

How will the Surface Urban Heat Island respond to changes in climate?

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1. Motivation

Surface Urban Heat Island (SUHI) behaviour differs based on background climate, and climate change is causing changes in climate variables.

Modelling the future climate of cities remains a challenge as resolution of global climate models is too coarse to capture the scale of a city, and regional climate models are computationally expensive.

A combination of satellite data (with 1km resolution) and statistical models based on climate can be used to address these issues.





- The aim of this research is to explore the impacts of climate change on the SUHI.
- To address challenges associated with climate models (resolution and computational expense), a statistical model is developed.
- Cities are chosen based on location (aiming to capture understudied areas) and similarity of city features (such as population and variation of elevation) to isolate the impacts of climate.
- Test statistics show promising performance for the range of climate regimes.
- This model can now be used to predict the impact of changes in climate variables, for example relative humidity, on SUHI magnitudes.

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5. Next steps

Sensitivity tests: evaluate the impact of changing climate variables on SUHI magnitude

Climate Model based predictions: generate predictions of the SUHI using input variables from climate model outputs

Datasets

- NASA MODIS Land Surface Temperature (LST), Albedo, Enhanced Vegetation Index (EVI) (Resolution 1km)
- ESA CCI Land cover (Resolution 300m)
- ERA5-Land Reanalysis (Resolution ~9km)
- United Nations Population of urban agglomerations
- GloboLakes: high resolution global limology v1 (Resolution 300m)
- Global Land One-kilometer Base Elevation (GLOBE) Digital Elevation Model (Resolution 1km)
- NASA Goddard Space Flight centre Ocean Color Group distance to nearest coastline (Resolution ~1km)



1. Hoerl, A. E. and Kennard, R. W. (1970) 'Ridge Regression: Biased Estimation for Nonorthogonal Problems', Technometrics, 12(1), pp. 55–67. doi: 10.1080/00401706.1970.10488634.

2. Nowack, P. et al. (2021) 'Machine learning calibration of low-cost NO2 and PM10 sensors: Non-linear algorithms and their impact on site transferability', Atmospheric Measurement Techniques, 14(8), pp. 5637–5655. doi: 10.5194/ amt-14-5637-2021.

The SUHI is defined as;

 $SUHI_{mean} = \sum_{i}^{n_{urban}} LST_{urban} - \sum_{i}^{n_{rural}} LST_{rural}$

Where LST_{urban}, n_{urban}, LST_{rural}, n_{rural} represents the LST and number of urban and rural pixels respectively

3. Predictors: Climate Related Variables

A combination of predictor variables was selected by choosing the model with best performance based on r² and RMSE. Examples of variables, averaged to monthly means, include relative humidity, total precipitation per day, urban EVI and EVI difference (urban - rural).

Ridge Regression is a statistical model that addresses the issues surrounding multiple linear regression by adding a regularisation parameter to penalise overfitting^[1]

It has been shown to perform well under extrapolation settings^[2], essential criteria for using the model to predict future SUHI magnitude.

Overall performance of train and test data split by time is shown below.







2. Target: SUHI Magnitude

4. Model: Ridge Regression