Milan: A Sensor-Based Study

- Analyzing the Air Temperature Variation in Giardini Indro Montanelli and Surroundings

Smart Buildings, Neighborhoods and Cities – 057689

Academic Year 2023/24

Second Semester

Group project:

Bagni, Felipe (MSc. in Computer Engineering)

Hüntemann, Lisa Marie (MSc. In Building Architecture)

F. Petrucci, Marcos V. (MSc. in Computer Engineering)

Prof. Andrea Antonio Caragliu

Prof. Luca Mottola

1.0 Introduction

In this essay, we will explore how air temperature changes in the environment of an urban park, as one moves from the edges to the center of Giardini Indro Montanelli in Milan. The City of Milan suffers a lot from hot air temperature in the summer, which affects us directly and is therefore very interesting for us. We want to study the spatial aspects of the park and how it influences the temperature. More specifically we want to focus on the impact of green areas, the proximity to main streets and how the temperature changes from the external perimeter with respect to the internal perimeter and inside the park. Ideally, we aim to identify the main factors contributing to the increase in temperature and evaluate the effective can ness of changes that can be made in a park through urban design. Through our analysis, we expect to make statements about the influence of park size, the presence of trees or water features, and the traffic levels on surrounding roads.

The study will be based on data self-collected through sensors. The programming of these sensors was an integral part of the project. We will discuss the methodology of collecting the data, the programming process, and the analysis of the collected data.

Additionally, the essay will examine the environmental factors contributing to temperature variations within the Urban environment and draw conclusions considering applied economics.

1.1 Understanding Urban Heat Islands and the Impact of Impervious Surfaces

Milan is a densely populated city with approximately 7.551 inhabitants per square kilometer[1]. The high population density results in increased human activities with several economic benefits but also in a significant number of sealed surfaces due to the concentration of buildings and roads, leading to a loss of natural habitats within the urban environment. In contrast to the principles of agglomeration and the reduction of costs due to a larger concentration of multiple economic activities in an urban area, the consequence is that the natural thermal characteristics, including air and surface temperature, change. This results in noticeable higher temperatures within the urban area of a city like Milan compared to the rural area outside the city. This phenomenon is called the Urban Heat Island (UHI).

[1] https://www.citypopulation.de/en/italy/lombardia/milano/015146__milano/

Unsealed surfaces play a crucial role in an urban environment by storing rainwater and supporting plant growth, which absorbs CO_2 and provides shade. These areas are essential for regulating air temperatures. When urban areas lack unsealed surfaces and instead are covered by impervious surfaces such as asphalt, concrete, and buildings, they not only save heat throughout the day and slow nighttime cooling but also reduce space for plant growth and water storage. Consequently, urban areas with high proportions of impermeable surfaces tend to be hotter than areas with more green spaces and vegetation[2].

Managing and reducing impermeable surfaces are important strategies to mitigate the negative impacts of urban heat islands on local climate and human health. Especially in the economic sector, controlling urban heat islands is crucial. By naturally reducing urban heat islands, not only can human health be improved, but energy costs can also be reduced, public health can be enhanced, and property values can be increased.

1.2 The Location of Giardini Indro Montanelli within Milan's Urban Environment

The park that we chose to consider is situated in the northeastern center of Milan in the neighborhood "Porta Venezia". Milan, like many cities, is organized into districts to manage and regulate traffic flow. The innermost district "Zone C" is only accessible by a toll road, a measure and cost method aimed at controlling individual car traffic. It also contributes to the efficient financing of public roads through user fees. Within this central district, which is the city center, green spaces are relatively rare. There are two notable larger parks in this area, one of which is the park currently under study.

This park is adjacent to a heavily trafficked ring road, the road "Bastioni di Porta Venezia", to the north, that divides the Part of Milan with and without Maut.

The park is popular among dog owners because it is allowed to have leash-less dogs, distinguishing it from the larger "Parco Sempione." Furthermore, it also attracts athletes due to its outdoor gym facilities.

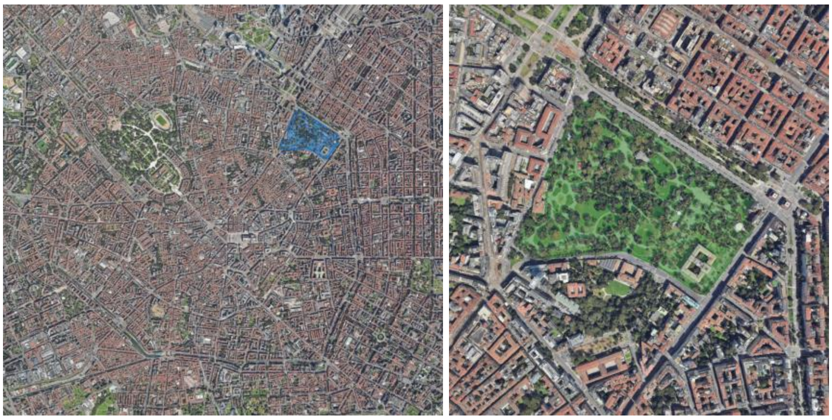
---

[2] Masoudi, Mahyar, and Puay Yok Tan. *"Multi-year comparison of the effects of spatial pattern of urban green spaces on urban land surface temperature."* Landscape and Urban Planning 184 (2019): 44-58.

The park's location in the heart of Milan's densely urbanized environment makes it an ideal candidate for studying and defining innovative and effective strategies necessary for effective urban green spaces that lead to maximum economic benefits. The adjacent location to one of the city's main roads gives us useful information about how traffic and built environment affects air temperature, which we can understand by looking at data, we will be collecting. Additionally, the park's approximately round shape lends itself well to defining a measurable diameter for analysis and comparison purposes, when it comes to a radius.

Since the park itself does not generate income, applying urbanization economy methods is challenging. However, cost reductions occur through localization and urbanization economies. Located in the city center near other green spaces like Parco Sempione, maintenance costs are reduced. The park benefits from existing infrastructure, including the urban water supply, which is lowering expenses. While maintenance costs, funded by taxes, may seem negative, urban green spaces offer numerous economic advantages.

Urban green spaces increase property values, leading to higher tax revenues. They attract tourists and residents, boosting local businesses. Additionally, green spaces improve public health, here in particular by providing facilities for athletes, which lead to a preventive function for their health, thereby reducing overall healthcare costs. Besides that, Urban Greenery contributes to energy savings by cooling urban areas, thus lowering air conditioning expenses. Overall, urban green areas provide significant economic benefits and enhance residents' quality of life.



Giardini Indro Montanelli

Circumfence: 1.948 m

Area: 191.590 m^2

(Source: googleEarth)

Figure 1: Location of the park "Garidini Indro Montanelli" in Milan

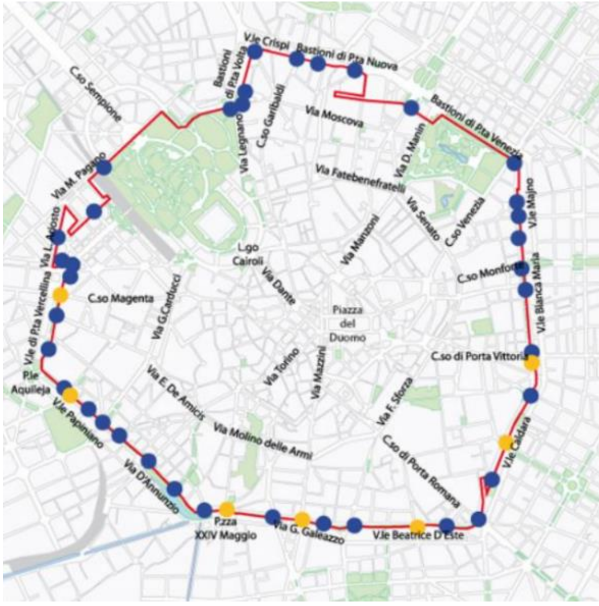


Figure 2: Area C in Milan and the toll road.

1.3 Economic Implications and Significance

1.3.1 Economic impact of UHI and temperature variations on Urban Planning

The Urban Heat Island (UHI) effect which can be drawn back on the lack of unsealed surfaces is a big challenge of the increasing Urbanization. One of the most immediate economic impacts of UHI is increased energy consumption, for cooling buildings and infrastructure during hot periods. Urban areas which suffer from Urban Heat Islands experience heightened demand for air conditioning and refrigeration, leading to higher electricity bills for households and businesses.[3] Moreover, the risk of disasters such as floods increases due to higher urban runoff from stormwater caused by the lack of unsealed surfaces, leading to significant costs once a disaster occurs.

Properties in cooler urban areas with effective UHI mitigation strategies have higher values in sales prices and are more attractive. Studies have shown that cooler urban areas with more green spaces attract higher property prices.[4] For example, research indicates that properties in areas

[3] Li, Xiaoma, et al. *"Urban heat island impacts on building energy consumption: A review of approaches and findings."* Energy 174 (2019): 407-419

[4] World Bank, 2021. *A Catalogue of Nature-based Solutions for Urban Resilience*. Washington, D.C. World Bank Group (S.103)

with green space, such as green belts, can have an increase of perceived value of 79%.[5] The economic benefits of such investments include improved public health, reduced energy expenditures, and enhanced property values in cooler urban environments. Consequently, investing in green spaces and other UHI mitigation strategies can lead to substantial economic gains for urban areas.

A significant economic burden can also be heat-related health issues, such as for example heat strokes and respiratory problems which lead to increasing medical expenses and besides that to increase the risk of illness and incapacity for work. These conditions result in higher healthcare costs and lose of workdays, affecting the overall economic performance of an Urban Area. Effective UHI mitigation and heat reduction can alleviate these health issues, thereby reducing medical expenses and improving productivity.

1.3.2 Value of smart digital technologies in addressing urban climate issues

In the consideration of innovation and user-centric needs, smart technologies offer a response to optimize processes effectively. These technologies include sensors to collect and process real-time data, enabling adaptive responses through system adjustments.

Whether applied in private homes or urban settings, smart systems strategically activate devices based on sensor feedback to mitigate energy consumption. This proactive and continuous deployment of smart technologies not only enhances operational efficiencies but can also introduce, as in our case, a nature-based solution, a final environmental solution that got found with the smart digital technology. By utilizing sensors to gather environmental data, these solutions are designed to address climatic challenges exacerbated by urbanization.

Moreover, integrating smart technologies into an urban environment can yield economic benefits by improving the effective management of limited resources such as space and reducing operational costs. By integrating innovation in sustainability practices, these technologies lead to economic growth and resilience. This dual impact: enhancing environmental sustainability while

---

[5] RIAZ, ATIF, et al. "Green areas: a source of healthy environment for people and value addition to property." Labour 37 (2002): 41

supporting economic efficiency, underscores their critical role in modern urban development strategies.

As cities face increasing pressures from climate change and rapid urbanization, the proactive deployment of smart technologies emerges as a vital tool for supporting sustainable growth and resilience in urban environment.

2.0 Analysis

2.1 Methodology and Preliminary Planning

To analyze temperature differences in and around an urban park, we need data. Since there is no specific data available, we decided to collect it ourselves using sensors. The data collection strategy involves using sensors connected to a Raspberry Pi, provided by Politecnico di Milano, to gather data independently. To make accurate comparisons, we decided to collect data simultaneously. Due to schedule restraints caused by the time needed for the arrival of materials and other external factors, data collection had to be done in one day. Given the large area of the park, it is important for all group members to collect data at the same time. This ensures we get a complete and consistent set of data.

Ideally, data collection should occur on a cloudy, windless, and rain-free afternoon to minimize the influence of direct sunlight and tree shadows, which could complicate result evaluation. It makes most sense performing the data collection around 4 PM, when temperatures peak and asphalt surfaces have been heated by the sun. Additionally, it aligns with rush hour, which also contributes to air pollution and air temperature. Significant differences within the park are anticipated during this summer period. Our approach includes transporting pre-programmed Raspberry Pis and sensors in a portable box, with each group member simultaneously walking through and around the park to gather data.

The Raspberry Pis will record the current temperature every 10 seconds, along with its current geographic coordinates (via GPS), the air quality and air humidity. All this data shall be stored on the local memory of the Raspberry Pi in a CSV file, which will be collected afterwards.

We collaborate with another group studying air quality in the same park, allowing us to collect comprehensive shared data. The data collecting program has been jointly developed, fostering collaborative skills and making working processes more engaging and effective. Our objective is to create a map using GPS coordinates pointing out the temperature, giving us an overview of the temperature around the whole park and enabling a precise data analysis.

For these measurements, the following items are needed (per person): a power bank to power the sensor, a micro-USB cable, a Raspberry Pi equipped with a groove hat, temperature and humidity sensor, a GPS module, an LCD display (for debugging while in action), and additionally, an air pollution sensor to collect data for the other group. We requested this hardware from Professor Mottola, who ordered and provided it for our use.

2.2 Development of the Node-Red flow and its functionalities

2.2.1 Introduction to Node-Red and its relevance in this project

Given that Professor Mottola's classes taught us a lot about Node-red and that we could have the same hardware used during class at our disposal, we decided from the beginning that we would use it for our project.

Node-red is a browser-based programming tool that lets the user connect different functional blocks to create a meaningful flow of information. This tool allows a myriad of combinations and possibilities. We could not only make use of function blocks – short JavaScript programs that perform a direct task – but also place specific blocks such as a port reader, for the GPS, or the temperature and humidity block, a plug-and-play add-on designed to allow seamless integration with our sensors.

Therefore, with all these tools, we designed a simple flow that measures all the data in a 10 second interval, combining all this information and storing it in a single entry of an CSV file. This program was loaded onto all our Raspberry Pis and was how we collected all our data.

2.2.2 Detailed list of components used

As discussed, prior, we utilized a variety of hardware and different sensors. Here we provide the detailed list of everything that was used by each reading node.

- Raspberry Pi 3
- Grove - Base Hat for Raspberry Pi
- Grove - GPS Air530z
- Grove - Temperature&Humidity sensor SHT31
- Grove - Air Quality Sensor v1.3
- Grove – OLED Display 128x64 v1.1
- 1000mAh power bank

Further details and circuit image is shown in Figure 3

2.2.3 Step-by-step process of programming

When we got the Raspberry Pis in hand, we first needed to connect them to our local Wi-Fi to program them. The first step was accessing the local file system in our PC via an SD card adapter. We searched for the following file */etc/wpa_supplicant/wpa_supplicant.conf,* which stores the SSID and corresponding password of the Wi-Fi and added our personal access information.

Once connected in the same Wi-Fi as the Raspberry Pi, we plugged all the sensors as shown in Figure 3:

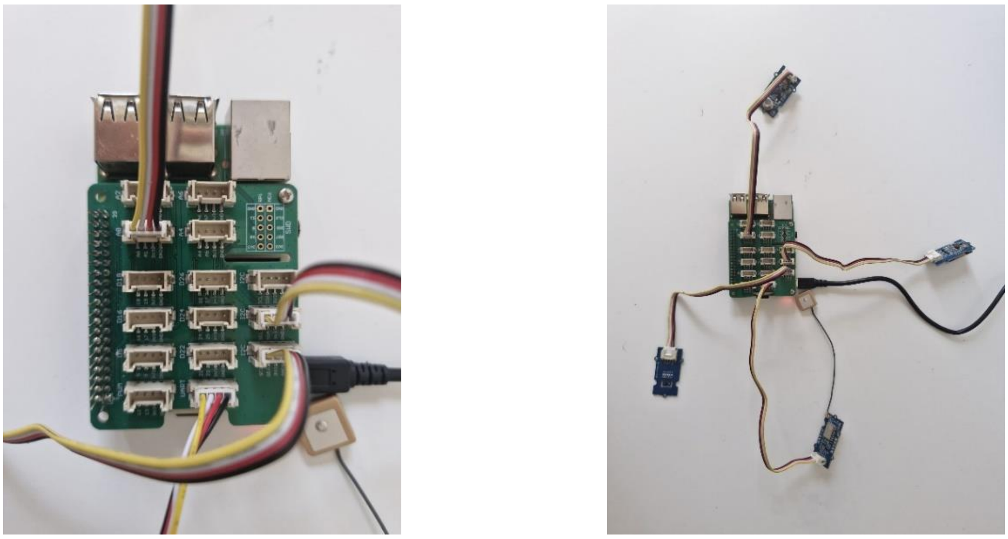


Figure 3: Photos of Raspberry Pi with all the sensors connected

Following that, we started to use the Node-red installed in the Raspberry Pi, accessing it via browser by writing: board_ip:1880. We developed this flow shown in Figure 4, which, in short terms, reads the values from the sensors and combines them every in one single entry in a CSV file, every 10 seconds.

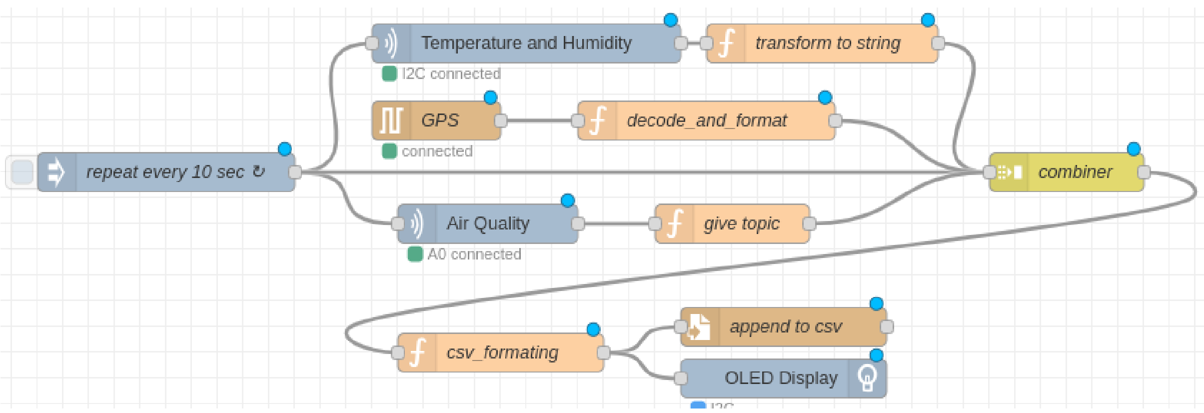


Figure 4: Screenshot of the Node-red flow running on the boards.

Here is a brief explanation of each block of the flow:

- **Repeat every 10 sec:** Triggers the measurement and repeats itself every 10 seconds
- **GPS**: Access the Raspberry Pi internal port and retrieve the GPS raw data
- **decode_and_format:** Uses a regular expression to get the raw information of the GPS and format it in both coordinates and timestamp
- **Air Quality:** Grove block to read air quality
- **Temperature and Humidity:** Grove block to read temperature and humidity
- **Transform to string:** Get both temperature and humidity values and format them to a string; it also gives the correct CSV header for the information
- **give topic:** Give the air quality value the correct CSV header
- **combiner:** Waits for an input of the 4 incoming connections before combining them and sending them forward.
- **csv_formating:** Disassembles the combined payload and format the data for the insertion on the CSV file
- **Append to csv:** Performs access to the file system and save data in a CSV
- **OLED Display**: Receives the string to be saved in CSV. Was used to verify if everything was running as expected

2.2.3 Overview on the code of the main blocks

Let us analyze a detailed examination of the main function blocks, giving a general overview of the code written.

The first block to be analyzed is *decode_and_format*, responsible for, as the name suggests, decoding and cleaning the raw data that comes from the GPS sensor. The main function begins as shown in Figure 5.

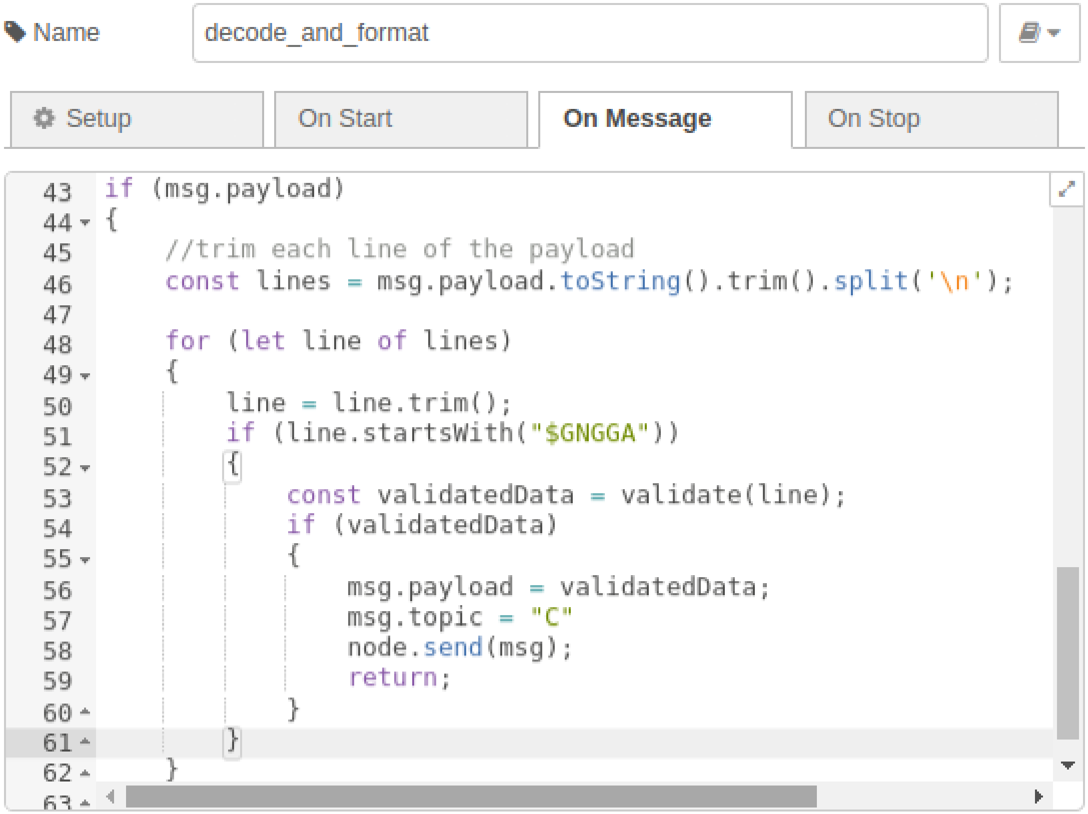


Figure 5: Main part of node decode_and_format

Whenever a payload arrives for the node, it will detect and separate it into individual lines. For each line it will check if it begins with *$GNGGA* – identifying if it is in standard GPS format – then proceeds to validate this data, if it is successful, the data will receive its topic ("C" for coordinates) and be sent forward.

The validation process, shown in Figure 6, extracts the coordinate information from the message. First it splits the line in commas, getting individual attributes from the received payload, as the GNGGA format has an object-oriented structure with several attributes (latitude and longitude among them). Then it iterates through the patterns array, checking if our attributes match the expected Pattern (Figure 7). Finally, it gets the coordinates out of the correct attributes of the GNGGA "object".

```
function validate(line)
{
    const gga = line.split(",");
    if (gga.length < 15) return false;

    for (let i = 0; i < patterns.length; i++) {
        if (!patterns[i].test(gga[i])) return false;
    }

    try {
        const latitude = convertToDecimalDegrees(parseFloat(gga[2]), gga[3]);
        const longitude = convertToDecimalDegrees(parseFloat(gga[4]), gga[5]);
        return `${latitude}, ${longitude}`;
    } catch {
        return false;
    }
}
```

Figure 6: validate function from the block decode_and_format

```
const patterns = [
    /^\$GNGGA/,
    /\d{6}\.\d+/,
    /\d{4}\.\d+/,
    /[NS]/,
    /\d{5}\.\d+/,
    /[EW]/,
    /[012]/,
    /\d+/,
    /\d*\.\d*/,
    /-?\d*\.\d*/,
    /M/
];
```

Figure 7: Regular expression of the desired GNGAA pattern to be matched

To correctly retrieve the latitude and longitude in decimal value, a small conversion is needed, from degrees, minutes and directions (‘N’ for North, ‘S’ for south and so on) to a more standard version of decimal coordinates values (with positive and negative signal indicating directions). This conversion process is shown in Figure 8.

```
function convertToDecimalDegrees(value, direction)
{
    const degrees = Math.floor(value / 100);
    const minutes = value % 100;
    let decimalDegrees = degrees + minutes / 60;
    if (direction === 'S' || direction === 'W') decimalDegrees = -decimalDegrees;
    return decimalDegrees;
}
```

Figure 8: Function converts a degree-minute value with a corresponding direction into decimal.

Now let's investigate "transform to string", present in Figure 9. This block has the only purpose of getting temperature and humidity values, adding them to a single string and giving it the proper topic, which serves the purpose of identifying this data after combination, easily retrieving it in the flow afterwards.

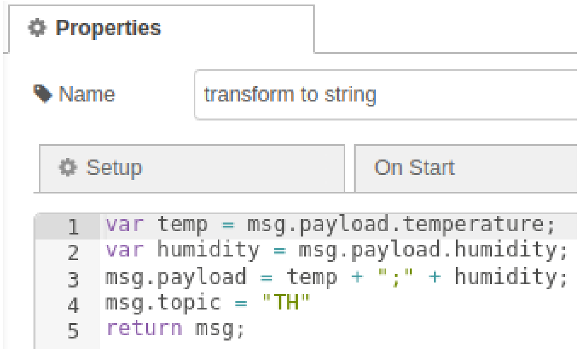


Figure 9: Transform to string code

Finally, let's analyze the "csv_formatting" code, present in Figure 11. It starts by receiving a combined payload, a string containing all measures separated by a semi-colon. It then splits the message, retrieving an array with all the data, after which it creates the string to be inserted in the CSV, separating every measure by a colon. This string is sent to a file writer, finishing the flow.

```
var payload = msg.payload;
var th = payload.TH.split(';');
var temperature = th[0];
var humidity = th[1];

var date = new Date(payload.T);
var formattedDate = date.toLocaleString('it-IT', { timeZone: 'Europe/Rome', hour12: false }).replace(',', '');

// Format: "dd/mm/yyyy hh:mm:ss"
msg.payload = formattedDate + "," + temperature + "," + humidity + "," + payload.Q + "," + payload.C;
return msg;
```

Figure 10: CSV_formating function that receives a combined string and formats it to CSV standard

2.3 Execution of Data Collection

On Thursday, June 20th, 2024, a cloudy day, we, the two groups met in the park at around 2:30 PM to prepare for data collection. Figure 12 shows the climate conditions during the data collection as reported on Time and Date Weather[6]:

[6] Time and Date AS 1995-2024. (20.06.2024). https://www.timeanddate.com/weather/italy/milan/historic?month=6&year=2024

	Conditions			Comfort		
Time		Temp	Weather	Wind		Humidity
13:50		26 °C	Scattered clouds.	9 km/h	↘	65%
14:20		26 °C	Scattered clouds.	9 km/h	↘	65%
14:50		26 °C	Scattered clouds.	20 km/h	↓	61%
15:20		28 °C	Scattered clouds.	17 km/h	↘	55%
15:50		28 °C	Scattered clouds.	13 km/h	↘	51%
16:20		29 °C	Scattered clouds.	11 km/h	↘	51%
16:50		29 °C	Scattered clouds.	9 km/h	↘	48%
17:20		29 °C	Scattered clouds.	7 km/h	→	51%

Figure 11: Weather report that the time of the measurement

We set up 4 Raspberry Pis with Node-RED at home to test the devices. In the park, it was possible to reconnect to the Node-Red Flows using the hotspot that was previously set.

At around 3:25 PM, we began collecting data, walking individually through the park. Beforehand, we clarified who would walk along which paths to efficiently collect data from every part of the park. It was crucial to gather data also along the park's edges, as our goal is to investigate these vulnerable areas and, along with other environmental findings, draw conclusions about the relationship between the distance from the park's borders and temperature variations. The boards were pre-programmed to store the data collected in the Raspberry Pi itself, so the data could be easily retreated, and no need for a hotspot would be required during the data collection process.

We started our walk simultaneously, transporting the Raspberry Pis with sensors in shoeboxes for simplicity and ease of handling. For about 45 minutes, we walked through the park. But for the purposes of the data analysis, a timespan of 31 minutes will be considered. Here it is possible to see the 4 paths taken during the data collection from 3:25 PM to 3:55 PM, the red arrows indicate the point of start and the red circle the point of end:

- For Path 1, the data was collected in the external perimeter of the park:

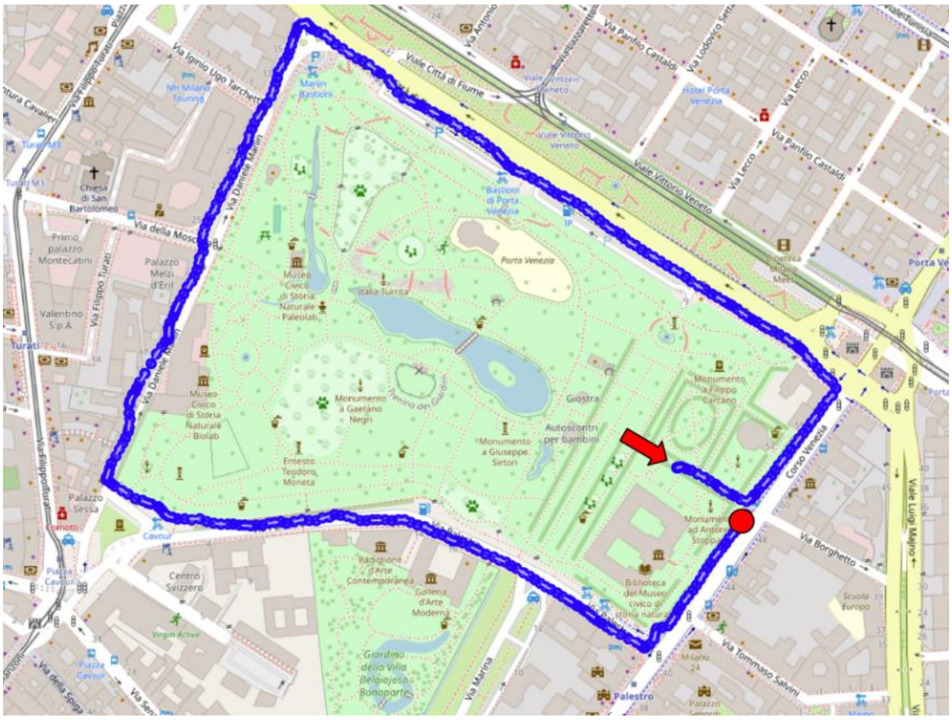


Figure 12: Data Collection, Path 1

- For Path 2, the data was collected in the internal perimeter of the park:

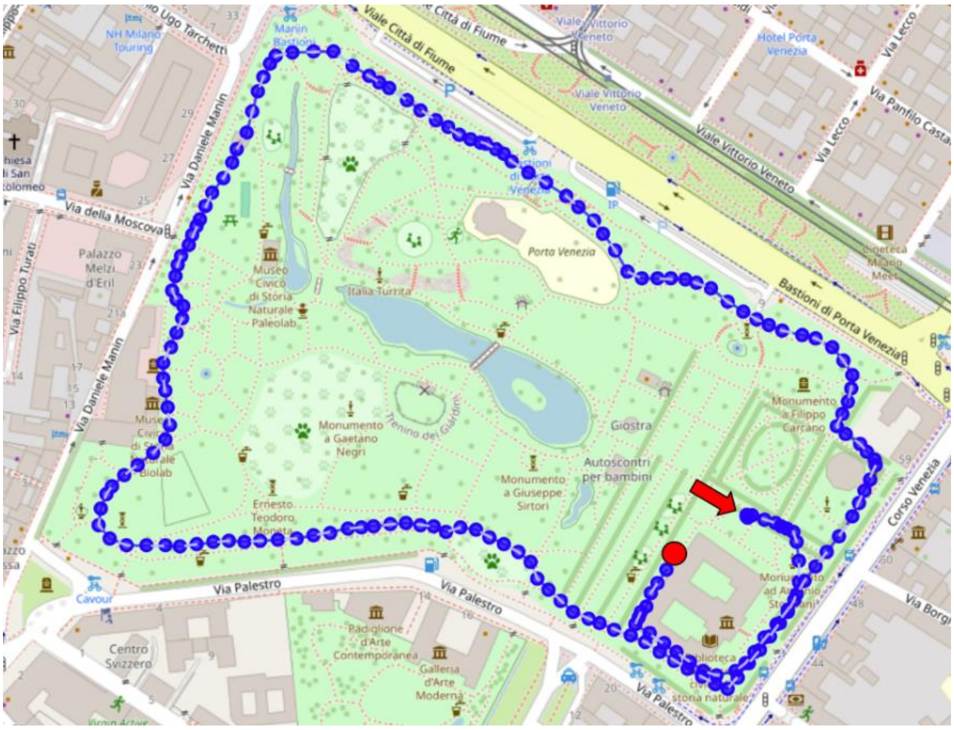


Figure 13: Data Collection, Path 2

- For Path 3, the data was collected in an internal section of the park:

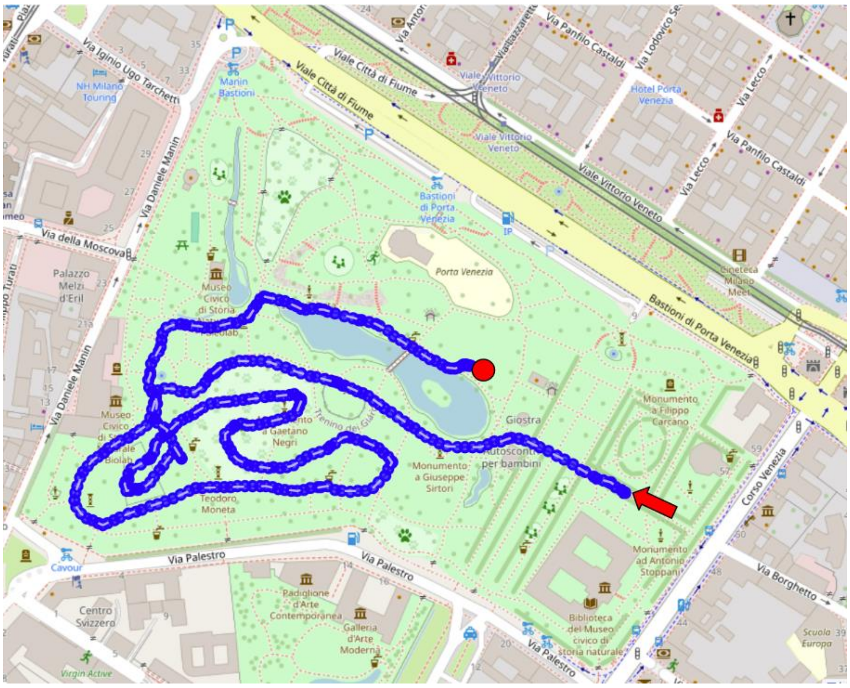


Figure 14: Data Collection, Path 3

- For Path 4, the data was collected in another internal section of the park:

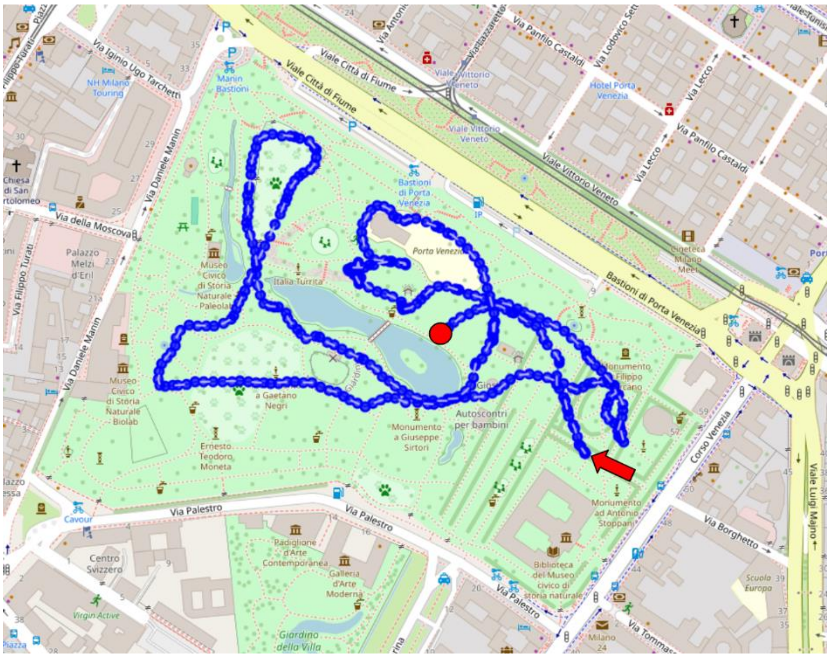


Figure 15: Data Collection, Path 4

With these 4 paths, the park's coverage was considered satisfactory for the intended analysis. Here we can see all the points of data collection:

Figure 16: Data Collection, all measuring points

Afterwards, we gathered in a café in the park to extract the data from the Raspberry Pis and share it. We also generated initial results using Excel charts to test if everything had worked properly. After sharing the data collection, we discussed the next steps in the process.

Figure 17: Data Collection, all measuring points

2.4 Data Analysis

After collecting the data, as mentioned above, we had 4 CSV files each one corresponding to one of the paths taken. So, as a first step, an analysis was performed on four distinct datasets: db1.csv, db2.csv, db3.csv, and db4.csv. Each dataset underwent an initial analysis, but they all were merged for a comprehensive and unified analysis and visualization. For the data analysis, we chose to use Python and primarily Plt, it is worth mentioning that the Python Notebooks of the analysis and the CSV files mentioned above can all be found in this GitHub Repository.[7]

2.4.1 Data Loading, Merging and Pre-Processing

For each dataset (db1, db2, db3, and db4), data was loaded from specified sources, typically CSV files, into pandas DataFrames. After looking at each dataset on its own, we combined them into one DataFrame to make it easier to analyze everything together.

The next step was to do some basic data cleaning to deal with any missing values and make sure everything was consistent. This included converting timestamp columns to datetime objects for accurate temporal analysis, filtering per timestamp to have the data collected between '2024-06-20 15:24:00' and '2024-06-20 15:55:00'.

To handle missing values in a DataFrame, we used the *dropna()* method due to its simplicity. This method removes any rows that contain at least one missing value (*NaN*). While this approach is straightforward and easy to implement, our data frame did not have any missing values prior to the usage of this method, which is kept for future use.

Outliers can significantly affect the analysis of data. To handle them in the temperature column of the DataFrame, first, we computed the mean (average) and standard deviation of the temperature values. These statistical measures help us to understand the distribution of the data. Then, based on the empirical rule (also known as the 68-95-99.7 rule), for a normal distribution, almost all data points lie within three standard deviations of the mean. Thus, we defined the outliers as those values that are more than three standard deviations away from the mean. Finally, we kept only those rows where the temperature values are within this range. As above, for the unified analysis, we had only one outlier in our dataset (which is temperature of 31.17°C), which proves that the data collection was done in a consistent manner. However, we decided to leave this processing of data for probable future use.

[7] https://github.com/febagni/smart-cities-temperature-analysis/

By following these steps, we ensure that our dataset is clean and free from missing values and extreme outliers, making it more suitable for analysis.

2.4.2 Exploratory Data Analysis (EDA)

For some initial EDA, we performed initial visualizations to inspect the data, such as the data frame's head. Here we can see the structure of the merged data frame, we can see the columns of the dataset (Timestamp, Temperature, Humidity, Air Quality, Latitude, Longitude):

	Timestamp	Temperature	Humidity	Air Quality	Latitude	Longitude
0	2024-06-20 15:24:02	28.69	50.97	28	45.473469	9.202674
1	2024-06-20 15:24:07	28.73	50.74	27	45.473470	9.202674
2	2024-06-20 15:24:12	28.78	49.94	27	45.473470	9.202674
3	2024-06-20 15:24:17	28.80	49.66	29	45.473470	9.202674
4	2024-06-20 15:24:22	28.77	49.70	27	45.473470	9.202673

Figure 18: Head of the Dataset.

Then, we printed basic descriptive statistics to understand the central tendencies, dispersion, and overall distribution. Measures included mean, median, standard deviation, and quartiles. Here we can see the descriptive statistics for the merged dataset after the data cleaning.

	count	mean	std	min	25%	50%	75%	max
Temperature	1301.0	28.930254	0.714416	27.370000	28.420000	28.900000	29.370000	30.940000
Humidity	1301.0	48.558640	2.678094	43.030000	46.500000	48.250000	49.980000	59.470000
Air Quality	1301.0	39.676403	11.490155	24.000000	28.000000	37.000000	46.000000	74.000000
Latitude	1301.0	45.474263	0.001065	45.471935	45.473489	45.474105	45.474860	45.477260
Longitude	1301.0	9.200010	0.002211	9.195724	9.198159	9.199916	9.201978	9.204596

Figure 19: Descriptive Statistics of the Dataset..

Here we can see that the lowest temperature was 27.37°C and the highest temperature was 30.94°C. The mean temperature was 28.93°C and the standard deviation was 0.714, with this, we can see the distribution of temperatures of our dataset:

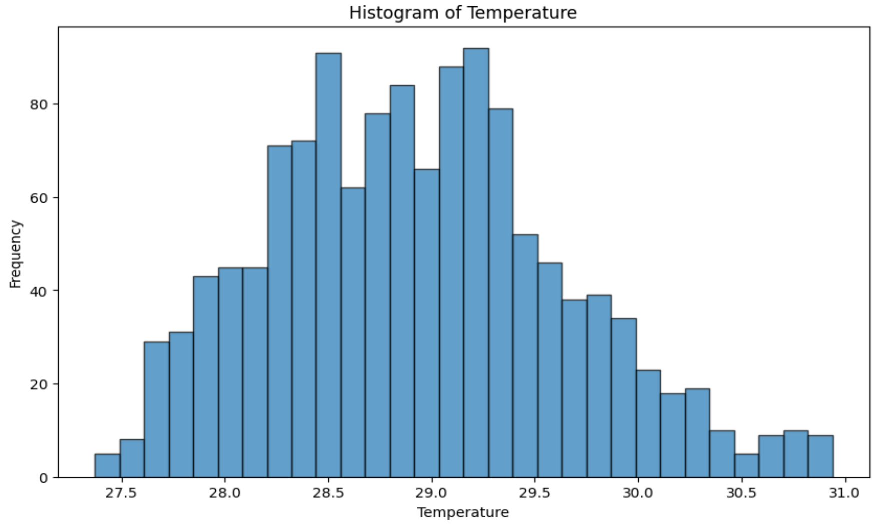


Figure 20: Distribution of temperature on the Dataset.

From the histogram, we can see a roughly normal distribution of temperatures, mostly between 28.5 and 29.5 degrees, with a range from 27.5 to just over 31 degrees. The slight right skew and frequency peaks around 28.5 and 29 degrees suggest these are common temperatures. This helps us understand the temperature patterns for interpreting the data.

Besides this, we also decided to plot temperature over time for identification of temperature patterns and trends during the data collection time span.

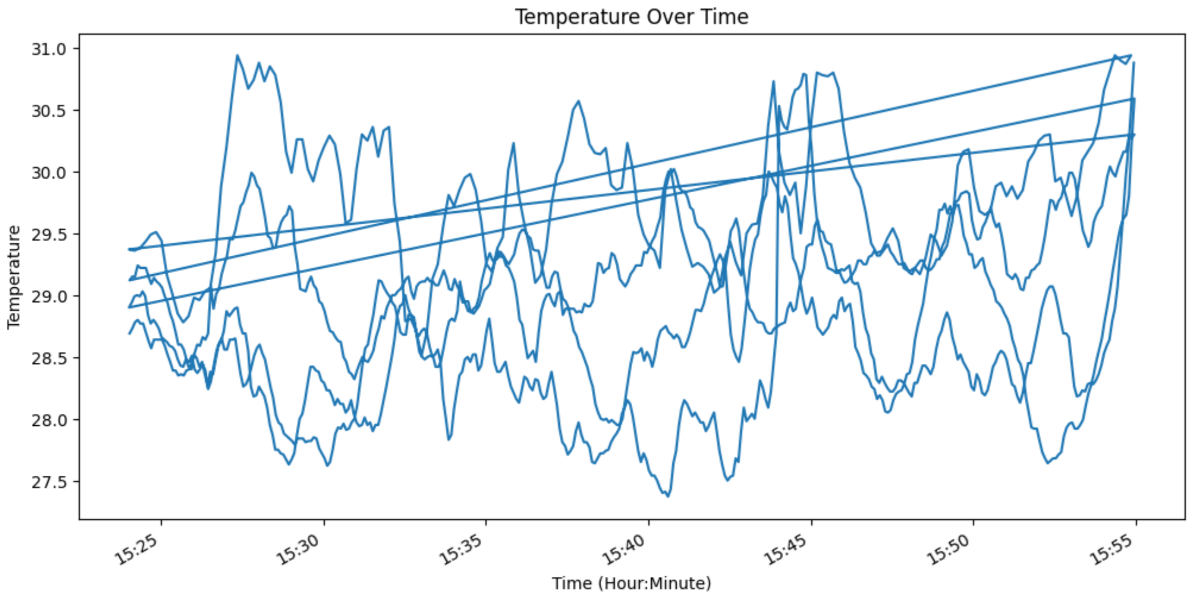


Figure 21: Variation of temperature per path taken across the time and its deltas.

By the lines of the deltas, we can see an overall growth in the temperature through the period of analysis, which is something to be considered in the interpretation of the results. Lastly, we plotted on a graph how the temperature varies by position:

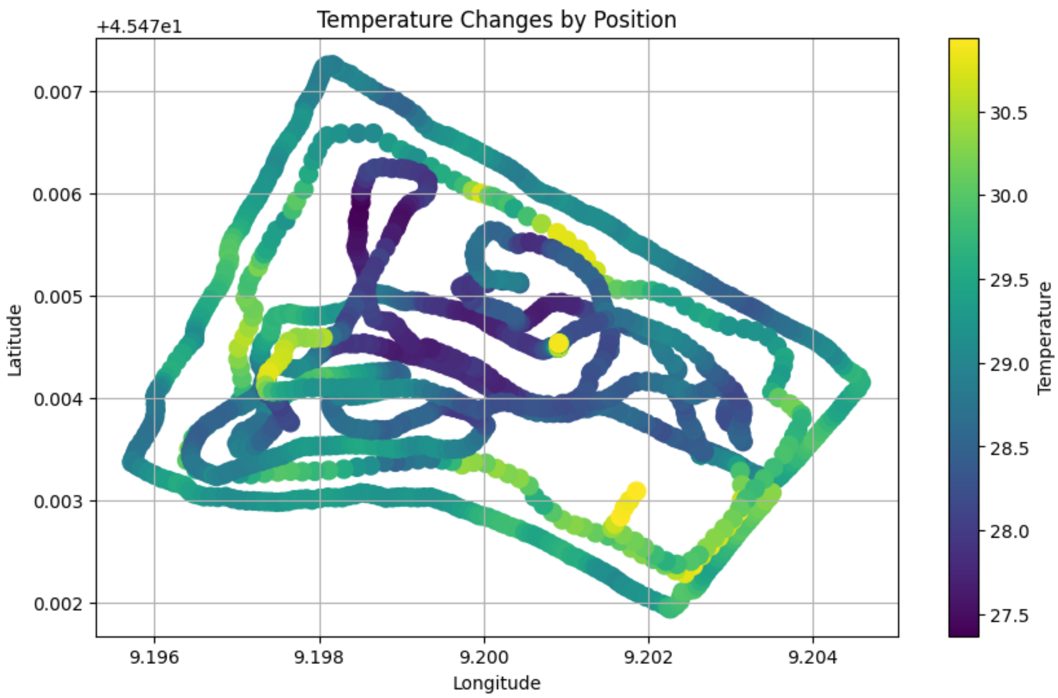


Figure 22: Plot of temperature changes by position

From this, we can already see that there is a trend for lower temperatures as you go deeper into the park. So, let us analyze the behavior of temperature with respect to the distance from the perimeter and the park center.

2.4.3 Distance Analysis

Following EDA, we decided to study the behavior of the temperature with respect to the distance to the barycenter of the park as well as with respect to the distance to the closest point of the external perimeter. The expected outcome is that the deeper in the park, the lower the temperature. We decided to perform both analyses to compare the results when taking different distance as measurement, but both are expected to lead to the same conclusion.

For this analysis, let us first study the behavior of the temperature with respect to the barycenter of the park. We begin by taking just the coordinates that compose the external perimeter of the park:

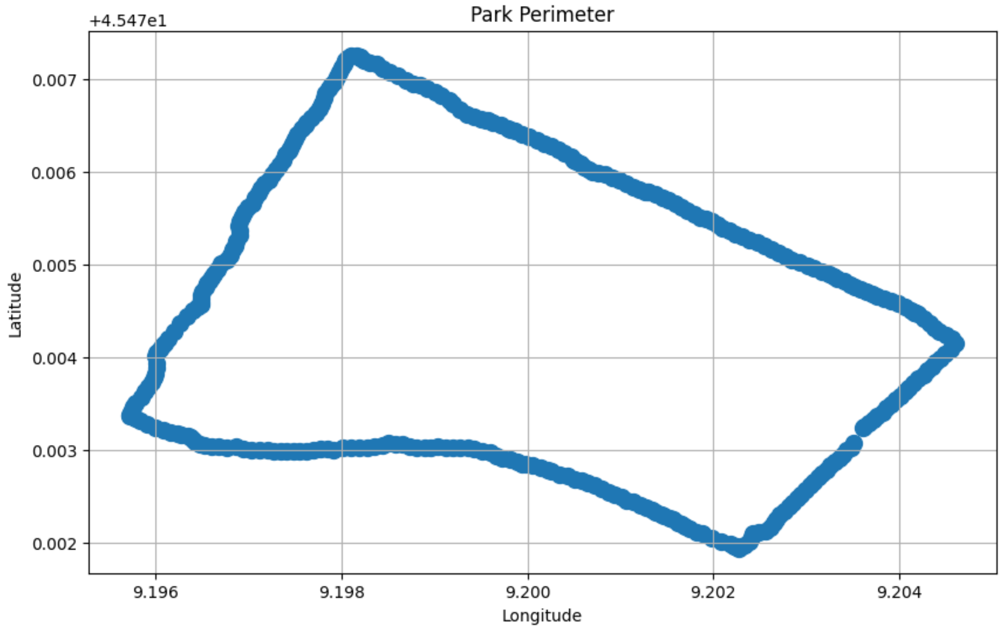


Figure 23: External Perimeter of the Park.

After that we take the average latitude and longitude of this subset of coordinates to find the Barycenter coordinates, which are: (45.4743487718254, 9.19991987797619). And can be visualized as follows:

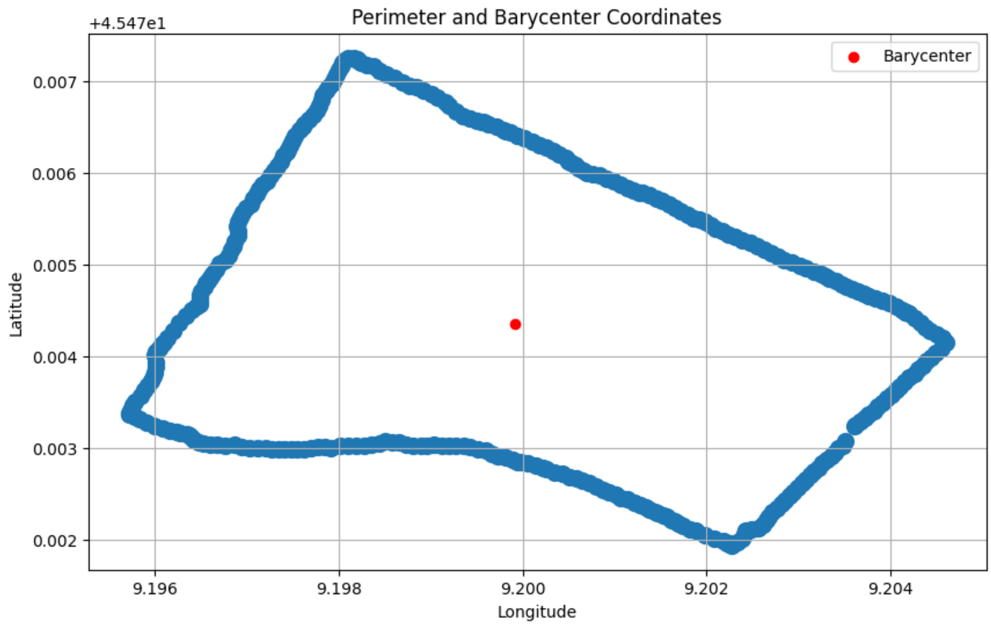
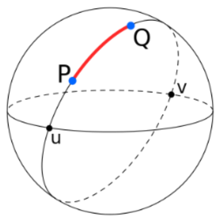


Figure 24: External Perimeter of the Park and its Barycenter.

Then, we used the Haversine formula to calculate the distance between each point where data was collected with respect to the barycenter. The Haversine formula calculates the shortest distance between two points on a sphere using their latitudes and longitudes measured along the surface.



$$d = 2r \arcsin\left(\sqrt{\frac{1-\cos(\varphi_2-\varphi_1)+\cos\varphi_1\cdot\cos\varphi_2\cdot(1-\cos(\lambda_2-\lambda_1))}{2}}\right)$$

Figure 25: Haversine Formula

Where *d* is the distance between the two points along a great circle of the sphere, *r* is the radius of the sphere, the latitude is represented by ϕ and longitude represented by λ.

With this, we have the following distances:

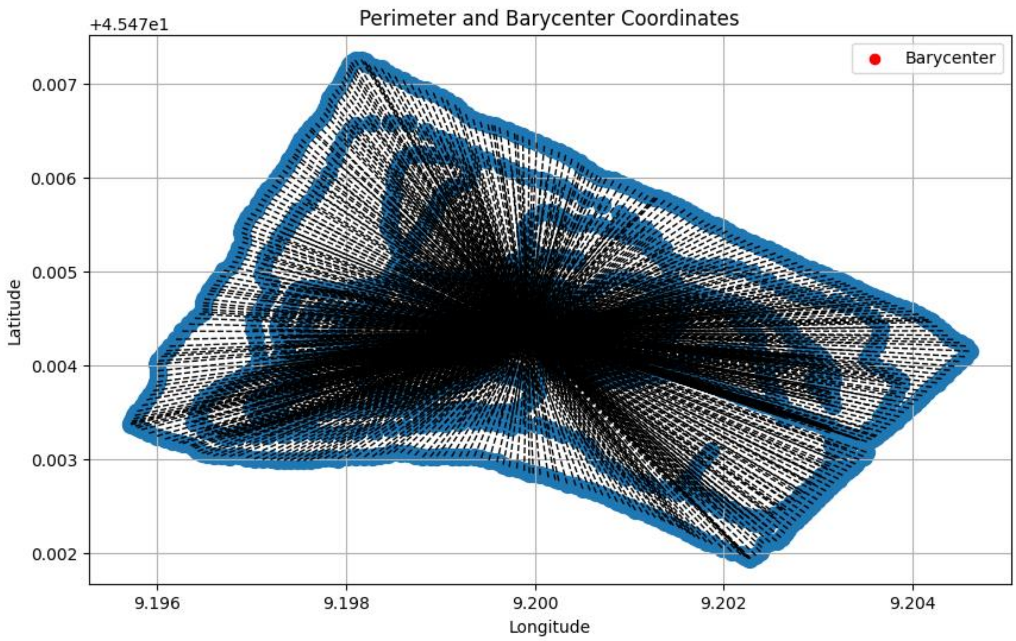


Figure 26: Plot of distance between each point where data was collected with respect to the barycenter.

By taking the distance as X and temperature as Y, we performed a linear regression and plotted the temperatures against the distance from the barycenter with the linear regression line:

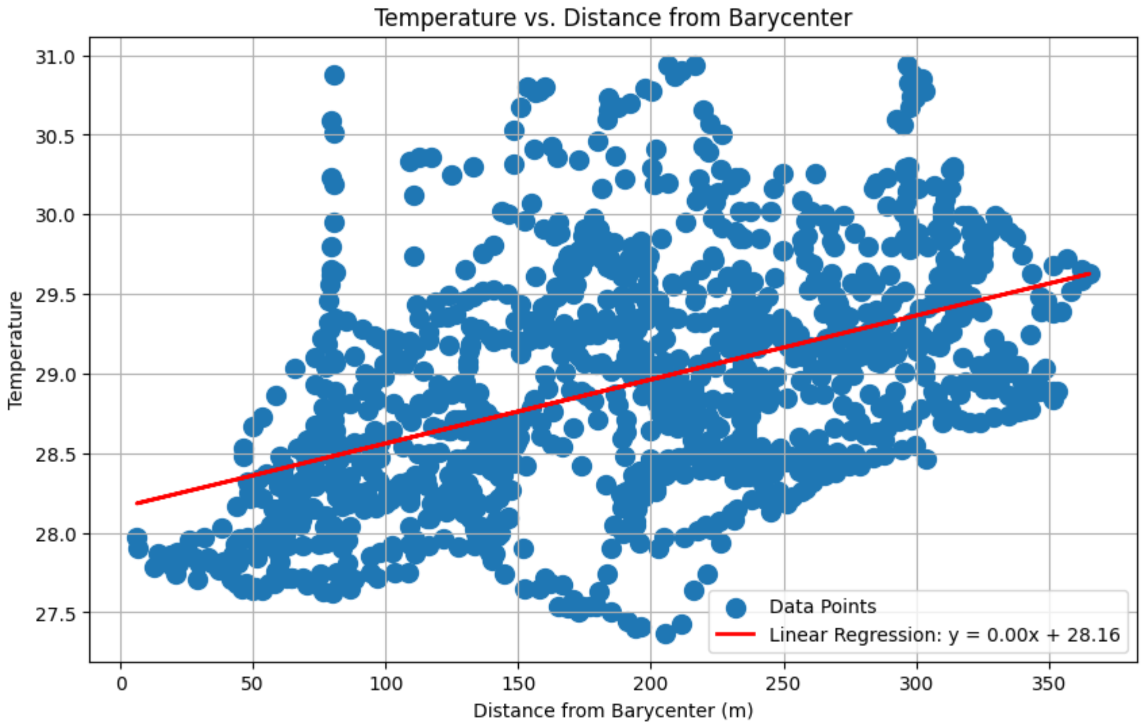


Figure 27: Scatter plot of Temperature vs Distance from Barycenter and its Linear Regression.

Here we can see that despite the high dispersion of the temperatures with respect to the distance from the barycenter, we observe a growth shown by the linear regression. So as the distance from the center of the park increases, the temperature also increases.

Now, instead of using the barycenter, let us study the temperature behavior with respect to the proximity to the border of the park. For this, we first calculate the Haversine distance to closest point on perimeter, which we can see in the following chart:

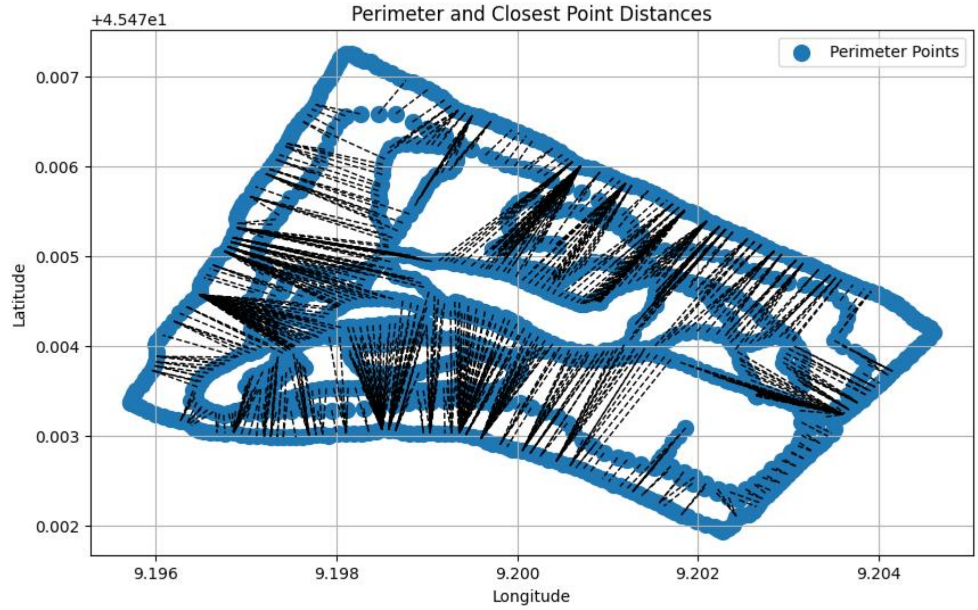


Figure 28: Plot of distance between each point where data was collected with respect to the closest border.

By taking the distance as X and temperature as Y, we performed a linear regression and plotted the temperatures against the distance from the border with the linear regression line:

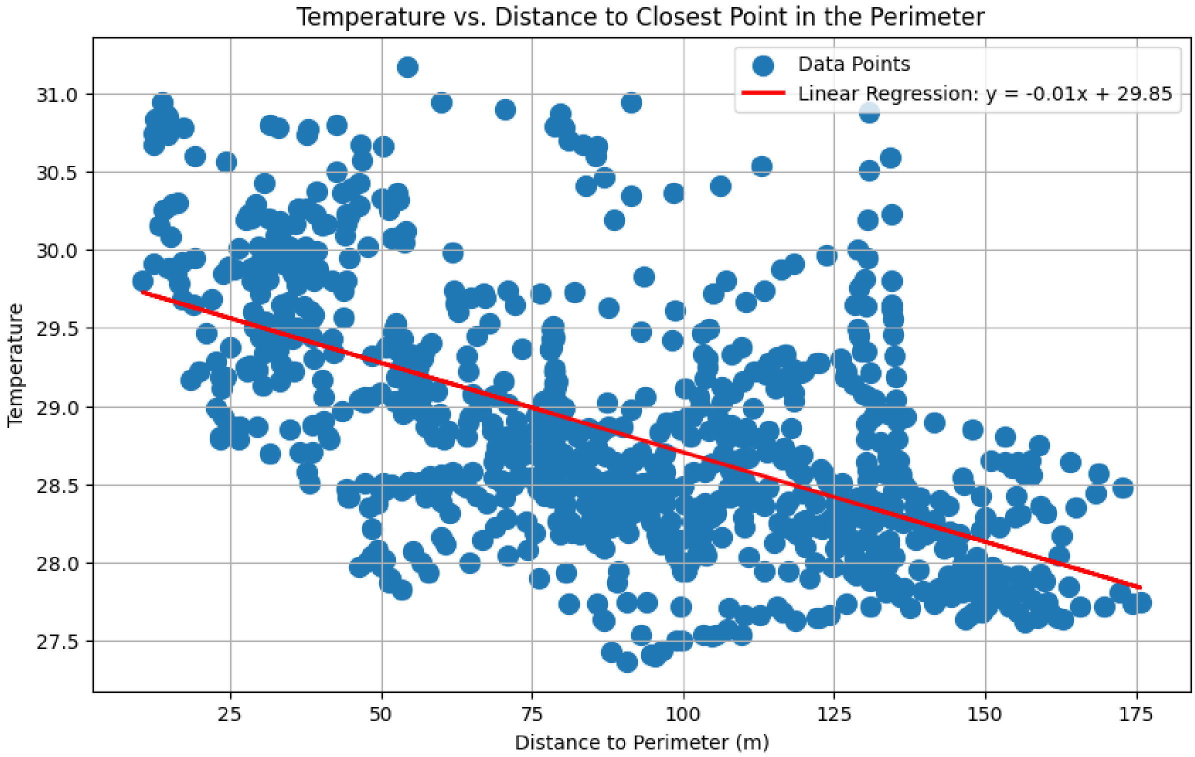


Figure 29: Scatter plot of Temperature vs Distance to Closest Point in the Perimeter and its Linear Regression

Again, we can see that despite the high dispersion of the temperatures with respect to the distance to the perimeter, we verify a decreasing trend shown by the linear regression. So as the distance from the closest border of the park increases, the temperature decreases. We can tell that within 50m the temperature drops approximately about half a degree.

Both analyses lead to the same conclusion: the deeper in the park, the lower the temperature. However, we should notice the high dispersion in the temperatures, although the trends capture the phenomenon, there are more external factors that must be considered. To understand better what those factors are and how they influence the temperature, we decided to perform a geospatial analysis.

2.4.4 Geospatial Analysis

For the Geospatial Analysis, firstly, a folium map was created, centered around the mean latitude and longitude of the data points. Temperature data was visualized using circle markers, with colors representing temperature values. A colormap was employed to provide a legend for the temperature values. Here we can see the map with the temperature variations:

Figure 30: Temperature measurements across the park

In order to have a more complete geospatial analysis, a satellite view was integrated into the folium map to provide a more detailed and realistic representation of the geographical context, aiding in a more comprehensive visual inspection. As an example, we can see that the tree coverage is much more in evidence than in the satellite view than in the default view, whereas the lake is only visible in the default view.

Figure 31: Temperature measurements plotted on satellite view of the park

Based on the geospatial analysis and visualization shown above as well as the distance analysis, here are our top 6 key insights about temperature variation within the park. Our initial assumptions were confirmed, but we were also surprised by some other findings.

1. By the images above, we can say that the external perimeter of the park displays higher temperatures compared to the internal areas. This is especially noticeable along the streets such as Corso Venezia (east), Via Palestro (south), and Via Daniele Manin (west). The higher temperatures are due to the urban environment and the asphalt surfaces, as well as buildings that act as heat reservoirs. Additionally, emissions and heat generated by running vehicle engines contribute to the increased temperatures.
2. Contrary to our expectations, Viale Città di Fiume, the only surrounding road in the toll-free zone and known for its heavy traffic, has lower temperatures. This is likely due to the road's width. The lanes are separated by greenery, and there is an additional 50-meter-wide green strip adjacent to it. In comparison, the other roads are much narrower.

3. From the satellite view, we can infer that the interior of the park, which has more extensive tree coverage, shows lower temperatures. Areas around the Museo Civico di Storia Naturale, do not benefit from substantial shading, leading to higher temperatures, whereas parts in the center of the park can profit from great tree coverage.
4. From the map view, we can see that the area around the pond within the park shows cooler temperatures. Water bodies act as heat sinks, moderating the local temperature and providing a cooling effect in their vicinity.
5. It is also noticeable that the temperatures are higher near the massive buildings located in the park, both to the east and the west. This is very likely due to the building mass storing heat from the sun throughout the day. Additionally, there are no trees providing shade in these areas, and the buildings might contain equipment that generates heat.
6. Overall, it is noticeable that the temperatures inside the park are lower. As expected, this is due to the large amount of unsealed ground, the infiltration and saving of water, and more vegetation providing shadow.

We can clearly see that the temperatures inside the park are significantly lower, by about 2 degrees, compared to the edges. The park's cooling effect reveals its vital role in enhancing urban livability and public health.

2.4.5 Economic Interpretation

Our data analysis shows a strong link between how a park is designed and the temperature inside it. As we have mentioned before, lowering temperatures can bring big economic benefits. However, there is still a dilemma: while parks provide advantages like cooler temperatures, better health, and higher property values, they also take up space that could be used for other economic purposes.

Based on the data results, we want to figure out the best ways for making an urban park as effective and innovative as possible. We found that lots of trees providing shade significantly lower temperatures. Water features also contribute to cool the Urban Greenery down. Considering the buildings in the park, there should not be any because of the internal heating and heat retention in the construction mass during the day, which slows down nighttime cooling. If there need to be any buildings, they should be lightweight and simple, like the cafes already there, as they do not significantly affect the temperature. Paths which are not planted are hotter, so reducing their area and adding more grass would help be beneficial for cooling. We also confirmed the hypothesis of temperature drop as the distance from the borders (or proximity to park center) increase. Being the slopes of both linear regressions close to each other, the effect both distances have in the temperature trends is similar, and both lead to the same conclusion. Economically, this can help reduce the Urban Heat Island (UHI) effect, leading to lower cooling costs and better public health, which means less healthcare costs and more productive workers.

From an urban planning perspective, a logical consequence would be to integrate more of these types of microparks. It might be feasible to develop a grid of developments where parks are regularly included, or even within courtyards. Having these parks close by could save on maintenance costs. By creating a network of small parks, urban planners could improve the quality of life for residents while also reaping economic benefits such as increased property values and reduced energy consumption.

In summary, investing in well-designed urban parks can pay off maximize their cooling effect can provide substantial economic returns. This strategy supports sustainable urban development and creates a healthier, more pleasant living environment for city residents. Overall, this leads besides a rise of property value to economic strength of a city.

2.4.6 Identifying and Explaining Limitations

It is important to discuss as well some of the limitations of the study and analysis we conducted, spotting some possible sources of errors.

First, the data collection occurred over a single day, introducing temporal variations. Additionally, the fact that our team was moving and consisted of four different boards could contribute to these anomalies. Besides that, the data collection was conducted on a cloudy day, making the results less dependent on vegetation. Integrating vegetation into the analysis is challenging due to factors like shadow casting, which varies with the time of day. However, there were brief periods when the sun emerged, causing temporary spikes in temperature due to direct sunlight. The sensors were directly exposed to sunlight during these moments, which leads to a heat up and a sudden temperature increase.

Overall, the combination of fluctuating sunlight, sensor exposure, and equipment variation likely accounts for the outliers observed in our data. These factors underscore the complexity of ensuring consistent and accurate measurements in field studies.

3.0 Conclusion

Given all the data and discussions, we can confidently state that parks significantly reduce temperature and provide much-needed heat relief in urban areas. Our study, although conducted over a limited time with restricted measuring capabilities, offers insights that can be extended to typical days in any urban park.

The implications of our findings are substantial. Green areas around properties not only reduce temperature but also increase perceived property value and reduce energy consumption. Parks enhance urban livability, providing numerous social and economic benefits to the surrounding region, making them invaluable assets for any city.

From an economic perspective, our analysis shows that well-designed urban parks can provide substantial returns. While parks occupy space that could be used for other economic purposes, their benefits in terms of cooling, health improvement, and property value enhancement far outweigh these concerns. Policymakers and urban planners should recognize that green spaces are more than just legal requirements. They are strategic investments in the city's future.

As climate change continues to set challenges to urban living, the role of parks in mitigating heat and improving quality of life should not be underestimated. The effectiveness of green spaces as a simple solution to urban issues underscores the need for more parks in urban planning. This approach should be seen not only as a matter of environmental responsibility but also as a crucial economic strategy and public health measure. Green spaces should be distributed more evenly across urban areas in the form of micro forests within the city. The regional government needs to define where to have open green spaces for this purpose. Using an index that compares built area with unbuilt area of a property, the amount of unsealed surface can be defined. Additionally, backyard greening should be mandatory and financially supported.

In summary, investing in strategically designed urban parks leads to sustainable urban development, creating healthier and more pleasant living environments, boosting property values, and strengthening the economic resilience of cities. Our study emphasizes the importance of urban green spaces in mitigating the adverse effects of urbanization and improving overall economic and environmental outcomes.

4.0 Appendix

4.1 List of References

Citypopulation (17.06.2024): https://www.citypopulation.de/en/italy/lombardia/milano/015146__milano/

GitHub, Inc. (17.06.2024): https://github.com/febagni/smart-cities-temperature-analysis/

Li, Xiaoma, et al. "Urban heat island impacts on building energy consumption: A review of approaches and findings." Energy 174 (2019): 407-419

Masoudi, Mahyar, and Puay Yok Tan. "Multi-year comparison of the effects of spatial pattern of urban green spaces on urban land surface temperature." Landscape and Urban Planning 184 (2019): 44-58.

RIAZ, ATIF, et al. "Green areas: a source of healthy environment for people and value addition to property." Labour 37 (2002): 41

Time and Date AS 1995-2024. (20.06.2024). https://www.timeanddate.com/weather/italy/milan/historic?month=6&year=2024

World Bank, 2021. A Catalogue of Nature-based Solutions for Urban Resilience. Washington, D.C. World Bank Group (S.103)

4.2 Table of Contents