



### Analysis of Urban Climate Sensor Data -Recommendations for the 2032 Olympics in Brisbane

# Masterarbeit

zur Erlangung des akademischen Grades "Master of Science (M.Sc.)" im Studiengang Wirtschaftswissenschaft der Wirtschaftswissenschaftlichen Fakultät der Leibniz Universität Hannover

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Hannover, den 15. Dezember 2023

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# 1 Introduction

#### 1.1 Background

In July 2021, Brisbane was selected as the city for hosting the 2032 Olympic Games with more than 10,000 Olympic athletes, coaches, and an additional 5,000 Paralympic participants. Soon after this announcement, the Northshore Hamilton PDA was declared as the chosen location for the Brisbane Athletes' Village. Figure 1 provides a visual overview of the Northshore Hamilton PDA structure and size.



Figure 1: Northshore Hamilton PDA by State of Queensland (2022)

The village's development plan, which is still in its early stages, includes both permanent and temporary structures for the accomondation of the athletes (State of Queensland, 2022). The special thing about these Olmypic games is that Brisbane is contractually obliged to deliver the world's first climate-positive games that places the event in the broader framework of environmental awareness (Queensland Government, 2022). Energy efficiency, renewable energy sources, long-term planning and flexibility are the core focus of the event. Reports by the government, emphasizes the overall thorough shape and design considerations for the area's development, naming e.g. the strategic integration of actions for considering the UHI effect, which could influence energy efficiency goals.

The UHI phenomenon refers to the higher temperatures experienced in urban areas compared to their surrounding rural regions (Oke, 1973). It occurs due to various factors, including the concentration of buildings and infrastructure and a lack of vegetation which result in increased heat absorption and limited heat dissipation (Tuczek

et al., 2022). This phenomenon can also be observed at micro level where temperature differences also exists between different parts of an urban area. Take, for instance, the albedo effect, where diverse surfaces within a small area generate temperature distinctions owing to variations in reflectivity (Watkins et al., 2007). Similarly, proximity to water bodies or green spaces introduces temperature differences in specific small environment. (Ho et al., 2016). The resulting temperature increases, due to the creation of heat island effects, then have an effect on the efficient use of energy, for example (e.g.), through the increased use of air conditioning systems. This in turn can have an impact on the implementation of the climate-positive aspect of the Olympic games (Kikegawa et al., 2006).

To take into consideration the UHI effect during the construction period in Northshore Hamilton PDA, the government of Queensland directly names avoidance strategies. They list the integration of vegetation in built form, such as green walls, roofs and open space areas, as well as the design of civic open space areas with a right balance of green areas and building development (State of Queensland, 2022).

To account for the UHI effect, it is important to have a well-founded database that provides information about the climatic conditions at a site for identifying critical regions in this regard. For the analysis of this thesis, sensor data is available at four locations in Northshore Hamilton PDA, which record the microclimatic data such as temperature, humidity, wind speeds and wind direction. All sites have different environmental characteristics, that probably could influence the temperature and therefore the formation of UHI in a varying way.

The explicit research question of the thesis is explained in the following chapter.

#### **1.2** Motivation and Objective

The basis of this master thesis and the research question is the *Energy Informatics Framework* by Watson et al. (2010) shown in Figure 2. They embed their framework in the context of optimal energy distribution and consumption networks with the aim of reducing energy consumption with the help of Information System (IS). The core of the *Energy Informatics Framework*, the IS, consists of three main components, the sensor network, the flow network and the sensitized object, that could also be transferred to the application scenarios of this work.

A sensor network consists of various sensors that are strategically placed at specific locations to monitor and collect data about a physical item or various environmental conditions. In the use case of this work, the sensor network consists of the eight different Atmos and Netvox sensors at four different locations that have been strategically placed



Figure 2: Energy Informatics Framework by Watson et al. (2010)

in the Northshore Hamilton PDA area to collect data about microclimatic conditions such as temperature, humidity and wind directions in context of the UHI effect. A sensor network provides data through the sensors, that can be used to optimize a flow network.

A flow network is a network of interconnected transport elements designed to facilitate the movement of continuous matter or discrete objects. Within this network, the components can be directed from one point to another by predefined pathways and capacities. An example of a flow network is a power generation plant producing electricity, which is then transmitted through various transmission lines to reach homes and businesses. The flow of electricity needs to be carefully managed to ensure that the transmission lines are not overloaded and that electricity is supplied efficiently to all consumers. Flow network in the sense of this thesis represents the communication channels or routes through which microclimate data flows from different sensor locations in Northshore Hamilton PDA to a central point for analysis, that is responsible for the construction of the athlete village and therefore responsible for optimization of the UHI effect in Northshore Hamilton PDA. Involved stakeholders in the context of urban planning for the 2032 Olympics in Brisbane can ,e.g., be city administration like city planners, government or inhabitants (Degirmenci et al., 2021).

The last important component of the framework is the sensitized object, which is a physical good that is owned by a particular consumer. In the case of this research the sensitized object is the specific area for which the climate data is collected, using the sensor network. Specifically it is the land area in in Northshore Hamilton PDA where the sensors are deployed and which is partly owned by the Queensland Government in Australia (State of Queensland, 2022).

Moreover Watson et al. (2010) introduces the concept of granularity as part of its Energy

*Informatics Framework* and defines the concept in two levels; the *level of detail* and the *frequency*. They state that one of the main problems is to create a sensor network that has sufficient granularity to provide appropriate data in the end. That includes the knowledge of the provider, where to place the sensors or how often to query the data. This is also emphasized by other authors, that highlight the importance of the topic of minimizing the gap between technologically motivated increase of information and the right level of granularity for efficient decision making (Dalén et al., 2013). In the course of this, Watson et al. (2010) poses various research questions for future research where the focus of this master thesis will be on the following:

# What is the optimum level of information granularity of the sensor network to optimize a given flow network?

Consequently the goal is to find an optimal level of granularity for the sensor network to best possible represent the microclimate conditions of Northshore Hamilton PDA in order to give decision support for the construction of the athlete village in terms of mitigating the UHI effect. This implies at first the identification of mircoclimate differences at the four sites, even in this small area and second the choice of the optimal granularity level for the identification of possible UHI effects, which maybe arise not only in the city-rural comparison.

The trade-off of cost and benefits also plays an important role in finding the optimal granularity level. A denser network, with more detailed data, provides better or more high quality data however, the cost of, e.g., more sensors that need to be set up must be weighed against the benefits (Watson et al., 2010). Costs can also arise in relation to computational effort, where extreme finely granulated data can be very computationally burdensome and may not add any additional information value at the end (Kools and Phillipson, 2016).

The following subchapter explains the structure and procedure of the work.

#### 1.3 Structure

Chapter 2 begins with a thorough literature review on the subject of granularity in order to identify the various methods and concepts used and to find a suitable granularity procedure for optimizing the sensor network considered in this thesis. For this purpose, the methodological procedure of the literature analysis is described in a first step and the identified articles are conceptualized in a second step. Subsequently, in chapter 3 the explorative spatio-temporal data analysis follows. The considered sensor network in Northshore Hamilton PDA is analysed in more detail. For this purpose, relevant factors influencing the formation of UHIs are identified and the four locations are analyzed in this respect. After that, the data are examined at different granularity levels with the goal to uncover possible significant differences between sites with different environmental characteristics, which is important to detect critical factors for the formation of UHIs. Based on this, three spatio-temporal interpolation methods are performed in chapter 4 to discover UHIs in the small area. For this purpose, the different methodologies used are explained theoretical and then are performed within the application procedure afterwards. To optimize the granularity of the sensor network, the interpolation is applied for different temporal and spatial granularities, that are chosen based on the exploratory data analysis. Finally, the discussion follows in chapter 5, which contains the summary of the results, decision support for the construction of the athlete village, as well as implications for further research.

|                | Temperature in (° <i>C</i> ) |        |        |        |        |        |        |        |
|----------------|------------------------------|--------|--------|--------|--------|--------|--------|--------|
|                | Atmos                        |        |        |        | Netvox |        |        |        |
| Month          | Site 1                       | Site 2 | Site 3 | Site 4 | Site 1 | Site 2 | Site 3 | Site 4 |
| January        | 26.64                        | 26.26  | 26.59  | 26.74  | 26.72  | 26.78  | 27.03  | 26.80  |
| February       | 25.78                        | 23.75  | 25.75  | 25.85  | 25.97  | 26.34  | 25.98  | 26.05  |
| March          | 24.10                        | 22.54  | 24.00  | 24.13  | 24.22  | 23.83  | 23.64  | 24.19  |
| April          | 22.95                        | 19.23  | 22.95  | 23.06  | 23.13  | 23.08  | 22.90  | 23.04  |
| May            | 18.57                        | 17.51  | 18.58  | 18.67  | 18.89  | 18.72  | 18.59  | 18.78  |
| June           | 17.15                        | 16.52  | 17.17  | 17.28  | 17.38  | 17.27  | 17.16  | 17.32  |
| July           | 16.19                        | 17.34  | 16.21  | 16.34  | 16.11  | 16.34  | 16.12  | 16.18  |
| August         | 17.38                        | 19.74  | 17.33  | 17.48  | 17.20  | 17.49  | 17.22  | 17.31  |
| September      | 20.07                        | 21.20  | 19.87  | 20.02  | 19.64  | 20.00  | 19.74  | 19.74  |
| October        | 22.14                        | 23.09  | 21.90  | 22.03  | 21.50  | 21.96  | 21.62  | 21.68  |
| November       | 23.94                        | 25.15  | 23.65  | 23.80  | 23.42  | 23.75  | 23.52  | 23.56  |
| December       | 25.54                        | 25.26  | 25.38  | 25.46  | 25.42  | 25.42  | 25.35  | 25.48  |
| Annual average | 21.70                        | 21.47  | 21.61  | 21.74  | 21.63  | 21.75  | 21.57  | 21.68  |

Table 18: Comparison of the monthly temperature means between the Atmos and<br/>Netvox sensors

is especially important for the proposal of splitting the sensors to eight locations.

When looking at the weather data, no extreme weather events are included in the analysis, neither the data is adjusted for these events. These include, e.g., events such as *el niño* and *la niña*, which could lead to temperature fluctuations and distort the data (Delage and Power, 2020).

In addition, the data is recorded during the corona pandemic and could show comparatively changed values of the climate variables in this respect, as traffic and everyday life are severely restricted during the lockdown, which could have had an influence on the climatic conditions. In particular, exhaust fumes from cars have an effect on temperatures and thus the UHI effect, which may now be slightly distorted.

For future research, days with extreme weather events could be identified for the years studied and data could be examined or adjusted accordingly. To take into account possible effects of the corona pandemic, the sensors could continue to run in the future and a comparative analysis of the years in the corona pandemic and the years with normal conditions could be performed, e.g., by the investigation of structural breaks or changes.

#### 5.4 Conclusion and Outlook

In this thesis, a sensor network in Northshore Hamilton PDA is investigated with regard to the optimal granularity for the identification of UHIs in order to provide recommendations for the construction of the Olympic Village in this region. Using various interpolation techniques, it can be shown that a finely granular resolution at all levels under consideration leads to increased prediction accuracy. The application of the kriging method has shown that a spatial granularity of more than four locations is required in order to carry out the methodology. With the help of spatio-temporal interpolations and the explorative analyses used, heat islands within the Northshore Hamilton PDA could also be identified, which means that the UHI effect is not necessarily only observed in an urban-rural comparison. In particular, negative effects of a blacktop and asphalt surfaces on the formation of UHI are identified, as they cooled down less than other surfaces, especially at night.

The results of this study have a number of implications for the optimizing of the sensor network in Northshore Hamilton PDA, as well as for the construction of the Athlete Village. It stresses the importance of the extension of the sensor network and thus an extension of the spatial granularity for the optimal representation of the microclimate in Northshore Hamilton PDA. In addition, the inclusion of the albedo effect as the main factor in the selection of wood for the construction of the village is emphasized as well as the beneficial effects of tree placement for the green village. The sensor network and the representation of the microclimate in Northshore Hamilton PDA should be further optimized in the future to best facilitate the construction of the Olympic Village.