Modelling the cooling effects of urban canals

DOI:
10.5281/zenodo.10927599

Modelling the cooling effects of urban canals

Tomkins MD*[1], McDonald H†[2], Huck JJ‡[1], Tippett J§[3], Elliott Sα[4], Harris Eβ[4] and Maxwell Cγ[4]

[1]Department of Geography, School of Environment, Education and Development, The University of Manchester

[2]Department of Electrical & Electronic Engineering, School of Engineering, The University of Manchester

[3]Department of Planning, Property and Environmental Management, School of Environment, Education and Development, The University of Manchester

[4]Canal and River Trust, Registered Charity No. 1146792

GISRUK 2024

Summary

We investigate the effects of canals on urban air temperatures, performing a national-scale analysis of urban canals in the UK and Ireland. Using canal characteristics and high-temporal resolution weather data, we model variability in water temperatures for 2022 at 15-minute intervals and use these data to analyse the effects on surrounding air temperatures. In addition, we incorporate the effects of shading by buildings, which can play a key role in water energy balance. In turn, this has implications for the effectiveness of canals in offsetting temperature extremes as well as the management and regulation of adjacent urban areas.

KEYWORDS: Canals, Urban Heat Island, Cooling, Shading, Building height

1. Introduction

Urban populations are particularly vulnerable to threats posed by climate change. Rising average temperatures and heatwaves (Perkins et al., 2012) can be exacerbated by the urban heat island, in which cities are typically warmer than surrounding areas (Grimmond, 2007). Addressing the drivers of climate change will necessitate global cooperation, but adaptation at the urban scale can be used to minimise adverse impacts.

Examples of this include expansion of *green infrastructure* (e.g., tree-planting) and *blue infrastructure* (e.g., canals), both of which have the potential to cool surrounding areas (Gunawardena et al., 2017). However, while the effects of blue infrastructure have been measured in small-scale studies (Hathway and Sharples, 2012), it has received comparatively little attention (Veerkamp et al., 2021) and there remains uncertainty as to the magnitude of daytime cooling, both for individual cities and at a national scale.

To address this, we have produced a model to evaluate the cooling effects of the urban canals of Great Britain and Ireland (**Figure 1**). This abstract provides an overview of the approach, the input data, and the characteristics of the model, as well as some preliminary results.

* matthew.tomkins@manchester.ac.uk
† harry.mcdonald@manchester.ac.uk
‡ jonathan.huck@manchester.ac.uk
§ joanne.tippett@manchester.ac.uk
α stephanie.elliott@canalrivertrust.org.uk
β eoin.harris@canalrivertrust.org.uk
γ cem.maxwell@canalrivertrust.org.uk

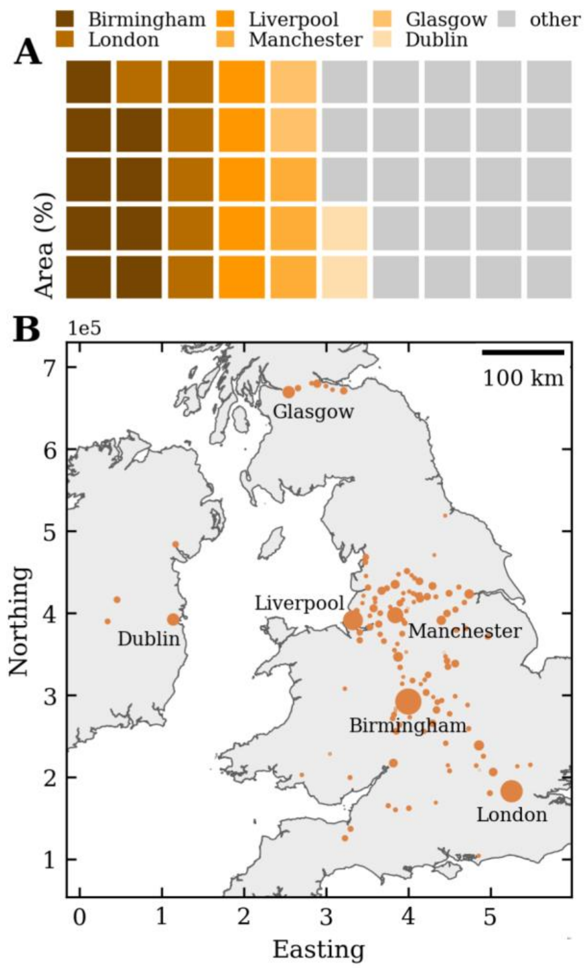

Figure 1 The modelled canals, showcasing (A) area and (B) spatial variability.

2. Data

This analysis utilises three primary inputs, comprising canal geometries and depths (n=2,356), building geometries and heights, and weather data for each canal (air temperature (K), humidity (%), cloud cover (%), wind speed (m/s), air pressure). Data sources are outlined in **Table 1**.

Table 1 Data sources

Data	Great Britain	Ireland
Canal geometries	OS MasterMap Topography layer	OpenStreetMap
Canal depths	Canal and River Trust (*and others*)	*Estimated*
Building geometries	OS MasterMap Topography layer	OpenStreetMap
Building heights	OS MasterMap Topography layer	Keany et al. (2022)
Hourly weather	OpenWeather	OpenWeather

Other supplementary datasets are utilised in the analysis, however, such as the UKCEH 2021 Land Cover Map (Marston et al., 2022), and the CORINE 2018 Land Cover Map (CLC, 2018), which were used to filter canal geometries to urban areas for Great Britain and Ireland, respectively.

3. Data preparation

To facilitate efficient model completion (~165 million model steps), two key tasks were completed prior to model running.

The first involved obtaining weather data in advance, which is more efficient than obtaining data dynamically during model running e.g., via an Application Programming Interface. The second involved calculating the canal shading proportion [0-1] for all canal features and for all time intervals. This utilises the Python package *pybdshadow* (Yu, 2024), and *PySolar* (Stafford, 2021) for calculating solar azimuths and altitudes. A typical shading output is shown in **Figure 2**.

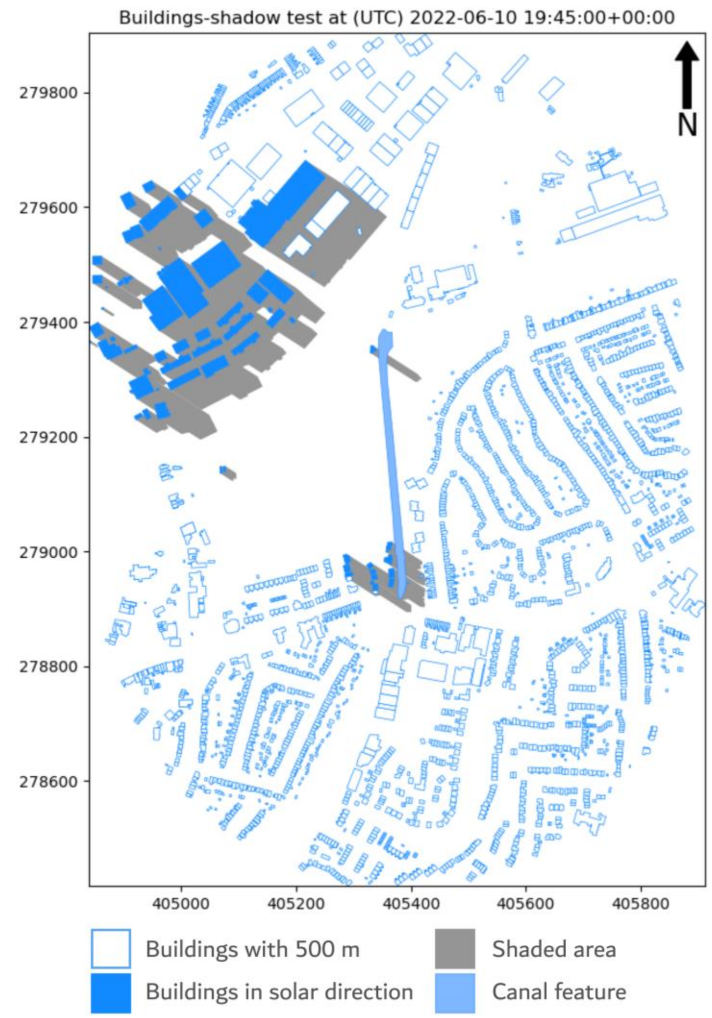

Figure 2 Example of shading results for a feature of the Worcester and Birmingham canal. Buildings are extracted within a set distance of the canal and then filtered based on the solar azimuth for that datetime. Shading geometries are modelled and the shading proportion calculated (0.22).

4. Model

Once complete, the model utilises the above inputs to quantify water energy balance. The overall approach is outlined in the following pseudo-code (**Figure 3**), with key steps described in text.

Algorithm: Canal Cooling (*canalData, shadingData, weatherData*):

where:

canalData = canal geometries and depths
shadingData = shading proportion for each canal
weatherData = weather data for each canal
wT = water temperature (K)
cT = concrete temperature (K)
wJ = water energy (J)
ΔT = air temperature change (K)

```
for each canal in canalData:
    output = empty data object for canal
    profile = modelled water profile (Figure 4)
    modelled_area = air temperature buffer (Figure 6)
    wT, cT, wJ = starting values following model spin-up (Figure 5)
    for each step in 2022 (15-minute intervals):
        Extract weatherData [step]
        Extract shadingData [step]
        Model change in wT (for profile)
        Model change in wJ (for profile)
        Model change in cT
        Estimate ΔT for modelled_area
        output [step] = wT, cT, wJ, ΔT
    write output to canal file
```

Figure 3 A simplified pseudo-code representation of the algorithm.

For each contiguous feature of the canal network, the model begins by splitting the estimated canal depth (m) into *n* 0.2 m layers. At each model step, radiative, evaporative, and conductive–convective exchanges are used to estimate changes in *wT* and *wJ* for each layer (**Figure 4**).

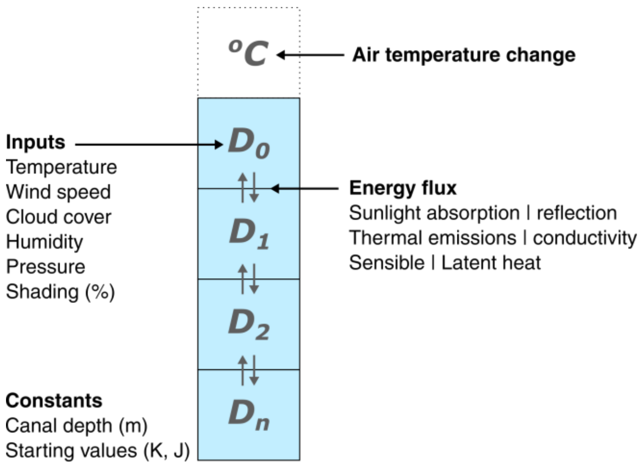

Figure 4 A schematic of the model structure, with energy exchanges modelled between the surface (D_0) and the deeper layers (D_n), based on the weather–shading inputs.

To achieve this, an initial model spin-up is used to produce realistic starting values for *wT*, *cT* and *wJ*. This produces a surface *wT* of ~8.9°C (**Figure 5**; 2022–01–01 00:00:00), which matches empirical measurements by the Canal and River Trust for the same datetime (9.0 ± 0.5°C, mean ± sd).

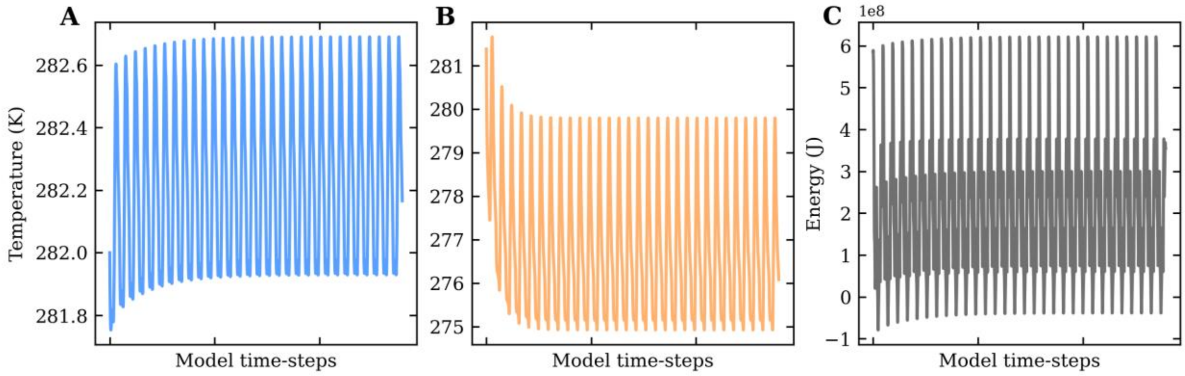

Figure 5 Results of model spin-up for surface (**A**) water temperature (K), (**B**) concrete temperature (K) and (**C**) water energy (J). Each parameter reaches equilibrium with the input weather data, with a clear diurnal pattern.

Following spin-up, the model iterates at 15-minute intervals (for model stability) for 2022 where fluctuations in *wT* are used as a baseline for estimating air temperature change (Δ*T*), relative to *cT* i.e., canal present or absent. Δ*T* is calculated for a shape-normalised 100-m wide, 10-m high buffer around the canal (**Figure 6**).

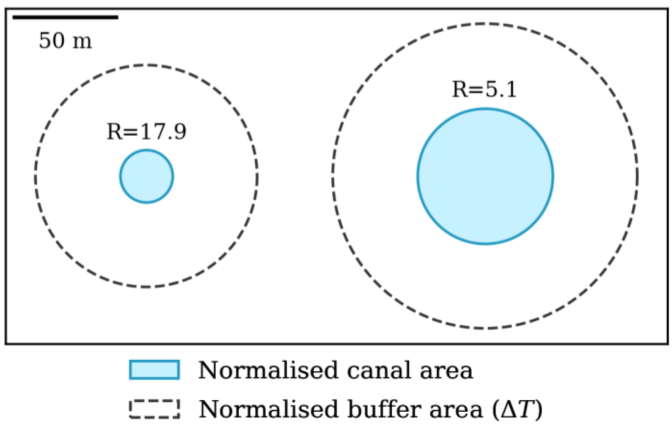

Figure 6 A shape-normalised buffer. Rather than utilising the canal geometries directly, a circle is constructed of the same area as the canal, which is then buffered by the desired distance (50-m). The ratio (R) of these two areas strongly controls Δ*T*.

There are several advantages to this approach. Firstly, as Δ*T* is strongly controlled by the ratio of the canal area to the area of the buffer (as the ratio increases, Δ*T* decreases), consistent buffers are required across canals of varying sizes and shapes. This is not possible using standard geometric buffers, which are influenced by shape complexity, as shown in **Figure 7A** i.e., canals with identical areas have vastly different buffer areas and thus produce significantly different Δ*T*. Although the geometry of canals likely plays a role in water energy balance, this is not explicitly included in our non-spatial model (**Figure 4**). By comparison, using a shape-normalised approach produces a near-linear relationship between canal and buffer areas (**Figure 7B**) and ensures that canals of the same area and the same current state (*wT*, *cT*, *wJ*) produce the same Δ*T*. A second advantage is that this approach retains the role of canal area as a predictor of Δ*T* i.e., larger canals have a larger cooling effect.

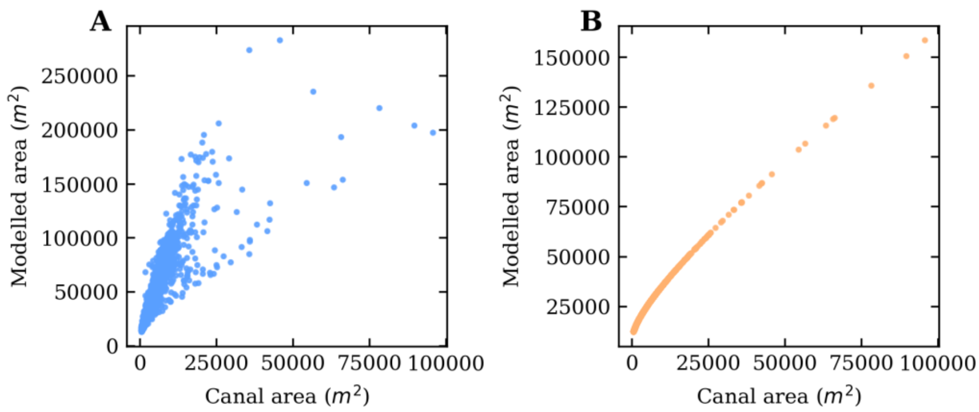

Figure 7 Scatter plots of canal area compared to (**A**) a standard geometric buffer (50 m) and (**B**) a shape-normalised buffer, as described above.

5. Preliminary results

It is not within the scope of this abstract to outline the results in detail, although an example model output is shown in **Figure 8**. The model reproduces many key physical processes, with canals exerting daytime cooling and nighttime warming (Gunawardena et al., 2017). Relative specific heat capacities are also reproduced (**Figure 8C**), with slow *wT* warming and cooling, compared to *cT*. Seasonal trends in *wT* and *cT* are also evident (**Figure 8A**), while the magnitude of daytime cooling is broadly consistent with empirical measurements (Hathaway and Sharples, 2012). Further work is required to validate and contextualise the results, which we hope to present in future. Understanding the effects of canals on urban temperatures, and the degree to which this is modified by urban form (i.e., building shading), is an important prerequisite for effective management of canals and adjacent areas. Maximising the cooling effects of existing canals, which could include restrictions on the proximity and height of buildings, among other approaches, could be critical for offsetting temperature extremes.

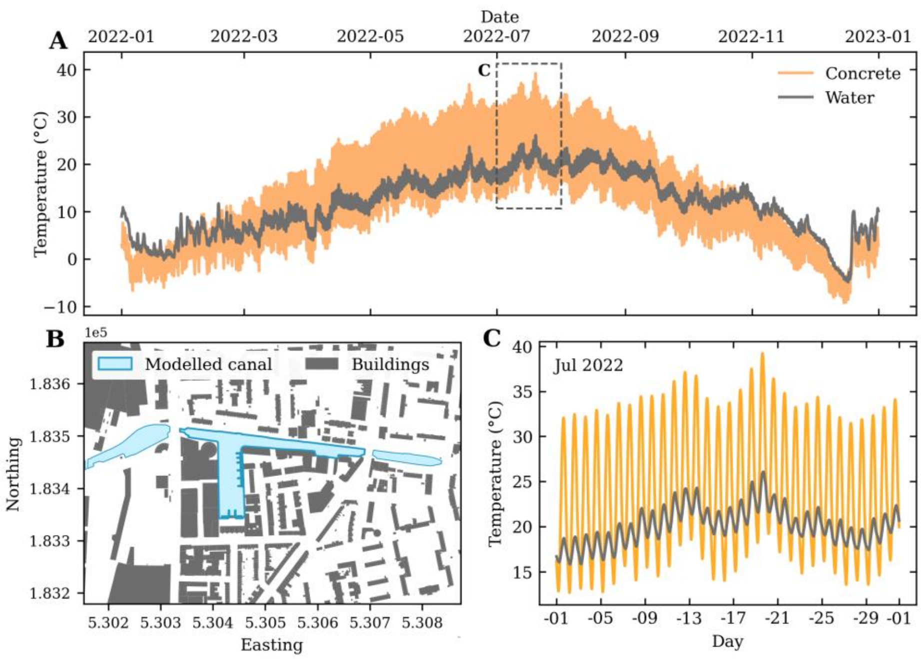

Figure 8 Example model output (excluding shading) for a feature of the Regent's Canal (**B**), showcasing changing *wT* and *cT* for (**A**) 2022 and (**C**) July only.

6. Acknowledgements

Funding and support for this project was provided by the Canal and River Trust, with the current national scale up generously supported thanks to funds raised by players of People's Postcode Lottery. We would like to thank the Ordnance Survey for providing the OS MasterMap Topography layer for Great Britain, Eoghan Keany and co-authors (Met Éireann) for providing their building height model for Ireland, and Dr. Kirsty Watkinson for assistance running our models on the Geography department server.

References

Corine Land Cover (CLC) (2018). Version 20. https://doi.org/10.2909/960998c1-1870-4e82-8051-6485205ebbac

Grimmond SUE (2007). Urbanization and global environmental change: local effects of urban warming. *The Geographical Journal*, 173(1), 83-88.

Gunawardena KR, Wells MJ, and Kershaw T (2017). Utilising green and bluespace to mitigate urban heat island intensity. *Science of the Total Environment*, 584, 1040-1055.

Hathway EA, and Sharples S (2012). The interaction of rivers and urban form in mitigating the Urban Heat Island effect: A UK case study. *Building and environment*, 58, 14-22.

Keany E, Bessardon G and Gleeson E (2022). Using machine learning to produce a cost-effective national building height map of Ireland to categorise local climate zones. *Advances in Science and Research*, 19k, 13-27.

Marston C, Rowland CS, O'Neil AW, and Morton RD (2022). Land Cover Map 2021 (10m classified pixels, GB). NERC EDS Environmental Information Data Centre. https://doi.org/10.5285/a22baa7c-5809-4a02-87e0-3cf87d4e223a

Perkins SE, Alexander LV, and Nairn, JR (2012). Increasing frequency, intensity and duration of observed global heatwaves and warm spells. *Geophysical Research Letters*, 39(20).

Stafford B (2021). *Pysolar*. https://doi.org/10.5281/zenodo.8184418

Veerkamp CJ, Schipper AM, Hedlund K, Lazarova T, Nordin A, and Hanson HI (2021). A review of studies assessing ecosystem services provided by urban green and blue infrastructure. *Ecosystem Services*, 52.

Yu W (2023) *pybdshadow*. https://github.com/ni1o1/pybdshadow

Biographies

Dr. Matt Tomkins is a Lecturer in Geographical Information Science at The University of Manchester, with a background in Physical Geography.

Dr. Harry McDonald is a Research Associate at The University of Manchester.

Dr. Jonny Huck is a Senior Lecturer in Geographical Information Science at the University of Manchester and Chair of the GISRUK National Steering Committee.

Dr. Joanne Tippett is Senior Lecturer in Spatial Planning at The University of Manchester, with a focus on designing for sustainability, community engagement and systems thinking.
Stephanie Elliott is the Outcomes Measurement Analyst at the Canal and River Trust.

Eoin Harris (CEnv.) is the Head of Environment & Climate Action at the Canal and River Trust.

Cem Maxwell is the Head of Insight and Evidence at the Canal and River Trust.