Improving Ice Surface Temperatures from Space:

Regional Climate Trend Analyses & Progress Towards a Merged Product

By Abigail Marie Waring (PhD candidate)

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land surface temperature cci

Improving Ice Surface Temperatures From Space

- Topics:
  - Land & Ice surface temperatures
  - Regional climate trends & case study
  - The clear-sky bias problem
  - Machine learning method for all-sky product

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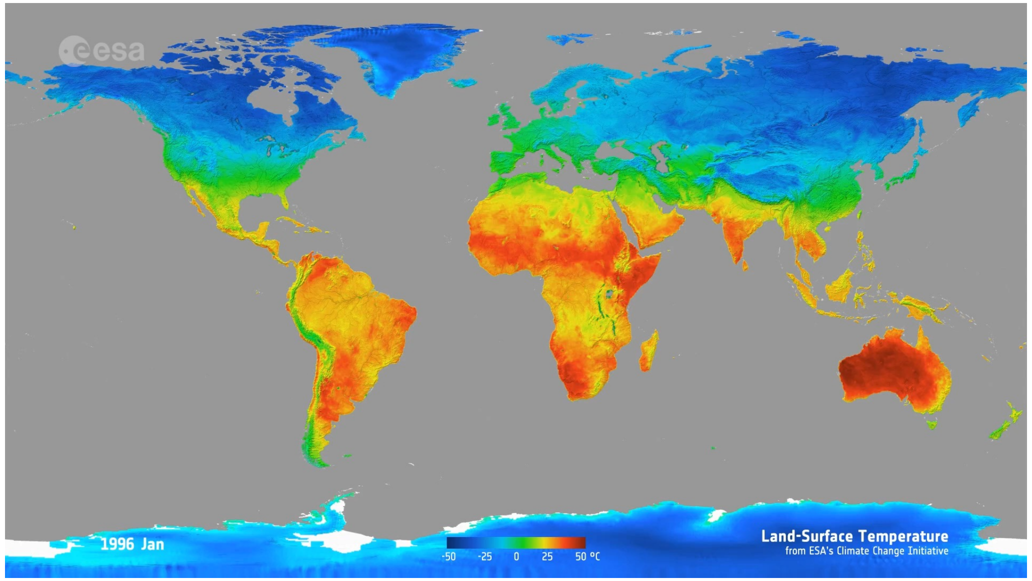
What is Land Surface Temperature?



- LST is defined as the skin temperature of the Earth's surface
    - Which approximates the thermodynamic temperature as a measurement of radiance on regional and global scales. LST drives outgoing long-wave radiation and heat fluxes between the atmosphere and land .

LST is considered an essential climate variable (ECV) by GCOS

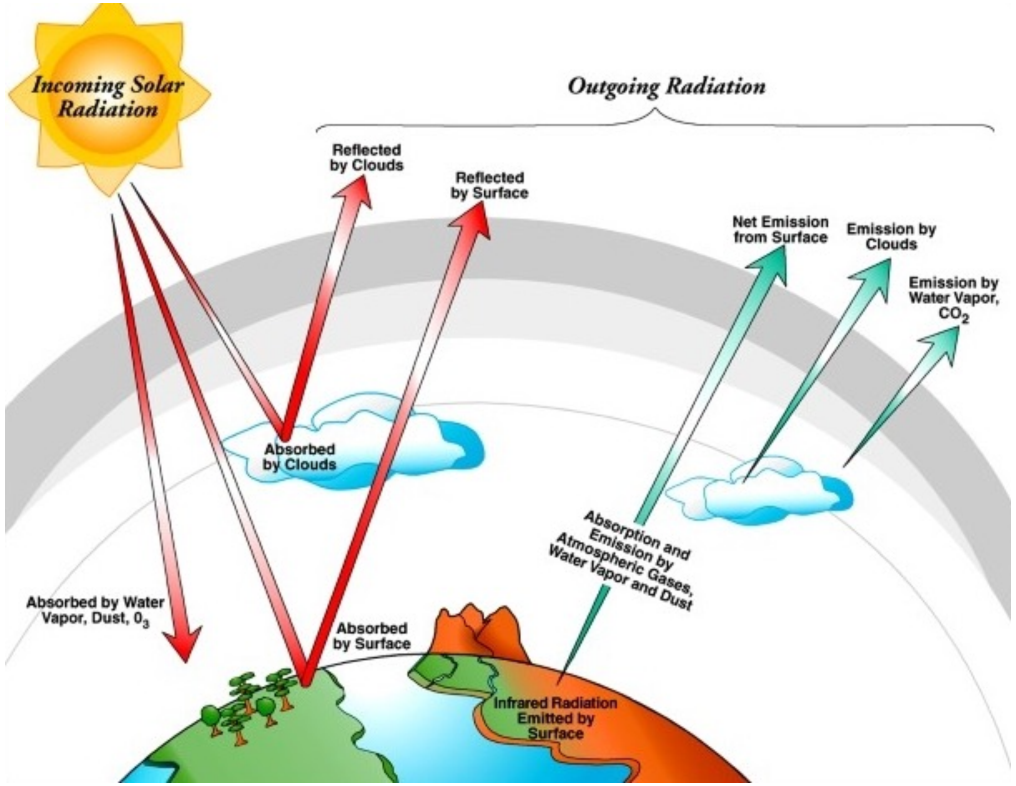
Retrieved via measurements in the infrared (IR) or microwave (MW) wavelength range by remote sensing

Controls energy partition into latent and sensible heat and is an indicator of strong surface warming trends.

The ST heating imbalance drives Earth's dynamic equilibrium.

The Significance of IST

- Understanding energy balance, emissivity and land-atmosphere interactions
- Arctic/Antarctic & cryosphere research is critical to understanding global climate regimes & changes
- ISTs are indicator of climate change, and we can monitor the Earth's dynamic equillibrium
- Remote sensing data interpretation, helping correct atmospheric effects & important for climate models
- Climate & weather applications of LST are extremely important – ice sheet mass balance, surface/energy balances, glaciology & sea-ice & snow phase understanding



Ice Surface Signals

Infrared	Microwave
Skin Temperature	
Skin surface	Penetration depth
Emissivity of Ice & Snow	
High emissivity's when clean and clear & efficient emitters	Usually lower than TIR & less effective but can get more variation out of signal
Surface properties	
Specular emissivity's of various surfaces	Susceptible to penetration depth, water content, polarization & surface characteristics
Spatial Resolution	
High-resolution (MODIS/LANDSAT)	Low-resolution (25-12.5km
Atmospheric influence	
Clear-sky bias	All-sky (minus large cumulonimbus)

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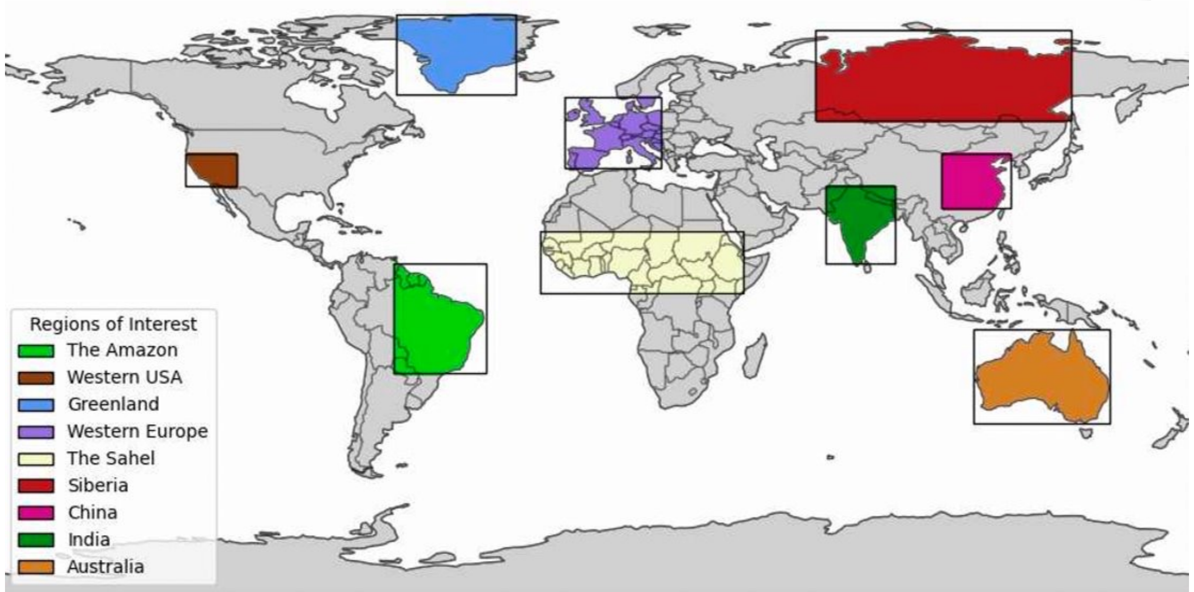
- A.M.Waring et al. 2023
- Climate trend analyses over 9 regions across Earth

AQUA MODIS
Regional Climate Trends

- Regional timeseries analyses for 9 regions
- Representative of different biomes & surface types all with a propagated uncertainty budget
- We found substantial LST trend increases for W USA, Siberia and the Amazon.



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Regional climate trend analyses for Aqua MODIS land surface temperatures

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ABSTRACT
Land surface temperature (LST) is the skin surface temperature of the Earth's land surface and is an essential climate variable (ECV) that critically characterizes the Earth's climate and surface energy processes. This is the first regional trend analysis for LST with uncertainties, using a stable LST climate data record suitable for climate trend analyses: the Aqua Moderate Imaging Spectroradiometer (MODIS) dataset (MYDCCI) produced in the European Space Agency (ESA) LST Climate Change Initiative (LST_cci) Project. The quality of the trends is verified here for Western Europe, for which consistent trends per decade of 0.5 K and 0.57 K across daytime and night-time data, respectively. Eight regions representative of a range of biomes and, including the Amazon, Western U.S.A., Greenland, the Sahel, Siberia, China, India, and Australia, have been analysed. Our most significant findings show substantial LST increases for Siberia and the Amazon, as well as evidence of recent increasing trends for the Western U.S.A. Siberia showed the most substantial daytime and night-time changes per decade of +0.87 K and +0.93 K, respectively. Furthermore, the Amazon and Western U.S.A. showed significant daytime LST trend increases of +0.82 K and +0.51 K, respectively. Western Europe and Western U.S.A. show the largest night-time change of +0.57 K and +0.54 K, respectively. India presents an atypical time series with a decreasing daytime and increasing night-time trend per decade of −0.62 K and +0.44 K, respectively, consistent with reported air temperatures. Overall the results show significant positive regional LST trends, against a background of both strong seasonal cycles and intermittent disruptive events, which demonstrate the importance of continued LST observations. The results also incentivize remote sensing science to derive ever more rigorous LST datasets and to continue to investigate emissivity and error correlations to allow improved trend analyses for smaller regions and individual locations.

ARTICLE HISTORY
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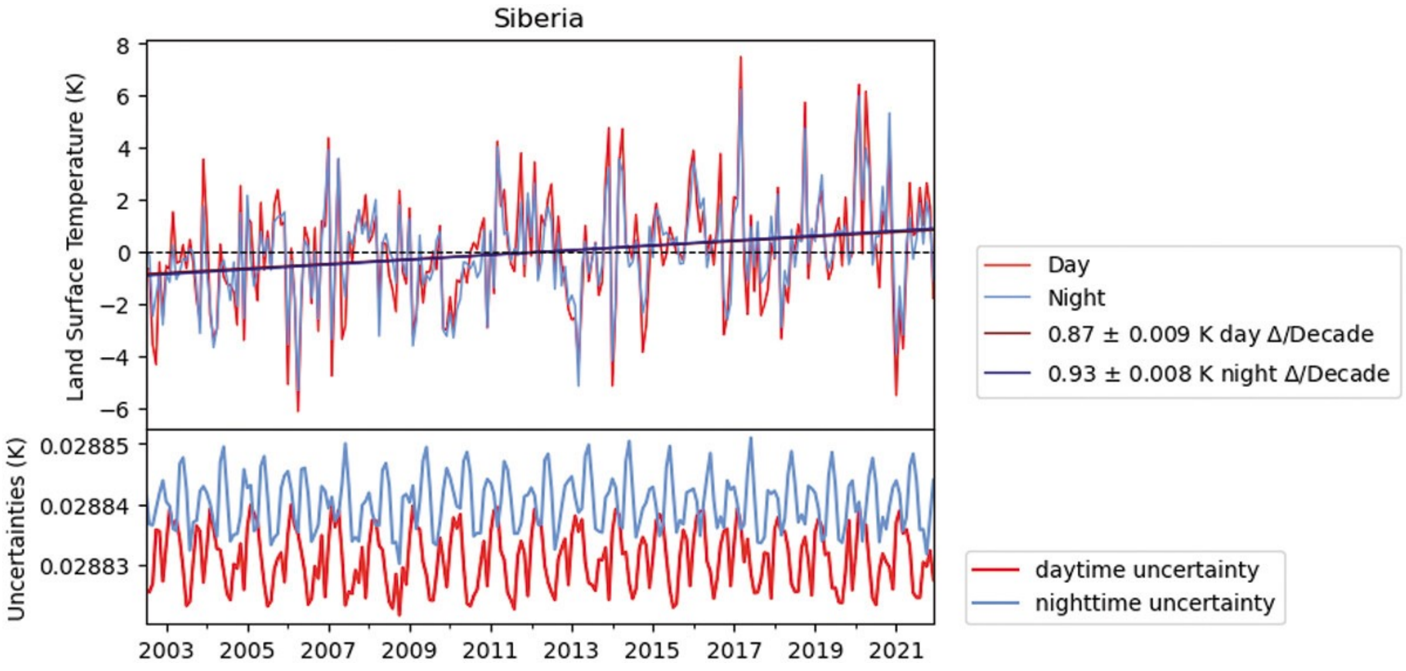
Siberia

- Most significant change per decades
  - 0.87 K day
  - 0.93 K night
- *p*-values rejects the null hypothesis that the time-series is likely to be a climate trend
  - Highly significant for both day and night
- IST changes influenced by:
  - Surface properties dominated by permafrost i.e., thawing & positive feedback
  - Extreme precipitation events linked to permafrost melting
  - NH extreme cold anticyclone events i.e., Siberian High explain cold anomalies

p-values

Region	Daytime *p*-value	Nighttime *p*-value
TheAmazon	**0.001**	.06
U.S.A.	**0.005**	**0.0003**
Greenland	0.3	0.4
Europe	**0.006**	**0.0003**
The Sahel	0.4	**0.000000005**
Siberia	**0.0005**	**0.00001**
China	**0.0009**	0.01
India	**0.0009**	**0.0001**
Australia	0.3	**0.001**



Greenland

- *p*-values supports the null hypothesis that the time-series is less likely to be a climate trend and more likely natural variability
  - Probably related large-scale atmospheric circulation variability & cloud misclassification
- IST changes influenced by:
  - Natural variability & Arctic amplification
  - Surface dry-snow reduction linked to rising T2M (2002-2005)
  - GBI & NOA linked to significant warm anomalies (2010-2012) & seasonal cycles

p-values

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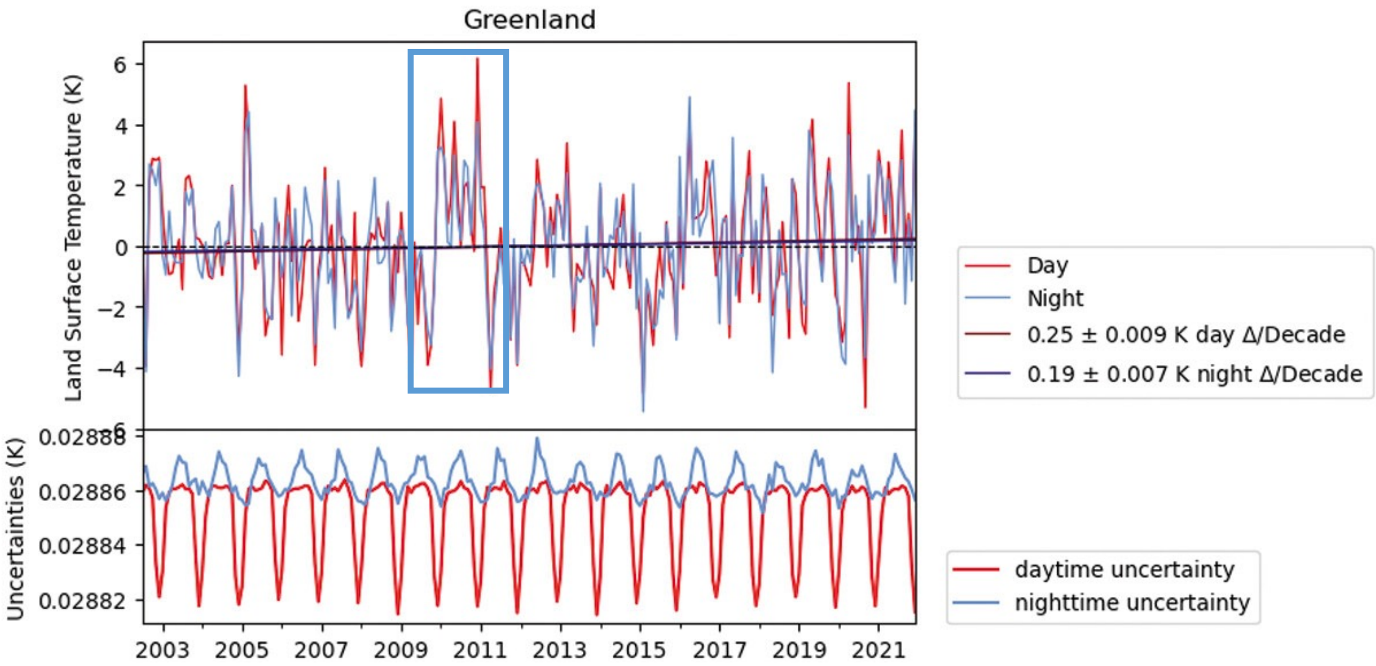
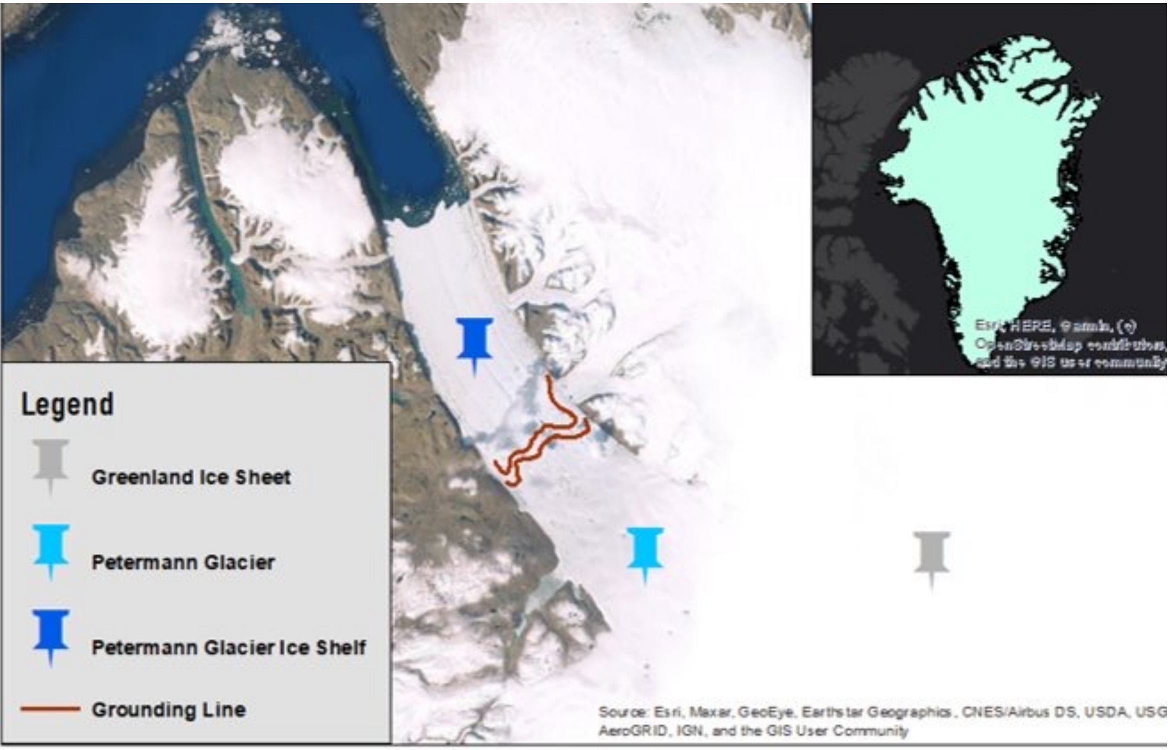


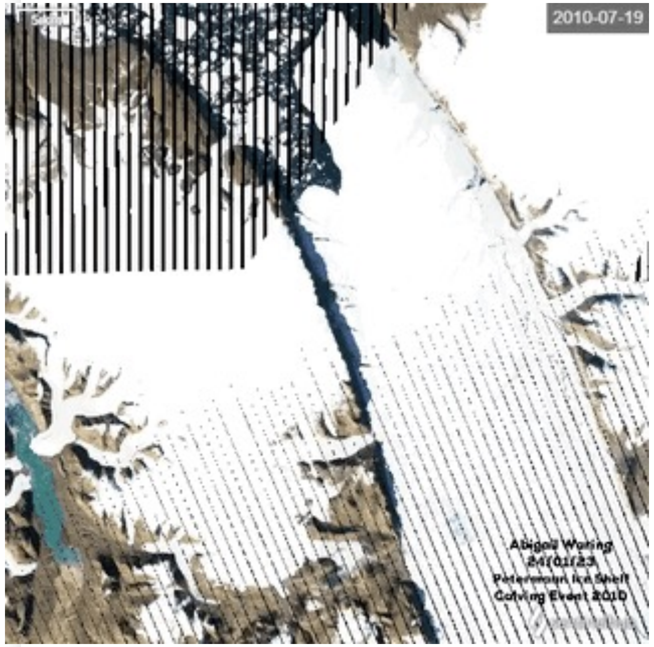
IST Polar & Cryosphere Applications

Petermann Glacier Ice Shelf, Greenland

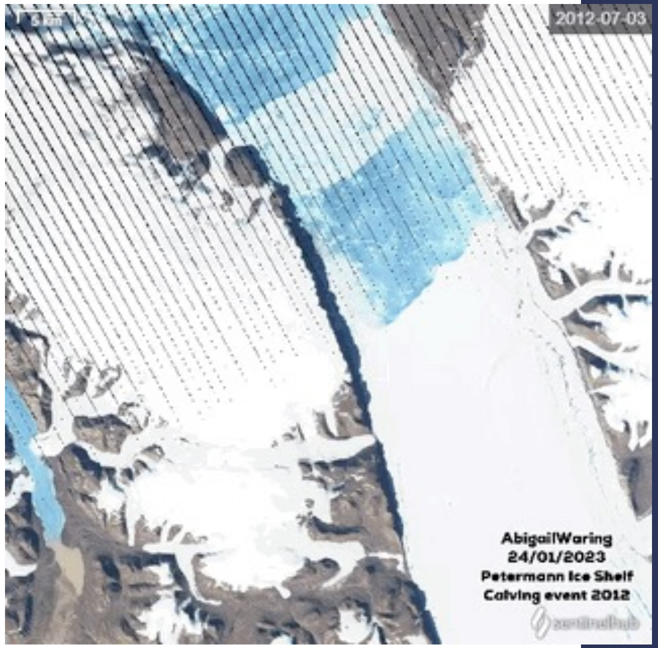
- An **ice shelf** is a large floating platform (tongue) of ice that forms where a tidewater glacier or ice sheet flows past the grounding line onto the ocean surface.



2010



2012



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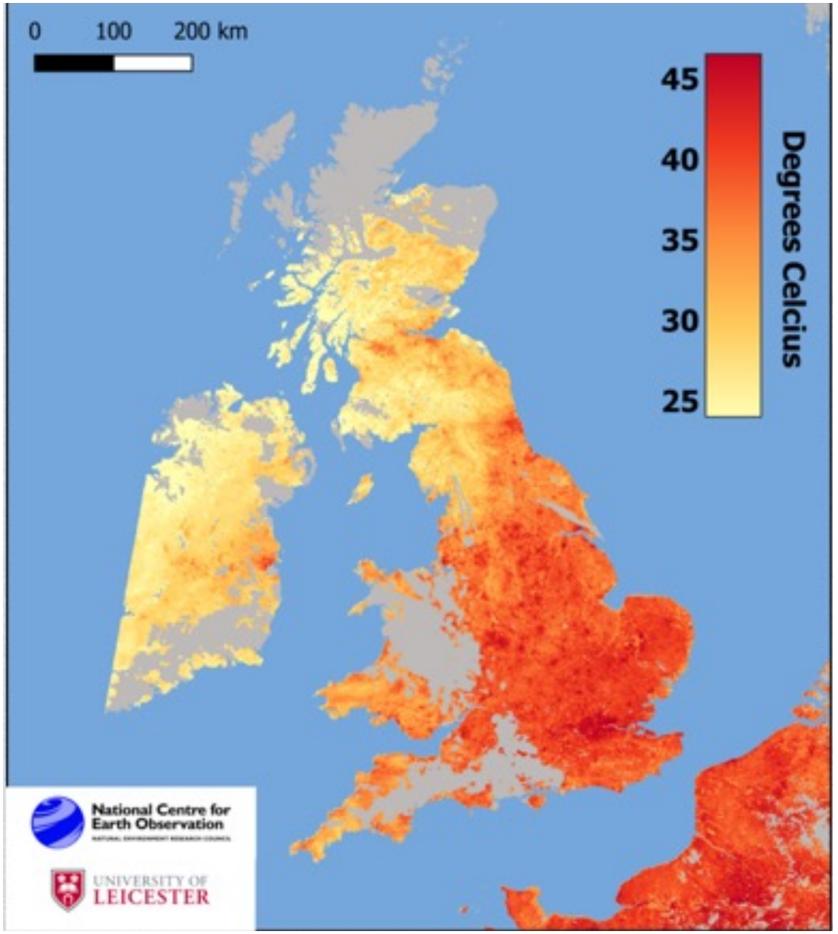
The Clear-Sky Bias Problem



BBC article on the 2022 UK heatwave. SLSTR infrared compiled by the University of Leicester/NCEO's surface temperature group

The problem:

- Infrared signal is blocked by clouds
- Huge data gaps means our weather & climate trends are only indicative of a clear sky
- Greenland & Antarctica are some of the cloudiest places on Earth

Why is this important?:

- Lack of data == higher uncertainty of the Earth's total energy budget

What now?:

- We build an **all-sky** LST dataset that merges other LST data
- Aim to use dataset to understand IST's more

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All-Sky Merged Model

- LST data:
  - IR LST has a clear-sky bias due to cloud cover BUT is high resolution
  - MW is all-sky BUT much lower resolution
- Initial merge:
  - NASA's Aqua MODIS & AMSR-E
  - Same temporal resolution but different spatial resolution

- NASA's LEO Aqua satellite carries two passive instruments:
- **The Moderate Resolution Imaging Spectroradiometer (MODIS) (IR)**
  - 1 km spatial resolution (high res)
  - 1-2 days temporal resolution
- **The Advanced Microwave Scanning Radiometer (AMSR-E) (MW)**
  - 12.5 km spatial resolution (coarse)
  - 1-2 days temporal resolution

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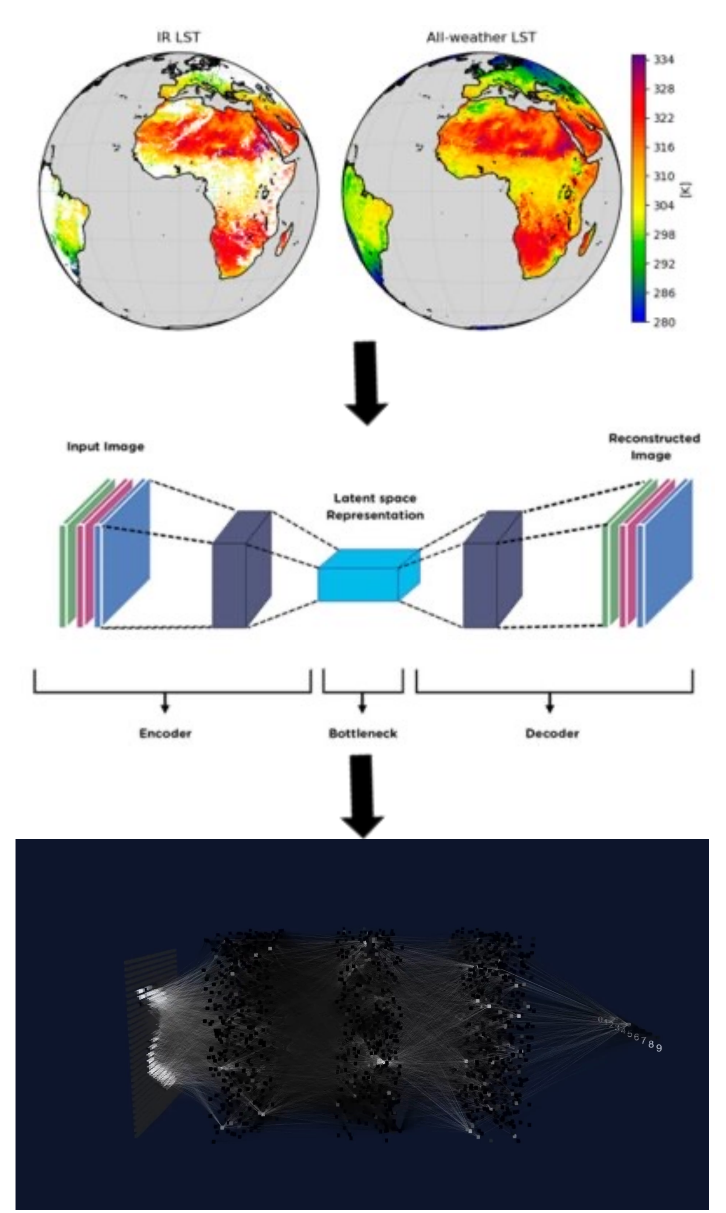


Machine Learning Method

- Building a convolution neural network (CNN) to merge both infrared and microwave LST
  - The autoencoder-decoder is a neural network architecture that learns to encode, and then decodes data by compressing and reconstructing it
- How?
  - Train a model with IR & MW coincident scenes across Earth representative of different biomes, climates & surface types
  - The CNN will downscale the MW data and 'gap-fill' with IR

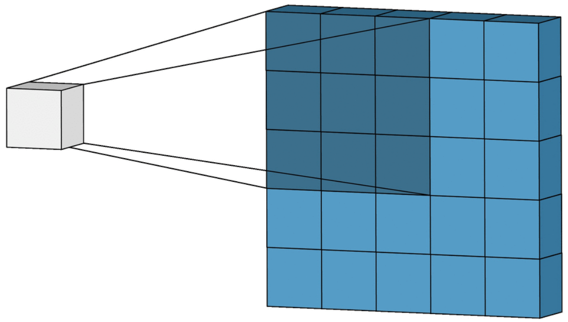
What is a Convolutional Neural Network?

1. Convolutional layer
    - Core building block of the CNN
    - Performs feature extraction from input data using kernels
    - Kernels are small matrices designed to detect specific patterns or features as feature maps

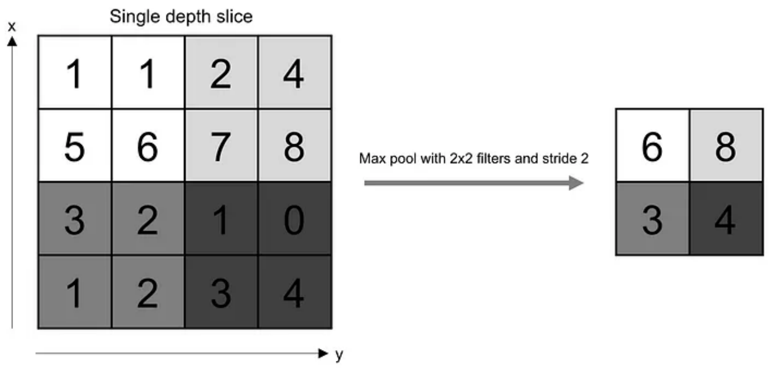
2. Pooling layer
    - Used to reduce spatial dimensions of the feature maps generated
    - Can be performed by max-pooling or averaging
    - Pooling helps to reduce computational complexity

3. Fully connected layer
    - Each neuron in a layer is connected to every neuron in the previous and subsequent layers
    - Used to learn complex relationships and patterns in the data
    - Connects to output layer to produce final predictions

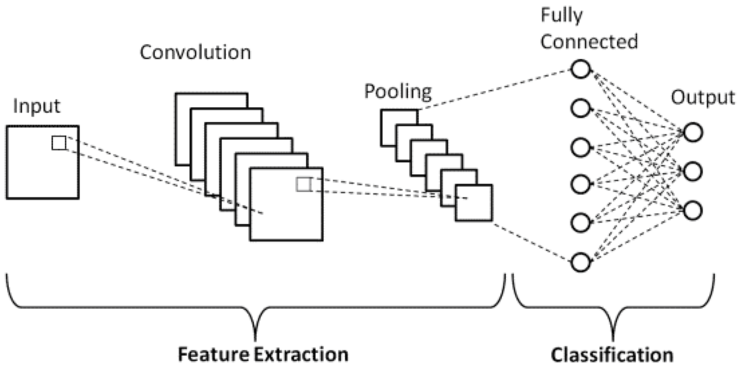
1. Convolutional layer



2. Pooling layer



3. Fully Connected layer



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What is an Autoencoder-Decoder?

- Encoding layers:
  - Takes high-resolution as input
  - Convolutional layers down sample & extract
  - Reduces spatial dimensions
  - Produces a low-dimensional input representation
- Decoding layers:
  - Takes the encoded low-dimensional output as an input
  - Convolutional layers increase spatial dimensions
  - Produces a reconstructed image with a higher resolution

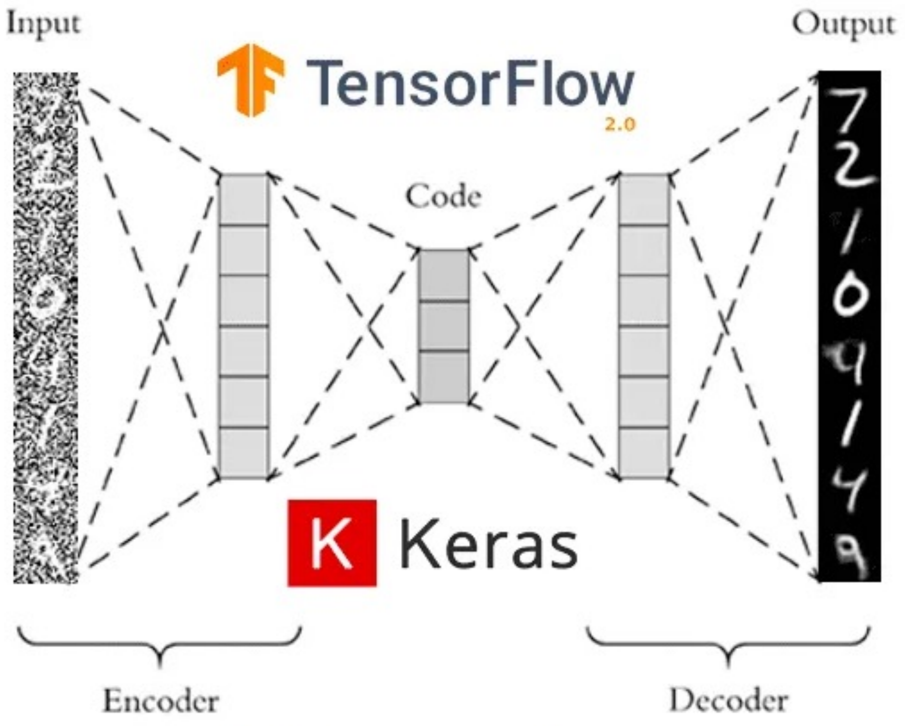


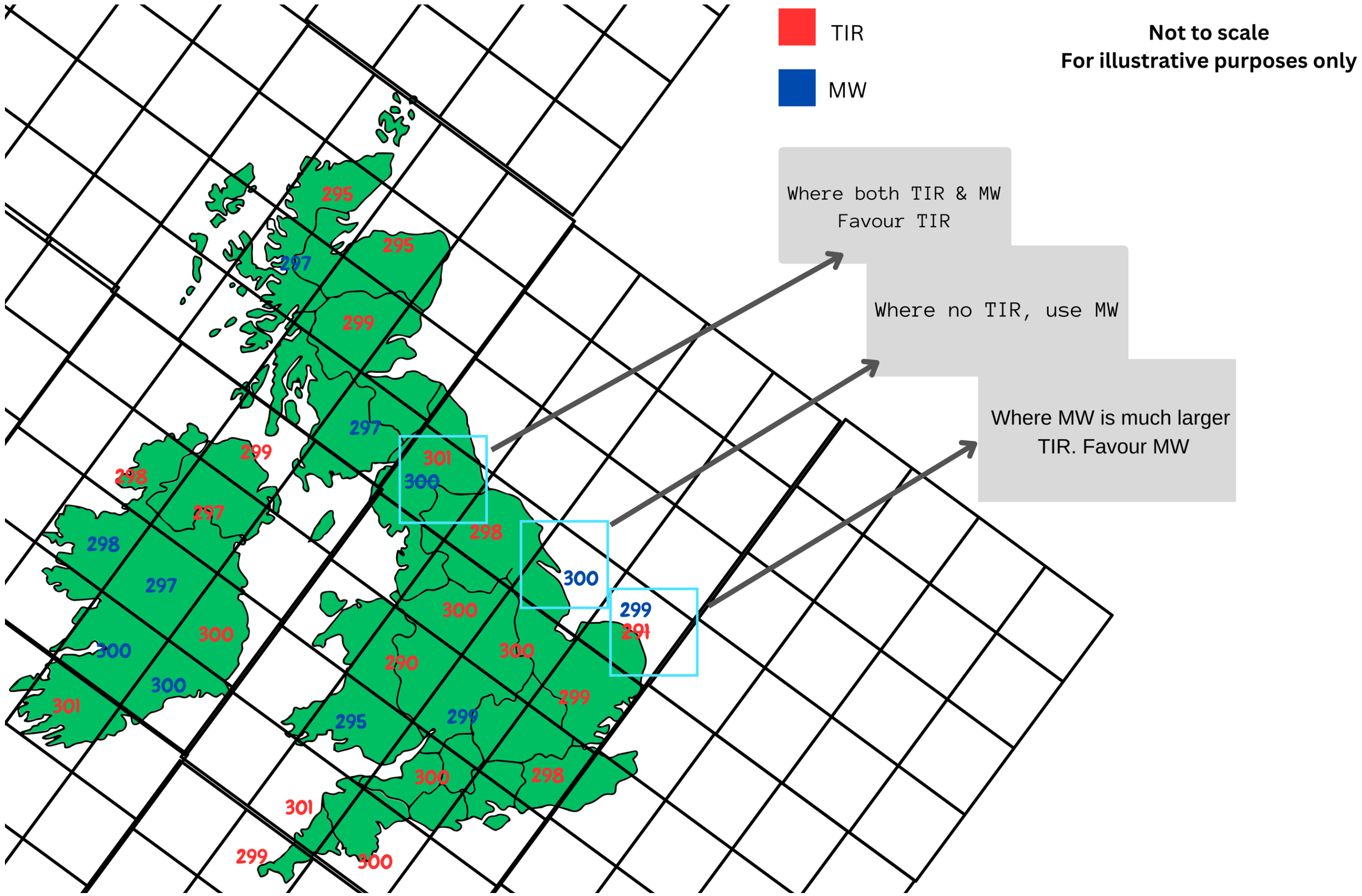
Photo Credit: pyimagesearch.com

Merged Dataset Product Outcome

- A merged all-sky LST for the globe at 5 km resolution

Selection of LST data:

- Where pixel == TIR & MW, favour TIR over MW
    - (lower uncertainties)
- Where pixel == cloud, fill with MW
- Where TIR < MW, favour MW
    - (TIR likely seeing cloud top height not the surface, MW can penetrate the misclassified cloud)



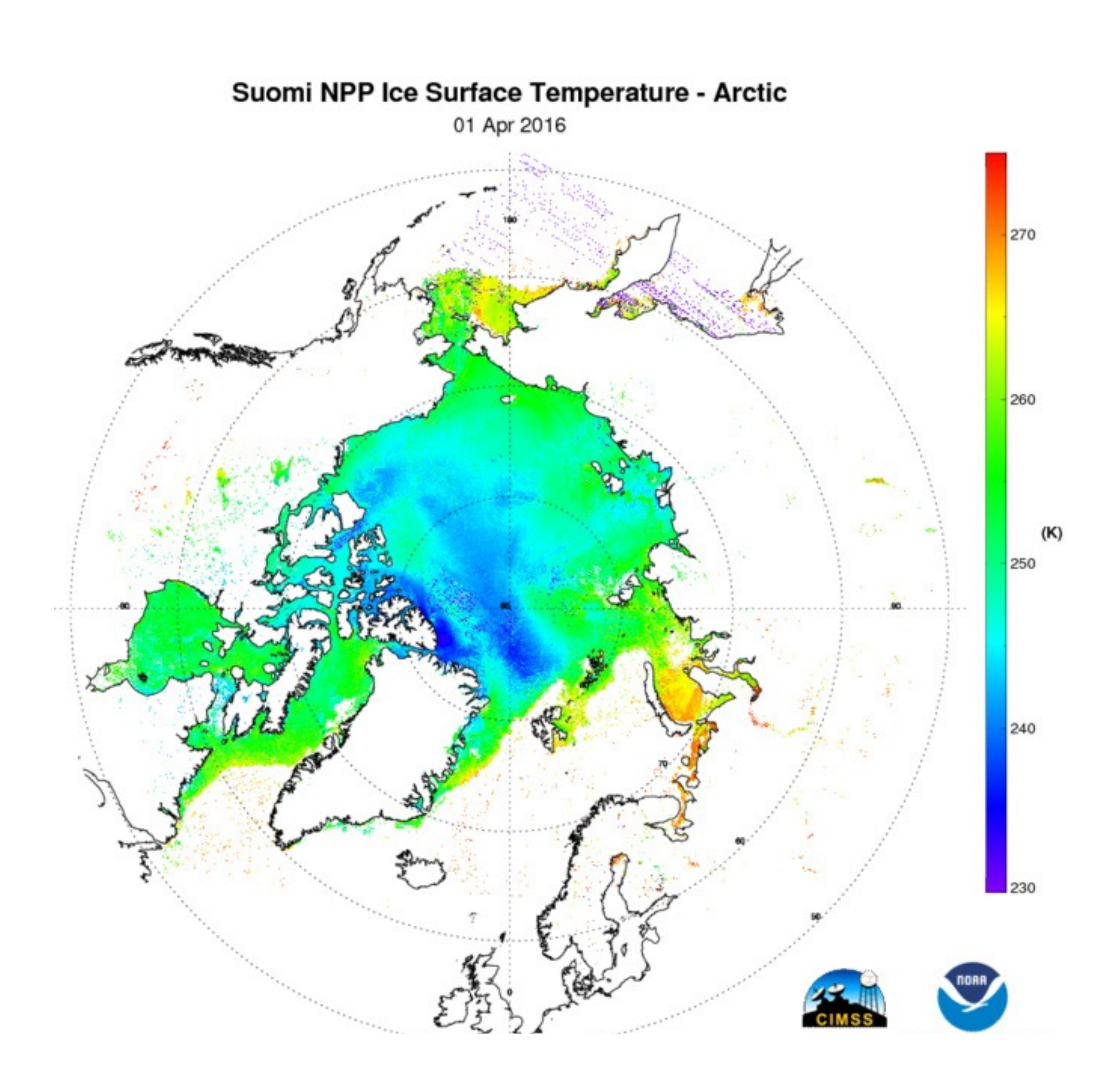
```
[11]: next(day_gen)

      IR path found: /lustre_scratch/abiwaring/modis_amsre_matchup_0.25_DAY_20080101.nc
      MW path found: /lustre_scratch/abiwaring/modis_amsre_matchup_0.25_DAY_20080101.nc

[11]: (<xarray.DataArray 'lst' (lat: 40, lon: 40)>
       array([[283.88    , 288.03998, 287.50998, ...,       nan,       nan,       nan],
              [291.31    , 289.88    , 285.81    , ...,       nan,       nan,       nan],
              [      nan,       nan, 287.44    , ...,       nan,       nan,       nan],
              ...,
              [      nan,       nan,       nan, ..., 276.83    , 277.97    ,       nan],
              [      nan,       nan,       nan, ..., 277.25    , 276.53    , 273.58    ],
              [      nan,       nan,       nan, ..., 278.5     , 278.19    , 277.91998]],
             dtype=float32)
       Coordinates:
           time     datetime64[ns] 2008-01-01
         * lat      (lat) float32 37.72 37.97 38.22 38.47 ... 46.72 46.97 47.22 47.47
         * lon      (lon) float32 -7.875 -7.625 -7.375 -7.125 ... 1.375 1.625 1.875
       Attributes:
           long_name:  land surface temperature
           units:      kelvin
           valid_min:  -8315
           valid_max:  7685,
       <xarray.DataArray 'amsre_lst' (lat: 40, lon: 40)>
       [1600 values with dtype=float64]
       Coordinates:
         * lat      (lat) float32 37.72 37.97 38.22 38.47 ... 46.72 46.97 47.22 47.47
         * lon      (lon) float32 -7.875 -7.625 -7.375 -7.125 ... 1.375 1.625 1.875)

[12]: next(day_gen)

[12]: (<xarray.DataArray 'lst' (lat: 40, lon: 40)>
       array([[287.16,    nan,    nan, ...,    nan,    nan,    nan],
              [   nan,    nan,    nan, ...,    nan,    nan,    nan],
              [285.52,    nan,    nan, ...,    nan,    nan,    nan],
              ...,
              [   nan,    nan,    nan, ..., 277.05, 277.6 , 277.88],
              [   nan,    nan,    nan, ..., 276.53, 275.63, 278.44],
              [   nan,    nan,    nan, ..., 277.33, 277.07, 278.08]], dtype=float32)
       Coordinates:
           time     datetime64[ns] 2008-01-01
         * lat      (lat) float32 37.72 37.97 38.22 38.47 ... 46.72 46.97 47.22 47.47
         * lon      (lon) float32 -5.375 -5.125 -4.875 -4.625 ... 3.875 4.125 4.375
       Attributes:
           long_name:  land surface temperature
           units:      kelvin
           valid_min:  -8315
           valid_max:  7685,
       <xarray.DataArray 'amsre_lst' (lat: 40, lon: 40)>
       [1600 values with dtype=float64]
       Coordinates:
         * lat      (lat) float32 37.72 37.97 38.22 38.47 ... 46.72 46.97 47.22 47.47
         * lon      (lon) float32 -5.375 -5.125 -4.875 -4.625 ... 3.875 4.125 4.375)

[13]: next(day_gen)
```

Method Process (so far)

- *Match up MODIS & AMSRE*
  - Currently matched up on the same grid to train the model with
  - When the new MW AMSR-E dataset is available at 12.5 km, we will re-run the match up
- *Create a data generator*
  - Generates TIR & MW tiles over the same location with selected LST data
- *Train the model*
  - Train the model with IR & MW region pairs
  - Train with 60-70% data & test with 40-30% data

Summary

- LST is a significant ECV that determines Earth's climate
- IST research is imperative for understanding global energy balances & ice/snow dynamics
- It can be retrieved in the TIR & MW wavelengths
  - However, TIR cannot be retrieved under cloud & MW is at a very coarse resolution
- To solve the problem & improve LST observations we are building an all-sky merged LST product using machine learning techniques
- The all-sky LST product will cover the globe at a resolution of 5 km with its associated uncertainties
- The final product will aid in significant climate & weather applications where observations are scarce, particular in the polar regions
- Future work = expanding IST in TIR to other regions such as Iceland, Arctic Canada, Svalbard & Antarctica
  - Also compare data from merged product



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Thank you!

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