Precision long-term monitoring of local weather at household level

Ioan Florin VOICU,
ING Hubs, PhD Candidate University of Bucharest, Bucharest, Romania
ioan-florin.voicu@ing.com

Dragos Cristian DIACONU,
Bucharest University of Economic Studies, Bucharest, Romania
diaconudragos23@stud.ase.ro

Daniel Constantin DIACONU,
Dr., Interdisciplinary Center for Advanced Studies (CISA), Research Institute of University of Bucharest, Bucharest, Romania
daniel.diaconu@unibuc.ro

Abstract
Objectives: This research aims to show that there are discrepancies between city-wide weather forecasts and household-level realtime conditions, which can help with disaster preparedness & mitigation, as well as improve the daily lives of residents with access to the data. **Prior work:** Previous studies have shown that, while weather forecasting systems are constantly increasing their precision and, due to the desire to avoid loss of lives & property, provide ever more frequent warnings for evacuation or sheltering, they still lack the precision necessary to provide forecasts for very small areas. **Approach:** A case study was conducted, in which a household solution for monitoring outdoor precipitation quantities, atmospheric pressure, humidity & temperature was implemented, with its results stored over a period of approximately 2 years and compared with statistical data for the city for the same interval. **Results:** The analyzed outcome showed that meteorological conditions at household level don't always match the citywide forecasts, with significant differences in humidity, temperature & precipitation quantities versus the statistics recorded for the region. **Implications:** The extra data granularity proved that certain factors appear earlier or can linger for quite a while longer than the regional statistics show, which, if the solution would be applied on a larger scale, would improve issues like disaster response or yearly budgeting by the authorities, especially given the problems raised by climate change worldwide. **Value:** The results show that the sensors & software monitoring implemented at such granular level can greatly improve the precision of weather forecasting, with Machine Learning models being able to use the historical data to accurately predict the impact of regional weather patterns at household level.

Keywords: climate change, microclimate, precipitation analysis, IoT, weather patterns.

1. Introduction

As climate change continues, weather monitoring and forecasting alongside air particle measurements are becoming ever more important as pollution-related deaths and illnesses continue to grow in number. Mortality rates associated with annual exposure to air pollutants in Bucharest have revealed an increasing proportion of mortality due to PM 2.5 pollution [1].

Urban microclimates can influence local weather patterns [2] and this study aims to show that these microclimates should be of much more interest to the average citizen than the overall weather forecast for the city. Local topography can also add to the discrepancy, even in urban environments [3].

IoT devices provide opportunities for much more granularity in weather monitoring, but previously required using platforms such as Arduino [4]. With the increasing maturity of the Home Assistant platform, however, it has become much more straightforward for researchers to set up case studies, or even production-ready platforms for such monitoring, since Home Assistant can connect to essentially any local (and most cloud) APIs and combine the data in any manner the researcher or user desires. Its reach can also go beyond monitoring, to automations that control physical devices in response to (or in expectance of) certain weather phenomena. It is also possible to use this platform alongside various air quality sensors (outdoor PM 2.5 & indoor CO2 are monitored by the Netatmo system of sensors) to provide localized information and warnings in case of certain thresholds being breached.

With more precise measurements and monitoring in place, it is also possible to evaluate the effect of urban heat islands on heating and cooling energy needs [5] and use or modify building climate systems appropriately in order to get as close as possible to passive building projects. This study could also be of use to other research efforts in the matter of urban heat islands, by providing a conclusive methodology. Other studies in this regard attempt to split large territorial units such as the United Kingdom into smaller climate zones for building design [6], but there is no significant body of work looking into hyper-local data, such as at household or small neighborhood level, even though it is the level which directly affects most people in cities or rural communities. This can also be considered as part of the steps needed to transition from a “smart city” to a “smart nation” [7].

The effects of land cover in a city are not only limited to temperature differences, but also precipitation [8], with the buildings channeling water in ways which are usually not visible to the official weather sensor systems or not visible quickly enough in case of a disaster.

Through this article we want to show the added precision of meteorological predictions at a small-scale level in urban environments. This is also useful in order to prevent damage to homes and disturbed circulation during floods, thus contributing to flood risk management efforts [9].

2. Methodology

This case study used a combination of open-source software (Grafana, Home Assistant, InfluxDB) and off-the-shelf hardware (Netatmo sensors with a Raspberry Pi 5 as the server, a ZTE MF833 4G USB modem for failover Internet access and a VARTA Fast Energy backup power bank in case of power outages).

Official historical temperature & precipitation data for Bucharest coming from Baneasa measuring station was obtained from the European Climate Assessment & Dataset (www.ecad.eu). This was then added to a spreadsheet and compared to the InfluxDB data from the Netatmo sensors for the same period, focusing on the hourly temperature & precipitation data.

The results can also be used as input data for Machine Learning or Data Science models, such as GenCast [10]. With hardware such as the Google Coral TPU, it is even possible to run certain machine learning models with high performance locally, thus not requiring cloud computing to obtain rapid results.

Local measurements for PM 2.5 emissions were also consulted, but since in this case the official data for Bucharest varies widely depending on the area of the city, the season and the time of day, it was not possible to do a comparison that would provide useful research data or serve as a basis for extrapolation.

2.1. Case study hardware setup

The sensors used for this case study are made by Netatmo and include a rain sensor, an outdoor temperature/humidity/particle sensor and an indoor CO_2 sensor. This solution was chosen both for its ready availability and for being part of the Netatmo cloud network of weather sensors, which could potentially be used to connect official weather monitoring systems to the much more granular sensors that are currently present in residences & businesses. Having rechargeable batteries and Wi-Fi connectivity allows for quite a bit of freedom in their placement, with the indoor sensor also functioning as a “relay station” for the sensors placed outdoors, ensuring their connectivity remained constant within the ~20m radius that was used for the case study.

It is also possible to choose a completely local and open-source solution, such as a custom one based on an ESP32 board and attached sensors. This offers the benefit of full control over both the hardware and software (by flashing an open-source firmware on the ESP32 boards, such as ESPHome or Tasmota), but does not have an associated cloud network as is currently provided by Netatmo to its users, which in the case of worldwide weather readings could be beneficial.

Fig. 1. Netatmo outdoor sensors & indoor relay station
Source: www.netatmo.com

Besides the sensors, the hardware stack is a typical Raspberry Pi 5 8GB + M.2 HAT + NVME SSD combination, which offers enough computing power for our use case and has the added benefit of failover Internet and power provided by a 4G USB modem & a power bank.

The cases in which the Raspberry Pi could be inserted depend on the level of ruggedness required, with shock/water/dustproof ones an option, as well as fanless ones with no moving parts. The newly-released Raspberry Pi 5 Compute Module could be used in future research. It offers the option of being embedded in industrial-style enclosures that can also provide an extra PCI-E slot for a TPU chip, a GPU or an addon for Power-over-Ethernet, thus reducing the number of cables required and providing remote control over the server hardware itself. A GPU would be especially useful if attempting to process AI/ML tasks locally.

For our research, the OEM Raspberry Pi case was used, as it allows adding the optional M.2 HAT and provides active cooling. Storage is in the form of an 512GB M.2 NVME SSD and backup is done via the Home Assistant Backup functionality and uploaded daily to Google Drive.

The off-site cloud backup upload thus also makes sure that a physical incident in the area of the sensors does not affect the historical data. The NVME SSD solution for storage, meanwhile, besides having much better performance, also offers significantly improved storage resiliency than the more common MicroSD storage option for the Raspberry Pi, especially for a frequent-write environment like a multi-sensor database with constant updates.

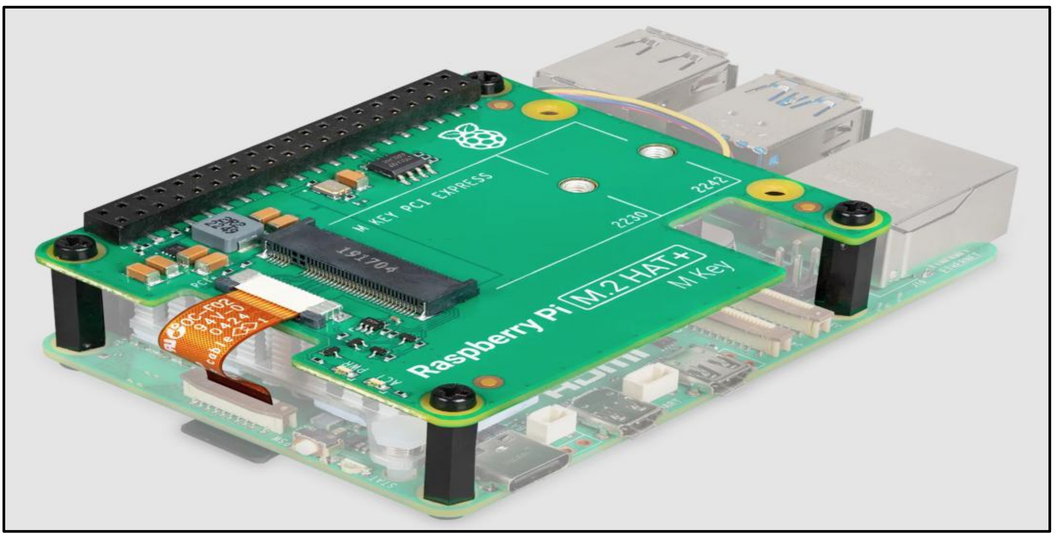

Fig. 2. Raspberry Pi 5 with M.2 HAT
Source: www.raspberrypi.com

For linking the Raspberry Pi server with the Netatmo sensors, it is possible to use any commercial Wi-Fi solution. For the current case study a Unifi Security Gateway router & Unifi Access Point AC Pro were used, due to their superior management software and security options, but one can choose any combination router/access point which would fit the project's budget.

2.2. Case study software setup

In terms of software, Home Assistant OS is by now a mature Linux-based platform on which various integrations can run, including InfluxDB as a performant IoT history database & Grafana for visualizing the data in real-time in various dashboards.

They were used in order to obtain and store the data from the Netatmo sensors locally, but for redundancy purposes the sensor data was also stored in Netatmo's cloud software as well as in Google Drive via the daily Home Assistant backup.

It is also possible for alerts and automations to be created on the basis of this data, with instant notification via Telegram when there is at least 0.1mm of rain registered and the possibility to trigger shutters, skylights or other such IoT-integrated items in order to protect property. Notably, there is also the option of creating "actionable notifications", through which a semi-automatic solution can be implemented, if human oversight over the data is required before actually triggering an effect.

Security was also a significant concern, with remote access to the system provided only via the Tailscale mesh VPN solution, thus not requiring any router port forwarding or other exposure of the server to the internet.

Fig. 3. Grafana rain sensor dashboard for the past 14 days
Source: author's testing

This type of setup can also have applicability in agriculture, with such a software solution being comparatively cheap and scalable to ensure there is no over-watering and offering much more reliable data than official Internet-provided weather/humidity data.

One use case would be having a database of local air humidity & pressure readings (combined with a soil humidity sensor) that could make sure that not only is watering not done in an already humid situation, but also not before rainfall is about to occur. Professional systems of this nature are significantly more expensive and generally geared towards large farms, whereas a relatively "DIY" system such as this could provide comparable benefits even to practitioners of small-scale/subsistence agriculture.

3. Results

The case study occurred over a nearly 2-year period, with a 10-month selection between April 2023 & January 2024 chosen due to the ending of the pandemic-era restrictions and city traffic returning to normal (and thus affecting inner-city temperatures much the same as before the pandemic).

The results showed some striking discrepancies in both temperature and precipitation data between the local and city-wide readings.

Whereas, on average, a 2.5-3 degree Celsius difference between the test sensor and the official weather measurements can be seen (likely attributable to the test sensor's inner-city location as well as traffic & other sources of emissions which raise the temperature in the measured area), a sample study by hour shows much more interesting results.

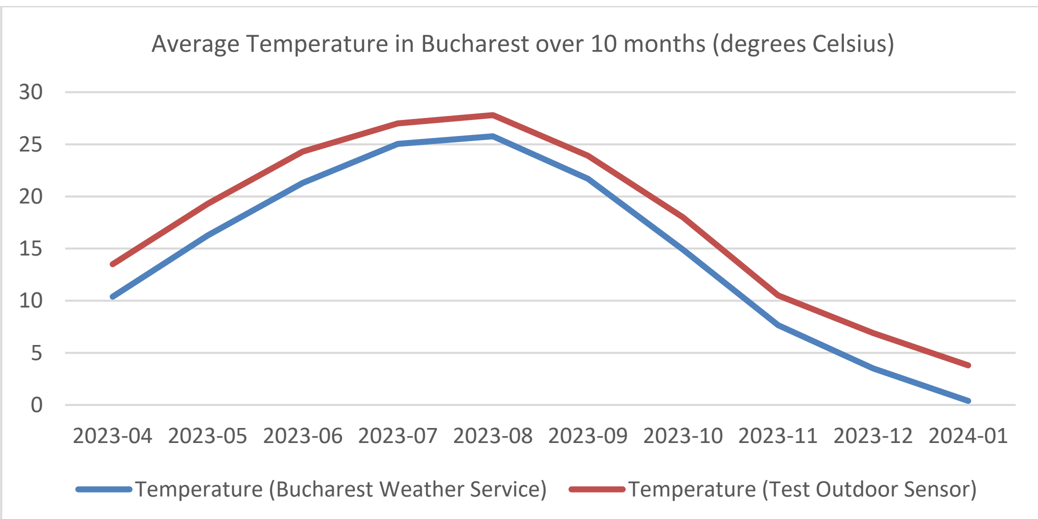

Fig. 4. Average temperature readings
Source: author's testing & www.ecad.eu

What can be seen in the temperature by hour recorded on a typical day in November 2024 (chosen randomly, but with data being consistent with other selected days) is that there are certain hours when the officially reported temperature for Bucharest overall vs. the actual temperature in the studied location has even a 6 degree Celsius gap, which can significantly affect the lives of citizens.

This was confirmed by empirical observation outdoors, with the 0-degree Celsius officially reported between 7:00-8:00 AM not having corresponding phenomena like frozen puddle water on the streets.

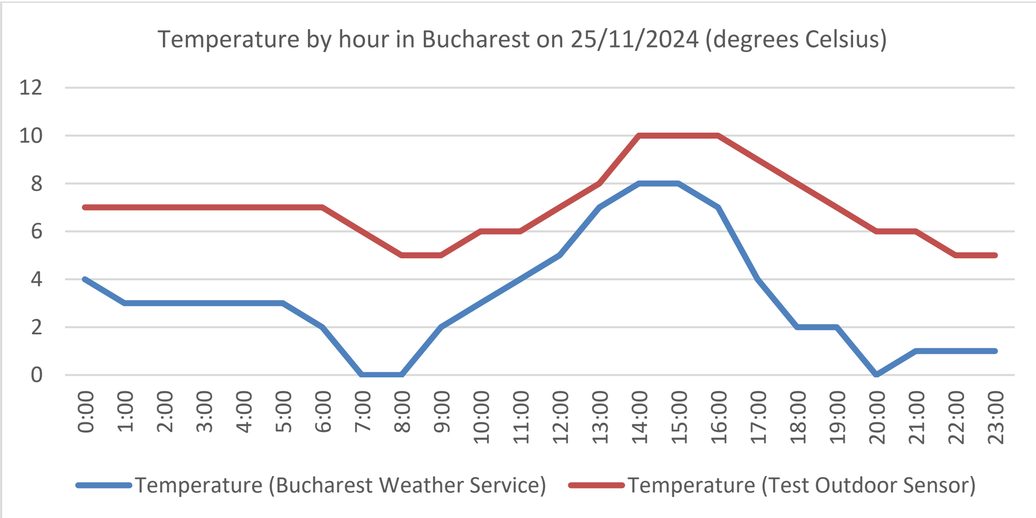

Fig. 5. Hourly temperature readings
Source: author's testing & www.ecad.eu

When checking the precipitation data, once again on a cumulative monthly basis there are some discrepancies, but the graphs generally follow the same trend for the local and official data.

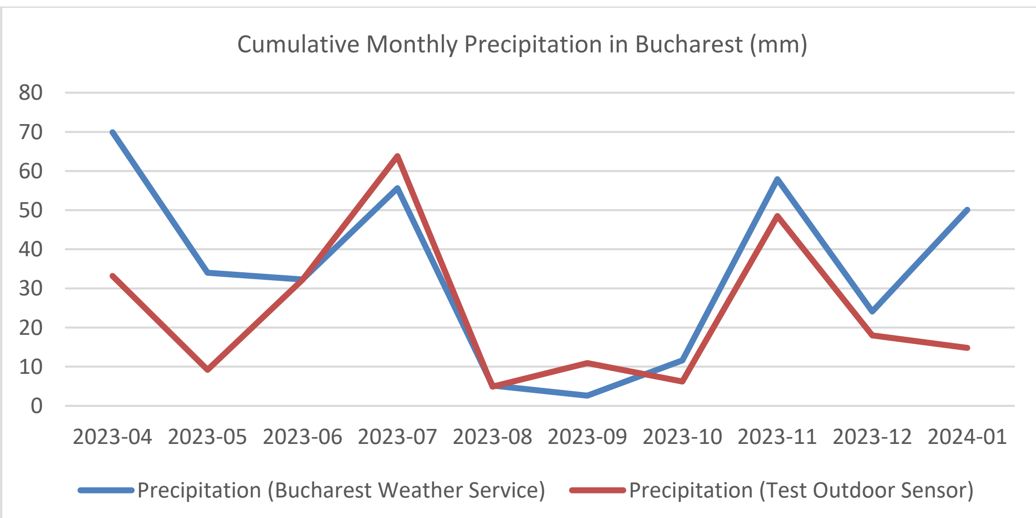

Fig. 6. Monthly precipitation comparison
Source: author's testing & www.ecad.eu

However, when looking at a single month, certain more significant differences appear. For the sample month of April 2023 (chosen due to being a relatively rainy month and thus offering more data points than others), the graphs show that overall there is less precipitation.

This is most likely due to the sensor being located in a more built-up area vs. the National Metereology Administration’s sensors located in the Baneasa area on the outskirts of Bucharest.

However, it also shows that the rains sometimes occurred a day earlier or a day later compared to the official recordings. This can have a significant impact on the population, because it is of definite interest if in your actual location it will start raining many hours before or after the official forecast or if the duration of the rainy period is much shorter or longer.

The data thus serves to highlight one of our assumptions, namely that weather forecasting is usually very accurate at the point of data collection, but just not granular enough in its publicly-available data to highlight the relevant movement of weather patterns across an area the size of a large city (228 square km in the case of Bucharest). If weather data could also be “crowdsourced” from a mesh of sensors throughout the city (by connecting to Netatmo’s or another provider’s API), any shifts would be immediately visible and reportable to citizens. This would also establish citizens as stakeholders in their “smart city” [11].

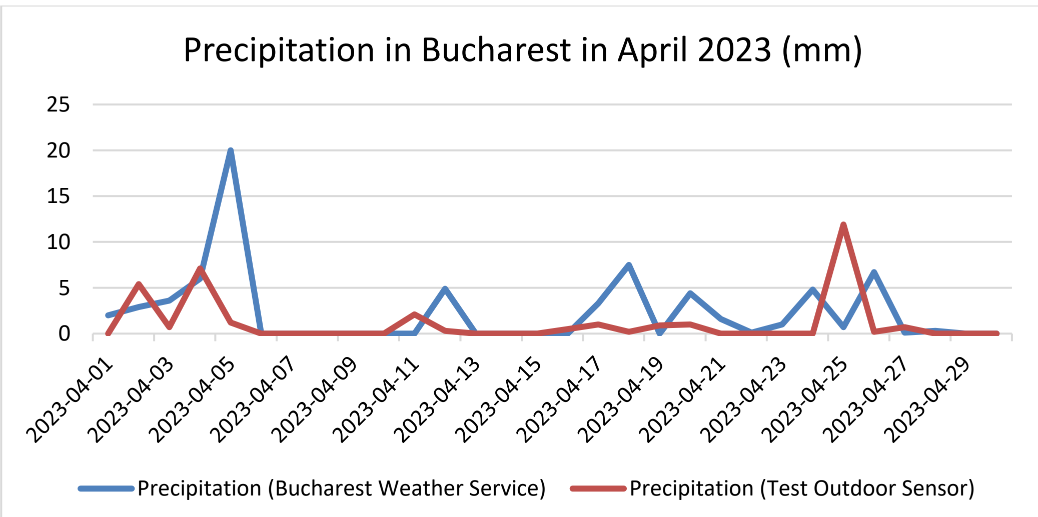

Fig. 7. Single-month precipitation comparison
Source: author’s testing & www.ecad.eu

4. Discussions

4.1. Applicability

This case study aimed to show the opportunities offered by localized weather monitoring, especially if integrated with a coordinating system of automations like Home Assistant.

The barrier of entry is low due to the cheap sensors that are currently available (or that can even be custom-built from base components) and the results can be the basis of better quality of life for citizens that have access to the data and the alerts.

Such granular weather data can be used also as a source of data input for Machine Learning models that improve the precision of agriculture, as well as Deep Learning options for enhanced forecasting on demand [12].

While not in the scope of this article, the sensors used in this case study also monitor atmospheric pressure and PM 2.5 concentration for air quality and can include an additional anemometer, so that an even more complete snapshot of the local conditions can be obtained. Air quality, in particular, has been a focus of urban climate monitoring [13], with additional granularity in this sense being helpful in improving health conditions for citizens.

Accurate large-scale data collection could lead to improving studies about urban air temperatures and limitations of heat adaptation.

4.2. Limitations of case study

Some of the limitations of this case study are that only one sensor setup was used, which can thus only show the similarities or differences in a single area of Bucharest vs. the official measurements, as well as the fact that how built-up the tested region of the city is can affect measurable precipitation quantities.

In our case, the neighborhood is of medium-height, with most buildings 3-4 stories high. We expect that regions with higher density and 8-10 storey buildings will exhibit an even larger discrepancy compared to the wide-open area in Baneasa where the National Metereology Administration’s measurements take place.

5. Conclusions

For decades the general population has relied on the official weather forecasts when planning their daily activities, but with the advent of inexpensive IoT solutions this information can be obtained much more easily than before and with much greater precision for the actual area in which the interested party is located.

The research showed just how much of a gap there is between weather monitoring for the entire metropolitan area vs. the conditions in a certain part of the city, with the results offering many possibilities for cases like savings in water consumption (both municipal and private) and more effective climate control in buildings.

This is especially relevant in urban areas, where land-use can have a significant impact on the spatial distribution of temperature [14], whereas in rural areas the weather patterns tend to be represented accurately enough by the official weather station measurements.

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