

SoilNet: A Spatio-temporal Deep Learning Framework for Digital Soil Mapping

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At a glance

What:

Soil Organic Carbon (SOC) prediction across Europe.

Why:

SOC is a crucial component of the global *carbon cycle* and plays a vital role in regulating *climate change*. Two-thirds of the carbon in the terrestrial environment is found in the form of SOC.

How:

We develop **SoilNet**, a novel hybrid deep learning architecture. It takes into account both spatial information from *Remote Sensing* data using a CNN-based architecture along with *spatial attention* and temporal information from climate data using an LSTM, thereby improving the model's accuracy.

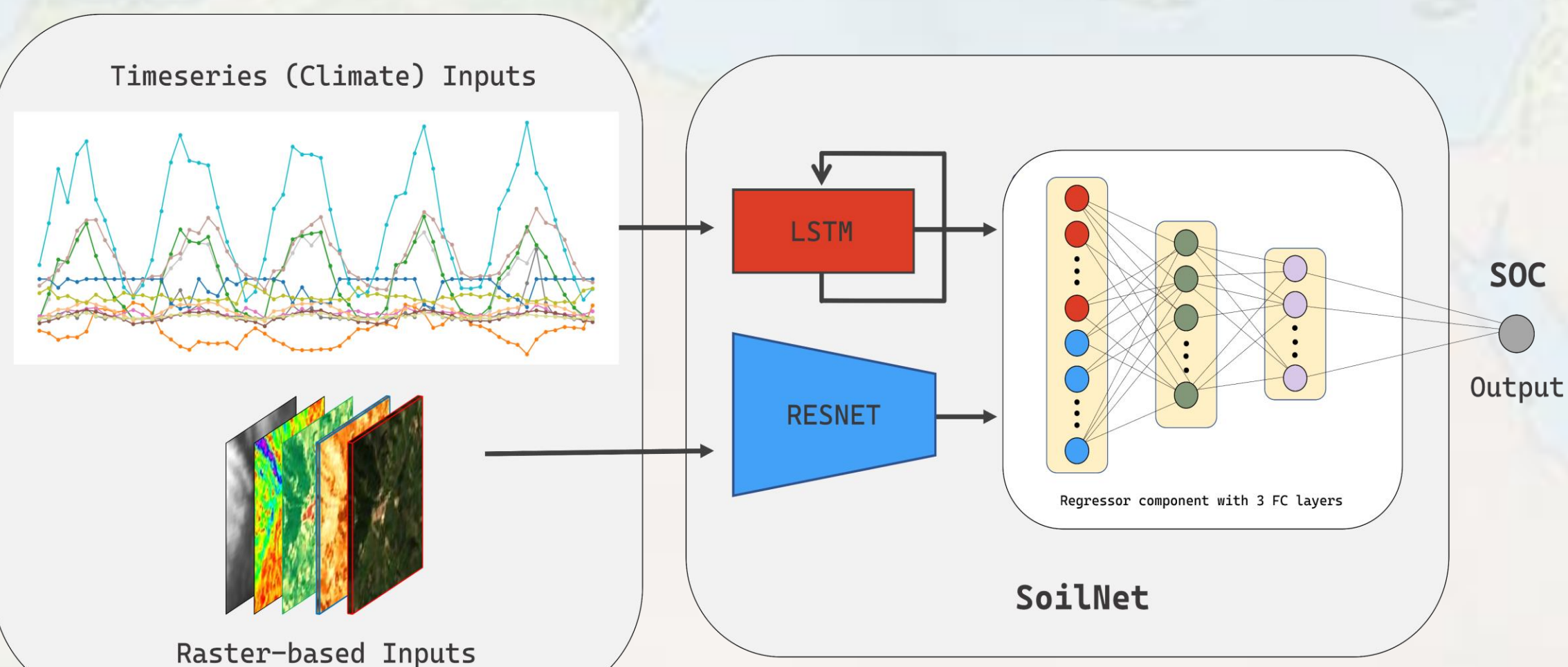


Figure 1. Overview of SoilNet architecture



1 - Data Preparation

1 Raster Inputs:

- Remote Sensing satellite (LandSat-8) Surface Reflectance (SR) images
- Geological and vegetation indices
- Topography

These inputs comprise all the data for the CNN-based section. They have undergone preprocessing, correction, and layering.

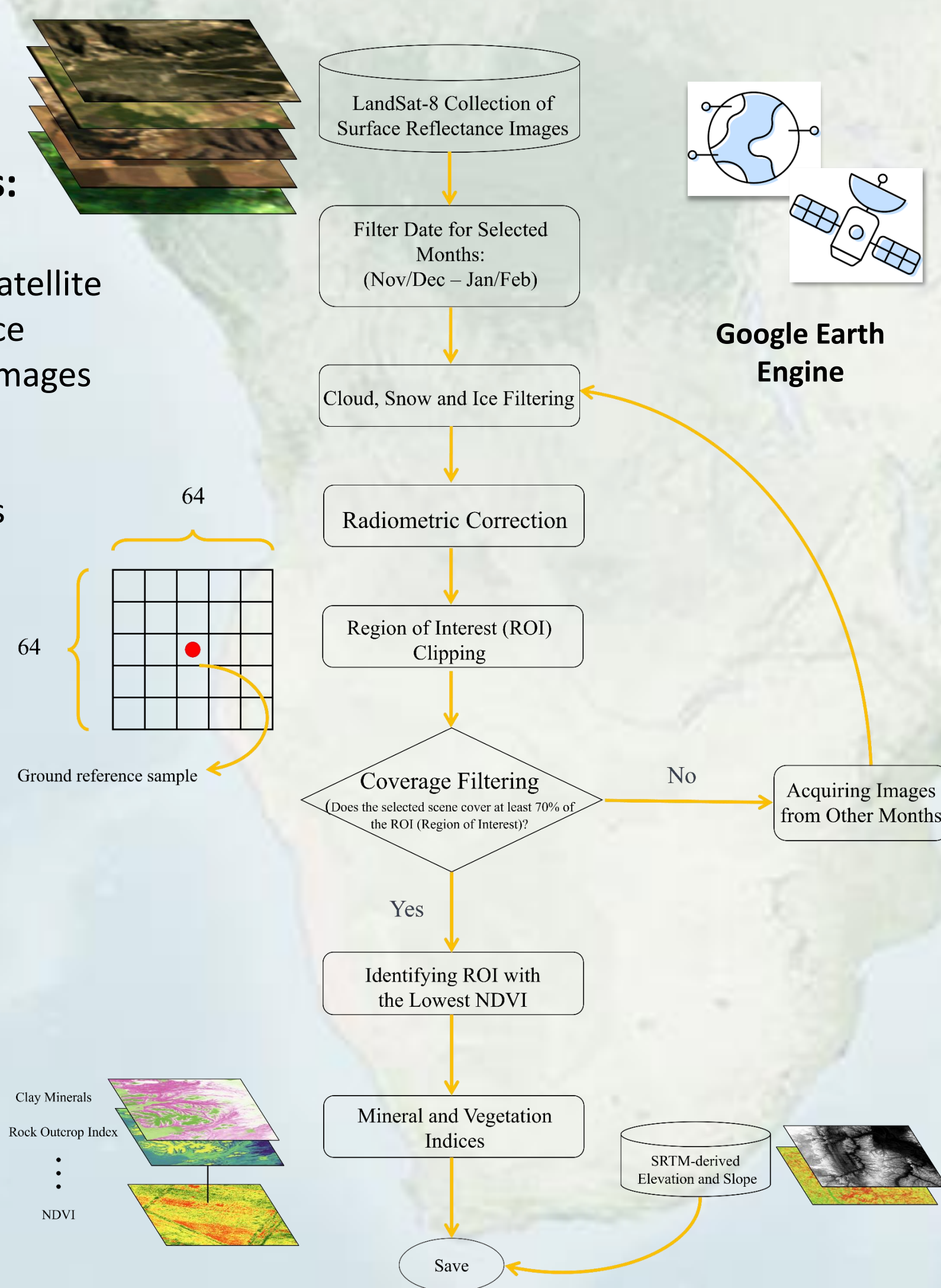


Figure 2. Raster-based data preparation

2 Timeseries Inputs:

12 climate features from *TerraClimate* dataset including: temperature, evapotranspiration, vapor pressure, etc.

These inputs constitute all the data for the LSTM section.

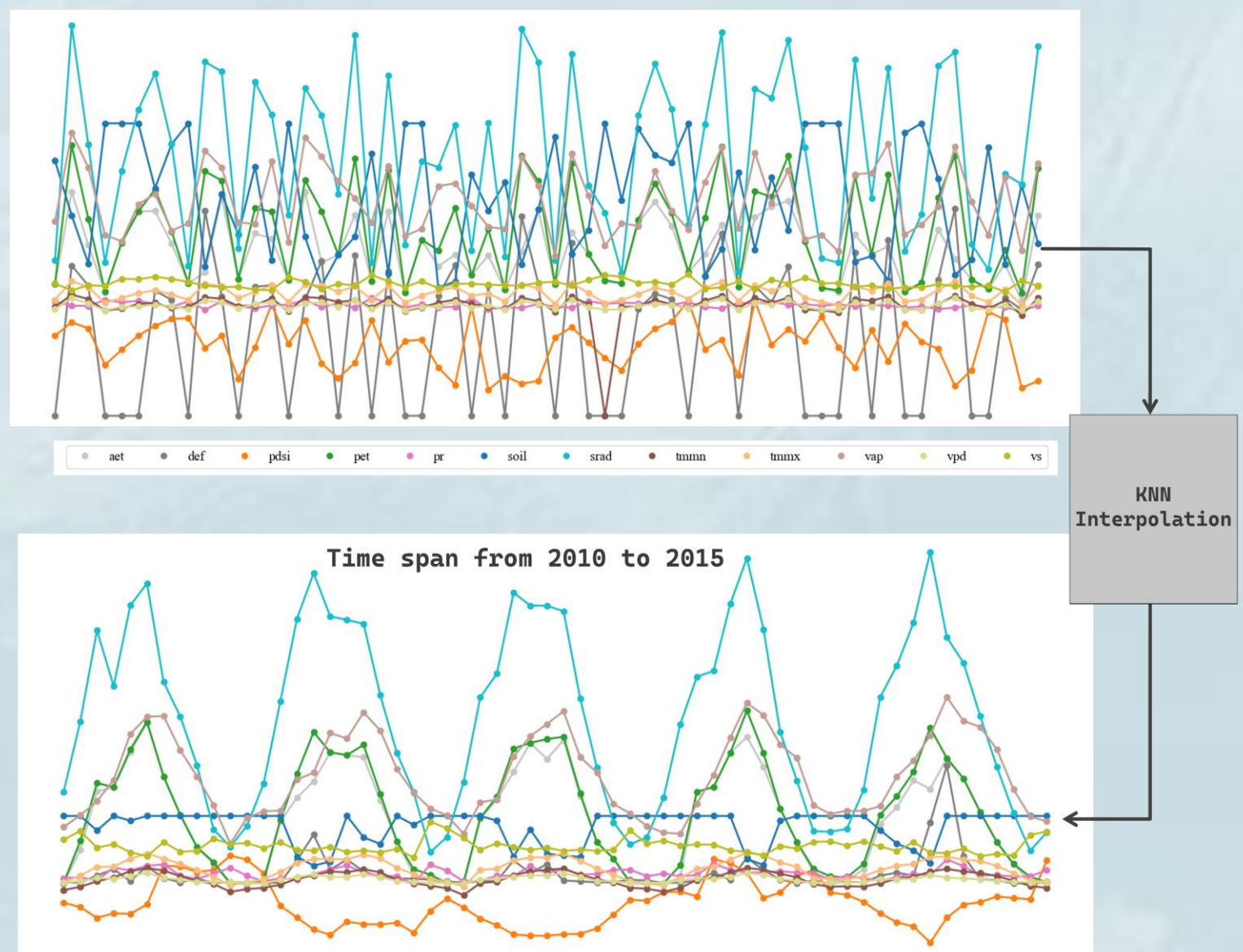
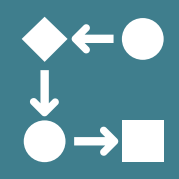


Figure 3. Timeseries (climate) data preparation



2 - Proposed Approach

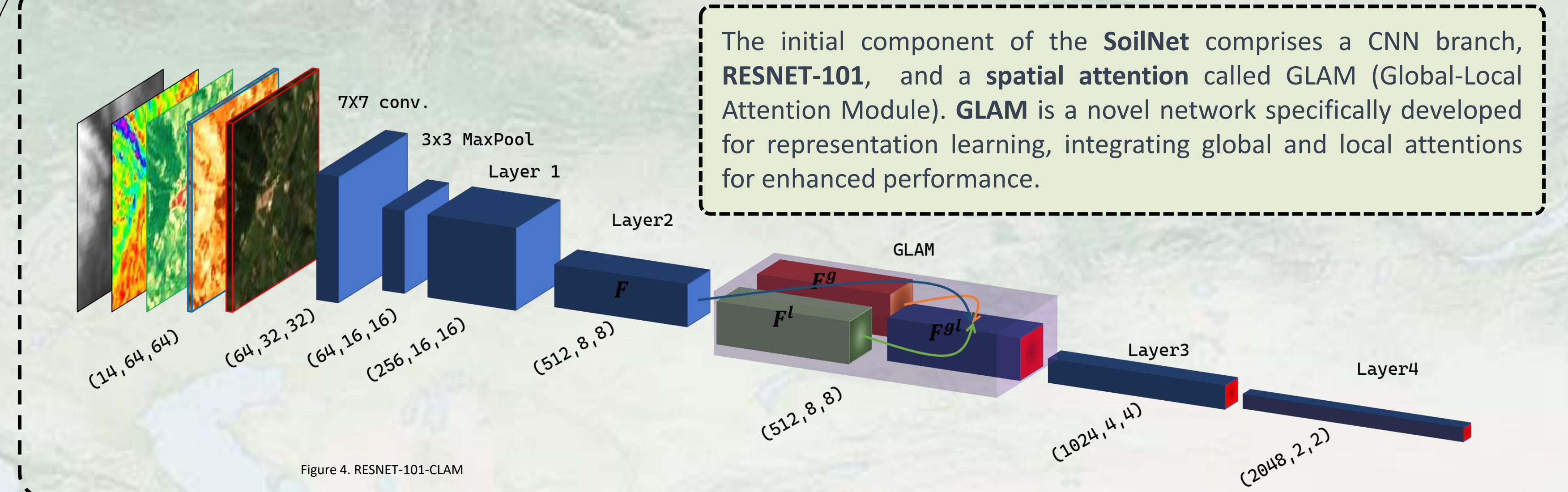


Figure 4. RESNET-101-CLAM

These two components are incorporated using a regressor head with a fully connection.

The second component includes an LSTM branch for encoding timeseries-climate data.

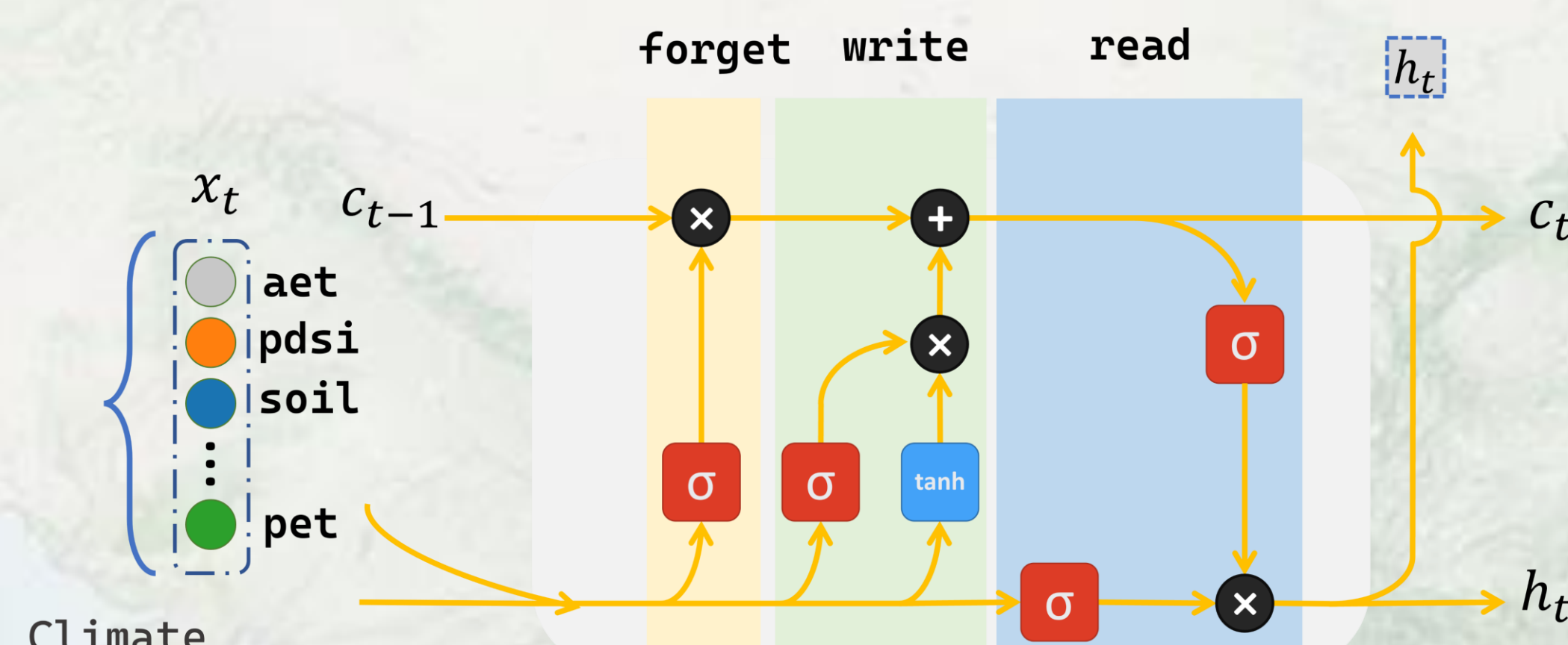


Figure 5. LSTM



3 - Experimental Analysis

- The proposed model consistently outperforms other simpler models and Random Forest.
- The proposed model achieves the lowest RMSE, indicating higher prediction accuracy.
- It also demonstrates stronger correlation (R^2) and relative improvement (RPIQ) compared to other setups and the RF Model.
- Additionally, SoilNet has the lowest MAE and highest CCC, showcasing superior overall performance and potential for accurate predictions.

Table 1. Performance results of SoilNet modifications

Model	RMSE↓	R ² ↑	MAE↓	CCC↑
RESNET-101	19.88	0.34	14.42	0.52
RESNET-101-GLAM	19.74	0.35	14.44	0.54
RESNET-101-GLAM + LSTM	18.99	0.40	13.83	0.58
Random Forest	21.25	0.25	16.02	0.37

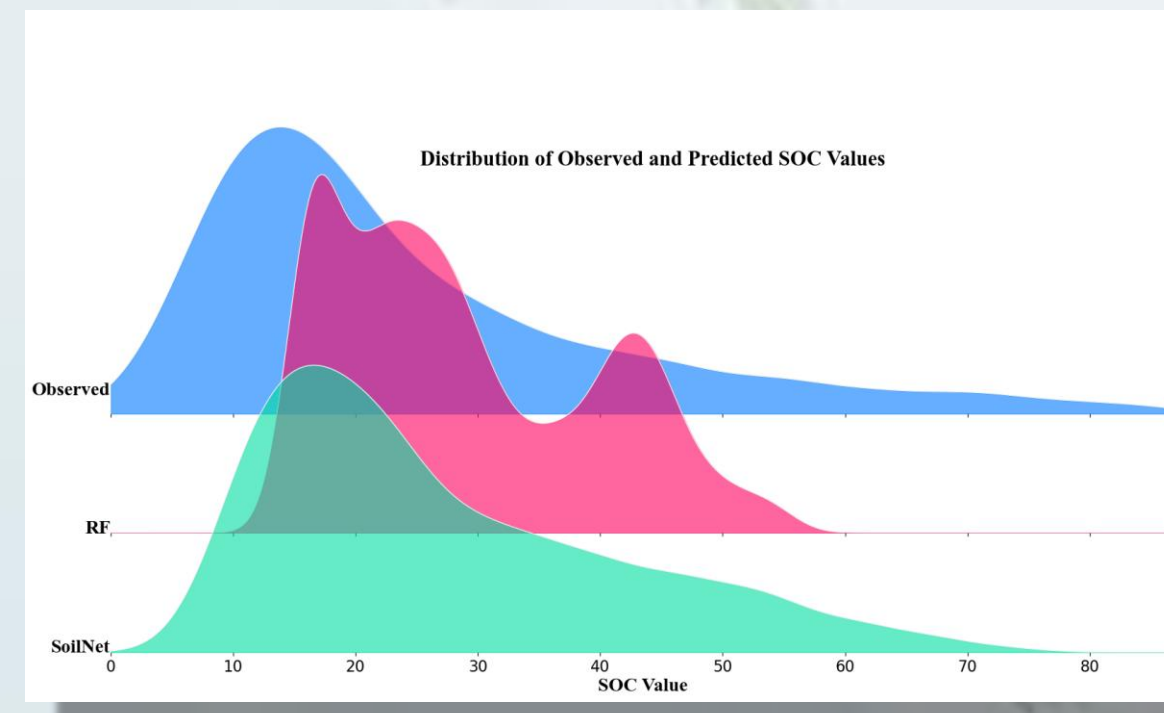


Figure 6. Distribution of observed and predicted SOC (g/Kg) values

- Comparing the statistical distribution of SOC (g/Kg) between the RF and SoilNet models reveals that SoilNet closely resembles the observed data.



4 - Results and Discussion

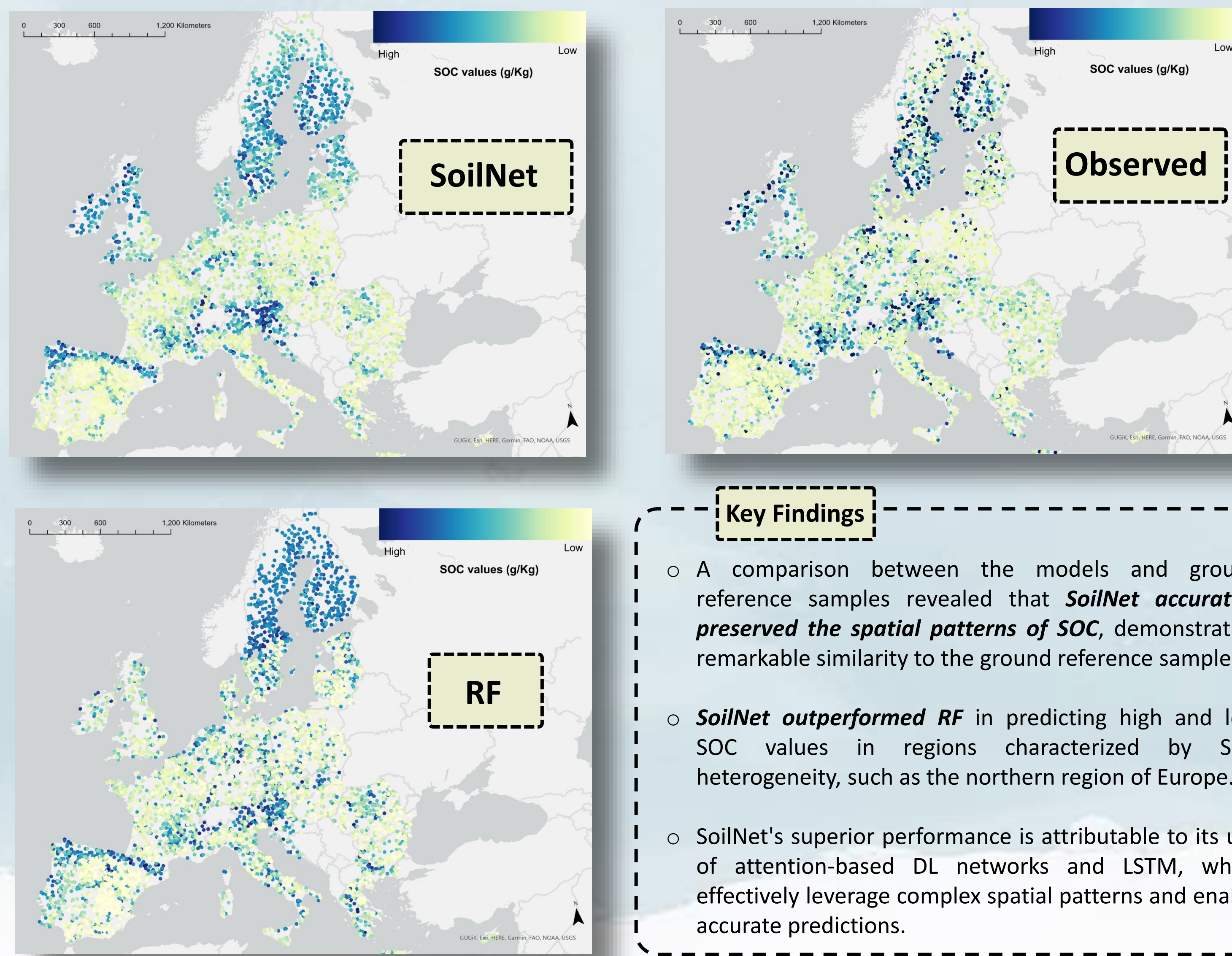


Figure 7. Spatial distribution of SOC (g/Kg)

SoilNet
on GitHub

