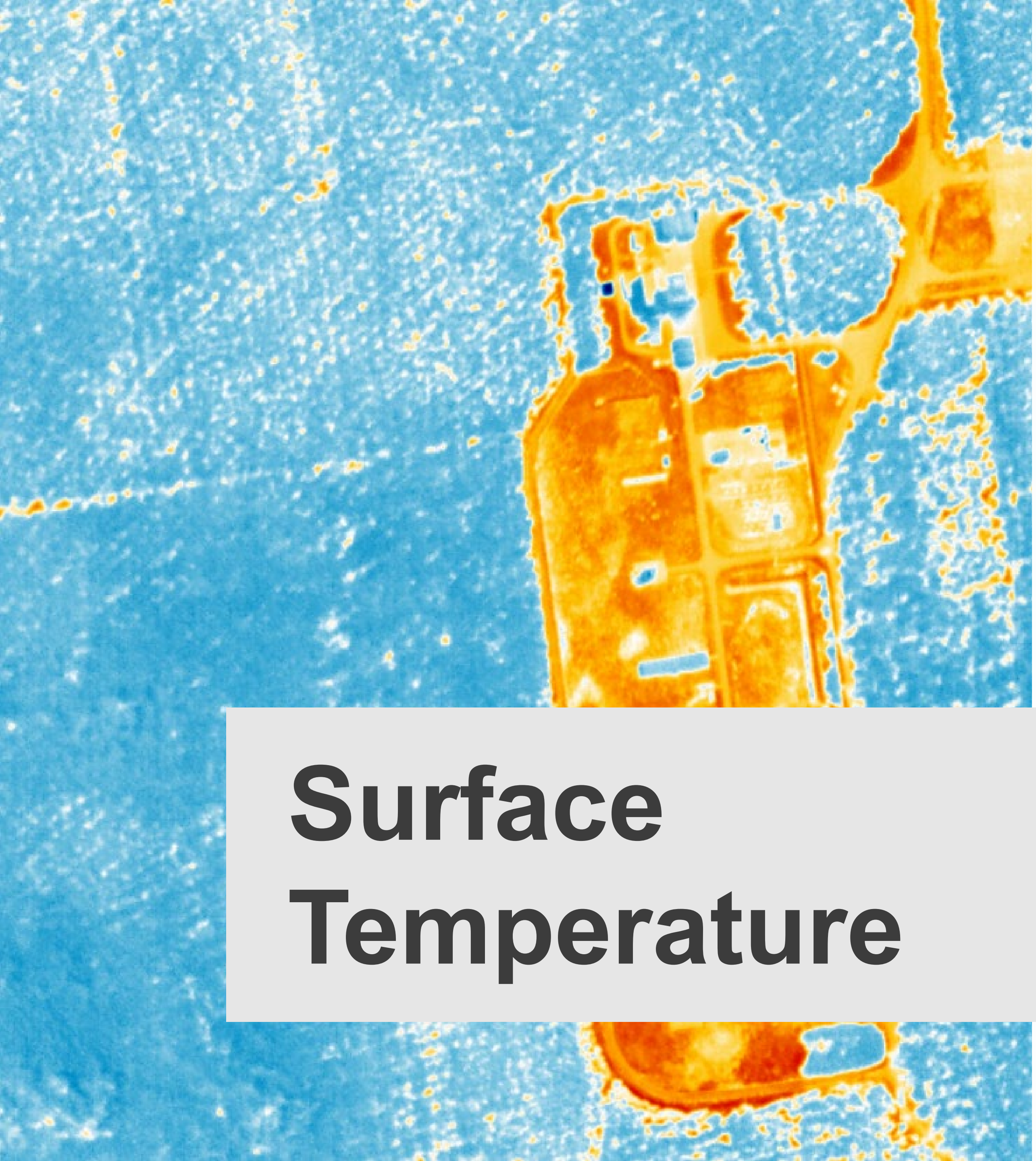


Surface Temperature

Agnieszka Soszynska
Michael Perry, Darren Ghent

agnieszka.soszynska@le.ac.uk

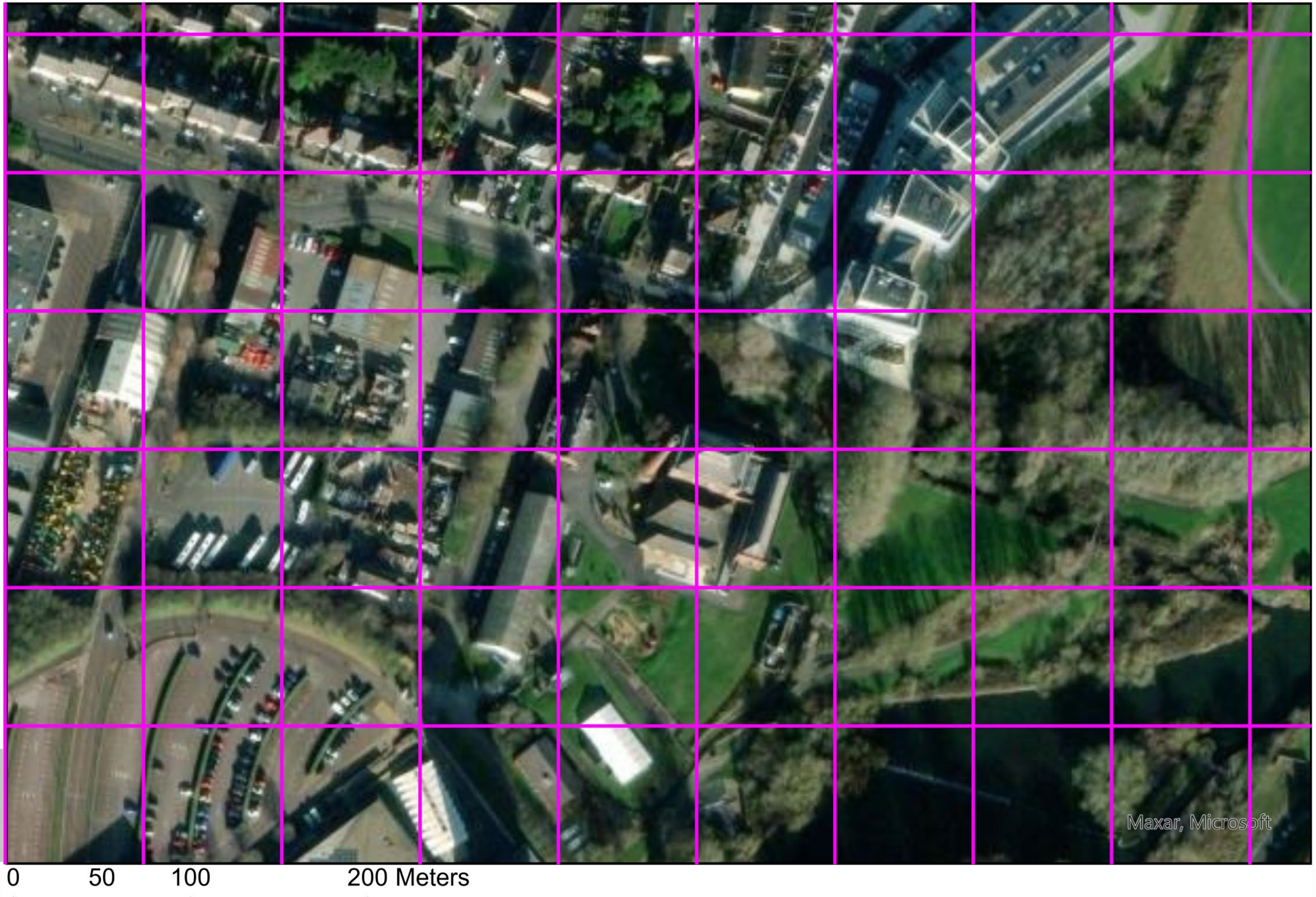
What we will cover in this lecture

- Components of the signal recorded in a thermal camera
- Radiative transfer
- Different algorithms for surface temperature retrieval
- Algorithm intercomparison

What does a camera see?

Different surfaces in a pixel – different reflectances in VNIR wavelengths

Mixed-pixel problem



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What does a thermal sensor see?

Emissivity + Temperature

↓

Radiation at surface

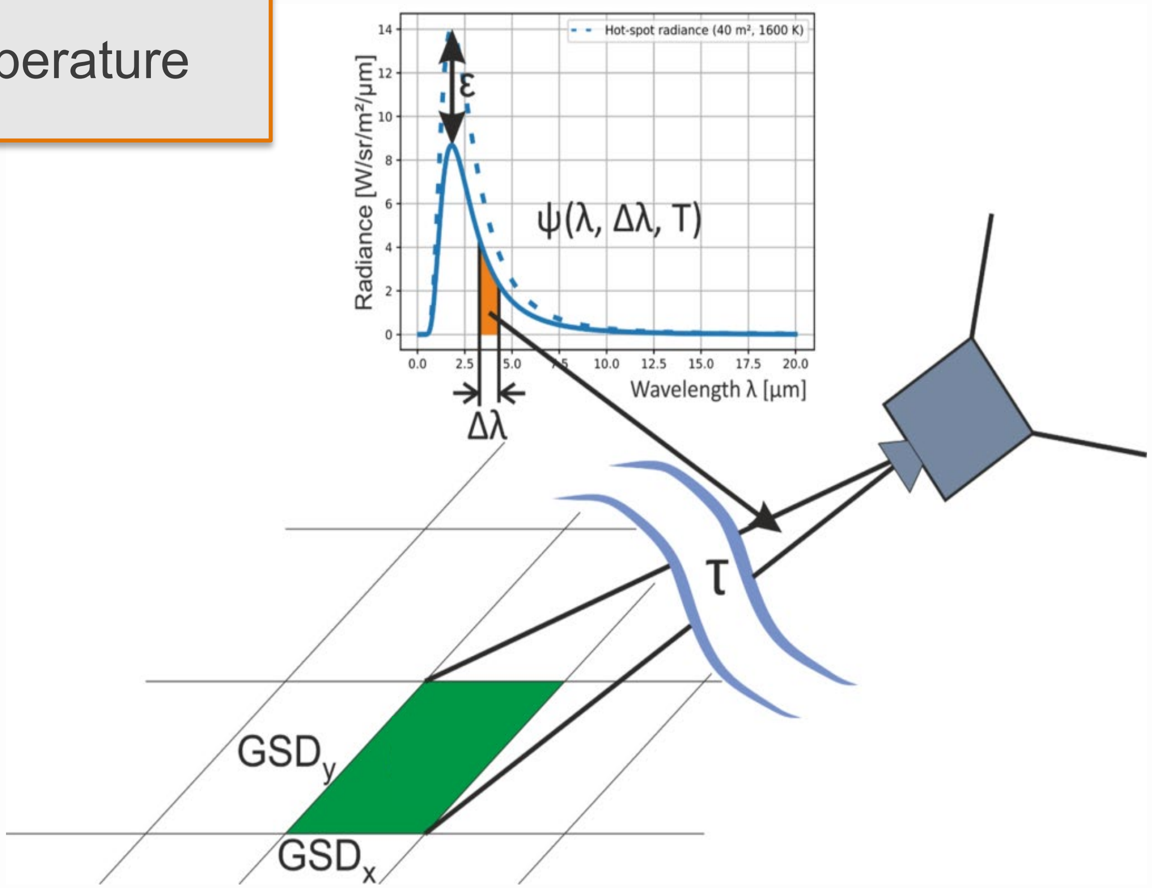
↓

Atmosphere

↓

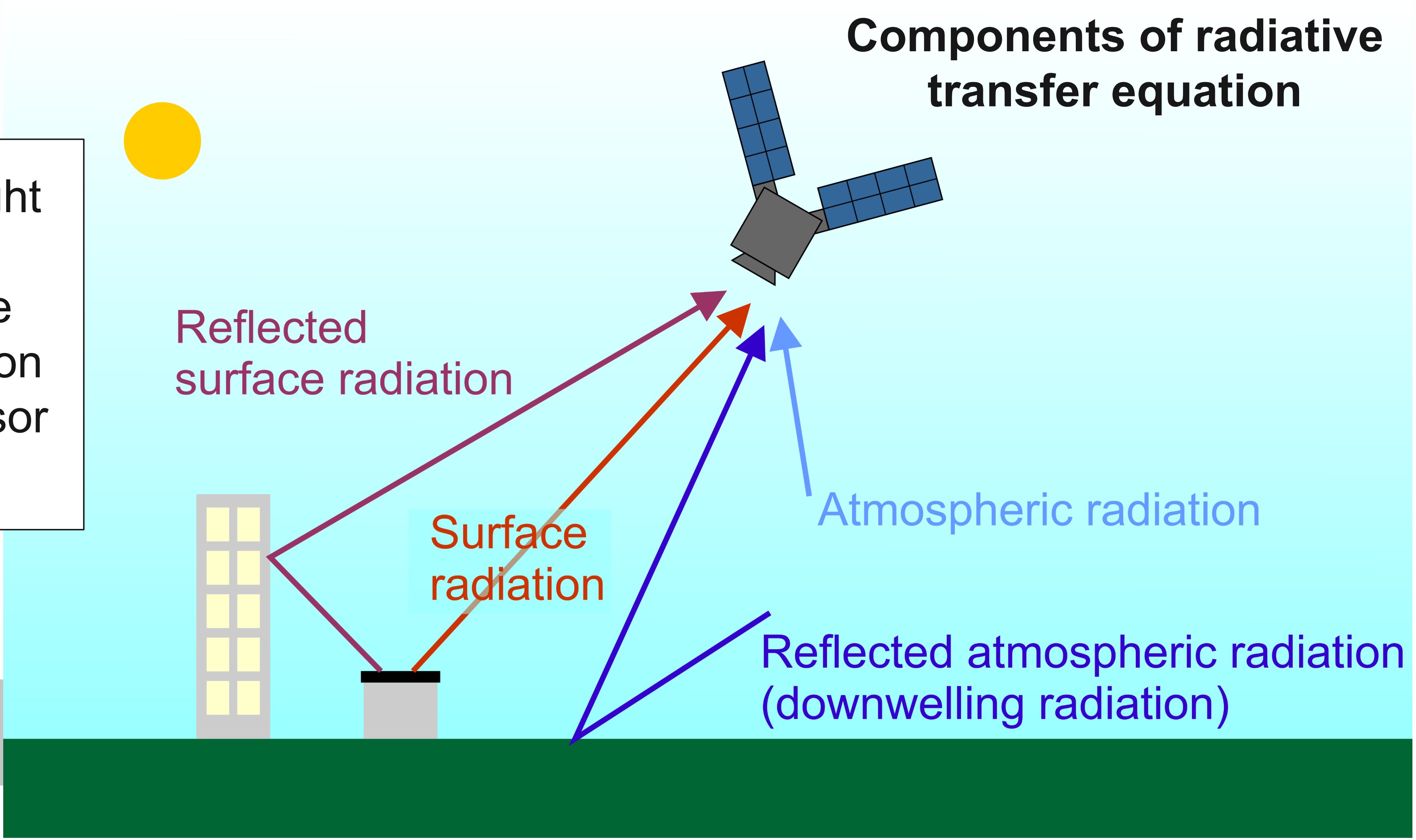
Signal at sensor

~~Reflectance~~



What does a thermal sensor see?

Every time the light crosses the atmosphere, the amount of radiation reaching the sensor is reduced!



Components of radiative transfer equation

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Characteristics of radiative transfer components

Temperature

- **Highly dynamic** dependent on time of day, season, etc.
- **Wavelength independent**

Emissivity

- **Weakly dynamic** dependent on surface materials and state
- **Wavelength dependent** (but 11-12 um have a strong similarity)

Atmosphere

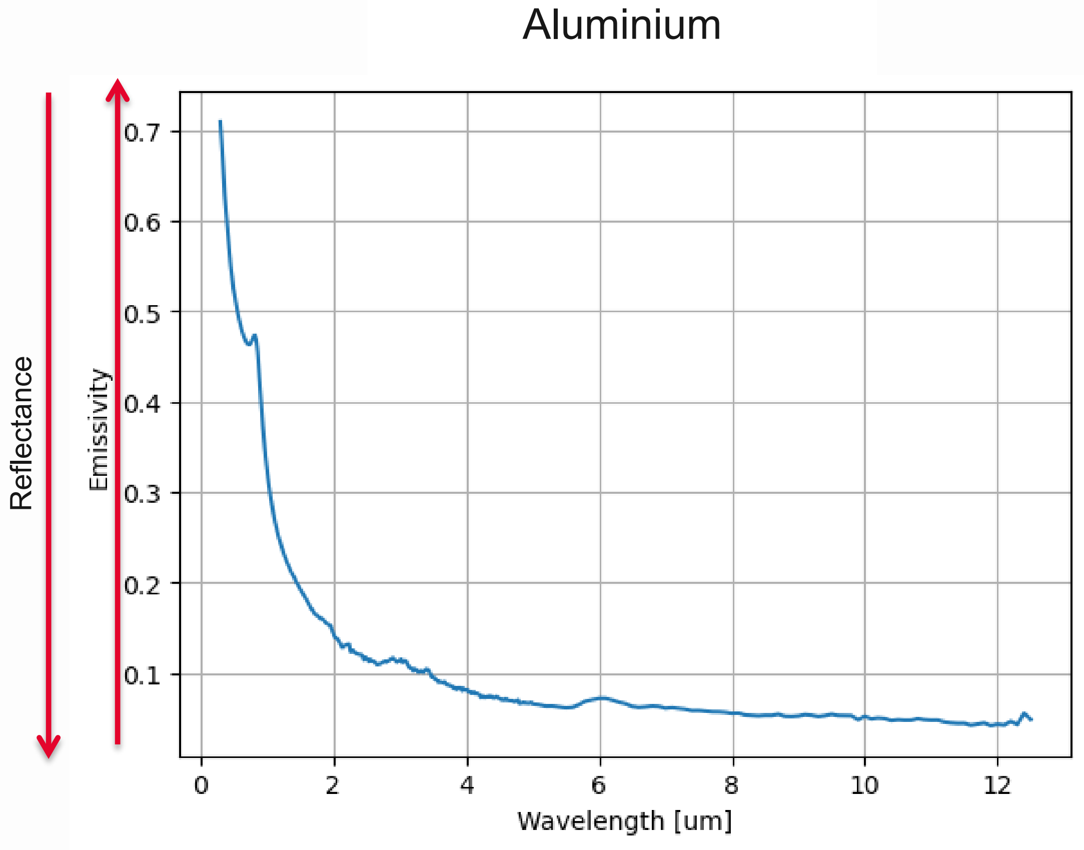
- **Highly dynamic** dependent on weather conditions, season, etc.
- **Wavelength dependent**

Emission vs reflection

Transmission + Absorption + Reflection = 1

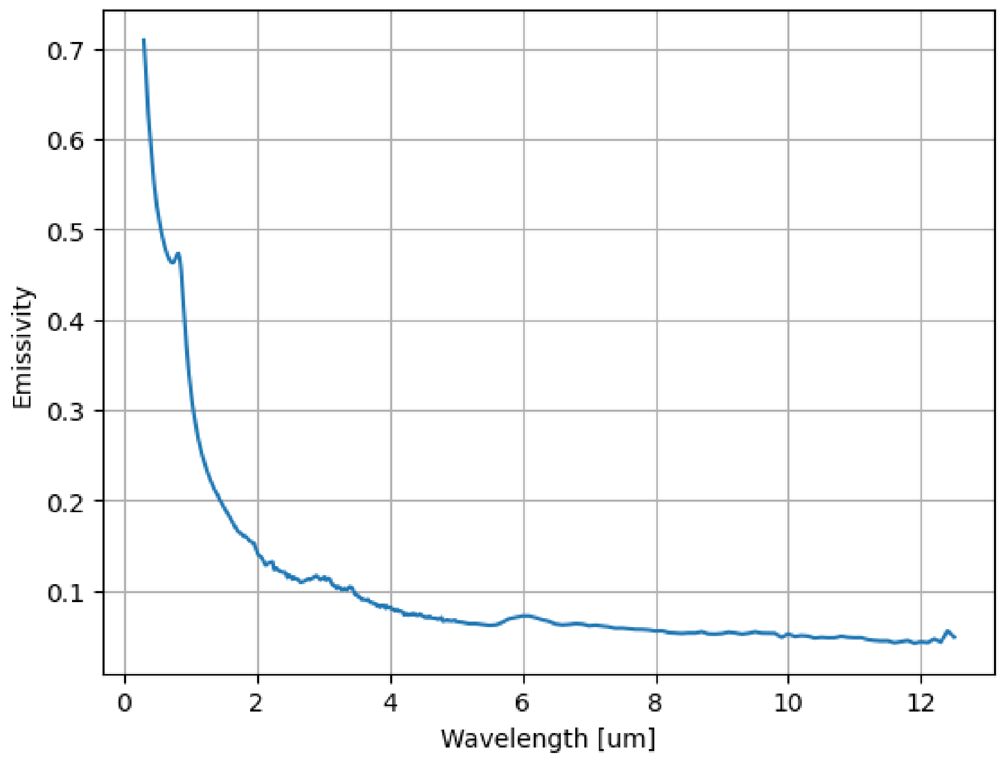
For non-transparent (opaque materials):
Transmission = 0

Absorption = 1 – Reflection
Emission = 1 – Reflection

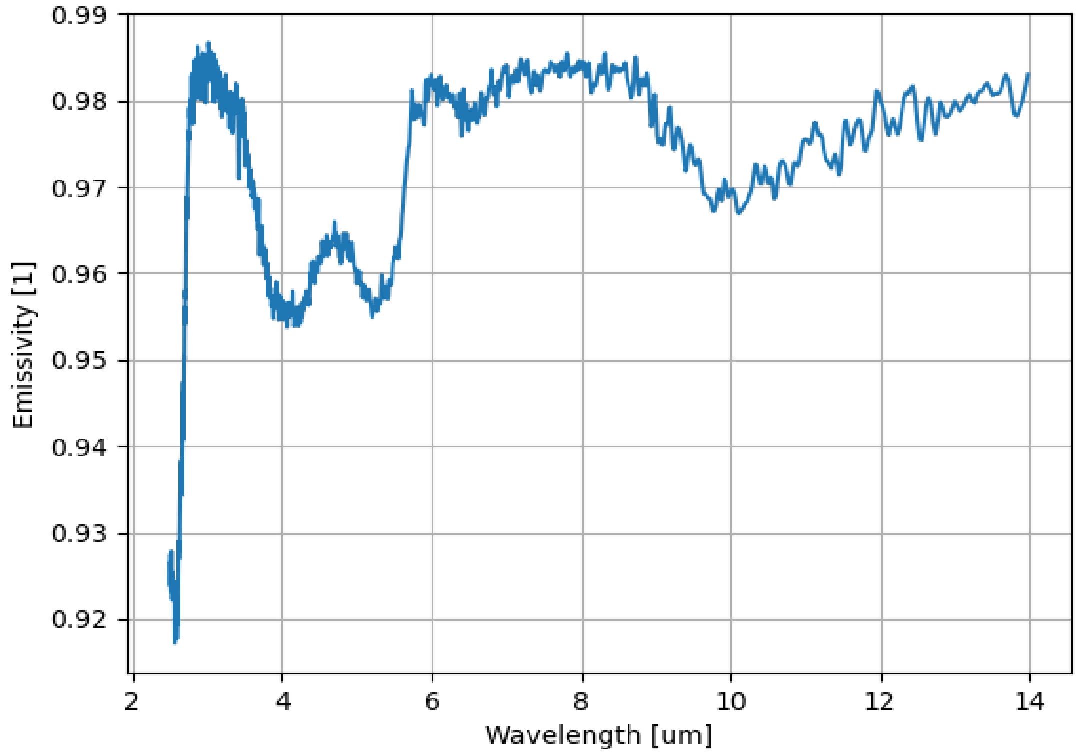


Emission spectrum

Aluminium



Grass



Credits: KCL

How to retrieve the components?

- More unknowns than measurements (mathematically *undetermined* problem)
- Measurements in thermal wavelengths are highly correlated

- But: the more measurements, the less uncertainty

- But: the more is known about the state, the better
    - E.g., atmospheric parameters can be taken from other sources
    - Understanding of the spectrum: e.g., similarity in the 11-12 um bands (*split-window*)

Radiative transfer

Example 1, simplified

$$L_{at\ sensor} = L_{ground} + L_{atmosphere} + L_{atmosphere\ reflected}$$

Radiative transfer

Example 2, more complex

$$L_i(T_{at\ sensor}) = [\varepsilon_i \cdot L_i(T) + (\boxed{1 - \varepsilon_i) \cdot L_i^{\downarrow}]} \cdot \tau_i + L_i^{\uparrow}$$

Reflected atmospheric radiation

$T_{at\ sensor}$ - temperature at sensor
T – surface temperature
$L_i(T_{at\ sensor})$ – Radiation measured by the sensor channel i
ε – surface emissivity
$L_i^{\uparrow}, L_i^{\downarrow}$ – Atmospheric radiance (upwelling and downwelling)
τ – Atmospheric transmittance

Radiative transfer

Example 2, more complex

$$L_i(T_{at\ sensor}) = [\boxed{\varepsilon_i} \cdot L_i(T) + (1 - \boxed{\varepsilon_i}) \cdot L_i^{\downarrow}] \cdot \tau_i + L_i^{\uparrow}$$

Surface emissivity

$T_{at\ sensor}$ - temperature at sensor

T – surface temperature

$L_i(T_{at\ sensor})$ – Radiation measured by the sensor channel i

ε – surface emissivity

$L_i^{\uparrow}, L_i^{\downarrow}$ – Atmospheric radiance (upwelling and downwelling)

τ – Atmospheric transmittance

Radiative transfer

Example 2, more complex

$$L_i(T_{at\ sensor}) = [\varepsilon_i \cdot \boxed{L_i(T)} + (1 - \varepsilon_i) \cdot L_i^{\downarrow}] \cdot \tau_i + L_i^{\uparrow}$$

Blackbody radiation

$T_{at\ sensor}$ - temperature at sensor
T – surface temperature
$L_i(T_{at\ sensor})$ – Radiation measured by the sensor channel i
ε – surface emissivity
$L_i^{\uparrow}, L_i^{\downarrow}$ – Atmospheric radiance (upwelling and downwelling)
τ – Atmospheric transmittance

Radiative transfer

Example 3, even more complex

	$L_i(\theta,\varphi) =$
Surface emission	$\varepsilon_i(\theta,\varphi)\cdot L_i(T) +$
Surface reflected downwelling atmospheric emission	$[1-\varepsilon_i(\theta,\varphi)]\cdot L_{atm_i}^{\downarrow} +$
Surface reflected downwelling atmospheric scattering	$[1-\varepsilon_i(\theta,\varphi)]\cdot L_{s_i}^{\downarrow} +$
Surface reflected downwelling solar beam	$\rho_{b_i}(\theta,\varphi,\theta_s,\varphi_s)\cdot E_i\cos(\theta_s)\tau_i(\theta_s\varphi_s)$

Li, Zhao-Liang, et al. "Satellite-derived land surface temperature: Current status and perspectives." *Remote sensing of environment* 131 (2013): 14-37.

Groups of algorithms

Mono-window algorithms

Mono-window for Landsat

Algorithms assuming emissivity

UoL Split Window (operational for Sentinel-3 SLSTR)

Generalised Split Window (operational for MODIS in LST_cci)

Algorithms retrieving emissivity

Temperature-Emissivity Separation (TES) (operational for ECOSTRESS and MODIS NASA data)

DirecTES (operational for future mission TRISHNA)

Optimal Estimation (operational for future mission LSTM)

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Mono-window algorithms

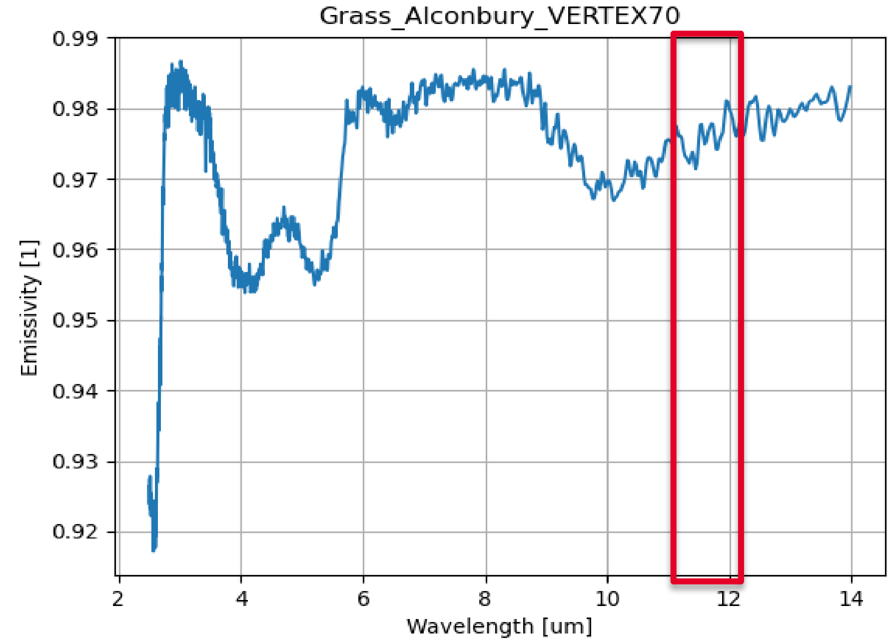
- Emissivity is assumed
- Radiative transfer equation is inverted
- Requires good knowledge on atmospheric profile

$$L_i(T_{at\ sensor}) = \left[\boxed{\varepsilon_i} \cdot L_i(T) + \boxed{(1 - \varepsilon_i)} \cdot \boxed{L_i^{\downarrow}}\right] \cdot \boxed{\tau_i} + \boxed{L_i^{\uparrow}}$$

assumed or known

Split Window algorithms

- Base on the high similarity of emissivity within two neighbouring bands
- Two measurements, two unknowns (LST, LSE) (+ good knowledge of the atmosphere)
- Use coefficients to parameterise emissivity of the surface



UoL split-window algorithm

Nadir retrievals, only 2-channels

$$
\begin{aligned}
LST &\\
= d(\sec(\theta) - 1)pw &+ \left(f a_{v,i} + (1-f) a_{s,i}\right) + (f b_{v,i} + (1-f) b_{s,i})(T_{11} - T_{12})^{1\,/\,(\cos(\theta\,/\,m))}\\
&+ \left((f b_{v,i} + (1-f) b_{s,i}) + (f c_{v,i} + (1-f) c_{s,i})\right) T_{12}
\end{aligned}
$$

T_{11} and T_{12} are 11 and 12 μm channel brightness temperatures (BT)

a, *b*, *c* – retrieval coefficients dependent on:

- Surface/vegetation type (*i*) - biome
- Vegetation fraction (*f*) – seasonally dependent
- Precipitable water (*pw*) – seasonally dependent
- Satellite zenith view pointing angle ($p(\theta)$)

Generalised Split Window

The Generalised Split Window (GSW) algorithm is based on the formulation:

$$LST = \left(A_1 + A_2\frac{1-\varepsilon}{\varepsilon} + A_3\frac{\Delta\varepsilon}{\varepsilon^2}\right)\frac{T_{11}+T_{12}}{2} + \left(B_1 + B_2\frac{1-\varepsilon}{\varepsilon} + B_3\frac{\Delta\varepsilon}{\varepsilon^2}\right)\frac{T_{11}-T_{12}}{2} + C$$

Where:

T_{11} and T_{12} are the TOA-BTs for channels centred around 11µm and 12µm respectively,

ε is the mean land surface emissivity of the two channels,

$\Delta\varepsilon$ the emissivity difference between the channels ($\varepsilon_{11} - \varepsilon_{12}$)

Retrieval coefficients: A_j, B_j $(j = 1,2,3)$ and C are dependent on water vapour and zenith view angle

Operationally implemented for MODIS and SEVIRI

Temperature-Emissivity Separation

- Retrieves both temperature and emissivity
- Fits the retrieved spectral contrast (minimum-maximum difference) to the lab-measured minimum emissivity
- Requires inputs corrected for the atmosphere (*bottom-of-atmosphere radiance*)
- Iterative process using a number of sensor-dependent thresholds
- Operational in all major NASA products (ECOSTRESS, ASTER, VIIRS, MODIS)

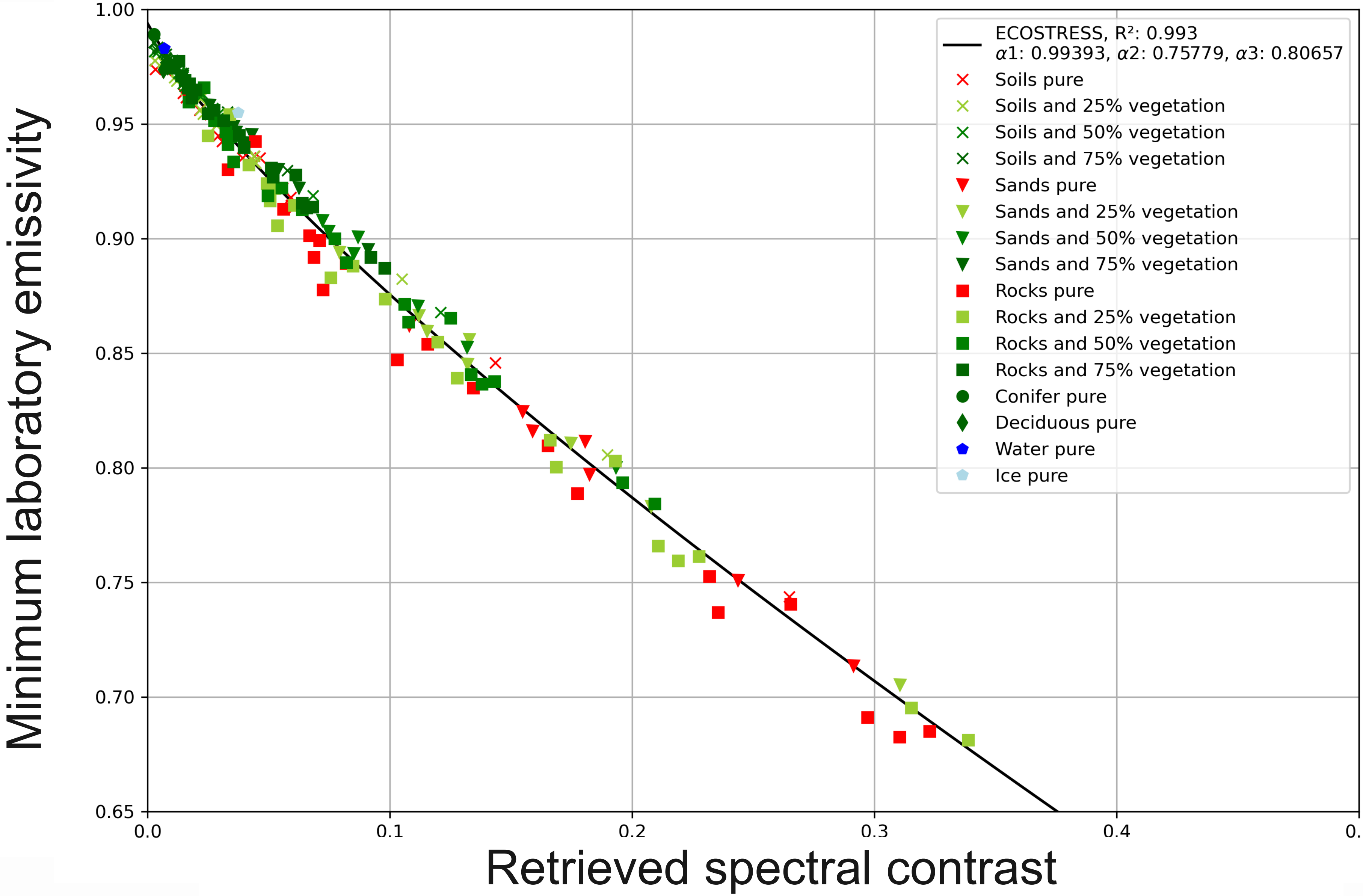
Temperature-Emissivity Separation

NEM
- Iterative process of refining the parameters in RTE
- Emissivity refinement basing on sensor parameters (NEΔT)

RAT
- Calculates the so-called β-spectrum as preparation to the MMD module

MMD
- Relates the retrieved spectral contrast to the lab measurements

Temperature-Emissivity Separation



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DirecTES

Uses brute force to match the measurements to the spectral library of **emissions**

$$L_{BB}^{k,m} = \frac{1}{\varepsilon_m^k}\left(\frac{\left(L_{TOA}^{k} - L_{atm}^{\uparrow,k}\right)}{\tau^{\uparrow,k}} - \left(1 - \varepsilon_m^k\right) \cdot L_{atm}^{\downarrow,k}\right)$$

k – spectral band

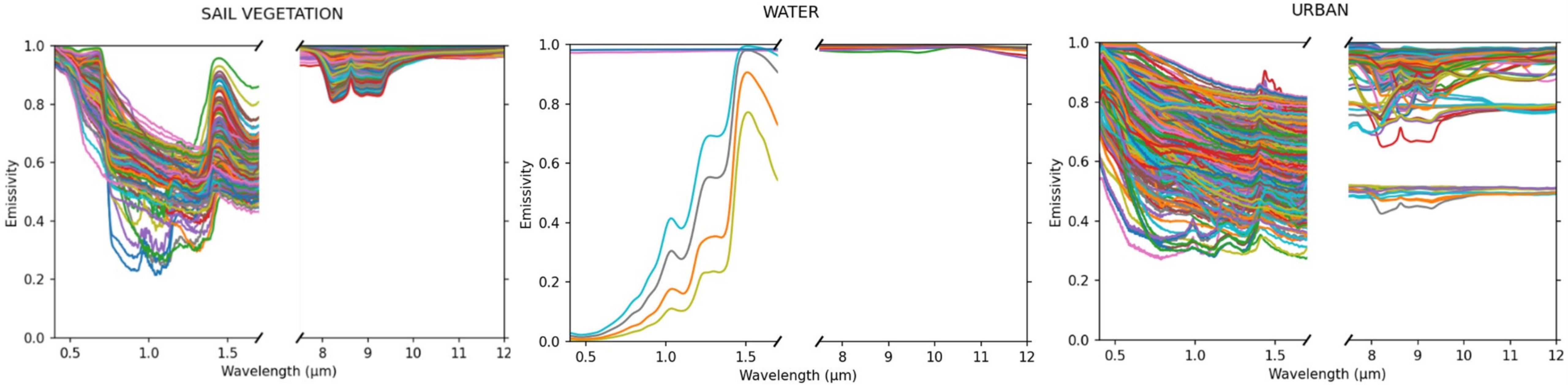
m – material

$L_{BB}^{k,m}$ – emitted spectral radiation of material m in band k

The temperature is derived by inverting the black body equation using $L_{BB}^{k,m}$ and match in the database is sought

DirecTES

- Initial reduction of materials is conducted using VNIR-SWIR channels
- Uses spectral library divided into groups: vegetation, water, urban, 3690 altogether
- Spectral angle mapper is used to narrow down the population



Marcq, Sébastien, et al. "DirecTES: A Direct Method for Land and Sea Surface Temperature and Emissivity Separation for Thermal Infrared Sensors—Application to TRISHNA and ECOSTRESS." *Remote Sensing* 15.2 (2023): 517.

Optimal Estimation

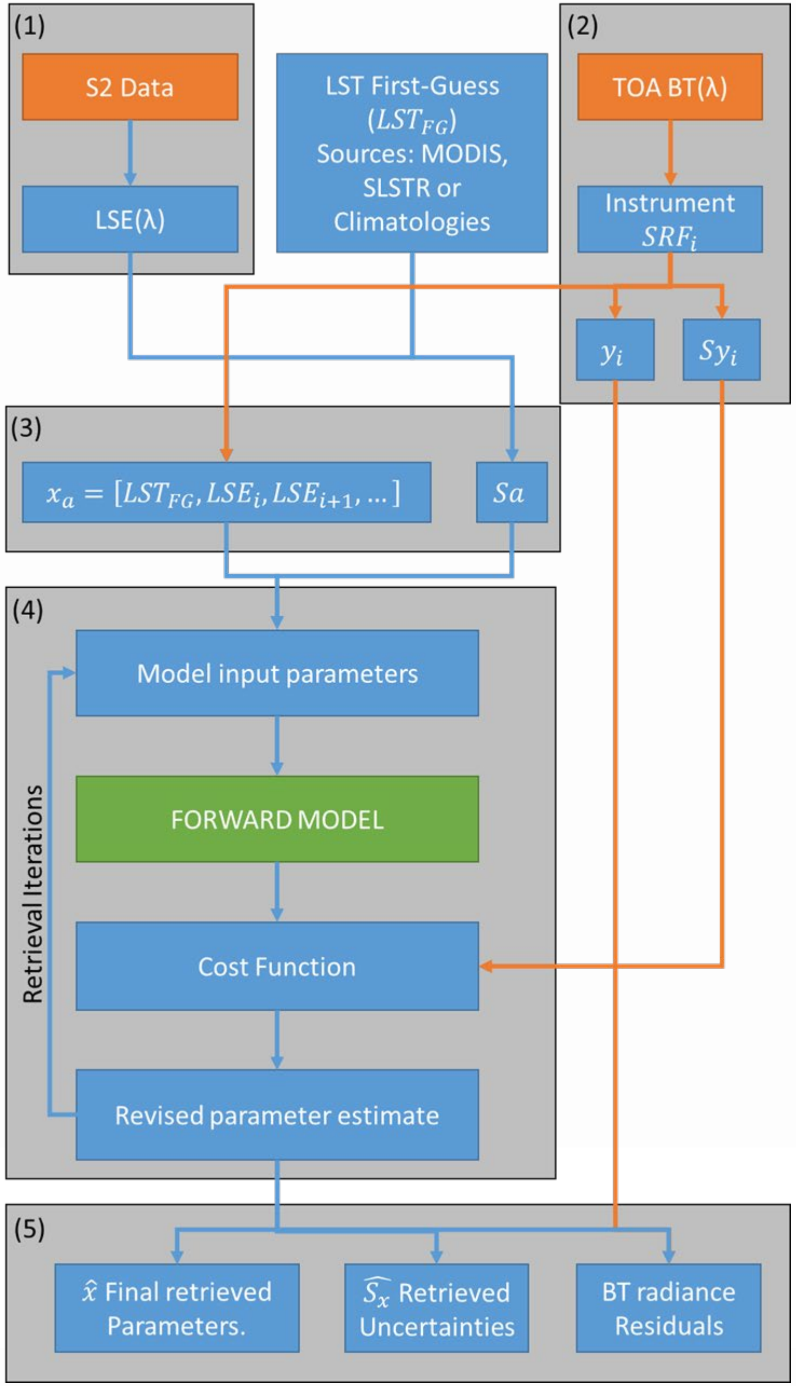
“*Bayesian interpretation of probability, where probability expresses* ***a degree of belief in an event****. The degree of belief may be* ***based on prior knowledge*** *about the event, such as the results of previous experiments, or on personal beliefs about the event*.”
(Wikipedia)

Optimal Estimation

Maximum probability solution via minimisation of the cost function

$$C(\boldsymbol{x}) = (\boldsymbol{x}-\boldsymbol{x}_a)^T \boldsymbol{S}_a^{-1} (\boldsymbol{x}-\boldsymbol{x}_a) + \left(\mathbf{y}-\mathbf{F}(\boldsymbol{x})\right)^T \boldsymbol{S}_y^{-1} \left(\mathbf{y}-\mathbf{F}(\boldsymbol{x})\right)$$

- OE can use the a priori knowledge of the surface and atmospheric parameters
- Creates a simulated BT for the observed radiance, which is compared to the actual observed BT
- Offset between simulated and observed BT used to provide an improved retrieval which is an improved estimate of the true parameters



(1)

S2 Data

LSE(λ)

LST First-Guess (LST_{FG}) Sources: MODIS, SLSTR or Climatologies

(2)

TOA BT(λ)

Instrument SRF_i

y_i

Sy_i

(3)

$x_a = [LST_{FG}, LSE_i, LSE_{i+1}, \ldots]$

Sa

(4)

Retrieval Iterations

Model input parameters

FORWARD MODEL

Cost Function

Revised parameter estimate

(5)

$\hat{x}$ Final retrieved Parameters.

$\hat{S}_x$ Retrieved Uncertainties

BT radiance Residuals

Optimal Estimation

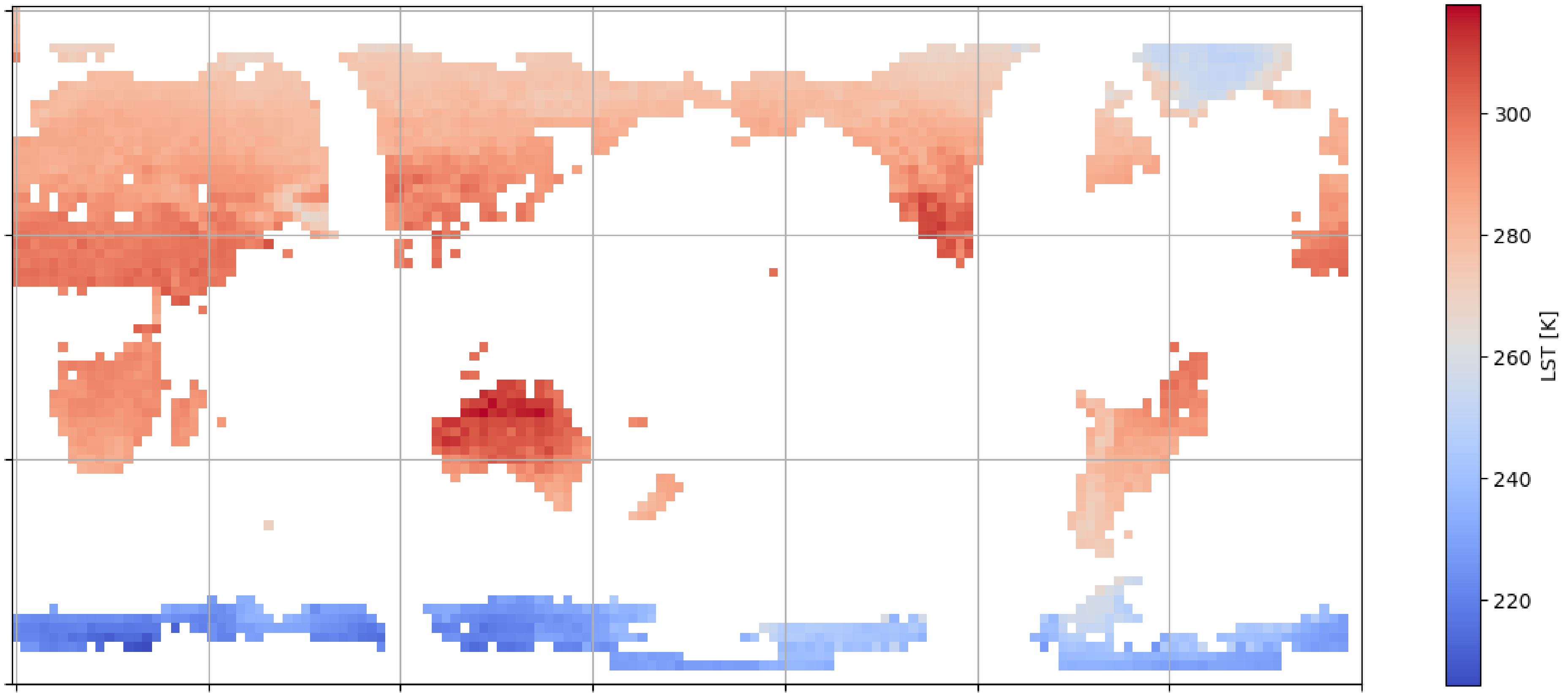
- NDVI threshold method (Sobrino et al., 2008) for example can be used to estimate the *prior* LSE
- The *prior* LST is then used with the *prior* LSE:
  - Two sets of BOA BTs are evaluated and the differences used to iteratively update the estimates for LST and LSE used in the retrieval until an empirically determined threshold where there is no longer any significant improvement to be made by further iteration.
- Produces a full traceable uncertainty budget

Algorithms have different assumptions

And different inputs…

	UoL	**GSW**	**OE**	**TES**	**DirecTES**
Total Column Water Vapour	X	X			
Fraction of Vegetation	X				
Biome	X				
Downwelling radiance				X	X
Upwelling radiance					X
Bottom of Atmosphere radiance				X	X
Top of Atmosphere Brightness Temperature	X	X	X		
First guess emissivity		X	X		
First guess skin temperature			X		

Algorithm intercomparison: simulation database



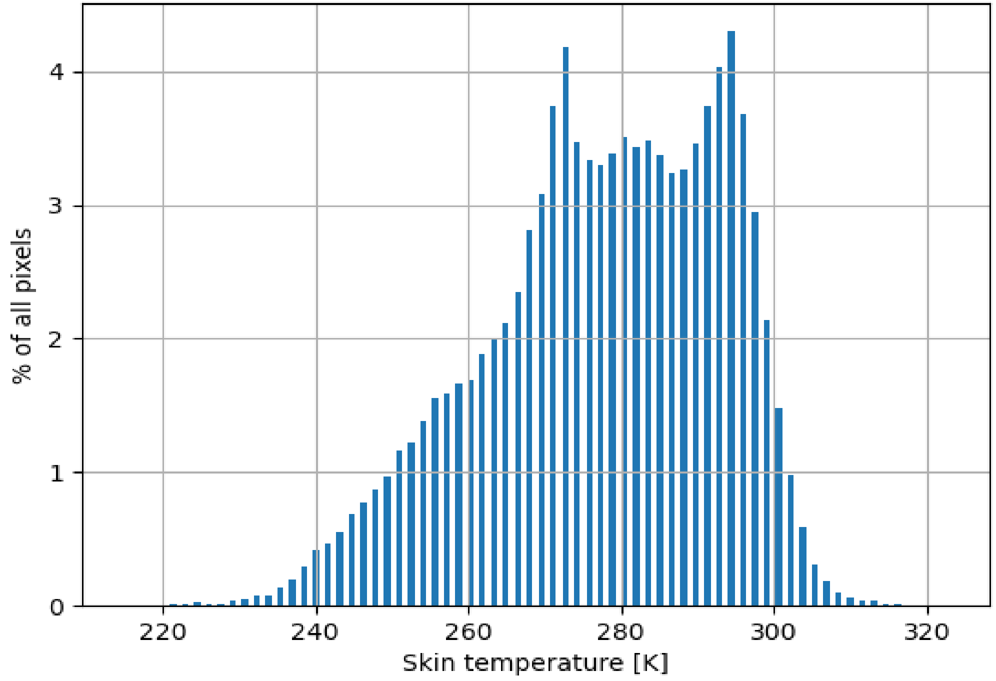
20 years
12 months
15th day of each month
144*72 pixels

altogether
157 478 pixels
(excluding cloudy pixels)

Algorithm intercomparison: simulation database

True variables and perturbed variables

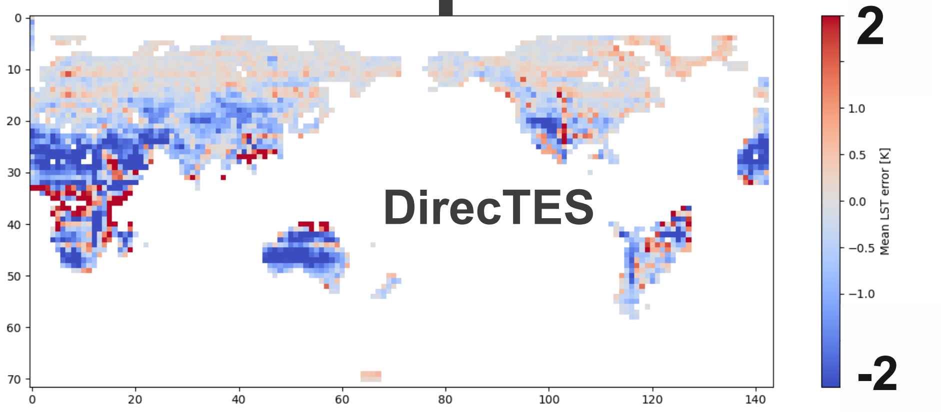
- Vegetation fraction
- Biome
- Elevation
- Skin temperature
- Total column water vapour
- Upwelling irradiance
- Downwelling irradiance
- TOA BT (or L)
- BOA BT (or L)
- Transmissivity
- Emissivity

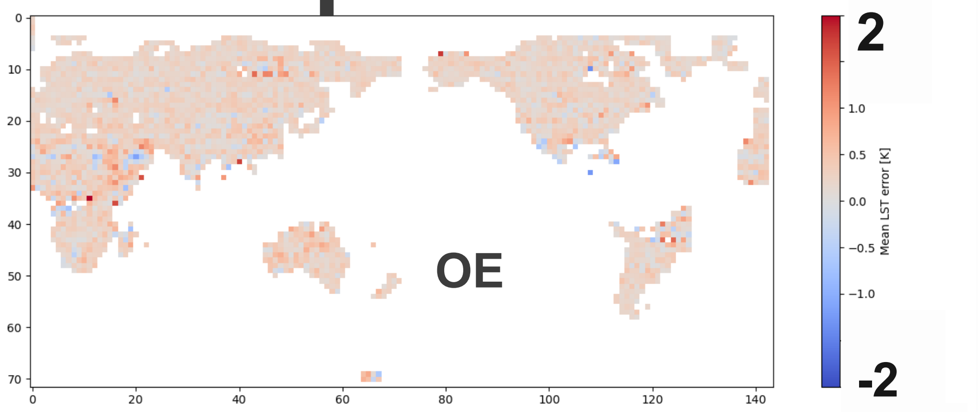


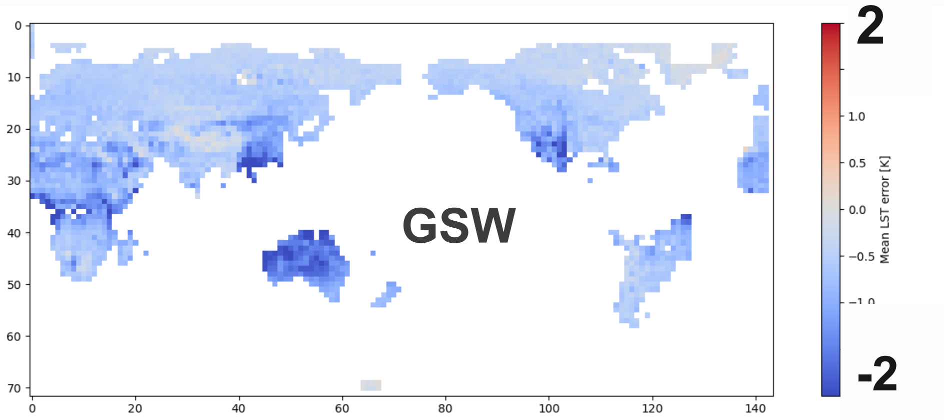
Algorithm intercomparison: bias and precision

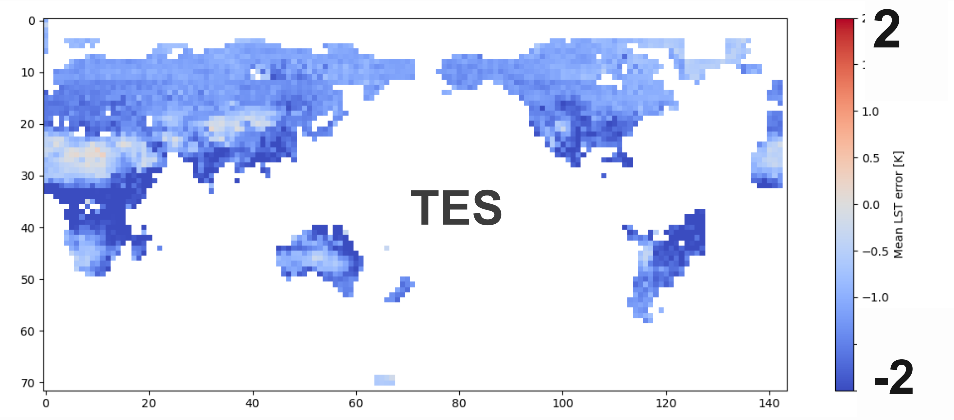
	UOL	GSW	OE	TES	direcTES
Bias (mean absolute discrepancy) [K]	0.69	0.69	0.42	1.22	1.04
Bias (median absolute discrepancy) [K]	0.53	0.56	0.36	1.05	0.54
Precision (st. dev.) [K]	0.93	0.59	0.53	0.88	1.66
Precision (mean of cell st. dev.) [K]	0.88	0.56	0.53	0.84	1.63
Precision (median of cell st. dev.) [K]	0.87	0.56	0.53	0.84	1.61

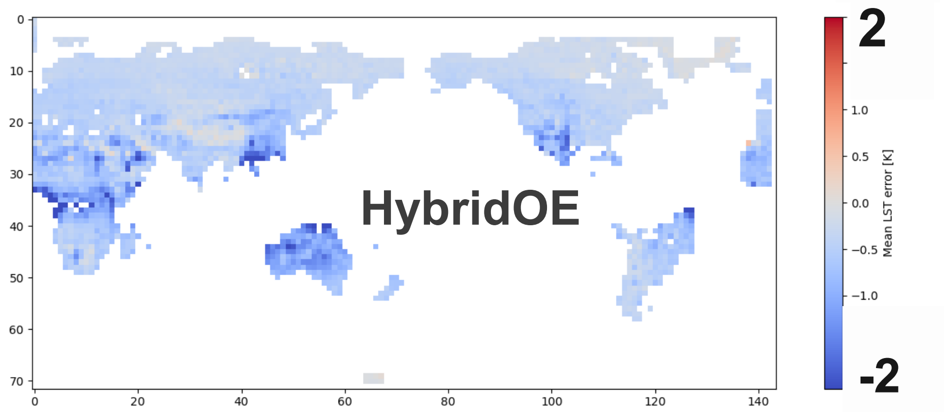
Algorithm intercomparison: bias and precision

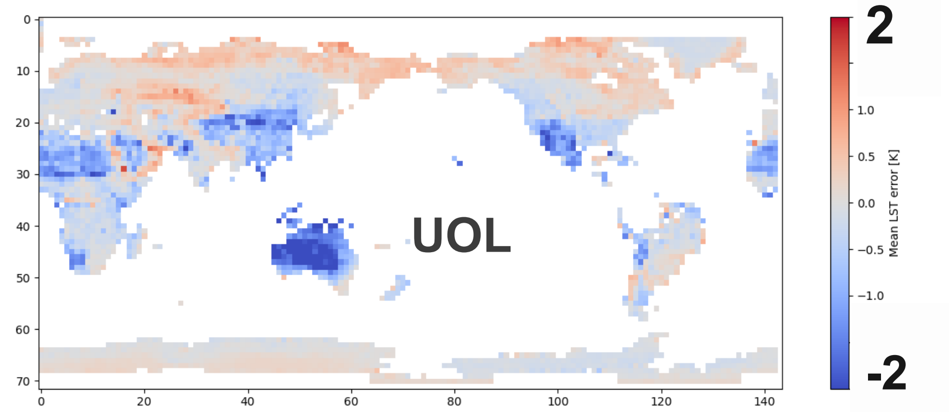












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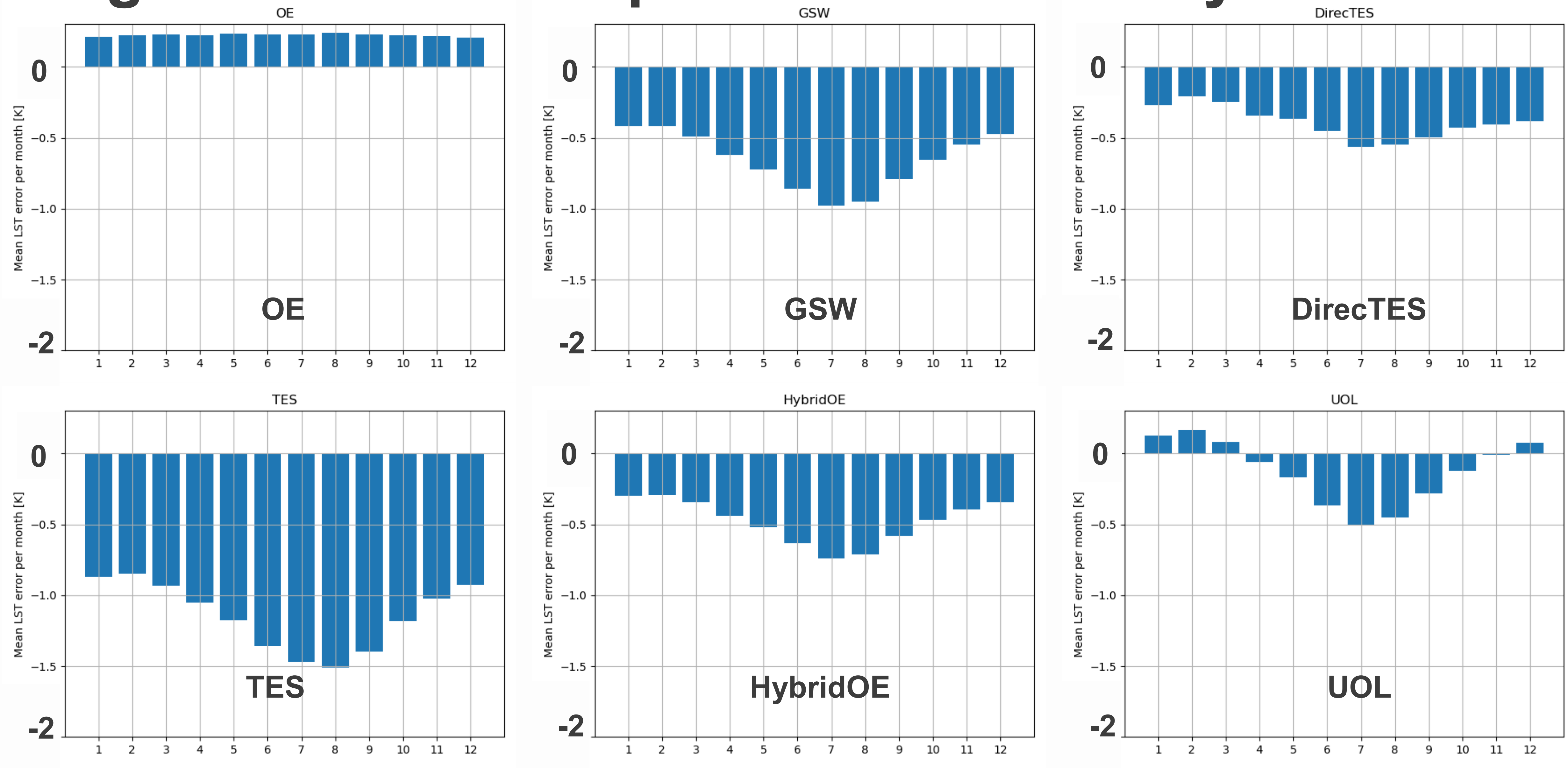
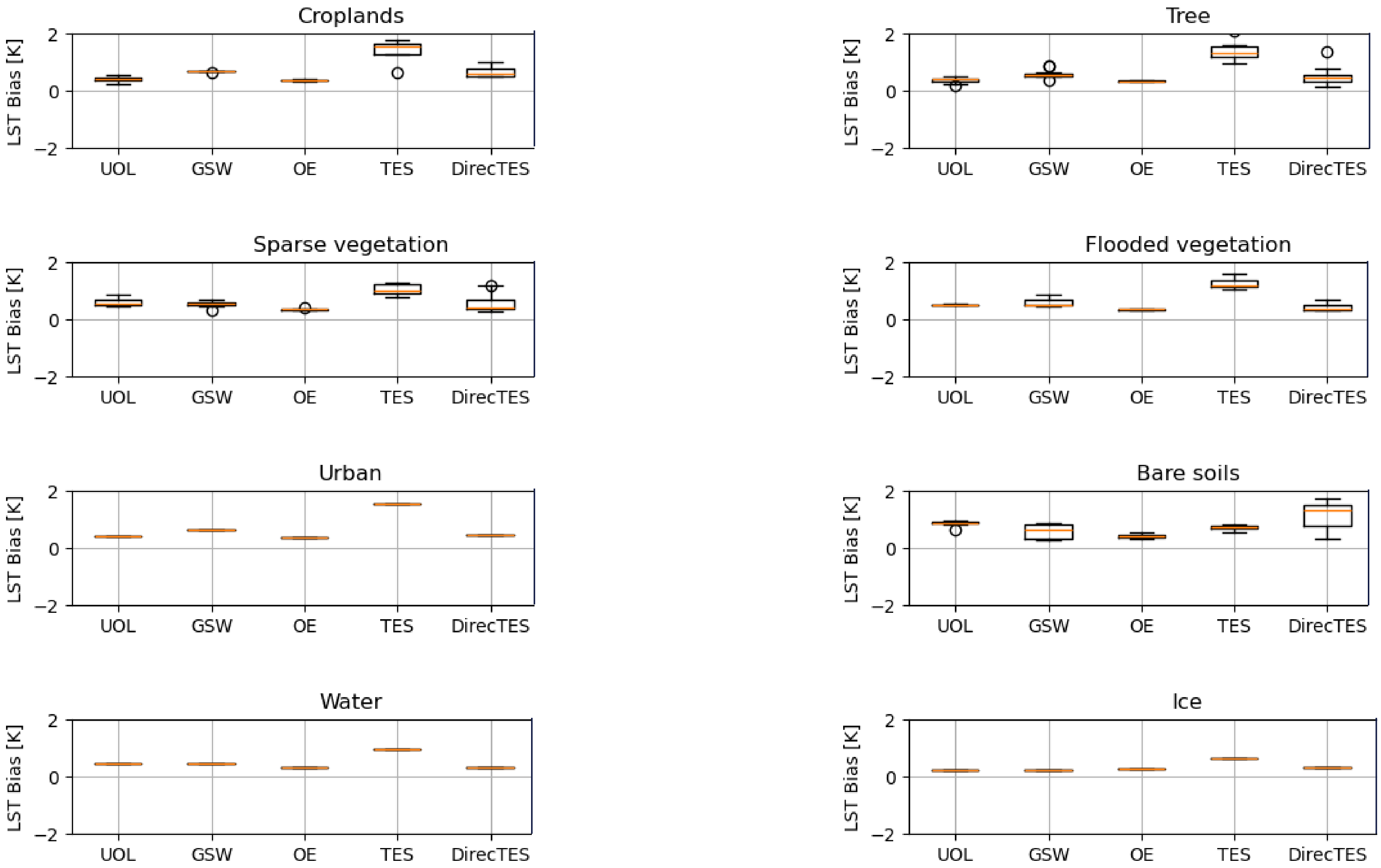
Algorithm intercomparison: seasonality



Results: sensitivity to biomes



Take home messages

- LST and LSE retrieval is an underdetermined problem

- There are various algorithms for LST/LSE retrieval

- All algorithms:
  - Behave slightly differently
  - Have different inputs
  - Have different accuracies
  - Are sensitive to different variables