Analysis of the impact of spatial planning on air pollutant trends using MODIS data

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ABSTRACT

Air pollution represents a significant challenge to the sustainability of urban areas and the public's health. The increasing concentrations of pollutants in the atmosphere, including various gases and particulate matter, result in poor outdoor air quality, which has a direct impact on the health of the population and the smooth functioning of everyday society. The objective of this study was to ascertain the impact of the Teilor Park development on the air quality in the area by monitoring the trend of the PM2.5 and PM10 indicators, as well as the land surface temperature (LST), using satellite images. The results of the analysis indicated that urban planning had a positive impact on the elements and air quality under study. The amount of AOD has decreased considerably over the period studied, by 8.9%. In terms of the elements determined on this basis, PM2.5 showed a decrease of 5.4% over the 2019-2022 timeframe and PM10 showed a decrease of 6.9%. The analysis was conducted using the Google Earth Engine platform, using MODIS sensor data for the period between 2019 and 2022.

Keywords: air pollution; MODIS; Google Earth Engine; remote sensing

1. INTRODUCTION

Air pollution is one of the most important problems of the developing countries and also of the developed countries, as it is an effect of urban expansion and social and eco-nomic activities undertaken [1]. Globally, in 2015, medical conditions caused by exposure to air pollutants accounted for approximately 9 million deaths [2]. The emissions generated by economic and social activities, as well as those produced by daily traffic, can result in a multitude of alterations to the Earth's atmosphere. These changes can also impact the quality of life, influencing the health of the population and the general well-being. A multitude of studies conducted across the globe have demonstrated a correlation between air pollution and an expanding array of detrimental health outcomes. [3]. Air pollutants have the potential to directly affect the respiratory system, contributing to the development of a range of associated diseases, as well as reproductive disorders and allergies. Carbon monoxide (CO), sulfur dioxide (SO2), ozone (O3), nitrogen dioxide (NO2) and particulate matter (PM2.5 and PM10) are the most important pollutants in urban areas [4, 5].

Ground-based air pollution monitoring represents a reliable source of data for the analysis of air quality, the mapping of pollution, and the estimation of population health effects. [6]. Ground monitoring is based on the continuous measurement of stations, which allows the concentrations of various indicators to be obtained directly. One disadvantage of ground stations is that the data obtained is not sufficiently granular. The maintenance costs of these stations are considerable, and they are predominantly situated in densely populated areas or in close proximity to city centres, thereby leaving a significant proportion of the geographical area unmonitored. The advent of low-cost portable monitoring devices has the potential to expand pollution monitoring. They are often used to carry out epidemiological studies, but also in analyses of household air pollution [7]. Naser Hossein Motlagh et. al have shown that the use of mobile sensors can capture subtle variations caused by different traffic routes, passenger density, location in a vehicle and other factors [8].

A source of data for the spatial and chronological examination of long-term air quality is provided by the principle of remote sensing, which allows spatial-temporal monitoring over a long period of time. Satellite imagery allows complex sets of quantitative and qualitative information to be obtained, reducing the complexity of field work and survey time. Since 1978, satellite imagery has been widely used to monitor air quality [1]. The concentration of particulate pollutants

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in the atmosphere is determined by comparing the rays emitted by the Earth's surface with those reflected by the atmosphere [9]. These systems allow the measurement of pollutants, the mapping of their distribution, as well as the monitoring of trends of pollutant changes. MODIS (Moderate Resolution Imaging Spectroradiometer), OMI (Ozone Monitoring Instrument), GOME (Global Ozone Monitoring Experiment), MOPITT (Measurement of Pollution in the Troposphere), TROPOMI (TROPOspheric Monitoring Instrument) or GEMS (Geostationary Environment Monitoring Spectrometer) are the main satellite instruments used in air quality analysis [10-14]. Numerous scientific articles present research on the determination of temporal and spatial variations of air pollution in different regions of the world. Yitong Zheng et. al [15] developed a model based on Landsat 8 OLI remote sensing spectral image data and ground monitoring station data for PM particle estimation, achieving satisfactory performance in the test area. Md Masudur Rahman et. al [16] analysed the spatial and temporal characteristics of NO2 , SO2 and AOD (Aerosol optical depth) in Asia over 10 years, determining their trend for different areas and identifying possible sources of pollution. Bo Zhang et.al [17] proposed a neural network-based method (BR-PMx) for determining PM concentrations in Landsat 8 imagery using the Google Earth Engine platform to obtain band reflectance data.

In contrast to CO, SO2, O3 or NO2 pollutants, the concentration of PMx cannot be determined directly from sensor records utilised in existing space missions. Aerosol observations are employed to ascertain these concentrations. Aerosol optical depth (AOD) is a quantitative measure of solid or liquid particles in the atmosphere, including dust, sand, volcanic ash, smoke and urban or industrial aerosols [18]. A considerable number of studies have been conducted with the objective of determining the concentrations of PM 2.5 and PM 10 from AOD observations, Yuanyuan Chu et al. [19] presenting an overview of the studies and methods used, thus also presenting the four prediction models used, namely: Multiple Linear Regression, Mixed-Effect Model, Chemical Transport Model and Geographically Weighted Regression, concluding that each has both advantages and limitations. Methods based on ground measurements and AOD values determined from satellite images were developed to determine PMx concentration [20], methods based on linear regression, weighted regression or statistical analysis are proposed. Wei You,Zengliang Zang et. al [21] proposed the GWR model for the estimation of PM2.5, based on the MODIS AOD 3 km product which was correlated with meteorological data. Using multiple linear regression and the Kriging technique, Thanh Thi Nhat Nguyen et. al [22] presented a methodology for mapping PM2.5, achieving a monitoring of its temporal trend in the studied area.

In terms of existing literature, a number of studies have focused on the monitoring, analysis and recovery of air pollutants using satellite imagery [23-28] or ground monitoring stations [8, 29, 30]. Satellite imagery is well-suited to large-scale or even global analysis over extended periods of time, whereas monitoring stations are a valuable alternative for small-scale area studies. With regard to the limitations of the studies conducted, the most frequently encountered are the frequency of measurement and the spatial resolution of the data, which preclude the possibility of carrying out a detailed analysis of a small area. Future studies will likely employ the interpolation of satellite data and data from monitoring stations in order to enhance the results obtained.

Land surface temperature (LST) is an important parameter for environmental monitoring, being essential in the interaction between soil and atmosphere [15]. By using high resolution satellite images and Thermal Infrared Sensors (TIR) it was possible to collect qualitative and quantitative information about LST [31-33]. At present, there are space missions whose objective is the analysis of the environment and the collection of data about LST. Among the most commonly used sensors for these analyses is MODIS. Studies such as [34] and [35] have used LST data to determine the effect of the heat island on the population, as well as the influence of atmospheric conditions and accelerated urbanization on the heat island effect. Regarding the determination of LST using meteorological station measurements, as in the case of terrestrial air quality sensors, their density does not lead to relevant results for large areas. Zitong Wen et. al [36] proposed a model for combining the two types of data to obtain city-level LST information with high spatial resolution.

The objective of the present study was to ascertain the temporal trend of the atmospheric pollutants of interest and to evaluate the impact of the Teilor Park development in District 3 of the Bucharest Municipality, using MODIS satellite images. Consequently, estimates of concentrations for PM2 and PM10, as well as LST for the time interval 2019-2022 were obtained, indicating an improvement.

2. MATERIALS AND METHODS

2.1 LOCATION OF THE STUDY AREA

The Teilor Park is situated within the District 3 of the Bucharest Municipality. Its establishment was the consequence of the transformation of an unused area, which resulted in the creation of a considerable green space and an artificial lake [37]. The park covers an area of 7 hectares and was created between September 2019 and August 2020. The existing vegetation has not yet reached maturity. The climate of the study area is temperate continental. There is a slight overshadowing and some air temperature differences due to additional warming.

(a) (b)

(c) (d) (e)

(f) (g) (h)

Figure 1. (a, b) Location of the study area (c) View of the study location [38]; (d) și (e) represent the status of existing vegetation in Teilor Park; (f), (g) and (h) represent the status of vegetation for the years 2007, 2011 and 2017 [38]

2.2 DATASETS

MODIS is the moderate resolution imaging spectroradiometer that records various sources of air pollution such as: smoke from ground level fires by observing unusual critical points, dust or dust storms, or gas and particle emissions from road traffic [39]. MODIS provides almost global coverage every day. The MODIS instrument operates onboard the Terra (launched 18 December 1999) and Aqua (launched 4 May 2002) satellites. It has a viewing width of 2,330 km and sees the entire surface of the Earth every one or two days. Its detectors measure 36 spectral bands and acquire data at three spatial resolutions: 250m, 500m and 1000m [40].

2.3 METHODOLOGY

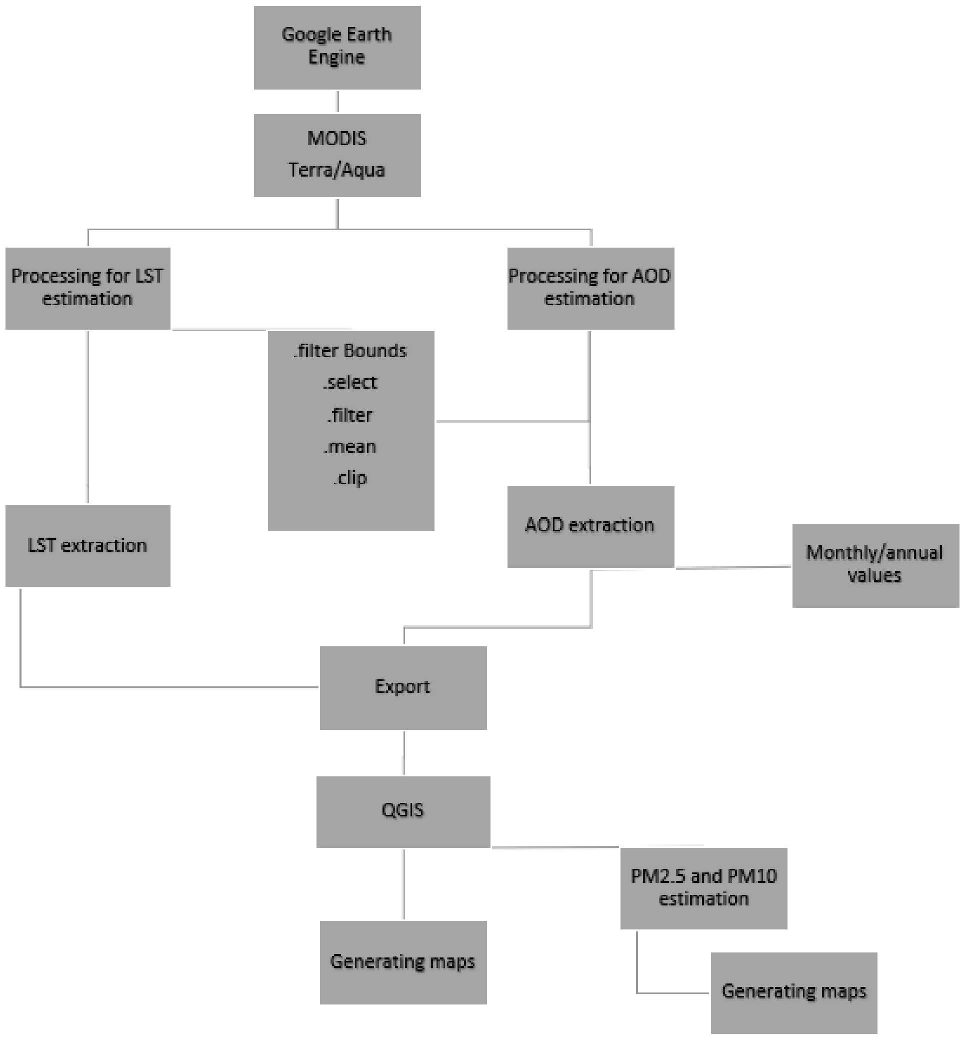

Figure 2. General presentation of the methodology used

In order to ascertain the trends of the pollutants under study and to generate the pollution maps, the following steps were carried out: firstly, the data sets necessary for the study were identified. Secondly, the results for the air pollutants were obtained by means of JavaScript coding using Google Earth Engine. As a third step, the results obtained in Google Earth Engine were validated against data from existing pollution measurement stations in the surrounding areas. This was followed by the generation of pollution representation maps in QGIS. Figure 2 provides a brief overview of the methodology employed.

PM 2.5 and PM10 data cannot be recorded directly by existing sensors. Thus, observations of the AOD obtained from the MODIS platform were used for the analysis. Level 2 grid data, calibrated and geo-referenced data produced daily at a resolution of 500m, were used for the analysis [41]. Currently, depending on the purpose of the analysis, two algorithms are used to extract AOD data using MODIS observations, namely: Dark-Target (DT) for dry surfaces without vegetation [42] and Deep-Blue (DB) for bright surfaces such as desert regions [43].

• Google Earth Engine for AOD extraction

Google Earth Engine was launched in 2010 with the goal of storing and processing Earth observation data in a reliable and time-efficient way [44], representing a geospatial data porcessing environment. GEE is a cloud computing platform, being an efficient tool for performing analyses on large data sets, providing a variety of Earth observation data sets, thus playing a vital role in environmental and pollution monitoring [45]. Over the years GEE has shown advantages for studying remote sensing data and time series, generating significant products for environmental monitoring [46-48].

In this study, MODIS level 2 observations were used to extract AOD data („MODIS/006/MCD19A2_GRANULES" [49] collection). After selecting the band of interest and applying spatial and temporal filters, the AOD data sets were generated in raster format at the level of Bucharest Municipality, for the period of interest. The data sets obtained show the average annual values, which are of interest for determining their trend and the impact of the development of the study area, for a spatial resolution of 500m x 500m.

• QGIS for AOD interpretation and PM2.5 and PM10 extraction

Using QGIS, the AOD data were interpreted to extract the annual average value for the area of interest, which were converted into PM2.5 [50] and PM10 [51] values using the following formulas:

$$y=271.34*x+22.24 \quad (1)$$

$$y=103*x+3.82 \quad (2)$$

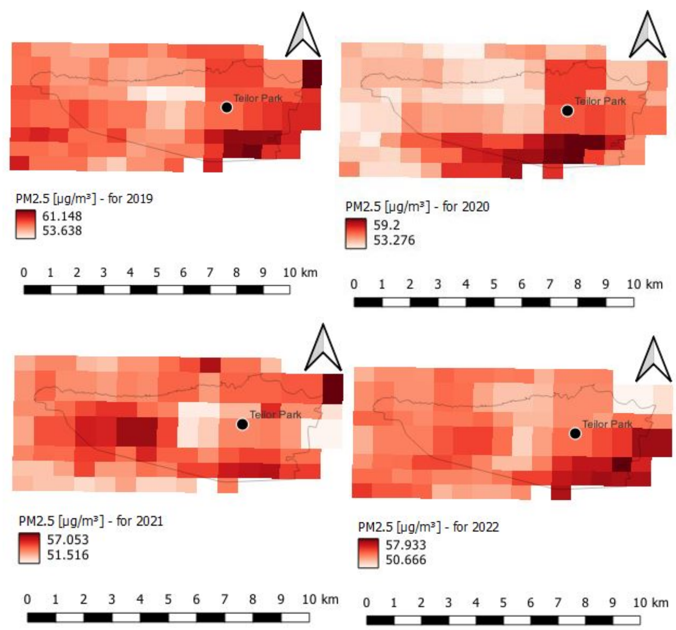

Figure 3. Spatio-temporal distribution of PM2.5 at the level of District 3 of the Municipality of Bucharest for the time interval 2019-2022

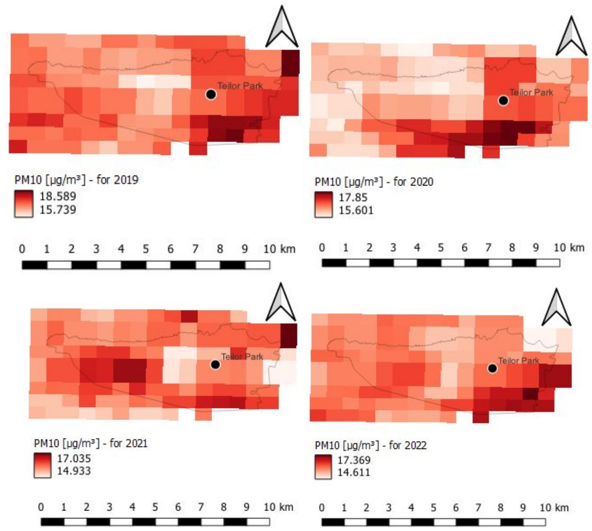

Figure 4. Spatio-temporal distribution of PM10 at the level of District 3 of the Municipality of Bucharest for the time interval 2019-2022

• LST extraction

Land Surface Temperature (LST) is a radiative temperature of the land surface and is an important parameter in environmental monitoring applications [52]. Traditionally, LST data are obtained from ground stations, which are very expensive and not evenly distributed [53]. One of the most widely used products for LST determination is the MODIS sensor. It offers a high temporal frequency (performing LST measurements 4 times a day through 2 satellites) at a high spatial resolution [54, 55].

In this study, using MODIS data ("MODIS/061/MOD11A2" [56] collection), after selecting the band of interest and applying spatial and temporal filters, the datasets presenting the annual mean values of LST in Bucharest Municipality were generated.

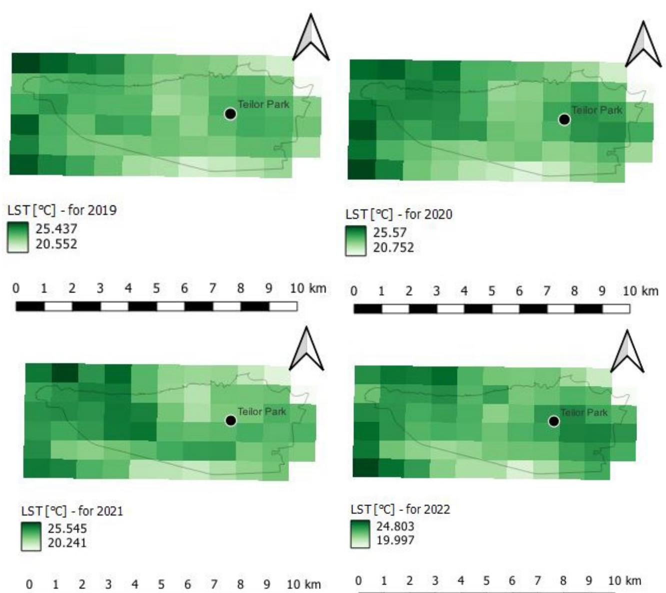

Figure 5. Spatio-temporal distribution of LST at the level of District 3 of the Municipality of Bucharest for the time interval 2019-2022

3. RESULTS

The Google Earth Engine application was employed to analyse satellite images captured by the MODIS sensor. This was achieved through the use of the JavaScript language, with the objective of extracting the annual values of PM2.5, PM10 and LST. Applying spatial and temporal filters, the values of the parameters under investigation were determined at the level of Bucharest Municipality with a spatial resolution of 500 meters. The spatial and temporal distribution of the results obtained is presented in Figures 3, 4 and 5. Table 1 presents the annual numerical values of the parameters under study for the Teilor Park area.

Table 1. Annual values of studied parameters for the time interval 2019-2022

Year	**AOD**	**PM2.5 [μg/m³]**	**PM10 [μg/m³]**	**LST [°C]**
2019	130.17	57.56	17.23	23.6
2020	127.03	56.71	16.90	24.0
2021	116.64	53.89	15.83	22.8
2022	118.60	54.42	16.04	23.5

As can be seen in Table 1, the values for PM2.5 and PM10 showed a decrease over the time interval studied, while the values for LST fluctuated. The values for PM2.5 a showed a greater decrease compared to PM10.

4. DISCUSSION

The quality of the air we breathe has a profound impact on human health, the environment and climate change. Therefore, it is of the utmost importance to have a detailed understanding of the current status of air quality.

Upon completion of the study, it can be observed that Google Earth Engine is a valuable platform for the management and processing of the substantial data volumes required for the execution of long-term analyses. In studies of air quality, the use of satellite imagery in processing leads to urban-relevant results, both spatially and temporally..

As can be seen from the results obtained, the development of the Teilor Park area and the new vegetation had a positive impact on the elements studied and on air quality. The amount of AOD has decreased considerably over the period studied, by 8.9%. In terms of the elements determined on this basis, PM2.5 showed a decrease of 5.4% over the 2019-2022 timeframe and PM10 showed a decrease of 6.9%.

In a study carried out by Heesung Chong et. al [19] it was concluded that in addition to determining the trend of air pollutants, satellite images can also be used to identify the main pollution points and sources, which is a perspective for future studies. Rui Luo et.al [57] presented the possibility of correlating multispectral data, air quality data and meteorological data from ground monitoring stations.

In a series of analyses [24, 26, 28, 29] identifying methods for combining satellite data with data from ground-based monitoring stations was an objective, the aim being to accurately assess air quality.

The use of the MODIS product for LST trend determination led to results with medium or low spatial resolution. [58]. A perspective for further research is the analysis of existing algorithms for MODIS LST downscaling in order to improve the spatial resolution of the obtained results.

The assessment of spatio-temporal trends of air pollutants and the impact of spatial planning on air quality can facilitate decision-making by local authorities to reduce air pollution and the negative effects on the health of the population..

It should be noted that although satellite imagery is a promising source of data for conducting analyses at high spatial resolution, it has limitations in terms of conducting studies over small areas. In future studies, it is recommended that these data sets be combined with additional data from ground-based sensors in order to improve the results obtained.

5. CONCLUSIONS

In the present study, MODIS satellite images were utilised and analysed within the Google Earth Engine platform with the objective of determining the temporal trend of atmospheric pollutants of interest and the impact of the development of Teilor Park in District 3 of Bucharest.

The analysis of satellite images in Google Earth Engine proved to be an effective approach in detecting and monitoring air pollution. This approach facilitated a good understanding of the spatial distribution of the studied elements, and it was possible to determine the impact of the development of the studied area. The analysed elements showed a decrease in the studied time interval. The results indicated a reduction in PM2.5 of 5.4% across the range, while PM10 exhibited a 6.9% decline.

Using Google Earth Engine and satellite imagery in time series analysis enables the assessment of trends in air pollutants, as well as the impact and effectiveness of applied measures. This information is of significant value to decision-makers in the development of intervention strategies to reduce air pollution. In this case, by analysing the spatial and temporal trends of air pollutants and the results obtained at the level of Teilor Park, as well as at the level of District 3, it is possible to generate strategies to improve air quality.

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