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Method to predict urban heat island hot spots at microscale level based on convolutional neural network land cover

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Abstract: The ongoing shifts in climate change suggest an increase in urban temperatures during hot periods, emphasising the need for supported public policy to be more efficient in reducing Urban Heat Island effects. This paper presents a CNN-based method to classify land cover and simulate micro-scale temperature variations for identifying UHI hot spots. The five primary urban heat sources – buildings, grass, trees, roads, and water – are analysed for their impact on local temperatures. Using a dataset of 775,000 tiles (60×60 pixels), dedicated CNN models are trained for each class. Model validation achieved over 97% accuracy for all classes except roads, which reached 89.1%. Simplified microscale models simulate temperature variations, producing a map that visualises UHI hot spots across urban areas. The results highlight the tool's effectiveness and practicality in identifying high-temperature zones, offering valuable support for UHI mitigation and targeted policy efforts.

Keywords: convolutional neural network; land cover; satellite image; urban heat island.

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Biographical notes: Laurent Mezeix earned his PhD in 2007 in Materials and Mechanical Engineering. Following this, he spent two years in the aerospace industry, working in research and development. He then completed a two-year Postdoctoral Fellowship in Malaysia, focusing on the numerical simulation of composite manufacturing. In 2015, he joined Burapha University as an Assistant Professor. Since 2018, one of his main research activities has focused on applying machine learning to remote sensing.

Cyrille Schwob earned his PhD in Mechanics in 2007 and subsequently completed a two-year Postdoctoral Fellowship at Tsinghua University in China. Since 2004, he has been with Airbus, where he is currently based in Singapore, serving as the Head of Technology for Asia Pacific at Airbus.

1 Introduction

The Urban Heat Island (UHI) phenomenon describes the increase in temperature in urban areas compared to nearby rural zones, driven by human activities and extensive urbanisation. This effect arises from the use of heat-absorbing materials like concrete and asphalt, a reduction in green spaces, and waste heat produced by vehicles, industries, and air conditioning systems (Jabbar et al., 2023). As a result, cities experience higher temperatures, lower humidity, and increased energy demands, while residents, particularly children, the elderly, and those with pre-existing health conditions, face greater health risks (Denpetkul and Phosri, 2021). The European heatwave of 2003, which caused an estimated 35,000 additional deaths, highlighted UHI's severe health impacts on urban populations (Kosatsky, 2005).

Addressing the UHI effect is challenging for urban planners, who employ measures such as expanding green spaces, utilising reflective building materials, and promoting sustainable urban design (Morales-Inzunza et al., 2023). Understanding UHI's spatial distribution is essential for implementing these solutions effectively, yet mapping urban hotspots requires robust data collection and analysis. In situ weather stations provide accurate microclimate data but are resource-intensive to install and maintain on a large scale. Alternatively, satellite-derived land surface temperature (LST) data, combined with statistical or machine learning methods, has been used to estimate urban air temperatures, though precision can be affected by atmospheric conditions (Kim and Kim, 2024).

Microclimate modelling using computational fluid dynamics (CFD) offers detailed simulations of urban heat profiles, capturing factors like temperature, wind, and radiation. ENVI-met, for example, is widely used for urban modelling, allowing planners to assess UHI dynamics at a high resolution. However, these models require significant computational resources, restricting their use to short-term studies or specific urban case studies (Huang et al., 2014). Recent advancements in machine learning, particularly convolutional neural networks (CNNs), provide a powerful alternative for urban land cover classification, often outperforming traditional algorithms like support vector machines and random forests (Ma et al., 2019). CNN-derived data, when integrated with physical models, enables simulation of urban cooling effects, such as those of vegetation and water bodies, as demonstrated in studies on Bangkok (Mentet et al., 2022). By combining CNN classification with physical modelling, this approach offers a promising tool for accurately mapping UHI hotspots and equipping planners with insights needed for targeted cooling strategies in urban environments.

In this research, UHI hot spots in urban areas are mapped using physical temperature variation models based on a CNN land cover analysis. The goal is to provide authorities with a tool for easily identifying hazardous areas from a single data source, thus aiding decision-making. The study focuses on Toulouse, France, a city with a temperate climate that has recently experienced increased summer heat waves. To map UHI hot spots, five classes are examined for their cooling and heating effects: buildings, grass, trees, roads,

and water. The paper describes the physical models used to simulate temperature variations for each class, presents CNN models with validation through confusion matrices, and illustrates the results. A land cover and temperature variation maps are provided, followed by a discussion of limitations and future perspectives before concluding the research

2 Study case

2.1 Area of interest

The Toulouse metropolitan area is the fifth most populous in France, with a population of 816,362 as of 2020. The region has experienced a population growth rate of 1.36% per year from 2009 to the 2020s, resulting in significant urbanisation and industrialisation. These trends have led to various environmental challenges, including air pollution, land subsidence, and UHI effects. Toulouse is characterised by a four-season humid subtropical climate, marked by hot summers, an average humidity level of approximately 70%, and low precipitation. UHI effects have been quantified through the use of 70 weather stations, indicating a temperature difference of approximately 5°C between urban and interurban areas during the afternoon (Masson et al., 2008).

2.2 Dataset creation

As the research delves into the effects of cooling and heating phenomena, it specifically focuses on five classes (Figure 1) deemed essential by the authors to achieve the overarching goal of the proposed tool.

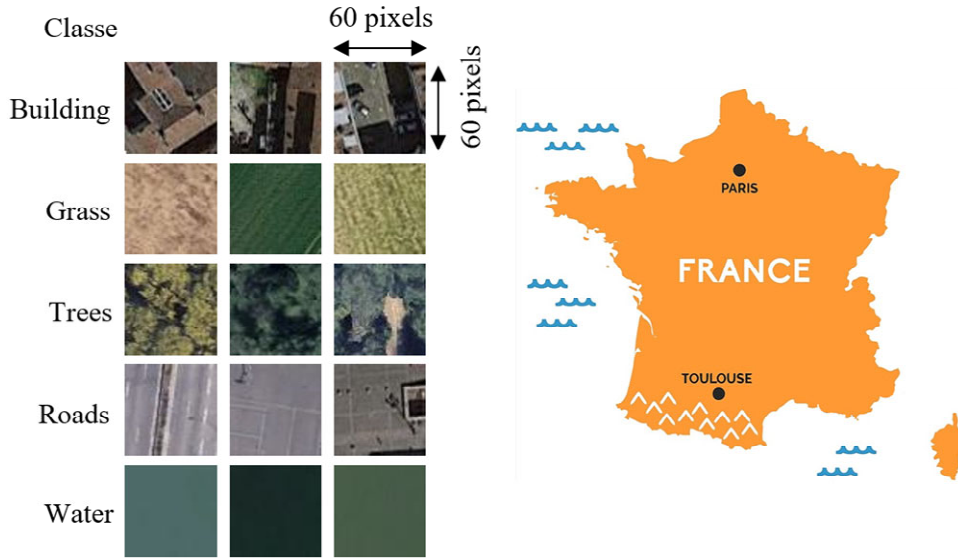
- Building: includes individual houses, large buildings, and dense urban constructions.
- Grass: refers to areas covered by grass.
- Trees: encompasses areas with dense or sparse tree coverage, including recreation parks and roads lined with trees.
- Roads: consists of roads and pavement surfaces.
- Water: represents bodies of river water.

For this study, tiles measuring 60×60 pixels (equivalent to $19.8 \times 19.8\text{m}^2$) were manually created from Google Earth images captured in June 2023, with a resolution of 0.33 m/pixel. Labeling was conducted following the methodology proposed by Mezeix and Casanova (2023). Given the substantial quantity of tiles required (Empananza et al., 2020), a total of 775,000 tiles were generated for this investigation.

A specific dataset is associated with each CNN model, resulting in the creation of five datasets. Each dataset consists of two subclasses: the primary class under investigation and a combination of the remaining classes. The investigated classes contain different numbers of tiles: building (175,000), grass (215,000), trees (130,000), roads (105,000), and water (150,000), with 125,000 tiles. This secondary category comprises 125,000 tiles representing the other four unexplored classes. Following recommendations from the literature, 70% of the total tile count was randomly assigned to the training set, while

15% was allocated to the validation set, and the remaining 15% was reserved for the testing set (Cihan et al., 2022).

Figure 1 Tiles example of the 5 classes and study area (see online version for colours)



2.3 Land cover

Recent studies Watanabe et al. (2020) have demonstrated the superior efficiency of CNN compared to other machine learning techniques. Consequently, CNN was chosen as the preferred approach for the present case study. Moreover, utilising the CNN approach allows for two main functionalities: firstly, the comprehensive mapping process, and secondly, the application of various physical models, such as temperature variation, all from a single source.

A brief description of the process used to generate land cover through the application of CNN models is provided, with further details available in the referenced publication (Fitton et al., 2022): For each specific class, a dedicated CNN model is employed to classify the land. An overlapping procedure is utilised to refine the classified areas in satellite images, enhancing the accuracy of the land cover representation (Chermprayong et al., 2021). Subsequent to classification, a post-processing step is undertaken to identify and eliminate classified regions deemed too small to accurately depict the intended features, considering both their size and class. Following this, land cover is established by aggregating the predictions from the different classes. Finally, external physical models are applied, with this study focusing on the variation of temperature in relation to the distance from classified areas (Mentet et al., 2022).

3 Variation of temperature models

Daily and local weather conditions, along with natural elements such as vegetation and anthropogenic structures, significantly influence temperature variations. In this study, it is assumed that meteorological conditions remain stable, characterised by anticyclonic conditions with no winds or clouds, and daily variations are not considered.

3.1 *Trees and water temperature variation distribution*

Assessing the impact of trees and water on the surrounding regions presents a challenging task, influenced by various factors such as geographical area, season, location, and urban structure (Hamada and Ohta, 2010). In this study, the method proposed by Mentet et al. (Mentet et al., 2022) for analysing temperature variation has been adopted. The approach to assessing temperature variation around trees can be summarised as follows:

- The size of tree spots is obtained from the CNN predictions.
- The number of trees is estimated using an average canopy size.
- The number of trees per spot is determined.
- The cooling effect around trees depends on the size of the spot, i.e., the number of trees (Martini et al., 2018). A larger trees area results in a greater reduction in temperature in terms of magnitude and distance from the spot's edge (Table 1).
- Under tree canopies, shading can reduce ambient temperatures by 5°C to 7°C (Armson et al., 2012).

Table 1 Intensity of influence of vegetation in the immediate environment for isolated trees, medium and large areas

<i>Temperature reduction depending on the distance</i>	<i>Isolated trees (< 2 trees)</i>	<i>Medium area (2–5 trees)</i>	<i>Large area (> 5 trees)</i>
0 m (under canopy)	–5°C	–5°C	–5°C
0–4 m	–0,58°C	–1,01°C	–1,32°C
4–7, 8 m	–0,52°C	–0,94°C	–1,14°C
7, 8–11, 7 m	–0,22°C	–0,57°C	–0,73°C

The cooling effect of water is associated with a reduction in temperature, influenced by several factors, including the geometry of the water body, prevailing wind conditions, ambient air temperature, and humidity levels. Furthermore, the size of the water body has demonstrated variable effects on both the extent of cooling and the distance over which this cooling is observed, presenting challenges for predictive modelling (Wang and Ouyang, 2021). This study utilises data from Mentet et al. (2022), which indicate that over the river, the temperature decreases by 0.23°C. A reduction of 0.2°C is recorded from the riverbank to a distance of 25 m. From 25 m to 50 m, the temperature further decreases by 0.14°C, and from 50 m to 100 m, a decrease of 0.09°C is observed.

3.2 House temperature variation distribution

The UHI effect is predominantly attributed to the absorption and re-emission of heat by urban infrastructure. Experimental evidence indicates that the temperature of red-brick building facades increases by 2.2°C, as demonstrated by the temperature variation data presented in Table 2 (Tabatabaei and Fayaz, 2023). From the wall surface to a distance of 1.5 m, the temperature increases by 1.8°C. Between 1.5 m and 2 m, an increase of 1.1°C is noted. From 2 m to 3 m, a further increase of 0.9°C is observed. Finally, from 3 m to 4 m, the temperature increases by an additional 0.6°C.

3.3 Roads and grass temperature variation

Grass significantly contributes to cooling urban areas and alleviating the UHI effect (Armson et al., 2012). Observations indicate that the globe temperature above grass is reduced by approximately 1.5°C. In contrast, the globe temperature above roads, particularly under direct sunlight, can increase by about 5°C.

3.4 Temperature models' superposition

The study of the interplay between cooling and heating effects presents challenges (Cruz et al., 2021), often leading to independent investigations (Cao et al., 2022). In this study, a primary hypothesis is proposed to validate the methodology and broadly represent the main effects:

- Air temperature tends to be cooler around trees and water (Martini et al., 2018).
- Temperatures near building walls tend to be higher than in the surrounding environment (Taleghani et al., 2014).

Subsequently, the different temperature variations have been simply superimposed. While this method significantly simplifies actual phenomena, it provides an initial localisation of UHI hot spots where temperatures may pose risks to vulnerable populations (such as children, the elderly, and pregnant women) and hinder outdoor activities (such as work), while also identifying areas where it may be more comfortable to stay.

4 CNN models

Multiple CNN models were developed, with one model designed for each class (Figure 1). These models featured varying numbers of layers, including four convolutional layers and either two or four dense layers, with an additional dropout layer to prevent overfitting (Figure 2). A pooling rate of 0.4 was utilised, and a learning rate of 0.0001 was applied to enhance accuracy and minimise validation loss. The input image dimensions were set at $60 \times 60 \times 3$ (Figure 2), and a 3×3 kernel size was employed. Various configurations were tested for each model, with the best configuration ultimately selected (Table 2). To further prevent overfitting, a callback of 50 epochs was implemented.

Figure 2 Flow chart of the convolutional neural network architecture (see online version for colours)

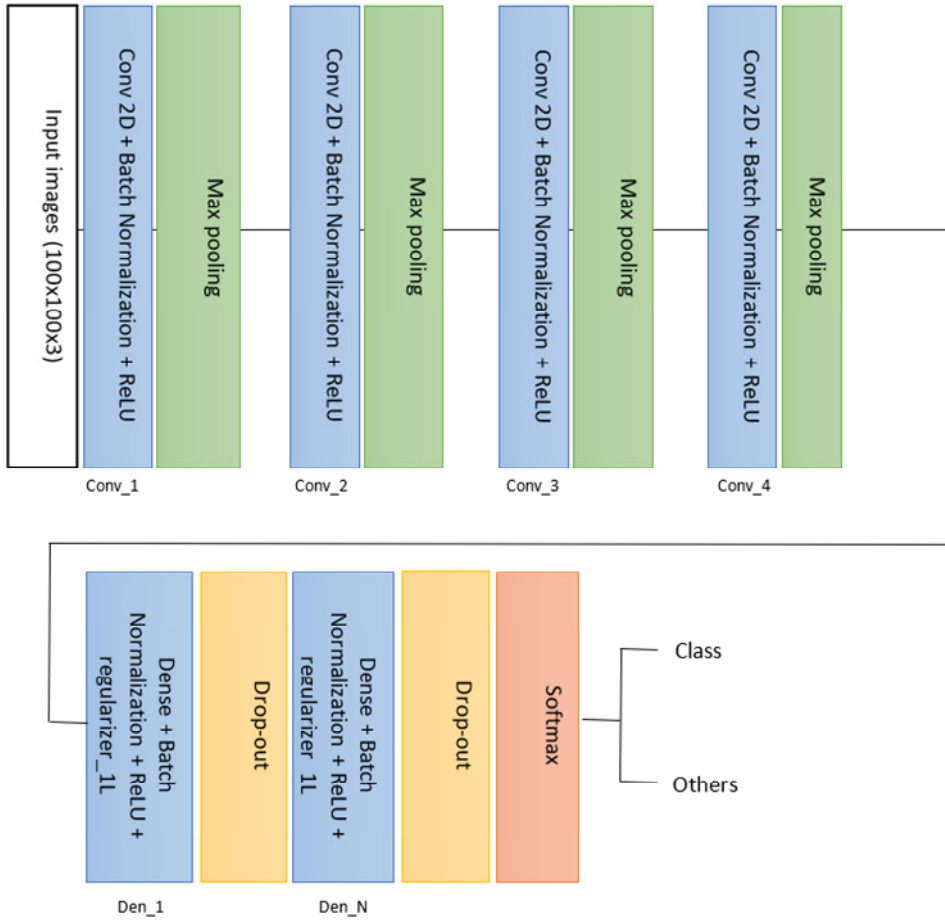


Table 2 Description of layers and bath size for each CNN model

<i>Layers\CNN model</i>	<i>Building CNN</i>	<i>Roads CNN</i>	<i>Trees CNN</i>	<i>Grass CNN</i>	<i>Water CNN</i>
Conv_1 to Conv_4	4 × 64	4 × 256	4 × 64	4 × 8	4 × 8
Dense	2 × 64	2 × 256	2 × 64	4 × 8	4 × 8
Batch size	512	256	256	256	256

5 Results

5.1 CNN validation

The precision and recall rates are used in the literature (Olson and Delen, 2008) to calculate detection performance precision. Confusion matrix are given in the Figure 3.

The accuracy of the different CNN models is higher than 97% except the roads CNN model that presents an accuracy of 89.1%. This limited accuracy may be attributed to the smaller quantity of tiles as outlined by Emparanza et al. (2020).

Figure 3 Confusion matrix for each of the 5 CNN models (see online version for colours)

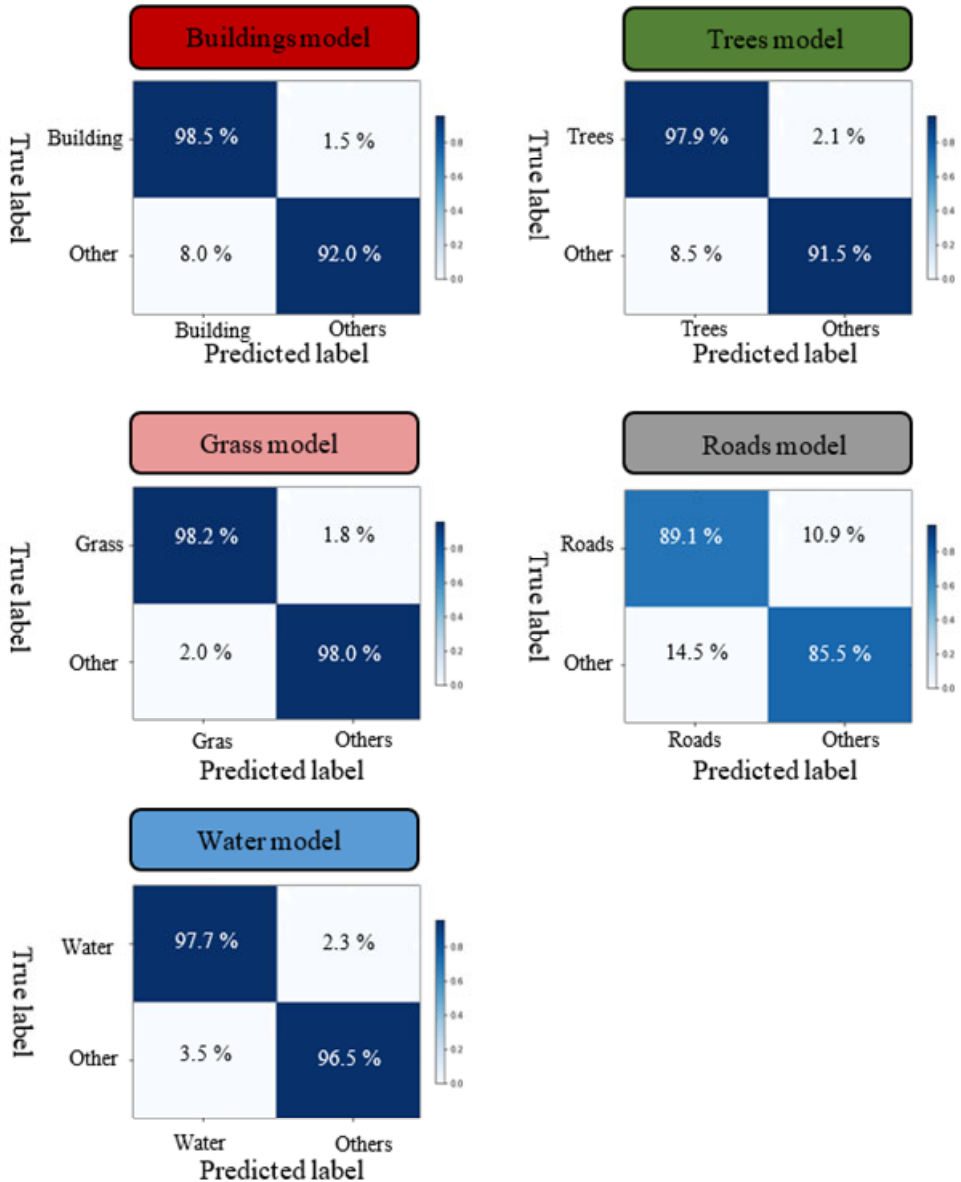
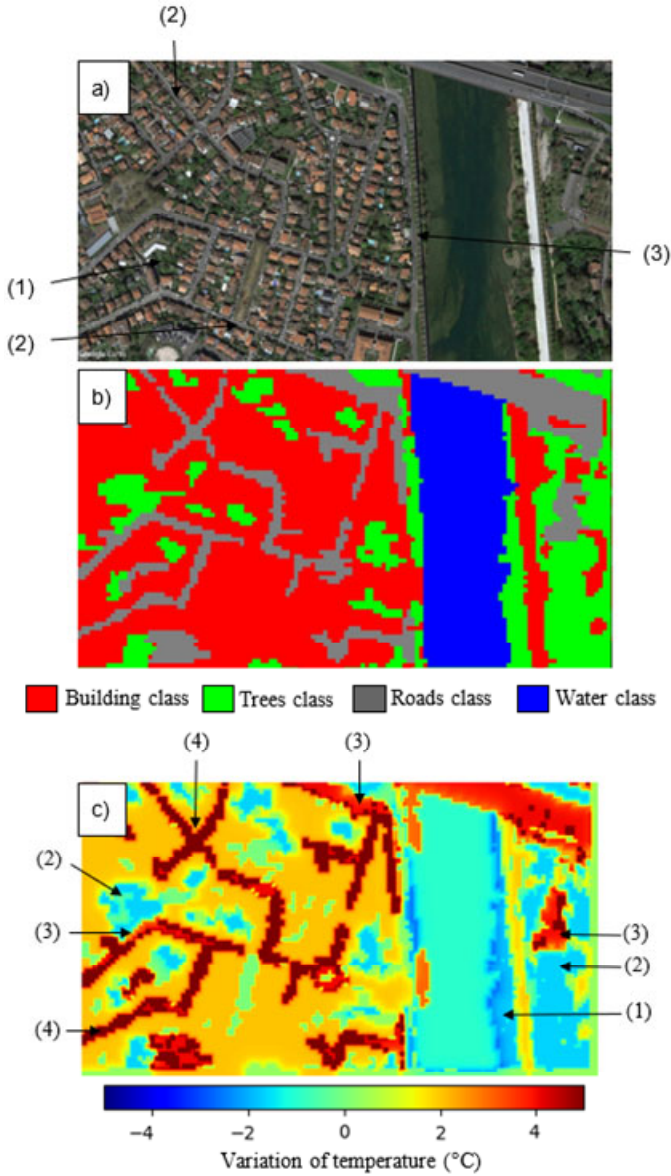


Figure 4 (a) Investigated satellite image (b) Land cover and (c) Urban heat island hot spots map (see online version for colours)

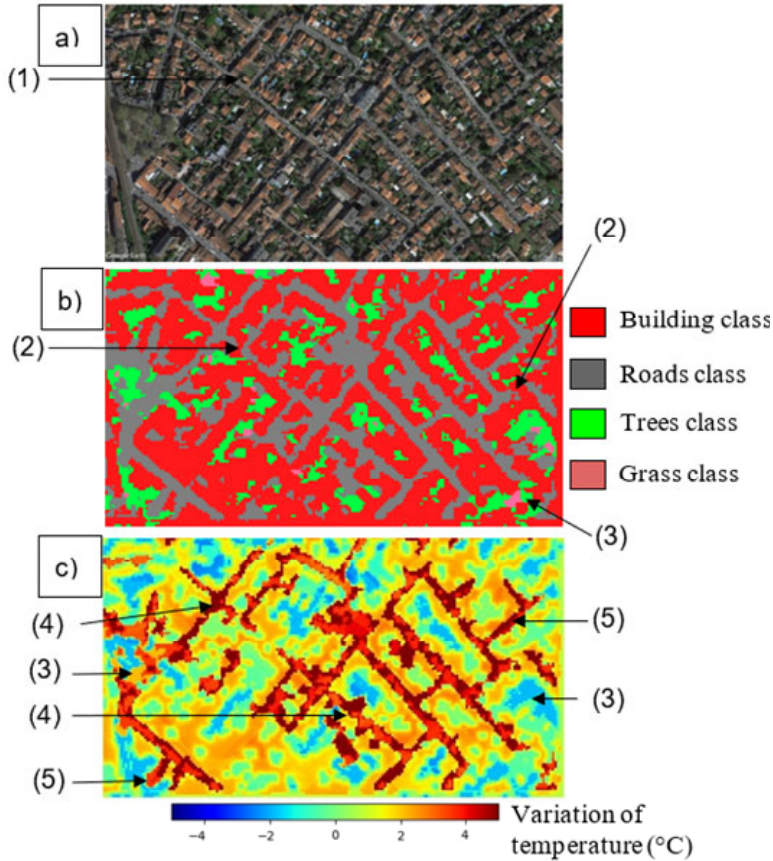


5.2 Land cover and microscale temperature mapping

The methodology has been applied on different urban area (Figures 4, 5, 6). Firstly, an area of 0.22 km² located near the Garonne River in Toulouse, characterised by individual houses is studied [Figure 4(a)]. Land cover classification has been performed by aggregating the results of each individual CNN [Figure 4(b)]. It is observed that the water

class is well classified. Large and small tree spots are identified, but private gardens are not classified due to their small surface area

Figure 5 (a) Satellite image, (b) land cover and (c) urban heat island hot spots map of subdivision community (see online version for colours)



- 1 Building areas, including private gardens, are successfully obtained.
- 2 The roads CNN model can detect major roads, but due to occlusions mainly caused by trees and building shadows, some areas are not detected.
- 3 Additionally, due to the dataset construction (Figure 2), roadside trees are classified under the trees class.

Finally, the obtained land cover can be utilised to simulate the cooling and heating effects. Variation of temperature, given by the equation (1), is mapped [Figure 4(c)].

- 1 It can be observed the cooling effect of the river on the surrounding environment.
- 2 Trees area show a reduction of the ambient temperature.
- 3 Roads having trees on its side show a smaller increase of temperature.
- 4 Roads without vegetation present a large increase of the ambient temperature.

A subdivision community is investigated [Figure 5(a)]. Initially, land cover analysis is conducted [Figure 5(b)], revealing certain limitations:

- 1 private gardens are poorly identified
- 2 tree areas are detected, and roads are only partially recognised due to occlusions
- 3 additionally, grass and open areas are classified in this sector.

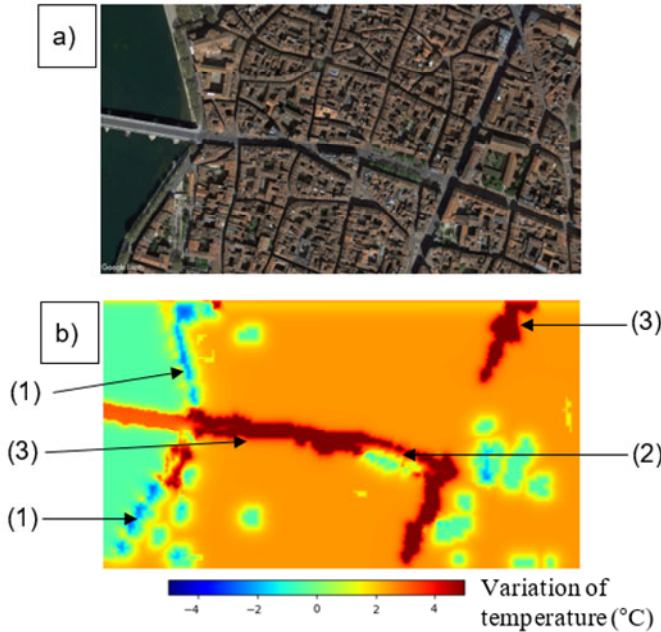
Utilising the CNN land cover, temperature variation mapping is conducted [Figure 5(c)]. The beneficial impact of trees on temperature is clearly demonstrated. Notably, roads surrounded by trees exhibit a reduction in temperature variation (4) compared to roads lacking vegetation (5).

This study investigates a dense urban area covering 0.22 km², located in the centre of Toulouse near the Garonne River, characterised by closely spaced buildings and narrow streets [Figure 6(a)]. The associated temperature variation map is presented in Figure 6(b).

- 1 The influence of the river is observed.
- 2 The impact of trees on air temperature is evident.
- 3 An increase in temperature is observed on the roads.

However, due to the limitations of the CNN land cover classification, some roads remain unclassified, rendering the model inapplicable at the local level.

Figure 6 (a) Satellite image (b) Land cover and (c) Urban heat island hot spots map of dense urban area (see online version for colours)



6 Discussion

6.1 Temperature model's validation

Temperature measurements were obtained using weather stations during the hot days of August 2021, with a resolution of $125 \times 125 \text{ m}^2$ (Martin, 2021). Although there is a difference in resolution, the primary trend in temperature variation can be identified using an average temperature of 25°C , which can be compared to the model results (Table 3). The model shows an underestimation of the water-cooling effect, reporting a decrease of -0.23°C compared to observed data of -0.7°C , attributed to the initial assumptions. Conversely, the model demonstrates strong predictive capability along the riverbank, with a discrepancy of less than 18% between observed temperatures ($+1.2^\circ\text{C}$) and model predictions ($+1.5^\circ\text{C}$). In the subdivision community and dense urban areas, the observed temperature differences are 17% and 13%, respectively, when comparing measurements ($+0.7^\circ\text{C}$ and $>+2.7^\circ\text{C}$) to model results ($+0.6^\circ\text{C}$ and $+3.1^\circ\text{C}$). Overall, despite model simplifications, it accurately predicts the magnitude of temperature variation.

6.2 Benefit of the method

Results can be compared with those from Lonjou (2023). In this work, a complex approach has been proposed to create a heat vulnerability map and a brief description of the process is given. On one hand, LST is captured through satellite imagery acquired in the thermal infrared, while on the other hand, remote sensing images from ECOSTRESS and ASTER are collected. A combination of a deep learning model and a physical approach is used to classify approximately 10 classes. Additionally, LIDAR is employed to identify low and high vegetation. Finally, a complex urban climate model (SURFEX) is applied to the land cover, enabling the creation of a heat map. Despite the method demonstrating performance, its complexity and cost limit its applicability in other countries. On the contrary, the work presented in this paper demonstrates that utilising a single source of data (remote sensing images) enables the creation of a CNN land cover (Figures 4–6). Aggregating various CNN models offers flexibility, allowing for the straightforward addition or modification of classes. Results indicate that applying physical models based on simple assumptions enables relatively accurate prediction of temperature variations (Figures 4–6). Consequently, this approach is easily applicable to different cities and countries by simply adjusting the temperature variation. In contrast, the work presented in this paper demonstrates that utilising a single remote sensing image as a data source enables the implementation of a CNN land cover. The aggregation of different CNN models' results provides flexibility, allowing for the easy addition or modification of classes. The results demonstrate that applying physical models based on simple assumptions enables accurate prediction of temperature variations. Therefore, this approach can be easily applied to different cities and countries.

6.3 Limitation

6.3.1 CNN model limitation

CNN models were trained using images of the city of Toulouse, France (Figure 2). While this study demonstrates interesting results in classification, the applicability of CNN

models is limited to this city and its surrounding province, with uncertain accuracy in other regions. To extend their use to other areas, new datasets must be constructed.

CNN models exhibit limitations, particularly in the detection of road classes. Roads are only partially detected when occlusions are absent. As discussed in the literature, extracting roads from remote sensing images is challenging due to occlusions by trees, buildings, and large shadows cast by buildings (Mattyus et al., 2017). In this study, a 20-pixel (6.6 m) overlap was employed, thus limiting road class detection. Although classification performance could be enhanced by reducing the overlap value, this adjustment would increase computational expenses. Alternative strategies for road detection, such as amalgamating diverse models (Choudhury et al., 2020), incorporating Lidar data (Parajuli et al., 2018), and utilising an object-oriented classification approach (Mhangara et al., 2011), have proven successful but are complex and computationally intensive. Additionally, private gardens are not classified due to their complex features, which include a mix of grass, single or few trees, and small constructions not covered by any class. Creating a new dataset for private gardens poses challenges in data collection. Furthermore, the chosen tile size of 60×60 pixels is considered slightly too large. Reducing the tile size might aid in private garden classification. However, shrinking the tile dimensions reduces contextual information available for predicting the class, potentially making classification more challenging (Mezeix and Casanova, 2023). City planners must consider the impact of climate warming on the future of urban areas. One effective strategy for mitigating rising temperatures is to increase canopy coverage while reducing the extent of impermeable built-up surfaces (Salim et al., 2020). Trees have demonstrated significant effectiveness in reducing temperatures (Vailshery et al., 2013). By creating a new class called ‘Roadside Trees,’ representing roads bordered by trees, it would be possible to study the influence of road improvement.

6.3.2 *Cooling and heating model’s limitation*

The proposed method is based on CNN land cover where different types of land are classified. This enables the application of a large type of physical models such as humidity, complex heat release building model or Urban Heat Island Risk Indicator (UHRI).

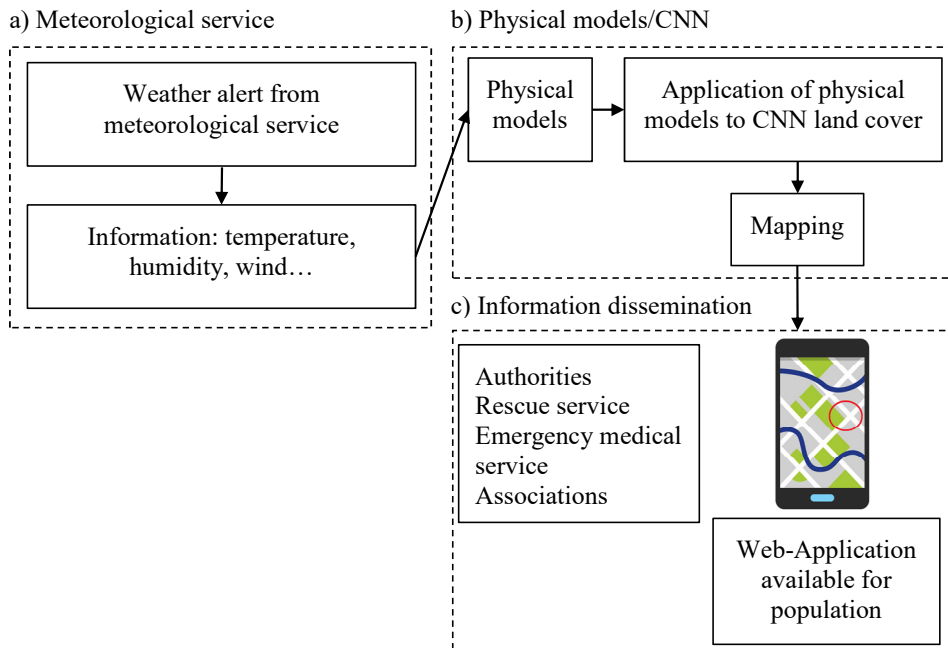
Living organisms, including humans, can only thrive within a specific temperature range. In situations of excessive ambient temperature, humans regulate their body temperature by sweating, thereby lowering it below the surrounding environment. This mechanism serves to protect against potentially life-threatening hyperthermia caused by heat stress (Wills, 2016). The efficiency of evaporative cooling relies on factors such as humidity (Haldane, 1905), and therefore it plays an important role for human health (Takebayashi, 2022). Furthermore, numerous research studies have demonstrated that trees can influence air temperature and relative humidity by providing shade, engaging in transpiration, and facilitating evaporative cooling (Tzortzi – Georgi and Dimitriou, 2010). Therefore, it is interesting to add humidity phenomenon into the physical model.

The release of heat from buildings constitutes a noteworthy contributor to anthropogenic heat, exerting a substantial impact on the urban microclimate. Nevertheless, urban climate and microclimate models often tend to oversimplify this aspect [Harrison et al., (1984), pp.1971–1976]. More complex models are proposed (Hong et al., 2020) and can be implemented in the CNN land cover in order to get more accurate temperature variation values.

6.4 Perspective

Urban Heat Islands risk indicator is established in order to enhance the effectiveness of public policy in addressing UHI and heatwave events. To be applicable at the local level, this indicator must be defined at the individual building level. The use of meso-scale or micro-scale models based on physical equations under the form of an urban energy balance linked with atmospheric models (Lafore et al., 1997) and applied to the city are proposed to achieve this resolution level. However, these models require a high level of detail and input data and also a high computational resource. A large number of simplified models have been proposed to circumvent these problems enabling to estimate the UHI risks at the building level (Marcel and Villot, 2021), and can be applied in the proposed work. Moreover, the temperature fluctuation influenced by natural factors like vegetation and human-made structures is contingent on the time of day and can be incorporated into the proposed methodology (Armson et al., 2012).

Figure 7 Global view of the HEWAS (a) meteorological service (b) physical models/CNN (c) Information dissemination (see online version for colours)



Elevated temperatures in urban environments can worsen the health dangers linked to heatwaves, leading to a greater likelihood and severity of heat-related ailments such as heat stroke, dehydration, and respiratory issues. Furthermore, specific groups at risk, such as the elderly, youngsters, and those with preexisting medical conditions, are especially vulnerable to the negative health impacts of UHIs (Campbell et al., 2018). Moreover, it has been shown that elderly and low-income populations present a higher risk of heat-related mortality in cities (Mallen et al., 2019). Therefore, it is necessary to inform the population and authorities using an Emergency Alert System. It can be taken as example the flood forecast alert and response, such as the European flood awareness

system (Thielen et al., 2009). These are essential components of modern flood preparedness systems enabling to reduce casualties and material losses (Mechler, 2016). Recently, a web-GIS fluvial flood forecast and alert system has been developed by Mourato et al. (2021). This advanced system distinguishes itself from others by employing a combined real-time hydrologic and 2D hydrodynamic modelling approach, which is bolstered by numerical weather prediction and a high-resolution digital terrain surface model. Additionally, it leverages web-GIS services to establish a platform that visualises flood hazards in an image format, facilitating the dissemination of information to both civil authorities and the general population. Following such an alert system, heat wave awareness system (HEWAS) could be created based on CNN land cover. Information given by meteorological service [Figure 7(a)] can be inputted into physical models and applied to the CNN land cover [Figure 7(b)]. The created map can be sent to the different services and authorities in order to take preventive actions such as: prepositioned medical service or send municipal social services to vulnerable peoples [Figure 7(c)]. The created map could also be diffused through web-application [Figure 7(c)], in order to give the population the information to avoid hazardous areas.

7 Conclusions

UHI effects are a global concern, especially for vulnerable groups like children, the elderly, and individuals with respiratory or cardiovascular conditions. Predicting UHI hot spots is essential for identifying high-risk areas and aiding authorities in effective decision-making. This study introduces a method to create a UHI hot spots map and has been applied for Toulouse, France, where temperature differences of up to +5°C have been observed between urban and interurban zones. The approach begins with land cover classification using five CNN models, focusing on buildings, grass, trees, roads, and water, based on a dataset of around 775,000 tiles. All CNN models achieved accuracy above 97%, except for roads at 89.1%.

In the next phase, cooling from trees, grass, and water, along with heat from roads and buildings, is simulated using CNN land cover data to create the UHI hot spots map. Applied to different areas in Toulouse, this method accurately identifies cooling near rivers and trees and heat spots on vegetation-free roads.

Future research aims to incorporate additional factors, like humidity and wind, to enhance model complexity. Ultimately, this method could evolve into a HEWAS, aiding authorities in making informed decisions to protect citizens, especially in the face of global warming and increased heat risks.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Authors would like to thanks Mr. Ghislain Imougar, Mr. Valenti Riba Revert, Mr. Benjamin Fol1 and Mr. Antonio Serran from INSA Toulouse, France, for their support.

References

- Armson, D., Stringer, P. and Ennos, A.R. (2012) 'The effect of tree shade and grass on surface and globe temperatures in an urban area', *Urban Forestry and Urban Greening*, Vol. 11, pp.245–255, <https://doi.org/10.1016/j.ufug.2012.05.002>.
- Campbell, S., Remenyi, T.A., White, C.J. and Johnston, F.H. (2018) 'Heatwave and health impact research: a global review', *Health and Place*, Vol. 53, pp.210–218, <https://doi.org/10.1016/j.healthplace.2018.08.017>.
- Cao, B., Chen, Q., Du, M., Cheng, Q., Li, Y. and Liu, R. (2022) 'Simulation analysis of the cooling effect of urban water bodies on the local thermal environment', *Water*, Vol. 14, p.3091, <https://doi.org/10.3390/w14193091>.
- Chermprayong, P., Hongkarnjanakul, N., Rouquette, D., Schwob, C. and Mezeix, L. (2021) 'Convolutional neural network for Thailand's eastern economic corridor (EEC) land cover classification using overlapping process on satellite images', *Remote Sensing Applications: Society and Environment*, Vol. 23, p.100543, <https://doi.org/10.1016/j.rsase.2021.100543>.
- Choudhury, A.R., Parajuli, B. and Kumar, P. (2020) 'QuadRoad: an ensemble of CNNs for road segmentation', in: *Procedia Computer Science. Presented at the 24th International Conference on Knowledge-Based and Intelligent Information and Engineering Systems (KES 2020)*.
- Cihan, M., Ceylan, M., Soyulu, H. and Konak, M. (2022) 'Fast evaluation of unhealthy and healthy neonates using hyperspectral features on 700–850 Nm Wavelengths', *ROI Extraction, and 3D-CNN, IRBM 43*, pp.362–371, <https://doi.org/10.1016/j.irbm.2021.06.009>.
- Cruz, J.A., Blanco, A.C., Garcia, J.J., Santos, J.A. and Moscoso, A.D. (2021) 'Evaluation of the cooling effect of green and blue spaces on urban microclimate through numerical simulation: a case study of Iloilo River Esplanade, Philippines', *Sustainable Cities and Society*, Vol. 74, p.103184, <https://doi.org/10.1016/j.scs.2021.103184>.
- Denpetkul, T. and Phosri, A. (2021) 'Daily ambient temperature and mortality in Thailand: Estimated effects, attributable risks, and effect modifications by greenness', *Science of The Total Environment*, Vol. 791, p.148373, <https://doi.org/10.1016/j.scitotenv.2021.148373>.
- Emparanza, P.R., Hongkarnjanakul, N., Rouquette, D., Schwob, C. and Mezeix, L. (2020) 'Land cover classification in Thailand's Eastern Economic Corridor (EEC) using convolutional neural network on satellite images', *Remote Sensing Applications: Society and Environment*, Vol. 20, p.100394, <https://doi.org/10.1016/j.rsase.2020.100394>.
- Fitton, D., Laurens, E., Hongkarnjanakul, N., Schwob, C. and Mezeix, L. (2022) 'Land cover classification through convolutional neural network model assembly: a case study of a local rural area in Thailand', *Remote Sensing Applications: Society and Environment*, Vol. 26, p.100740, <https://doi.org/10.1016/j.rsase.2022.100740>.
- Haldane, J.S. (1905) 'The influence of high air temperatures: No. 1', *J. Hyg. (Lond.)*, Vol. 5, pp.494–513, <https://doi.org/10.1017/s0022172400006811>.
- Hamada, S. and Ohta, T. (2010) 'Seasonal variations in the cooling effect of urban green areas on surrounding urban areas', *Urban Forestry and Urban Greening*, Vol. 9, pp.15–24, <https://doi.org/10.1016/j.ufug.2009.10.002>.
- Harrison, R., McGoldrick, B. and Williams, C.G.B. (1984) 'Artificial heat release from greater London, 1971–1976', *Atmospheric Environment* (1967), Vol. 18, pp.2291–2304, [https://doi.org/10.1016/0004-6981\(84\)90001-5](https://doi.org/10.1016/0004-6981(84)90001-5).
- Hong, T., Ferrando, M., Luo, X. and Causone, F. (2020) 'Modelling and analysis of heat emissions from buildings to ambient air', *Applied Energy*, Vol. 277, p.115566, <https://doi.org/10.1016/j.apenergy.2020.115566>.
- Huang, J., Laurent, J. and Spengler, J. (2014) 'CityComfort+: a simulation-based method for predicting mean radiant temperature in dense urban areas', *Building and Environment*, Vol. 80, pp.84–95, <https://doi.org/10.1016/j.buildenv.2014.05.019>.

- Jabbar, H.K., Hamoodi, M.N. and Al-Hameedawi, A.N. (2023) 'Urban heat islands: a review of contributing factors, effects and data', *IOP Conf. Ser.: Earth Environ. Sci.*, Vol. 1129, p.12038, <https://doi.org/10.1088/1755-1315/1129/1/012038>.
- Kim, Y. and Kim, Y. (2024) 'Deep learning-based analytic framework using comprehensive urbanization index for heat vulnerability assessment in urban areas', *Expert Systems with Applications*, Vol. 235, p.121140, <https://doi.org/10.1016/j.eswa.2023.121140>.
- Kosatsky, T. (2005) 'The 2003 European heat waves', *Eurosurveillance*, Vol. 10, pp.3–4, <https://doi.org/10.2807/esm.10.07.00552-en>.
- Lafore, J-P., Stein, J., Asencio, N., Bougeault, P., Ducrocq, V., Duron, J., Fischer, C., Hèreil, P., Mascart, P., Masson, V., Pinty, J-P., Redelsperger, J-L., Richard, E. and Arellano, J. (1997) 'The Meso-NH atmospheric simulation system. Part I: Adiabatic formulation and control simulations', *Annales Geophysicae*, Vol. 16, <https://doi.org/10.1007/s005850050582>.
- Lonjou, V. (2023) 'Thermicity', *La Thermique De La Ville Depuis L'espace*, Rapport_v2022_12_08, pp.1–38.
- Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G. and Johnson, B.A. (2019) 'Deep learning in remote sensing applications: a meta-analysis and review', *ISPRS Journal of Photogrammetry and Remote Sensing*, Vol. 152, pp.166–177.
- Mallen, E., Stone, B. and Lanza, K. (2019) 'A methodological assessment of extreme heat mortality modeling and heat vulnerability mapping in Dallas, Texas', *Urban Climate*, Vol. 30, p.100528, <https://doi.org/10.1016/j.uclim.2019.100528>.
- Marcel, C. and Villot, J. (2021) 'Urban heat island index based on a simplified micro scale model', *Urban Climate*, Vol. 39, p.100922, <https://doi.org/10.1016/j.uclim.2021.100922>.
- Martin, K. (2021) *Understanding Urban Heat Islands* [online] <https://news.cnrs.fr/articles/understanding-urban-heat-islands> (accessed 14 September 2021).
- Martini, A., Biondi, D. and Batista, A. (2018) 'Distance and intensity of microclimatic influence provided by urban forest typologies', *Floresta e Ambiente*, Vol. 25, <https://doi.org/10.1590/2179-8087.021317>.
- Masson, V., Gomes, L., Pigeon, G., Liousse, C., Pont, V., Lagouarde, J., Voogt, J., Salmond, J., Oke, T., Hidalgo, J., Legain, D., Garrouste, O., Lac, C., Connan, O., Briottet, X., Lachérade, S. and Tulet, P. (2008) 'The canopy and aerosol particles interactions in toulouse urban layer (CAPITOU) experiment', *Meteorology and Atmospheric Physics*, Vol. 102, pp.135–157, <http://dx.doi.org/10.1007/s00703-008-0289-4>.
- Mattyus, G., Luo, W. and Urtasun, R. (2017) 'DeepRoadMapper: extracting road topology from aerial images', <https://doi.org/10.1109/ICCV.2017.372>.
- Mechler, R. (2016) 'Reviewing estimates of the economic efficiency of disaster risk management: opportunities and limitations of using risk-based cost–benefit analysis', *Nat Hazards*, Vol. 81, pp.2121–2147, <https://doi.org/10.1007/s11069-016-2170-y>.
- Mentet, M., Hongkarnjanakul, N., Schwob, C. and Mezeix, L. (2022) 'Method to apply and visualize physical models associated to a land cover performed by CNN: a case study of vegetation and water cooling effect in Bangkok Thailand', *Remote Sensing Applications: Society and Environment*, Vol. 28, p.100856, <https://doi.org/10.1016/j.rsase.2022.100856>.
- Mezeix, L. and Casanova, M.G. (2023) 'Dataset creation methodology for CNN land use/cover classification: Thailand's rural area study case', *Defence Technology Academic Journal*, Vol. 5, pp.74–95.
- Mhangara, P., Odindi, J., Kleyn, L. and Remas, H. (2011) *Road Extraction Using Object Oriented Classification*.
- Morales-Inzunza, S., González-Trevizo, M.E., Martínez-Torres, K.E., Luna-León, A., Tamayo-Pérez, U.J., Fernández-Melchor, F. and Santamouris, M. (2023) 'On the potential of cool materials in the urban heat island context: scalability challenges and technological setbacks towards building decarbonization', *Energy and Buildings*, Vol. 296, p.113330, <https://doi.org/10.1016/j.enbuild.2023.113330>.

- Mourato, S., Fernandez, P., Marques, F., Rocha, A. and Pereira, L. (2021) 'An interactive Web-GIS fluvial flood forecast and alert system in operation in Portugal', *International Journal of Disaster Risk Reduction*, Vol. 58, p.102201, <https://doi.org/10.1016/j.ijdrr.2021.102201>.
- Nakata-Osaki, C.M., Souza, L.C.L. and Rodrigues, D.S. (2018) 'THIS – tool for heat island simulation: a GIS extension model to calculate urban heat island intensity based on urban geometry', *Computers, Environment and Urban Systems*, Vol. 67, pp.157–168, <https://doi.org/10.1016/j.compenvurbsys.2017.09.007>.
- Olson, D. and Delen, D. (2008) *Advanced Data Mining Techniques*, Springer. USA, <https://doi.org/10.1007/978-3-540-76917-0>.
- Parajuli, B., Kumar, P., Mukherjee, T., Pasiliao, E. and Jambawalikar, S. (2018) 'Fusion of aerial lidar and images for road segmentation with deep CNN', <https://doi.org/10.1145/3274895.3274993>.
- Salim, S., Zaki, S., Toh, A., Yakub, F., Mohd Saudi, A.S., Ardila-Rey, J. and Muhammad-Sukki, F. (2020) 'Effects of roadside trees and road orientation on thermal environment in a Tropical City', *Sustainability*, Vol. 12, p.1053, <https://doi.org/10.3390/su12031053>.
- Tabatabaei, S.S. and Fayaz, R. (2023) 'The effect of facade materials and coatings on urban heat island mitigation and outdoor thermal comfort in hot semi-arid climate', *Building and Environment*, Vol. 243, p.110701, <https://doi.org/10.1016/j.buildenv.2023.110701>.
- Takebayashi, H. (2022) 'Effects of air temperature, humidity, and wind velocity distribution on indoor cooling load and outdoor human thermal environment at urban scale', *Energy and Buildings*, Vol. 257, p.111792, <https://doi.org/10.1016/j.enbuild.2021.111792>.
- Taleghani, M., Sailor, D.J., Tenpierik, M. and van den Dobbelen, A. (2014) 'Thermal assessment of heat mitigation strategies: the case of Portland State University, Oregon, USA', *Building and Environment*, Vol. 73, pp.138–150, <https://doi.org/10.1016/j.buildenv.2013.12.006>.
- Thielen, J., Bartholmes, J., Ramos, M-H. and Roo, A. (2009) 'The European flood alert system – part 1: concept and development', *Hydrology and Earth System Sciences*, Vol. 13, pp.125–140.
- Tzortzi – Georgi, N-J. and Dimitriou, D. (2010) 'The contribution of urban green spaces to the improvement of environment in cities: case study of Chania, Greece', *Building and Environment*, Vol. 45, pp.1401–1414, <https://doi.org/10.1016/j.buildenv.2009.12.003>.
- Vailshery, L.S., Jaganmohan, M. and Nagendra, H. (2013) 'Effect of street trees on microclimate and air pollution in a tropical city', *Urban Forestry and Urban Greening*, Vol. 12, pp.408–415, <https://doi.org/10.1016/j.ufug.2013.03.002>.
- Wang, Y. and Ouyang, W. (2021) 'Investigating the heterogeneity of water cooling effect for cooler cities', *Sustainable Cities and Society*, Vol. 75, p.103281, <https://doi.org/10.1016/j.scs.2021.103281>.
- Watanabe, F., Miyoshi, G., Rodrigues, T., Bernardo, N., Rotta, L., Alcantara, E. and Imai, N. (2020) 'Inland water's trophic status classification based on machine learning and remote sensing data', *Remote Sensing Applications: Society and Environment*, Vol. 19, p.100326, <https://doi.org/10.1016/j.rsase.2020.100326>.
- Wills, S. (2016) 'Extremes of temperature: hyperthermia', *Encyclopedia of Forensic and Legal Medicine*, <https://doi.org/10.1016/B978-0-12-800034-2.00175-0>.