Urban Heat Island. Machine Learning Models for Analysis and Maker Approach for Mitigation

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Abstract

The combination of expertise from academic and maker environments could generate new valuable skills and initiatives to counter the urban heat island (UHI) problem, exacerbated by climate change. This article starts with a description of an ongoing UHI analysis conducted within the University of Modena and Reggio Emilia for the Municipality of Carpi, a town of almost seventy-two thousand inhabitants located near Modena in the central Po Valley, Italy. The study adopts long short-term memory (LSTM) neural networks. Meanwhile, extending beyond academic boundaries, open local communities of machine learning developers are also forming in the same region. They are often connected to public fab labs, that are spaces for *makers*: people dedicated to digital-artisan fabrication and related education. Hence, a social involvement is envisaged in possible future UHI analysis and mitigation mini-initiatives. Expert analysis and engineering could be combined with participation of citizens in data collection, sensor fabrication, and architectural solutions prototyping. All these emerging activities can enrich the already worldwide spreading *fab city* movement.

Keywords

Smart city, Urban heat island, LSTM neural networks, Makers, Fab city

1. Introduction

The urban heat island effect (UHI) refers to the phenomenon in which urban areas experience significantly higher temperatures compared to their surrounding rural regions. This temperature difference is mainly caused by urban development that transforms natural landscapes into built environments and human activities. The term "urban heat island" comes from maps showing temperature distributions, where urban zones appear as hot "islands" among cooler rural "seas". This article starts by describing an analysis of the UHI phenomenon using long short-term memory (LSTM) neural networks. This activity is now in progress, conducted by the author in a wider research project carried out by the University of Modena and Reggio Emilia (UniMoRe) for the Municipality of the Italian town of Carpi, near Modena. But in the same territorial area, bottom-up civic engagement in this kind of initiative is already envisageable, starting from citizens with analytical and/or maker-oriented mindsets. A *maker* [2] is an individual who designs or builds things, today usually merging traditional craftsmanship and

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digital technology. Web facilitates the worldwide exchange of open innovation. *Fab labs* [3], in less equipped versions called *makers' innovation labs, net garages* [4], etc., could serve as gathering points for different stakeholders and makers to prototype digital-artisan solutions. These spaces are typically equipped with computers, do-it-yourself (DIY) tools, and small manufacturing machines. Promoters are in general public administrations or universities, sometimes in partnership with schools and entrepreneurial associations. The initiatives promoted have an extensive public outreach [5]. *Machine learning local communities* are springing up now, as in the case of Modena [6], gathering experts, practitioners, and passionate people with meet-ups, coding workshops, and other initiatives. In part, people and physical spaces are the same as fab labs. The *fab city* could stem as a dimension of the smart city, promoted by the same institutions that support fab labs, thus transformed into *fab city hubs* oriented toward urban sustainability. "Fab City is for cities, regions and countries that want to pledge towards producing everything they consume by 2054" [7]. So says the statement of the first fab city hub project that was ideated and took shape in 2014 in Barcelona.

Researches since now typical of academic environments, like those on UHI, are rapidly becoming at the reach of machine learning local communities, connected to fab labs, and hence able to prototype low-cost solutions to monitor and counter UHI. But a joined data science, manufacturing, and architectural vision turns to be determinant.

2. UHI monitoring, analysis and consequent urban planning for Carpi

The summer UHI problem, combined with that of vehicular traffic, has been the starting point for the Smart City Project of Carpi, a town of seventy thousand inhabitants in the Italian central Po Valley. Carpi expanded mainly after the second world war, thanks to its textile industry and an abundant availability of low-cost labor in the construction sector. Grown around its historic center, the residential neighborhoods date mainly back to the 1950s - 1980s. Energy retrofitting is slowly spreading, while air conditioners are commonly used. The town's suburbs house an industrial hub and three smaller artisan centers. Climate change with hotter and longer summer heat waves tends to increase the accumulated heat. In summer, air temperatures in the city center can reach around 45 °C in the afternoon and 25 °C during "tropical nights". This threatens the health and lives of the elderly or otherwise fragile people. Since 2020, the Municipality of Carpi has been installing fixed IoT sensors across the city to collect climate, air quality, and vehicle traffic data. In September 2024, 77 were installed, integrating the most sparsely control units of the regional environmental agency ARPAE[8]. This municipal project is a pilot initiative in the Emilia-Romagna region conducted in partnership with the regional digital multi-utility Lepida, which manages data through its network, servers, and web interfaces [9]. In 2023 this data collection was integrated with satellite images specifically acquired for UHI analysis. In 2024 the Municipality of Carpi signed an agreement with the University of Modena and Reggio Emilia for data analysis. At the university are currently underway these activities:

- first data analysis trials through long short-term memory (LSTM) neural networks;
- UHI fluid dynamic modeling.

- study of pedestrian irradiation by different combinations of surface materials in sidewalk and roadway.

Satellite imagery analysis will be started soon, while a research has already been published on the correlation between remote sensing data and ground-based measurements for solar reflectance retrieval [10]. The combined results will give a provisional model for forecasting the temperature reduction in different city areas after urban improvements. Thus, it will become possible to assess in advance different urban planning strategies, with cost/benefit evaluations. In fact, a public administration can balance several interventions, for instance: diffusion of public green spaces and permeable surfaces, use of gray asphalt, rationalization of traffic flows, incentives for a kind of requalification of private buildings and open appurtenances that take into account UHI impact. The ultimate goal of this research is to provide digital tools that support the urban planning process mentioned above.

2.1. Analysis through LSTM neural networks

The extensive availability of time-series data collected by fixed sensors in Carpi led to the selection of LSTM neural networks to model air temperature as an output. Once trained, a neural network will forecast, for each climate sensor zone in the town, the air temperature resulting after simulated urban improvements. The inputs currently used for the test runs are sampled hourly and consist of absolute humidity, atmospheric pressure, wind velocity, rain, and solar radiation. At present, an LSTM neural network, run on TensorFlow, converges to a result that could have an innovative value when data that have yet to be processed will be added. These will include sky temperature, surface reflectance and emissivity, evapotranspiration, soil humidity, and anthropogenic heat, which is produced by traffic, methane combustion, and electricity consumption in both the residential and industrial sectors. Thus, Carpi's research will employ a broader set of input variables for its LSTM neural network than previous studies. This will be its main strength. Additional derived data, though limited to sensor locations, will be the perceived temperatures after urban improvements, forecast using standard statistic correlations from historic data. These data were measured in the same places in August 2024 with a wet bulb globe temperature (WBGT) field thermometer.

2.1.1. Overview of recent studies

The work related to Carpi is currently in progress, and a broader discussion is premature. The application of machine learning to UHI analysis is relatively new and is not widely practiced, so scientific contributions are still few and varied in nature. A search conducted on Scopus in September 2024 yielded 116 results for "UHI machine learning", 24 of which were relevant to the Carpi study. A more specific search for "UHI LSTM" returned five results, three of which were applicable and are summarized in the following.

Zhang et al. [2024], *Machine learning in modelling the urban thermal field variance index and assessing the impacts of urban land expansion on seasonal thermal environment* [11]. The study analyzes changes in land use and land cover (LULC) and their effect on seasonal thermal environments in the urban agglomeration of the Pearl River Delta from 2000 to 2030, focusing on land surface temperature (LST), urban thermal field variance index (UTFVI) and the effect of UHI.

Artificial neural network-cellular automata (ANN-CA) and whale optimization algorithm-long short-term memory (WOA-LSTM) models were used to simulate LULC changes and thermal characteristics in summer and winter. Urban land is predicted to increase by 91.29% between 2000 and 2030. The area of the strongest UTFVI is expected to grow by 83.64% from 2000 to 2030. The strongest levels of UTFVI for urban land are expected to extend from 2,404 km^2 in 2000 to 5,865 km^2 in 2030. The intensity of UHI is expected to continue to increase as urban sprawl progresses. In 2000, UHI values up to 1.776 °C were recorded. By 2030, UHI values as high as 6.142 °C are projected.

Shafi et al. [2023], *Machine learning based UHI data assessment to model the relationship between LULC and LST: case study of Srinagar City, Jammu & Kashmir, India* [12]. The study focuses on using machine learning and deep learning to assess the effects of UHI and model the relationship between LULC and LST. Regression and correlation analyzes are proposed to understand the relationship between independent variables and LST. The study examines changes in LULC and LST in Srinagar, Jammu and Kashmir, predicting a 23% increase in urban areas by 2025, which could lead to the destruction of 9.2% of vegetation and 3.1% of aquatic bodies. A 1.89 °C temperature increase has been recorded over the past 20 years, with a further 2.01 °C rise expected by 2025. LULC patterns have changed significantly over the past 20 years, with built-up areas increasing by 9.86%, while vegetation and water bodies have declined by 3.16% and 0.94%, respectively.

Menon et al. [2023] *Prediction Of Temperature In Indian Metropolitan Cities Using Linear Regression And Long Short-Term Memory Models* [13]. The study aimed to predict temperatures in various metropolitan cities using multiple linear regression (MLR) and LSTM models. MLR was found to outperform LSTM in predicting city temperatures, utilizing features such as wind speed, wind direction, maximum temperature, and population. In coastal cities like Mumbai, humidity was also included as an important predictive feature. The study analyzed temperature data from 2015-2022 and the results were found to be accurate on the basis of current statistics. Without proper intervention, cities are at risk of becoming ”oven-like” environments due to rising temperatures. The proposed solutions include rooftop and home gardens, tree planting by school and college students, rainwater harvesting, solar panels, and the adoption of electric vehicles.

The first two studies, both using LSTM neural networks, focus specifically on expanding towns. An application to Carpi, a town devoid of expansive impulse, has to be carefully evaluated. The study by Menon et al., which examines various Indian towns, found that multiple linear regression outperformed LSTM models. However, the range of variables considered in that study is more limited than that available for Carpi. Hence, further verification is necessary.

3. A maker perspective for a practical urban regeneration

In Carpi, industrial and artisan activities, once thriving, have been marked by decades of decline. The tertiary sector, where a growing literate workforce is employed, offers earnings with which purchasing and maintaining a home becomes a long-term burden [14]. Furthermore, the new European goals for the energetic redevelopment of buildings will create future challenges for the sale and rental of lower-quality constructions. As a result, the potential degradation of entire neighborhoods is foreseeable. While Carpi Municipality is taking its first steps to address the problem of UHI, complementary initiatives, separate from the plans currently foreseen for Carpi, are here devised to actively involve residents, designers, computer scientists, and artisans in urban UHI mitigation efforts. The public Creativity Hub soon to be built in Carpi could be an aggregating point for all this. When public and private finances are lacking, urban regeneration needs bottom-up initiatives to turn high research into a concrete resource.

3.1. Citizens' data science, fabrication and building for a better urban environment

Local communities of machine learning, often linked to the ones of fab labs, are the most recent element and have yet to glimpse their role in a fab city perspective, while open public data are available and underutilized. Three dynamics have to be managed in these communities by public administrations with qualified education and supervision:

- democratization of machine learning on open environmental data;
- data collection made by citizens;
- prototyping, with a maker approach, of mini-solutions, low-cost and highly effective, to monitor UHI values and improve urban fabric.

Hence, partnerships with educational institutions will be essential to avoid poor quality and disillusionment. This educational role could be part of university third mission projects. To better define the actions to be taken, some indications could be derived from recent literature, while the issues related to the balance between democratization and privacy in open machine learning remain beyond the scope of this research.

Hsu et al. [2022], *Empowering local communities using artificial intelligence*[15]. Collaborating on AI development with local communities can enable them to tackle regional challenges. Designing AI with a focus on social impact is essential to align AI research with community needs. Involving local communities in data curation can empower them and support AI research. Using AI to analyze data patterns can uncover local issues for public awareness and review.

Wang et al. [2023], *Citizen and machine learning-aided high-resolution mapping of urban heat exposure and stress*[16]. This study describes a method that combines satellite remote sensing with citizen-collected air temperature and humidity data using PocketLab (TM) weather sensors to create a high resolution (10 m) map of air temperature, humidity and heat stress. ML analysis was conducted by professional researchers, using multilinear regression (MLR), support vector regression (SVR), random forest (RF) and XGBoost. This method is scalable and cost-effective (or can be adapted for higher-cost sensors if funding allows), offering valuable insights for decision-makers and urban planners aiming to reduce urban heat and its impacts on public health.

Yang et al. [2023], *Machine learning to support citizen science in urban environmental management*[17]. This research investigates the use of ML to enhance the reliability of citizen science (CS) data to monitor urban trash conditions. The study focuses on integrating ML with CS to improve the accuracy and validation of CS data. ML can improve the perceived validity of CS data by minimizing the need for extensive volunteer training, making it easier to trust qualitative assessments from the public. The merging of ML and CS could not only improve urban environmental management but also foster public engagement, creating a symbiotic relationship in which both community insights and ML-backed reliability improve the quality of research data.

3.1.1. Contribution of makers - Examples

Project CityObs - Fab City hub Barcelona The project [18] is enhancing citizen observatories for healthy, sustainable, resilient, and inclusive cities, using co-creation for inclusive, local actions. With open source technologies such as Arduino, citizens and communities are enabled to gather information about their environment and make it available to the public through the Smart Citizen platform [19]. This platform includes customized sensing hardware, the Smart Citizen Kit, and an online platform with over 9,000 registered users and more than 1,900 unique sensors. In 2019, the latest hardware model, the Smart Citizen Kit 2.1, was introduced, featuring sensors for particulate matter, noise, temperature, and humidity. Both the software and hardware are open source and freely available under open licenses.

Arduino device, app and web tool for UHI monitoring and mapping Romero Rodríguez et al. [2023], *Simplifying the process to perform air temperature and UHI measurements at large scales: Design of a new APP and low-cost Arduino device* [20]. This research project introduces a low-cost device, an app, and a web tool to automate the collection and analysis of UHI data. Temperature data are collected through mobile transects built by makers with Arduino technology, and the app performs automatic UHI calculations. The Web Tool uses the Inverse Distance Weighting (IDW) interpolation method to create detailed heat maps of the temperature distribution. This solution enables the global adoption of UHI monitoring by reducing the cost and time requirements, making the methodology accessible to cities around the world without specialized research resources.

Vertical moving robot for facade greening - Green Fablab - Rhine-Waal University A vertical mowing robot [21] is being developed at the Green FabLab to support facade greening, where plants are grown on building walls to improve air quality, reduce noise, and regulate temperature. This robot will move up and down between the wall and the greenery structure to prevent the plant roots from damaging the wall.

Arduino solutions for the Emilia-Romagna IoT network Lepida, the regional digital multi-utility for Emilia-Romagna, supports maker solutions with Arduino as an integration of its IoT network [22]. The strength points envisaged are good coverage, low cost, availability on the market, quick installation, suitability for IoT sensing and actuation, push and pull data collection, compatibility with different standards and control with simple commands.

Project-based learning where differences in participants are a key resource In 2017, the author of this article organized and led a home automation workshop for adult makers at MakeitModena using a project-based learning approach. The projects, proposed and executed by participants, focused on energy-saving public lighting and home automation prototyping using Arduino, NodeMCU, Raspberry Pi, and beacons. The project-based learning methodology provided a framework for an highly engaging months-long experience, based on project management tools. A database of offered and searched competences gave value to the participants' great heterogeneity. This methodology is described in detail in an article regarding an earlier analog workshop on mini robotics [23].

Building activities: not attractive for makers? In the scientific literature explored, there is no reporting of architectural artisan skills combined with the typical fabrication and digital skills of makers. In addition, the involvement of building schools for artisans is absent. But a fab city aiming to regenerate itself requires this combination. The setup of tools for UHI monitoring and analysis matches well with the prototyping of mitigation solutions, such as green walls, thermal insulation, and permeable exterior pavements. A novel urban diffusion of these artisan skills can reduce construction and renovation costs. It is not difficult to create mini demonstrations in fab labs. Educational examples ready to implement for UHI mitigation are easy to find on the Web [24][25]. These prototypes could be equipped with digital do-it-yourself instruments that measure their environmental effectiveness. Projections of large-scale benefits can be obtained with open data science and machine learning. In addition, AI applications for design and assisted manufacturing, also in architecture, are emerging. However, this could be a topic for further specific research.

4. Conclusive remarks

This short essay outlines a multifaceted work in progress, framed within a UHI analysis undergoing and mitigation activities envisaged. In a literate and connected society, high-level skills are spreading also in niche environments such as makers and machine learning local communities. This shift suggests the potential for future active citizen participation in both highly digital and material improvements to the urban fabric. Open access to climate and other large datasets could democratize and demystify the use of machine learning models. In touch with this, innovative fabrication and building solutions, shared globally by makers, could foster a fab city culture and lighten the actual economic unsustainability of urban regeneration.

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