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High resolution NWP modelling in urban areas: evaluation

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Acknowledge: Those who provide site access and support day-to day operations

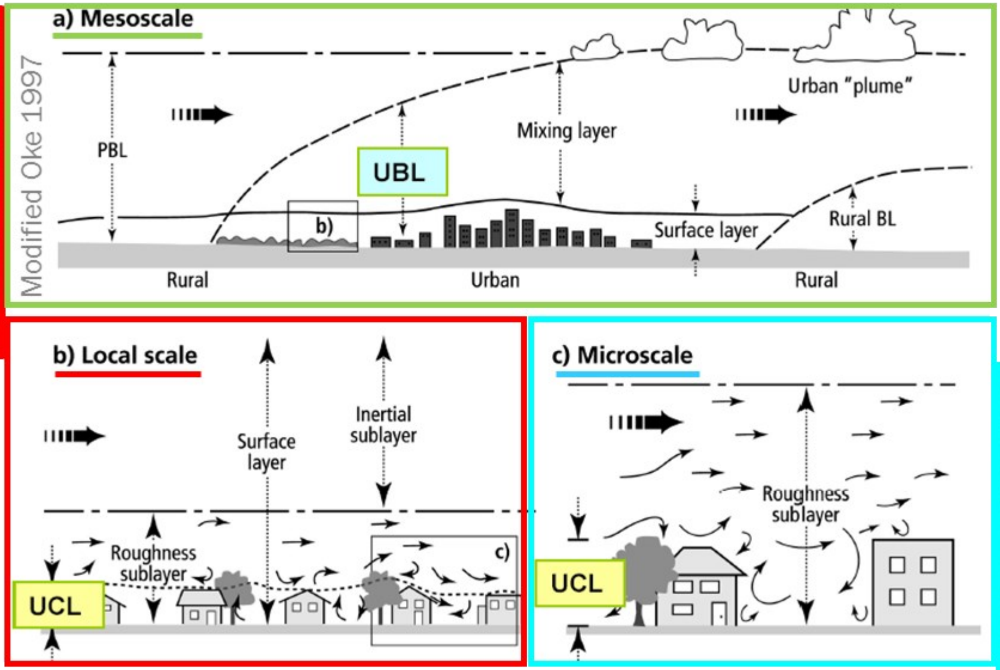
ERC *urbisphere* - coupling dynamic cities and climate
MO-SPF-CRP UM100 - 100m-scale modelling for Urban Climate Services
NERC CASE/MET OFFICE CASE
EPSRC DARE
NERC Scenario/EPSRC University of Reading

Challenge of Scale in Urban Areas

Impacts Modelling
- Computer resources
- Data needed and availability to characterise the surface

Impacts Observations
- Micro-scale variability
- Local scale need
- Horizontal and vertical variability
- Challenge of access

Impacts Services
- High impact events
- People - health
- Building design
- Street flooding
- Planning design
- Neighbourhood
- Energy use



Gothenburg

Chicago

Introduction

UK CLIMATE RESILIENCE PROGRAMME

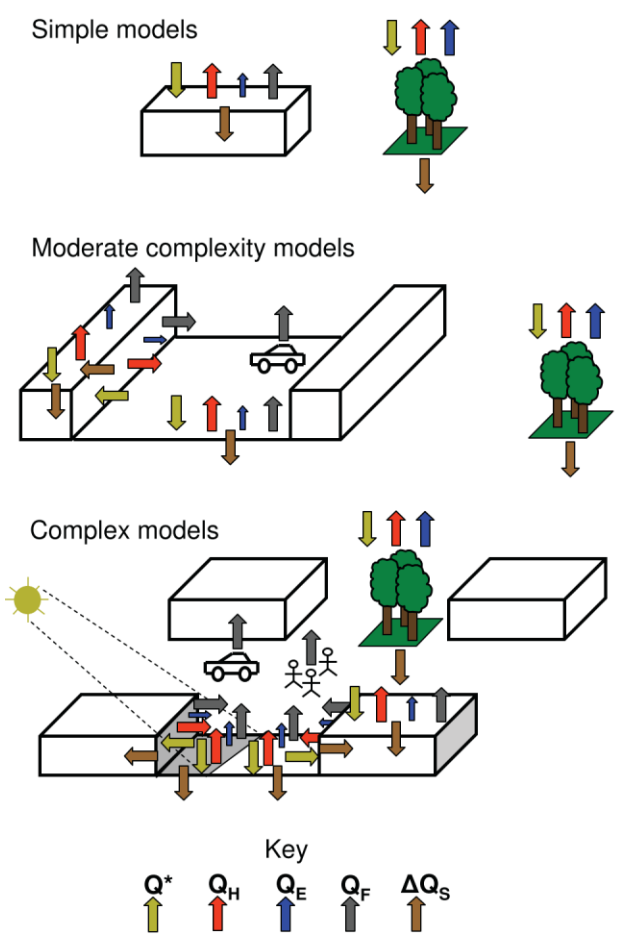
- As part of the UK Climate Resilience Programme the Met Office is exploring the use of high-resolution modelling (order 100 m) for delivering climate services
  - Integrated Urban Services (WMO 2019)– stakeholder and end users always interested in detailed spatial coverage

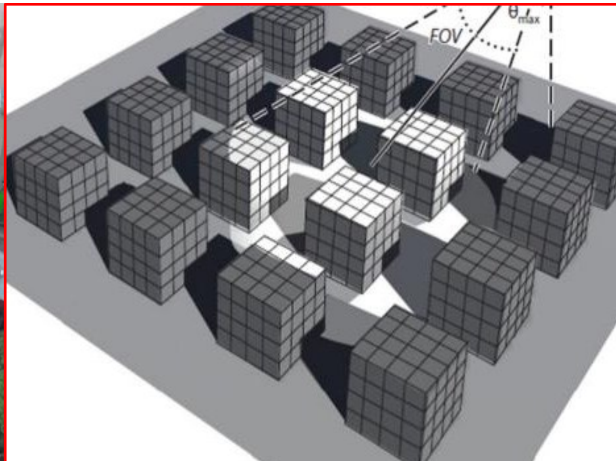
- Various observational datasets being considered to evaluate and help inform developments of high-resolution NWP models and components
  - Larger aperture scintillometry
  - Ground based thermal remote sensing
  - Satellite data
  - Wind and water tunnel observations

Grimmond et al. 2020 *Urban Climate*

WMO (2019) Guidance on IUS : Volume I: Concept and Methodology WMO- No. 1234

Best and Grimmond (2015) https://doi.org/10.1175/BAMS-D-14-00122.1

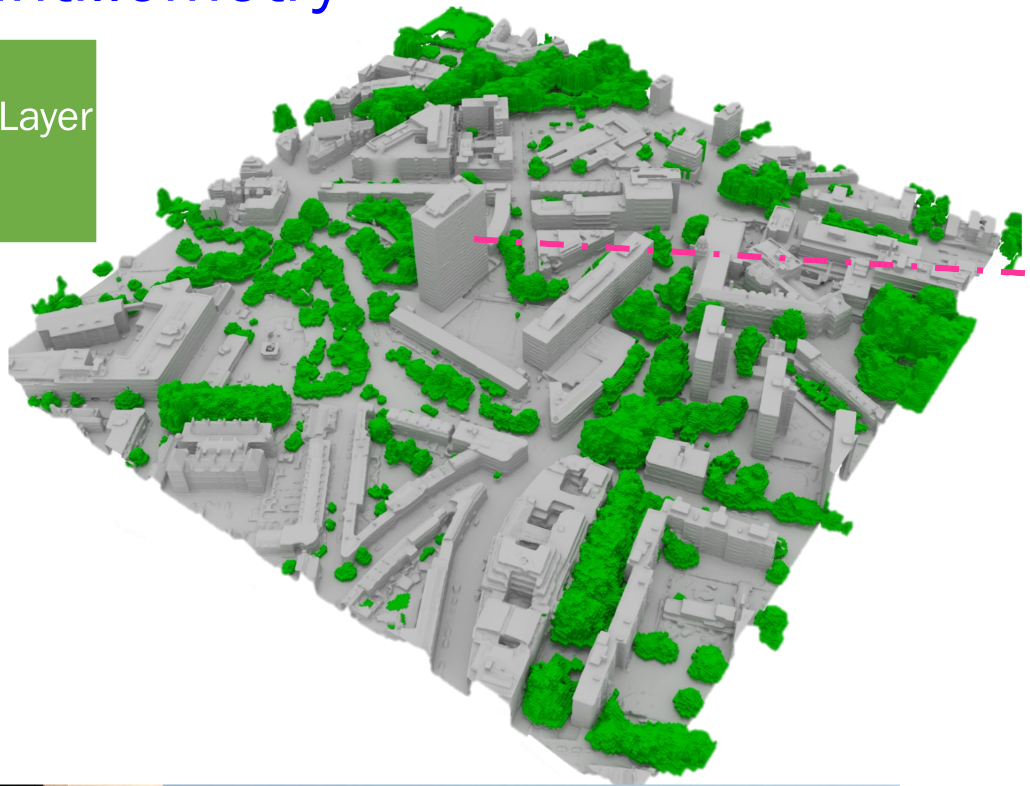


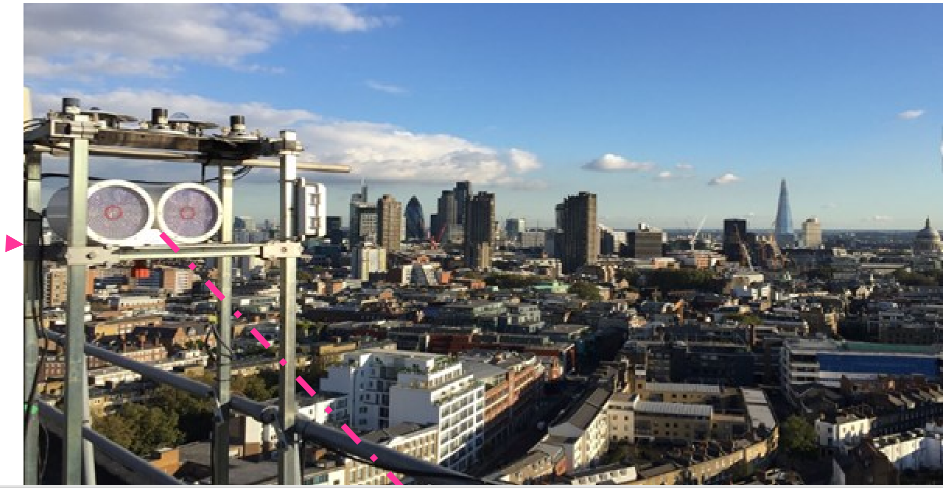


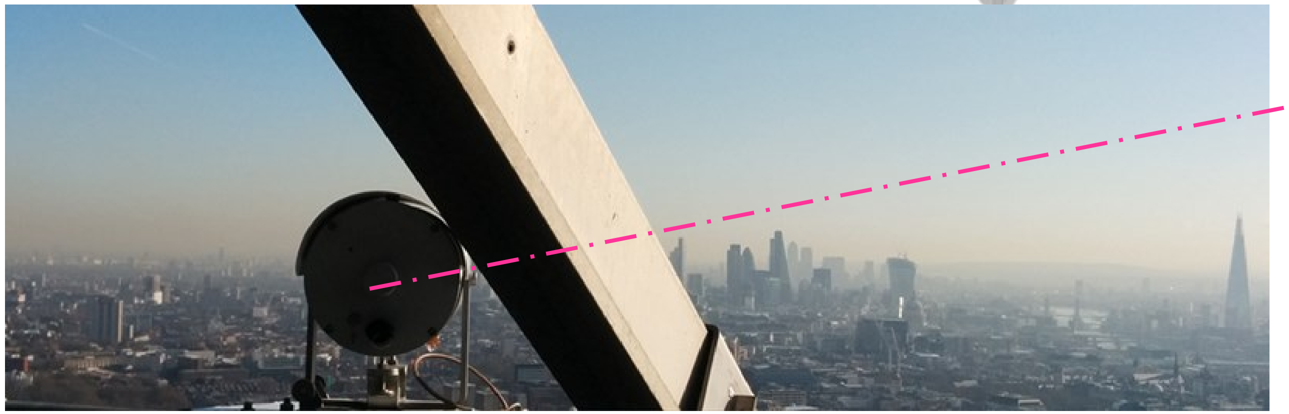
Morrison et al. (2020) https://doi.org/10.1016/j.rse.2019.111524

Local scale: Scintillometry

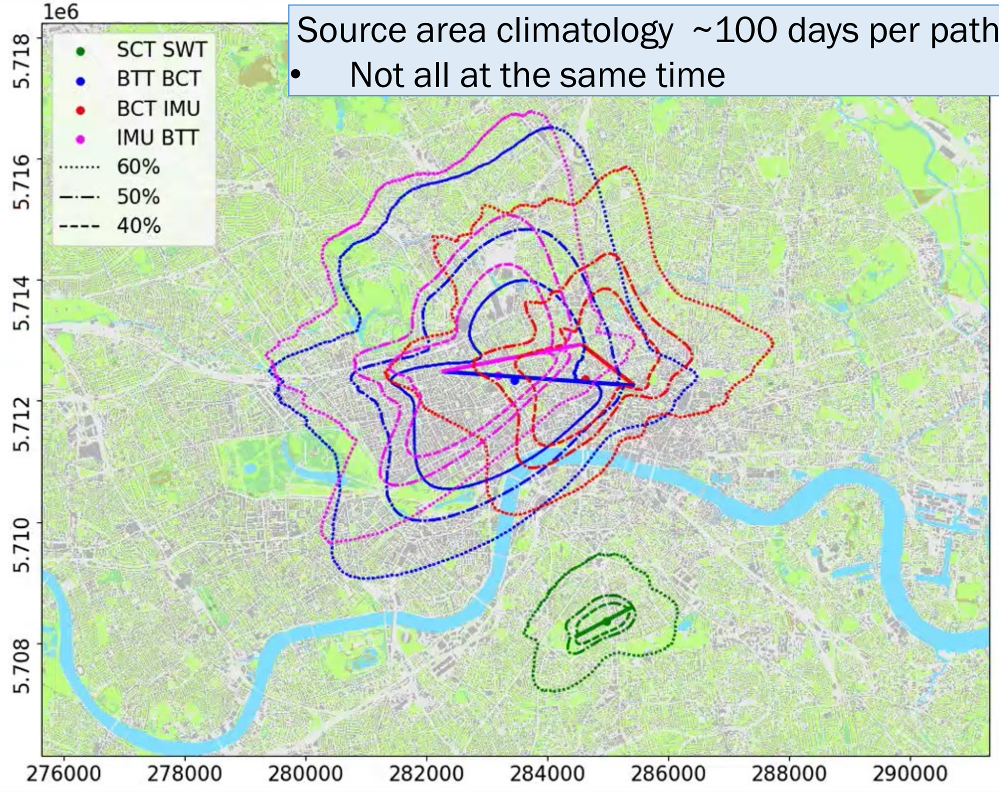
Measurements
- in Inertial Sub Layer
- Multiple paths
- Source areas







Source area climatology ~100 days per path
- Not all at the same time



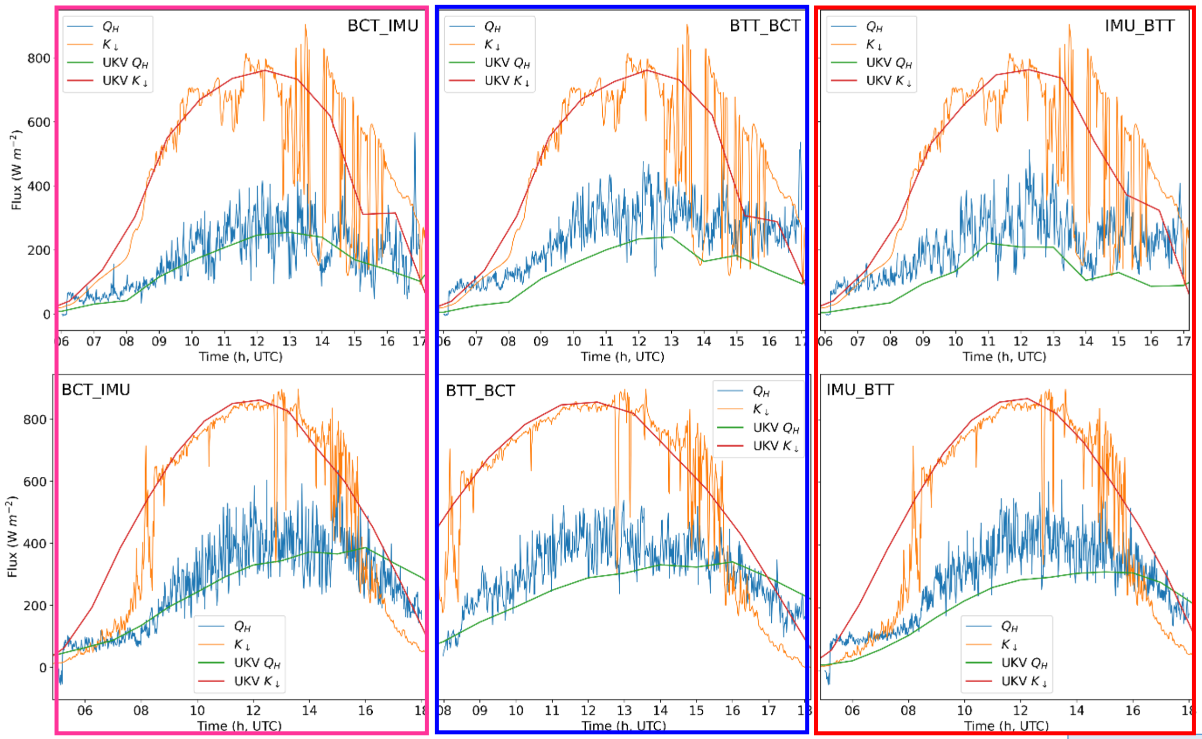
Morrison et al. 2020

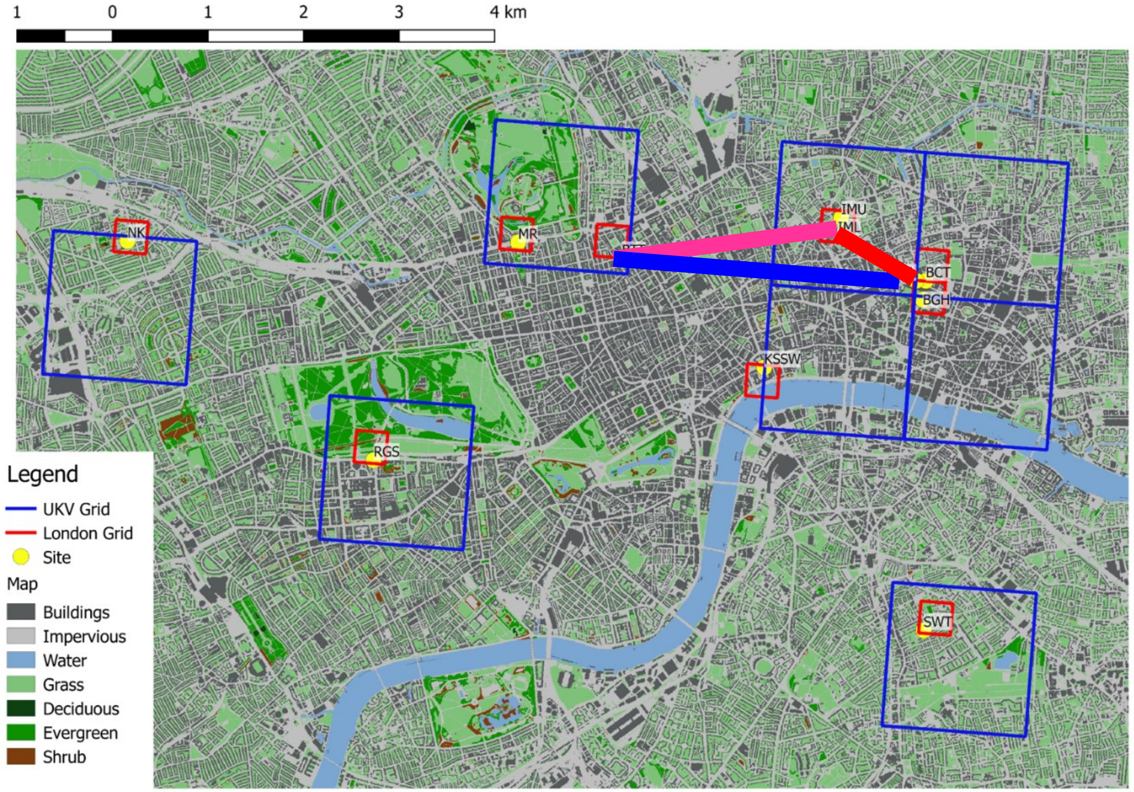
Saunders et al. (in prep)

Local scale: Scintillometry

Observations on two days (rows)
- 1 min fluxes
- Sensible heat flux Q_H - 3 paths (colour)
- Incoming shortwave radiation $K_{\downarrow}$

Model for grid-box centre of respective scintillometer path
- 60 min UKV fluxes
- Q_H at the 60 m model level
- $K_{\downarrow}$ at the surface



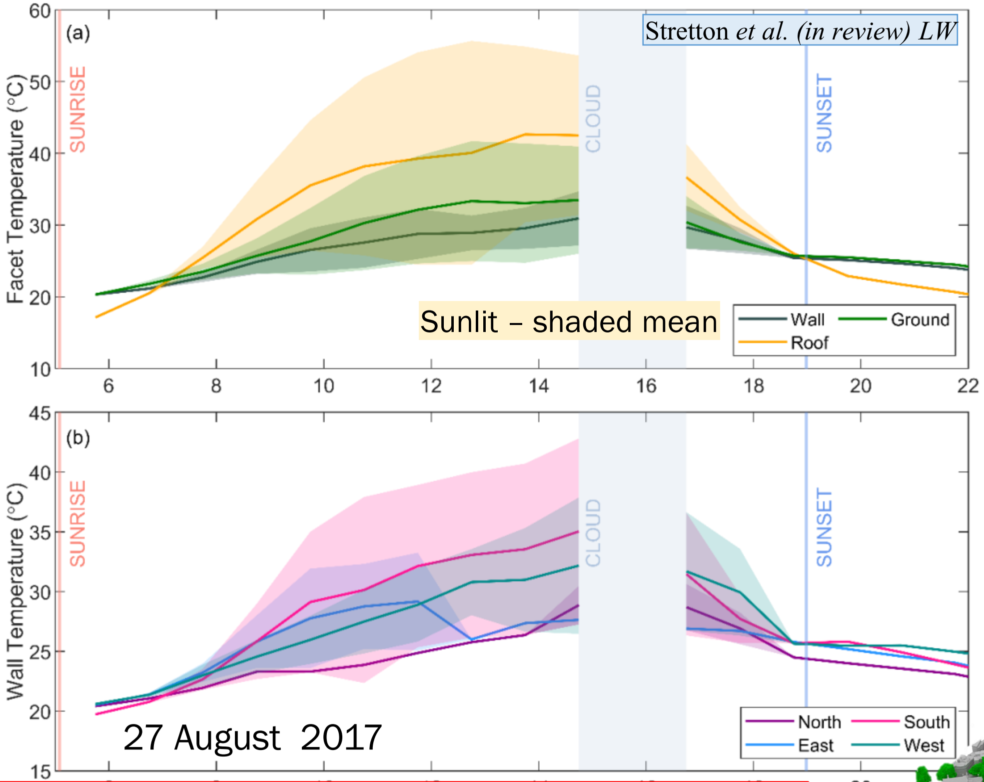


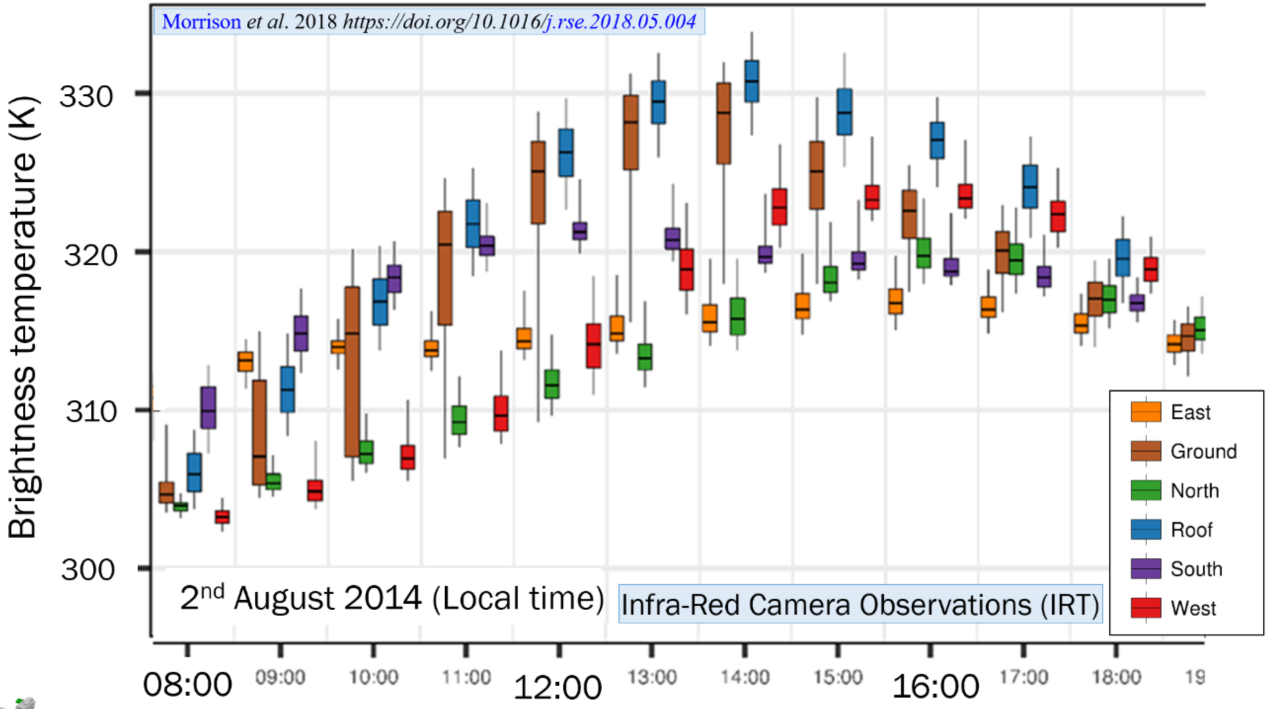
Saunders et al. (in prep); Warren et al. (2018)

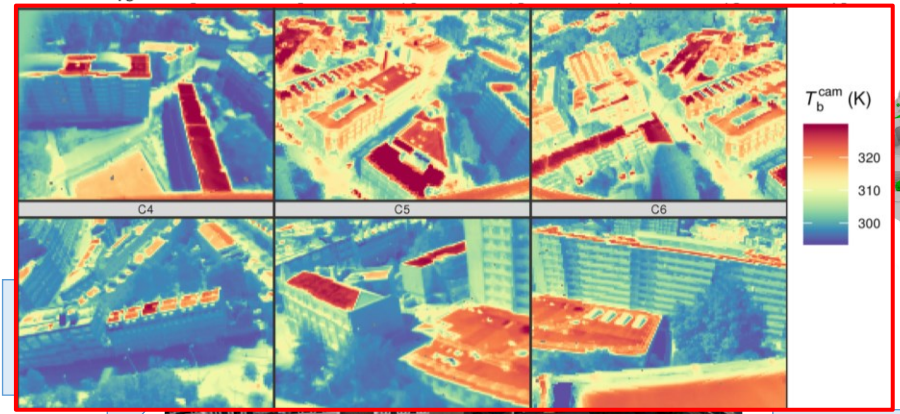
Micro-scale

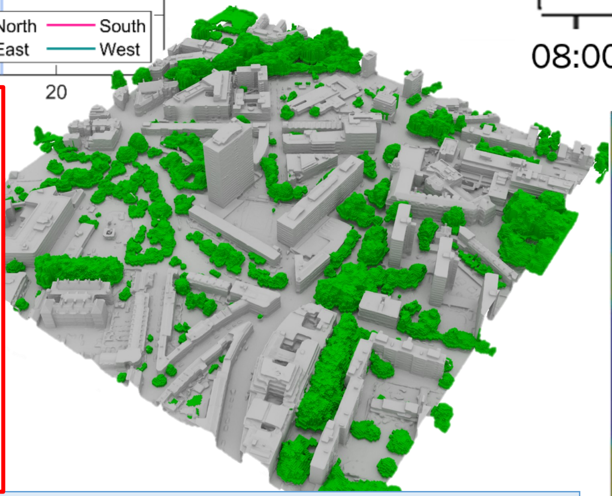
Variability of surface temperature

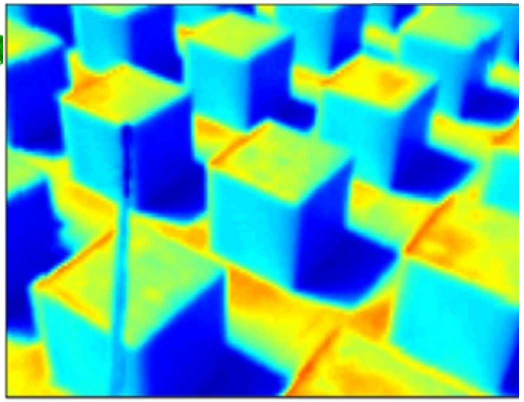
- Brightness temperatures differ by > 30 K
- Ground highly variable from shadows
- *Morning*: most variability; *Afternoon*: more isothermal

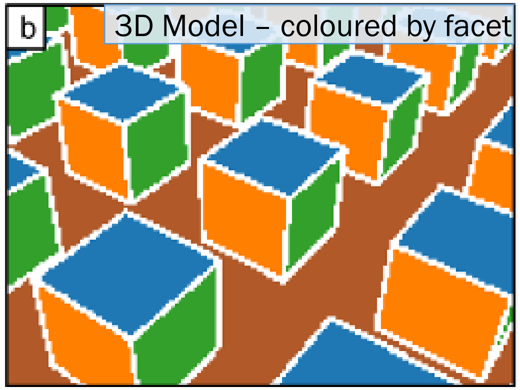








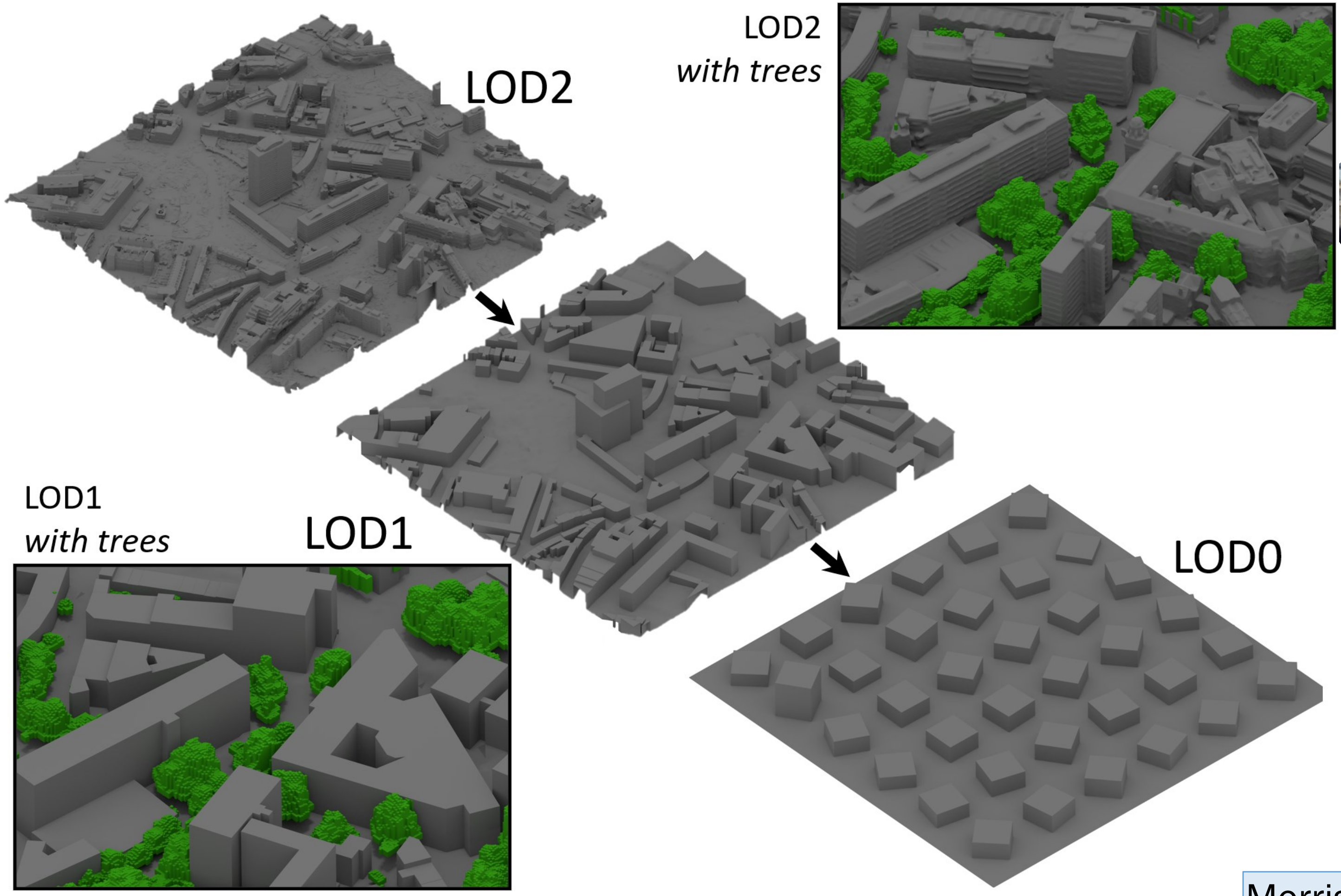


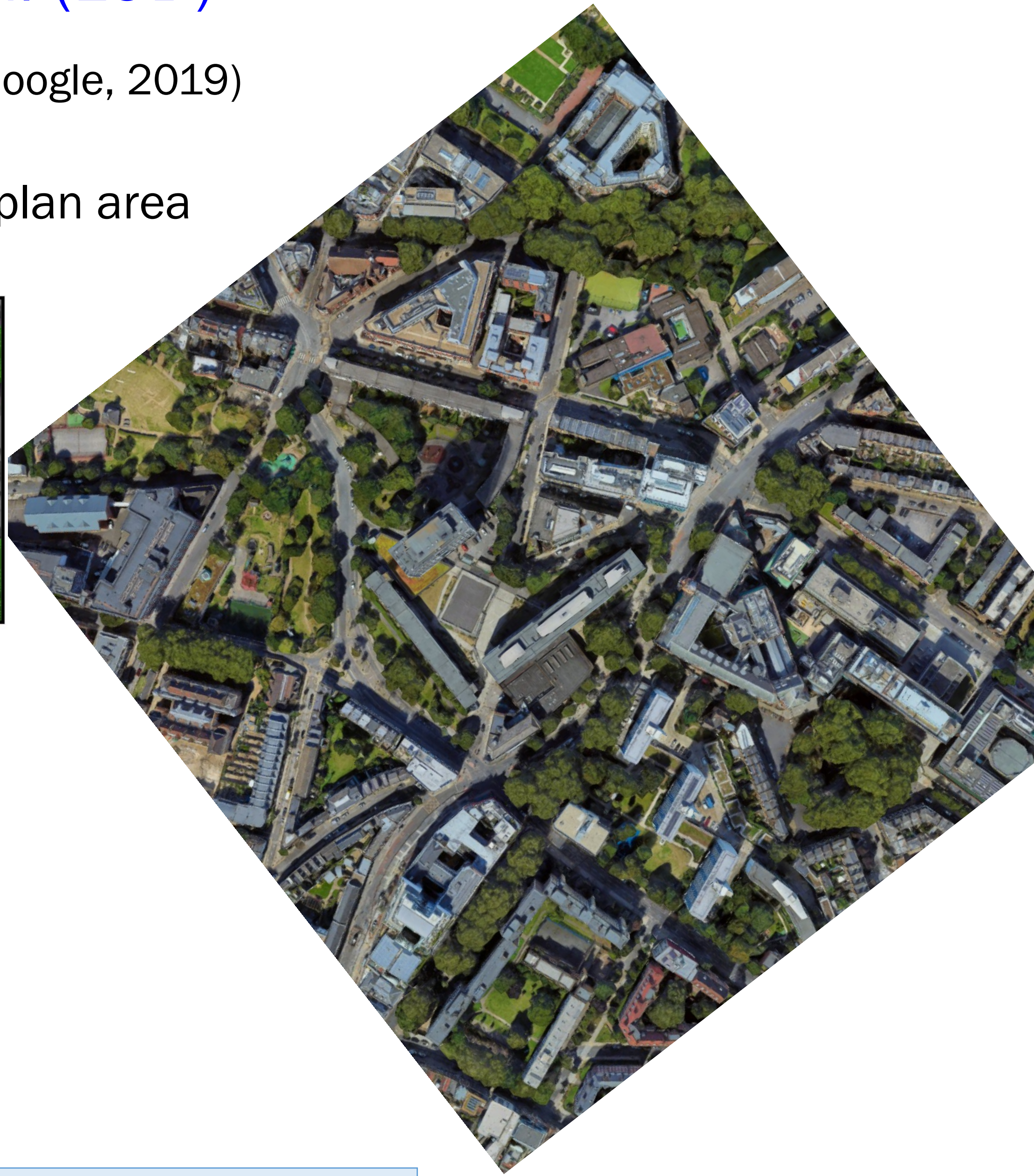


Morrison et al. (2020) https://doi.org/10.1016/j.rse.2019.111524

Variations in model landscapes: Level of detail (LOD)

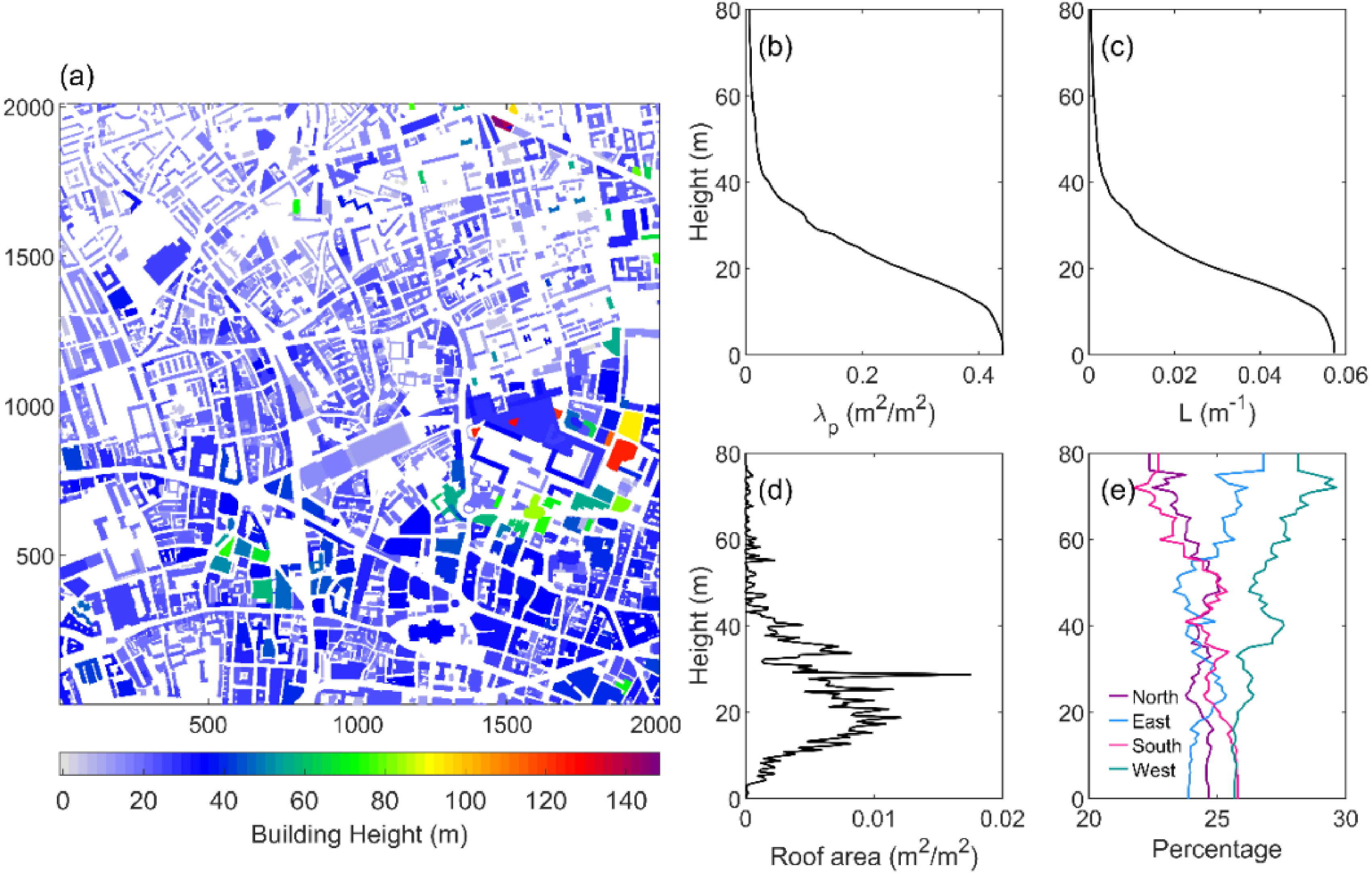
- LOD2: from Morrison et al. (2020) data: Google Earth Pro data (Google, 2019)
- LOD1: extruded building footprints (Evans et al., 2011)
- LOD0: Idealised with study area building height, number, and plan area





Morrison et al. (in review) RSE

Vertical variation of surface characteristics



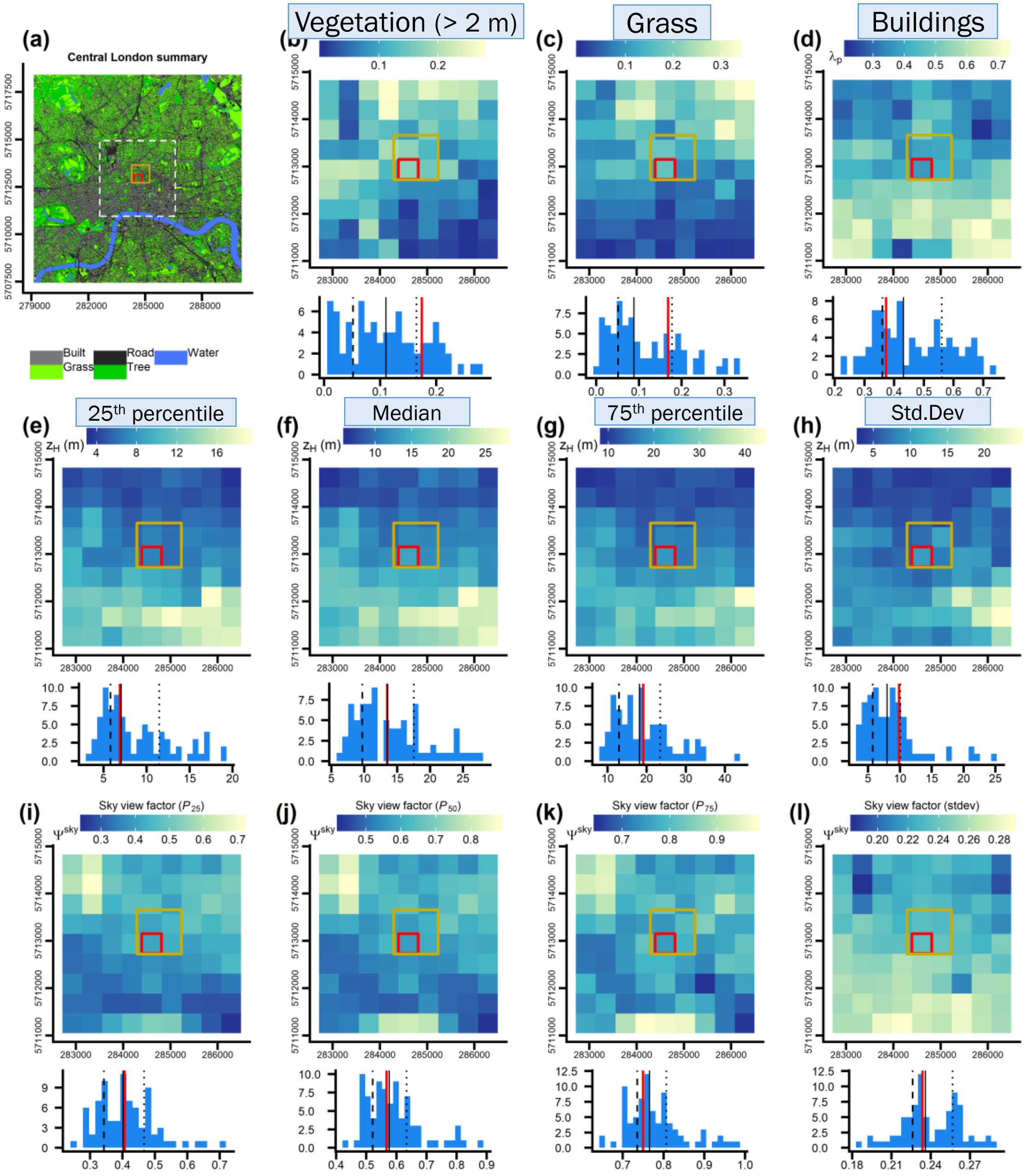
Stretton et al. (in review) LW

Variability of surface characteristics in central London

Plan area fraction

Building height

Sky View



Grids:

- n=81
- 420 m x 420 m area

Land cover

- 4 m resolution

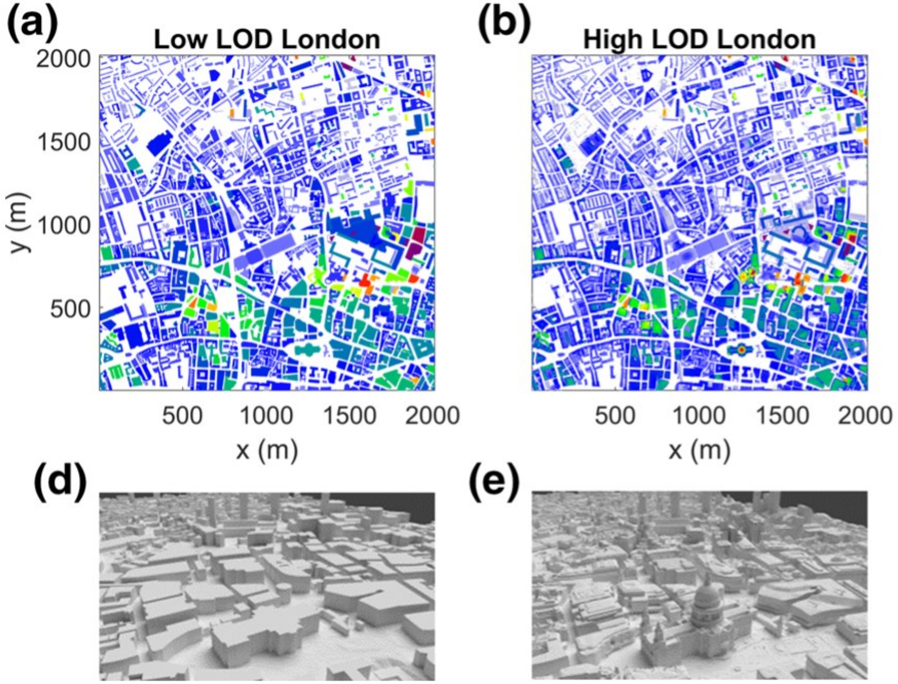
- MODIS M*D11A1 pixel

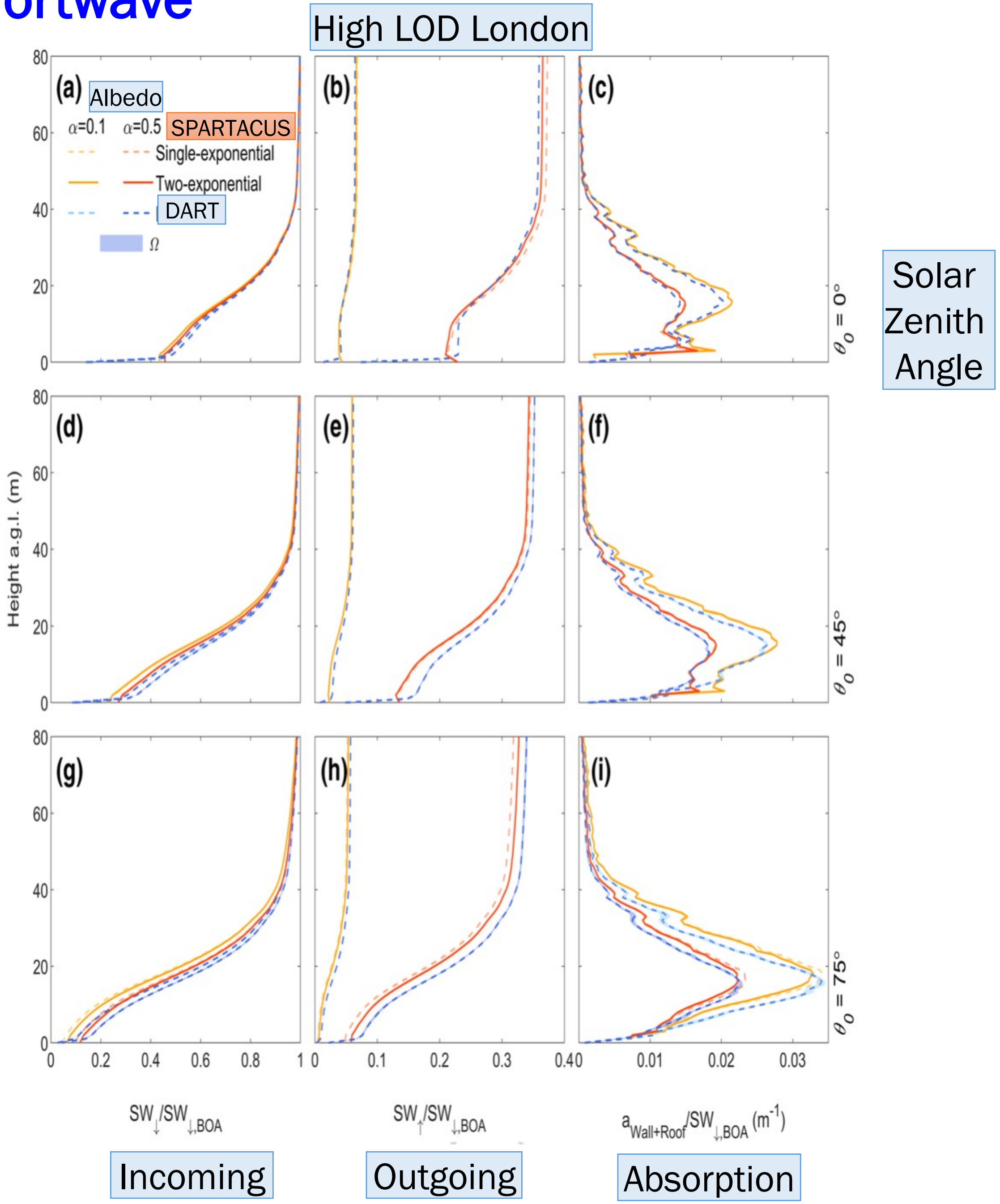
	Trees & Shrubs	Grass	Building
Plan area fraction	0.17	0.17	0.37
Percentiles	Height (m)	Sky view factor	Height (m)
P25	6.82	0.41	6.9
P50	10.01	0.57	13.49
P75	15.21	0.75	19.1

Morrison et al. (in review) RSE

Evaluation of **Vertical Profiles** of Radiation Fluxes**: Shortwave**

- SPARTACUS-Surface (Hogan 2019)
- Evaluated with: 3D obstacle resolving model (DART)(Gastellu-Etchegorry et al. 2015; Landier et al. 2018)

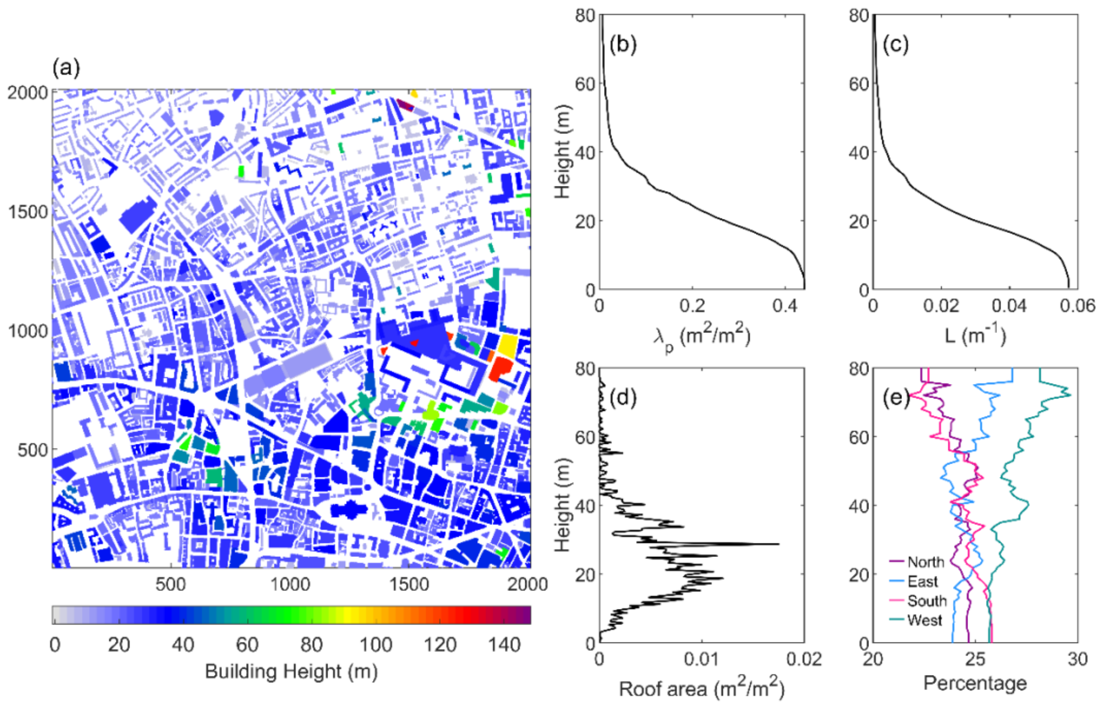




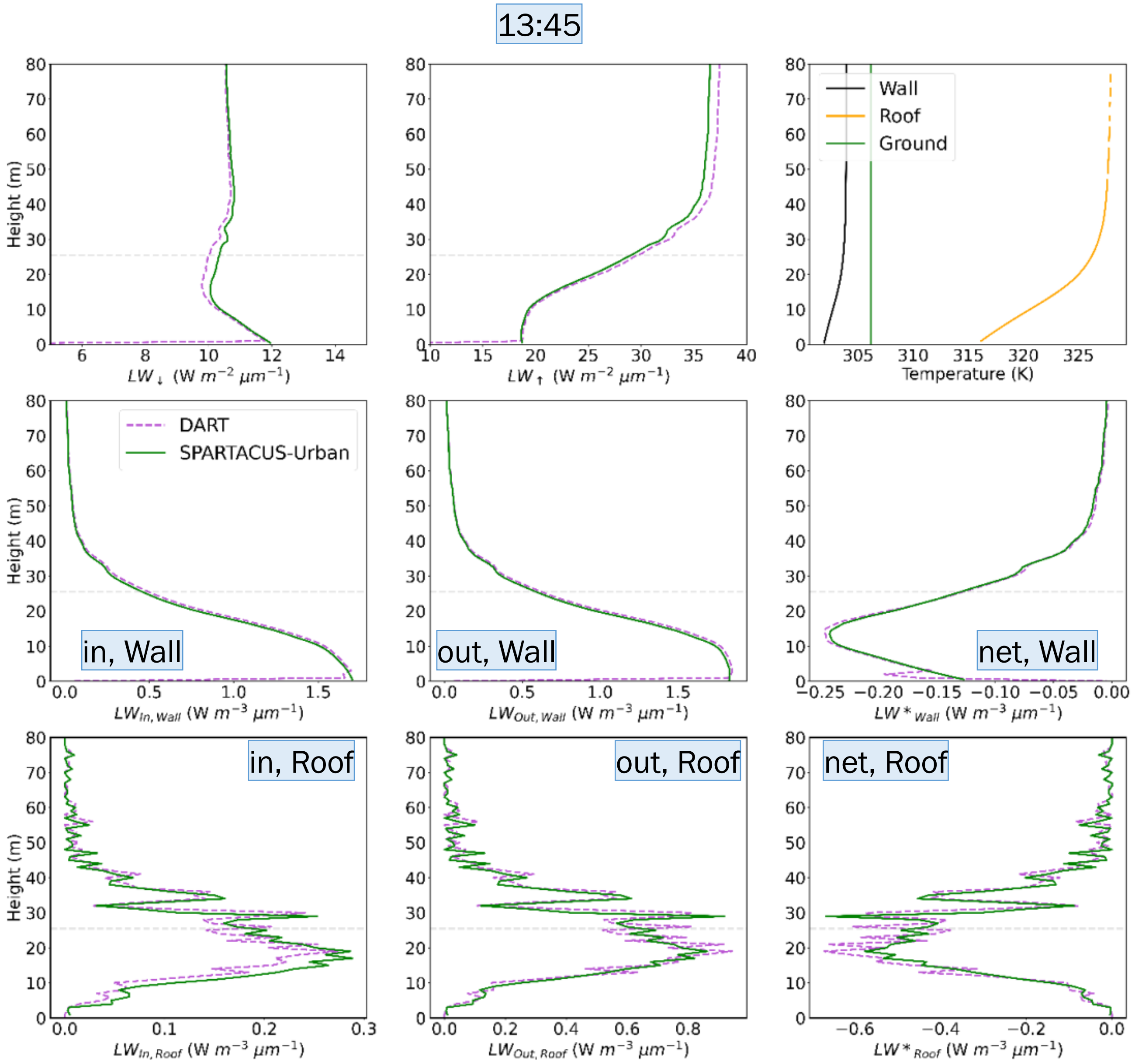
Stretton et al. 2022: *Boundary-Layer Meteorology* https://doi.org/10.1007/s10546-022-00706-9

Evaluation of Vertical Profiles of Radiation Fluxes: **Longwave**

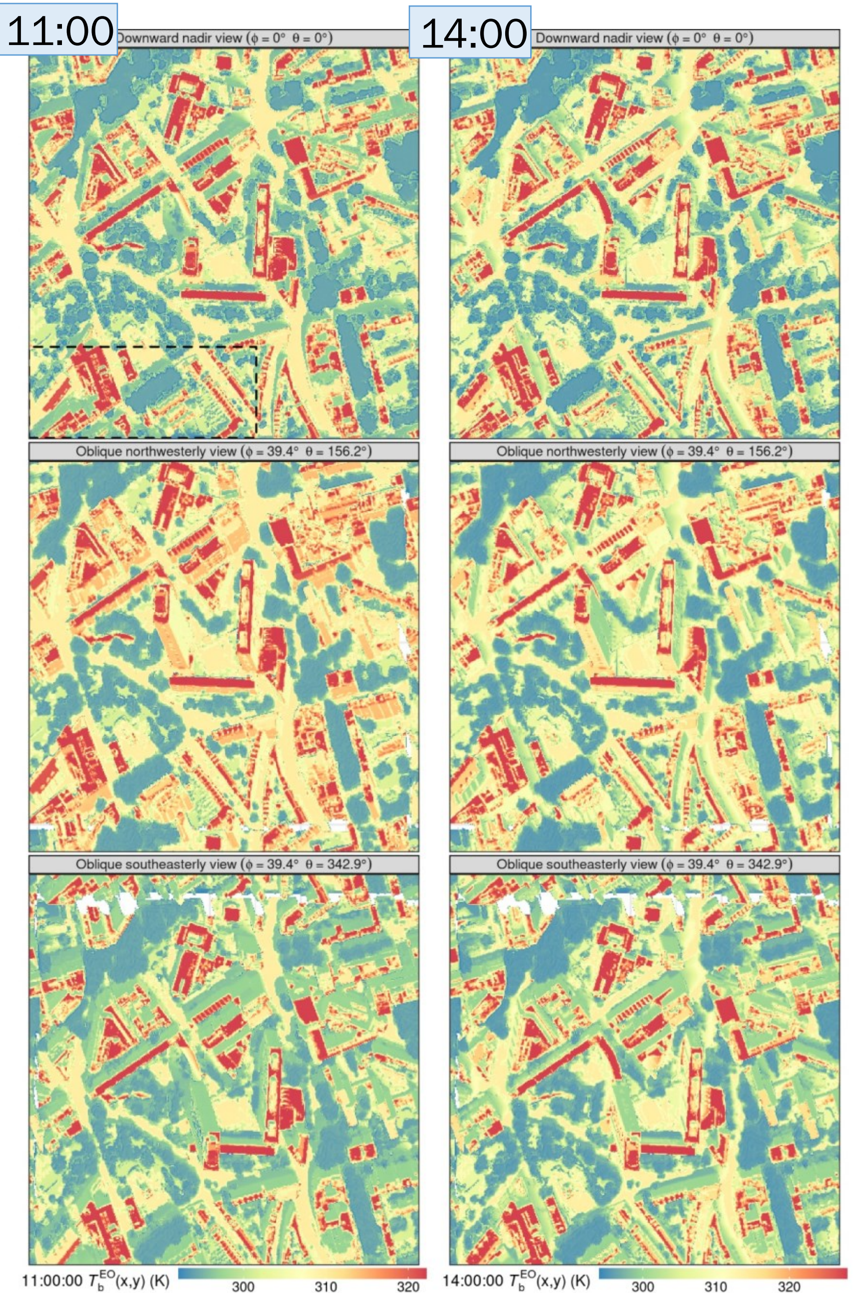
- SPARTACUS-Surface (Hogan 2019)
- Evaluated with: DART (Gastellu-Etchegorry et al. 2015; Landier et al. 2018)
- Facet Surface T prescribed based on modelled sunlit-shaded (i.e. wall orientations) conditions
- Model assumes no orientation



Stretton et al. (in review) LW



Surface-leaving radiance –simulated brightness temperature

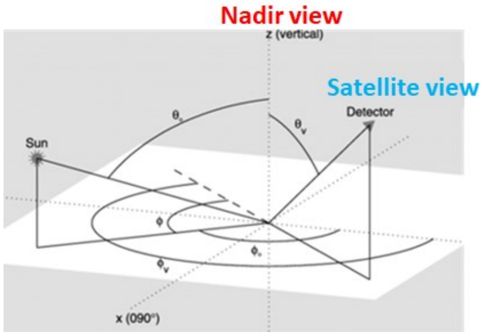


Nadir

Off –nadir Zenith angle

27th August 2017

- Satellite view simulations using:
  - 3D object resolving model DART radiative transfer model
  - Ground-based surface temperature obs
- View angle varies with satellite and time
  - Changes view of roof - ground – walls (and their orientation)
- UM100 – assume planar vertical and horizontal surfaces

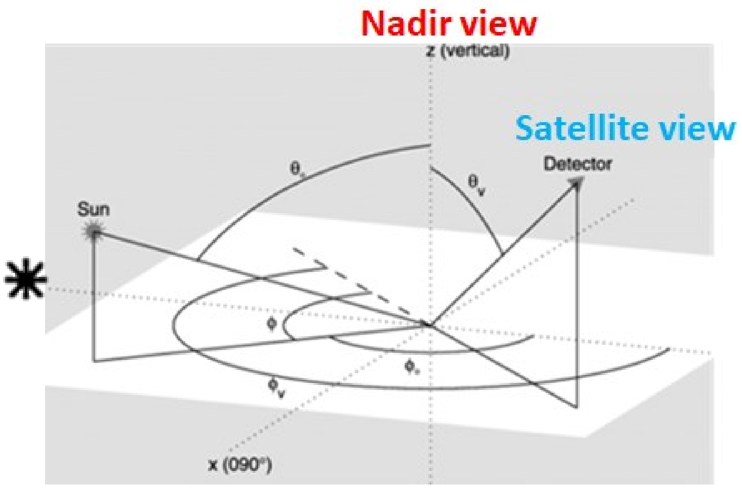


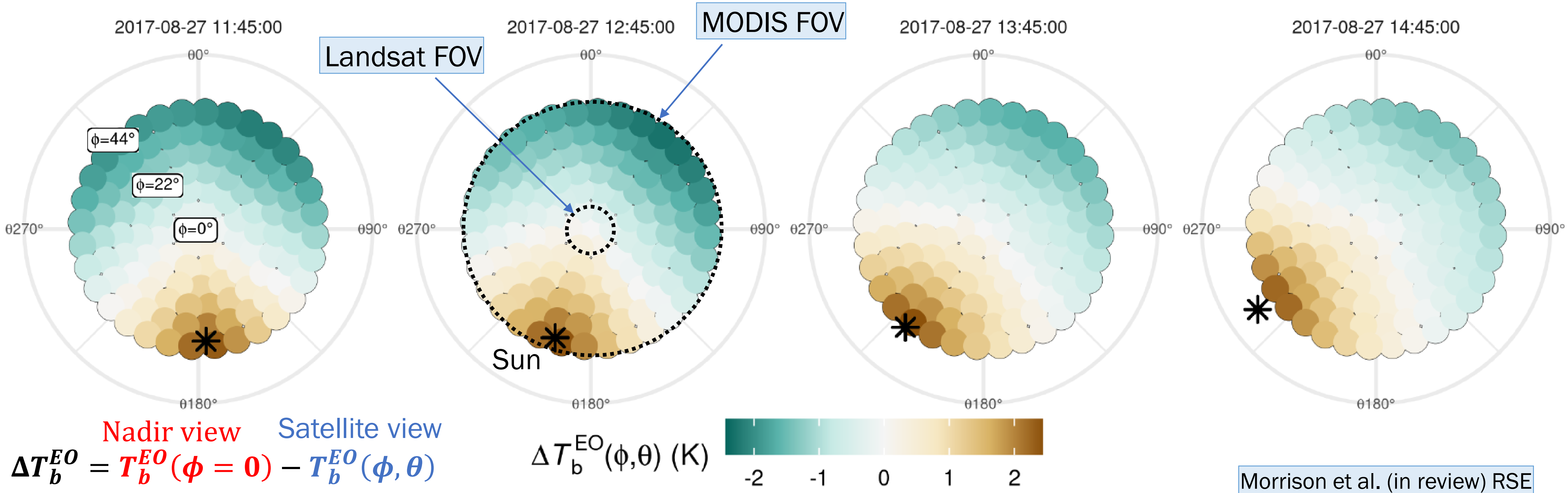
- θ = 0° north — θ = 90° east
- φ = 0° up from surface — φ = 90° parallel to surface

Morrison et al. (in review) RSE

Satellite view simulations

- Difference between nadir and angle (actual) view
- MODIS: up to ±45° view angle (typical of multi-day observations)
  - ~4.5 K view-angle variation
- Landsat: ±7.5° view angle
  - ~0.7 K view-angle variation





Nadir view Satellite view

$$\Delta T_b^{EO} = T_b^{EO}(\phi = 0) - T_b^{EO}(\phi, \theta)$$

Morrison et al. (in review) RSE

Satellite observations

- Can provide high spatial resolution surface temperature data *(in cloud-free conditions)* with complete (global) coverage
- Trade-off between temporal and spatial resolution

- Objective: assess use of Landsat data to evaluate the UM@100 m scale over London

- Landsat-8 data available: 2013-present
  - 16-day repeat cycle
    - Views London 22-23 days per year (if clear)
  - Overpass at ~11 UTC over London
  - Thermal resolution: order 100 m

Date	Comments
17/11/2017	
15/07/2018	Mostly dry month (small amount of rain central London on 13/07/18)
10/10/2018	Few contrails to NE of London
22/04/2020	

- London
  - UKV, ERA5 and Landsat cloud mask used to identify dates with minimal cloud cover

Hall et al. (in preparation)

Land surface temperature (LST) retrieval comparison

- Retrieved from Landsat Band 10 (one of two thermal channels)
  - Emissivity from ASTER Global Emissivity Dataset (GED): 100 m resolution
- cf. two other Landsat LST products: FORTH (RSLab) and NASA JPL (both use ASTER emissivity)
- Differences arise from auxiliary information in the retrieval, e.g. choice of radiative transfer model (RTM)
- Differences consistent with the expected uncertainty from Landsat-8
- Overall strong spatial correlation between the three products on both days (r>0.97)

15/07/18

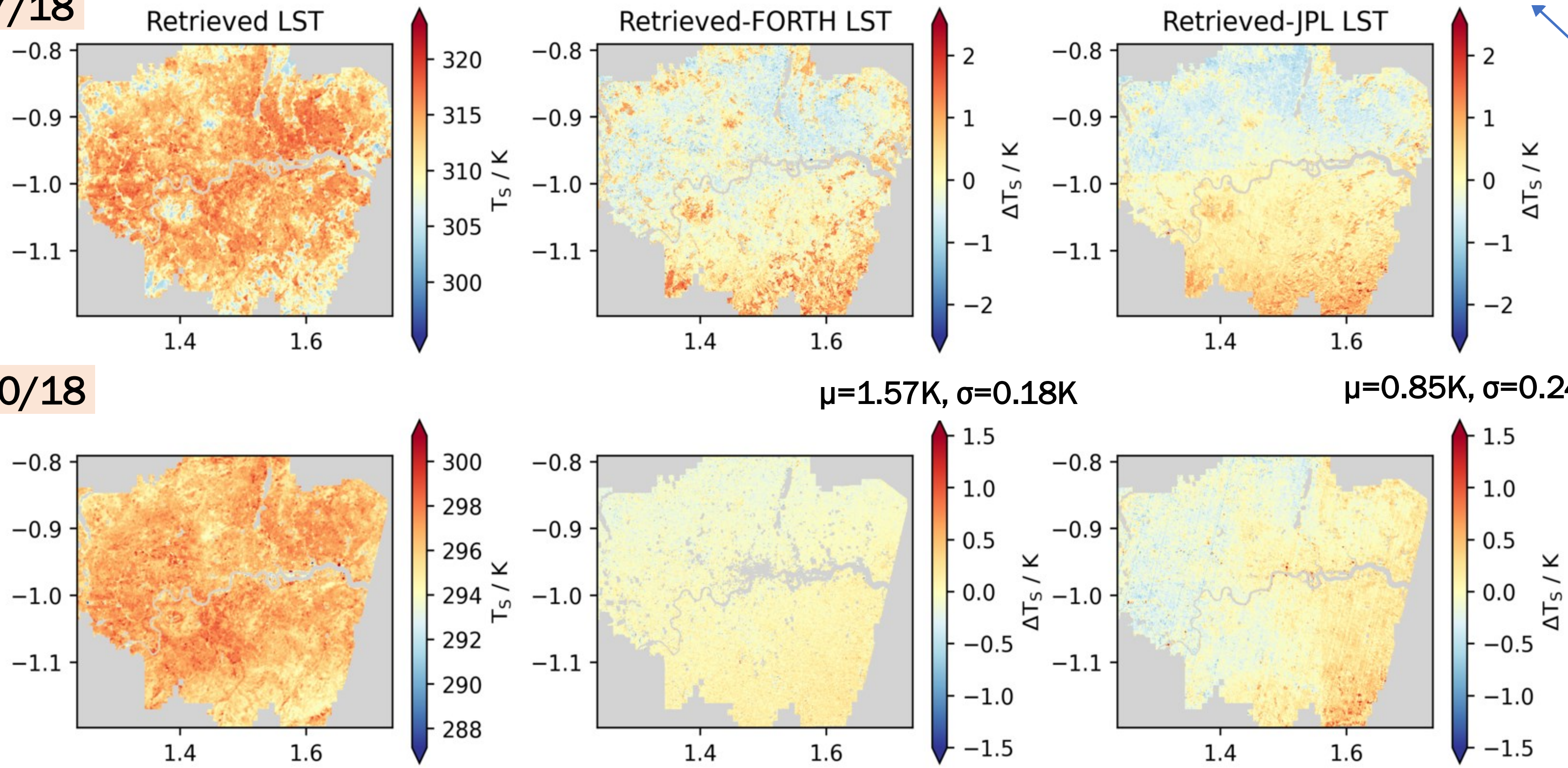
μ=-0.39K, σ=0.59K

μ=-0.41K, σ=0.49K

10/10/18

μ=1.57K, σ=0.18K

μ=0.85K, σ=0.24K



Zero-meaned differences shown

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UM100

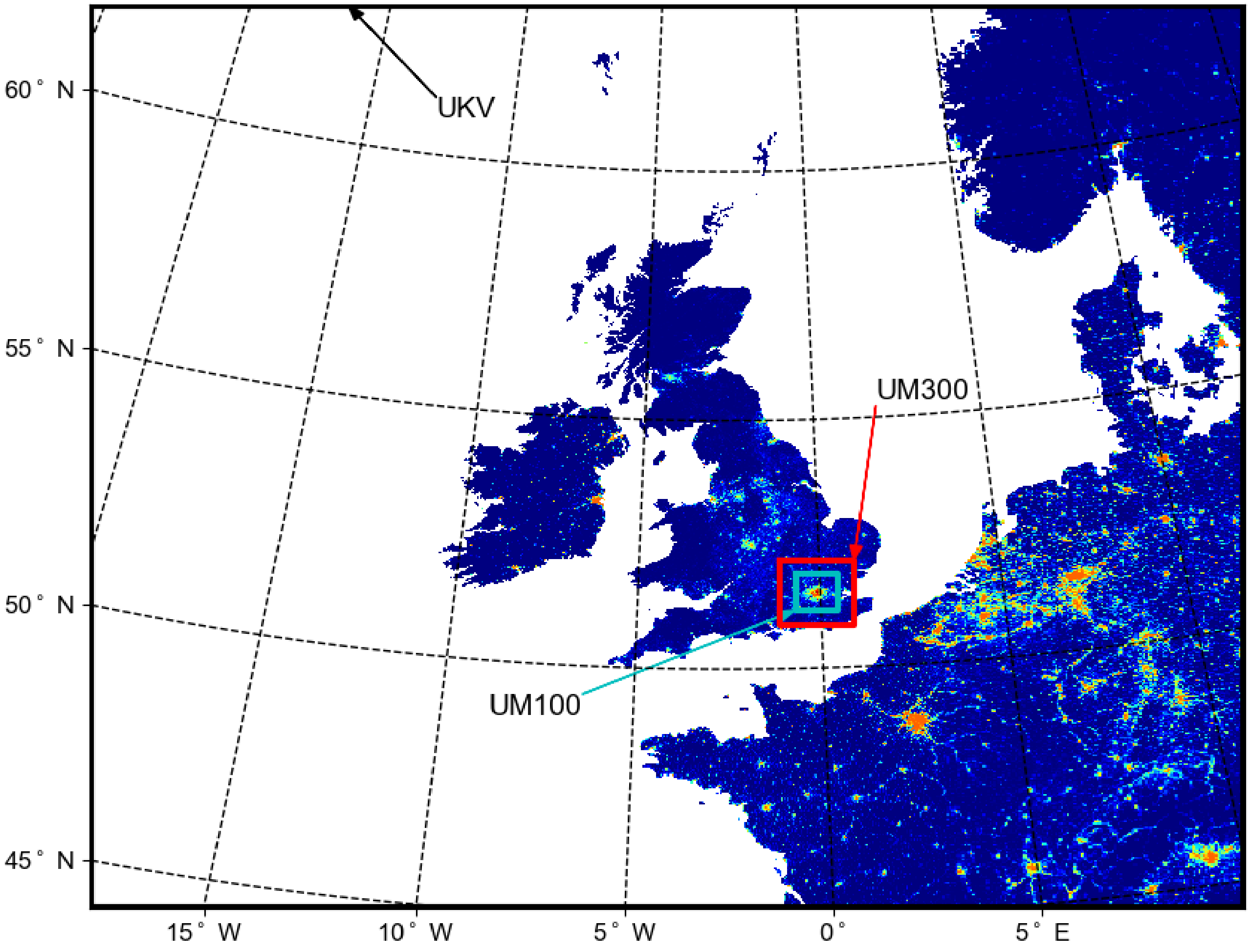
- 100 m research configuration of Met Office Unified Model (UM)

- Nesting suite:
  - Outer domain: UKV (1.5 km resolution)

- UM100 domain:
  - 80 km x 80 km
  - covering Greater London

- Land surface: JULES
  - 10 tiles
  - different properties (e.g. emissivity)
  - MORUSES

Model domain



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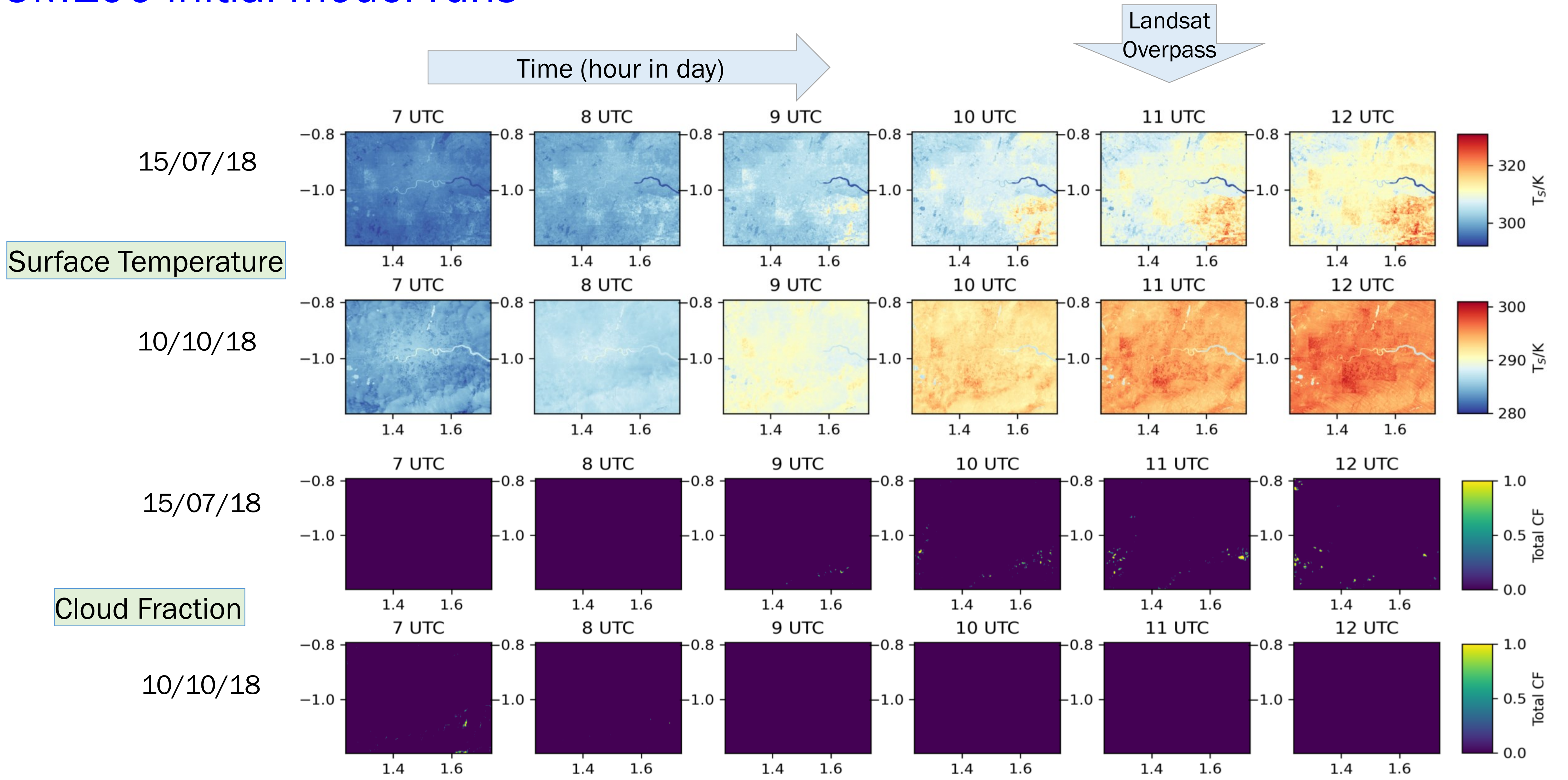
UM100 initial model runs



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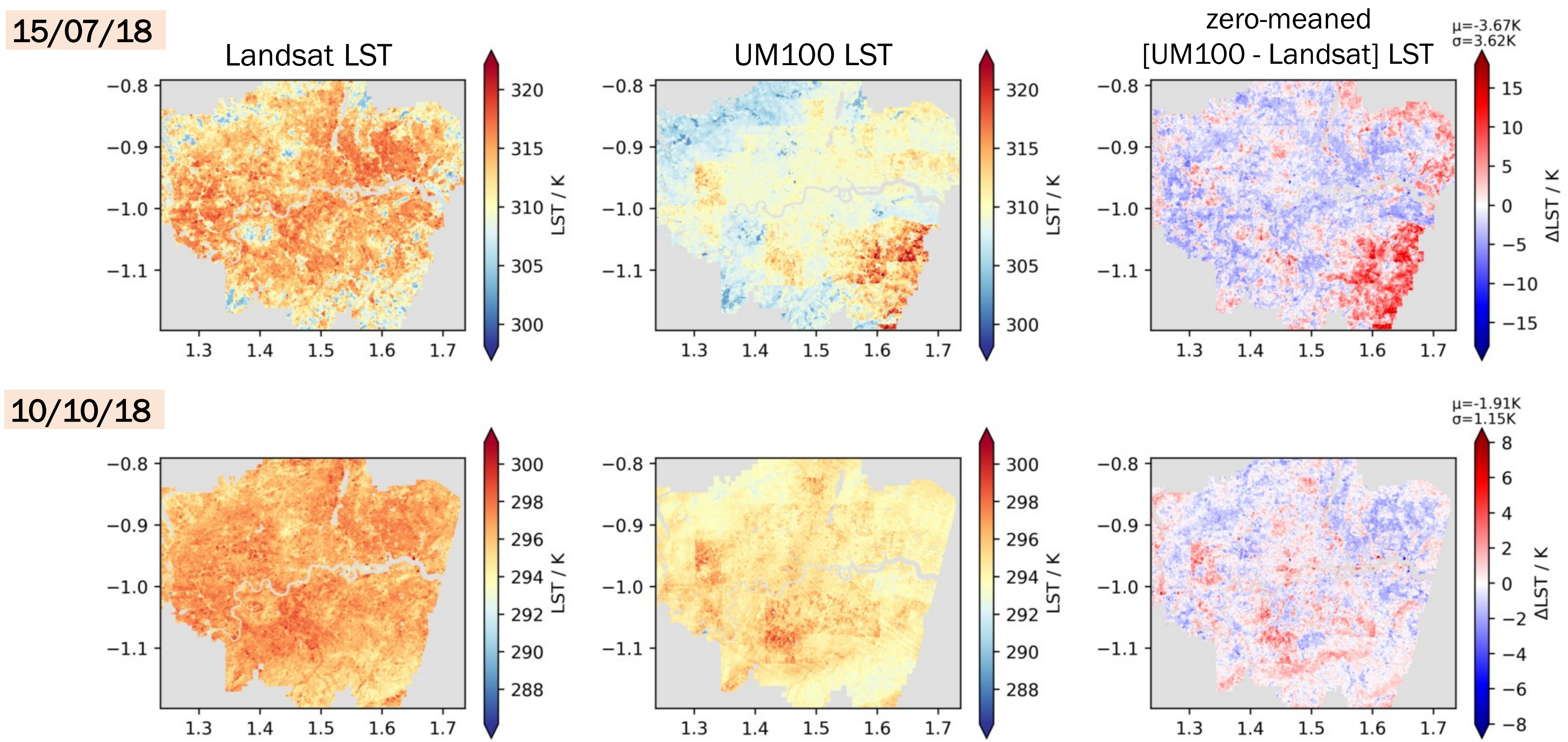
Comparison of UM100 with Landsat LST: initial model runs



- UM100 LST cooler on average than Landsat (particularly July case)
- Unrealistic blocky patterns over London…

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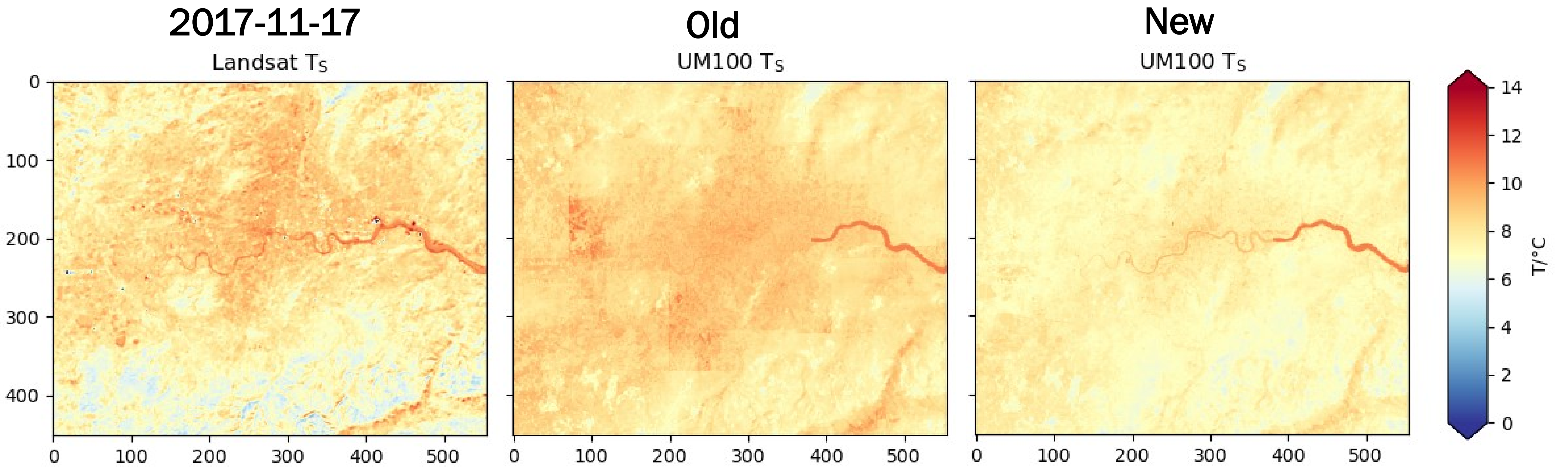

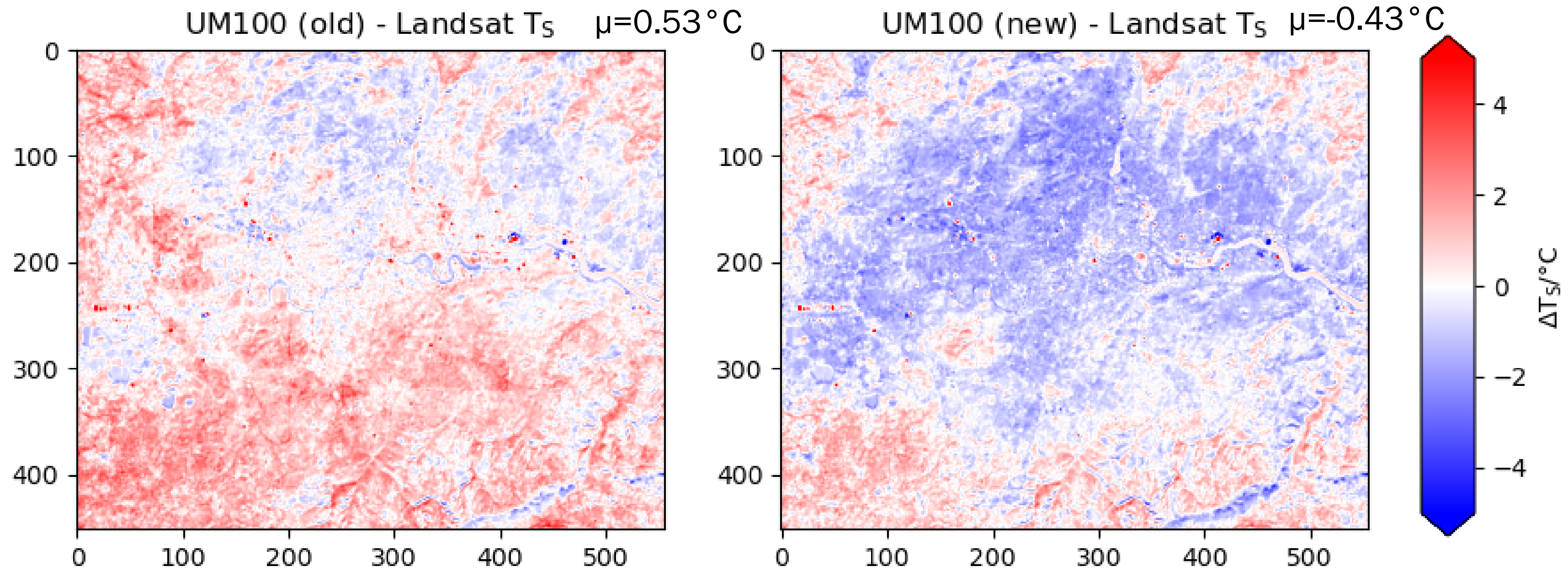

Changes to model configuration

- Soil moisture DA
- (LAI in nesting suite)

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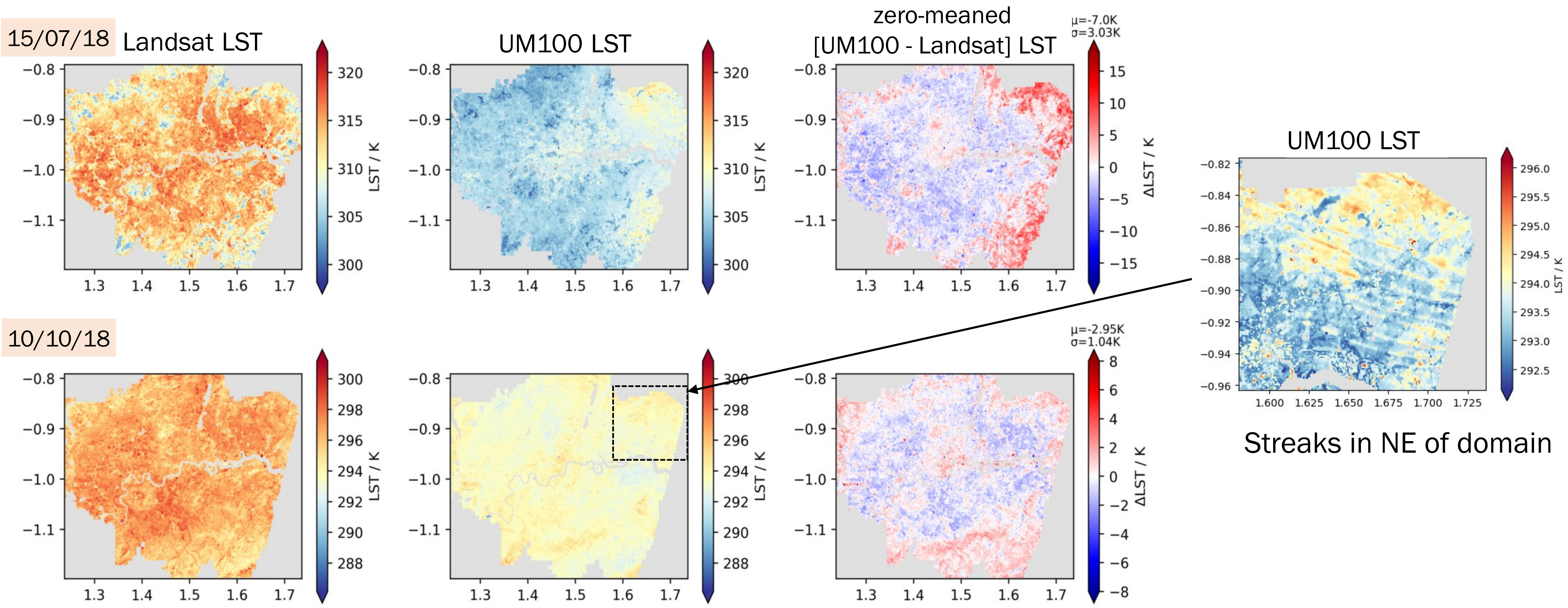
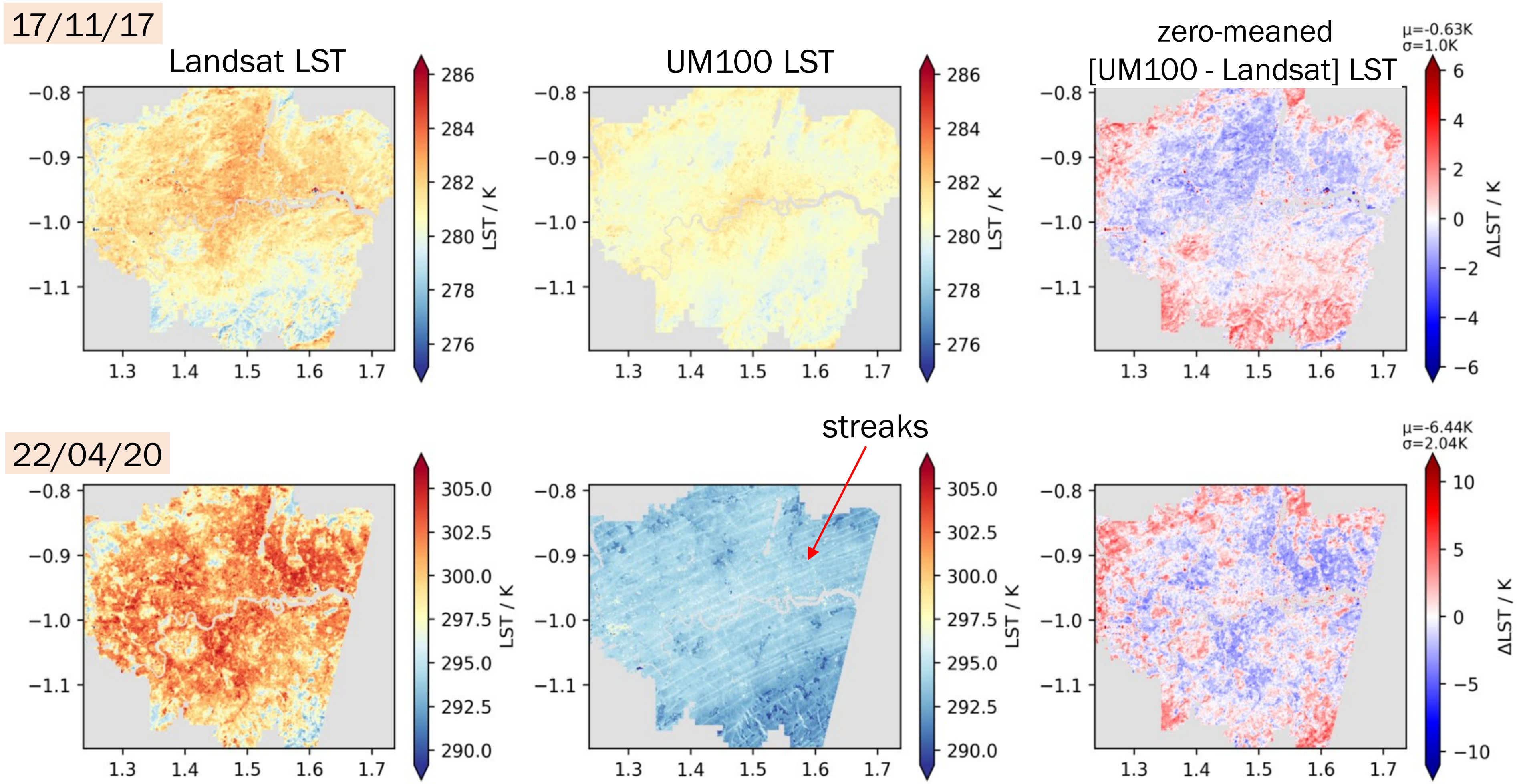
Comparison of UM100 with Landsat LST: new model runs



Streaks in NE of domain

Hall et al. (in preparation)

Comparison of UM100 with Landsat LST: new model runs



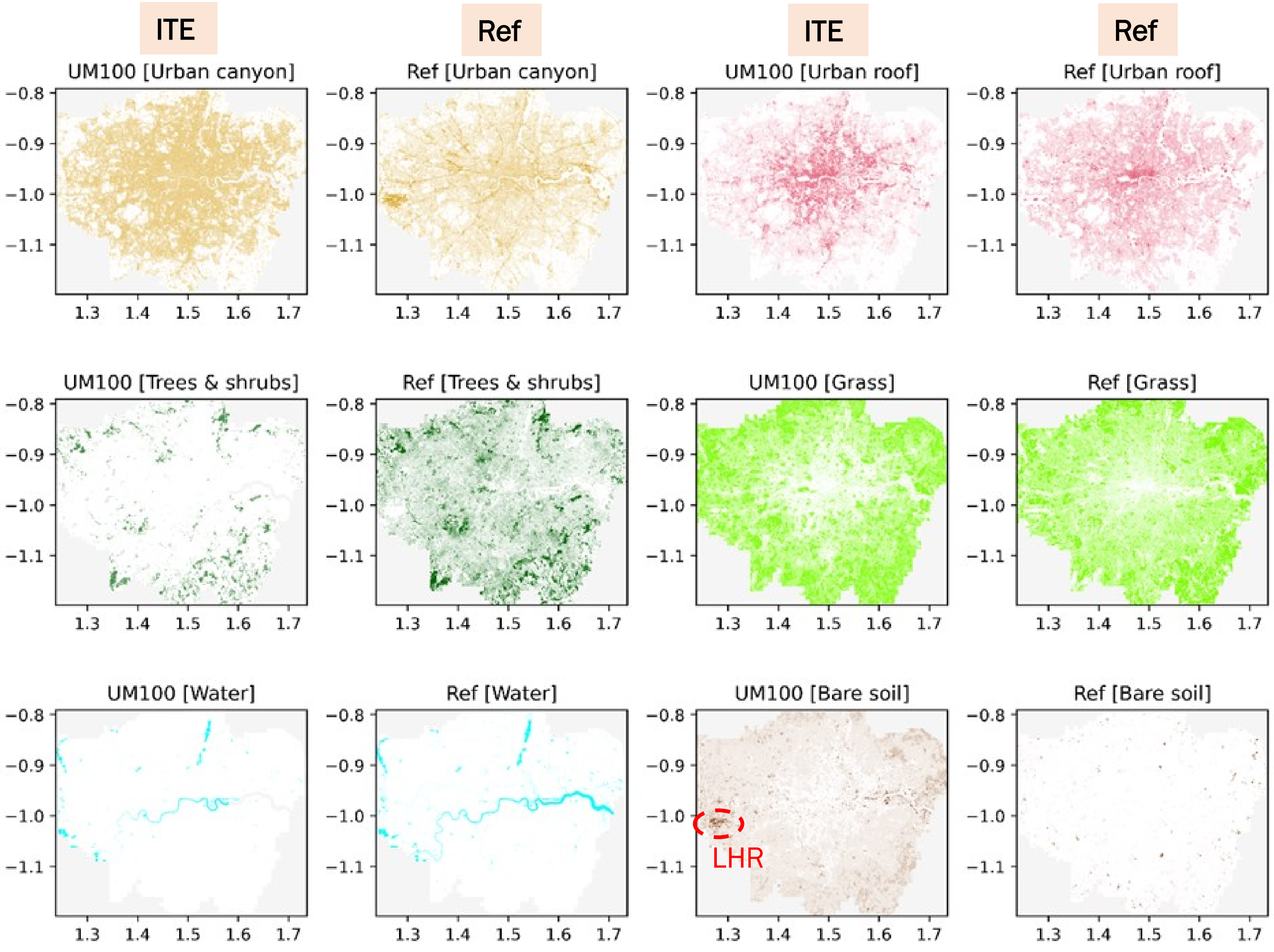
Summary statistics

Date	Mean ΔLST	St. dev. ΔLST	Corr. (r)
15/07/18	-7.00	3.03	0.36
10/10/18	-2.95	1.04	0.22
17/11/17	-0.63	1.00	0.34
22/04/20	-6.44	2.04	0.52

- Much greater mean bias (6-7K) in July & April cases cf. Oct & Nov cases
- Spatial correlation between UM100 vs Landsat LST between 0.22-0.52

Hall et al. (in preparation)

UM100 land cover description



- UM100 land cover
  - ITE (1990)
- Reference land cover &
  - 1 m LiDAR data – (details see: Lindberg and Grimmond (2011))

- ITE inconsistencies in fractions:
  - overestimates urban canyon (paved)
  - underestimates roof fraction in suburbs
  - underestimates trees/shrubs
  - overestimates bare soil

  LHR - runways ‘bare soil’ cf. ‘paved’

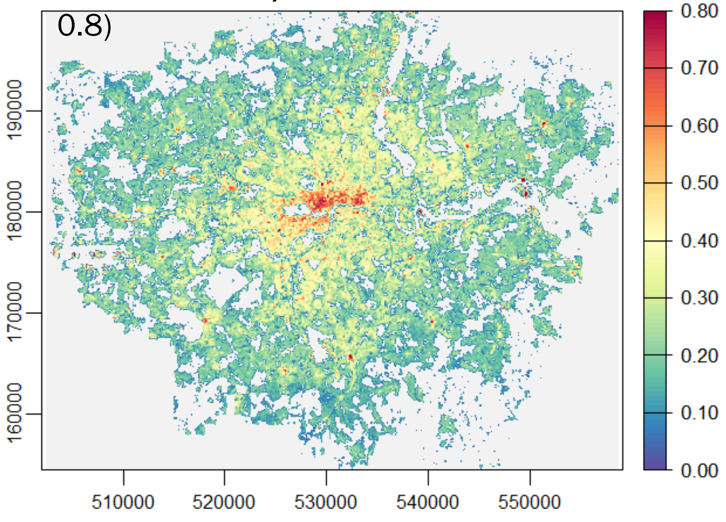
Hall et al. (in preparation)

UM100 urban form – evaluation using high resolution surface data

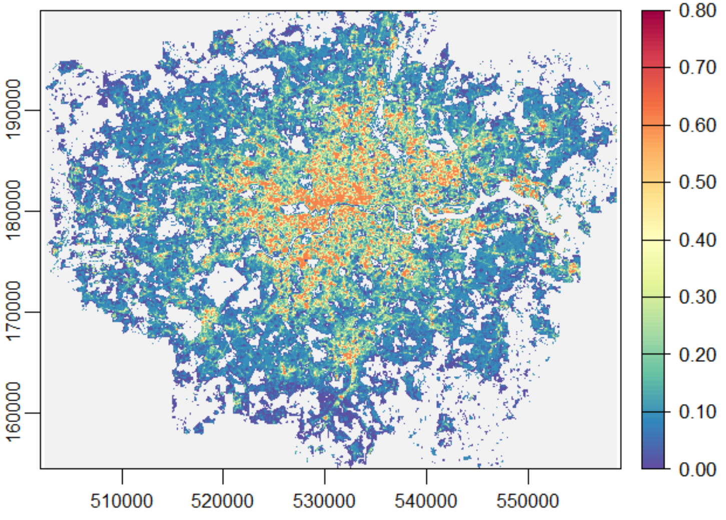
Hall et al. (in preparation)

Plan area index
Building fraction

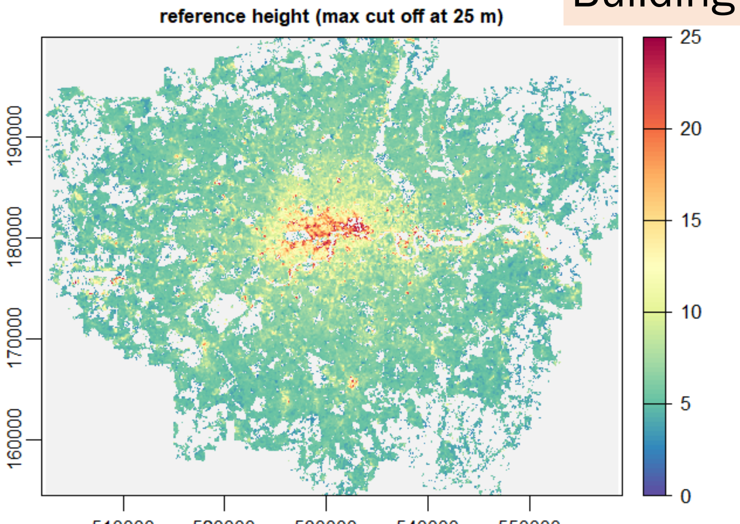
Reference /'Truth' (cutoff at 0.8)

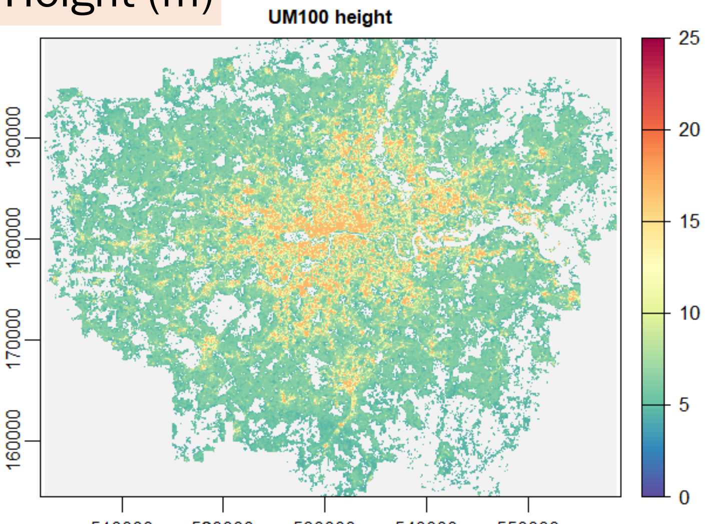


UM100



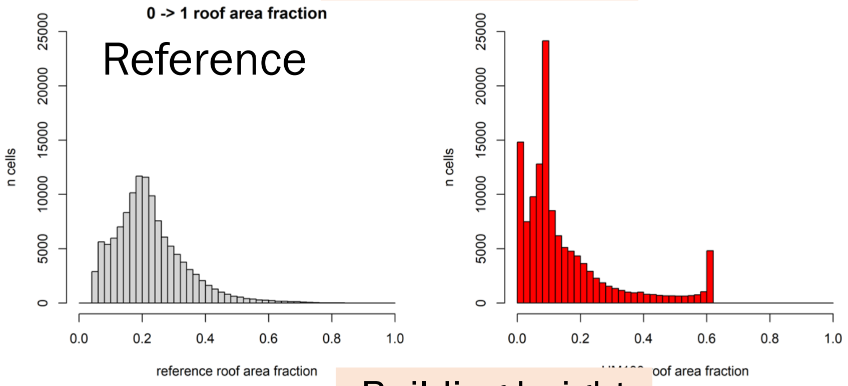
Building Height (m)



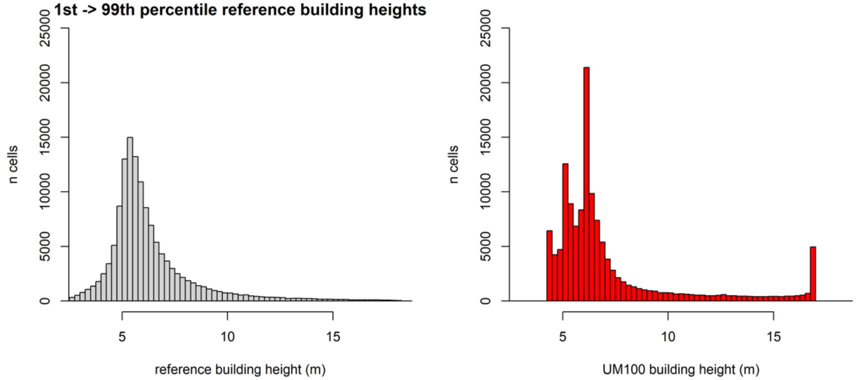


- Reference: 1 m LiDAR data aggregated to UM100 grid resolution
- UM100: ancillary data
- UM100
  - Overestimates roof area for dense areas
  - underestimates height of tall buildings

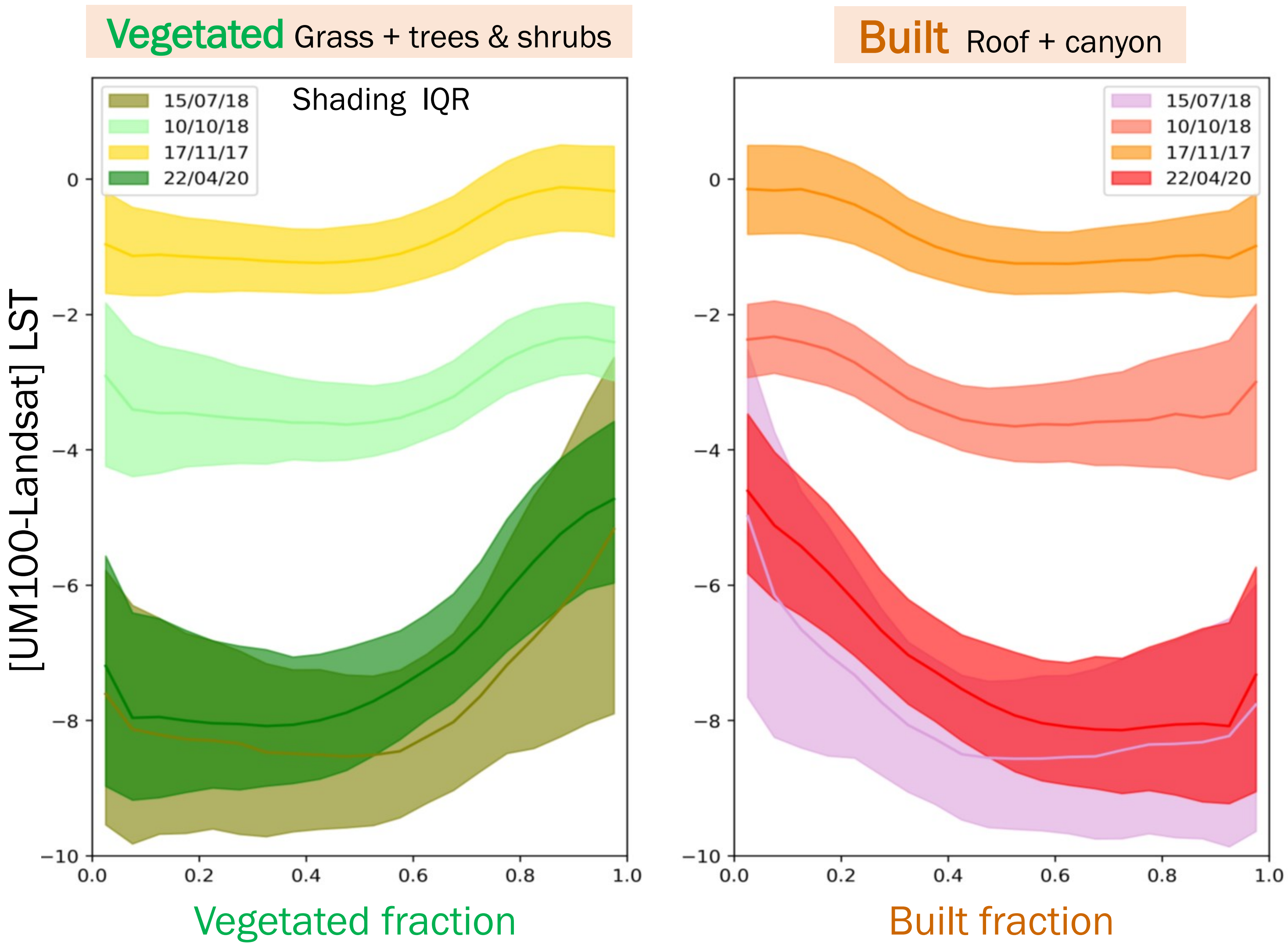
Building fraction



Building height



[UM100-Landsat]: surface dependence



REF dataset

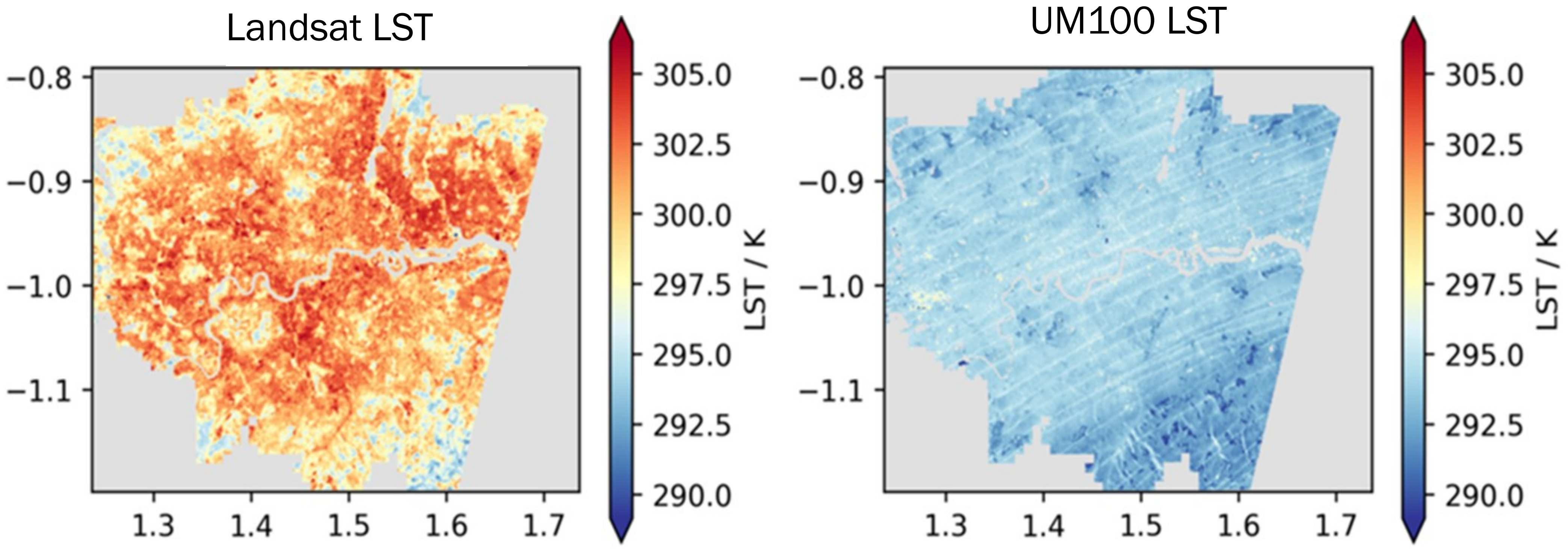
All 4 days:

- increase in bias with higher built fraction (lower vegetation)
- Stronger trends: July & April cases
  - mean bias much larger
- Increased bias with higher grass fraction (lower tree) in areas that are >80% vegetated (Ref)
- **Model bias clearly sensitive to surface type**

Hall et al. (in preparation)

Streaks/Stripes in UM100 LST

- 22/04/2020 – case investigated
- Present in UM100 but not LST
  - Three LST methods explored – and not present



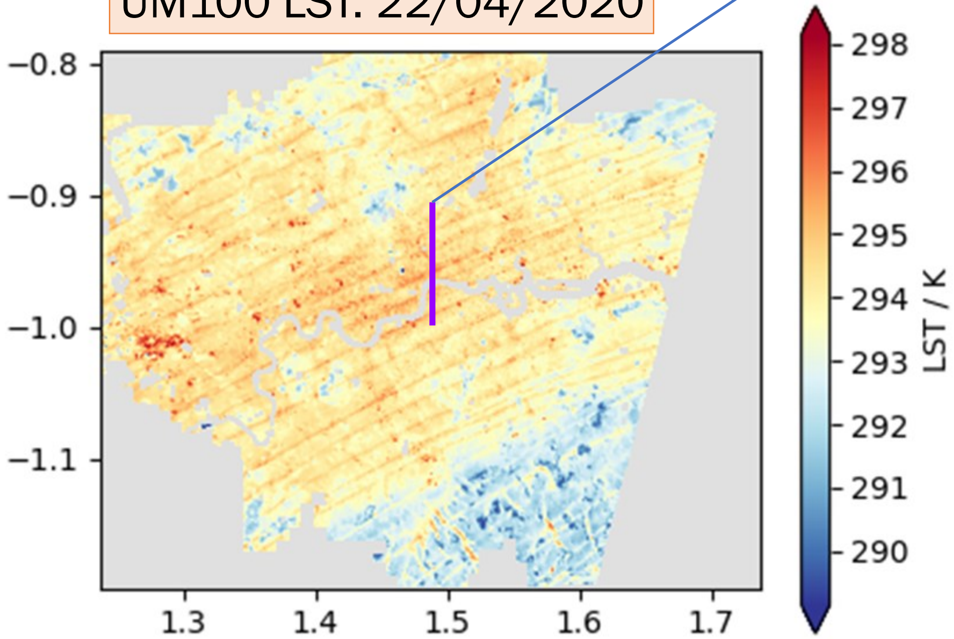
Hall et al. (in preparation)

Convective rolls?

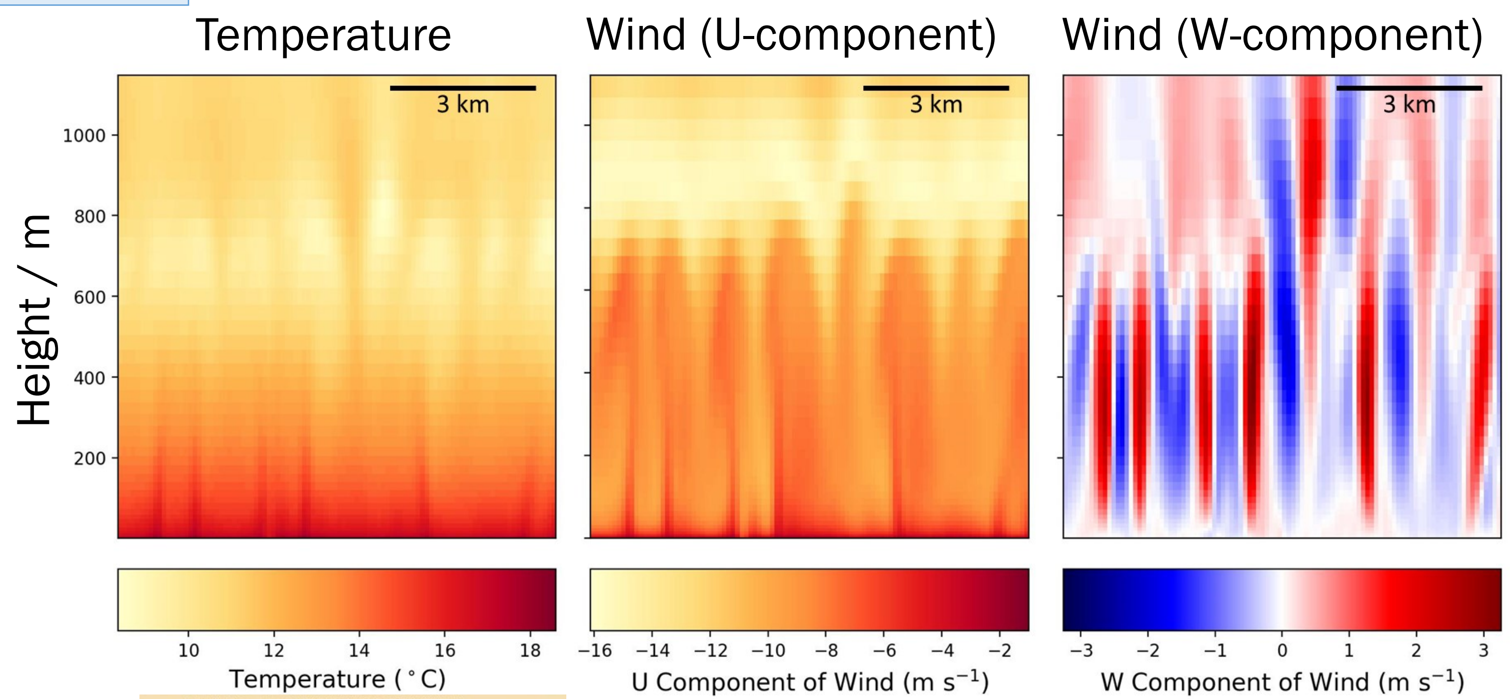
- W component indicates convective rolls
- MOST– being applied to the surface – extending impact to surface temperature

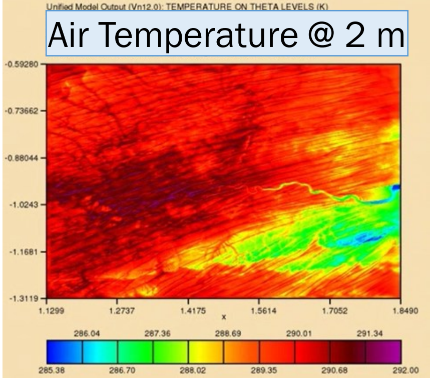
UM100 LST: 22/04/2020

Vertical cross section



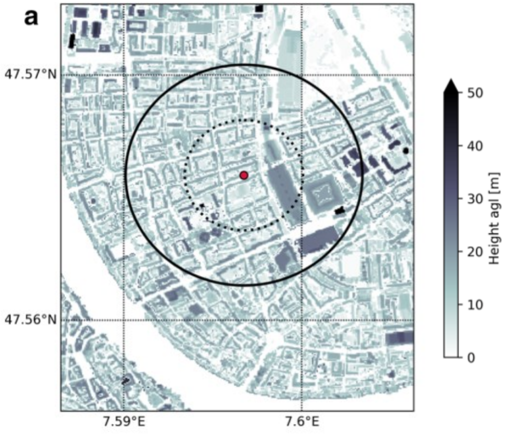
Vertical cross-sections



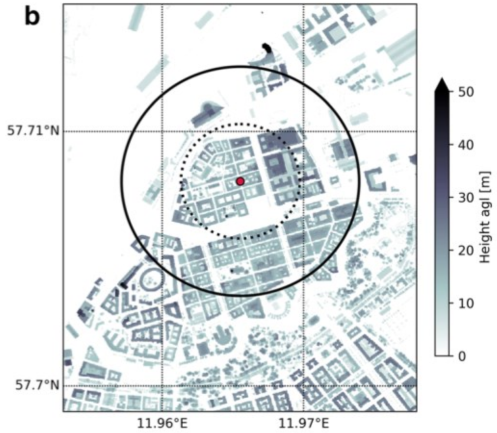


Hall et al. (in preparation)

Profiles of Eddy Covariance Sensors – Real World



Real World Observations
Basel-Sperrstrasse
Dense Uniform Terrain
Gothenburg



very unstable | unstable | Near neutral

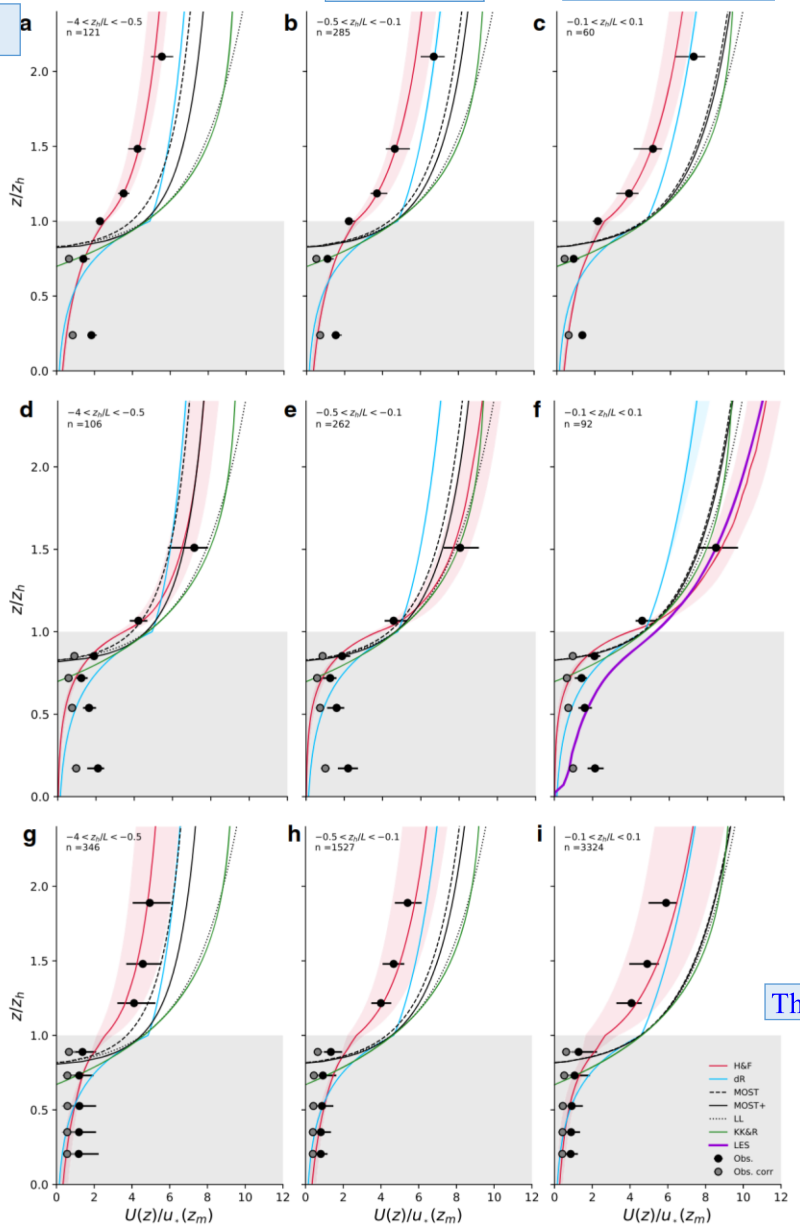
Basel-Sperrstrasse

flat-roof buildings

pitch-roof buildings

Gothenburg

perpendicular to the street canyon



Wind speed profiles normalized by friction velocity

Model

- Harman and Finnigan (2007)
- De Ridder (2010)
- Monin–Obukhov similarity theory
- MOST with stability dependent z_0
- Neutral logarithmic law
- Kastner-Klein & Rotach (2004)
- Giometto et al. (2016) LES

Observations

- Obs.
- Obs. corr

Theeuwes *et al*. (2019) *BLM* https://doi.org/10.1007/s10546-019-00472-1

Urban areas are more complex: Tall buildings (TB) large influence on wind profiles

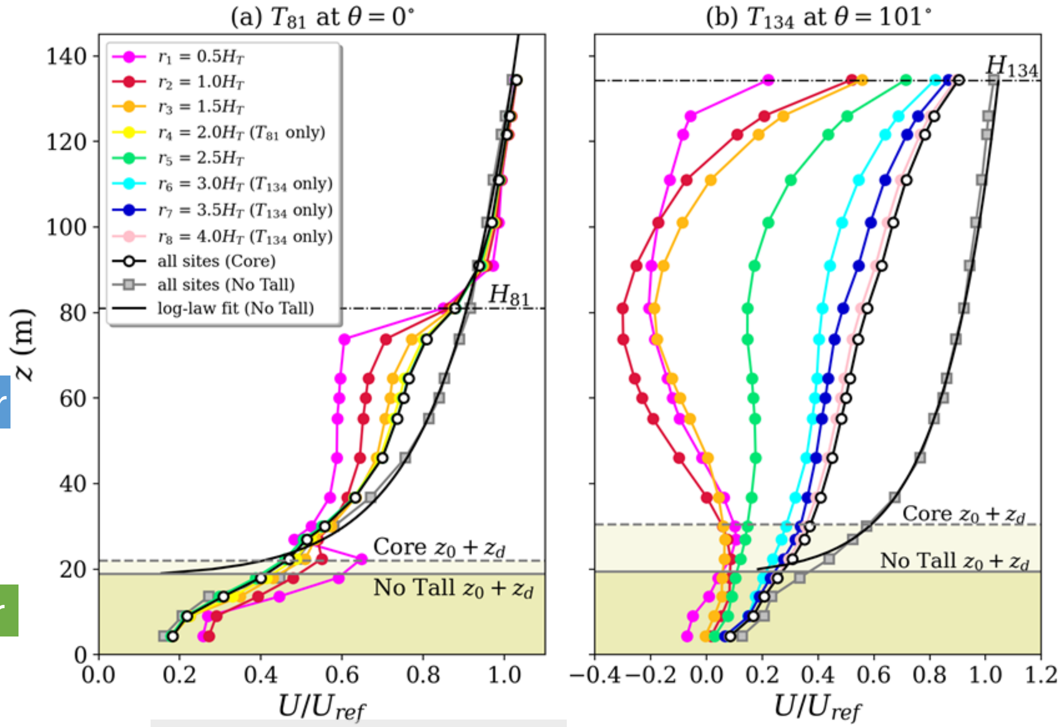
Mean longitudinal (along-wind) velocity (U/U_{ref}) ensemble mean

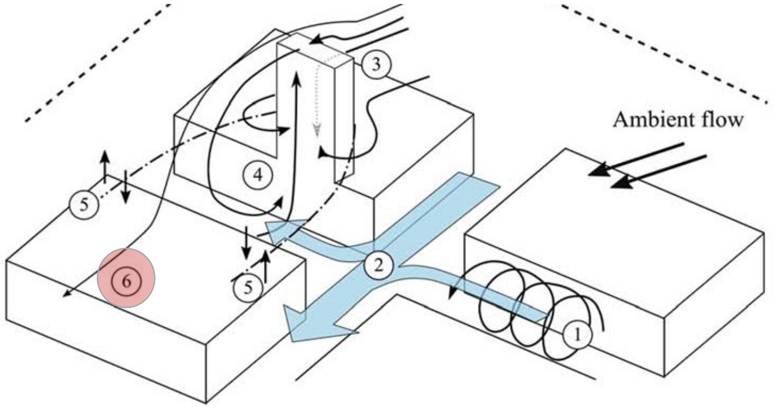
- all sites (Core)
- all sites (No Tall)
- log-law fit (No Tall)

Micro

Roughness sub layer

Urban Canopy Layer

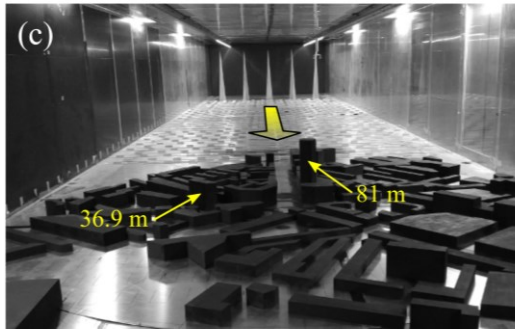


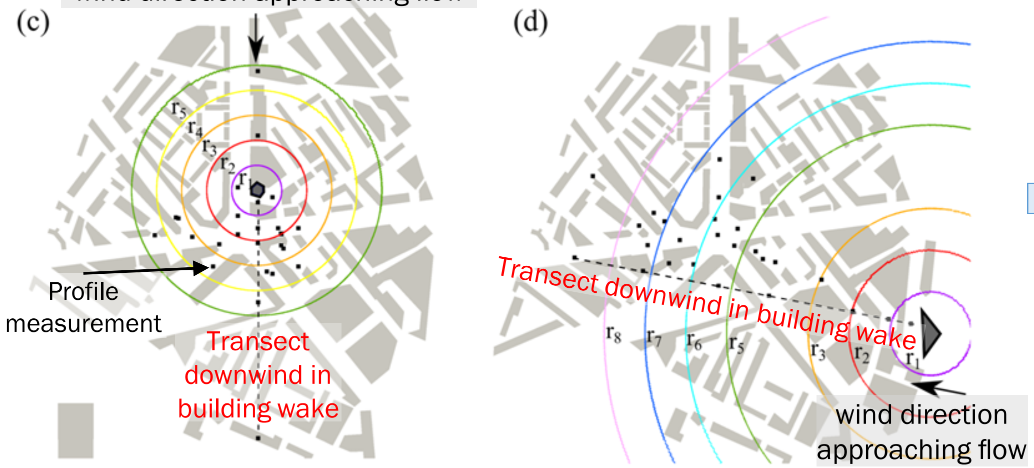


Street scale & tall-building flow

1. Helical street canyon vortex
2. Flow exchange in intersection
3. Down- and upward flow (windward face)
4. Near wake with recirculation and upward flow
5. Horseshoe vortex with secondary flow
6. Main wake

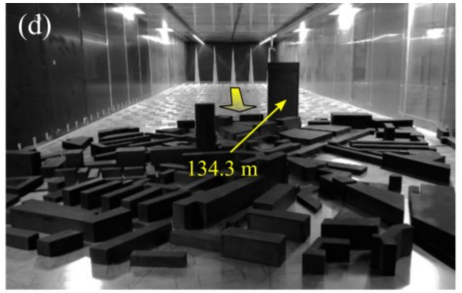
University of Surrey Wind Tunnel Isolated Tall Buildings (London)





Distance from TB: radii (colour arcs) *0.5 H_{TB} increments*

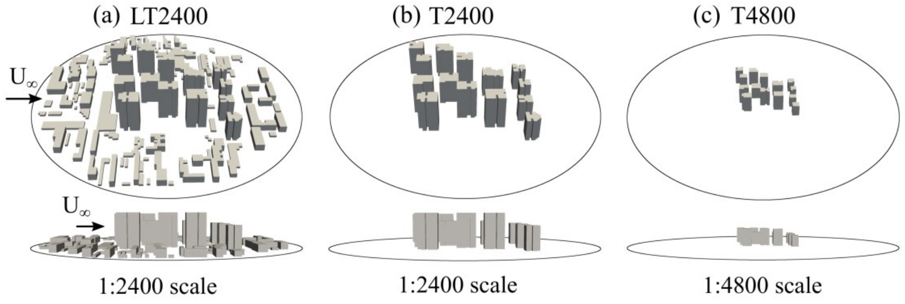
- $r_1 = 0.5H_T$
- $r_2 = 1.0H_T$
- $r_3 = 1.5H_T$
- $r_4 = 2.0H_T$ (T_{81} only)
- $r_5 = 2.5H_T$
- $r_6 = 3.0H_T$ (T_{134} only)
- $r_7 = 3.5H_T$ (T_{134} only)
- $r_8 = 4.0H_T$ (T_{134} only)

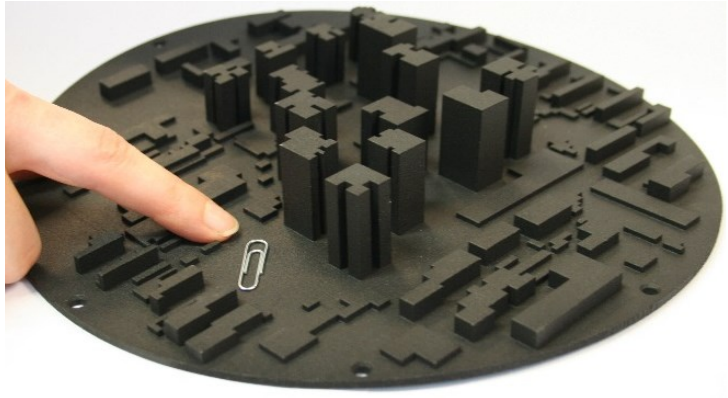


Hertwig *et al.* (2019) ***BLM*** https://doi.org/ 10.1007/s10546-019-00450-7

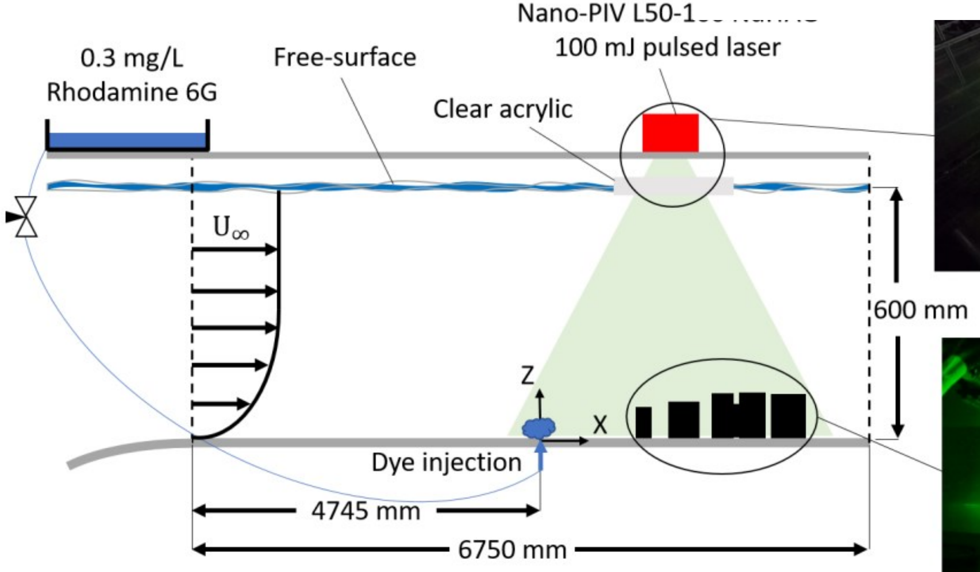
Hertwig et al. (2021) *Faraday Discussions* https://doi.org/10.1039/D0FD00098A

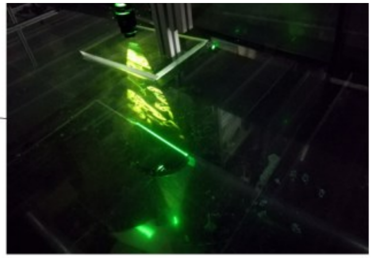
Cluster of Tall Buildings (Beijing) - Univ. of Southampton Water flume

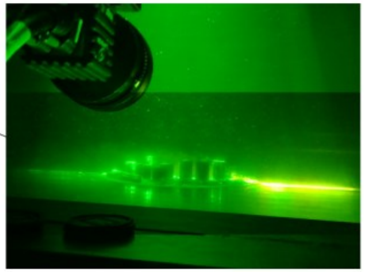


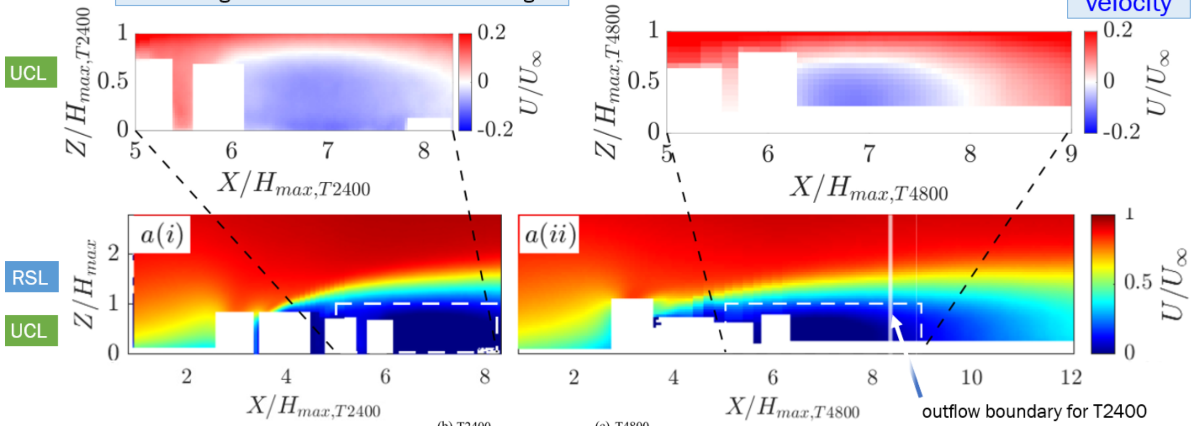


Particle Image Velocimetry (PIV) and Planar Laser Induced Fluorescence (PLIF)

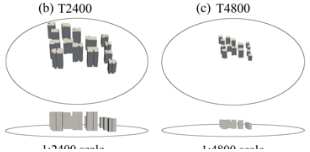








T2400



T4800

Lim et al. 2022: *Experiments in Fluids*

Hertwig et al. 2021 *Faraday Discussions* https://doi.org/10.1039/D0FD00098A
Lim et al. 2022: *Experiments in Fluids* 63:92 https://doi.org/10.1007/s00348-022-03439-0

Final Comments

- **Massive challenge characterising the city**
  - Form/Materials (surface, facets internal) for radiation and conduction/ Human activities
  - Needed for Observations, Modelling and Services – ideally consistent! Needs to be kept up to date
  - Known errors in model surface ancillary information (e.g. bare soil%) propagate into the modelled surface temperatures, complicating model evaluation

- **Vertical variations of radiation** - SPARTACUS-Surface perform well cf. DART
  - Assumes random horizontal position of obstacles (buildings) – with higher resolution – will become increasingly problematic
  - DART – ORM - computationally unfeasible for NWP but very helpful for evaluating simpler NWP schemes.

- Landsat LST data helps:
  - Identify model issues/biases e.g. unrealistic blocky spatial patterns in LST
  - → Updates to UM100 model configuration
  - → More realistic surface temperature distribution, although increased overall bias
  - Identification of small-scale features such as "convective rolls"
    - High resolution LST data essential
- Model bias appears to be greatest in more built-up areas
  - More work needed to fully understand the causes – including using **other observations and ORM**
  - Need to consider what satellite FOV

• LST retrieval details

Single band retrieval:

Upwelling — Emitted — Reflected

$$L_{TOA}(\lambda) = L_{\uparrow}(\lambda) + \varepsilon_\lambda L_s(\lambda) t_\lambda + (1 - \varepsilon_\lambda) t_\lambda L_{\downarrow}(\lambda)$$

$$= \sum_i B_\lambda(T_i)\Delta t + \varepsilon_\lambda B_\lambda(T_s) t_\lambda + (1 - \varepsilon_\lambda) t_\lambda \sum_i \frac{B_\lambda(T_i)\Delta t}{t_{i-0.5} t_{i+0.5}}$$

From Saunders et al. (1999)

L_{TOA} top-of-atmosphere radiance [observed]
T_s surface temperature
B_λ Planck function
ε_λ surface emissivity
t_λ transmittance (from surface) [RTM]
t_i level *i* to space transmittance
T_i temperature at level *i* [NWP]

- RTM = RTTOV used to obtain transmittance, upwelling and downwelling radiances
  - Atmospheric profiles from ERA5 used as input to RTM

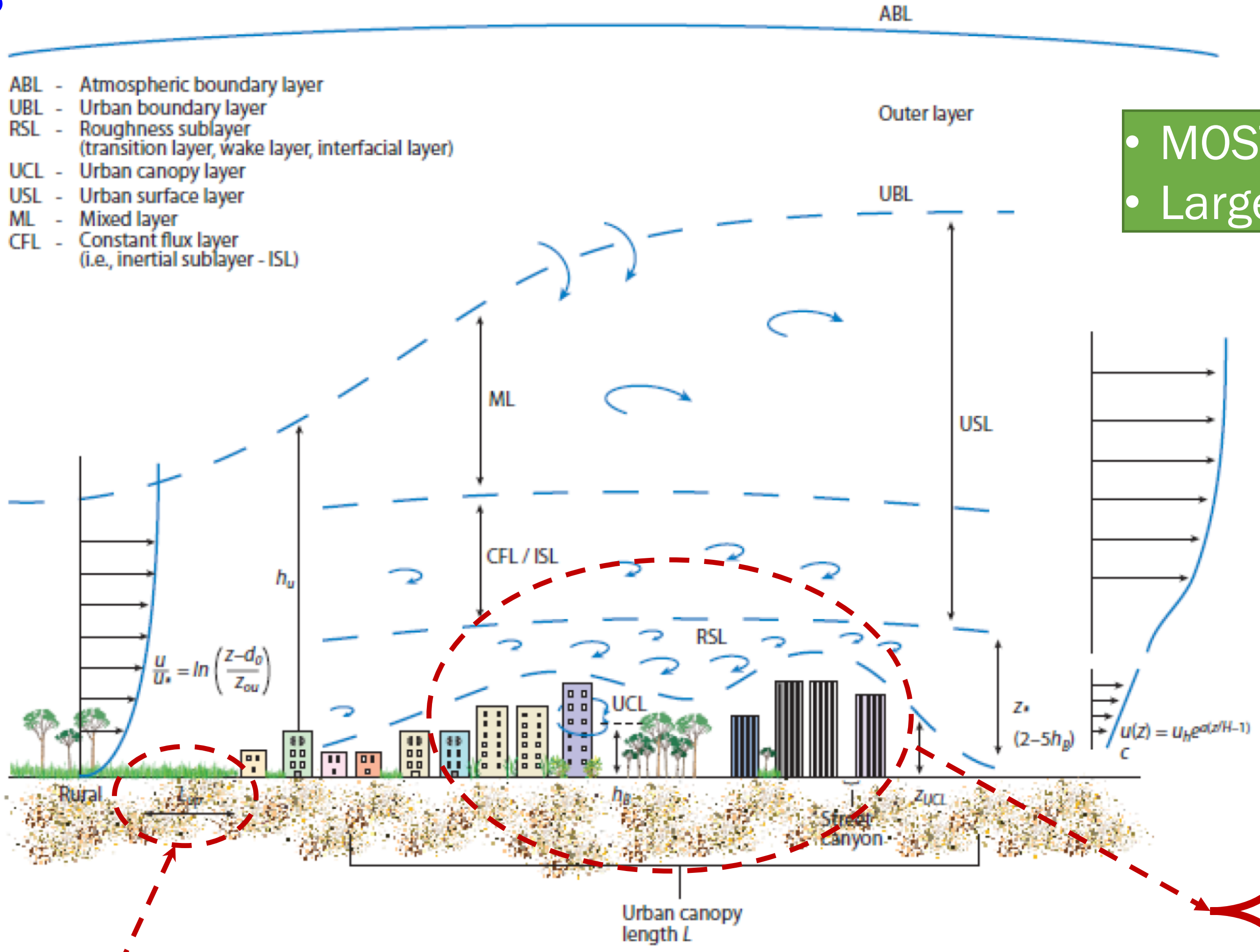
- Emissivity (ε_λ) from ASTER Global Emissivity Dataset (GED)

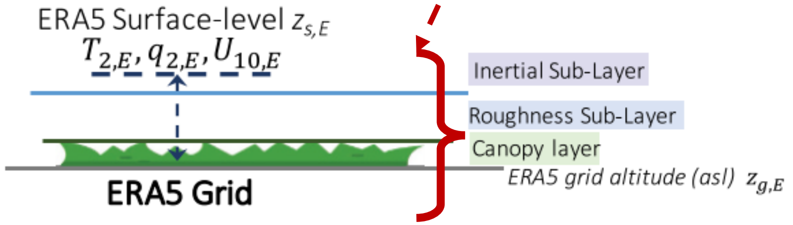
UK CLIMATE RESILIENCE PROGRAMME

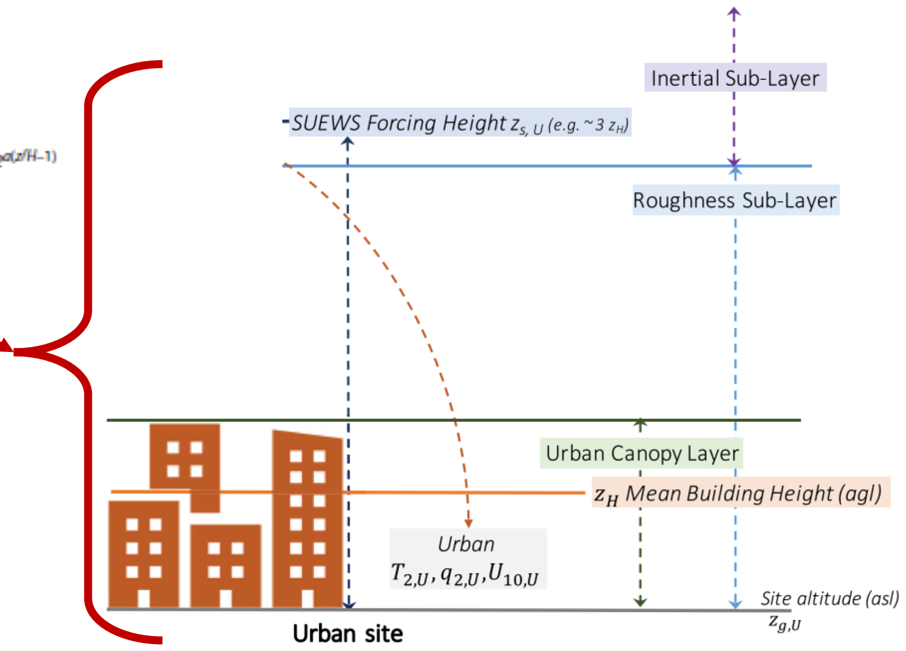
Met Office UK Research and Innovation

Challenges

- MOST – breaks down close to the surface
- Large roughness elements







Fernando 2010: https://doi.org/10.1146/annurev-fluid-121108-145459

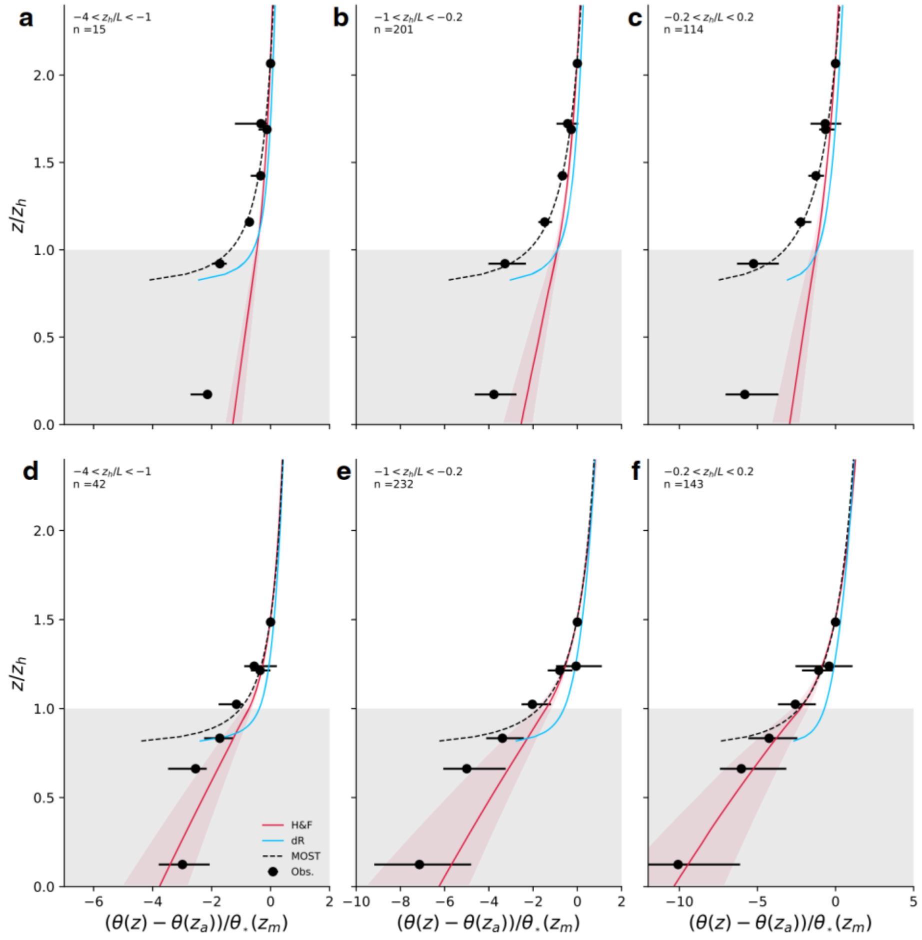
Tang et al. 2021: Building and Environment, https://doi.org/10.1016/j.buildenv.2021.108088

Temperature Profile - Different stabilities

very unstable | unstable | Near neutral

flat-roof buildings

pitch-roof buildings



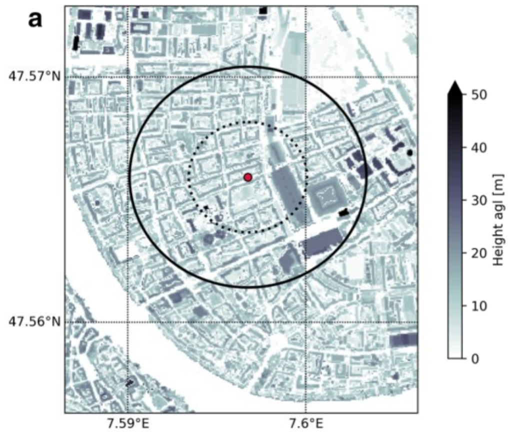
H&F — Harman and Finnigan (2007)

dR — De Ridder (2010)

MOST — Monin–Obukhov similarity theory

Obs.

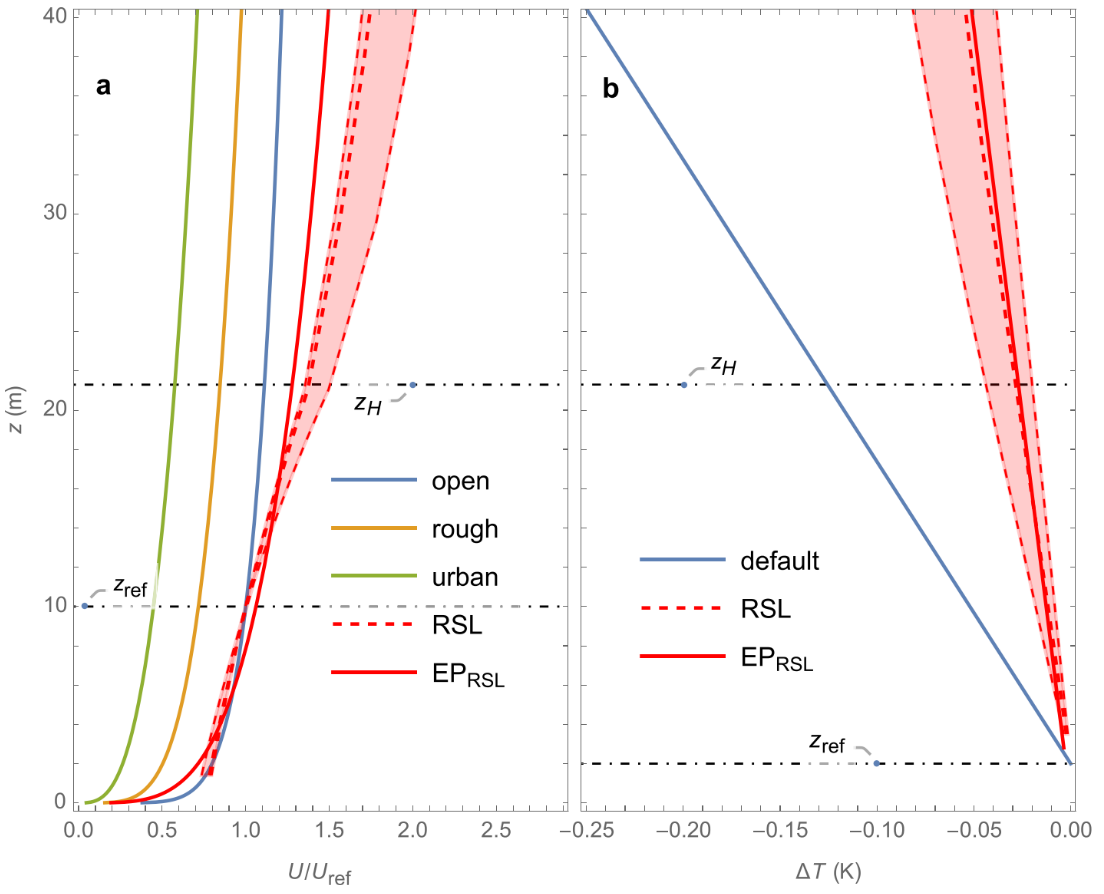
Basel-Sperrstrasse

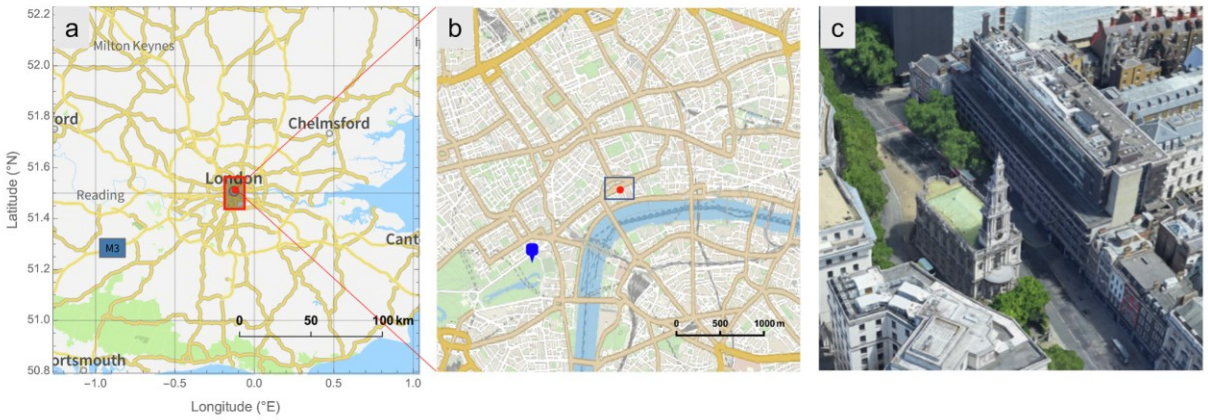


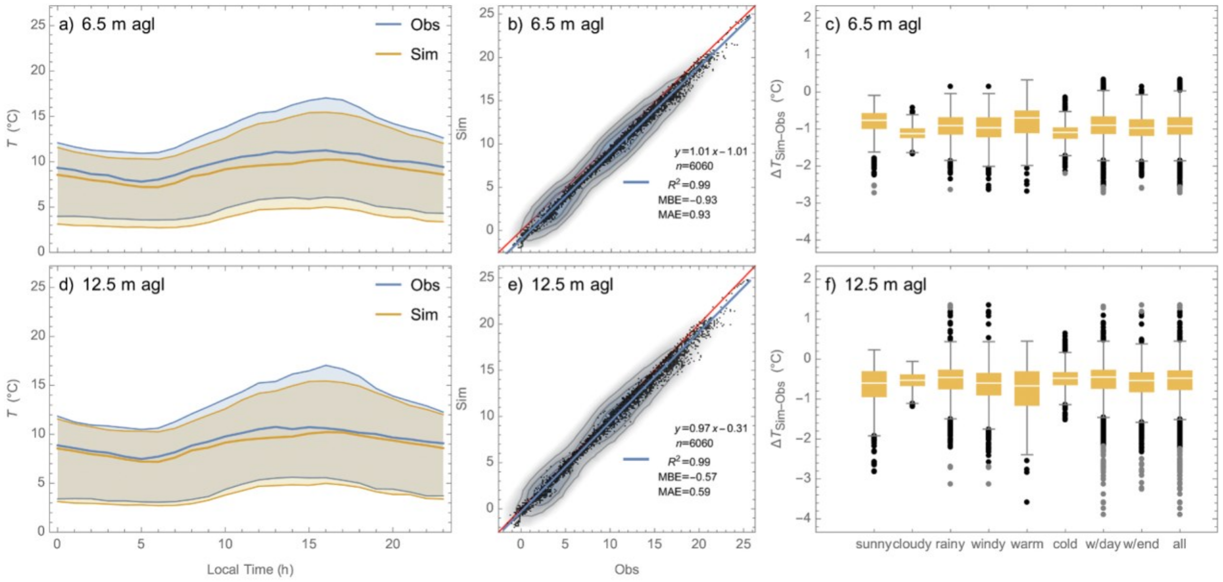
Theeuwes *et al*. (2019) *BLM* https://doi.org/10.1007/s10546-019-00472-1

Couple RSL Profile Evaluation in London

- Couple Harman and Finnigan RSL model to local scale urban canopy model (SUEWS)
- Diagnose profiles down to the ground





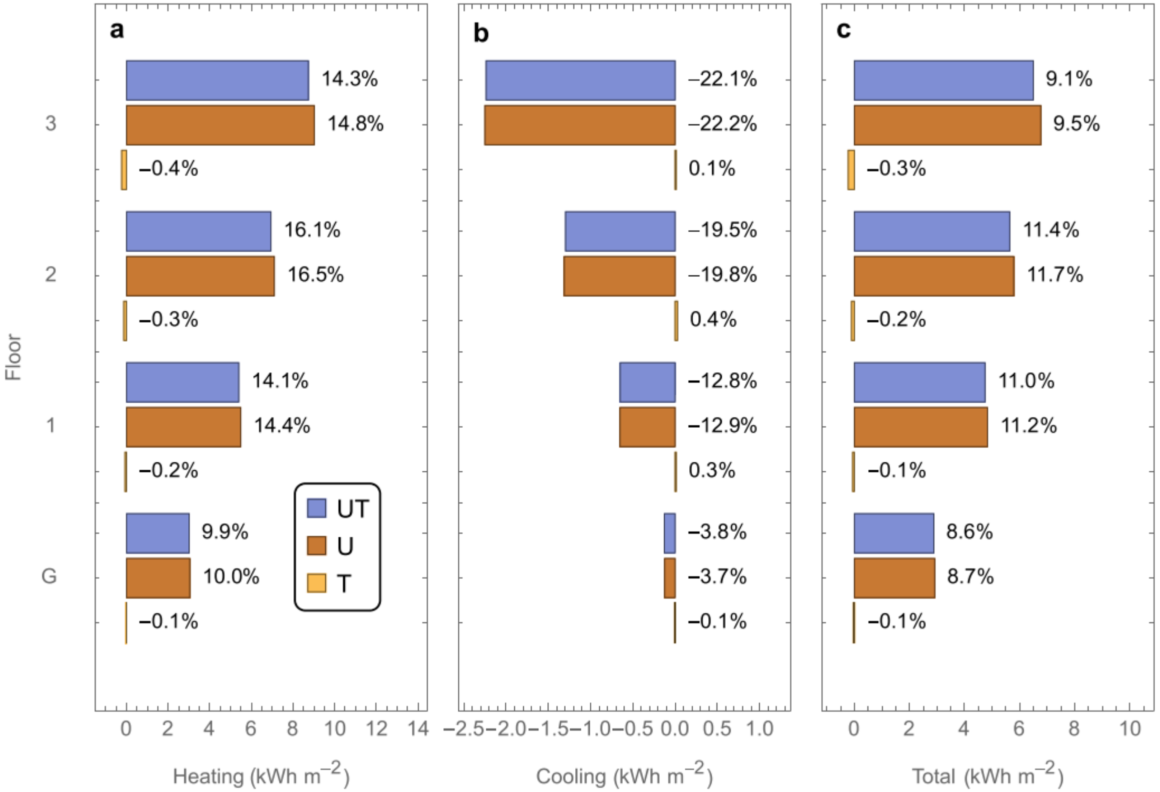


Tang et al. 2021: Building and Environment, https://doi.org/10.1016/j.buildenv.2021.108088

Improving urban services (building energy consumption, overheating) using coupled ULSM/RSL

EnergyPlus simulated annual energy load

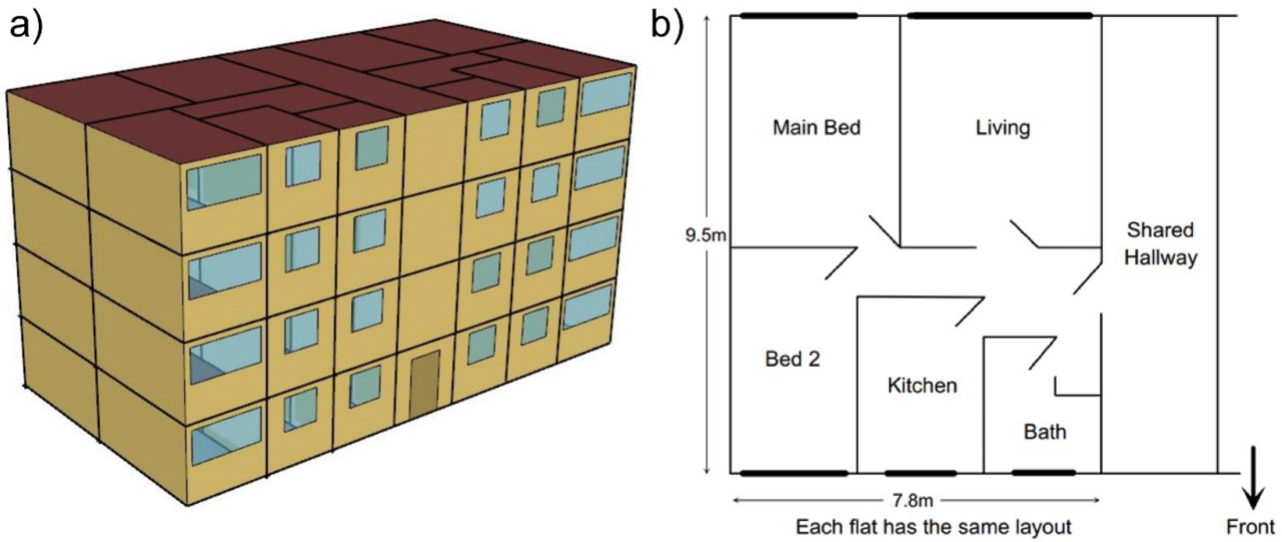
Heating | Cooling | Total



U Wind
T Temperature
UT U & T

[new – default$_{open\ terrain}$]
(%): diff. normalised by open terrain values

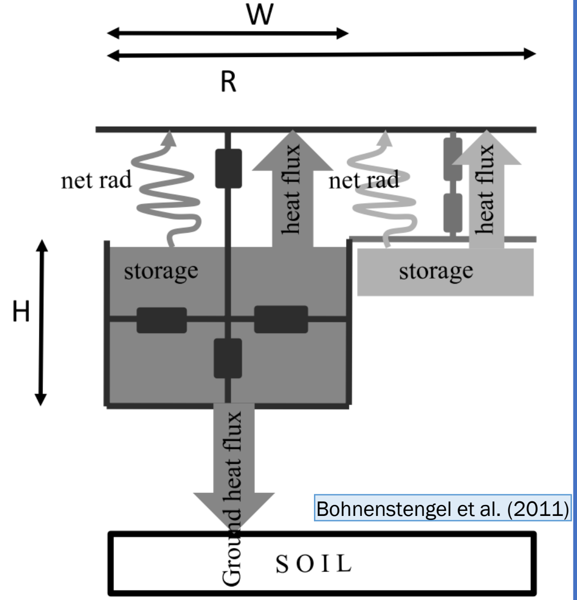
- Improved weather forcing at neighbourhood scale to for neighbourhood and building scale applications
- Implications (examples):
  - Human comfort
  - Energy needs
  - CO_2 emissions



Tang et al. 2021: Building and Environment, https://doi.org/10.1016/j.buildenv.2021.108088

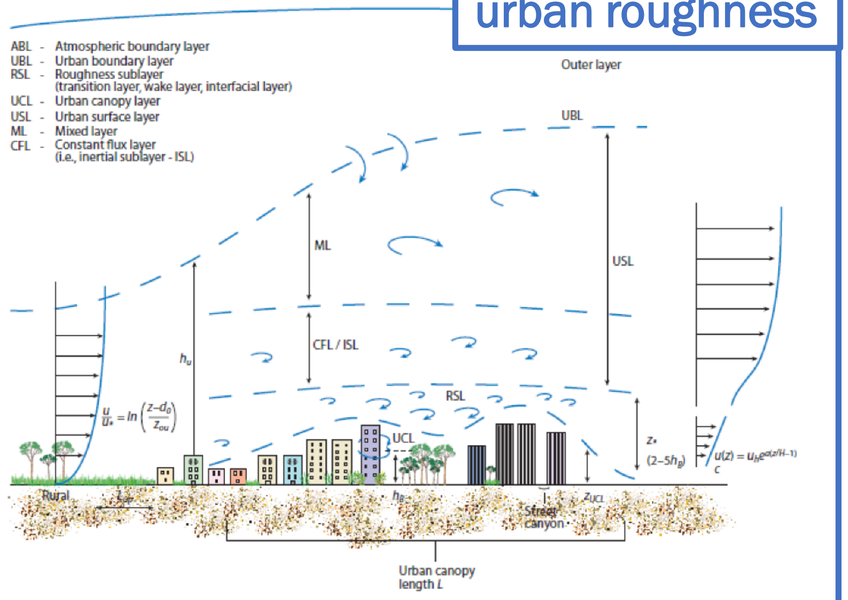
Urban Characteristics

urban morphology

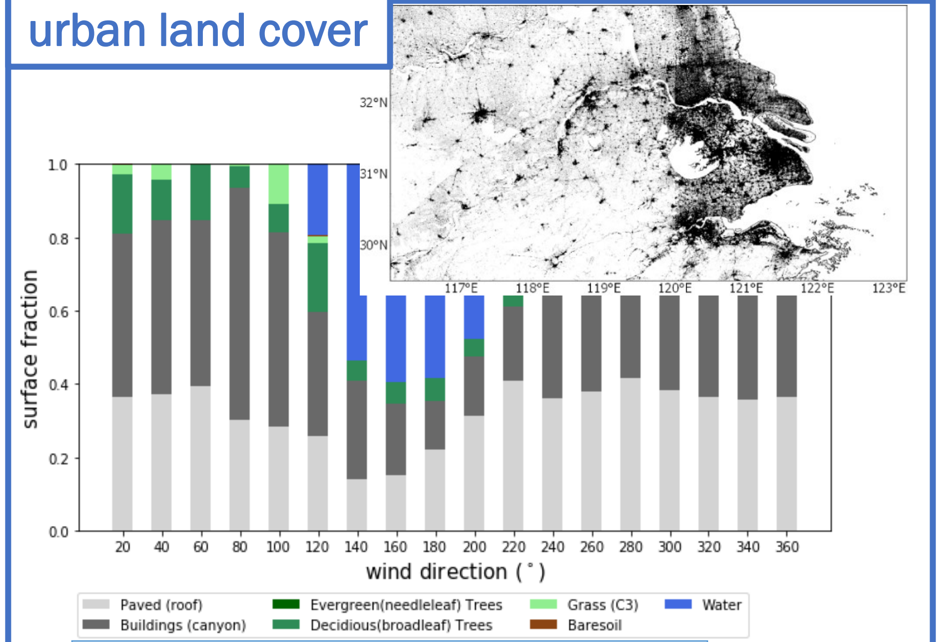


Bohnenstengel et al. (2011)

urban roughness



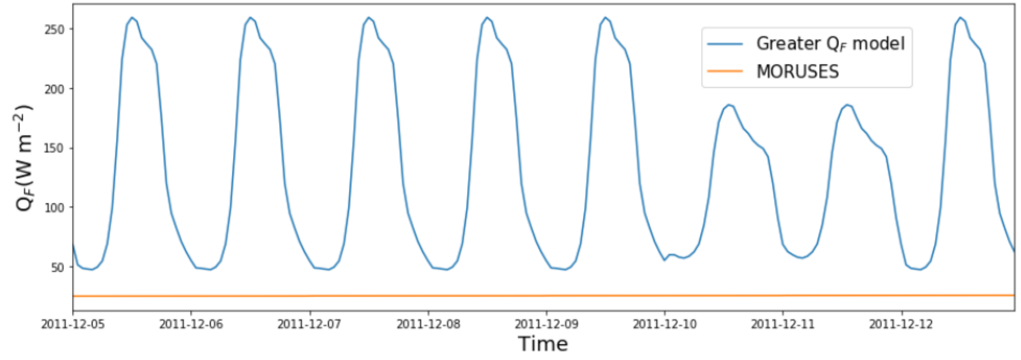
urban land cover



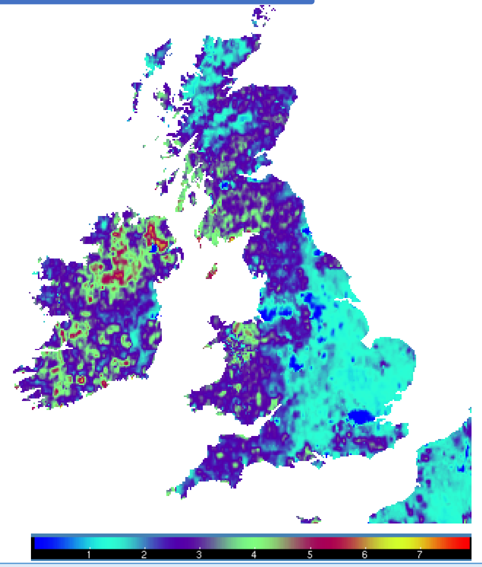
Hertwig et al. (2021) https://doi.org/10.1002/joc.7018

anthropogenic heat

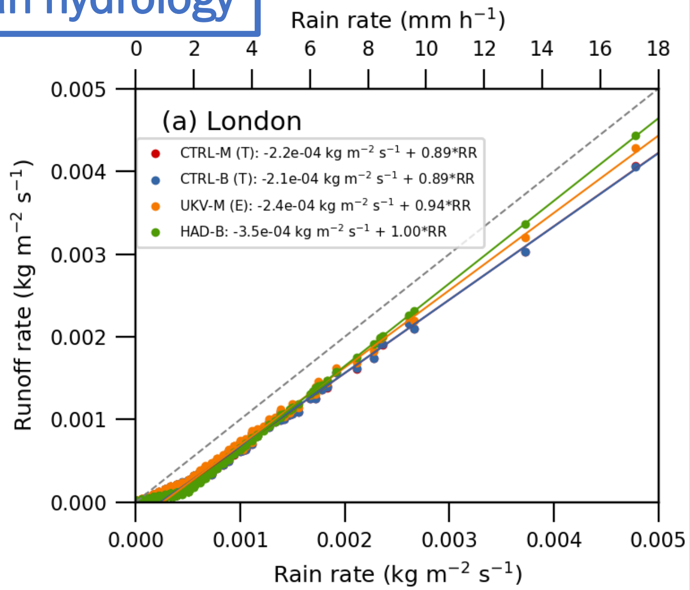
Treated as parameter- should be dynamic



urban phenology



urban hydrology

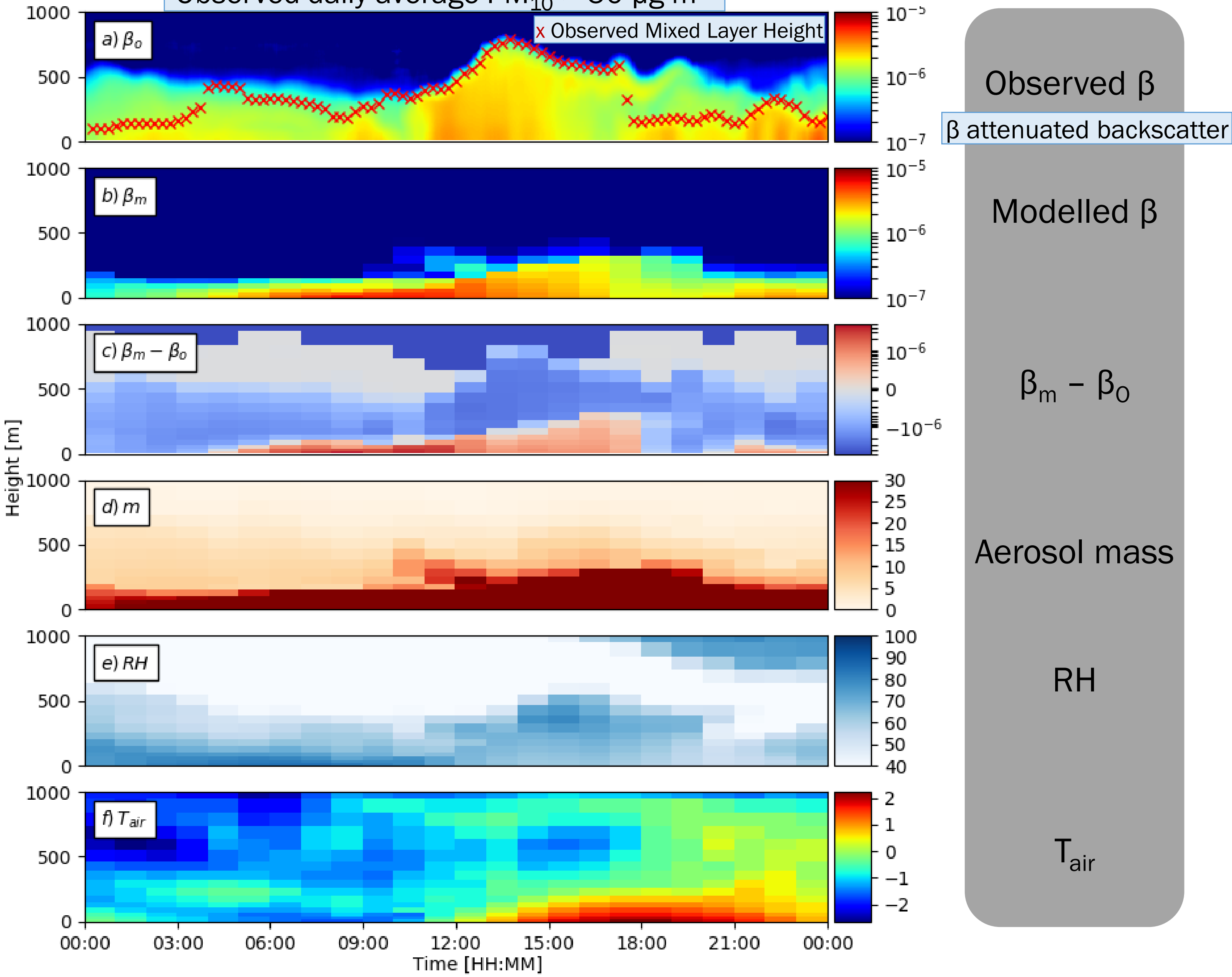


Hertwig et al. (2021) *TAAC* https://doi.org/10.1007/s00704-020-03294-1

Model: Operational NWP Met Office UKV with Best-1T scheme
Observations: Ceilometer with Forward Operator (aerFO)

Automatic Lidar and Ceilometer ALC

High pollution day London (19 January 2016)
Observed daily average PM_{10} > 50 µg m^{-3}

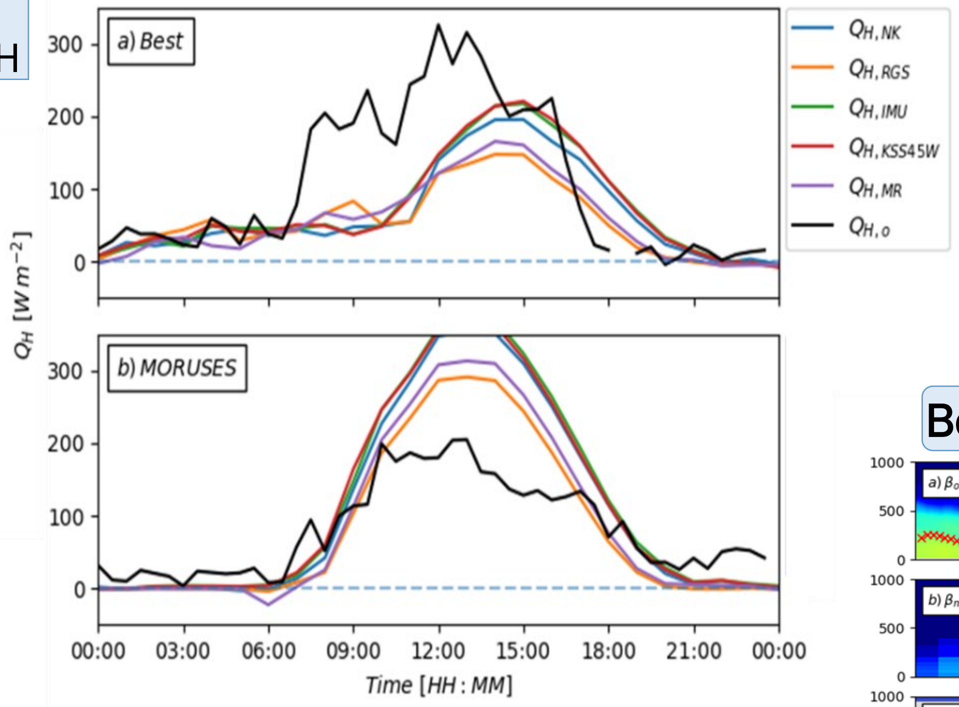


- Persistent high β_m near the surface
- Aerosol: insufficiently mixed in the vertical due to **lack of aerosol dispersion**
- Earlier dates – could identify emission inventory problems

Warren et al. (2018) https://doi.org/10.1016/j.atmosenv.2018.04.045

Model: UKV: changed urban scheme: Best 1-tile → MORUSES (*15/Mar/16*)
Observations: Eddy covariance, Ceilometer with Forward Operator (aerFO)

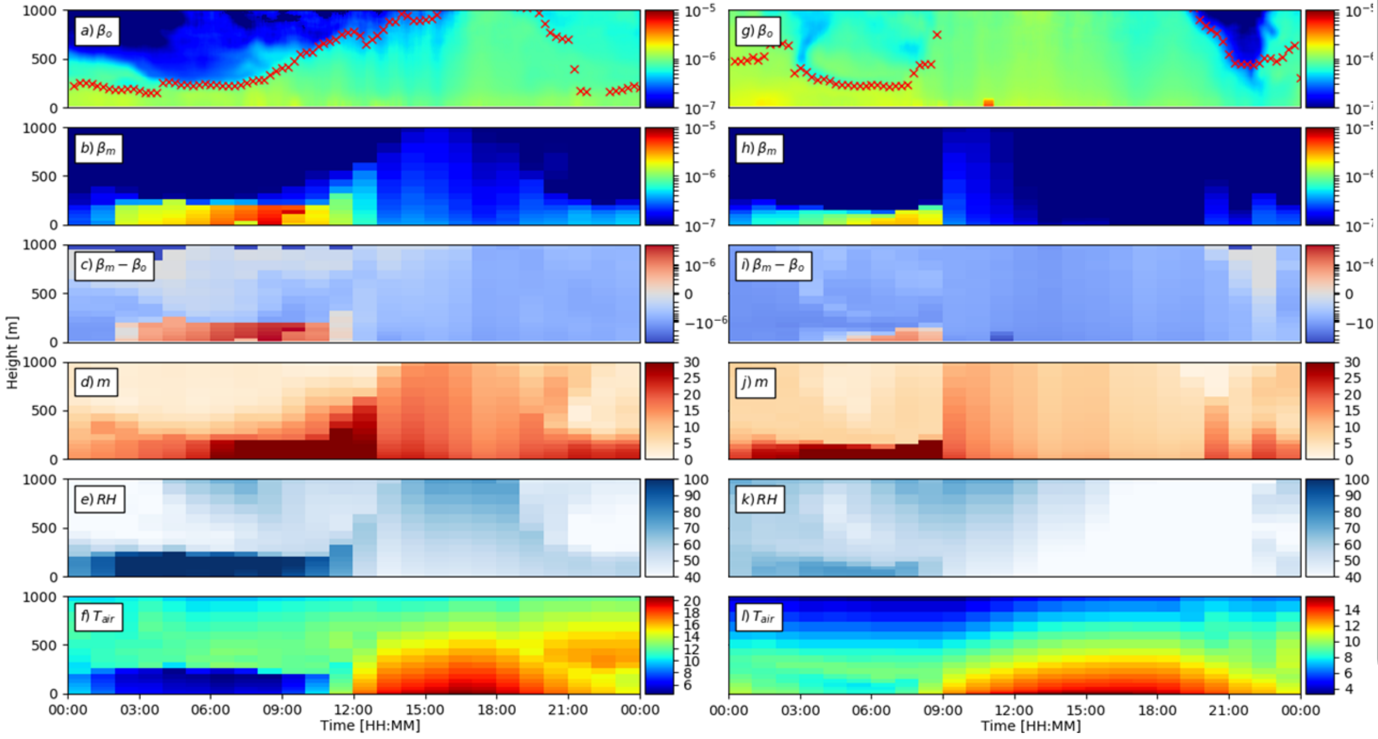
Q_H



Sensible heat flux near surface evaluation

- Morning near-surface β_m
  - 1-tile - high throughout
  - MORUSES – less
- Cold surface bias →delayed vertical mixing of m_{MURK} and high RH

Best 1 tile - 14 April 2015 **MORUSES** - 04 May 2016



X Observed Mixed Layer Height

Observed β

β attenuated backscatter

Modelled β

$\beta_m - \beta_o$

Aerosol mass

RH

T_{air}

Warren et al. (2018) https://doi.org/10.1016/j.atmosenv.2018.04.045

Fluxes: EC - long term measurements

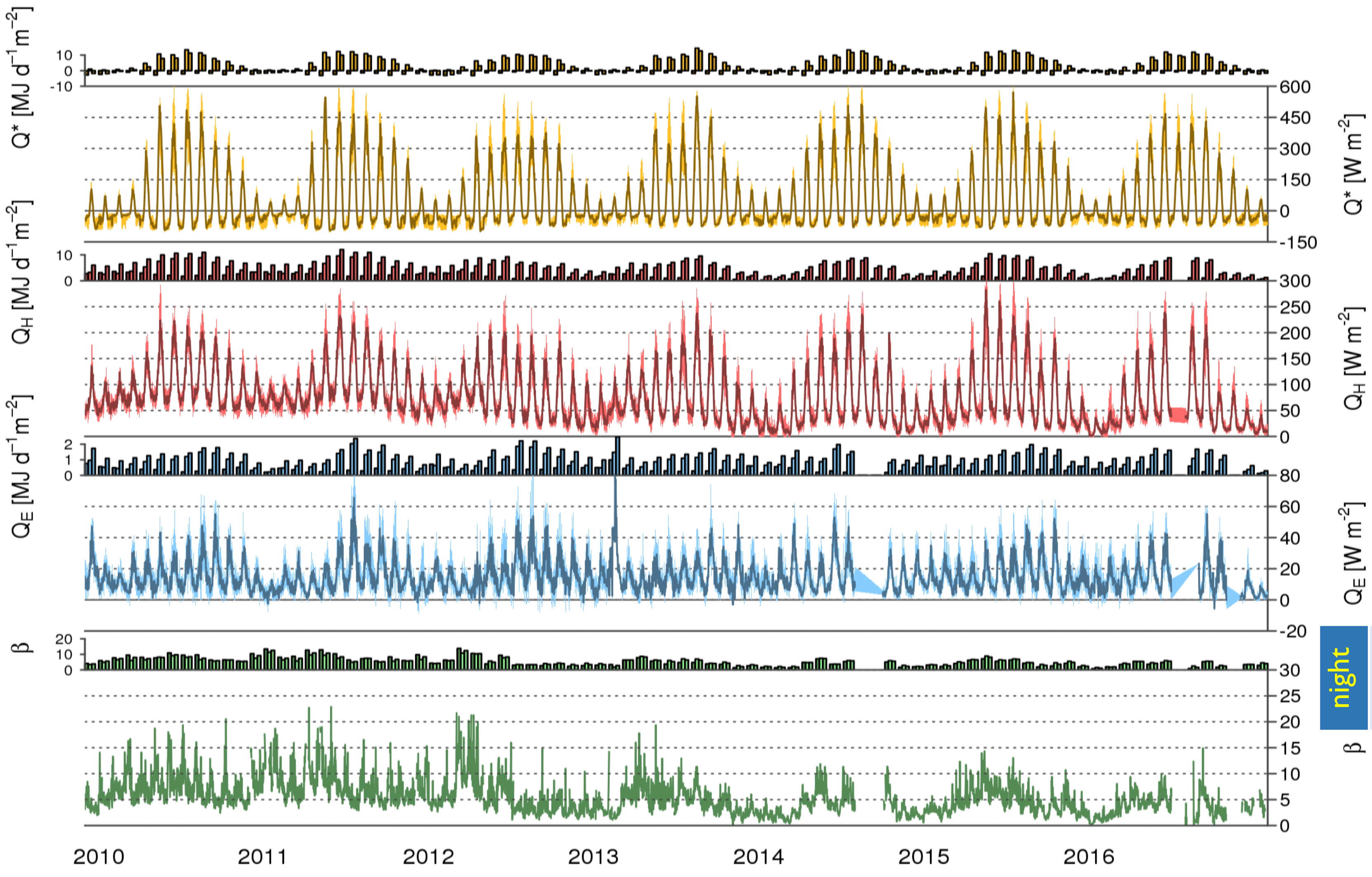
Monthly Median Diurnal Cycle, shaded IQR, KSS

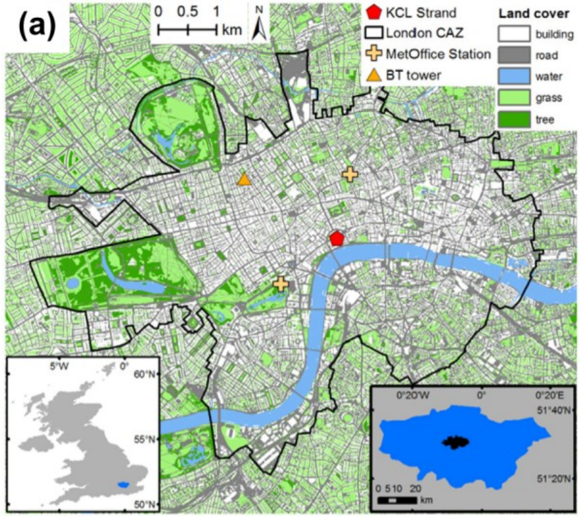
Q*

Q_H

Q_E

β



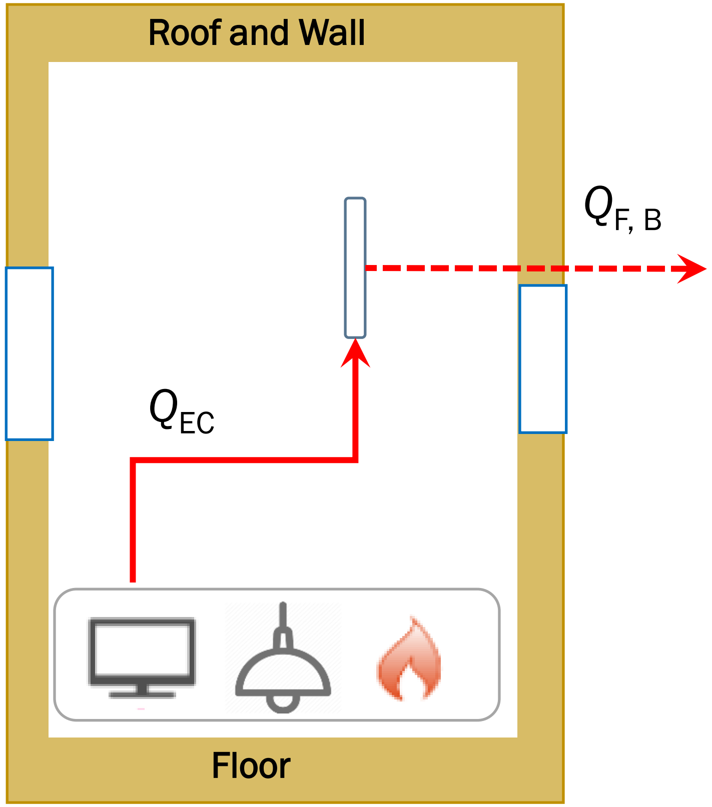


Kotthaus & Grimmond (2014a) *Urban Climate*

Anthropogenic heat flux from buildings $Q_{F,B}$

- Inventory methods to estimate $Q_{F,\,B}$ ⇒ Building energy consumption data

⇓



Assumptions:

$$Q_{F,\,B} = Q_{EC}$$

Consumed energy is emitted outdoors immediately

Liu et al. 2022: *Atmos. Chem. Phys.*, 22, 4721–4735, https://doi.org/10.5194/acp-22-4721-2022