RESEARCH PAPER

SURFACE URBAN HEAT ISLAND IN MOSCOW DURING THE COVID-19 PANDEMIC LOCKDOWN IN 2020

Mikhail A. Lokoshchenko[1,2*] and Eugeniya A. Enukova[3]
[1]Lomonosov Moscow State University (MSU), Faculty of Geography, Department of Meteorology and Climatology. Lengory 1, Moscow, 119991, Russian Federation
[2]Obukhov Institute of Atmospheric Physics, Russian Academy of Sciences, Pyzhyovskiy pereulok, 3, Moscow, 119017, Russian Federation
[3]'Dubna' State University, Department of Ecology and Earth Sciences. Universitetskaya str. 19, Dubna, Moscow region, 141980, Russian Federation
*Corresponding author: loko@geogr.msu.su
Received: October 10th, 2021 / Accepted: November 11th, 2022 / Published: December 31st, 2022
https://DOI-10.24057/2071-9388-2021-116

ABSTRACT. The influence of the COronaVIrus Disease 2019 (COVID-19) pandemic lockdown (the period of strict quarantine measures) in the spring of 2020 on the 'Surface Urban Heat Island' (SUHI) geographical phenomenon in Moscow has been studied. For this purpose, we used the measurements of the surface temperature T_S made by Moderate Resolution Imaging Spectroradiometer (MODIS) radiometer installed on Terra and Aqua satellites. As a result, T_S during the 2020 lockdown, both in the city and surrounding rural zone, was found lower than at the same calendar time in the previous 20 years due to the relatively cold spring.

The SUHI intensity as the difference between T_S inside Moscow and the surrounding rural zone around it during the lockdown was also lower than usual (on average in the previous 20 years), but this decrease is relatively small and non-significant. The Normalized Difference Vegetation Index (NDVI) in Moscow and Moscow region during the lockdown was close to its usual values, but the leaf area index (LAI) was significantly lower than its average values in the previous 20 years. Thus, the weakening of the SUHI during the lockdown in 2020 was caused mostly by lower heat loss due to transpiration in the rural zone. This was associated with the slowdown in vegetation development as a result of the cold spring. Besides, an additional possible reason was the reduction of human activity due to the collapse of many anthropogenic heat sources in the city.

According to long-term MODIS data, the SUHI intensity in Moscow and the surface temperature in Moscow region, as well as the NDVI and LAI values, do not demonstrate statistically significant long-term trends in the spring season over the past 21 years, despite climate changes.

In spring, during faster snow melting in cities, when it still persists in the rural zone, the SUHI intensity can be record high (up to 8 °C).

KEYWORDS: satellite data, surface temperature, surface urban heat island, SUHI intensity, COVID-19 pandemic lockdown, NDVI, LAI, vegetation, snow cover

CITATION: Lokoshchenko M.A., Enukova E.A (2022). Surface Urban Heat Island In Moscow During The COID-19 Pandemic Lockdown In 2020. Geography, Environment, Sustainability, 4(15), 134-144
https://DOI-10.24057/2071-9388-2021-116

ACKNOWLEDGEMENTS: The authors are grateful to Dr. M.V.Zimin and his colleagues from ScanEx Engineering and Technology Center for their help with the software and to Dr. O.V.Tutubalina for her useful advices. This work was supported by the Russian Science Foundation (Project 21-17-00210).

Conflict of interests: The authors reported no potential conflict of interest.

INTRODUCTION

As it is known, at the beginning of 2020, the terrible COVID-19 pandemic quickly spread around the world and caused many dramatic changes in both humankind and natural processes. Studies of the influence of COVID-19 on different geographical phenomena were collected, e.g., at the special issue of GES Journal in Vol. 14, No. 4, 2021 (https://ges.rgo.ru/jour/search/sections/30). Quarantine measures, including self-isolation of people in their houses, were implemented for the first time in most countries in the spring and summer 2020 (later, during the second wave of the pandemic in the autumn of 2020, they were again implemented in many countries, but not in the Russian Federation). As a result, human activity sharply slowed down, including industry, transport, energy sector, etc. The most evident influence of quarantine periods on the geographic envelope is a strong reduction of air pollution, e.g., in Moscow (Ginzburg et al. 2020); in eight cities of Pakistan (Ali et al. 2021); in various locations, especially in small cities in the Middle East (El Kenawy et al. 2021). However, it should also be noted that specific weather conditions (calm and frequent inversions in anticyclones) lead to an increase in air pollution even during quarantine (Ginzburg et al. 2020). Among other things, the influence of the pandemic also led to the weakening of urban heat islands (UHI) in the surface air layer, e.g., in Moscow, according to Lokoshchenko and Alekseeva (2022). Possible reasons for this effect are the decrease of direct anthropogenic heat emissions and changes in the radiation balance in cities (weakening or disappearance of urban industrial haze, etc.).

Another phenomenon in urban climatology, besides the UHI, is the so-called 'surface urban heat island' (SUHI), i.e., a thermal anomaly in the surface temperature T_S field. This phenomenon has been studied in different cities of the world using satellite data of radiometric measurements (e.g., Rasul et al. 2015; Esau and Miles 2018; Lokoshchenko and Enukova 2020, etc.). The fundamental problems of satellite data use for urban climatology were discussed (Voogt and Oke 2003). As for Moscow, a comparison of satellite data about SUHI and *in situ* data of weather stations about UHI was carried out (Varentsov et al. 2019; Lokoshchenko and Enukova 2020; etc.). The SUHI is created not only due to the higher air temperature T over the city, but also due to different heat losses of the surface for precipitation evaporation and plants transpiration inside and outside cities. Thus, lower plant density in urban areas and artificial rainfall in cities lead to lower heat losses and, as a result, to a higher urban surface temperature.

Meanwhile, the available data on SUHI in the surface temperature field during the global lockdown in the spring of 2020, according to satellite data, are ambiguous. SUHI weakening was noted in several places. This is in the eight largest cities of Pakistan, according to MODIS data (i.e., data from Aqua and Terra satellites equipped with MODIS radiometer), on average by 20% (Ali et al. 2021), as well as in the cities of the United Arab Emirates (UAE), according to MODIS data, at least at night (Alqasemi et al. 2021). The surface of the urban area of New Delhi in April 2020 during the lockdown, according to MODIS data, was even marked by a strong 'cool island' instead of the usual 'heat island' in the T_S field (Mukherjee and Debnath 2020), just as it was observed in the dry season in Erbil (Rasul et al. 2015). The analysis of T_S in the seven biggest Indian megacities in April 2020 (during the lockdown) from Landsat-8 satellite images was presented (Dhruv Nanda et al. 2021). As a result, T_S in April 2020 was found 0.3÷7.1 ºC lower than in April of the two previous years (2018 and 2019) in urban areas of 6 out of 7 mega-urban agglomerations except for Kolkata. A similar analysis was conducted for the urban agglomeration of Yogyakarta, Indonesia, using the data of the same Landsat-8 satellite (Arrofiqoh and Setyaningrum 2021). It showed that T_S during the lockdown in May 2020 was also lower than before the pandemic and after the lockdown. However, neither Dhruv Nanda et al. (2021), nor Arrofiqoh and Setyaningrum (2021) estimated the SUHI values for Indian and Indonesian cities. In other words, it remains unclear whether T_S decreased only in urban areas or in adjacent rural zones as well.

In contrast to these results, the SUHI of cities in the Indus and Ganges basins, according to satellite data in the spring of 2020, increased by 0.2÷0.4 ºC in the daytime. This was due the delay in the winter crops harvest under the quarantine that led to additional greening of the countryside and, consequently to an increase in heat losses by transpiration (Chakraborty et al. 2021). The study of SUHI across 21 metropolitan areas in the Middle East with the use of MODIS data from Aqua satellite also demonstrates mixed results (El Kenawy et al. 2021). The mean intensity of daytime SUHI during the lockdown (from March to June 2020) in different cities either increased or slightly decreased. The intensity of daytime SUHI in many mega-cities such as Tehran, Ankara and Istanbul, showed anomalous increases of even more than 2 ºC compared to the long-term (2003÷2019) average.

Thus, the impact of the lockdown period on SUHI intensity is ambiguous and can be different depending on meteorological and geographic conditions. The main goal of the authors was to assess the influence of the lockdown on the land surface temperature and SUHI intensity for Moscow. To do this, we calculated the values of both parameters during the lockdown in 2020 and compared them with the values for the same calendar time, averaged over the previous 20 years. Another task was to analyze whether the observed differences are associated with additional heat losses by transpiration.

MATERIAL AND METHODS

We used the data from Terra and Aqua satellites launched in December 1999 and May 2002, respectively. These satellites in a Sun-synchronous orbit at an altitude of about 700 km above the Earth are the part of the so-called Earth Observing System (EOS). The imaging bandwidth of both satellites is 2330 km. They are equipped with MODIS radiometers with 36 channels ranging from 0.45 to 14.36 μm. Among other things, MODIS data provide measurements of the standard Land Surface Temperature parameter (LST, or T_S) by spectral brightness in two channels: 31st and 32nd with the wavelengths of 10.78÷11.28 and 11.77÷12.27 μm, respectively. T_S measurements have spatial resolution of 1 km and an accuracy of ±1 ºC for the land (Steitz et al. 1999). Besides T_S, special algorithms also allow calculating additional parameters from MODIS data, including NDVI, LAI, etc. The data from Terra and Aqua satellite images are available at the link:
https://ladsweb.modaps.eosdis.nasa.gov/archive/allData/61/MYD021KM/

Terra and Aqua fly over Moscow region twice a day with an interval of 1 hour and 50 minutes: in the late morning and early afternoon (from 11 to 12 a.m. and from 1 to 2 p.m. Moscow time, respectively) and at night. However, here we considered only daytime images of both satellites since the quality of their night-time data is worse. At night, especially in winter, Moscow is often located on the edge of the image band, which leads to large distortions. The methodical base of our study is detailed by Lokoshchenko and Enukova (2020).

The SUHI intensity (ΔT_S) was calculated as the mean difference of T_S values for the samples of all urban and rural elementary cells with an area of 1 km²:

$$\Delta T_S = \frac{\sum_{i=1}^{n} T_{U_i}}{n} - \frac{\sum_{j=1}^{m} T_{R_j}}{m} \quad (1)$$

where *n* and *m* are the number of cells in Moscow and Moscow region, respectively; T_U and T_R are surface temperatures in each cell inside the city and in rural zone, respectively. It is known that in 2012, the city territory was declared to be greatly expanded by 2.4 times, but so-called 'new Moscow' is still a rural area with low population density. Moreover, here we analyzed the period from 2000 to 2020. Thus, most of that time Moscow was in its old borders. That is why Moscow city was considered by authors within its traditional borders from 1992 to 2012, when the so-called 'old Moscow' had the shape of a turtle (a simple ellipsoid with six outer prominences); and its area was 1081 km^2. The surrounding rural zone was taken as a rectangle circumscribed around the administrative boundaries of Moscow region, including the entire territory of this region and, in addition, the adjacent districts of neighboring regions. Its area is 94,851 km^2. Evidently, both urban and rural areas are not homogeneous because the former includes urban green spaces, whereas the latter includes small towns in the suburbs outside the city borders (Climate of Moscow 2017).

The main problem with the satellite data in mid-latitudes is frequent cloudiness, which greatly reduces the number of images available for the surface temperature analysis; although recently a new approach has been suggested for the analysis of all-weather satellite data about SUHI. It is based on merging of satellite- and ground-based observational data using reanalysis, which allows indirectly reconstructing the LST under clouds (Yangsiyu Liao et al. 2021). As it is known, clouds and wind speed strongly affect the SUHI intensity (e.g., Morris et al. 2001). As a result, the SUHI is stronger in cloudless and calm conditions in anticyclones (e.g., Półrolniczak et al. 2017). This creates a bias in the SUHI intensity satellite estimations without an additional use of the ground-based data.

A clear sky over the entire Moscow region in strong anticyclonic conditions can be observed in rare cases (on average it is only 3% of the total sample of images). Numerical experiments conducted by the authors demonstrate that the analysis of the SUHI intensity is still possible if clouds cover less than 20% of the urban area and less than a half (50%) of the rural zone around the city. In such conditions the possible bias in the SUHI intensity due to clouds is within ±0.2 of the intensity value, i.e., this deviation is relatively small (Lokoshchenko and Enukova 2020). Thus, all images from both satellites were initially tested for a part of an open area without clouds, and then only the cases when this part exceeded critical values, were accepted for further analysis.

The standard normalized difference vegetation index (NDVI) is a well-known parameter regularly measured by satellites since 1981 (EOS Data Products Handbook 2000). It is determined as the ratio of the difference between reflectivity in the red (where it is lower due to radiation absorption by plants) and the near infrared bands of the spectrum to their sum. NDVI calculations using MODIS data are based on the comparison of two channels: 0.62÷0.67 μm (red) and 0.841÷0.876 μm (near infrared) bands. As it is known, NDVI can vary from -1 to 1, but negative values are associated with snow, ice, water, or artificial surfaces such as concrete and asphalt (https://gis-lab.info/qa/ndvi.html). Above green vegetation, NDVI is usually between 0.2 and 0.8, and values exceeding 0.5 indicate dense vegetation. The global distribution of NDVI is presented, e.g., in EOS Data Products Handbook (2000).

Another important parameter that indirectly indicates surface heat losses by transpiration is the so-called 'Leaf Area Index' (LAI). Various methods are used to determine LAI, including direct measurements. Among other things, satellite indirect LAI data are also calculated using MODIS software (e.g., MOD15A2 as one of Standard MODIS LAI/FPAR products) by special spectral analysis of the detected signal. The methodical basis and verification of the LAI measurements are presented by Wenze Yang et al. (2006). However, this parameter is available only outside urban areas and only on average over eight-day periods.

In general, the sequence of our analysis was as follows: preliminary visual selection of suitable images → their processing in the ScanEx Image program → their testing by the criterion of the highest permissible threshold of clouds cover → calculations of the T_S, SUHI intensity, NDVI and LAI mean values → adding them to databases.

RESULTS AND DISCUSSION

Surface Urban Heat Island in Moscow during lockdown in 2020

Strict quarantine measures (a full lockdown) during the COVID-19 pandemic were implemented in Moscow and other Russian cities only once from March 30 to June 8, 2020. At that time, the entire population had to stay inside their houses, except for the workers of the city emergency services. During these 71 days, only 12 images from both satellites were recorded in clear sky or at least with low cloudiness, which meets our criteria (no less than 80% of the urban area and no less than 50% of the outer comparison zone were open and available for analysis). These images are of April 1 (Terra), April 4 (Aqua), April 9 (Terra), April 22 (Terra), May 1 (Aqua), May 2 (both Terra and Aqua), May 3 (both Terra and Aqua), May 11 (both Terra and Aqua), and June 6.

Evidently, this number (12) is less than the classical statistical sample. Nevertheless, it is still enough for the mean value calculation in the first approximation. To test its reliability, we can use the data about T on weather stations. During the COVID-19 strict lockdown the maximum space UHI intensity as a difference between Moscow centre (Balchug station) and rural zone outside the city (on average of 13 rural weather stations) averaged 1.46 ºC per day over 71 days (Lokoshchenko and Alekseeva 2022). Separate calculation of the same parameter only at noon (the closest reading of T to Aqua and Terra flights) during 71 days showed the value of 0.60 ºC. This is not surprising because, as it is known, the UHI is weaker in the daytime. An additional calculation only at noon of nine clear or low-cloud days, when the satellite images were accepted for our analysis, gives nearly the same UHI intensity, and it is 0.58 ºC. Thus, the mean SUHI intensity reflects reality well and is not biased relative to the value for all days of the lockdown.

For the comparison with the lockdown period in 2020, all images from both satellites were analyzed for the same period (from March 30 to June 8) for the entire duration of their flight from 2000 to 2019, and the SUHI intensity in Moscow was calculated for each image. The total sample of images available for the analysis during 20 years until 2020 is 275. Average values of T_S both in Moscow urban area and in the rural zone are presented in Table 1. As it is evident, firstly, the surface temperature in the spring and early summer of 2020 was lower (by 4.3 ºC in Moscow and by 4.1 ºC in Moscow region) than usual for these seasons. Besides, the SUHI intensity as a difference between them was also lower than usual (2.6 ºC, which is 0.2 ºC lower than the average for the previous 20 years). As it was shown above, the SUHI weakening during the global lockdown was observed in many cities in Pakistan (Ali et al. 2021), UAE (Alqasemi et al. 2021), and India (Mukherjee and Debnath 2020; Dhruv Nanda et al. 2021), Indonesia (Arrofiqoh and Setyaningrum 2021), etc. However, this result does not appear to be statistically significant in Moscow conditions, given the large scatter in the data (shown by the confidence intervals in Fig. 1 a).

Let us use the well-known Student criterion Z to evaluate the statistical significance of the differences between conditions in 2020 and in the previous 20 years. It should be noted that Z criterion is parametric and may be used when the distribution corresponds to the Normal law.

Indeed, the SUHI intensity distribution is close to Normal law: Pearson's chi-square (χ^2) test has a relatively low value 10.2 at 6 freedom degrees which is less than the critical value (12.6) for the 5% significance level. So, we can accept correspondence to the Normal law at the 0.95 probability and, hence, correctly use the Student criterion:

$$Z = \frac{(\overline{X} - \overline{Y})}{\sqrt{\sigma^2(X)/n + \sigma^2(Y)/m}} \quad (2)$$

where X and Y are the average values of the two samples; $\sigma^2(X)$ and $\sigma^2(Y)$ are their dispersions; n and m are sample sizes. It was found that for the SUHI intensity Z = 0.39; for the surface temperature in Moscow and Moscow region Z values are 1.86 and 1.90, respectively. Therefore, all three values are less than the critical Z value (1.97) for the 5% significance level. Thus, neither SUHI intensity, nor T_S demonstrate significant differences between the lockdown period in 2020 and the same period on average in 2000÷2019.

It should be noted that during the lockdown in 2020, all images available for the analysis except for only one (of June 6) were taken before May 12. However, the annual course of SUHI intensity has a clear maximum in summer due to intensive vegetation in rural zone and, as a result, intense heat losses by transpiration of plants (Lokoshchenko and Enukova 2020). In other words, in late spring and early summer, the SUHI intensity grows rapidly due to vegetation development outside the city. Therefore, in June it is significantly higher than in March. However, May and early June in 2020 were observed in Moscow by cyclonic weather and high cloudiness (Lokoshchenko and Alekseeva 2022) so only one image was received for the analysis since May 12. That is why the results of comparing the SUHI intensity in 2020 and the 2000÷2019 average for the full lockdown period in 2020 (Table 1) may be distorted. Therefore, all results of the analysis were recalculated within a narrower lockdown period from March 30 only to May 11, not to June 8 (see Table 2 and Fig. 1 b).

As it can be seen from Fig. 1 b, the surface temperature T_S both in Moscow and in the rural zone varies until May 11th in a wide range from 7.8 ºC in 2005 to 25.5 ºC in 2000, and from 3.8 in 2005 to 23.1 in 2000, respectively (for the full lockdown period in Fig. 1 a) the dynamics is similar). The close relation between T_S inside and outside the city is obvious – the correlation coefficient between mean annual values of both parameters is 0.98. The total sample of all available Terra and Aqua images for the partial lockdown period until May 11th for 21 years is 167, including 11 images in 2020. On average for 2000÷2020, T_S is 18.11 ºC in Moscow and 15.56 ºC in the outer zone. In the city, this parameter is on average higher each year, so SUHI represents a thermal anomaly that is stable over time.

Table 1. Comparison of different parameters during COVID-19 full lockdown period in 2020 from March 30th to June 8th and at the same time in 2000÷2019 based on Aqua and Terra satellite data

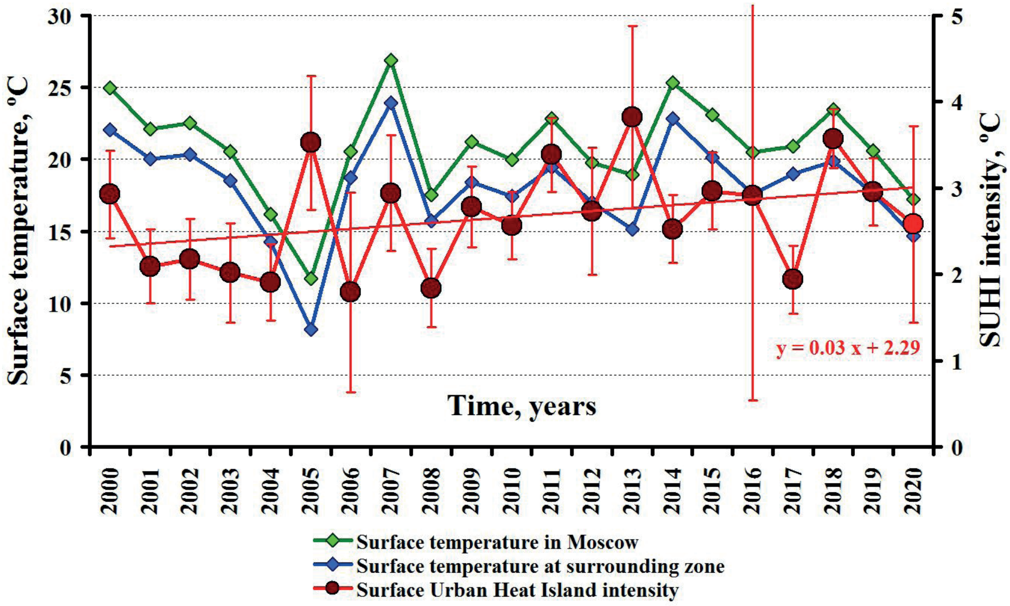
	Moscow	Moscow region (outer zone)	Difference
Surface temperature, ºC			
2020 (12)	17.2 ± 7.8	14.6 ± 7.2	2.6
2000÷2019 (275)	21.5 ± 6.4	18.7 ± 6.5	2.8
Normalized Difference Vegetation Index (NDVI)			
2020 (12)	0.28 ± 0.11	0.38 ± 0.13	-0.10
2000÷2019 (275)	0.35 ± 0.16	0.47 ± 0.19	-0.12
Leaf Area Index (LAI): up to June 9			
2020		1.7 ± 0.8	
2000÷2019		2.1 ± 1.3	

The first values are mean; the second are standard deviations (σ). Sample data (number of images) are given in brackets.

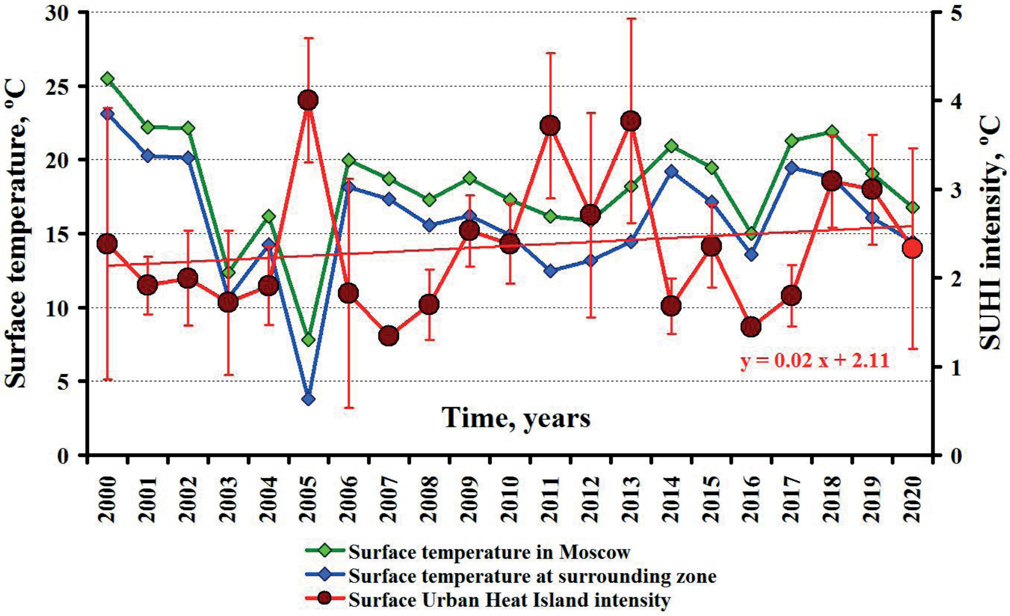
Table 2. Comparison of different parameters during COVID-19 partial lockdown period in 2020 from March 30th to May 11th and at the same time in 2000÷2019 based on Aqua and Terra satellite data

	Moscow	Moscow region (outer zone)	Difference
Surface temperature, ºC			
2020 (11)	16.7 ± 8.0	14.4 ± 7.5	2.3
2000÷2019 (156)	18.2 ± 6.3	15.6 ± 6.8	2.6
Normalized Difference Vegetation Index (NDVI)			
2020 (11)	0.26 ± 0.09	0.36 ± 0.11	-0.10
2000÷2019 (155)	0.25 ± 0.12	0.34 ± 0.15	-0.09
Leaf Area Index (LAI): up to May 16			
2020		1.2 ± 0.4	
2000÷2019		1.3 ± 0.6	

The first values are mean; the second are standard deviations (σ). Sample data (number of images) are given in brackets.



a) Full lockdown period (from March 30 to June 8);



b) Partial lockdown period (from March 30th to May 11th).

Fig. 1. Average surface temperature and Surface Urban Heat Island intensity in Moscow during the lockdown period in 2020 and on the same dates in other years (from 2000 to 2019), in °C

Confidence intervals are calculated with the 0.05 significance level

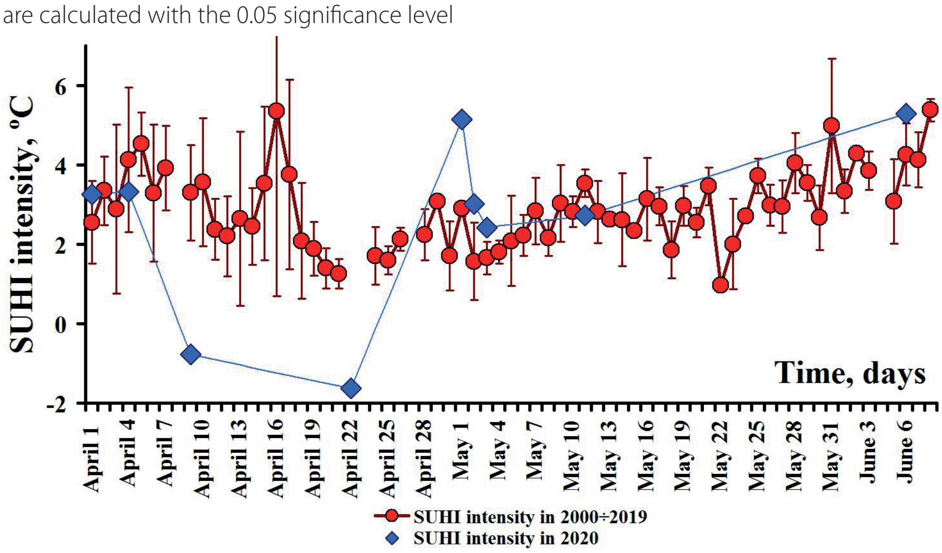


Fig. 2. Surface Urban Heat Island intensity in Moscow on certain days during the lockdown period in 2020 and on average from 2000 to 2019, in °C

Confidence intervals are calculated with the 0.05 significance level

The average annual SUHI intensity during this period varies from 1.3 ºC in 2007 to 4.0 ºC in 2005; on average for 21 years, the SUHI intensity from March 30 to May 11 is 2.55 ºC. Such large changes in this parameter from year to year are explained by the different dates of images taken for studying (early April or May), the presence or absence of snow cover, the degree of vegetation intensity, etc. For example, the SUHI intensity in 2005 was extremely high, since all 12 images before May 11 were recorded in the first decade of April (until April 10), when even in Moscow there was still a heavy snow cover, and its depth was extremely high (from 47 cm (!) in April 1 to 4 cm in April 9). Evidently, in any city there are many surfaces cleared of snow (roads, roofs of buildings, etc.) which contribute to a higher T_S. Besides, snow melts faster in the urban area than in the rural zone, so the difference between T_S inside and outside the city is especially large during the snowmelt. Strong influence of snow cover was also registered in 2013 when it finally disappeared on April 16th in Moscow (according to the data of MSU Meteorological Observatory) and several days later at rural zone. The SUHI intensity in 2013, as it is seen from Fig. 1 a), was 3.8ºC on average of the data of all 12 images during the full lockdown period, but it was equal to 5.4 ºC before and during snow cover disappearing (on average from 5 images from April 12 to April 17) and only 2.7 ºC later (on average from 7 images from May 2 to June 3). It is noteworthy that the highest SUHI intensity value of 7.7 ºC was observed on April 16, i.e. just on the day when snow cover disappeared in the city, but still remained at rural zone.

Regarding ΔT_S values on different days, it should be noted that the maximum value is 7.7 ºC on April 16, 2013, whereas the minimum value is -1.6 ºC on April 22, 2020. Such a high SUHI intensity on April 16, 2013, is not surprising, because the day before, the snow cover depth still was 15 cm in Moscow. Thus, such a strong SUHI is explained by the different rate of snow melting in the city and in the rural zone. On the contrary, only three times the SUHI intensity was negative, so this phenomenon was found as an inverse 'cool island', besides April 22, 2020, in two more cases: April 9, 2020 (-0.8 ºC) and May 2, 2006 (-0.1 ºC). It was shown that cases of a weak 'cool island' involving the entire city are extremely rare in Moscow. For 8 years (from 2008 to 2015) ΔT_S was slightly below 0 ºC in only 8 out of 561 images (Lokoshchenko and Enukova 2020).

In addition to the average value of the SUHI intensity during the lockdown, it is also important to study its dynamics during this period. Fig. 2 shows the values of this parameter during the lockdown in 2020 (either from one image, or an average from two images during the same day). For comparison, the average SUHI intensity for each day was calculated from all available images in 2000÷2019. As it is seen, SUHI in Moscow at the beginning of the lockdown (in the first days of April) was close to its usual intensity. Then it was significantly weaker than on average for 20 years until the end of April so its intensity on April 9 and April 22 was even negative and, finally, except for only one image with an unexpectedly high value (on May 1), it again became close to its usual intensity.

The results for the partial lockdown period are also shown in the two maps in Fig. 3. The spatial distribution of the surface temperature field is calculated using the standard interpolation software Surfer10.1 with a step of 1 ºC. Both maps were created by combining samples of images with a spatial resolution of 15 km by use of kriging interpolation method. The margins of Moscow city and the administrative boundaries of Moscow region are shown with small violet and orange circles, respectively. Both maps demonstrate two major features that are total geographical zoning (general growth of T_S values from northwest to southeast) and, besides, the SUHI as a positive thermal anomaly around Moscow city. As can be seen, on average for 20 years before the pandemic, the surface temperature both in Moscow and in Moscow region was higher than in 2020. The SUHI is expressed in both cases by three closed or semi-closed isotherms but they are quite different: from closed +20 ºC inside the city to semi-closed +18 ºC around the city on average for 2000÷2019, and much lower values from +15 to +13 ºC in 2020 on the right map.

Thus, during the lockdown in the spring of 2020, the SUHI intensity in Moscow was lower than the average for 20 previous years (by 0.3 ºC for the partial lockdown period until May 11 and by 0.2 ºC for the full lockdown until June 8). However, this reduction was found as statistically non-significant with the 0.95 confidence probability. Moreover, the weakening of SUHI in Moscow on average during the lockdown period is caused by extremely low values only in two days (Fig. 2). This result is unexpected, since the UHI in the surface air layer of Moscow during the lockdown was much weaker than in the same period in two previous years (Lokoshchenko and Alekseeva 2022). In fact, in 2018 and 2019 the SUHI as well as the UHI was stronger than in 2020 during the lockdown (as one can see in Fig. 1) but differences for the SUHI, unlike the UHI, are non-significant even for these two years. Possible reason is an additional influence of clouds, which weaken the UHI, as the UHI intensity was calculated for all days of the lockdown whereas satellite data is available only in 9 out of 71 days (Lokoshchenko and

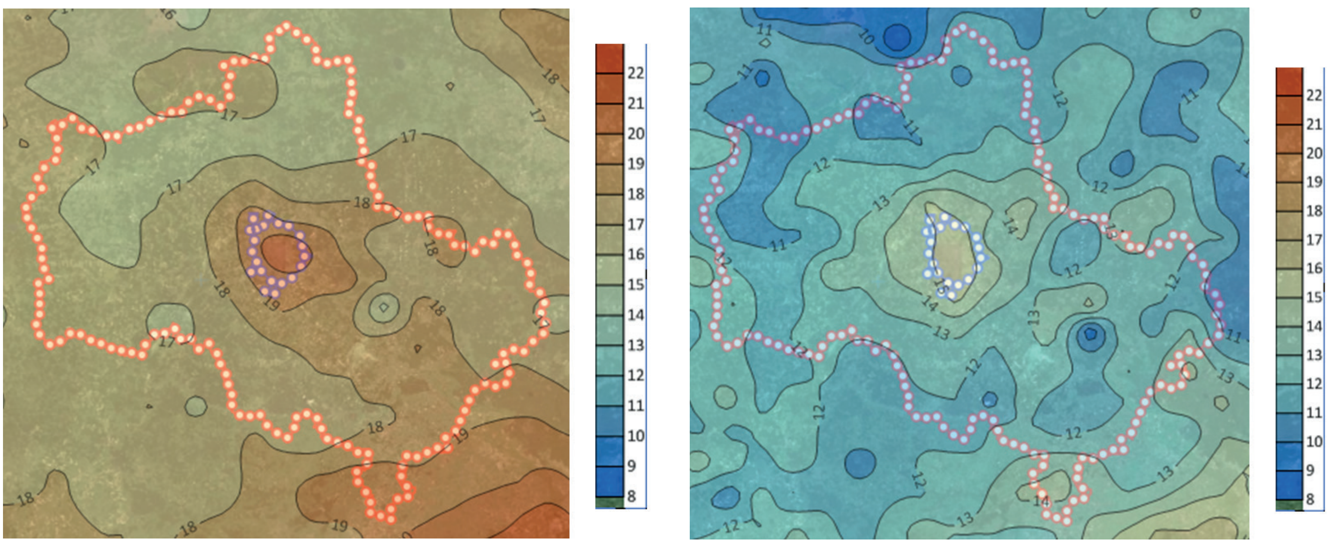


Fig. 3. Maps of the surface temperature T_S in Moscow region on average for the period from March 30 to May 11 in 2000÷2019 (left) and in 2020 (right), in ºC

Orange dots indicate Moscow region boundaries; the violet dots indicate the margins of Moscow city. The scale of T_S is shown to the right of each map

Alekseeva 2022). In other words, in conditions of clear sky the SUHI weakening during the lockdown was not such a strong as the UHI weakening during the entire lockdown period.

To explain this effect in detail, we should also analyze the weather conditions during the lockdown and, besides, should take into account the specifics of the SUHI phenomenon, the intensity of which is sensitive to vegetation activity.

Another additional result of our analysis is the slow changes in the Moscow SUHI intensity in time in the past 21 years. As it can be seen from Fig. 1, both linear trends of this parameter are positive, but the linear regression coefficients are extremely small. The SUHI intensity has been growing since 2000 by an average of only 0.03 °C/year during the full lockdown period and by 0.02 °C/year during the partial one. Evidently, both trends are statistically non-significant due to large dispersions of the mean annual data.

Weather features before and during the lockdown in 2020

Let us discuss the weather specifics in the winter and spring of 2020 in Moscow. Evidently, the weather influences both surface temperature and vegetation activity. The winter of 2019÷2020, which ended shortly before the start of the COVID-19 pandemic, was extremely warm in Moscow. Due to the intense Icelandic Low, strong southern and southwestern flows of warm maritime Polar air masses invaded Moscow region almost continuously, so that in the winter of 2020 there was not a single invasion of cold Arctic air masses. As a result, the air temperature T in Moscow was a record high during the entire season from December 1, 2019 to February 29 (it should be noted that almost regular meteorological measurements started in the city in October 1779). The mean monthly T in December 2019 was +0.6 °C (that is the second record value; since 1779, only once the air temperature in Moscow was even higher in December: +1.3 °C in 2006). In January 2020, the mean monthly T was -0.1 °C, which is a new absolute maximum since 1780 (the next, second record high value of T in January was -1.4 °C in 2007). Mean monthly T in February 2020 was also extremely high, that is -0.3 °C (this was the second record; T was higher only once: +0.2 °C in 1990). Thus, all three winter months in Moscow were extremely warm, so the mean winter air temperature became record high and, for the first time, positive during the history of meteorological measurements: +0.07 °C (see Fig. 4a). Until 2020, the warmest winter in Moscow was 2007÷2008 with the mean T = -2.9 °C which is much less.

March 2020 was also extremely warm in Moscow. The mean monthly T was +4.0 °C, which is the second high record value since 1780, as well as in December and February (only once it was higher in March: +4.9 °C in 2007). The inevitable consequence of such warm winter and early spring is almost snowless conditions. Steady snow cover (i.e., a cover which exists during the longest period in the cold season) in the winter of 2019÷2020 in Moscow appeared extremely late (on January 23), and finally melted extremely early (on March 2). Therefore, it

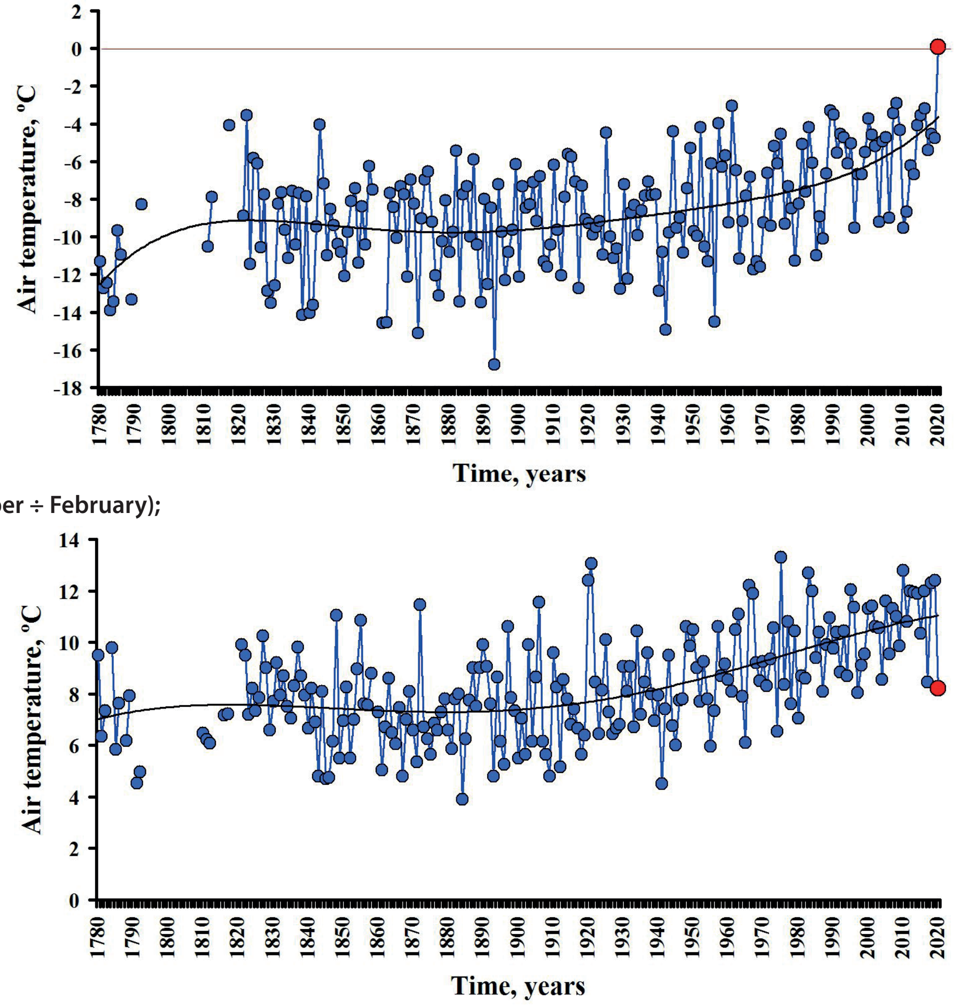


Fig. 4. Long-term dynamics of air temperature in Moscow averaged over certain seasons during the entire history of meteorological measurements, in °C

Data for 2020 is marked with a red dot.
Black lines are the 5th degree polynomial trends

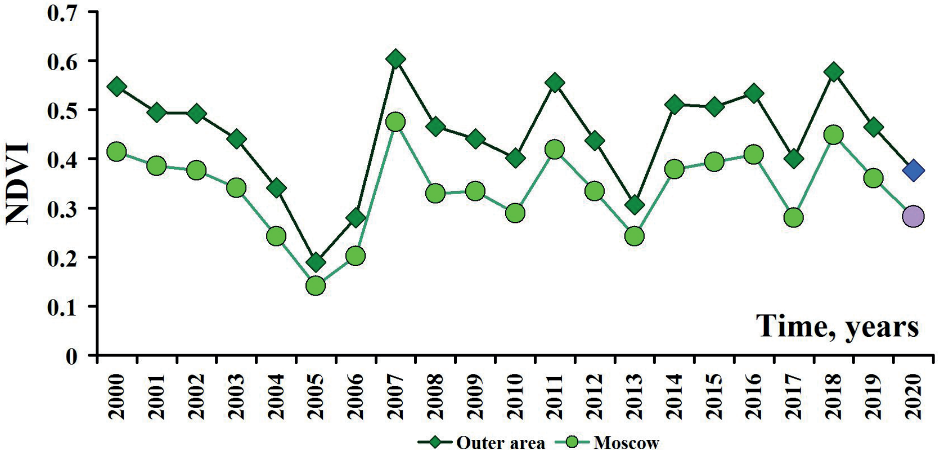
existed for an extremely short time (40 days only). In fact, the lifetime of steady snow cover was even shorter, since in the last days of February it remained only in places. Besides, steady snow cover was extremely thin (the highest depth for the entire cold season was only 15 cm, which is a record low value according to the data of MSU Meteorological Observatory since at least 1954). After March 2, there were only two episodes of short-living snow cover in the city lasting 4 and 3 days (from March 15 to March 18 and from March 31 to April 2).

However, unlike winter and March, the middle and late spring of 2020 in Moscow was cool and cloudy. Moscow was frequently located in frontal zones of Arctic cyclones, or at their rear. Sometimes Russian capital was also near centers of local cyclones. As a result, mean monthly T in April and May (4.8 ºC and 11.6 ºC, respectively) was significantly lower than the climatic norm for these months (7.0 ºC and 13.5 ºC, respectively, for April and May, on average for 1981÷2010 in Moscow by the data of MSU Meteorological Observatory). As can be seen from Fig. 4b, such a low mean air temperature in both months in Moscow was registered for the first time since 1997. Thus, we can assume that the unusually early vegetation development in 2020 dramatically slowed down in mid-spring and, as a result, the SUHI intensity decreased in April.

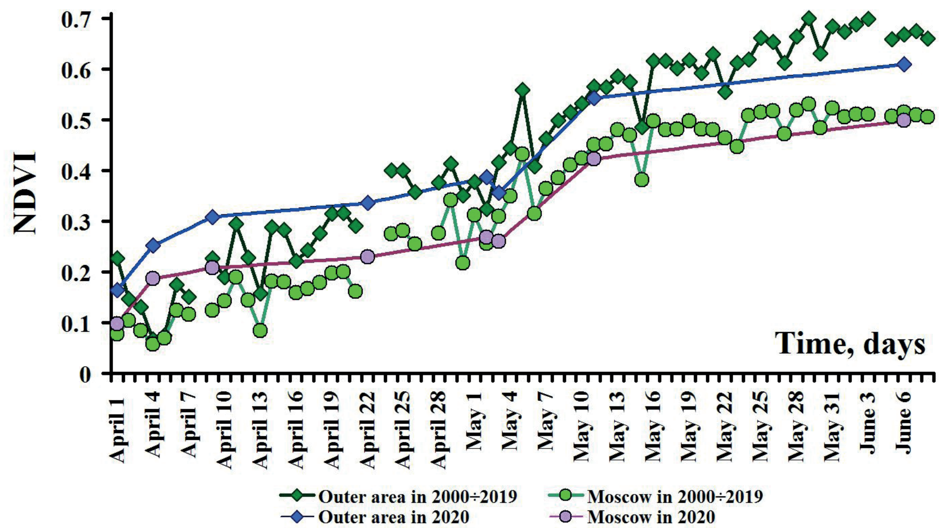
Normalized Difference Vegetation Index (NDVI) during the lockdown in 2020

One of the possible reasons for the SUHI intensity changes is vegetation growth, which leads to additional heat loss by the surface in green rural area compared to urban area. It is difficult to measure directly the heat loss for transpiration by plants. However, we can estimate this indirectly using satellite data for some indexes (e.g., NDVI) which indicate the vegetation intensity.

As well as the SUHI intensity, the NDVI values during the lockdown in Moscow in 2020 are available from the 12 images received from Aqua and Terra satellites for the total period from March 30 to June 8, including 11 images for the period until May 11. As can be seen from Table 1 and Fig. 5, the average NDVI value during the entire lockdown period is 0.28 ± 0.11 (the second value is standard deviation σ) in Moscow and 0.38 ± 0.13 in the outer rural zone outside the city. For an incomplete period only until May 11th (Table 2) NDVI values are 0.26 ± 0.09 and 0.36 ± 0.11 for the city and rural zone, respectively. Both the highest values in different images during the lockdown are 0.50 in Moscow and 0.61 in Moscow region; the lowest values are 0.10 and 0.16 in Moscow and Moscow region, respectively. The highest values were received on the last flight on June 6, whereas both the lowest ones were received on the first flight on April 1.



a) Average NDVI for the period from April 1 to June 8 in 2000÷2020;



b) NDVI values on certain days from April 1 to June 8 averaged over 2000÷2019 and in 2020.

Fig. 5. Comparison of NDVI values in Moscow and Moscow region based on MODIS data during the lockdown in 2020 and on the same dates in other years (in 2000÷2019)

As can be seen from Table 1, the average NDVI value for 2000÷2019 during the entire lockdown period in 2020 is 0.35 ± 0.16 in Moscow and 0.47 ± 0.19 in Moscow region. For the period from March 30 to May 11, the NDVI values are 0.25 ± 0.12 and 0.34 ± 0.15 in the city and rural zone, respectively. The highest NDVI values for 20 years at the dates of the full lockdown are 0.57 (May 26, 2014) in Moscow and 0.73 (May 29, 2018) in Moscow region. The lowest NDVI values in 20 years are 0.03 and 0.06 in the city and in rural zone, respectively. Both values were measured on April 3, 2011, when the snow cover depth at MSU MO was extremely high for that time, and it was 36 cm. Nearly the same NDVI values in the rural zone (0.06) were observed on April 4 and April 5, 2005, when the snow cover depth was also extremely high: 37 and 34 cm, respectively. Evidently, green vegetation in these conditions is almost absent, except for coniferous trees.

The average NDVI values during the calendar time of the lockdown period in 2020 in different years since 2000 are presented in Fig. 5a. As can be seen, firstly, the NDVI in Moscow region is always higher than in the city, which is not surprising due to the greater number of green areas in the rural zone. Secondly, the difference between average urban and rural values of NDVI is almost always the same (about -0.1) except only for rare cases (e.g., in 2005, when most images were taken in conditions of late snow cover, which remained until April 10, and there was almost no green vegetation both in the city and in the rural zone). Moreover, as it can be seen from Fig. 5a, both NDVI values and their difference in 2020 are quite usual compared to the previous 20 years. Indeed, average values of NDVI for both the city and rural zone for the period until May 11th in 2020 and from 2000 to 2019 are almost the same (Table 2). Their difference on average in the previous 20 years is also close to the value in 2020 (-0.12 for the full lockdown period and -0.09 for the period until May 11). It is noteworthy that the increase in the absolute value of this difference with the lengthening of the averaging period is quite logical due to the rapid vegetation growth in late May and early June.

Besides the average values of NDVI, it is also important to understand the dynamics of this parameter during the lockdown. To do this, the average NDVI values were calculated for certain days both in 2020 and in 2000÷2019 (Fig. 5b). As it can be seen at the beginning of the lockdown period (April 4 and April 9) NDVI was higher than the average for the previous 20 years. In the middle of this period (April 22, May 2, 3 and 11), the values in 2020 and on average for 2000÷2019 are close to each other. Finally, at the end of lockdown (on June 6), the NDVI in the rural zone in 2020 was, on the contrary, lower than usual. The evident reason for such dynamics is, firstly, the extremely hot and almost snowless winter in Moscow, which led to early vegetation development and, secondly, the cold spring, which later slowed down this development. Nevertheless, in general, the NDVI values during the lockdown in Moscow were close to usual ones both in the city and in the rural zone.

Leaf Area Index (LAI) during the lockdown in 2020

One more important parameter, which is available from satellite data, is the Leaf Area Index (LAI). It may be estimated only at rural zone and, hence, cannot indicate SUHI as a difference between values of LAI in urban and rural zones. Nevertheless, it clearly reflects the vegetation development and its changes in time. Thus, the LAI values significantly complement the data about NDVI.

The LAI values were calculated for the outer rural zone (rectangle around Moscow region margins not including the city) for nine separate periods of eight days from March 30 to June 9. The results are presented in Fig. 6 and in Tables 1 and 2. They were received for all years except 2001.

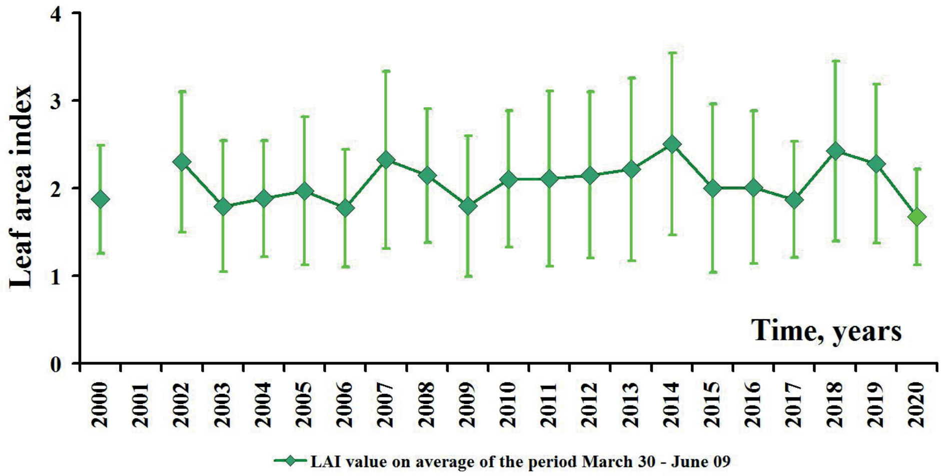
The LAI value in Moscow region averaged over this calendar time is equal to 2.08 for the period of 2000 and 2002÷2019, and 2.06 for the period of 2000 and 2002÷2020. As can be seen, the leaf area index value on average for the full lockdown period in 2020 (1.67) is the lowest among all other years for the period (Fig. 6a), although, taking into account confidence intervals with the 0.95 confidence probability, this reduction is not statistically significant.

The analysis of the average LAI value is insufficient. It is also important to study the dynamics of this parameter during the lockdown. That is why LAI was also compared for each separate 8-day period in 2020 and on average in the previous 19 years (Fig. 6b). It is not surprising that during the spring and early summer, in conditions of developing vegetation, the LAI value averaged over 2000 and 2002÷2019 increased monotonically from 0.77 on March 30÷April 6 to 3.95 on June 2÷9. It is also evident that this growth gradually slows down in June as leaf size approaches its upper limit. As we can see, at the beginning of the lockdown (during the first and second eight-day periods), the LAI in 2020 was slightly higher than usual, evidently due to the warm and almost snowless winter. However, later, their ratio became opposite. During the third and fourth eight-day periods in the second half of April, the LAI value in Moscow region in 2020 was only a bit lower than the average for the previous 19 years, but later the gap between them increased. Since the beginning of May, the difference between LAI values in 2020, and in 2000, 2002÷2019 became statistically significant and in the second half of May its absolute value increased to -1.1÷-1.2. The probable reason for this was the cold spring, which slowed down the development of vegetation. Thus, the LAI dynamics confirms that heat losses by transpiration during the COVID-19 lockdown in 2020 in Moscow region were significantly lower than usual as a result of cool spring.

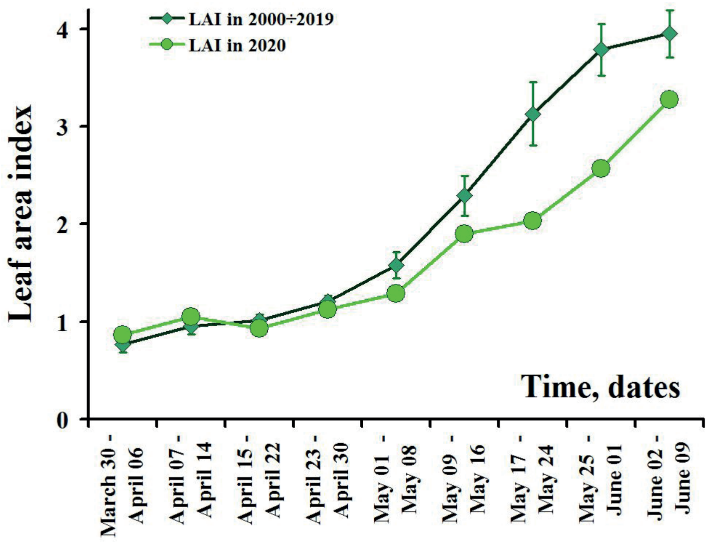
Influence of different factors on SUHI during the lockdown in 2020

Therefore, after analyzing of all parameters we can define the factors that really influenced on the SUHI in Moscow during the lockdown. Evidently, a decrease in human activity was not the main cause of the SUHI intensity decrease because it was insignificant in the comparison of other years. Apparently, the weakening of the SUHI in Moscow at that time was caused mostly by a slowdown of vegetation development due to specific weather conditions. The Pearson correlation coefficient between monthly-averaged values of the NDVI difference between rural zone and Moscow, and the SUHI intensity (i.e. the T_S difference between Moscow and rural zone) during the period from 2000 to 2019 is -0.47. According to the Fischer's Z-test , this coefficient is statistically significant at the 0.99 probability (for the sample size n = 40 of Aprils and Mays). Thus, the vegetation index really affects the SUHI intensity.

However, a reduction of anthropogenic heat sources during the lockdown is another factor, which, probably, also influenced on the SUHI intensity. Firstly, the contribution of reduced human activity to the weakening of the UHI in the surface air layer in Moscow at that time was shown in (Lokoshchenko and Alekseeva 2022). Evidently, both phenomena (UHI and SUHI) are related to each other. Secondly, we can indirectly demonstrate an impact of the COVID-19 lockdown by comparison of the SUHI intensity



a) LAI values averaged over the period from March 30 to June 9 in 2000 and 2002÷2020;



b) LAI values on certain days from March 30th to June 9th averaged over 2000, 2002÷2019 and 2020.

Fig. 6. Comparison of LAI values in Moscow region using MODIS data during the lockdown in 2020 and on the same days in 2000 and 2002÷2019

Confidence intervals are calculated with the 0.05 significance level

during this time and with the same period at some another year. As it is shown above, the SUHI depends on vegetation development. We should take into account a year under similar conditions. As an example, in 2019 an average difference between NDVI values in the city and at rural zone during the lockdown period was the same as in 2020 (-0.10). However, the SUHI intensity in 2019 was noticeably higher than in 2020, and it was 3.0 ºC during both the full lockdown period, and non-full period until May 11th. This example indirectly confirms the reduced influence of the human activity on the surface heat balance in 2020.

CONCLUSIONS

1. During the lockdown period in 2020, the surface temperature T_S both in Moscow city and in the surrounding rural zone was significantly lower than usual in this calendar time. Probable explanation is the cool spring.

2. The SUHI intensity in Moscow during the lockdown was also lower than the average for the previous 20 years. A probable explanation of this is the slowdown of vegetation development in the rural zone due to the cold spring which creates a weakening of the SUHI. Besides, the cooling of the surface air layer in Moscow due the reduction of human activity (the weakening of anthropogenic heat sources during the lockdown) could also create an additional weakening of the SUHI. However, the decrease of the SUHI intensity during the lockdown is statistically non-significant.

3. Extremely high SUHI intensity in spring in mid-latitudes is often associated with more rapid snow cover melting in cities.

4. On average of 21 years, the mean NDVI values in April and May are 0.3÷0.4 in Moscow and 0.4÷0.5 in Moscow region. Thus, the difference between the average urban and rural values of NDVI in spring in Moscow region is about -0.1. In the rare cases of deep snow cover in spring, the NDVI values are extremely low (from 0.03 to 0.07) and are close to each other both in the city and in the rural zone.

5. A relation between the monthly averaged differences between urban and rural values of SUHI and NDVI in spring in Moscow region is statistically significant with the 0.99 probability.

6. In conditions of cold spring, LAI values are significantly lower than usual (at the second half of May in Moscow region – 2.0÷2.6 in 2020 and 3.1÷3.8 on average of 19 previous years), which confirms the slowdown in vegetation growth.

7. No significant long-term changes in surface temperature, SUHI intensity, NDVI and LAI values have been found in the past 21 years, according to MODIS data, in Moscow region.

REFERENCES

Ali G., Abbas S., Qamer F.M., et al. (2021). Environmental impacts of shifts in energy, emissions, and urban heat island during the COVID-19 lockdown across Pakistan. Journal of Cleaner Production, 291, 125806.

Alqasemi A.S., Hereher M.E., Kaplan G. et al. (2021). Impact of COVID-19 lockdown upon the air quality and surface urban heat island intensity over the United Arab Emirates. Science of the Total Environment, 767, 144330.

Chakraborty T.C., Chandan S. and Xuhui Lee. (2021). Reduction in human activity can enhance the urban heat island: insights from the COVID-19 lockdown. Environ. Res. Lett., 16, 054060.

Climate of Moscow in conditions of global warming. (2017). Ed. by Kislov A.V. Moscow, Russia: Moscow University Press, 288, [in Russian].

Dhruv Nanda, Deepk R. Mishra and Debadatta Swain. (2021). COVID-19 lockdowns induced land surface temperature variability in mega urban agglomerations in India. Environ. Sci.: Processes & Impacts, 23(1), 144-159, DOI: 10.1039/D0EM00358A.

El Kenawy A.M., Lopez-Moreno J.I., McCabe M.F., Domínguez-Castro F., Peña-Angulo D., Gaber I.M., Alqasemi A.S., Al Kindi Kh.M., Al-Awadhi T., Hereher M.E., Robaa S.M., Al Nasiri N., and Vicente-Serrano S.M. (2021). The impact of COVID-19 lockdowns on surface urban heat island changes and air-quality improvements across 21 major cities in the Middle East. Environmental Pollution, 288, DOI: 10.1016/j.envpol.2021.117802.

EOS Data Products Handbook (2000). Ed. by Parkinson C.L. & Greenstone R. NASA Goddard Space Flight Center Greenbelt, Maryland, 2, 253.

Erlyna Nour Arrofiqoh, Devika Ayu Setyaningrum. (2021). The Impact of Covid-19 Pandemic on Land Surface Temperature in Yogyakarta Urban Agglomeration. Journal of Applied Geospatial Information, 5(1), 480-485, DOI: 10.30871/jagi.v5i1.2784.

Esau I., Miles V. (2018). Exogenous drivers of surface urban heat islands in Northern West Siberia. GEOGRAPHY, ENVIRONMENT, SUSTAINABILITY, 11(3), 83-99, DOI: 10.24057/2071-9388-2018-11-3-83-99.

Lokoshchenko M.A. and Enukova Ye.A. (2020). Urban Heat Island in Moscow Derived from Satellite Data. Russian Meteorology and Hydrology, 45(7), 488-497, DOI: 10.3103/S1068373920070043.

Lokoshchenko M.A. and Alekseeva L.I. (2022). About the Annual Course of Moscow Heat Island and the Impact on it of Quarantine Measures to Prevent the COVID-19 Pandemic in 2020. Izvestiya, Atmospheric and Oceanic Physics, 58(2), 168-177. DOI: 10.1134/S000143382020086.

Morris C. J. G., Simmonds I., and Plummer, N. (2001). Quantification of the influences of wind and cloud on the nocturnal urban heat island of a large city. Journal of Applied Meteorology, 40(2), 169-182, DOI: 10.1175/1520-0450(2001)040<0169:QOTIOW>2.0.CO;2.

Mukherjee S. and Debnath A. (2020). Correlation between Land Surface Temperature and Urban Heat Island with COVID-19 in New Delhi, India. Research Square, 1-11.

Półrolniczak M., Kolendowicz L., Majkowska A. and Czernecki B. (2017). The influence of atmospheric circulation on the intensity of urban heat island and urban cold island in Poznań, Poland. Theor. Appl. Climatology, 127, 611-625, DOI: 10.1007/s00704-015-1654-0.

Rasul A., Balzter H., and Smith C. (2015). Spatial Variation of the Daytime Surface Urban Cool Island during the Dry Season in Erbil, Iraqi Kurdistan, from Landsat 8. Urban Climate, 14, 176-186, DOI: 10.1016/j.uclim.2015.09.001

Steitz D., Kenitzer A., Diller G., Henry K., Ainsworth D., and M. Neiman (1999). Terra: Flag ship of the Earth Observing Sys tem, NASA Press Kit, Release, 99-120.

Varentsov M.I., Grishchenko M.Y. and Wouters H. (2019). Simultaneous assessment of the summer urban heat island in Moscow megacity based on in situ observations, thermal satellite images and mesoscale modeling. GEOGRAPHY, ENVIRONMENT, SUSTAINABILITY, 12(4), 74-95. DOI: 10.24057/2071-9388-2019-10.

Voogt J.A., Oke T.R. (2003). Thermal remote sensing of urban climates. Remote Sensing of Environment, 86, 370-384, DOI: 10.1016/S0034-4257(03)00079-8.

Wenze Yang, Bin Tan, Dong Huang, Miina Rautiainen, Nikolay V. Shabanov, Y. Wang, Jeffrey L. Privette, Karl Fred Huemmrich, Rasmus Fensholt, Inge Sandholt, M. Weiss, Douglas E. Ahl, Stith T. Gower, Ramakrishna R. Nemani, Yuri Knyazikhin, and Ranga B. Myneni (2006). MODIS Leaf Area Index Products: From Validation to Algorithm Improvement. IEEE Transactions on Geoscience and Remote Sensing, 44(7), 1885-1898, DOI: 10.1109/TGRS.2006.871215.

Yangsiyu Liao, Xi Shen, Ji Zhou, Jin Ma, Xiaodong Zhang, Wenbin Tang, Yongren Chen, Lirong Ding and Ziwei Wang (2022). Surface urban heat island detected by all-weather satellite land surface temperature. Science of the Total Environment, 811, 151405, DOI: 10.1016/j.scitotenv.2021.151405.