ML for Earth Observation:

Land Surface Temperature Super-Resolution (LST)

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Outline

- Problem: LST Super-Resolution
- Data Source and Pre-processing
- Methods applied
- Evaluation Metrics
- Conclusion

Problem Statement

- **Objective**

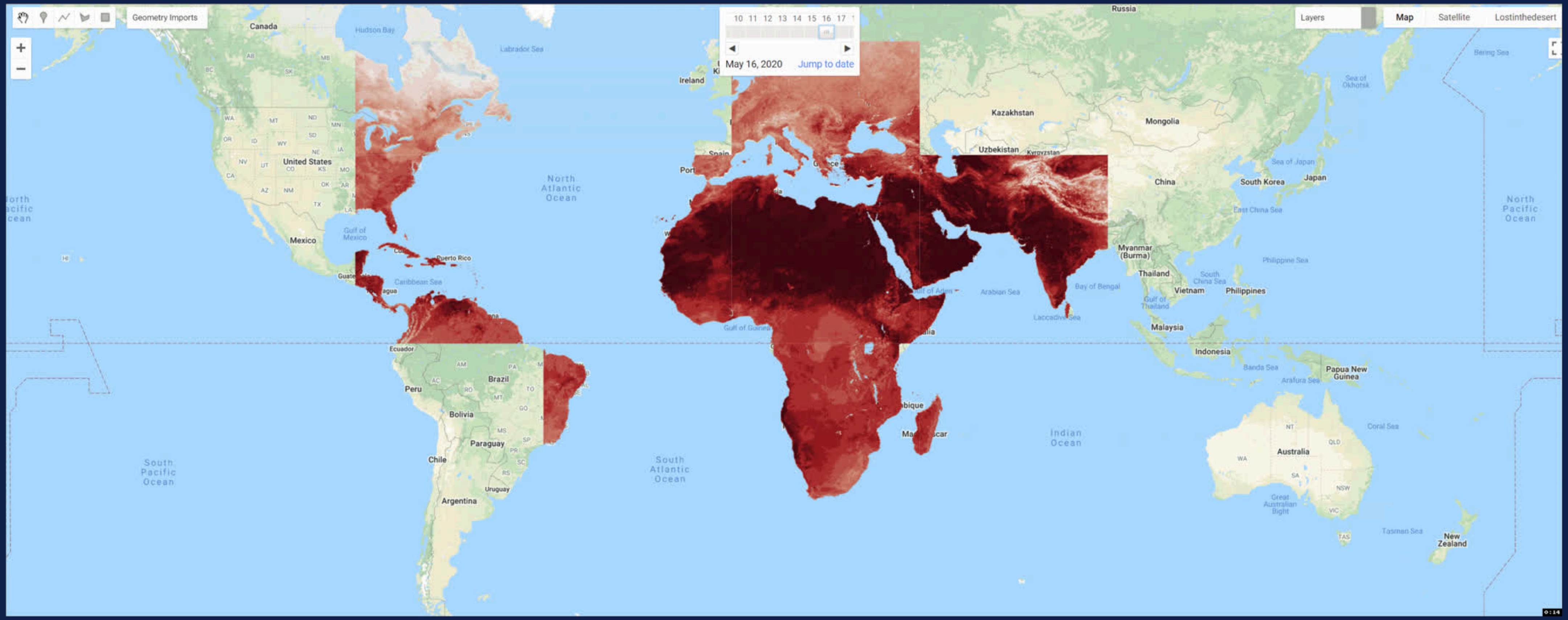
  Enhance low-resolution Land Surface Temperature (LST) data to high-resolution using auxiliary data like NDVI.

- **Challenge**

  LST data from satellites often has coarse spatial resolution, limiting its use in detailed urban and environmental studies.

- **Importance**

  High-resolution LST is crucial for:
  - Urban heat island analysis
  - Agricultural monitoring
  - Climate change studies



Land Surface Temperature, LST, MODIS, gapfilled , Landsat 8

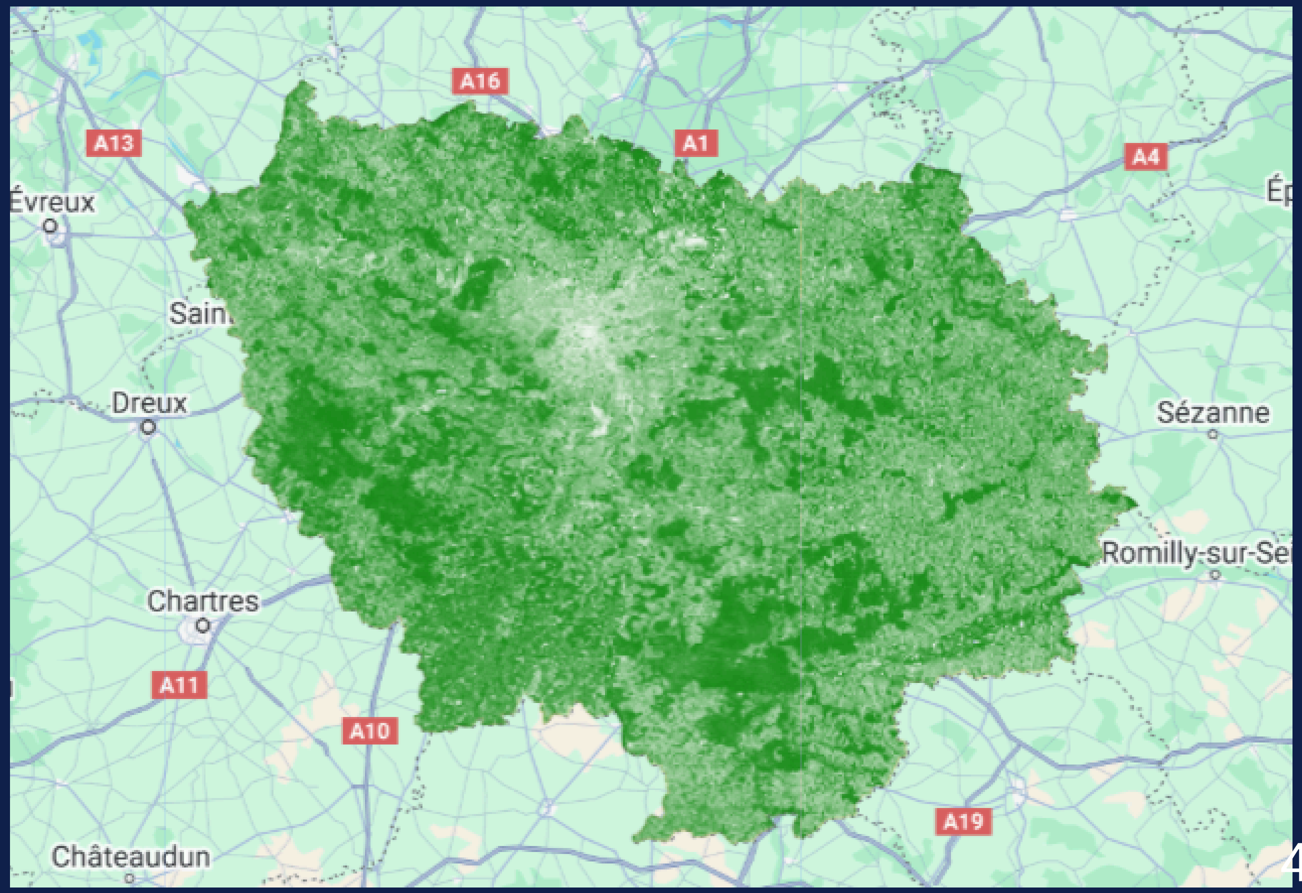
- **Approach**

  Use machine learning to integrate low-resolution LST with high-resolution land cover data to produce detailed LST maps.

Data source and Details

- **Source**: Google Earth Engine (GEE), MODIS/Landsat 8
- **Study Area**: Île-de-France, 2019
- applyScaleFactors() optical and thermal bands, cloudMask() to filter out bad pixels
- **Datasets**:
  - Ile_de_France_LST_Mean_2019.tif : Mean LST in Celsius
  - Ile_de_France_NDVI_Mean_2019.tif : Normalized Difference Vegetation Index
- **Details**:
  - **Format**: GeoTIFF files processed with rasterio library
  - **Resolution**: High-resolution data (served as baseline); low-resolution simulated at 1/4 scale
  - **Processing**: Cleaned LST (values < -100°C set to NaN), aligned masks using skimage.transform.resize
  - **Simulation**: Adjusted LST for urban (+3°C), vegetation (-1°C), water (-5°C); NDVI assigned as urban (0.1), vegetation (0.8), water (0.05)

Landsat 8 True Color



NDVI Ile-de-France

Data source and Preprocessing

The high-resolution LST data (from `high_res_lst.shape`) has dimensions of [Height] x [Width] pixels.

LST values less than -100 (often NoData values) were replaced with NaN

Data quality for ML models

Inspector | Console | Tasks

```
First image in collection:                                  JSON
▾Image (1 band)                                             JSON
   type: Image
 ▾bands: List (1 element)
   ▾0: "LST", double, EPSG:32631, 7821x7921 px
       id: LST
       crs: EPSG:32631
      ▸crs_transform: [30,0,448785,0,-30,5531415]
      ▸data_type: double
      ▸dimensions: [7821,7921]
 ▾properties: Object (2 properties)
     system:index: LC08_198026_20230606
     system:time_start: 1686047641711
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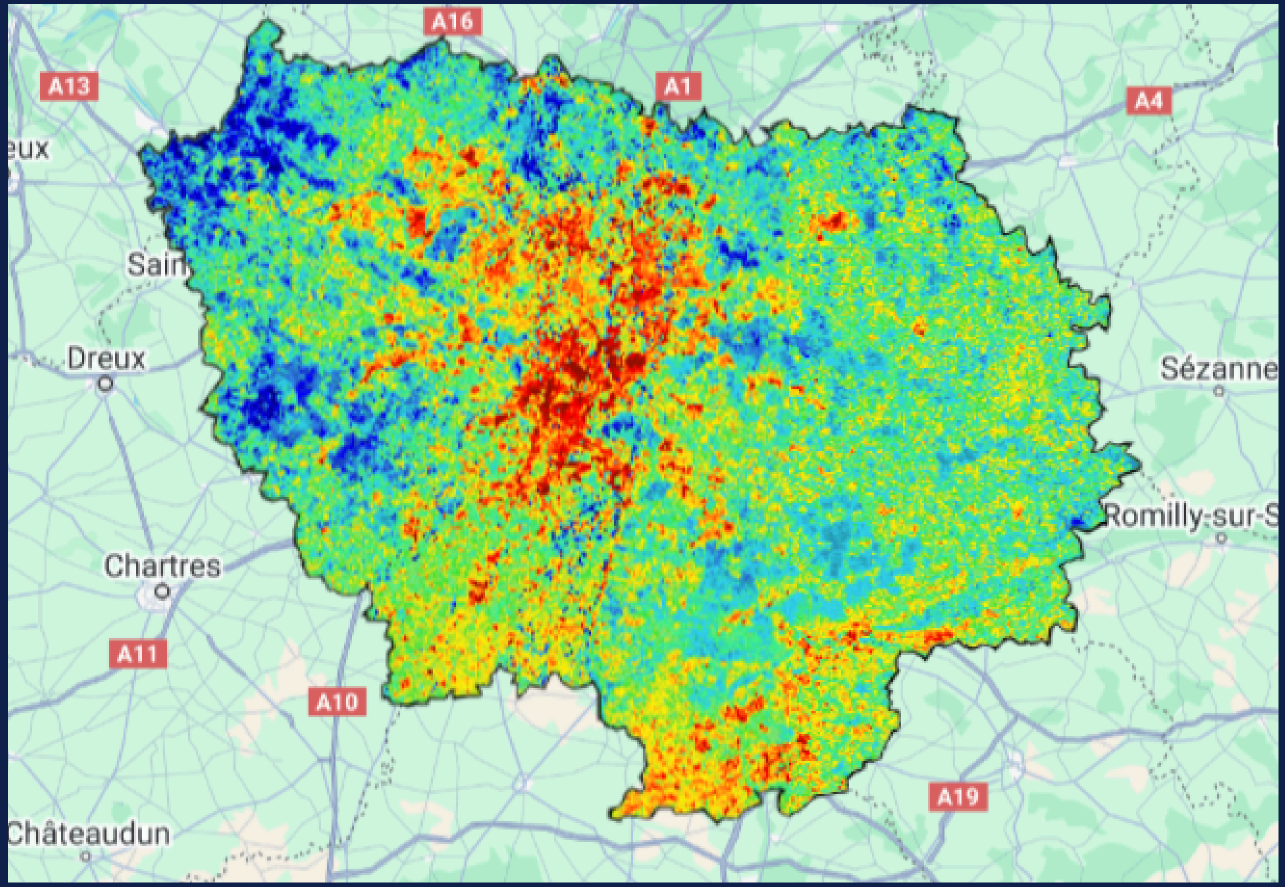
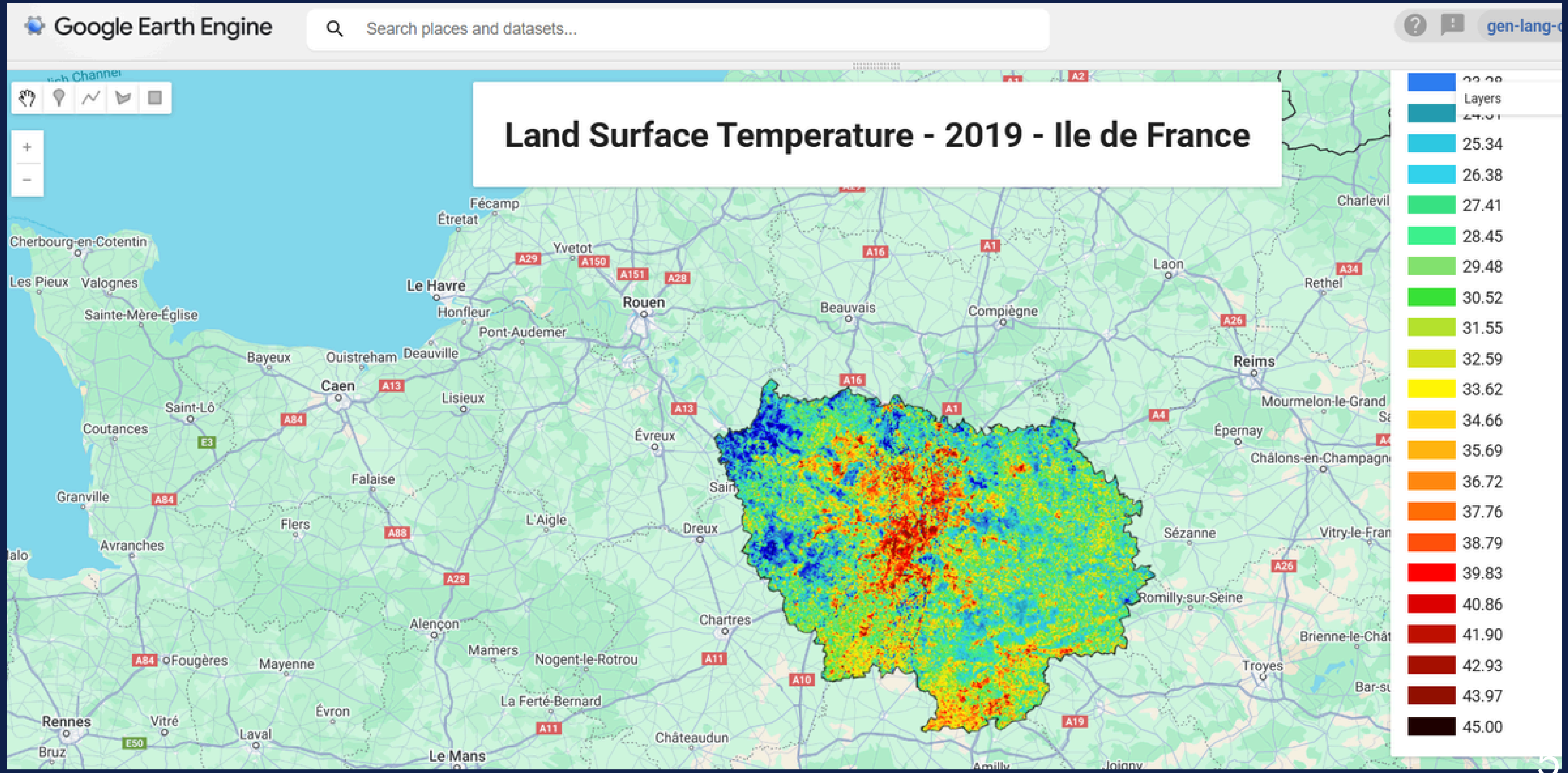




LST - Ile de France

Formula: (TB / (1 + (λ * (TB / 1.438)) * ln(em))) - 273.15

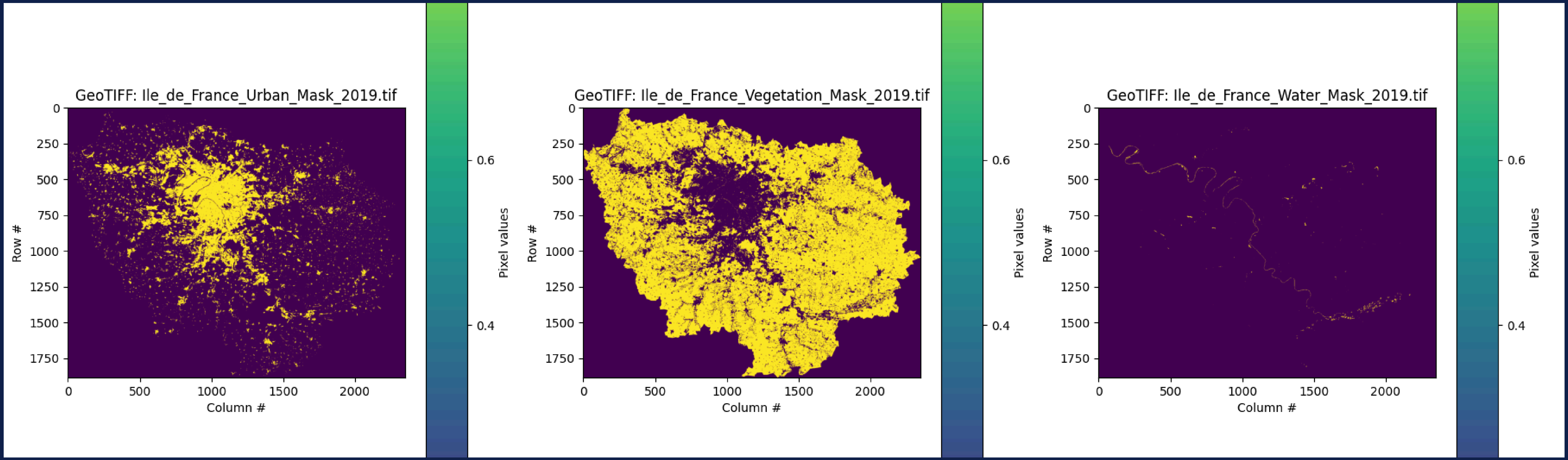
Satellite radiance → Brightness Temp (T_B)→ Adjusted for emissivity(ϵ\epsilon) and wavelength (λ \lambda) → LST in Celsius.

Data source and Preprocessing

- **Mask Alignment:**

Aligned land cover masks (urban, vegetation, water) to match the LST data dimensions by using 'skimage.transform.resize' library.

with 'anti_aliasing = False' and 'preserver_range = True'. to maintain data integrity



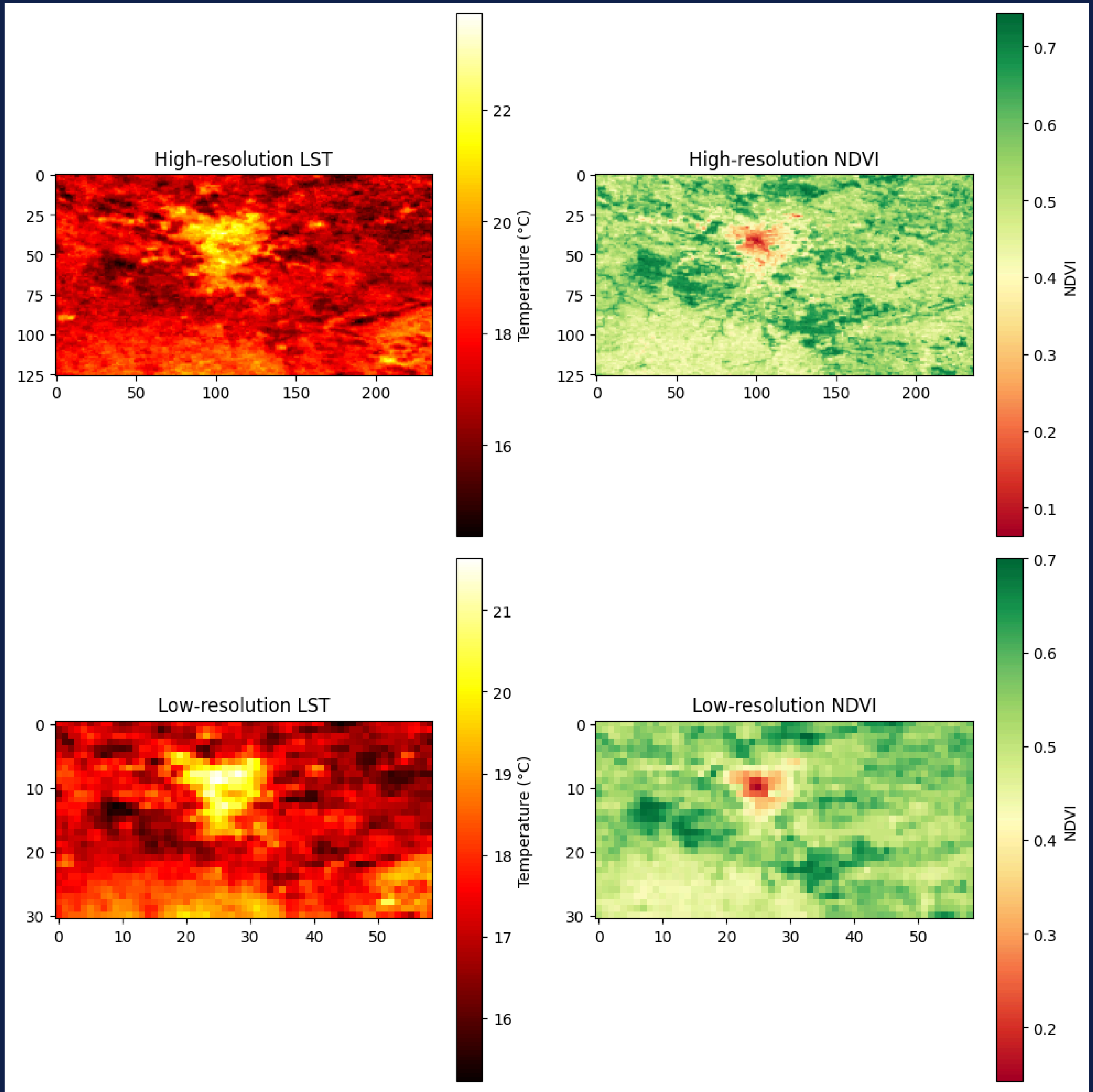
Data source and Preprocessing

- **Preprocessing**

A crucial first step for supervised Machine Learning-based super-resolution creating paired datasets

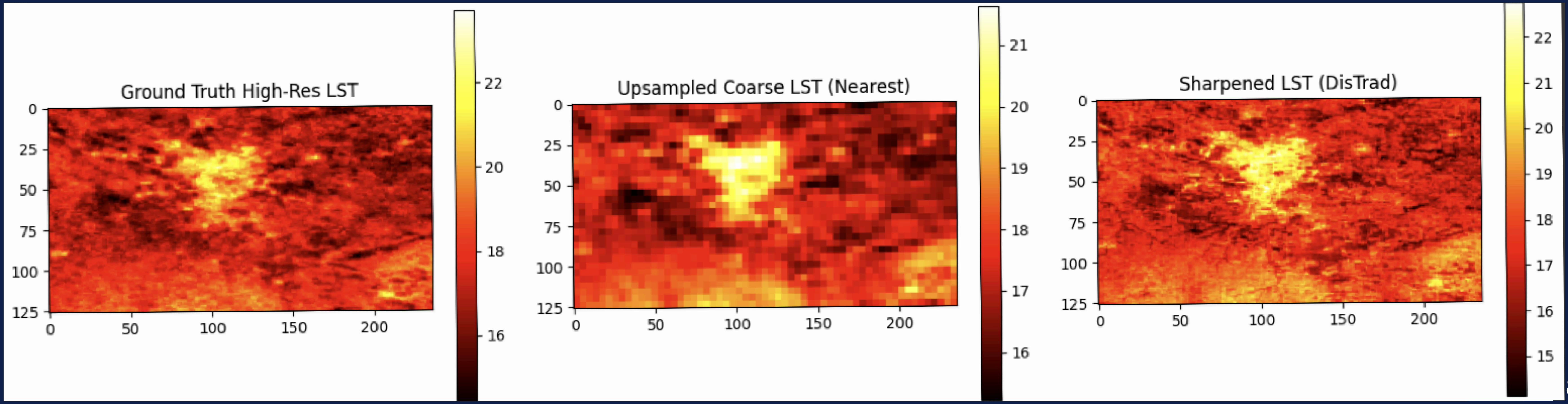
creates a synthetic high-resolution (HR) dataset and then downsamples it to generate a corresponding low-resolution (LR) dataset.

This paired LR to HR dataset is essential for training models to learn the mapping from LR to HR



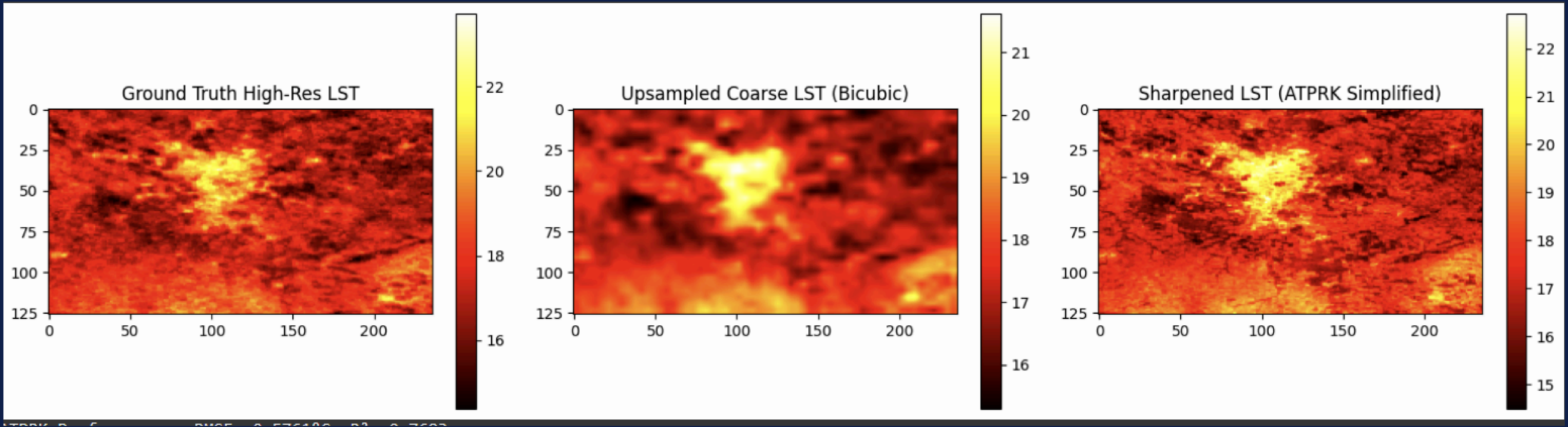
Method 1 : DisTrad (TsHarp)

- Linear regression between LST and NDVI at Low resolution.
- Apply regression to high-resolution NDVI to predict LST.
- Calculate residuals (differences between actual and predicted LST) to refine prediction.
- Upscale these residuals to the high resolution (nearest-neighbor interpolation) to preserve thermal energy consistency.
- Add the upscaled residuals to the initial high-resolution prediction to produce the Sharpened LST map



Method 2 : ATPRK

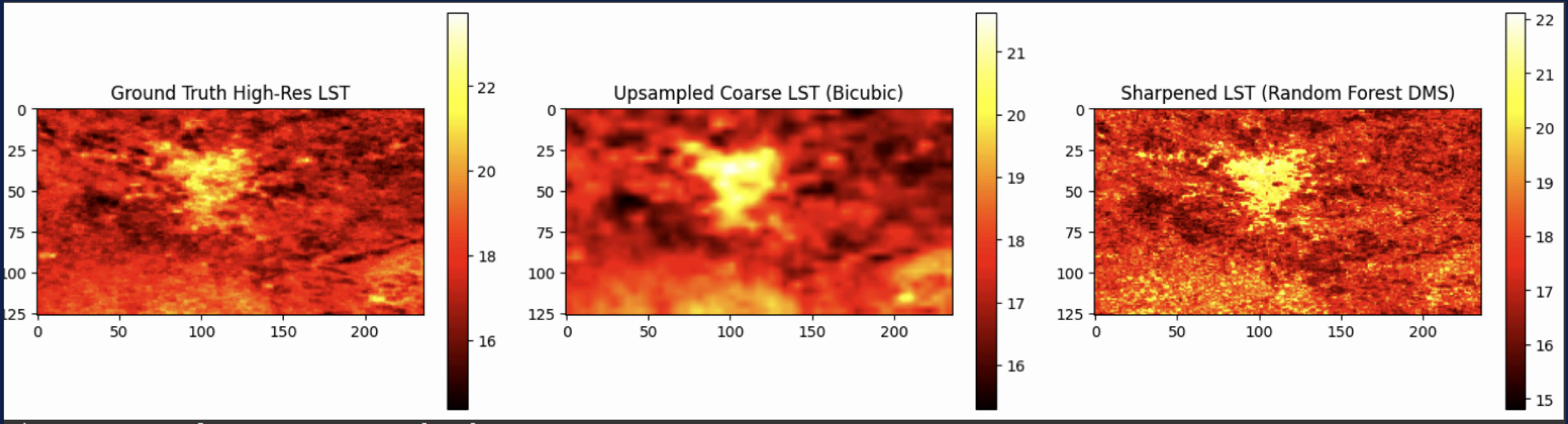
- Similar conceptual basis to DisTrad, utilizing the LST-NDVI relationship and residual correction.
- **Distinction:** Employs bilinear interpolation for upscaling the low-resolution residuals to the high resolution.
- Bilinear interpolation considers the values of the four nearest neighbors, potentially leading to a smoother transition of residuals compared to Distrad.



Method 3 : Random Forest - DMS

Allows learning more complex, non-linear relationships between LST and auxiliary features (NDVI)

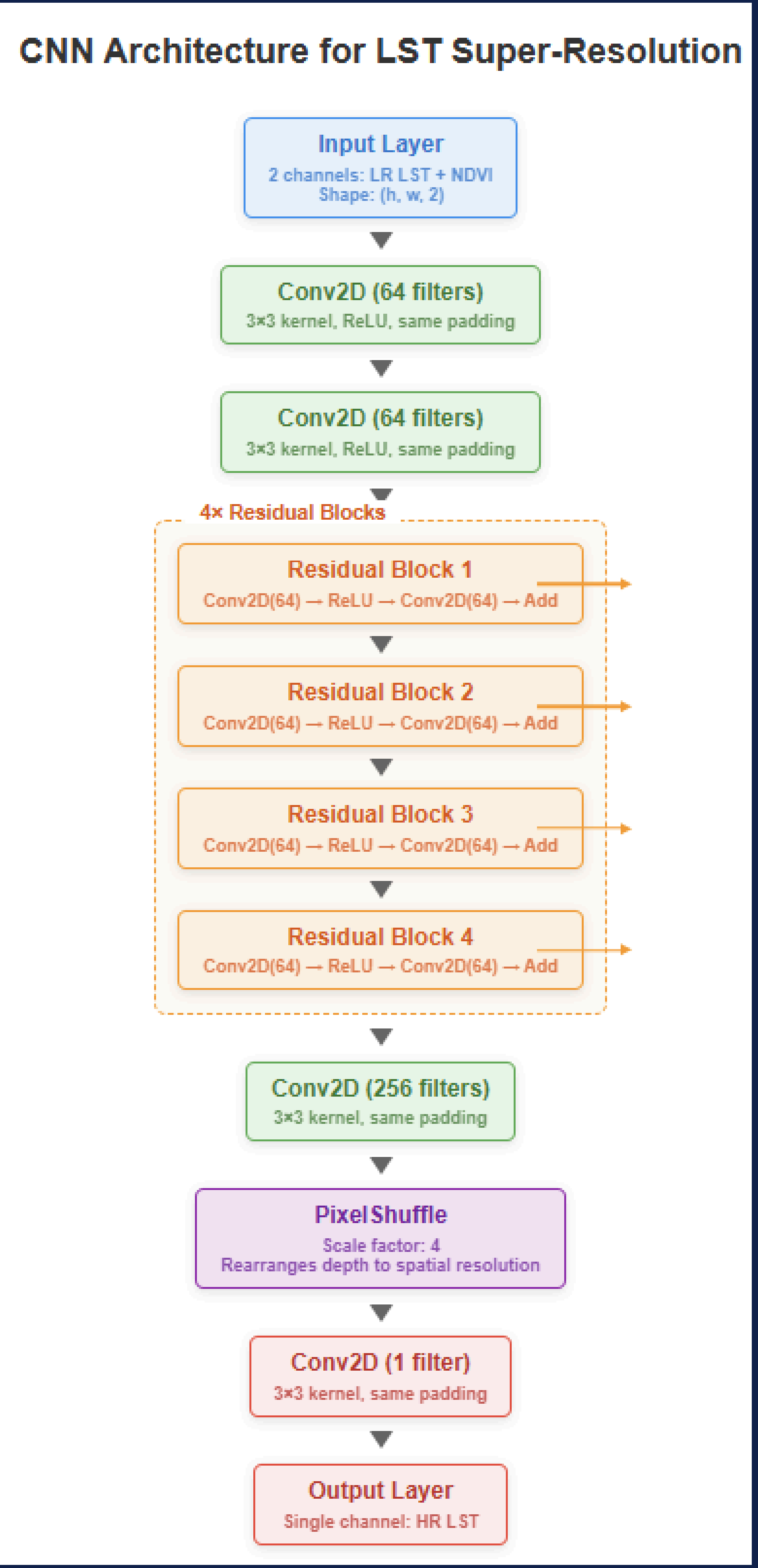
- Train a Random Forest model using LR LST and LR NDVI.
- Predict HR LST using HR NDVI as input to the trained model.
- Compute residuals between true and predicted LST at low resolution.
- Upscale residuals using nearest-neighbor interpolation.
- Add residuals to the initial HR prediction for final LST output.



Method 4 : CNN

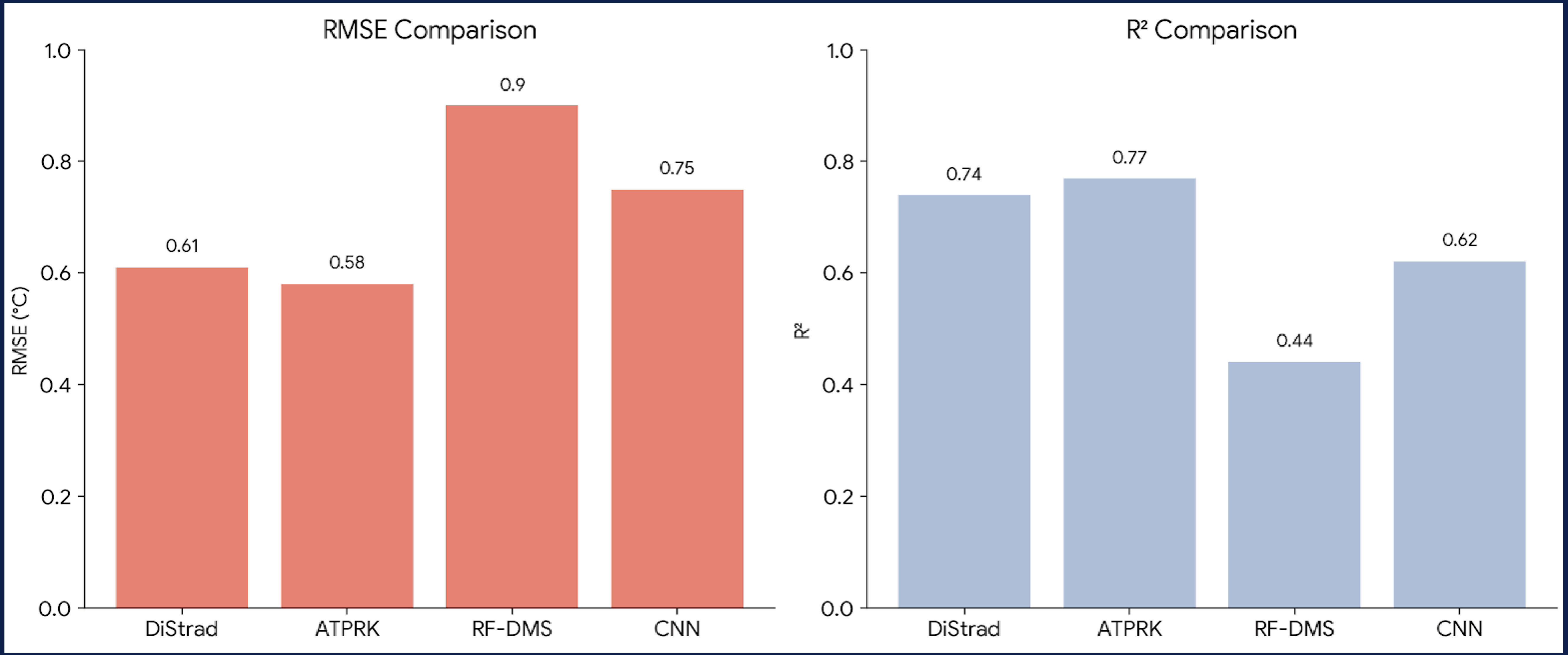
CNN WITH RESIDUAL BLOCKS

- **Objective :** To learn an end-to-end mapping from LR LST and NDVI to HR LST.
- **Feature Extraction:** Initial convolutional layers and **multiple Residual Blocks** (4 in this model) to improve training stability and allow deeper feature learning.
- **Upsampling:** PixelShuffle layer to efficiently upscale the feature maps to the desired high resolution.
- **Output:** A final convolutional layer generates the super-resolved single-channel LST image.
- **Training:** Optimized using Adam, minimizing MSE to reconstruct the HR LST accurately.



Evaluation Metrics and Model comparison

- **RMSE: Measures the average error between predicted and true LST values.**
- **R^2: Indicates how well the model explains the variance in the true LST**



- ATPRK shows the best overall performance, while DiStrad performs similarly to ATPRK, though slightly less accurate.

Conclusion

- Effective LST sharpening relies heavily on the availability and appropriate use of HR auxiliary data correlated with surface temperature.

- **Statistical models (DisTrad, ATPRK):**
  - Simpler, interpretable, efficient
  - ATPRK offers smoother results over DisTrad due to bilinear residual upscaling

- **ML/DL models (Random Forest, CNN):**
  -RF-DMS underperformed, possibly due to limited feature diversity or suboptimal training strategy
  -CNN may require larger datasets or improved architecture (e.g., UNet) to outperform traditional methods

- ATPRK provides a strong balance between simplicity and spatial quality — ideal when deep learning is not feasible.
- **Future work:** expand to multi-temporal data, test on other regions, and explore hybrid approaches.

Thank you!