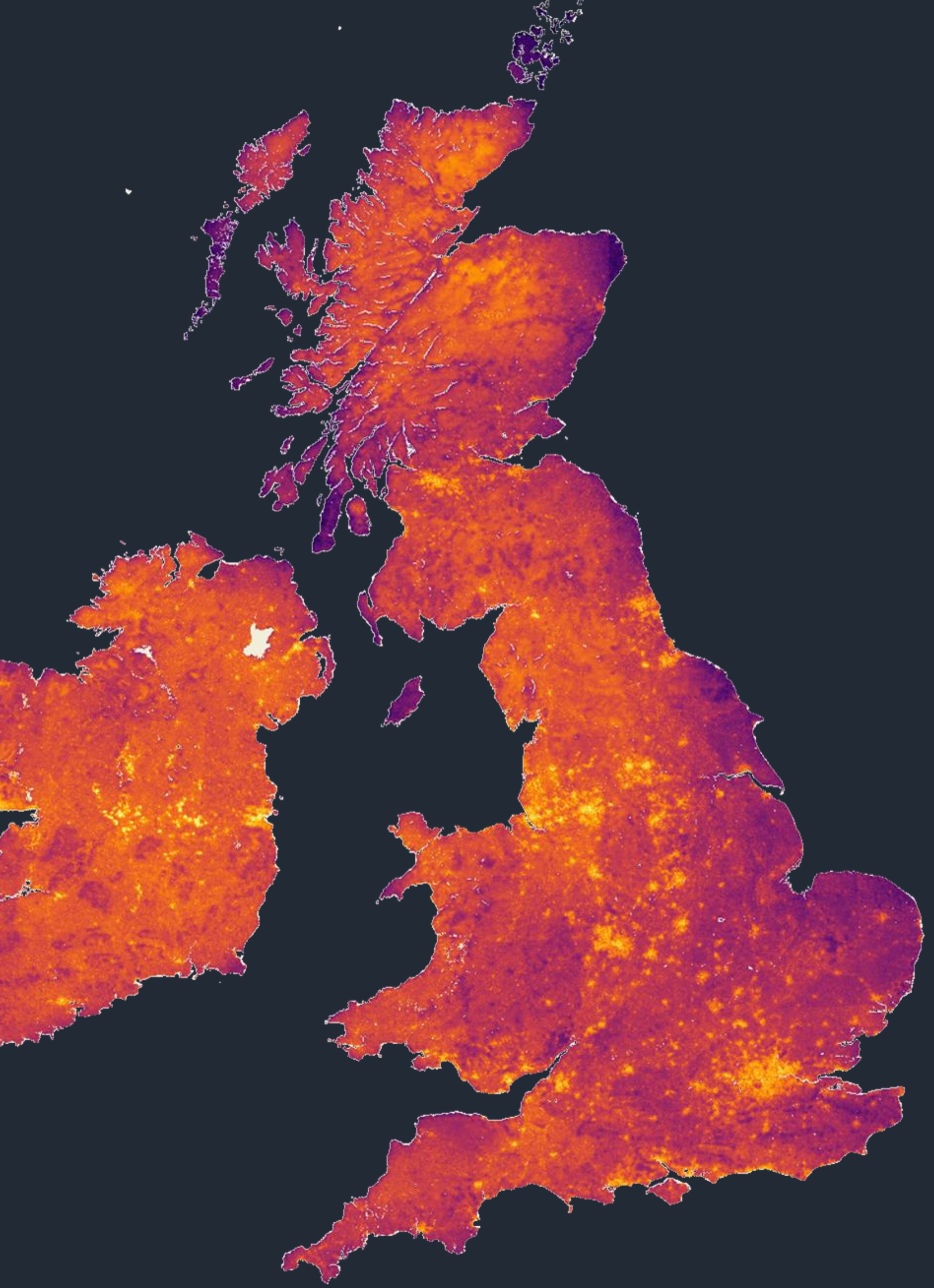


Understanding the Thermal Environment of UK Cities With Satellite Remote Sensing

Charlotte Paton, Darren Ghent, Mike Perry, John Remedios

cjp56@leicester.ac.uk

UNIVERSITY OF LEICESTER

National Centre for Earth Observation
NATURAL ENVIRONMENT RESEARCH COUNCIL

land surface temperature cci

URBAN HEAT AND LAND SURFACE TEMPERATURE

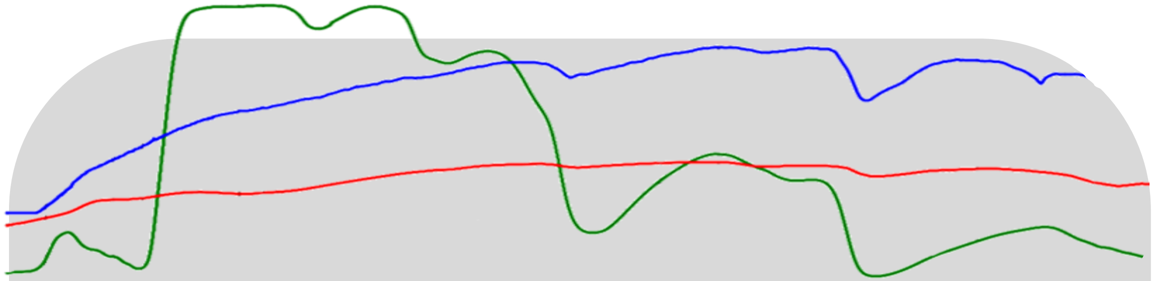
- Over 50% of the world's population already live within urban areas
- Their thermal environments, and increasing heat affects our infrastructure and our health
- Remote sensing of Land Surface Temperatures (LSTs) provides a way of studying these environments with spatially averaged data at high resolution, across wide areas.
- Many LST retrievals currently rely on auxiliary datasets to provide prior knowledge of surface and atmosphere parameters, specifically the Land Surface Emissivity (LSE).
- To address the gap in this information over cities, a novel thermal-based classification algorithm is presented.

DATA › CLASSIFICATION › EMISSIVITY › LST

Satellite data

Within urban environments, high resolution (ideally sub 100m) LST measurements are required as temperatures can vary considerably across cities and their sub-urban or rural surrounds

To achieve this data is acquired from Landsat 8 & 9 satellites

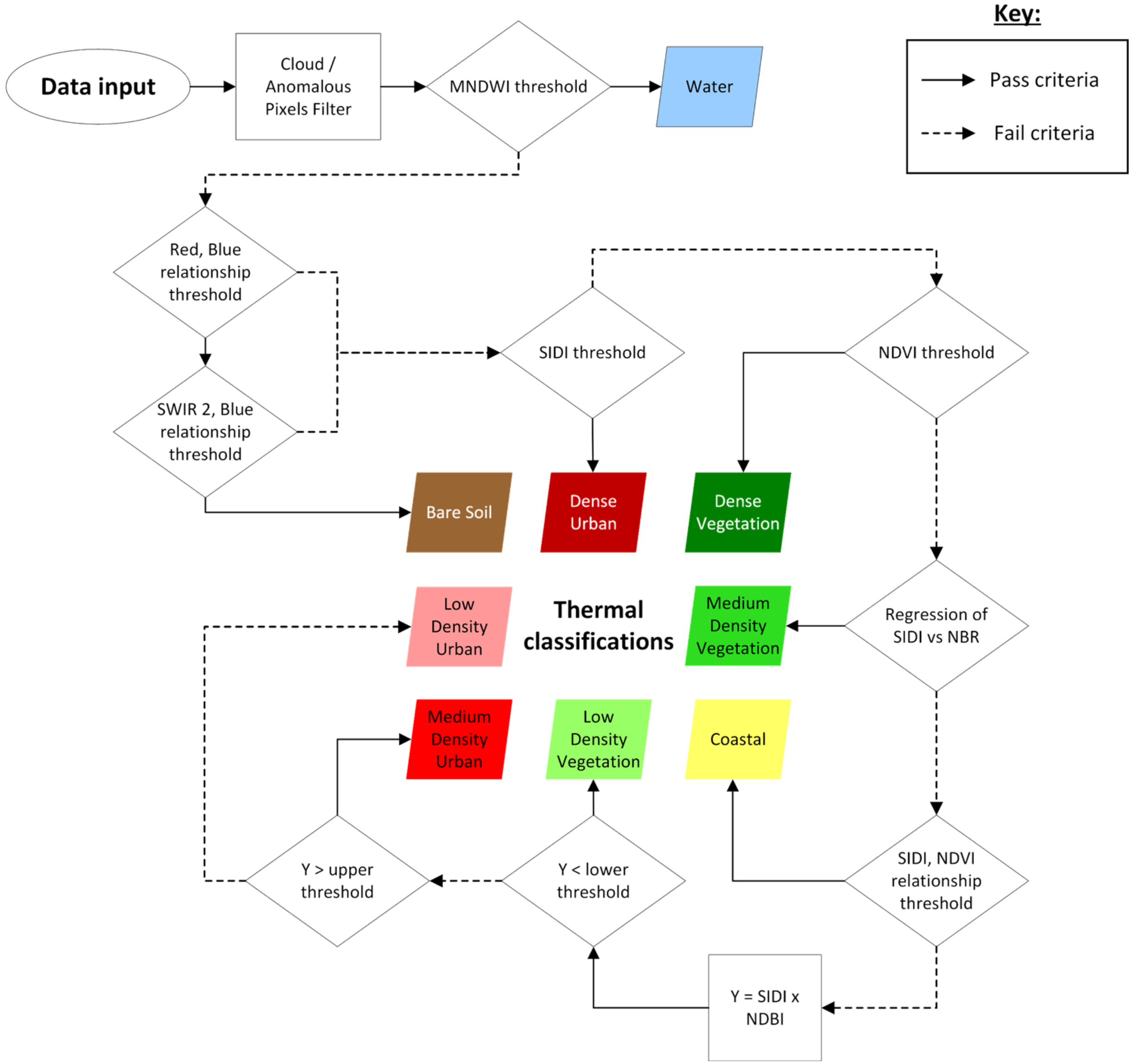


Spectral libraries

ECOSTRESS & SLUM spectral libraries are used to acquire VIS / SWIR and TIR data from samples

The ECOSTRESS library is then extended by creating mixed samples in ratios of 25%, 50% and 75%

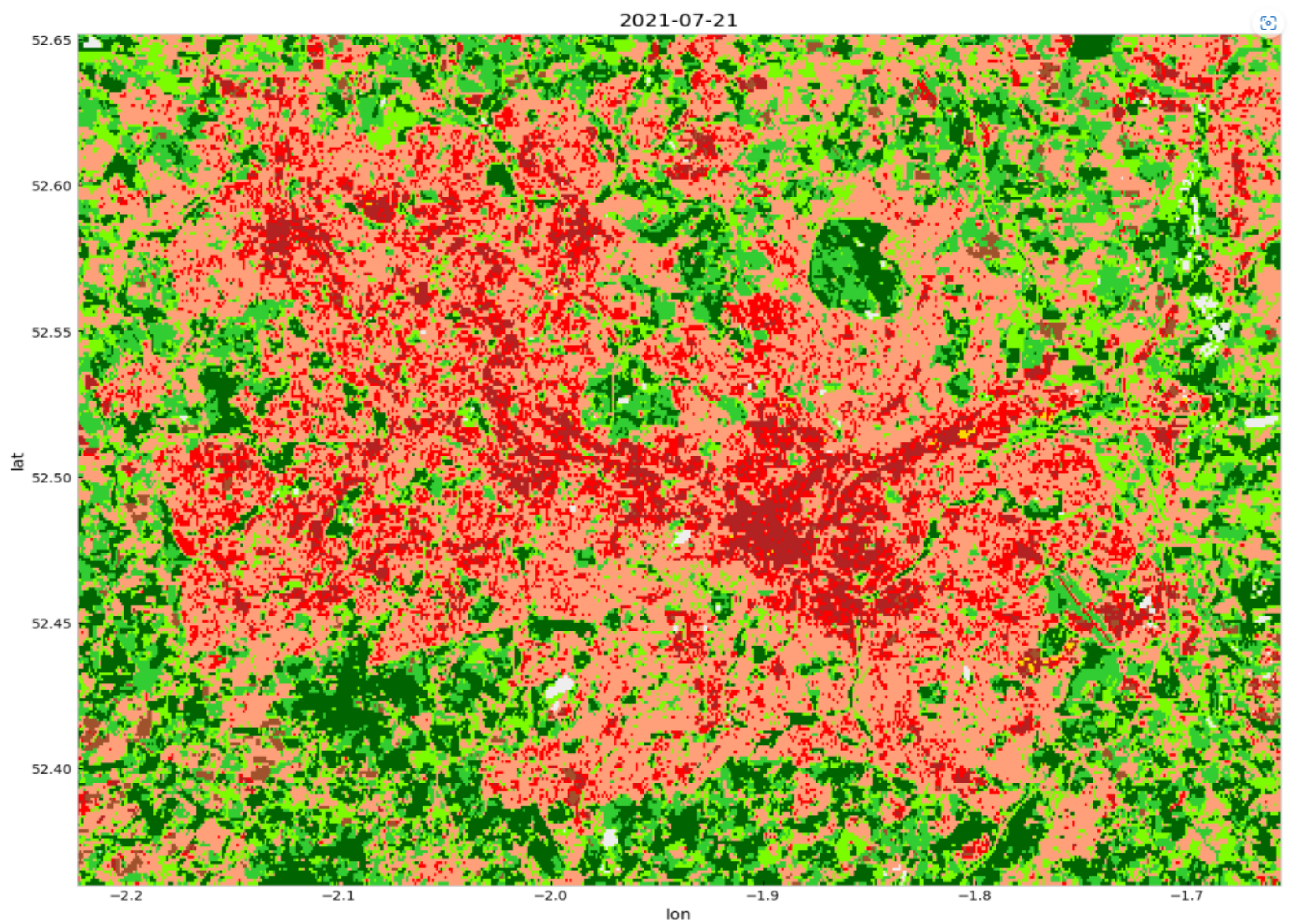
DATA › CLASSIFICATION › EMISSIVITY › LST



A series of indices are calculated using visible and short-wave infrared bands.

The scheme then works, through a series of statistically derived thresholds on the relationships between indices, to partition land into 8 classifications

DATA › CLASSIFICATION › EMISSIVITY › LST



The 8 output classifications:

Dense urban,

Mid density urban,

Low density urban,

Dense vegetation,

Mid density vegetation,

Low density vegetation,

Coastal,

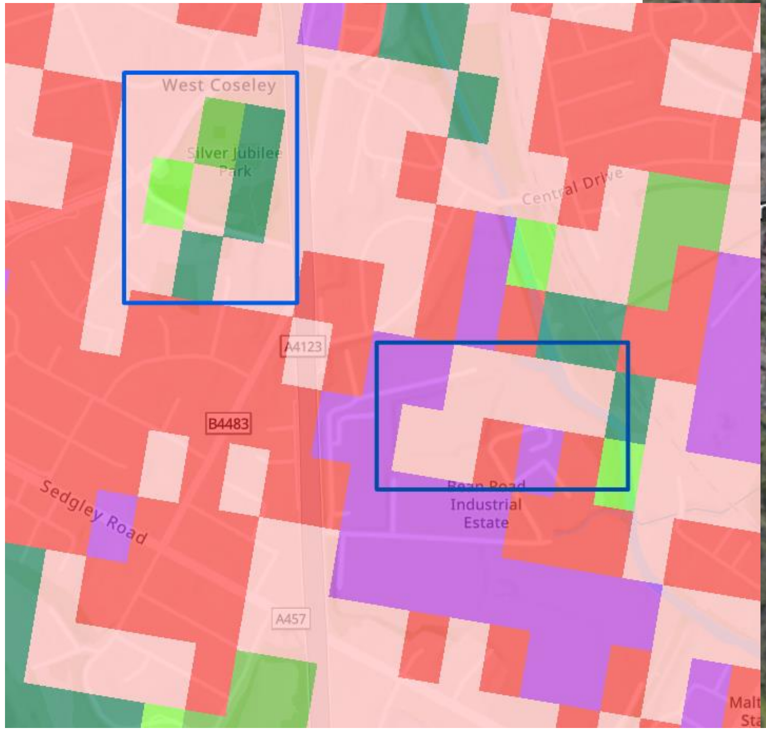
Bare soil

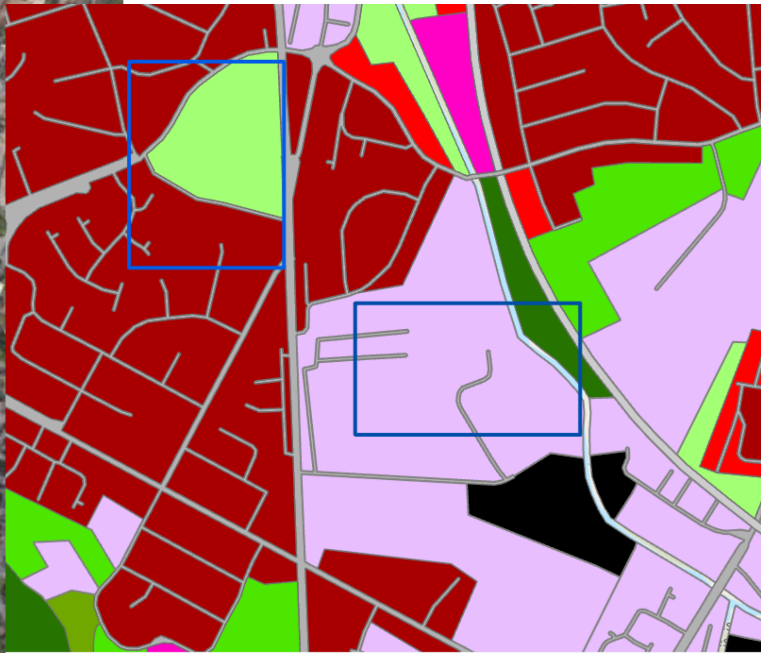
DATA › CLASSIFICATION › EMISSIVITY › LST

Low Density Vegetation
Medium Density Vegetation
Dense Vegetation
Low Density Urban Fabric
Medium Density Urban Fabric
Dense Urban Fabric

Bean Road Industrial Estate:

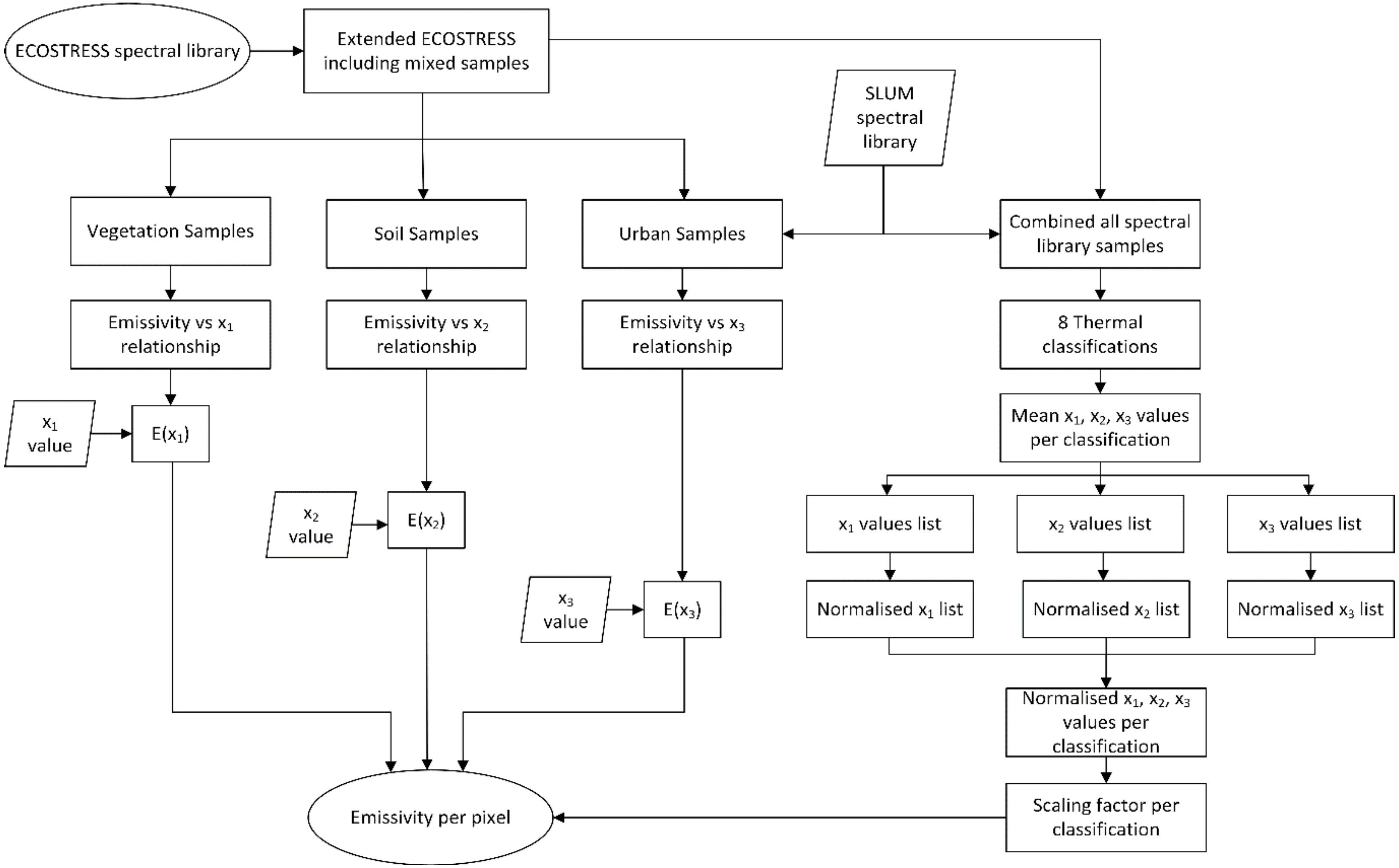
Discontinuous Medium Density Urban Fabric
Discontinuous Dense Urban Fabric
Continuous Urban Fabric / Industrial, commercial, public, military and private units
Sports and leisure facilities
Forests
Green Urban Areas
Pastures
Arable land (annual crops)
Land without current use
Railways and associated land
Fast transit roads and associated land / Other roads and associated land



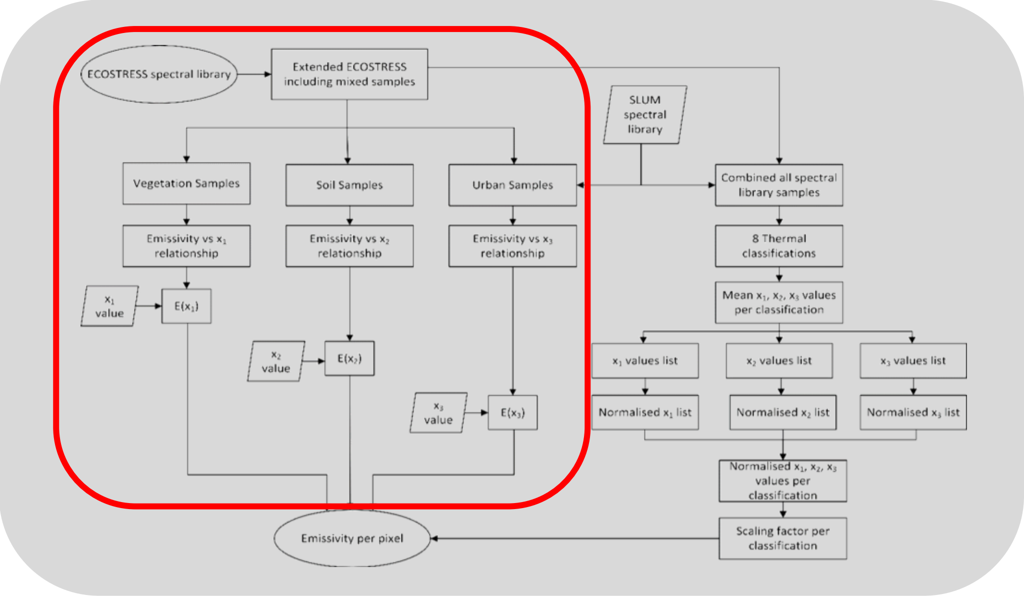


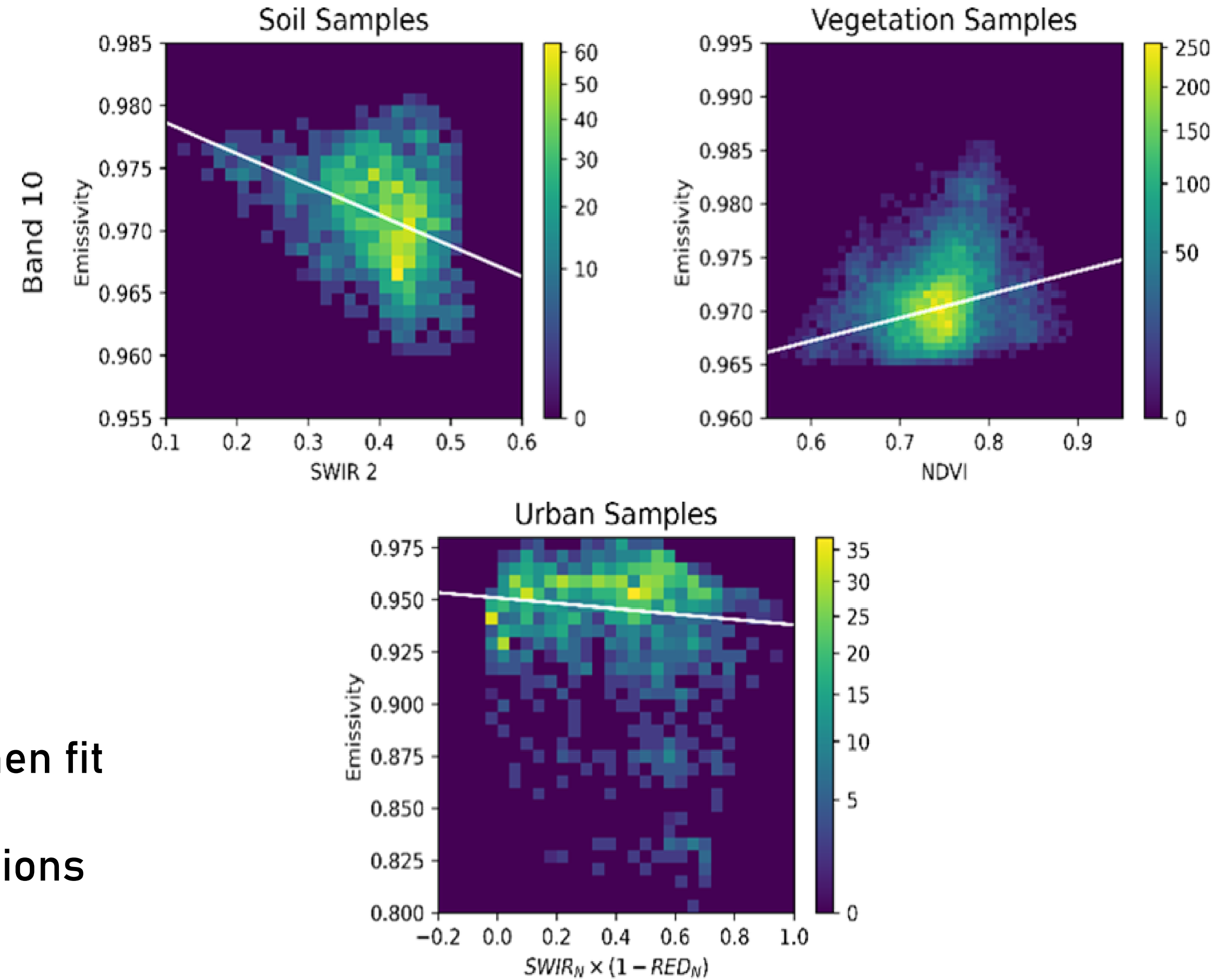
DATA › CLASSIFICATION › EMISSIVITY › LST

In order to provide a prior emissivity from the output classification samples from the spectral libraries are used, and their relationships to VIS / SWIR parameters are investigated



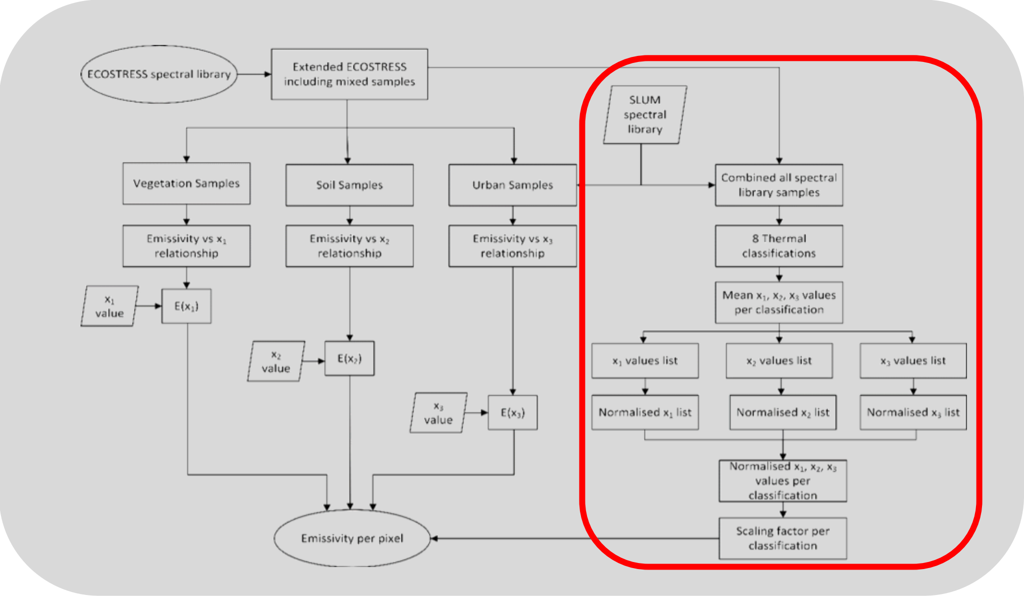
DATA › CLASSIFICATION › EMISSIVITY › LST





- Materials were split into three different types
- A regression between a unique VIS/SWIR parameter and the samples emissivity was then fit for each type
- This allows for three initial emissivity estimations

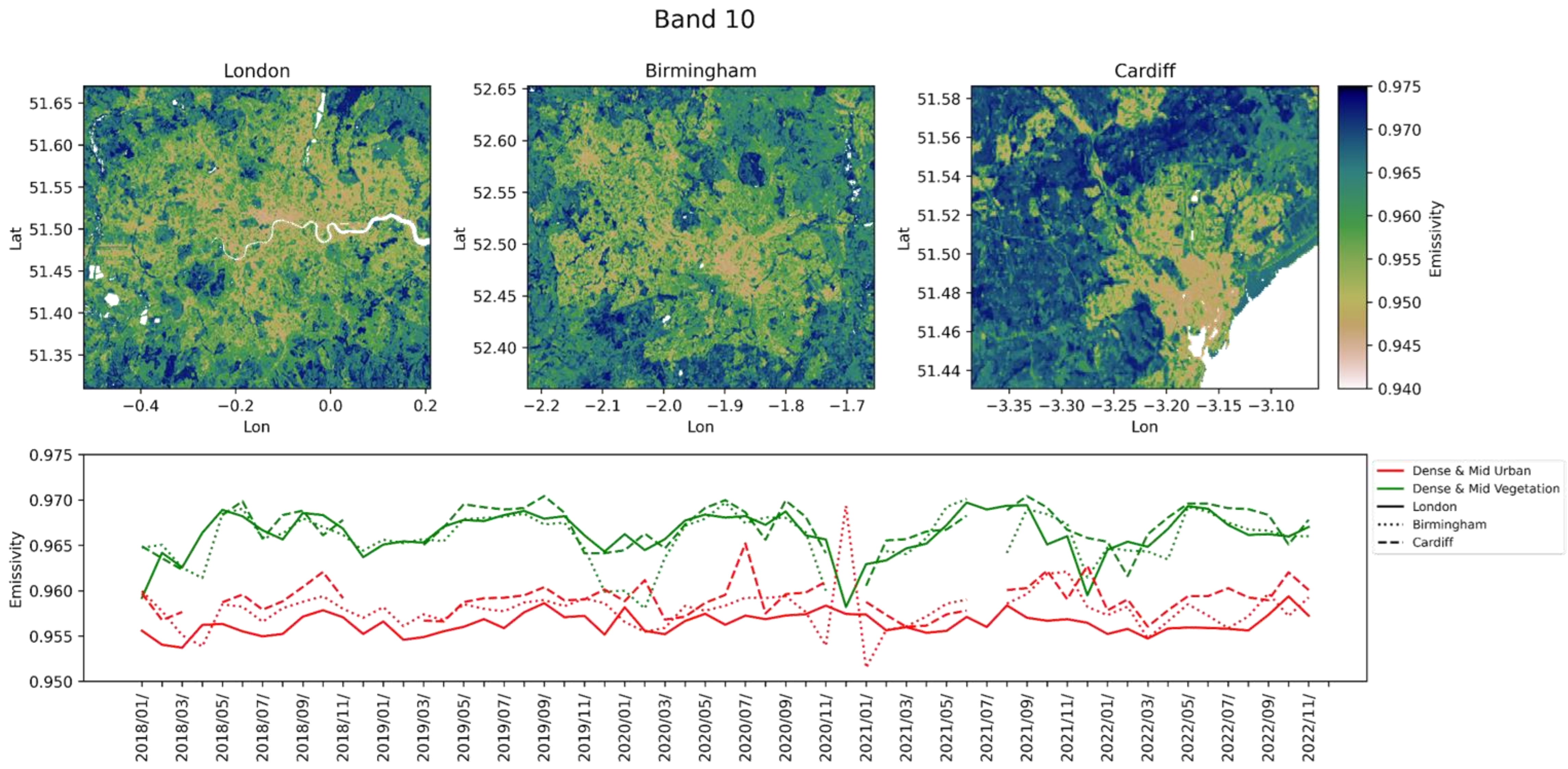
DATA › CLASSIFICATION › **EMISSIVITY** › LST

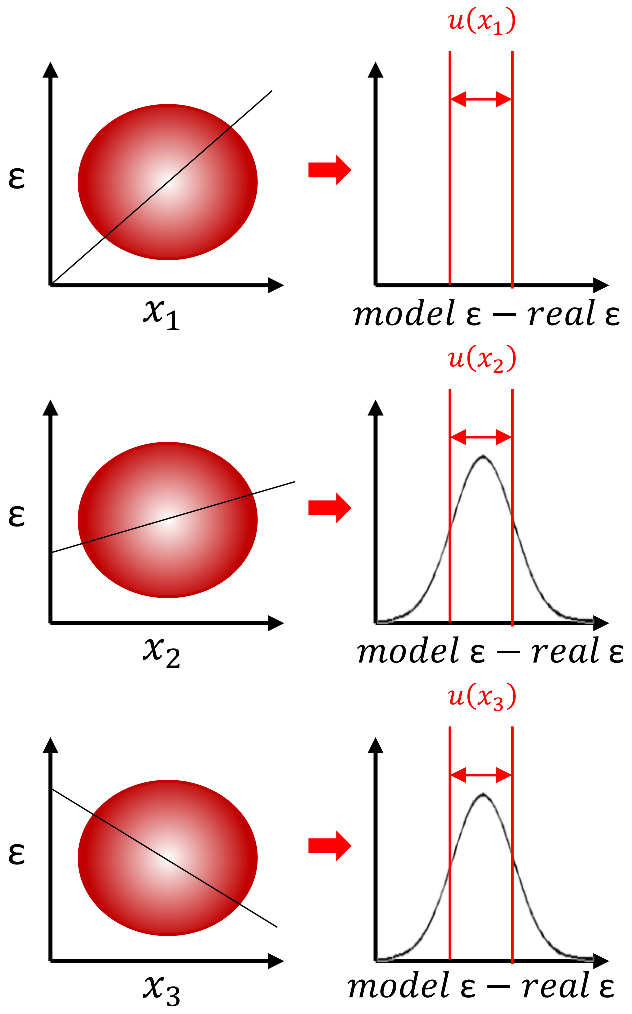


Mean values of the VIS / SWIR parameters are calculated per classification, these are then normalised over their range and scaled such that their total sums to 1 but their ratios are maintained

Classification	Percentage of emissivity / index relationship		
	Urban	Vegetation	Soil
Dense Urban	0.952	0.048	0.0
Mid Urban	0.619	0.381	0.0
Low Urban	0.389	0.611	0.0
Low Vegetation	0.120	0.880	0.0
Mid Vegetation	0.066	0.934	0.0
Dense Vegetation	0.0	1.0	0.0
Coastal	0.419	0.0	0.581
Bare Soil	0.401	0.122	0.476

DATA › CLASSIFICATION › EMISSIVITY › LST





$$y = (a \times x_1) + (b \times x_2) + (c \times x_3)$$

Where x_1, x_2, x_3 are the relationships between emissivity and the library sample indices, and a, b, c are the amounts of each relationship that are taken into account for the given classification

If you consider x_2, x_3 to be urban and soil relationships respectively (because these will have a correlation component as they are both based on the SWIR channels) then total uncertainty is found by:

$$u_c(y)^2 = \left(\frac{\partial f}{\partial x_1}\right)^2 u(x_1) + \left(\frac{\partial f}{\partial x_2}\right)^2 u(x_2) + \left(\frac{\partial f}{\partial x_3}\right)^2 u(x_3) + 2\left(\frac{\partial f}{\partial x_2}\frac{\partial f}{\partial x_3}\right) u(x_2)\, u(x_3)\, v(x_2, x_3)$$

and $\left(\frac{\partial f}{\partial x_1}\right) = a$, $\left(\frac{\partial f}{\partial x_2}\right) = b$, $\left(\frac{\partial f}{\partial x_3}\right) = c$, so this can be simplified to:

$$u_c(y) = \sqrt{a^2\, u(x_1) + b^2\, u(x_2) + c^2\, u(x_3) + 2\, b\, c\, u(x_2)\, u(x_3)\, v(x_2, x_3)}$$

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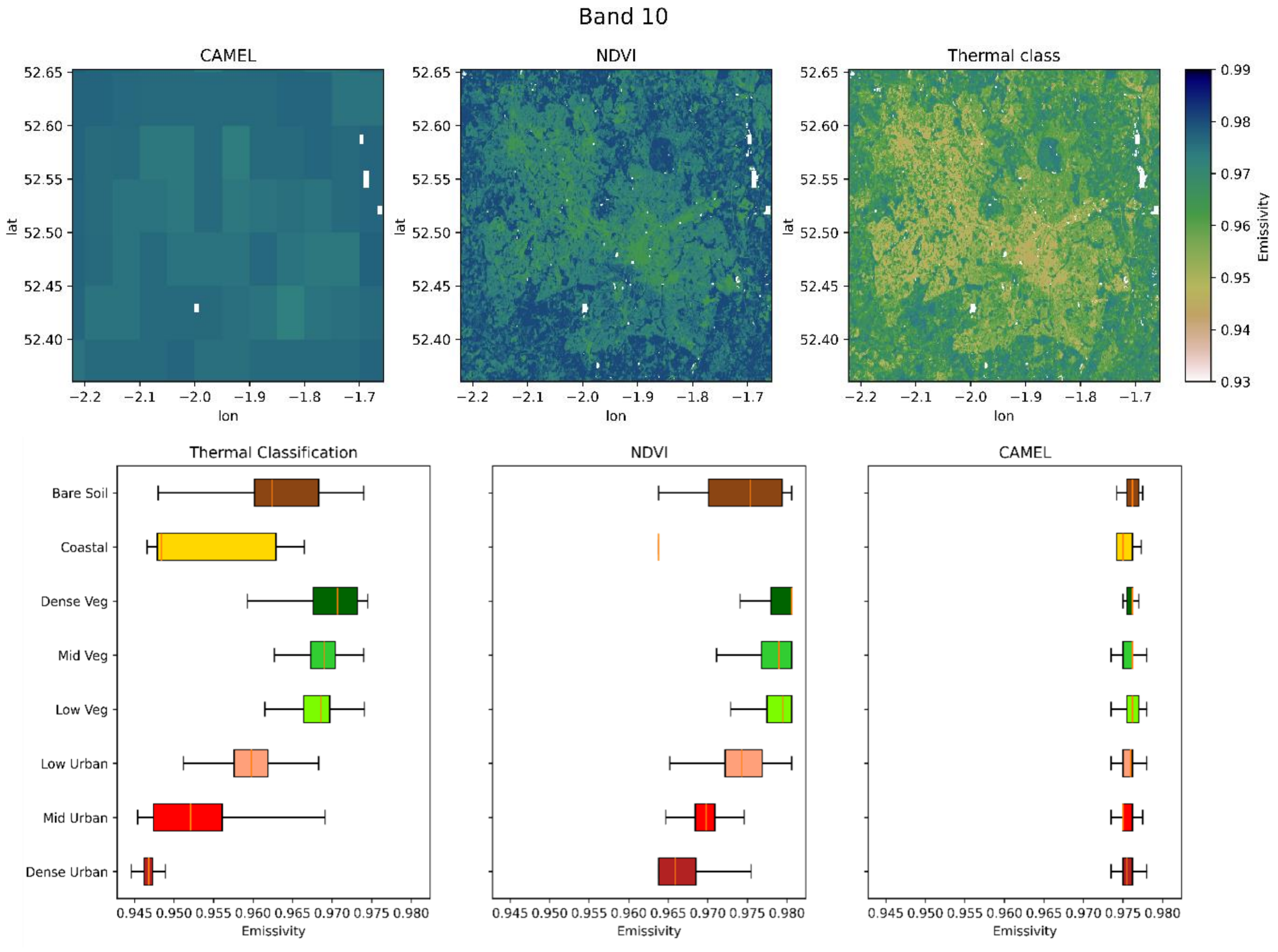


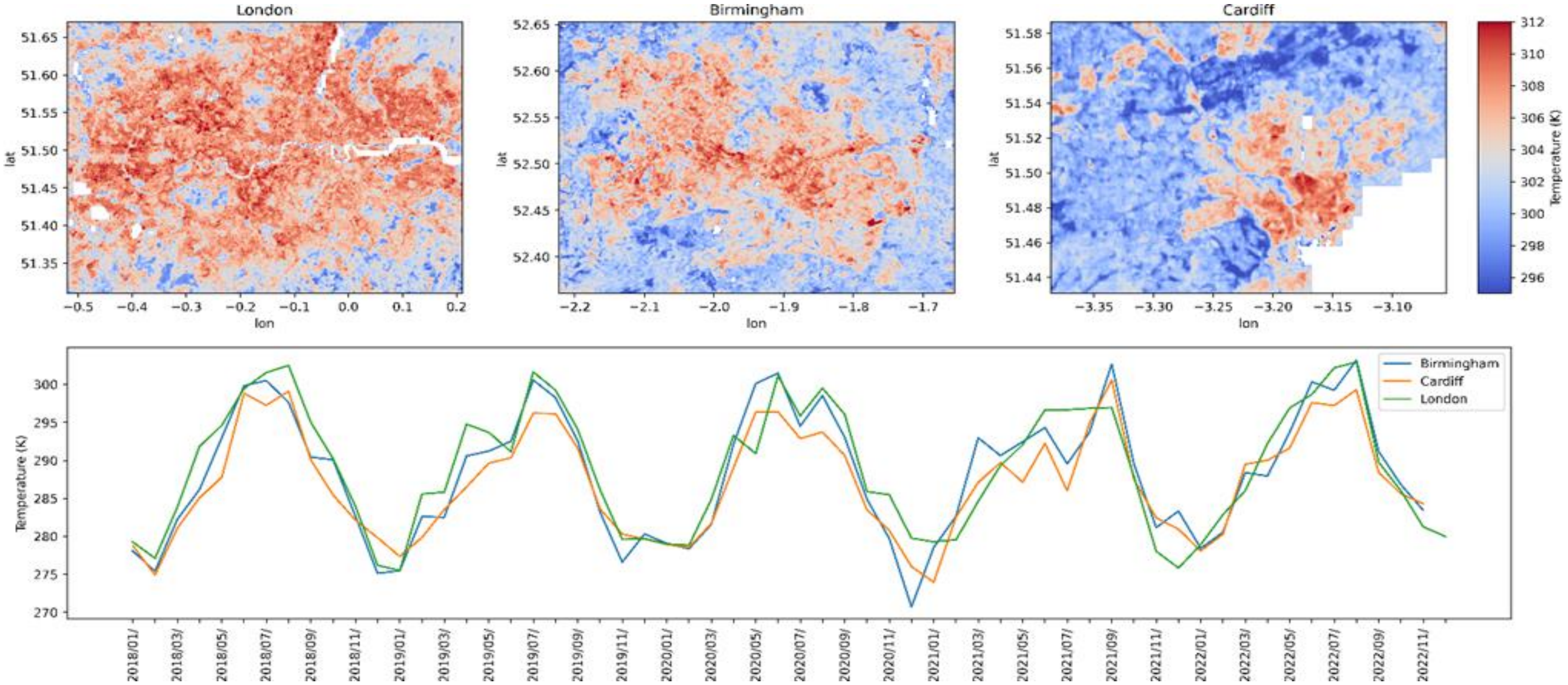
Two additional prior LSE methods:

1) NDVI Method by (Sobrino and Raissouni, 200)

$$LSE = \begin{cases} 0.98 - 0.042\rho & NDVI < 0.2 \\ \varepsilon_v P_v + \varepsilon_s(1 - P_v) + d_\varepsilon & 0.2 < NDVI < 0.5 \\ 0.99 & 0.5 < NDVI \end{cases}$$

2) Combined ASTER and MODIS Emissivity for Land (CAMEL) database

DATA › CLASSIFICATION › EMISSIVITY › LST



Calculated emissivities are input as priors into University of Leicester's generalised split window retrieval to get Land surface temperatures

DATA › CLASSIFICATION › EMISSIVITY › LST

Site	Thermal Classification RMSE	NDVI Method RMSE	CAMEL RMSE
Bondville, Illinois	3.84	4.83	4.13
Desert Rock, Nevada	3.3		3.16
Fort Peck, Montana	4.03	3.74	3.41
Goodwin Creek, Mississippi	2.98	4.15	3.88
Hyytiala, Finland	4.02	4.08	4.39
KIT Forest, Germany	2.09	2.37	2.61
Penn State University, Pennsylvania	2.85	3.18	3.24
Puechabon, France	2.61	2.7	2.66
Robson Creek, Australia	2.16	4.32	4.3
Sioux Falls, South Dakota	3.18	4.21	3.51
Svartberget, Sweden	2.89	4.23	4.4
Wicken Fen, UK	3.23	1.87	3.28
Wytham Woods, UK	2.09	3.55	2.35

Landsat LST using GSW was calculated using two additional prior LSE methods:

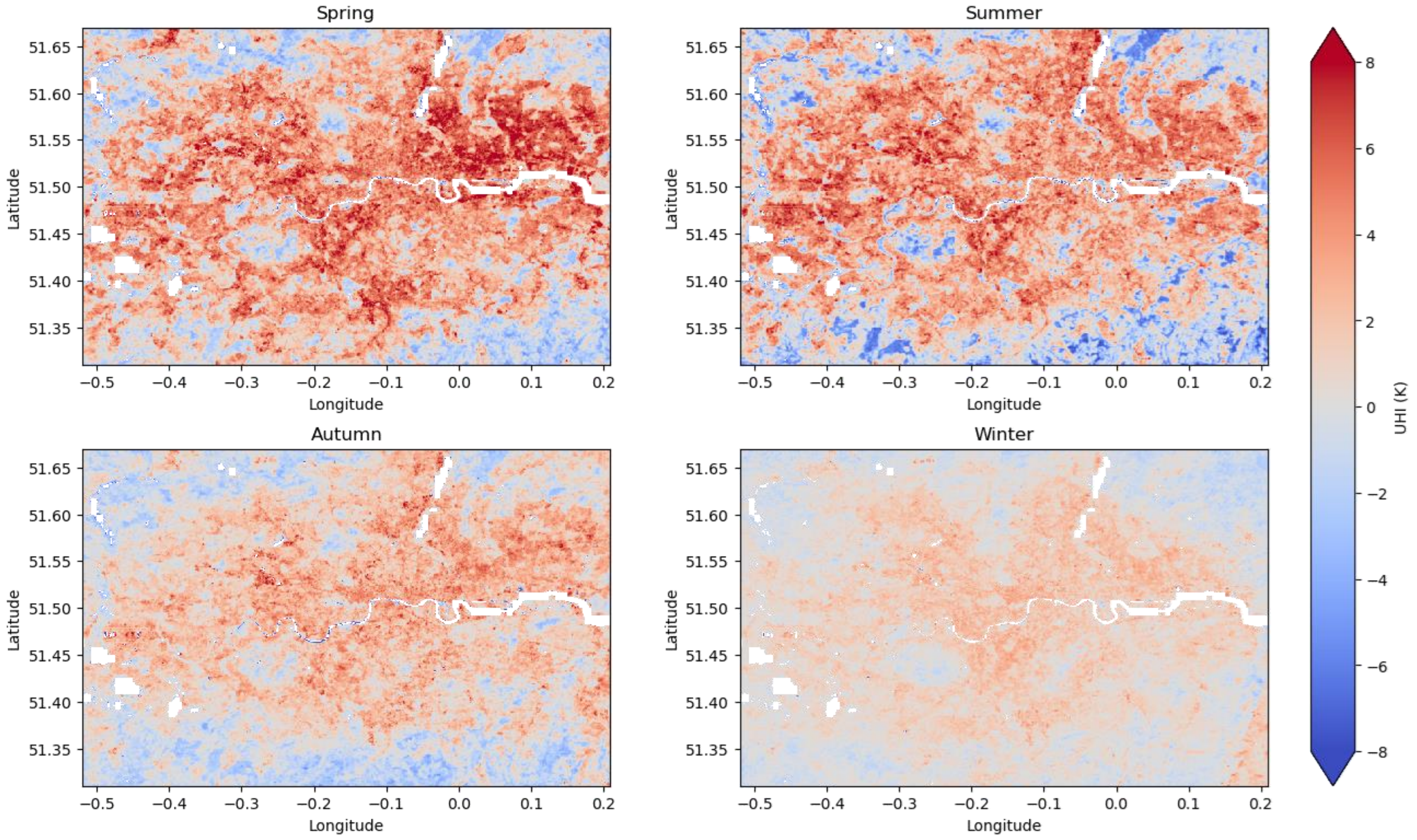
1) NDVI Method by (Sobrino and Raissouni, 200)

$$LSE = \begin{cases} 0.98 - 0.042\rho & NDVI < 0.2 \\ \varepsilon_v P_v + \varepsilon_s(1 - P_v) + d_\varepsilon & 0.2 < NDVI < 0.5 \\ 0.99 & 0.5 < NDVI \end{cases}$$

2) Combined ASTER and MODIS Emissivity for Land (CAMEL) database

Results show consistently better RMSE values when using the thermal classification

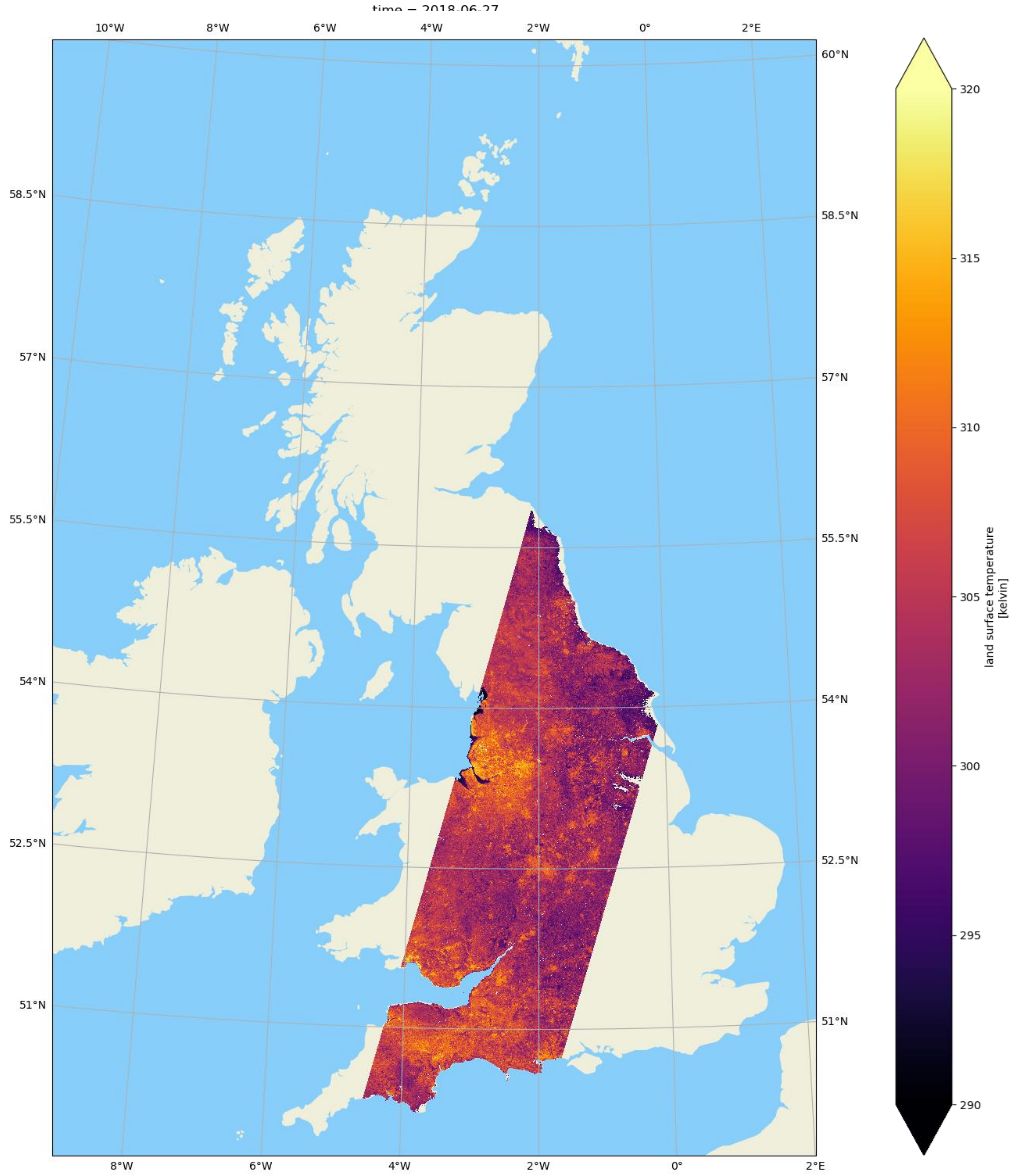
URBAN HEAT ISLAND



The thermal classification scheme then further allows for a robust methodology in determining rural background areas. This allows for UHIs across the UK to be calculated consistently and therefore compared

DOWNSCALING

Created LSEs are used within a bespoke LST downscaling method developed at the University of Leicester. This method utilises optimal estimation to transform data from MODIS at native 1km resolution data to 100m, allowing for greater temporal understanding of how LSTs across cities vary



For more information on the OE algorithm that the Downscaling is based on please see

Ben Courtier - *The Land Surface Temperature Retrieval Algorithm for LSTM: An Overview and Results*

8:30am FRIDAY
A.02.01 PART 1

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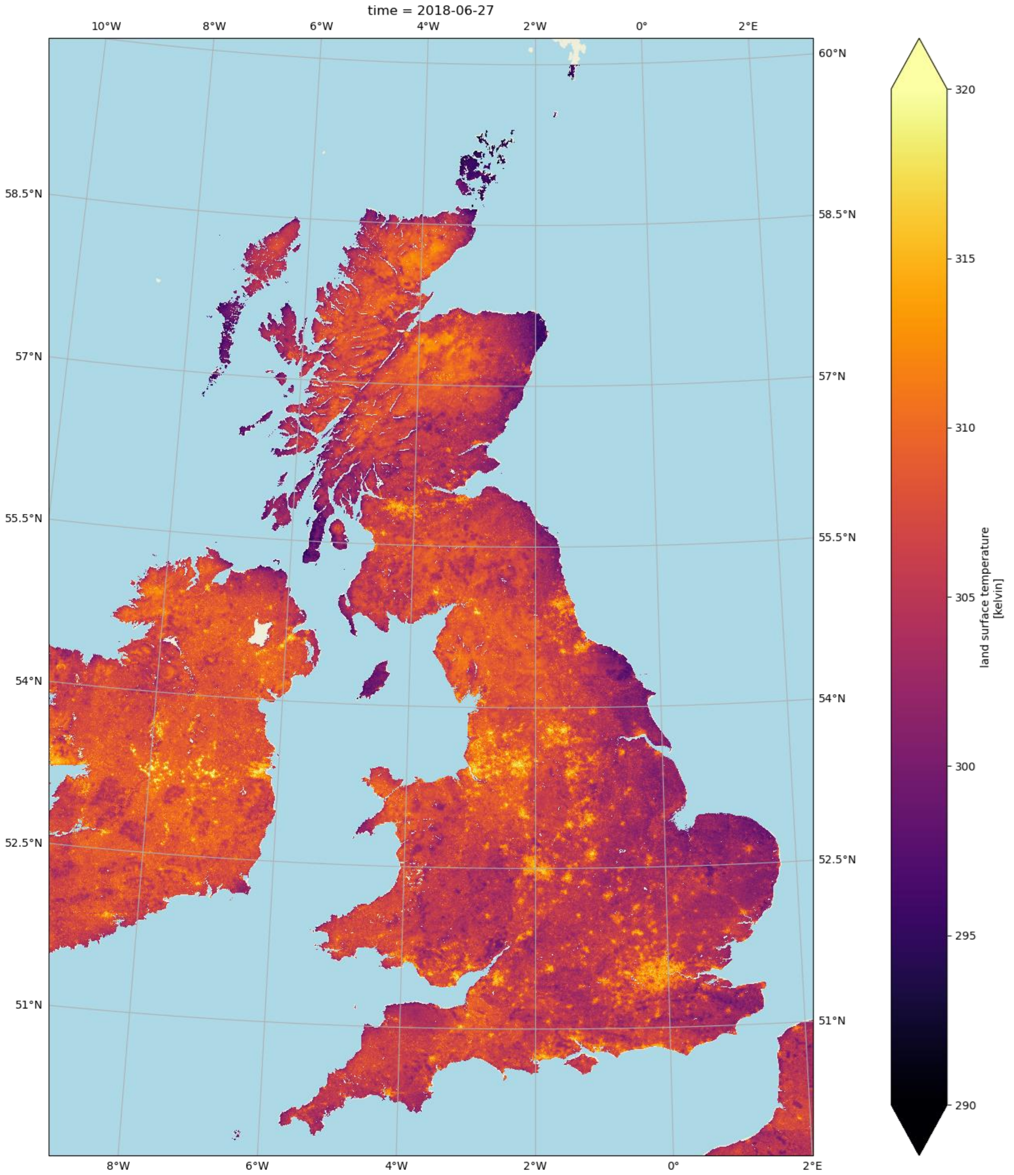

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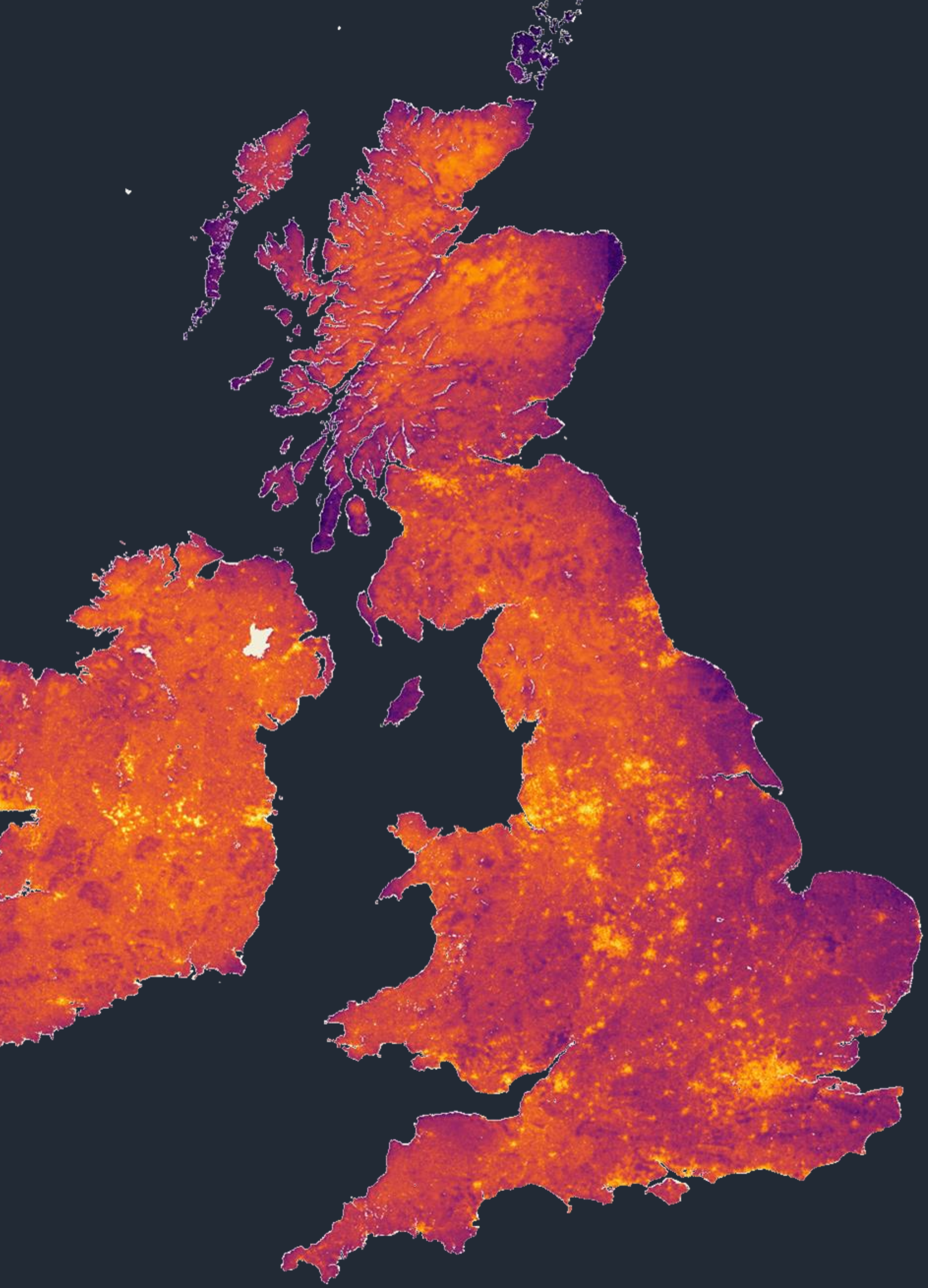

Thanks!

Please feel free to contact:

Charlotte Paton

cjp56@leicester.ac.uk