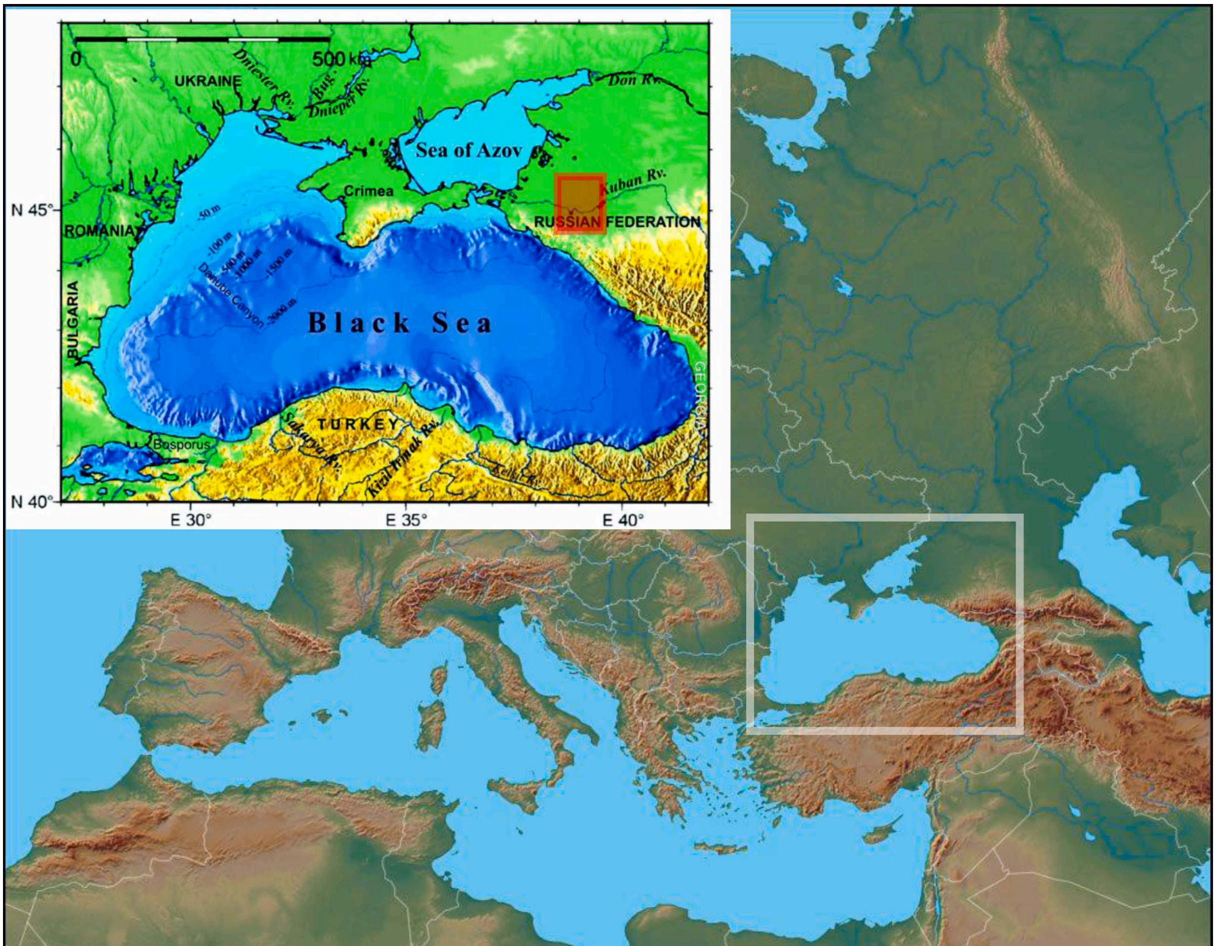

Fig. 1. The study area (red square): the ground Krasnodar station φ = N 45° 03′, λ = E 39° 02'; space observations φ = N 45° ± 0.5°, λ = E 39° ± 0.5° [https://geology.com/world/europe-physical-map.shtml; 30].

2. Analysis methods of ground and space based measurements of surface air temperature

The quality and reliability of the data analyzed have a decisive influence on the formation of our conclusions about the observed process of climate change.

The subject of our analysis is the local time series of temperature. Given the fact that the real temperature changes continuously, any analysis of the relevant time series is possible only as an approximation. In this work, numerical simulation methods are used. These methods belong to the category of statistical ones and are suitable for the analysis of any time series, including climatic ones. Approximation of data by a well-fitted statistical model may reveal uncertainties not accounted for by a structurally more complex model. Of course, achieving a deeper understanding of those causal mechanisms that determine the behavior of individual such series is associated with the analysis of more than one series, since the latter can reflect only one facet of a complex phenomenon.

It is important to find the relationship between temperature from ground- and space-observations. Where this difference is determined, there can be no doubt about its relative stability for a given location. In this case, any local extreme changes can be fixed.

2.1. Ground based observations. The task of preparing high quality data arrays necessary for studying changes in climatic conditions on the territory of Russia is one of the priority tasks within the framework of the scientific and technical target program of Roshydromet in direction 1.3 "Climate Research, its Changes and their Consequences. An Assessment of the Hydrometeorological Regime and Climate Resources". The list of created databases is determined based on the requirements of the Global Climate Observing System, and includes the main climatic parameters, such as air temperature, precipitation, free atmosphere parameters and others.

On the server of VNIIGMI-WDC (The Russian National Scientific Research Institute of Hydrometeorological Information - World Data Center) we obtained access to arrays of average monthly data (http://meteo.ru/data/156-temperature) [19]. Based on these data, the average surface air temperature values from 1981 to 2017 at the Krasnodar station ($\varphi = \text{N } 45^\circ\ 03'$, $\lambda = \text{E } 39^\circ\ 02'$) were calculated (Fig. 1). Discrete statistics of nonnormalized white noise in these data is determined by the parameters: mean $\overline{x} = 0.02$ °C, standard deviation of the random component $s = \pm 0.7$ °C.

2.2. Space based observations. The space-based measurements of surface air temperatures used by us in this work are presented in the form of monthly and yearly averaged values. These measurements obtained within the framework of the POWER (Prediction of Worldwide Energy Resource) Earth Science Research Program.

The POWER project was initiated to improve the current renewable energy dataset and generate new datasets from new satellite systems. The goal of this earth sciences project is to observe, understand and model the earth system in order to learn the laws of its change, better predict the changes and their consequences for life on earth. Satellite systems and surveys, while providing data for the study of climate and climate processes, have proven to be accurate enough (https://eosweb.larc.nasa.gov/sse) to provide reliable data on solar and meteorological resources in regions where surface measurements are rare, insufficiently accurate or absent.

The POWER solar data we use in this work are based on satellite observations, from which surface insolation values are derived at a local point on the Earth. Meteorological parameters are based on the MERRA-2 assimilation model. For more information on satellite assimilation models, see POWER Data Methodology (https://eosweb.larc.nasa.gov/sse/, https://www.ncei.noaa.gov/products, http://www.wdcb.ru, https://data.giss.nasa.gov/gistemp), [20]. A recent (improved) implementation of this program (POWER Release-8) provides data on a global grid with a spatial resolution of 0.5° latitude and 0.5° longitude. The root mean squared error (Root Mean Square Error, RMSE) is calculated as the root mean square difference between the corresponding MERRA-2 values

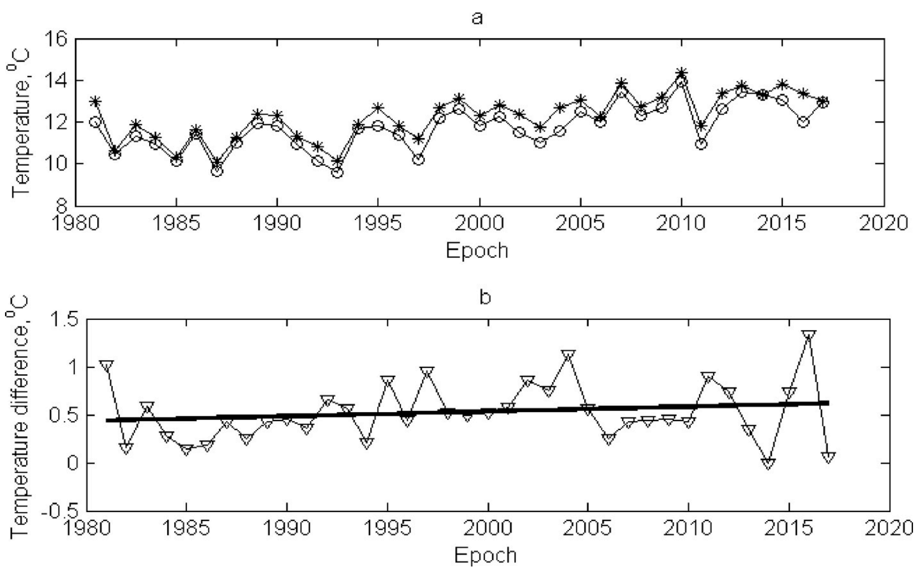

Fig. 2. Comparison of ground and space based observations of surface annual average air temperature at the Krasnodar station (Fig. 2a): - graphs of ground based measurements (asterisks) and space based measurements (circles) (Fig. 2b); - graphs of the differences between ground and space based measurements of surface temperature (triangles) and the linear trend (continuous line). The units of the horizontal axis are 1 year.

(assimilation model) and the observations.

POWER data is available to a wide range of users and free access is provided for scientific purposes. Taking into account the wish of the authors of the POWER project to assess the accuracy of their products by comparing them with ground-based observations, the authors of this paper chose the longest and most accurate time series of ground-based observations at the Krasnodar site. The discrete statistics of nonnormalized white noise calculated by us in the annual average surface temperature data in Krasnodar (Fig. 1) is: mean $\overline{x} = 0.02$ °C, standard deviation of the random component $s = \pm 0.7$ °C.

For analysis and construction of numerical models, comparison of the ground and space based average annual data on surface air temperature at Krasnodar station shown in Fig. 2.

The graphs (a, b) of ground and space based observations of surface annual average air temperature at Krasnodar station shown in Fig. 2 demonstrate good convergence of these two measurement methods. The linear trend graph (Fig. 2b) has a non-significant slope. Its mathematical description has the form

$$ftr(x) = p_1 x + p_2 \tag{1}$$

where x – timing intervals, the coefficients (with 95% confidence intervals - the range of values within which coefficients are likely to be 95%) in °C units are: $p_1 = 0.00496$ (-0.004489, 0.01441), $p_2 = 0.4319$ (0.2259, 0.6378).

In expression (Eq. (1)), the coefficient p_2 is equal to the magnitude of the constant shift between ground and space based temperature measurements.

2.1. Wavelet data conversion. The presence of sharp pulses in the sequence of surface air temperature measurements (and they are usually unpredictable and associated with extreme events on the earth, the sun and in space), it is important to identify their magnitude against the background of a smooth process of temperature change

In our analysis, the non-linear trend in surface air temperature change was obtained using wavelet transform of the data. The wavelet analysis method is indispensable in the case of uneven changes in the spatiotemporal parameters of the analyzed process and the presence of pulses in the converted data.

The choice of an appropriate family of wavelets for the wavelet transform procedure was carried out by us both empirically and taking into account the wavelet properties that provide the best approximation of the data.

We chose wavelets from the DMeyer family as a result of a preliminary analysis of the properties of suitable wavelets [21].

The main properties of *dmey* wavelets from the DMeyer family are: providing orthogonal and biorthogonal analysis and the possibility of continuous and discrete wavelet transforms. The corresponding wavelet function *dmey* and the scaling function are [22]:

$$\widehat{\psi}(\omega) = (2\pi)^{-1/2} e^{i\omega/2} \sin(\pi\nu / 2(3 / 2\pi|\omega| - 1)) \text{ if } 2\pi / 3 \leq |\omega| \leq 4\pi / 3$$

$$\widehat{\psi}(\omega) = (2\pi)^{-1/2} e^{i\omega/2} \cos(\pi\nu / 2(3 / 4\pi|\omega|) - 1) \text{ if } 4\pi / 3 \leq |\omega| \leq 8\pi / 3 \tag{2}$$

where $\nu(a) = a^4(35 - 84a + 70a^2 - 20a^3)$, $a \in [0, 1]$

$$\widehat{\varphi}(\omega) = (2\pi)^{-1/2} \text{ if } |\omega| \leq 2\pi / 3$$

$$\widehat{\varphi}(\omega) = (2\pi)^{1/2} \cos(\pi\nu / 2(3 / 2\pi|\omega| - 1)), \text{if } 2\pi / 3 \leq |\omega| \leq 4\pi / 3 \tag{3}$$

$$\widehat{\varphi}(\omega) = 0, \text{if } |\omega| > 4\pi/3.$$

In the given mathematical descriptions (Eq. (2)) and (Eq. (3)), the parameter ν is an auxiliary function, changing it allows us to obtain the various wavelets of the family.

2.4. The method of constructing numerical models. When constructing a numerical model, the following facts were taken into account: the currently existing multiparameter models describe some averaged global process of temperature change; local trends in temperature changes do not always coincide with global trends, especially over short time intervals; at the same time, extreme deviations from a smooth trend existing at short time intervals are often unpredictable and make different energetic contributions to changes in local temperature depending on the time and location of the observation point.

The limited size of the data sample and insufficient knowledge about the a priori model of the distribution of measurement errors determine the choice of simple numerical models. When choosing the type of model, its implementation and calculating estimates of the approximation accuracy of the analyzed data, we used the recommendations and programs in the field of mathematical software MATLAB.

Our analysis of discrete time series and the method of numerical modeling belong to the category of statistical ones, which are suitable for the analysis of any one-dimensional discrete time series, including climatic ones.

Of course, the ultimate goal of any analysis is a deeper understanding of the causal mechanisms that determine the behavior of individual such series, which is associated with the analysis of more than one series, since the latter reflects only one facet of a complex phenomenon (for example, a global temperature change). Nevertheless, we can assume that our model is only part of a structurally more complex system and " … this approach does not entail any logical inconsistency" [23].

The smooth curves obtained using the wavelet transform are described by us with a numerical nonlinear model [24]. The most accurate approximation was obtained using the Fourier series. In this case, the construction of the model refers to nonlinear least squares algorithms. Nonlinear models are more difficult to implement than linear ones since coefficients cannot be estimated using simple matrix methods. Instead, an iterative approach is required.

In this work, the choice of the model most suitable for approximating our data was made by comparing the quality of approximation with the following models: "Polynomial", "Fourier", "Gaussian", "Sum of sines".

The order of the model and the quality of data fitting were determined by an iterative method of comparing the degree of agreement: SSE (sum of squared errors), SSE is the sum of squared differences between each observation and its group mean; R-squared is a statistical measure that represents the proportion of variance for the dependent variable, which is explained by the independent variable or variables in the regression model; the adjusted R-square is a modified version of the R-square that has been adjusted for the number of predictors in the model, and RMSE (Root Mean Square Error) is the standard deviation of the residuals (prediction errors). In other words, it tells you how concentrated the data is around the line of best fit. Root mean square error is commonly used in climatology, forecasting and regression analysis to test experimental results.

3. Results

3.1 Wavelet analysis. Fluctuations in the mean annual surface temperature are unsteady. Such non-stationary processes require space-time analysis. At the same time, smoothing over 5 years by the moving average method, adopted in the practice of analyzing such natural observation series, smoothes out short-term temperature pulses and shifts their localization in time (see Fig. 3). The wavelet analysis we use allows us to analyze the pulses in the data with respect to a smooth non-linear trend without changing their location and magnitude (Fig. 3).

To study the spectral composition of data on the average annual surface air temperature, the method of frequency-time wavelet transform was used.

Results of continuous frequency-time wavelet transform of space measurements of mean annual air temperature at a height of 2 m for the period 1981–2020 presented in Fig. 4. The main frequency composition of the analyzed data is seasonal fluctuations, the power of which varies at different time intervals (see the color indicator on the right). However, the main frequency content is stable, which makes it possible to predict these fluctuations.

3.2. The numerical model. We construct a numerical model of the long-period trend (Fig. 3) as the sum of the three harmonics of the Fourier series. The mathematical description of this model corresponds to the best estimates of the quality of the nonlinear trend approximation and has the form (Eq. (4)):

$$f(x) = a_0 + \sum_{1=i}^{3} (a_i \cos(i\nu x) + b_i \sin(i\nu x)) \tag{4}$$

where x is the time interval counted in years from the beginning of the simulated time series; i – is the number of harmonics, ν – the main frequency, corresponds to the period of 60.18 years.

The coefficients (with 95% confidence intervals) calculated from ground-based observations in °C units are (Eq. (5)):

$$a_0 = 12.04\ (11.83, 12.26)$$

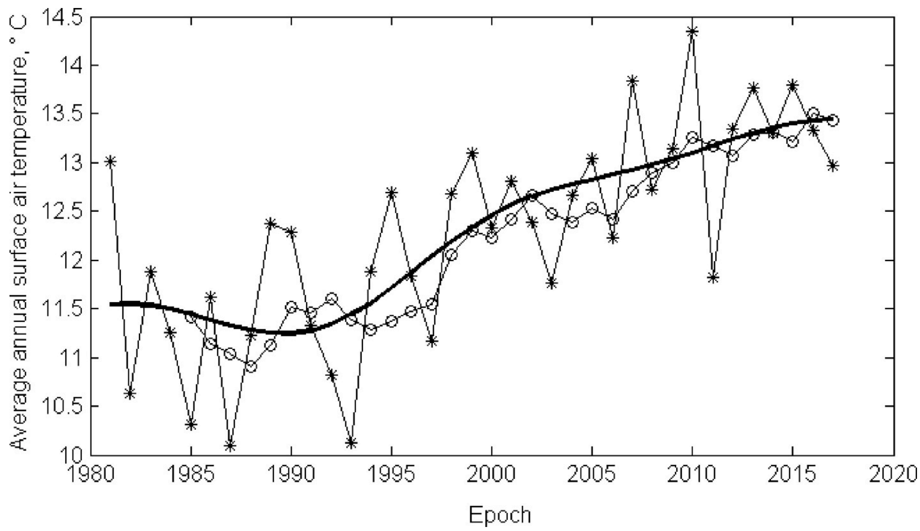

Fig. 3. Graphs of data on the surface average annual air temperature at the Krasnodar station: initial ground based observations (marked with asterisks); values smoothed by the moving average method over 5-year intervals (marked by circles); the solid curve is a smooth nonlinear trend, obtained using the wavelet transform of the initial data. The units of the horizontal axis are 1 year.

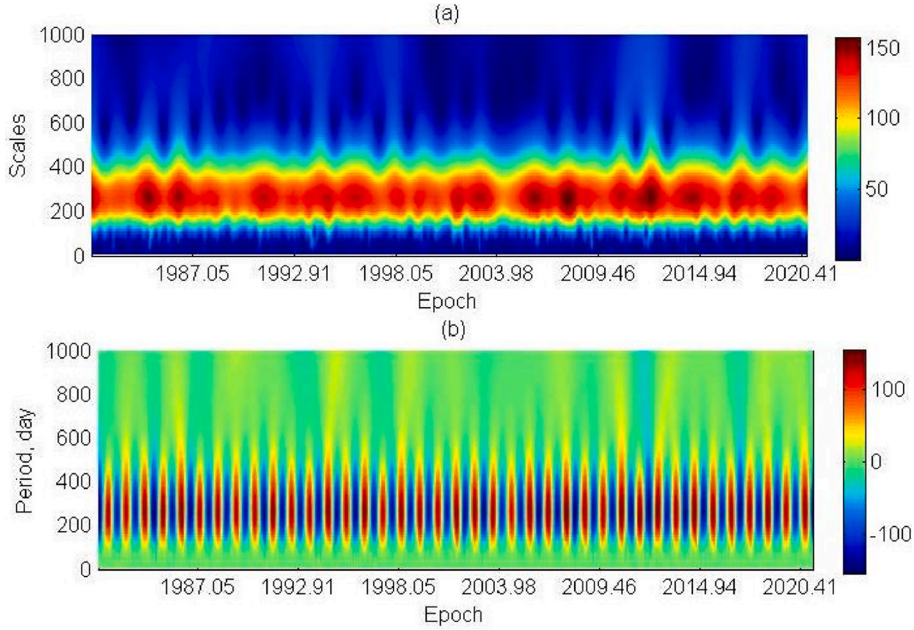

Fig. 4. (Fig. 4a). - continuous wavelet transform (Fig. 4b), - time-frequency analysis with CWT. 'Paul' wavelets. On the right is a colored energy indicator. The units of the horizontal axis are 1 year.

$$
\begin{aligned}
a_1 &= -1.108\ (-1.289,\ -0.9273)\\
a_1 &= -0.06834\ (-0.5709, 0.4342)\\
a_2 &= 0.2561\ (-0.01327, 0.5254)\\
a_2 &= 0.2986\ (0.1702, 0.427)\\
a_3 &= 0.3104\ (0.2164, 0.4044)\\
a_3 &= 0.001608\ (-0.138, 0.1413)
\end{aligned}
\tag{5}
$$

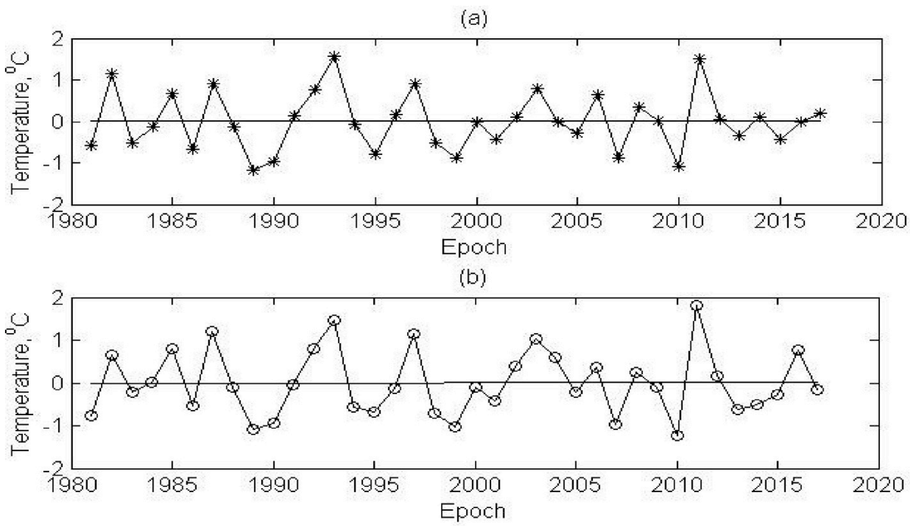

Fig. 5. Deviations of ground (Fig. 5a) and space (Fig. 5b) based measurements of the average annual surface air temperature at Krasnodar station from the numerical model (Eq. (4)).

$v = 0.1044\ (0.09735, 0.1114)$

Where a_0 is a permanent member; v– the frequency of the main harmonic corresponds to a period of 60.18 years. Estimates of the accuracy of approximation of the nonlinear trend by this model: R -square is 1; the standard error (*RMSE*) is $\pm 6.358 \times 10^{-5}$ °C.

A similar numerical model was obtained for space-based measurements of average annual temperatures at Krasnodar station.

3.3. Analysis of the deviations of the initial data from the model. The graph of the deviations of the initial data from the model is shown

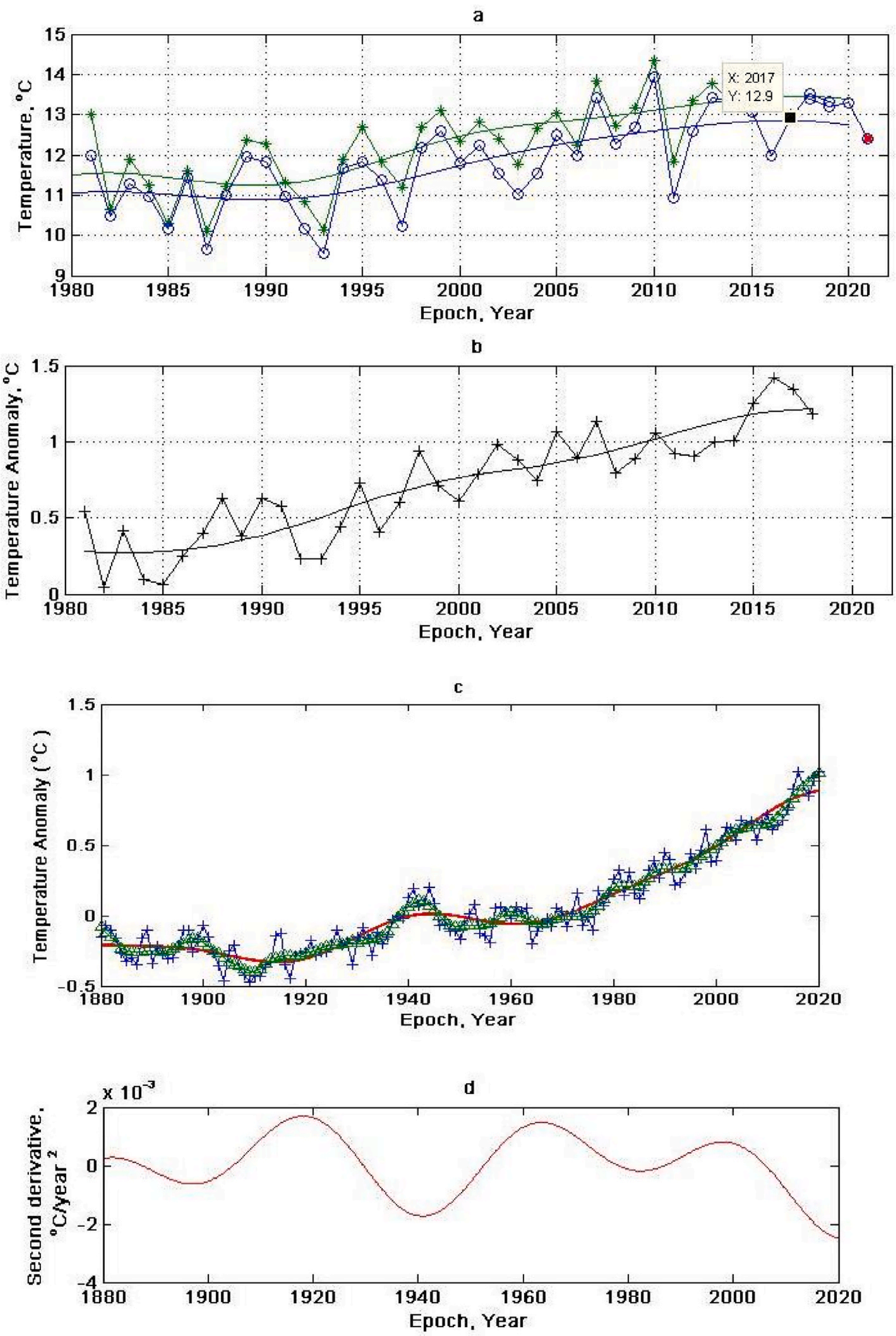

Fig. 6. The graphs show (Fig. 6a): – ground (green) and space (blue) measurements and (Fig. 6b) – Global Land – Ocean Temperature Index (1980–2020); continuous curves represent smooth, non-linear trends. After 2017 (Fig. 6a), a forecast of long-term trends and real observations is presented (Fig. 6c); – Global Land – Ocean Temperature Index (1880–2020): Annual Mean (+), 5-year Running Mean (green), fitted curve (red) (Fig. 6d); – Second Derivative (fitted curve).

in Fig. 5. Discrete statistics of the deviation vector are equal: mean = - 0.0035 °C, standard error = ± 0.73 °C.

We will carry out statistical testing in order to verify the null hypothesis that the array of differences (see Fig. 5) belongs to a sample with a standard normal distribution. The results of statistical testing (null hypothesis: the analyzed temperature differences are based on a standard normal distribution) using the Kolmogorov-Smirnov tests [25] and the Lillifors test [26] support the null hypothesis. This means that in the period 1981–2017, the deviations of the surface temperature measurements from the numerical model do not contain a systematic component.

3.4. Possible forecast based on numerical models. Our forecast defines a long-term smooth trend of temperature change and does not take into account jumps caused by the influence of short-term external and terrestrial energy phenomena on the atmosphere, both of global and local origin.

The graphs of smooth long-term trends (see Fig. 6a) are calculated based on data for the period 1981–2017. After 2017, the forecast (red dot) for the next two years and real observations for these years are given.

Since the time series we are analyzing have a limited duration, the models of the identified long-term trends may turn out to be only part of a certain long-term oscillatory process (Fig. 6a,b).

Some information on causal relationships can be obtained by comparing two time series of satellite observations (SSE) in Krasnodar: air temperature at a height of 2 m and total insolation falling on the earth's surface in Krasnodar from 1983 to 2019.

The assumption about the influence of All Sky insolation on Air temperature at a height of 2 m confirms the high correlation coefficient (R = 0.88) between the nonlinear trends in Fig. 7a,b. Moreover, the maximum value of All Sky insolation is ahead of the maximum value of Air temperature at a height of 2 m by ~3 years.

4. Discussion

Climate changes occur gradually over millennia and are accompanied by cyclical temperature fluctuations at individual intervals, the intensity of which increases with the manifestation of extreme endogenous and exogenous activity in the Earth system [3,10,14,15,27].

Uncertainty in climate projections is a result of natural variability and uncertainty about future emission rates and climate responses. They may also be due to the fact that the representation in the models of some known processes is still imperfect, and some

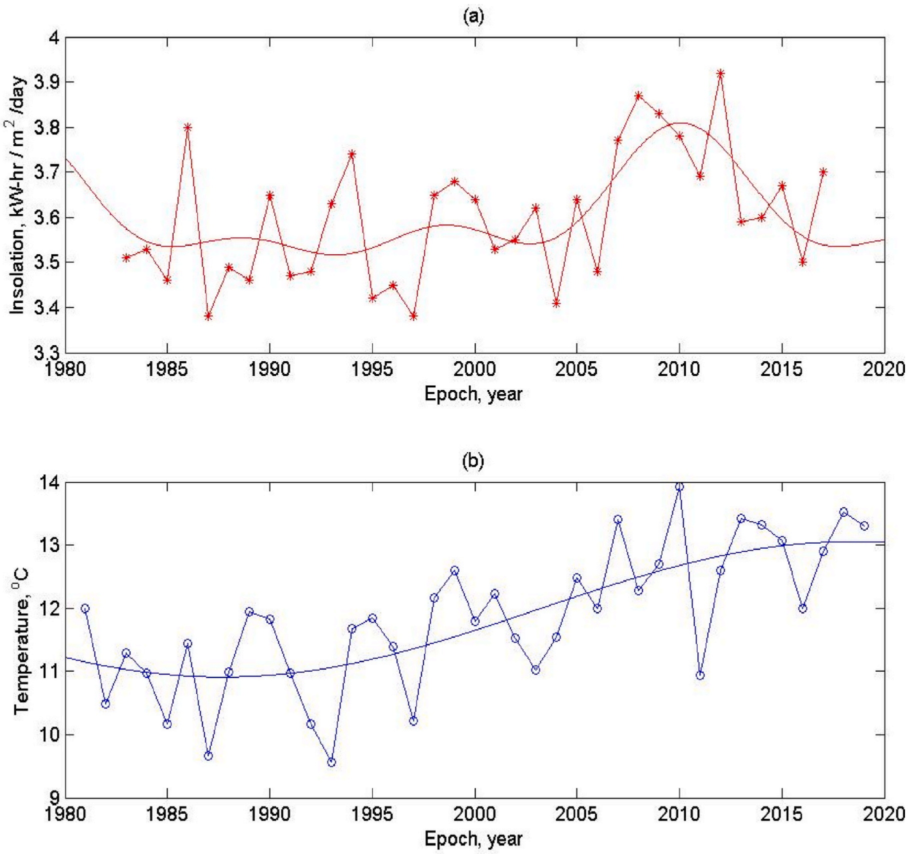

Fig. 7. The graphs of average annual satellite measurements and long-term trends are given (Fig. 7a): – All Sky insolation on a horizontal surface (1983–2019) and (Fig. 7b) - Air temperature at a height of 2 m (1981–2019) at Krasnodar station.

processes are not taken into account in the models.

Natural variability has a greater impact on uncertainty at regional and local scales than at continental or global scales. This is inherent in the Earth system and increasing knowledge will not eliminate the associated uncertainty. However, some progress is possible, especially for projections up to several years ahead that use advances in knowledge of, for example, states and processes in the cryosphere or ocean. This is an area of active research. The complexity of the Earth system means that in the future, the climate can evolve in many different scenarios and still be consistent with current understanding and models. As the observation period lengthens and models improve, researchers are able to narrow down, within the range of natural variability, this interval in terms of likely temperature over the next few years and even decades.

The solution of these problems is connected with the development and accuracy of satellite observations. The expansion of the coverage areas of these observations contributes to the refinement of regional and local climatic conditions. So in the work [28] examines the reliability of air temperature data obtained from the European Remote Sensing 5 (ERA5) satellite. The results show that satellite temperature performs better in the temperate region than in the tropics. This suggests that the time of year and climate region affect the accuracy of satellite data, as milder temperatures give better approximations.

Variations in average annual surface air temperature are pulsed. Unsteady processes of this kind require spatiotemporal analysis. In this case, smoothing over 5 years by the moving average method, accepted in the practice of analyzing such natural series of observations, smooths out short-term temperature jumps and shifts their localization in time (see Fig. 3).

A comparison of ground and space based measurements, the creation of numerical models and the study of trends in local temperature changes contributes to the creation of a forecast of its changes for the coming years. This forecast may differ from the global one, but may be more reliable and useful for this location. To build numerical models of changes in climate parameters in a single location, both ground and space based observations are needed.

Methods for building statistical models are based on existing rules [23]. Nevertheless, the choice of the function approximating the observation depends on a priori information about the spectral composition of the data (in our case, the presence of seasonal fluctuations). In Ref. [29] develop a Seasonal Auto-regressive Integrated Moving Average (SARIMA) model based on a greedy algorithm for forecasting the monthly average temperature via ground-based data.

This model performs well in long-term average monthly forecasting. An exponential smoothing based method for accurate temperature prediction using historical values is proposed by Ref. [29].

Against the background of long-term stable fluctuations generated by astronomical global cycles, sharp changes and deviations from stationary in continuous series of observations of climatic and geophysical characteristics can serve as a signal of environmentally unfavorable events.

In this case, the analysis of long series of measurements of air temperature at various points on the Earth's surface contributes to the establishment of global cause and effect relationships.

5. Conclusion

The main motivation for this work is as follows:

- satellite observations covering the entire globe can provide reliable information on local surface temperatures even in the absence of ground observation stations above the ocean level;
- local forecast does not always coincide with the global one;
- local numerical models of climatic parameters and short-term forecasts built on their basis can be more useful than global ones for solving immediate local economic problems.

1. Temporal averaging in the analysis of observations allows one to distinguish long-term fluctuations, ignoring the effect of short-term variations and single emissions, that can be considered separately and their prediction is often impossible due to a lack of knowledge about the phenomena that generate them. Fluctuations in average annual temperature are spasmodic. Unsteady processes of this kind require spatiotemporal analysis. In this case, smoothing over 5 years by the moving average method, accepted in the practice of analyzing such natural series of observations, smooths out short-term temperature jumps and shifts their localization in time (see Fig. 3).
2. In this paper, it is proposed to use the wavelet analysis method at the stage of identifying long-term fluctuations, taking into account the non-stationarity of the process of changing data.
3. An analysis of deviations of the measured surface air temperatures from model (Eq. (3)) does not reveal a long-term systematic component.
4. Analysis of the forecast of long-term trends in the mean annual surface temperature indicates a gradual decrease in the growth rates of the mean annual surface air temperature even in the presence of short-term jumps (see Fig. 6d).
5. The analysis of the discrete time series considered in this work is possible only as an approximation. However, we can assume that a well-chosen model is part of a more structurally complex model and, taking into account rapidly changing local conditions, complements it. The quality and duration of the forecast, in this case, depends on the completeness of the information presented by the measurements on which the numerical models were built.
6. Comparison of ground and satellite measurements showed their good convergence in the studied time interval at the Krasnodar station.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Data is available through the electronic resource: https://eosweb.larc.nasa.gov, https://www.ncei.noaa.gov, http://www.wdcb.ru, https://data.giss.nasa.gov, http://meteo.ru.

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