Harnessing Artificial Intelligence and Machine Learning for Robust All-Sky Land Surface Temperature Monitoring of Earth in Climate Physics

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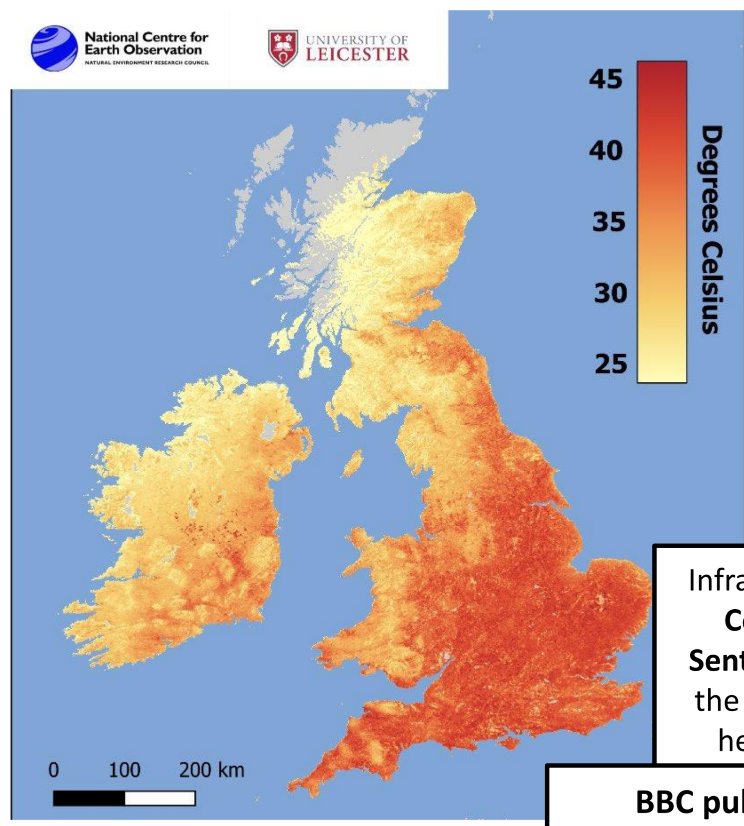
What's the challenge?

- Land surface temperature (LST) is the 'skin' temperature of the Earth's surface and is used to measure the Earth's energy budget.
- More commonly it is measured by thermal infrared radiation from Space using satellites. These satellite measurements are naturally blocked by clouds, resulting in data gaps.



Infrared LST from **Copernicus' Sentinel 2** during the August 2022 heatwave [1]

BBC publication: https://www.bbc.co.uk/news/science-environment-62257163

How do I solve this?

- While microwave (MW) LST data can see through clouds and complements the more accurate with lower uncertainties thermal infrared (TIR) data, it holds a coarser resolution.
- Artificial intelligence and machine learning methods will enhance the resolution of microwave LST, so to integrate the strengths of both datasets to produce a merged all-sky LST product for the entire planet, *which has not yet been done successfully!*

Why should we care?

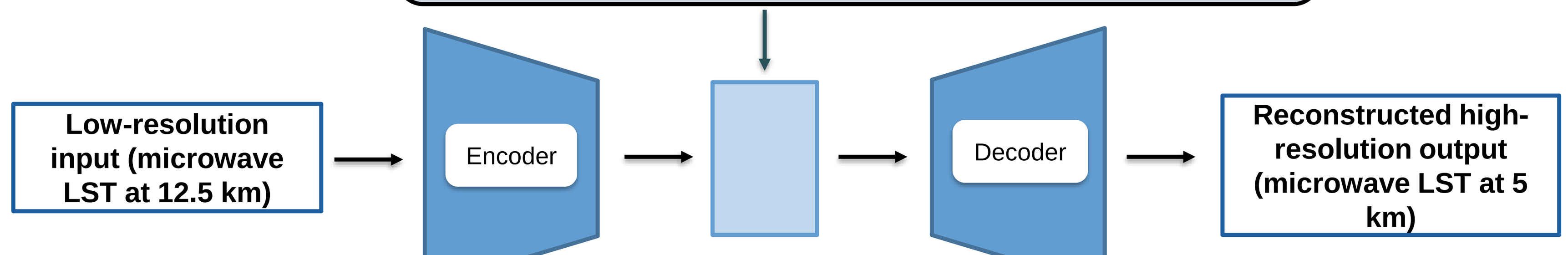
- LST is an essential climate variable (ECV) and is used to measure the Earth's total energy budget at both global and local scales.
- The robust LST data products hold the advantage of showcasing significant temperature variability at high-resolutions.
- Closing these gaps will provide further understanding of the energy budget, which is critical for understanding climate dynamics.
- It will provide accurate climate data for informed decision-making and policies that address climate change and challenges.

The Solution:

- Reconstruct the coarse microwave LST (25km) to match the high-resolution infrared LST (5 km).
- How? - Using a Convolutional Neural Network (CNN) in the form of a U-Net [2].

Encoder-Decoder Summary

A CNN encoder-decoder is a neural network that compresses input data to extract features (encode), then is trained to expand these features (decode) to increase the spatial resolution.

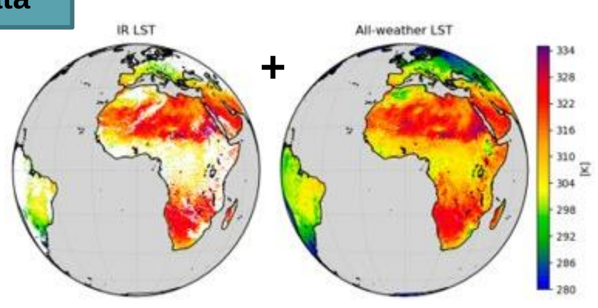


Data:

- Using *ESA Climate Change Initiative* (CCI) data from two instruments (MODIS & AMSR-E) aboard the Aqua satellite [3]
- Will look to add microwave data from other *Copernicus Sentinel satellites*
- They have the same temporal resolution (overpass time) but different spatial resolutions.

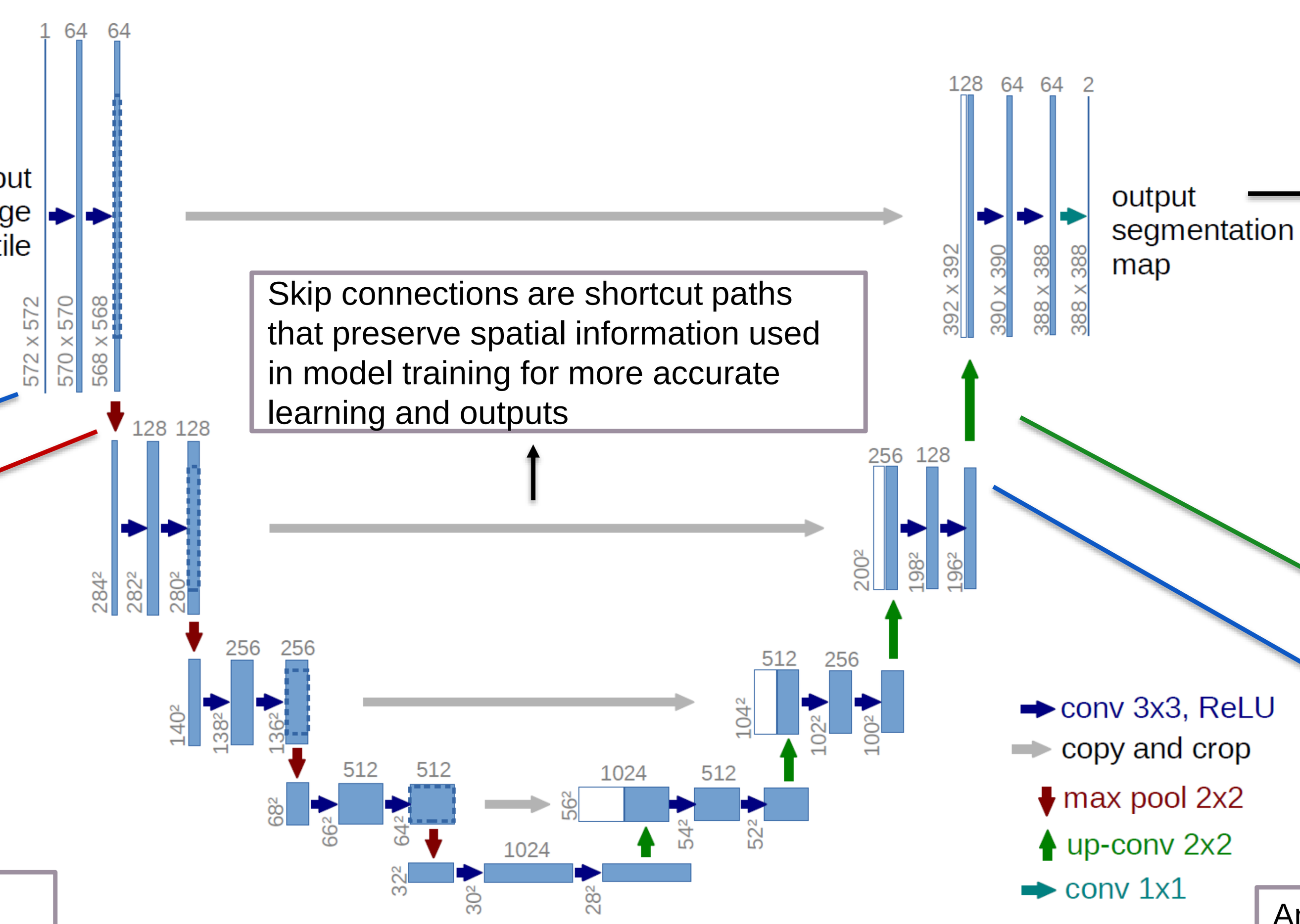
Step 1: CNN U-Net Structure for Spatial Reconstruction:

1. Input data



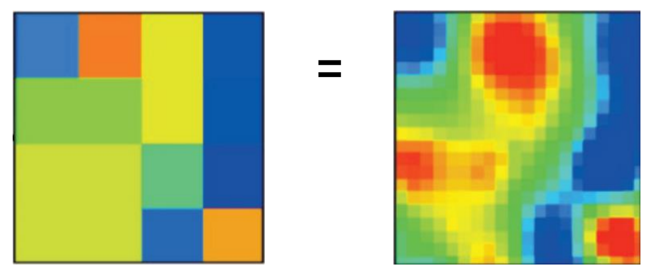
[4]

Tiles of infrared and microwave LST data for Earth during cloud-free days are fed in as inputs.



Skip connections are shortcut paths that preserve spatial information used in model training for more accurate learning and outputs

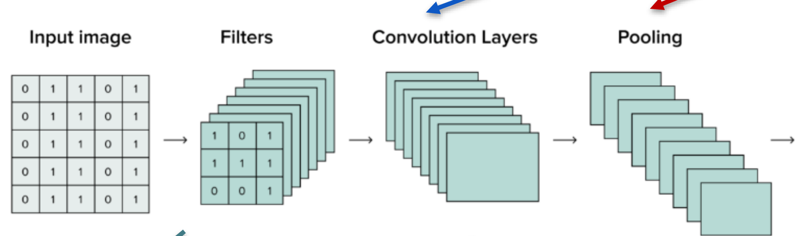
5. Output data



[5]

A convolutional operation combines features from different channels whilst preserving spatial dimensions to produce a predicted output.

2. Encoding (Data Contraction)



Data is put through layers that reduce the size of the input data to extracting key features into kernels

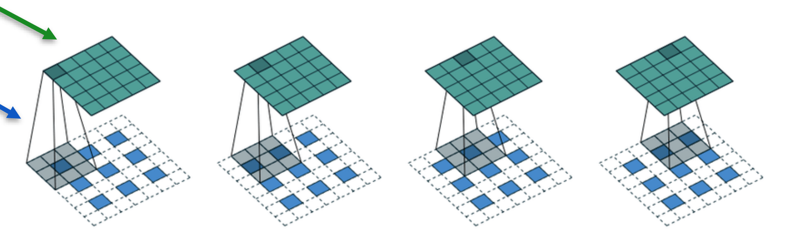
A mathematical function is applied to extracted features to introduce non-linearity when learning.

A pooling operation downsamples the grouped data by taking the maximum value

3. The Bottleneck

This is where the U-Net switches from encoder to decoder.

4. Decoding (Data Expansion)



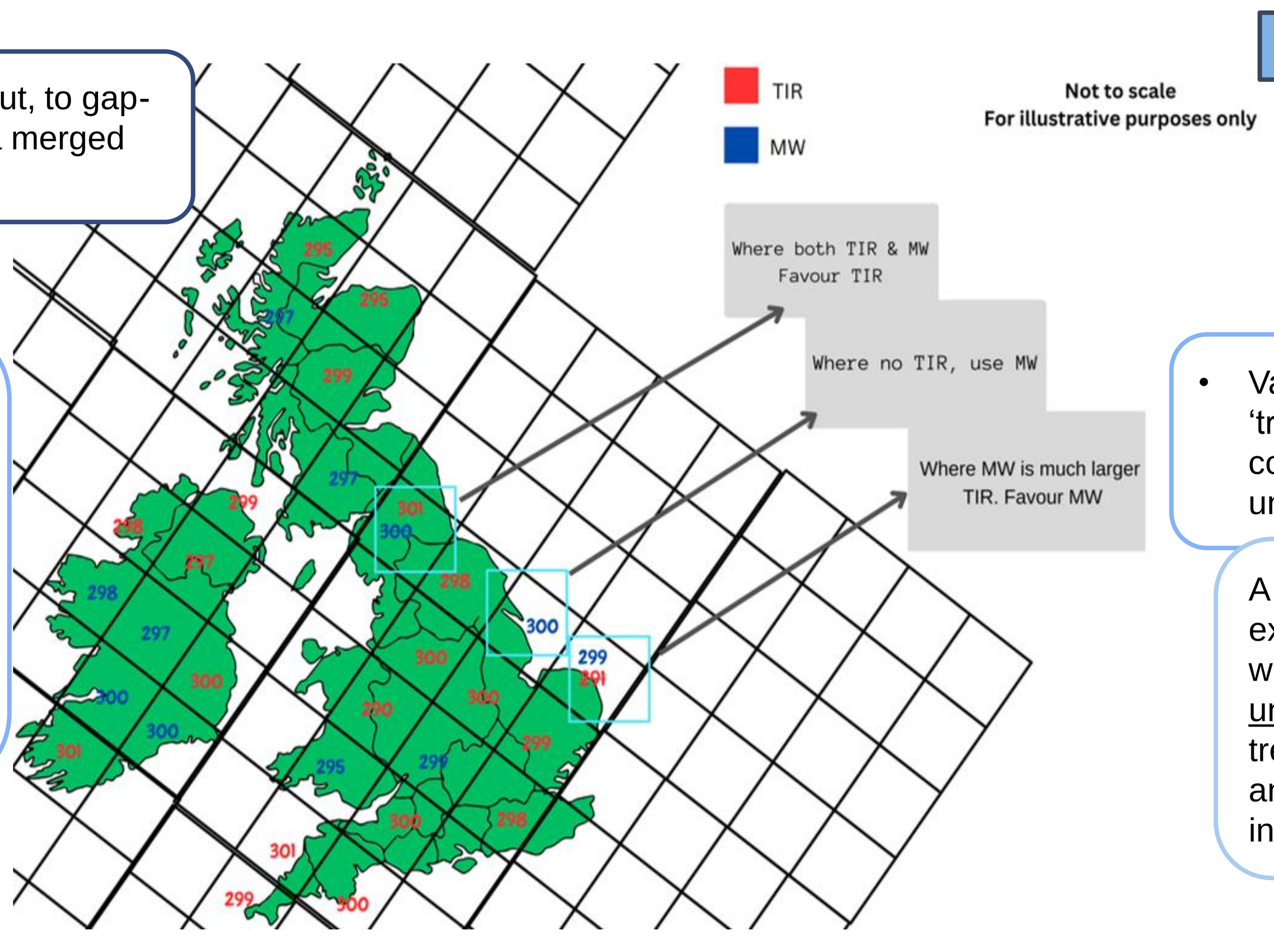
An extra layer will be added to increase the MW LST to the desired resolution of 5 km

The layers refine the extracted features to reproduce detailed spatial patterns

The maps produced are expanded and upsampled to produce a more refined output

Step 2:

Use the reconstructed microwave output, to gap-fill the missing infrared data to create a merged LST dataset for the globe.



Selection of LST data:
- We will filter per pixel, and prioritise the TIR temperatures as they are high-quality with lower uncertainties.

End product:
- A merged all-sky land surface temperature product for the globe at 5 km resolution with uncertainties

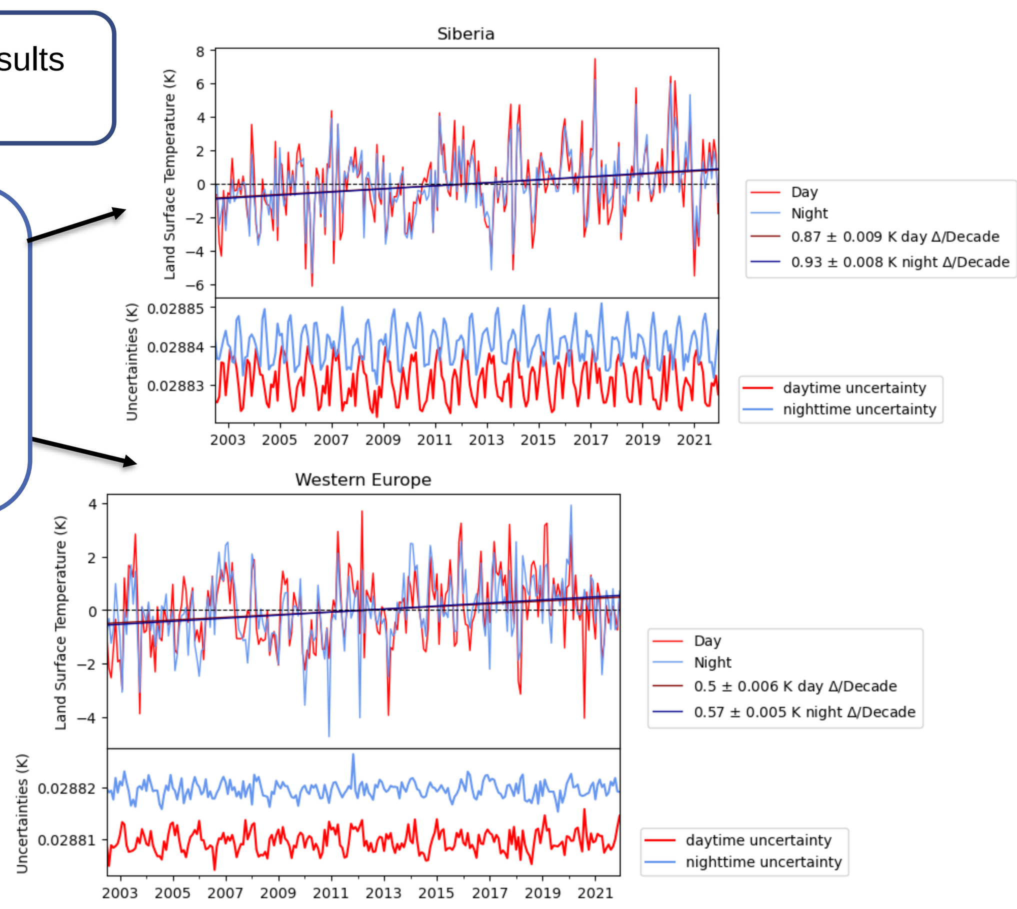
Step 3:

Validate the merged dataset and compare results with existing robust climate data records.

- Validation assesses the 'true' quality of the data compared to estimated uncertainties.

EO data from the satellite Aqua MODIS produces regional LST trends here to assess temperature change over two decades [6]

A global all-sky product using existing robust climate data will allow enhanced understanding of climate trends both globally, regionally and locally to assess changes in LST



Contributions to Targets and Objectives

2023 was the planet's warmest year on record, meaning LST data advancements used to track temperature change is critically important now more than ever!

Key objectives that involve investigating how Earth Observation from Space can contribute to balancing Earth's energy budget include:
- The United Nations Framework Convention on Climate Change (UNFCCC)
- The Paris Agreement (2015)

Improving global LST observations by creating a merged LST dataset, to refine climate warming predictions and further understand the fundamental physics of climate and LST, is paramount to fulfilling these objectives and meeting targets.

Real World Impact

This *innovative research* will yield results by improving global LST observations from Space, leading to a better understanding of global and local temperature dynamics.

Impact:
- Datasets aim to enhance surface temperature accuracy and aid the reliability of climate models.
- Real-world applications across Earth including vulnerable regions undergoing rapid changes (Arctic and Antarctic) or monitoring regional climate events such as heatwaves (Western Europe and the UK).
- Will inform evidence-based policies for adapting to climate change and fostering sustainable development.
- Offers policymakers accurate and actional climate information for informed decision-making to address climate change.

Take Home Message:

Improving LST data from Space using an AI & ML method will provide essential advancements into temperature variations and heat fluxes, integral for climate physics and modelling.
A merged IR & MW LST product aims to encourage climate model accuracy, facilitate precise evaluation of Earth's radiation budget and refine LST estimations used for policy and adaptation purposes, thereby ensuring a sustainable and resilient future for generations to come

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