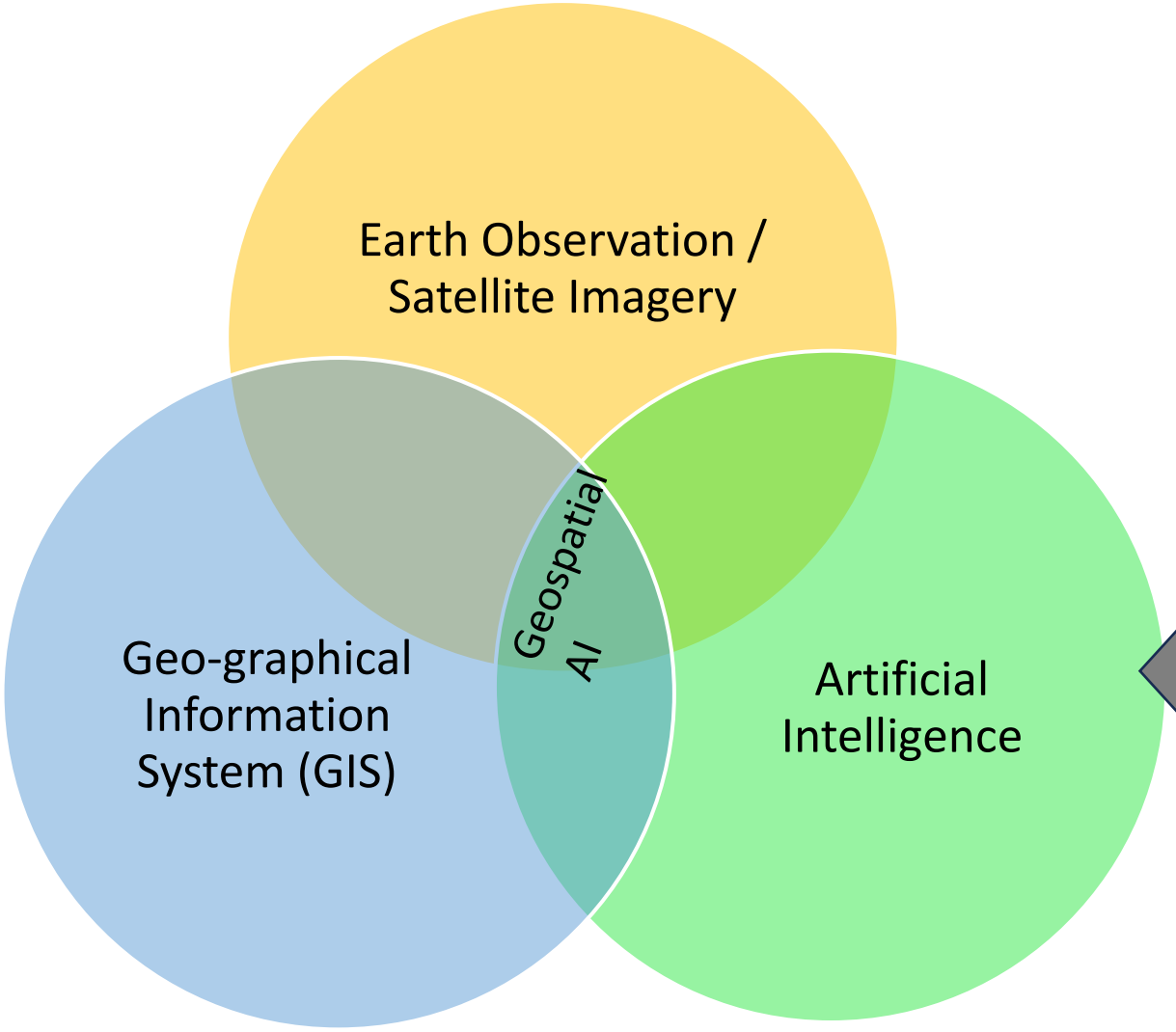
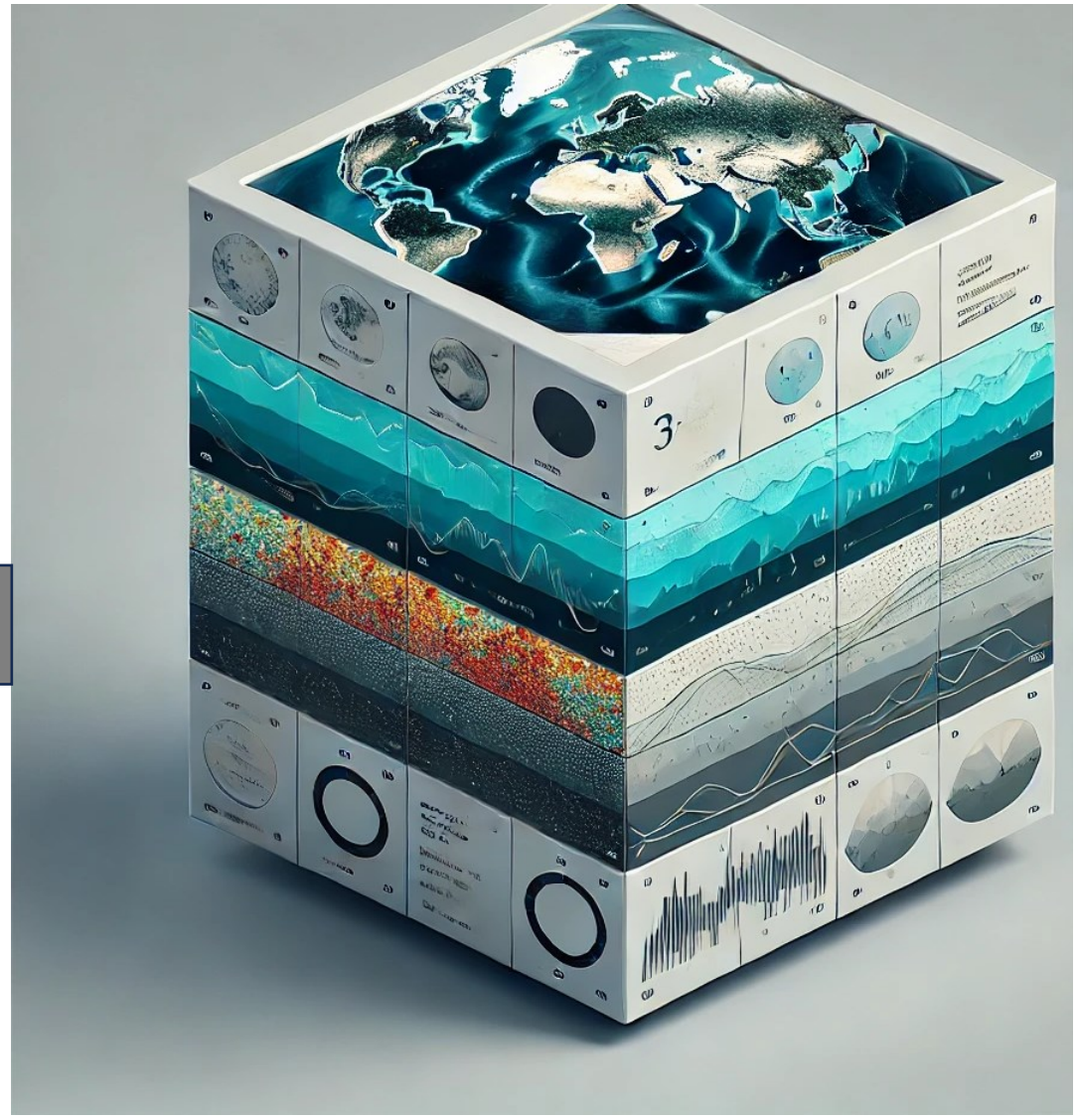
Fundamental and Application of Geospatial AI

Jadu Dash and Somnath Bar

What is Geospatial AI ?



Geospatial Data cube

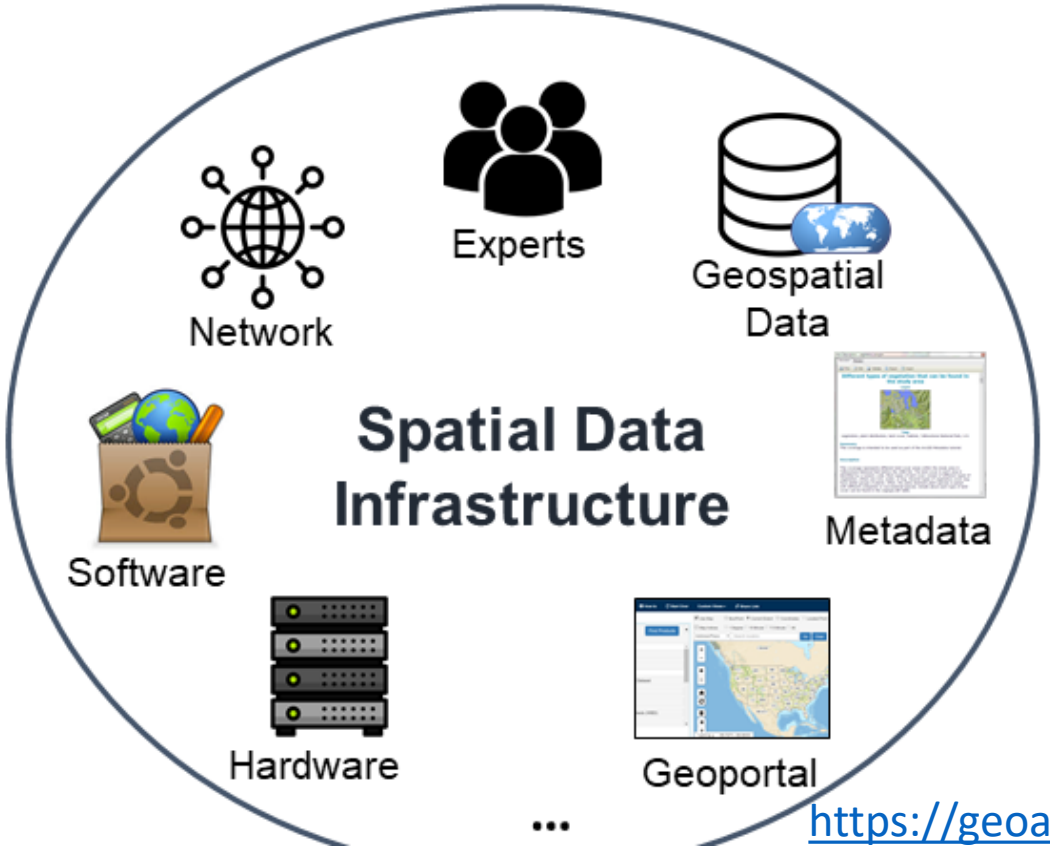


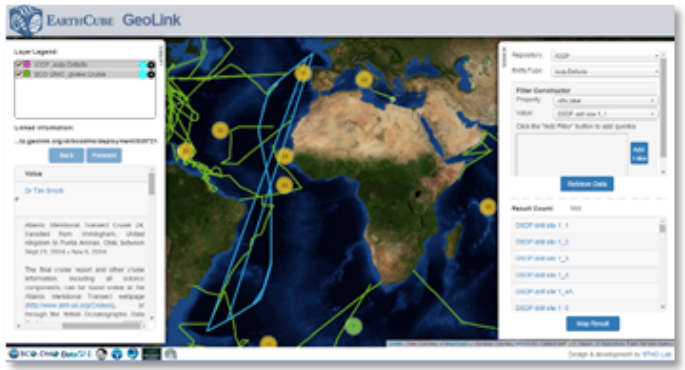
Fundamental Components of Geospatial AI

- **Data sources**: Satellite imagery (MODIS, Landsat, Sentinel), UAV/drone data, LiDAR, SAR radar, in-situ environmental sensors, IoT devices, socio-economic survey data (census, OpenStreetMap), and climate models.

- **Algorithms**: Machine learning models (decision trees, random forests, neural networks, support vector machines, CNNs, and deep learning) .

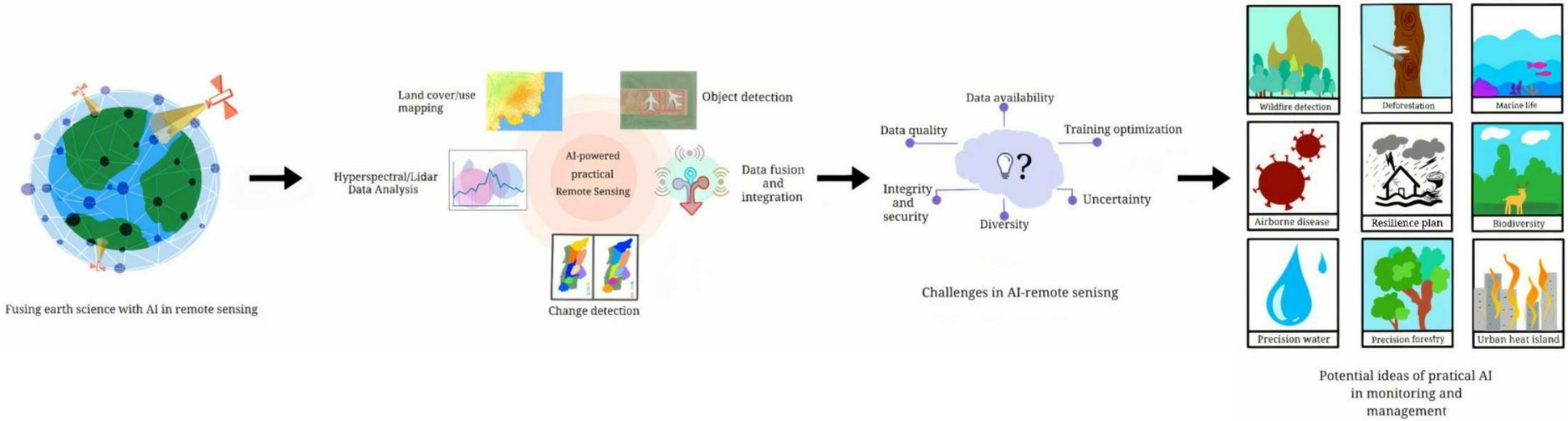
- **Tools**: Google Earth Engine, Python (with libraries like GeoPandas, rasterio, scikit-learn), R (with packages like rgdal, raster), TensorFlow, Google Colab, and PostGIS etc.





https://geoai.geog.buffalo.edu

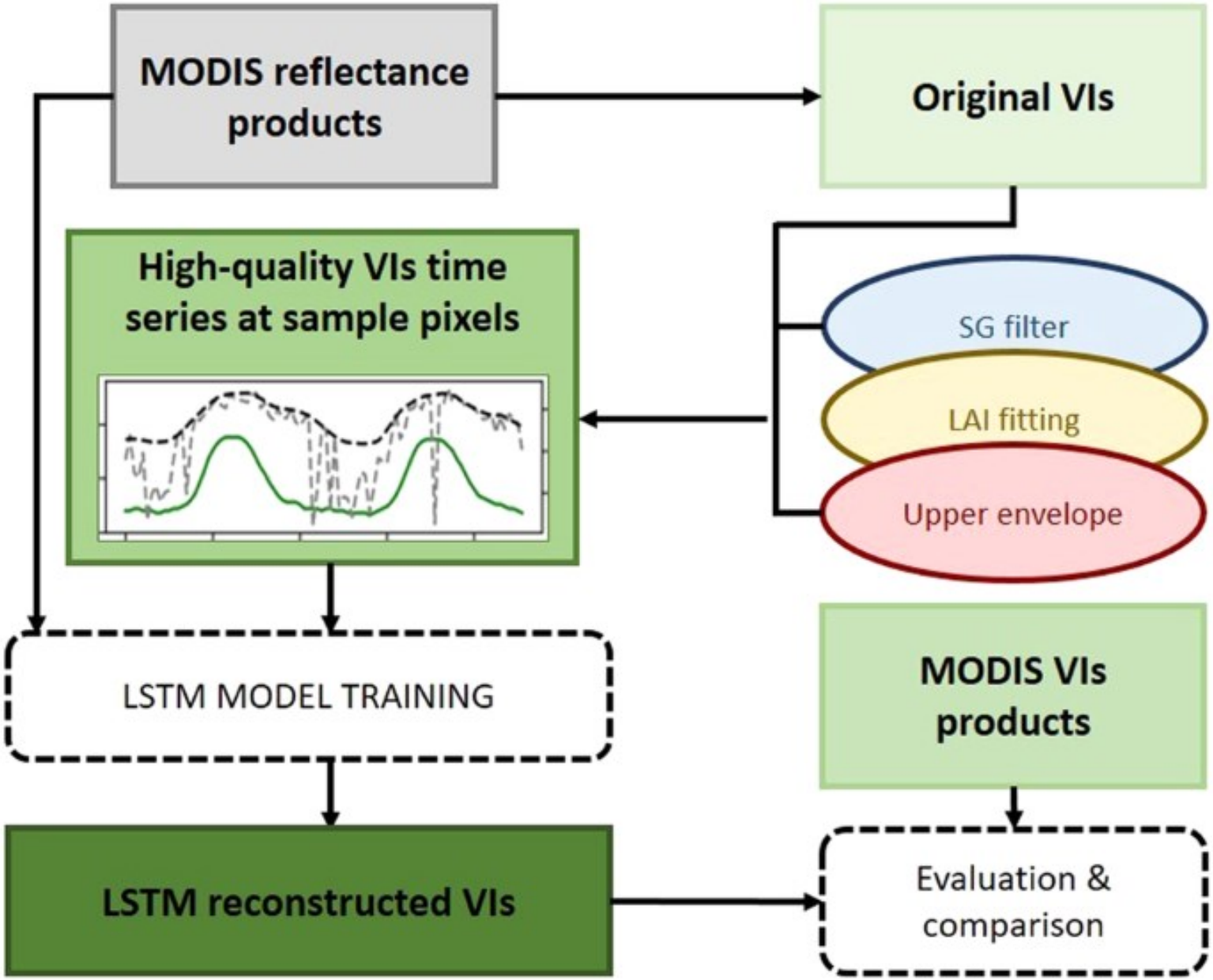
Fields of Geospatial Applications



https://www.mdpi.com/2072-4292/15/16/4112

Geospatial AI on Vegetation Dynamics

- Geospatial AI leverages spatial data and machine learning to understand and monitor ecosystems. It provides insights into vegetation dynamics, ecosystem productivity, and helps in detecting environmental changes over time

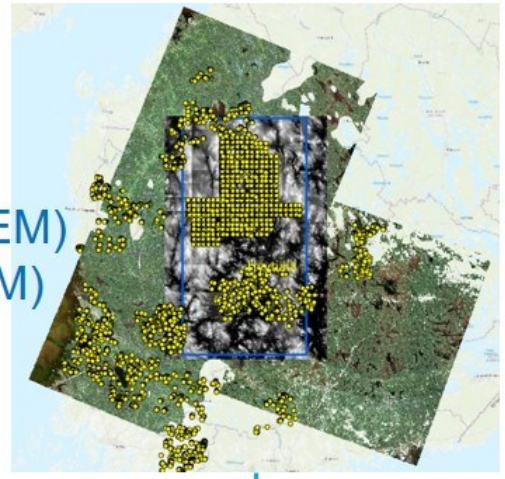


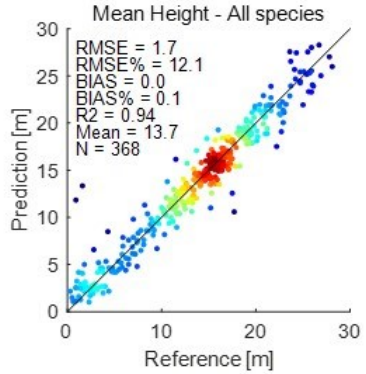
https://www.nature.com/articles/s41597-023-02695-x

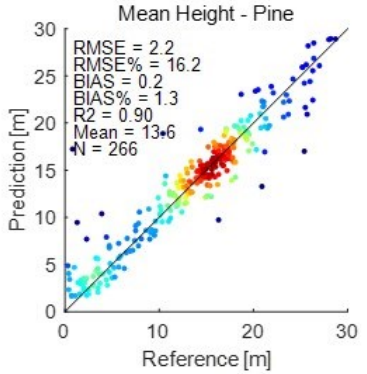
Geospatial AI on Forest Bio-physical components

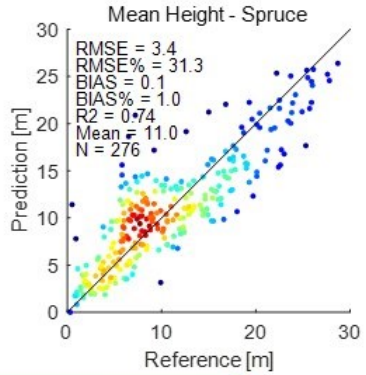
Deep neural networks (DNN) with transfer learning for forest variable estimation

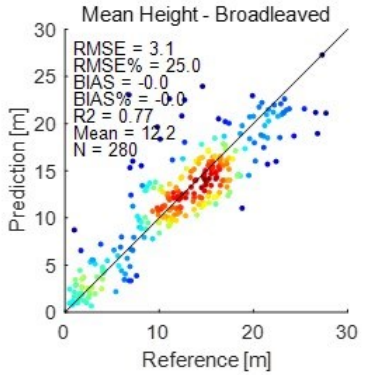
Model inputs
- Sentinel-2 imagery
- Digital Elevation Model (DEM)
- Canopy Height Model (CHM)
- Field reference data

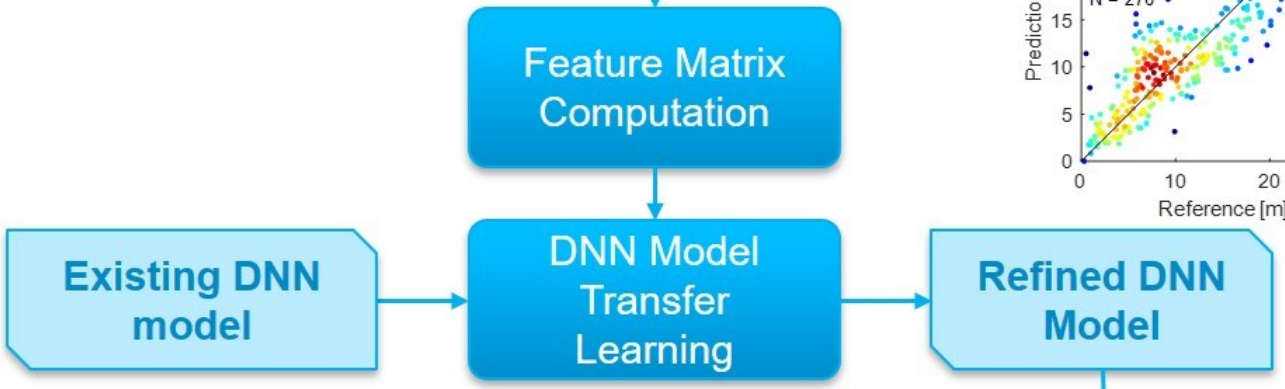








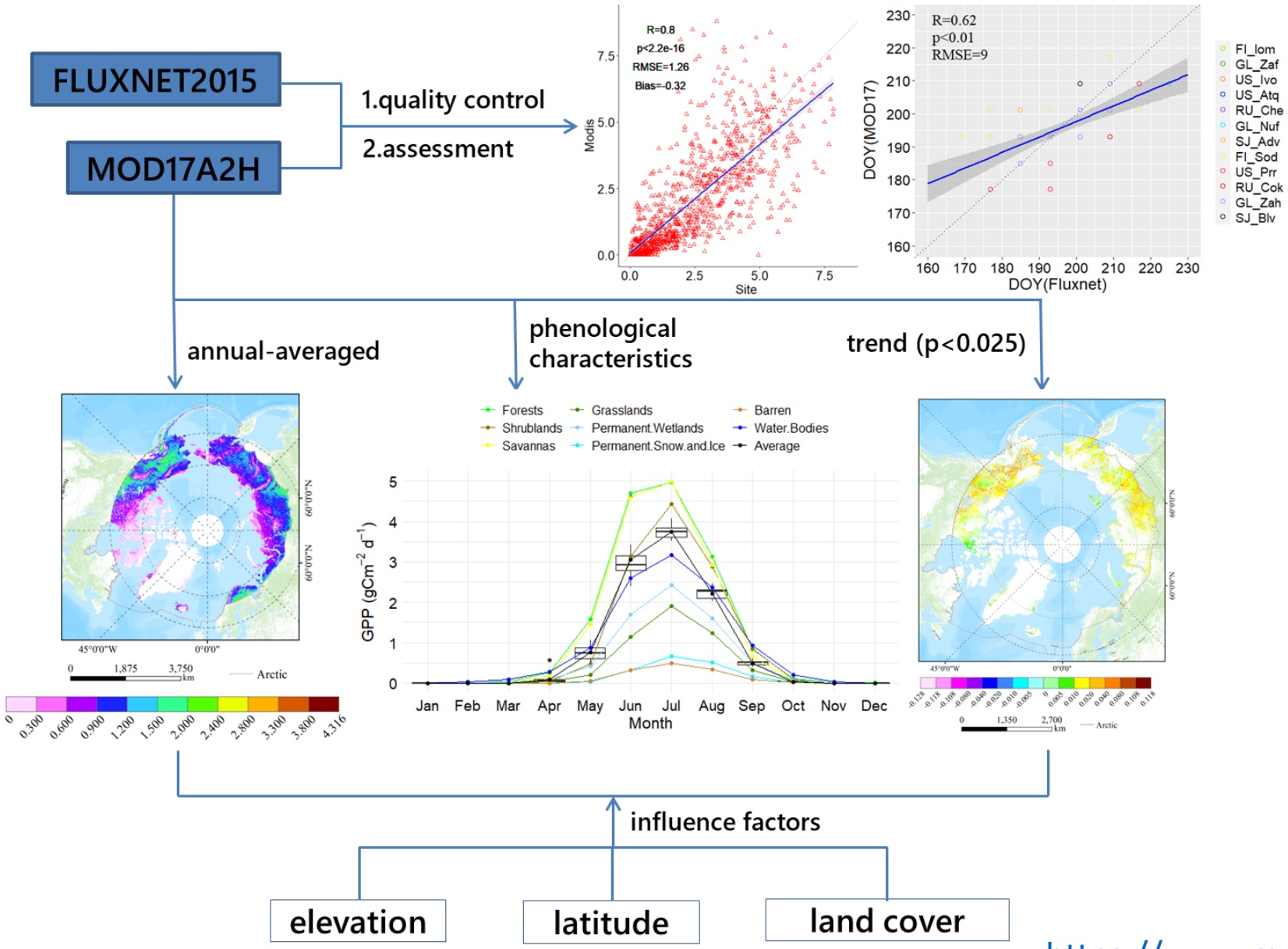




Forest variable estimates

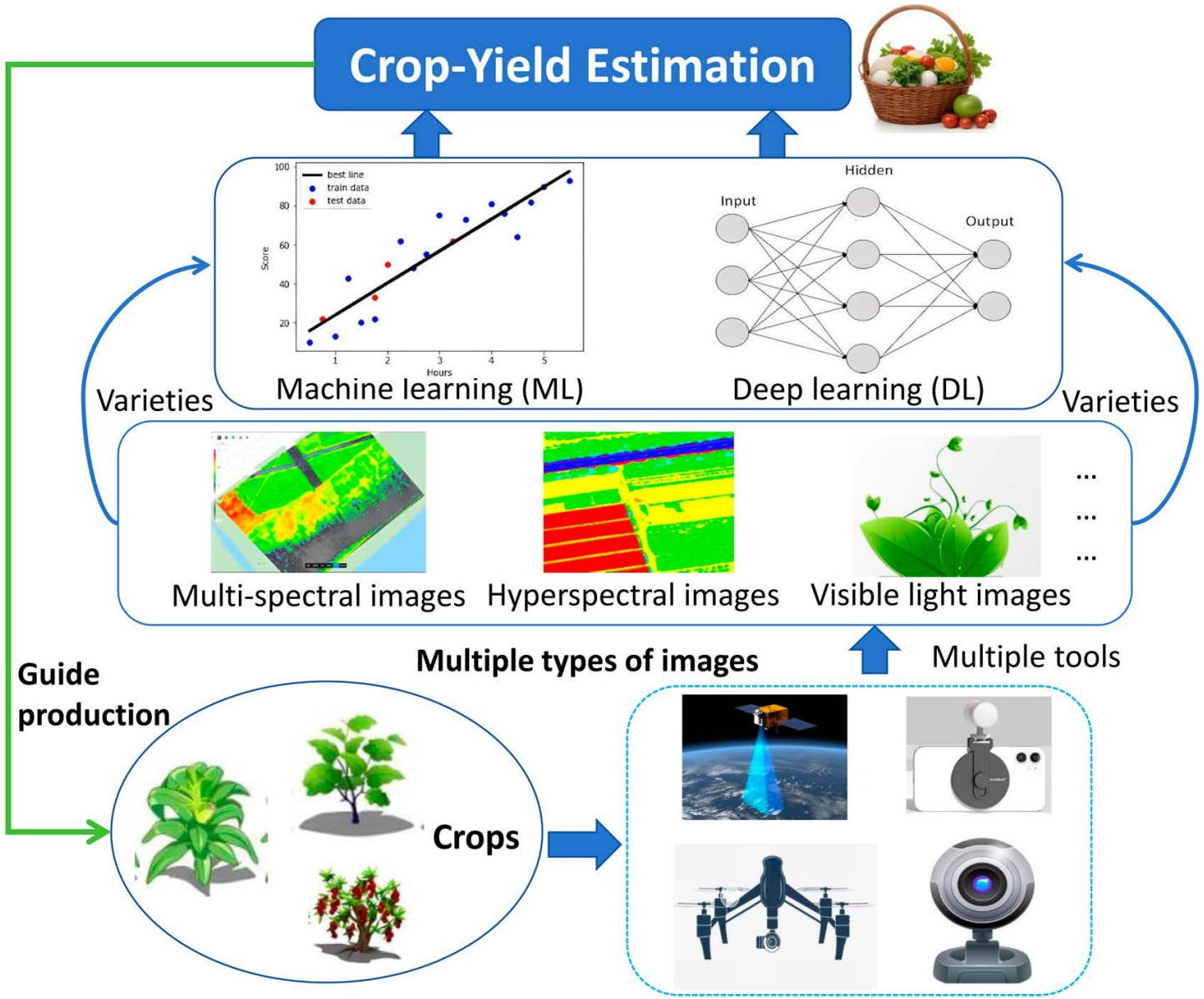
https://www.mdpi.com/2072-4292/13/12/2392#

Geospatial AI on Vegetation Productivity



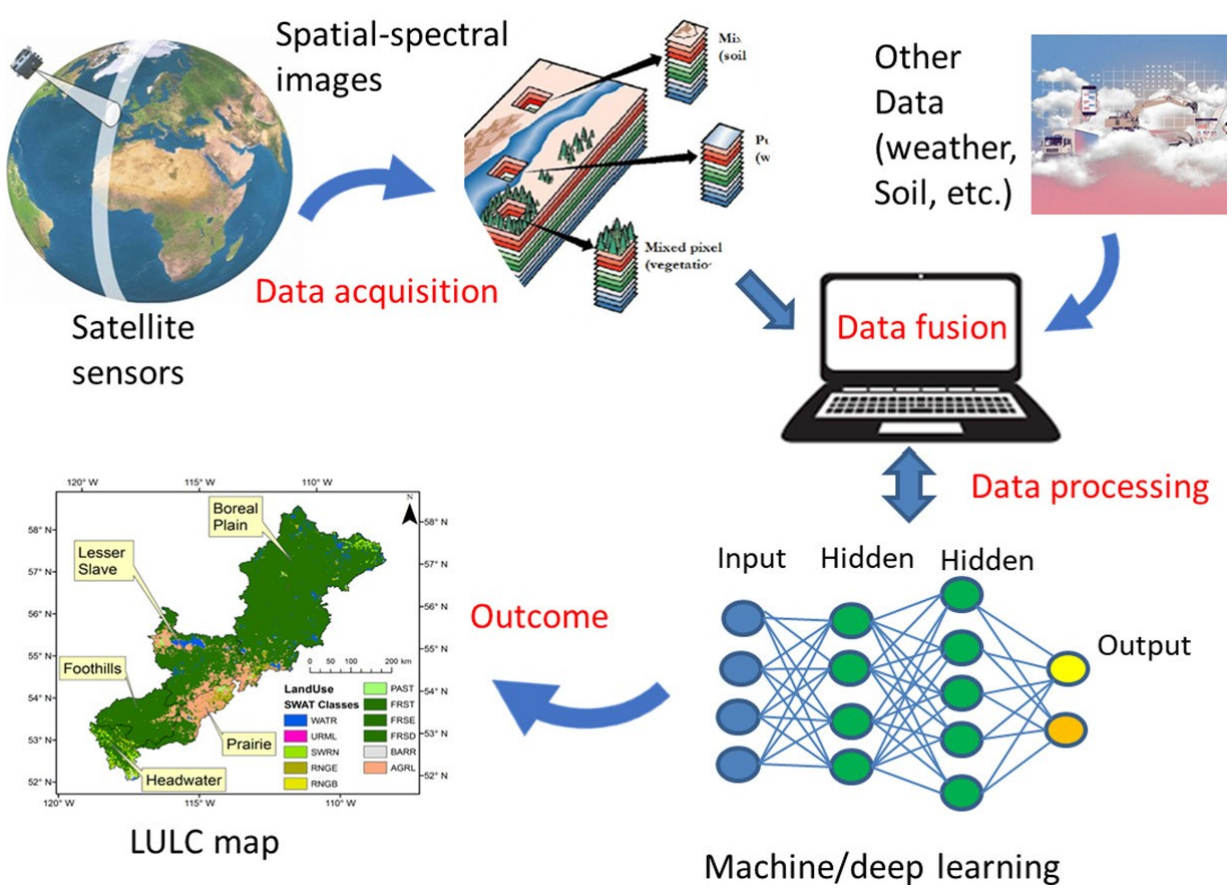
https://www.mdpi.com/2072-4292/13/15/2875#

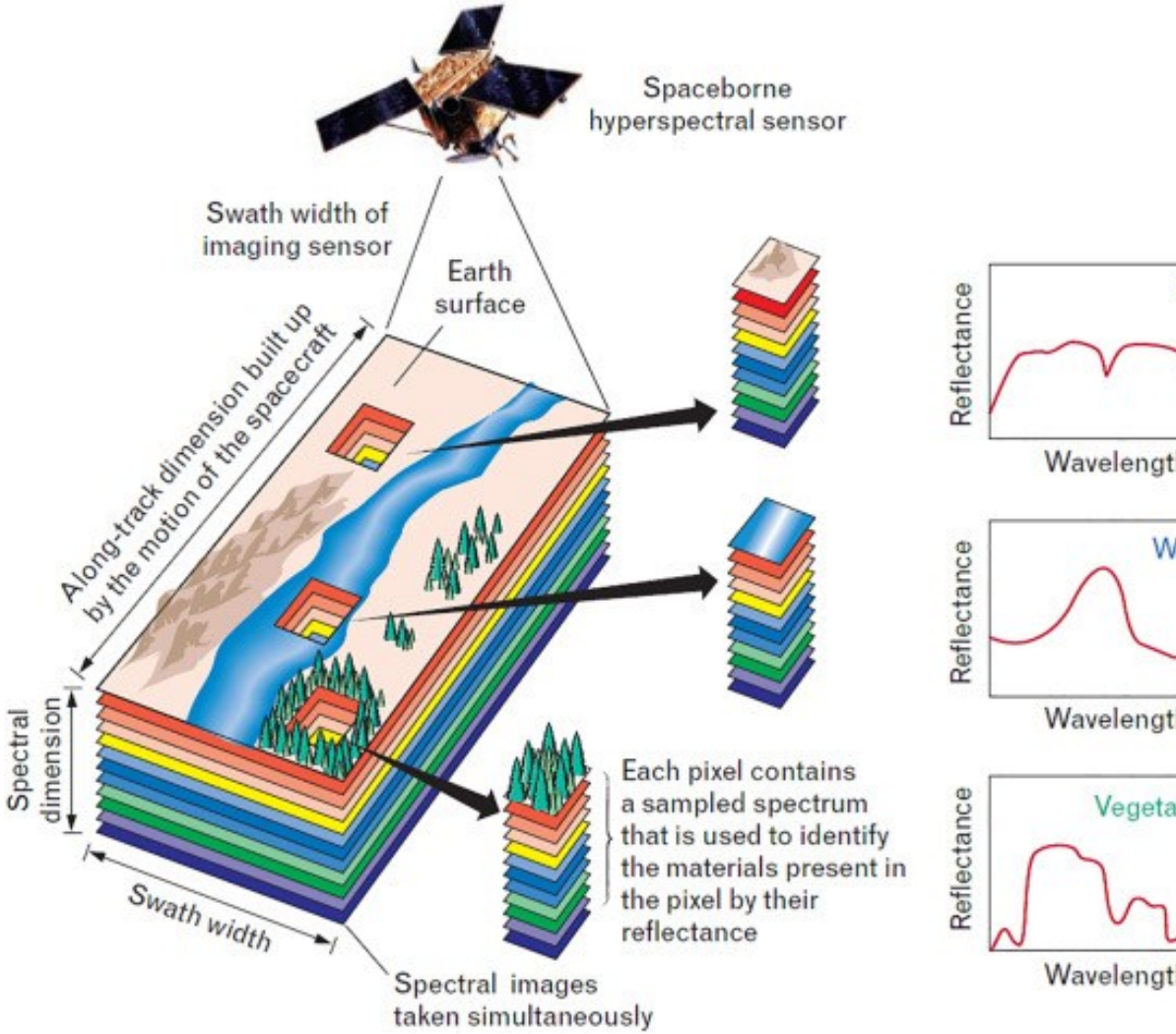
Geospatial AI on Crop Yield estimation



https://www.mdpi.com/2072-4292/16/6/1003#

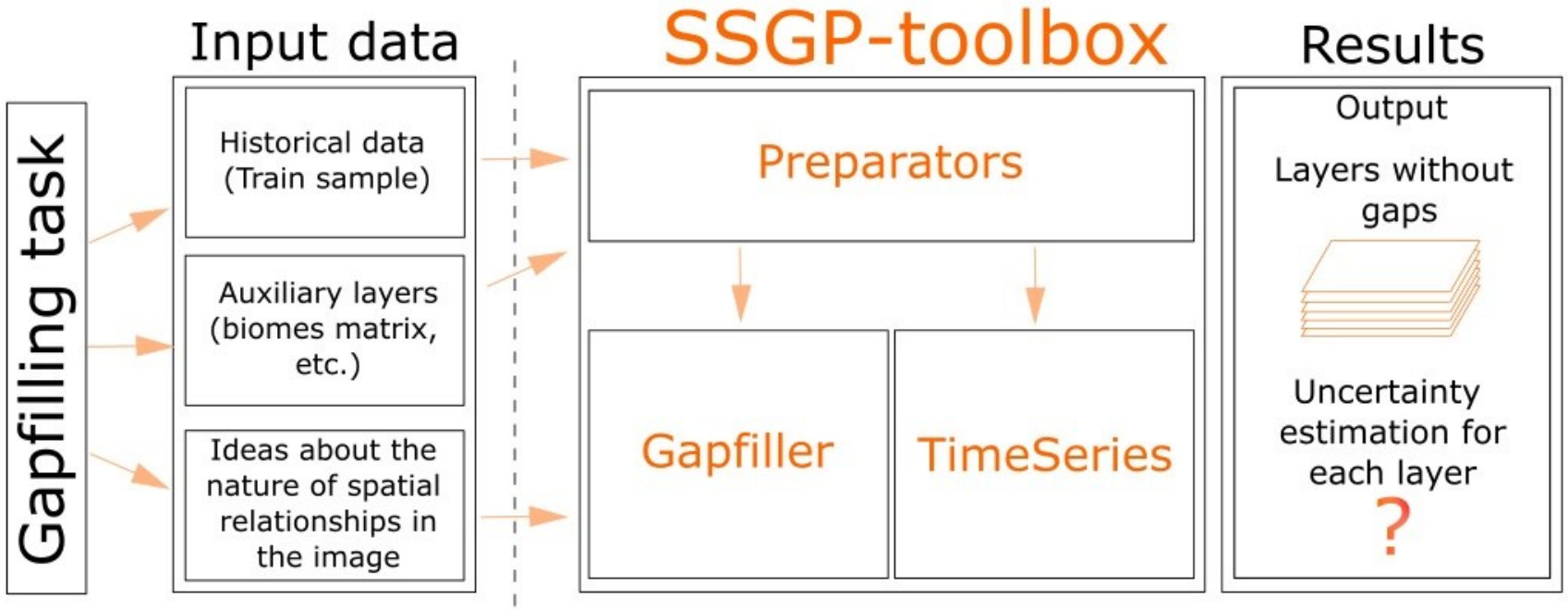
Geospatial AI on land-use and land cover-change

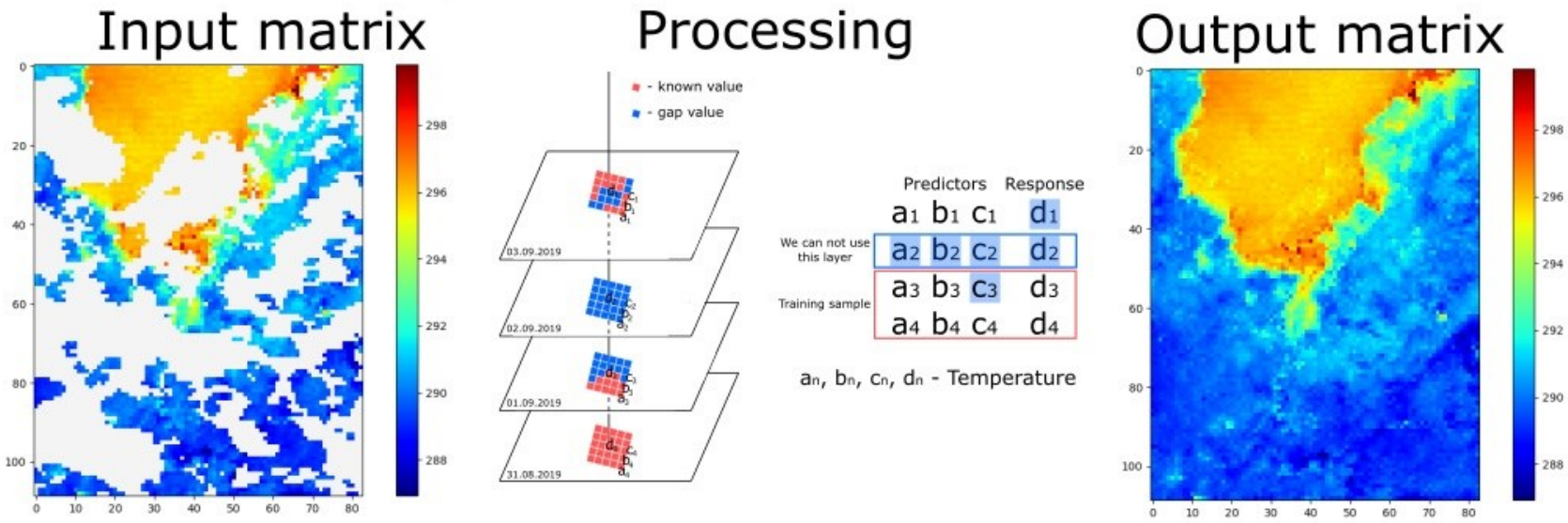




https://www.sciencedirect.com/science/article/abs/pii/S0048969722006519

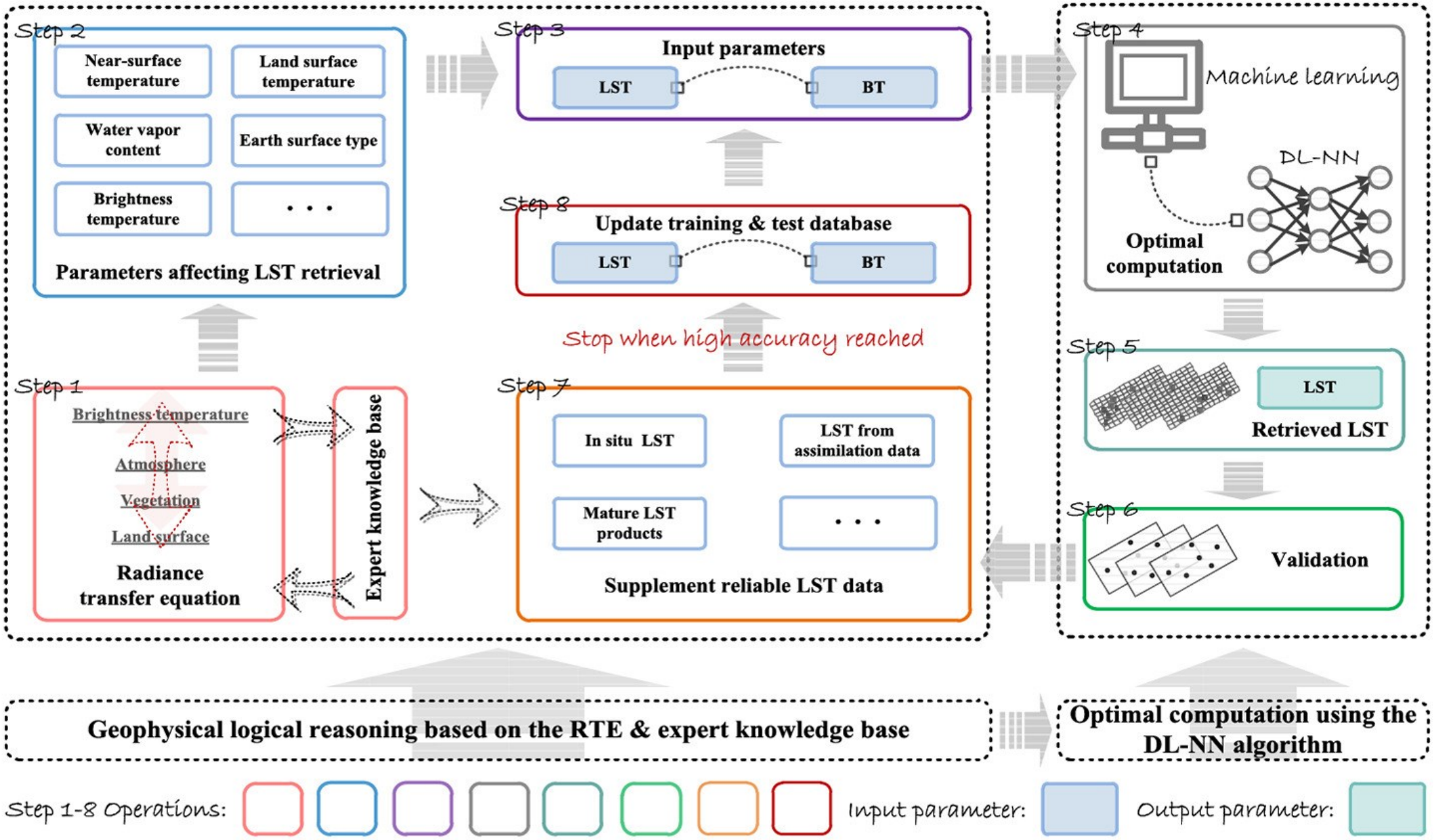
Gap filling of Regarding Land Surface Temperature, Surface Albedo and NDVI





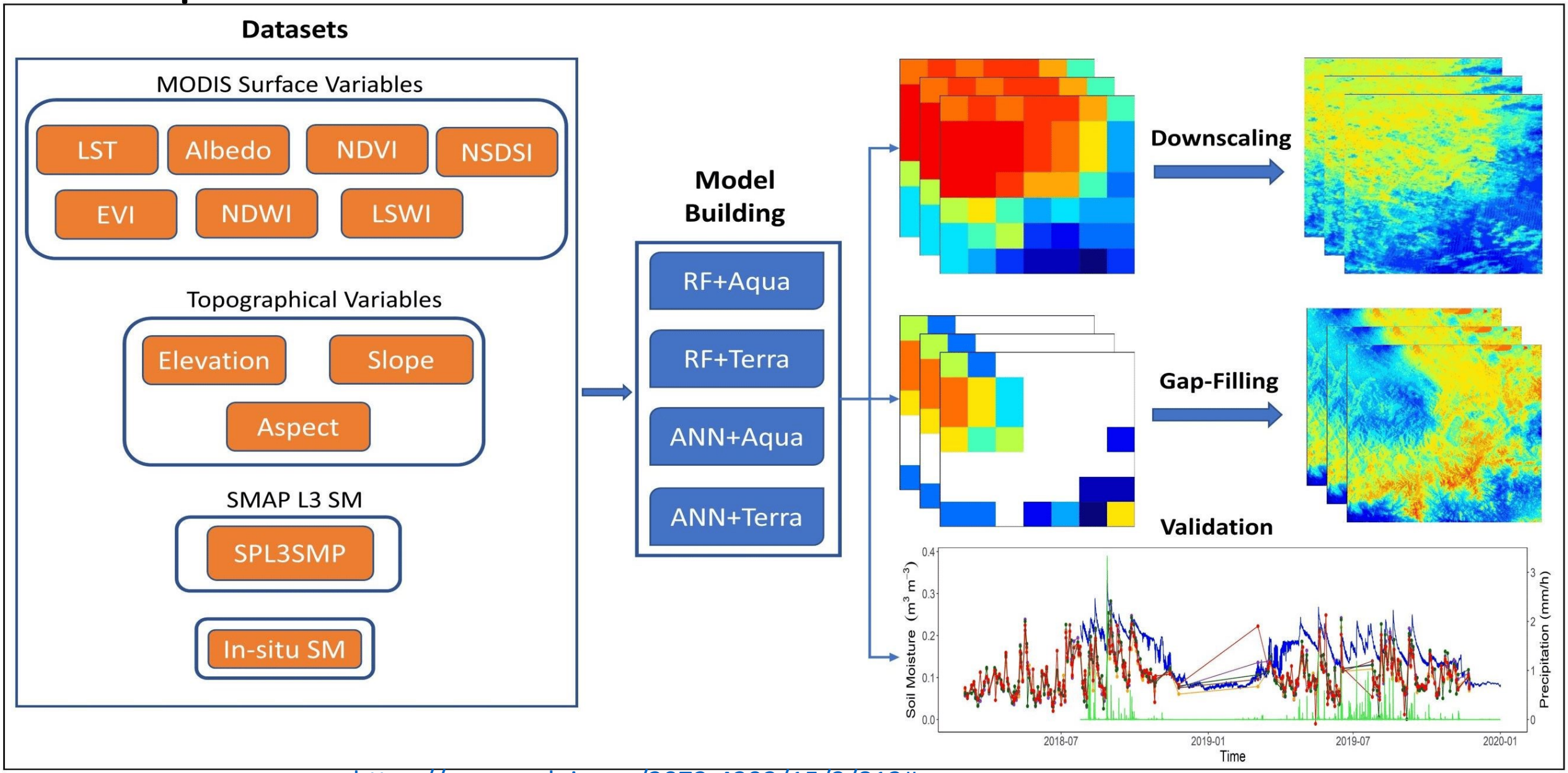
https://www.mdpi.com/2072-4292/12/23/3865#

Geospatial AI on Land Surface Temperature retrieval



https://www.sciencedirect.com/science/article/pii/S0034425721003850

Geospatial AI on Soil Moisture



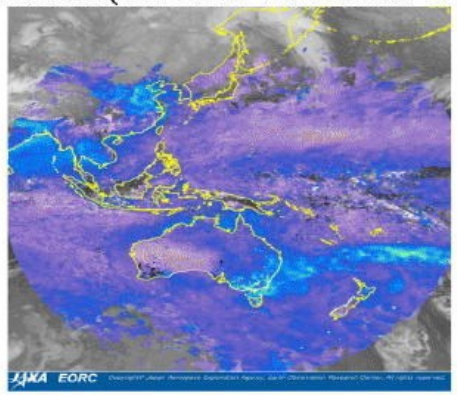
https://www.mdpi.com/2072-4292/15/3/812#

Geospatial AI on AOD Gap filling

Input:

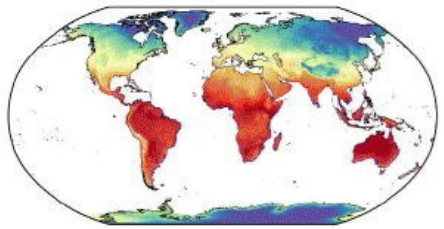
Aerosol Optical Depth

AHI-AOD(80°E–160°W and 60°N–60°S)

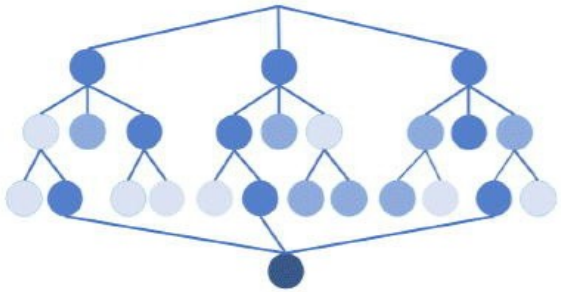


Geographical Data

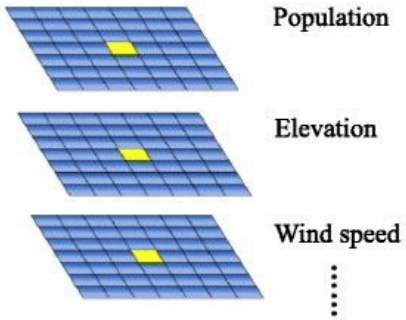
Meteorological Data



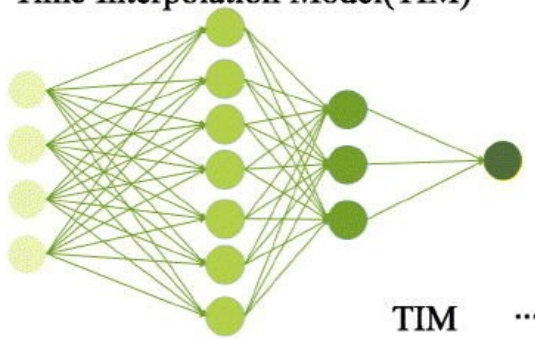
Method: Space Interpolation Model(SIM)



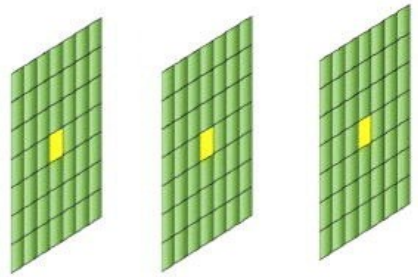
Spatial information

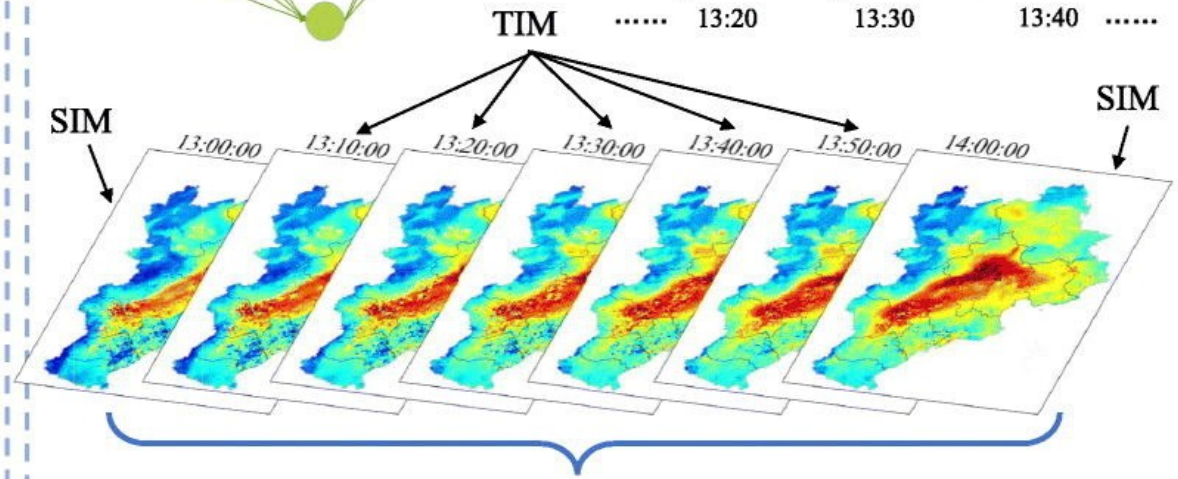


Time Interpolation Model(TIM)



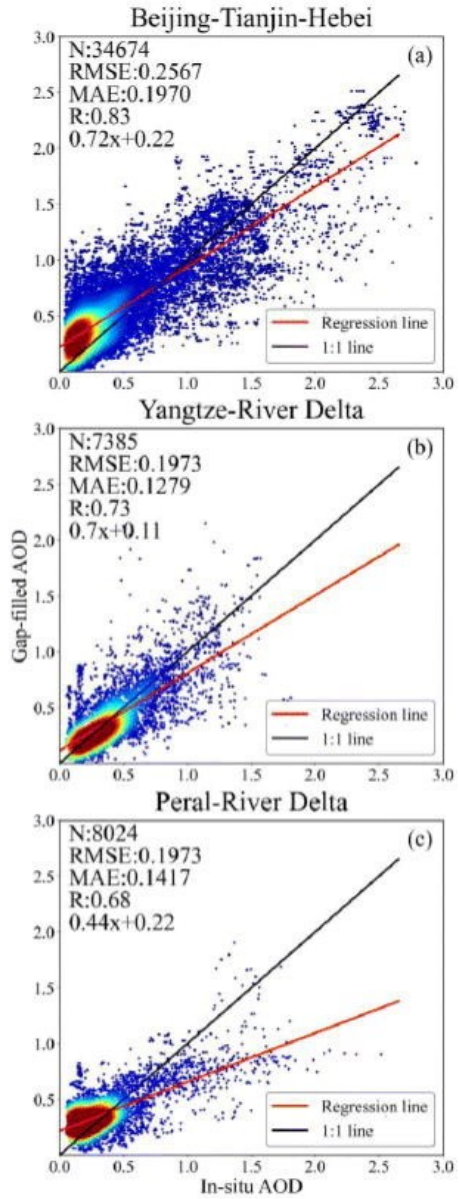
Temporal information



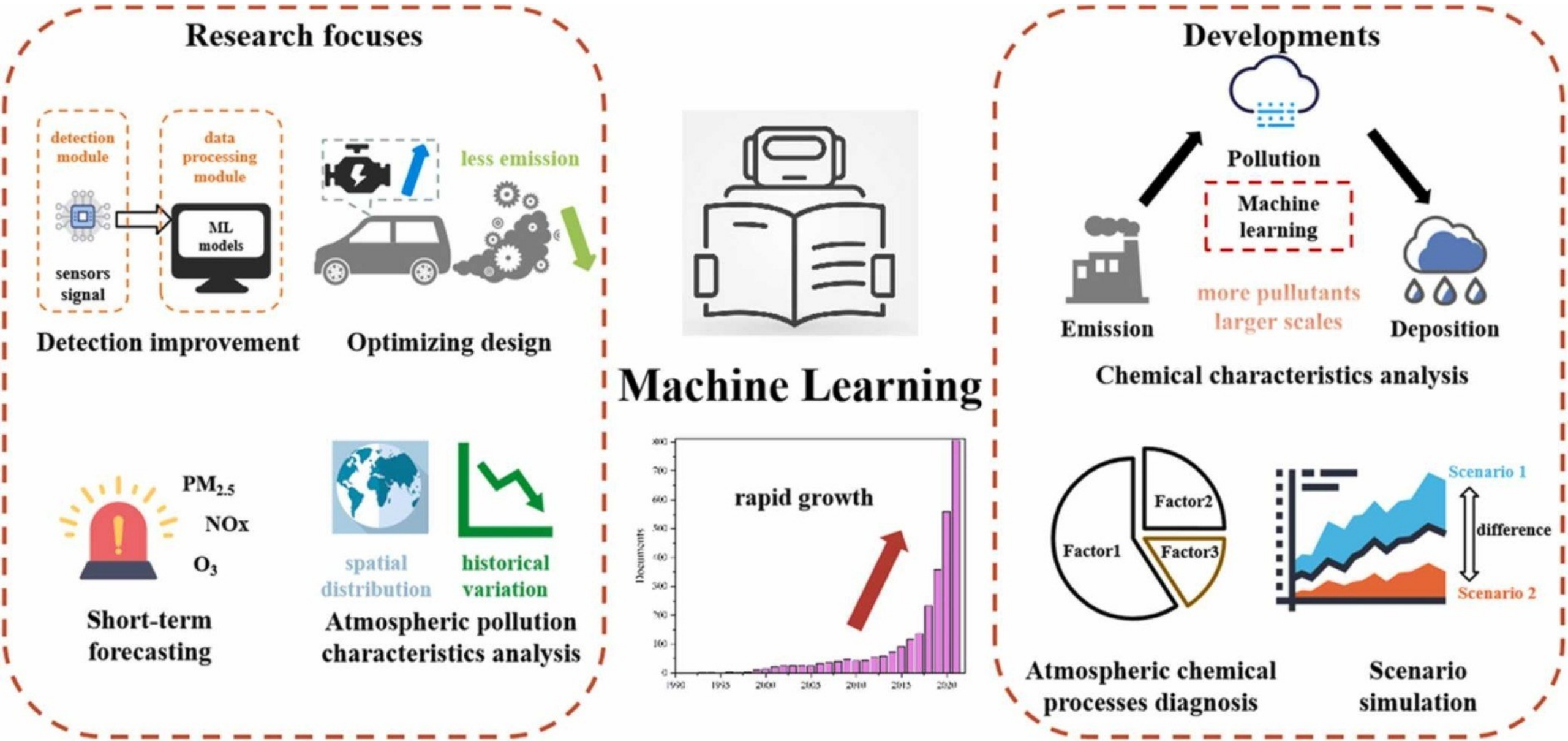


Output: **High Spatiotemporal resolution(0.05°,10 minutes) gap-filled AOD**

Validation:

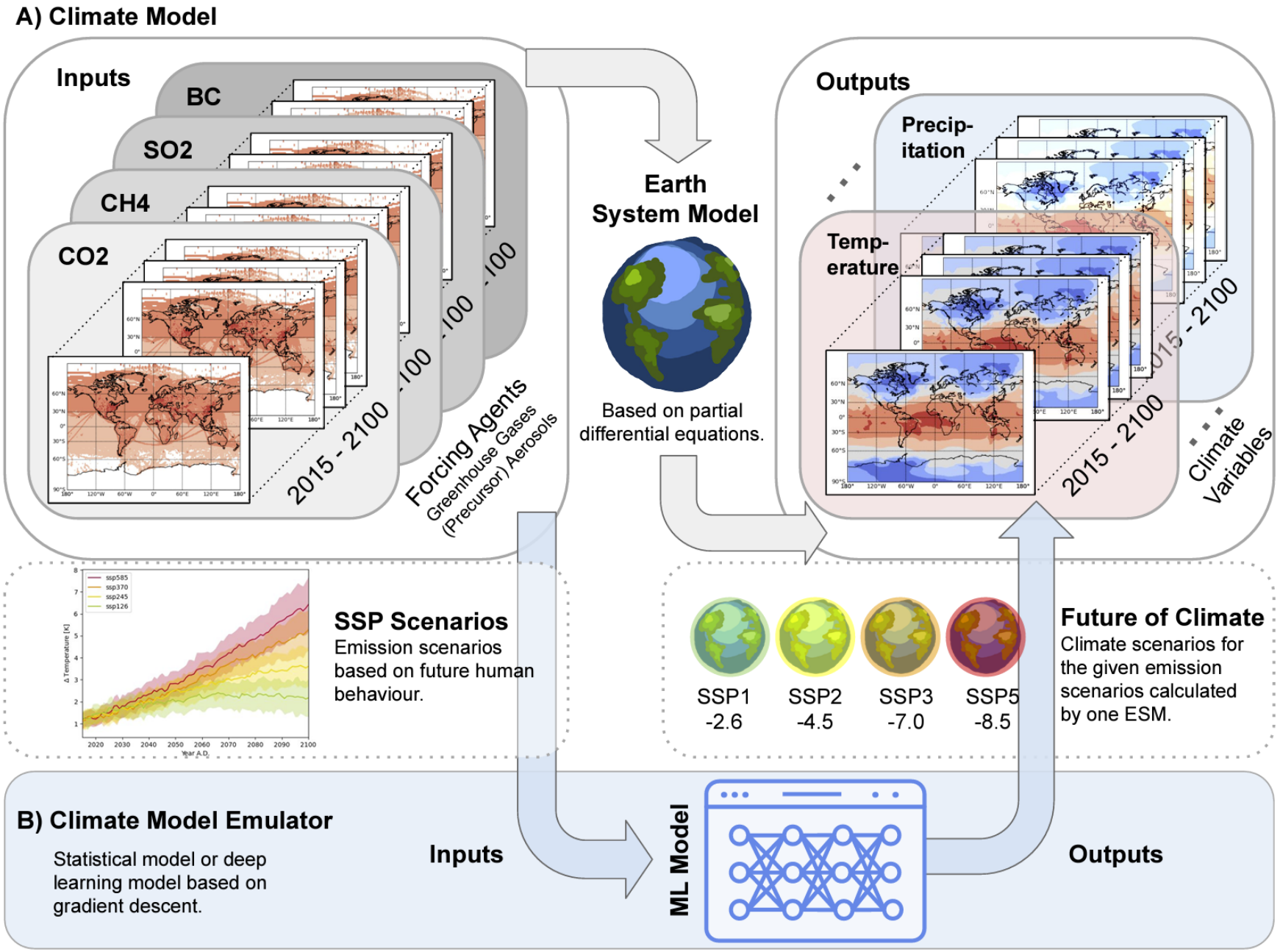


Geospatial AI on Air pollution



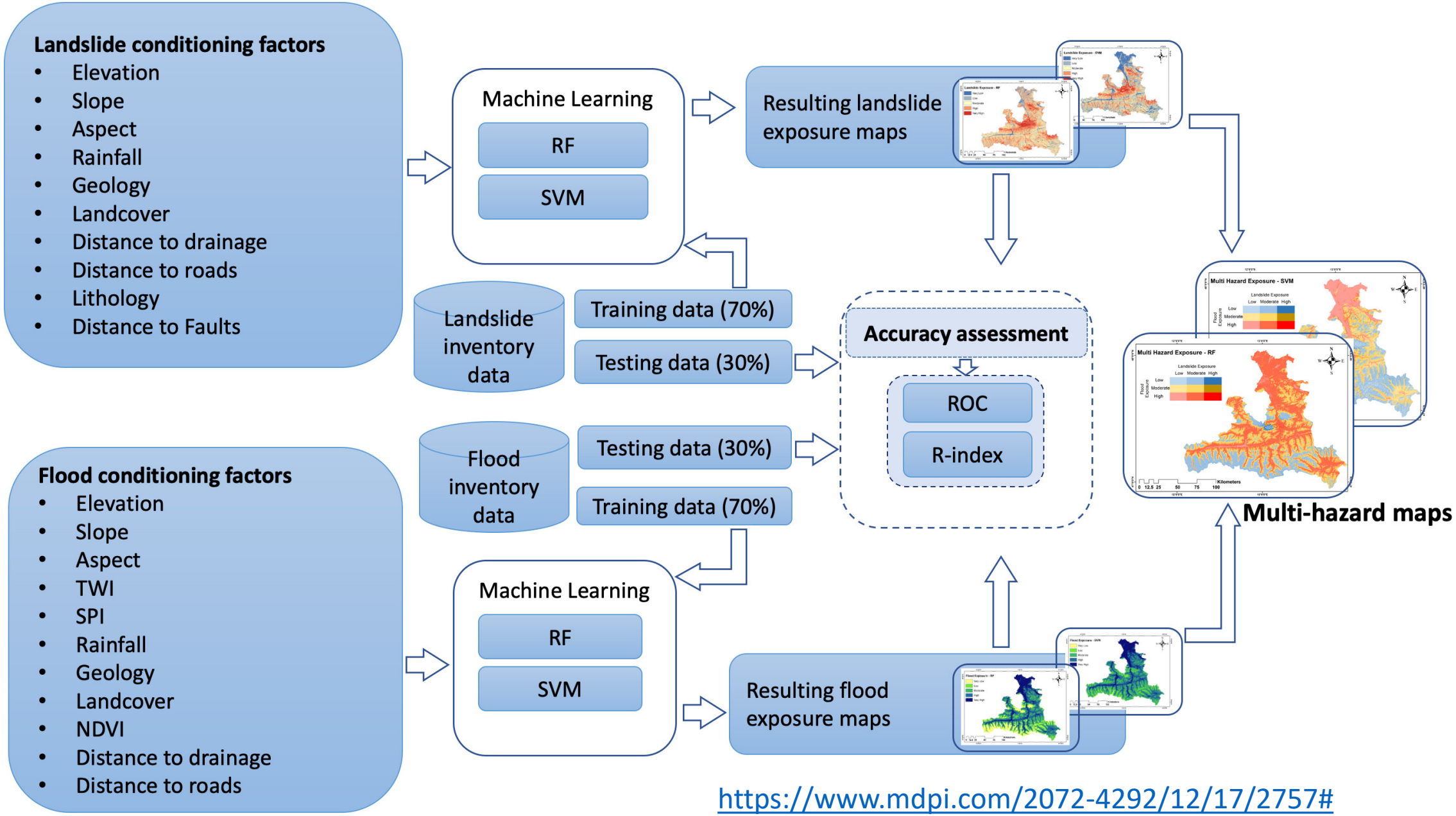
https://www.sciencedirect.com/science/article/pii/S0147651323004153

Geospatial AI on climate modelling



https://ki-klima.iti.kit.edu/81.php

Geospatial AI on Multi-Hazard Exposure Mapping



https://www.mdpi.com/2072-4292/12/17/2757#

Geospatial Foundation models

A geospatial foundation model is a type of ***large-scale deep learning model*** specifically trained on a wide array of geospatial data, including satellite imagery, topographical maps, and other location-specific datasets. This type of model learns to understand and interpret the complex patterns and relationships inherent in location data.

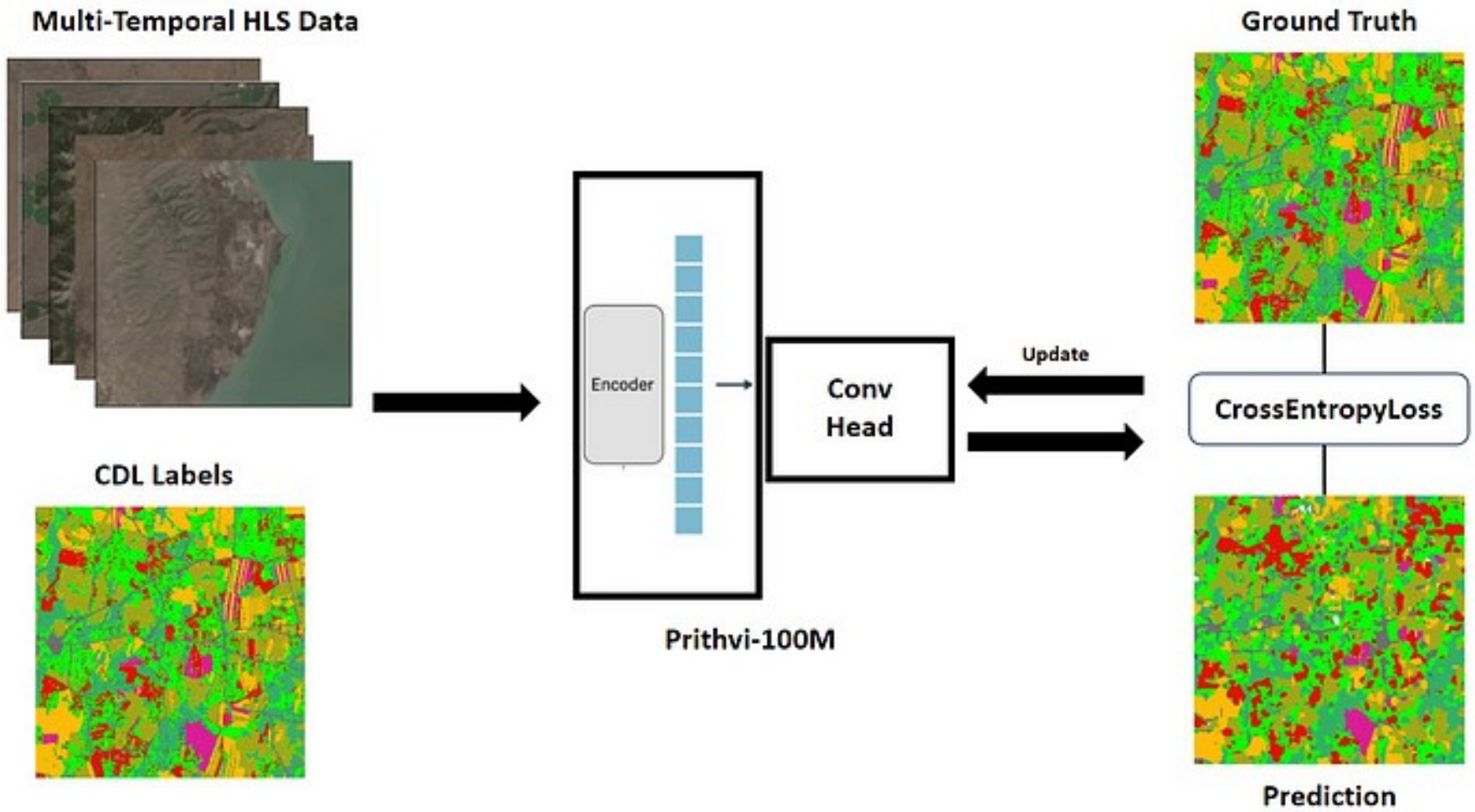
Forecasting Planetary & Societal Change: predict environmental changes, urban development, climate patterns, and even socio-economic trends

Enhancing Image Recognition: Land cover classification

Contextualization of Geospatial Data: what is happening, what has changed

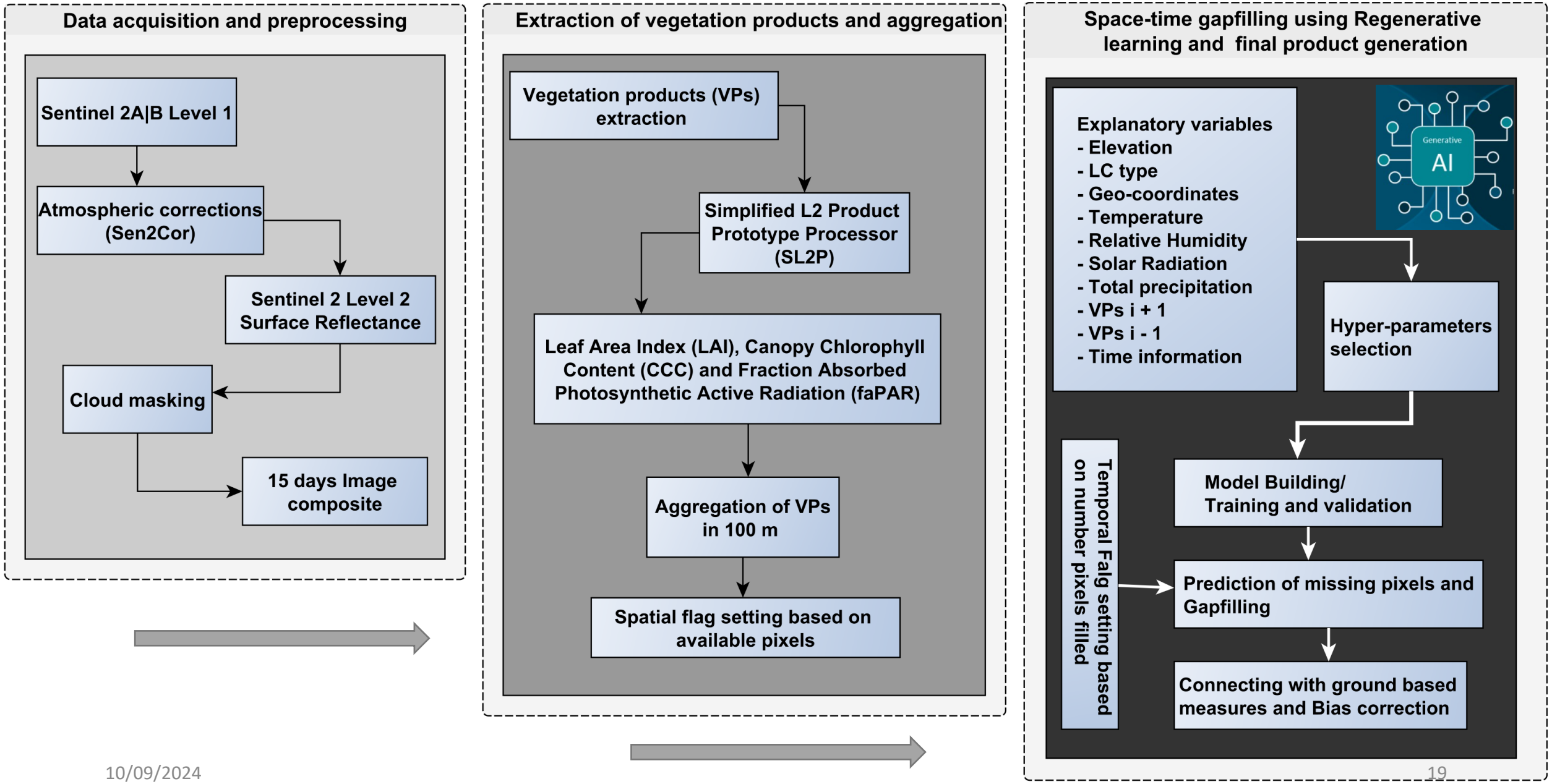
Prithvi Foundation Model (Collaboration with NASA and IBM)

Geospatial Foundation models



https://huggingface.co/ibm-nasa-geospatial/Prithvi-100M

Drafted methodology (EOCIS products)



Experiment-Approach-1: Reconstructing S2 LAI dynamics through ML

Sentinel -2

- Sen2Cor – Surface ref.
- Cloud masking
- 15 days Image composite

Simplified L2 Product Prototype Processor(SL2P)

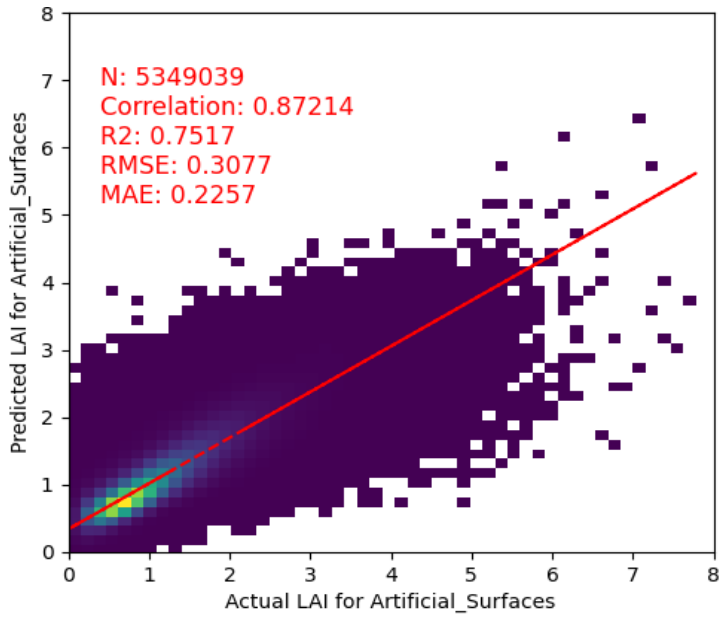
Leaf Area Index (LAI)

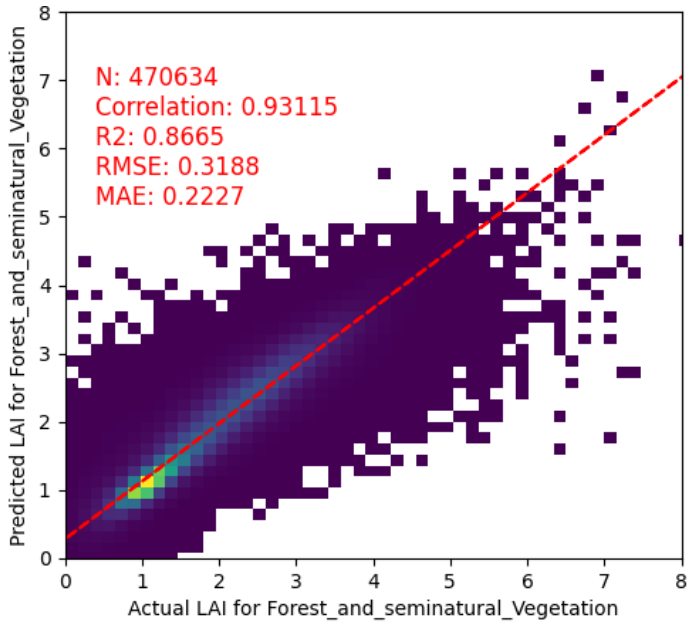
Aggregation in 100 m

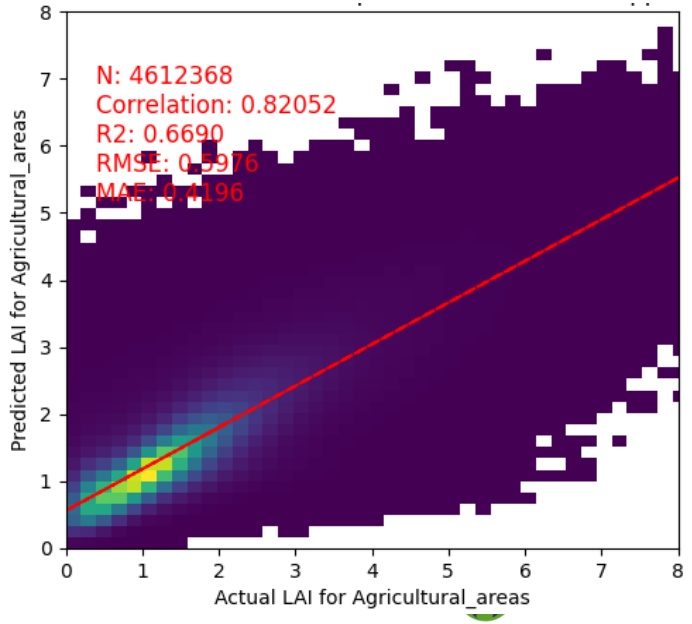
Spatial flag setting

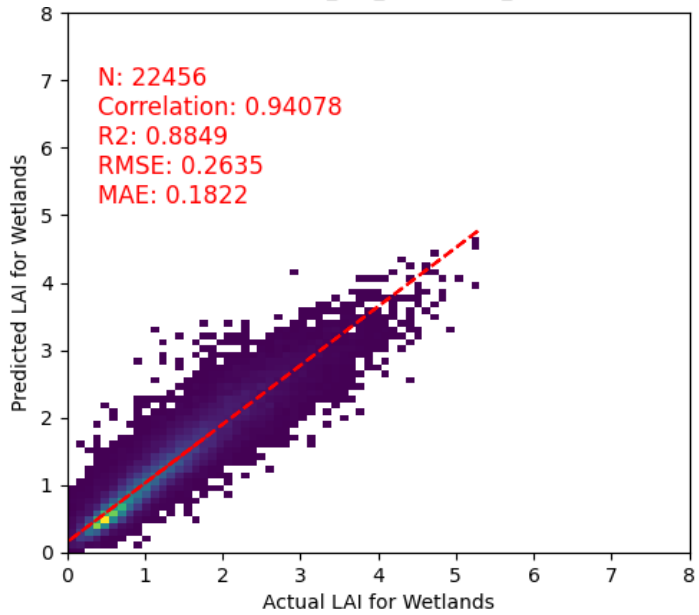
Explanatory variables
- Elevation
- LC type
- Geo-coordinates
- Temperature
- Relative Humidity
- Solar Radiation
- Total precipitation
- Time information

Model Building| Training and validation









EARTH OBSERVATION CLIMATE INFORMATION SERVICE

Experiment-Approach-2: Reconstructing S2 surface-reflectance through ML

Sentinel -2

- Sen2Cor – Surface ref.
- Cloud masking
- 15 days Image composite

S2B4|S2B6|S2B8|S2B8A| S2Bs

Aggregation in 100 m

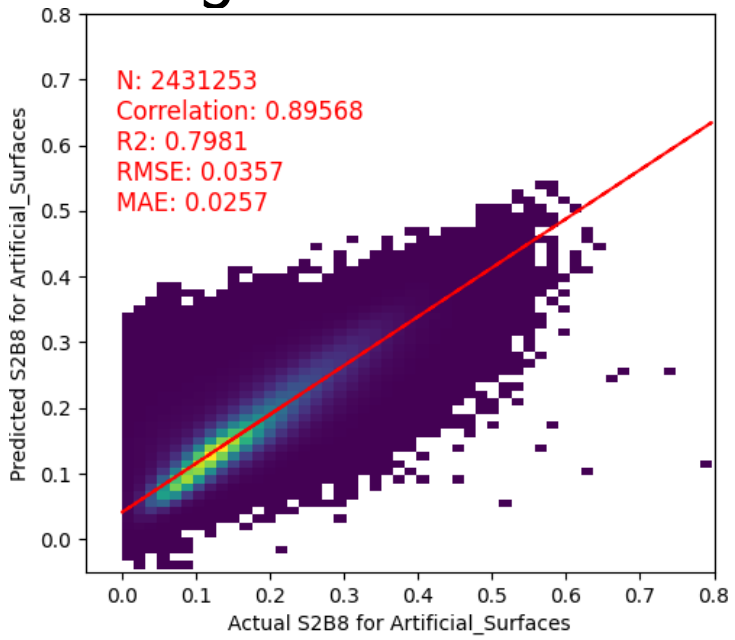
Spatial flag setting

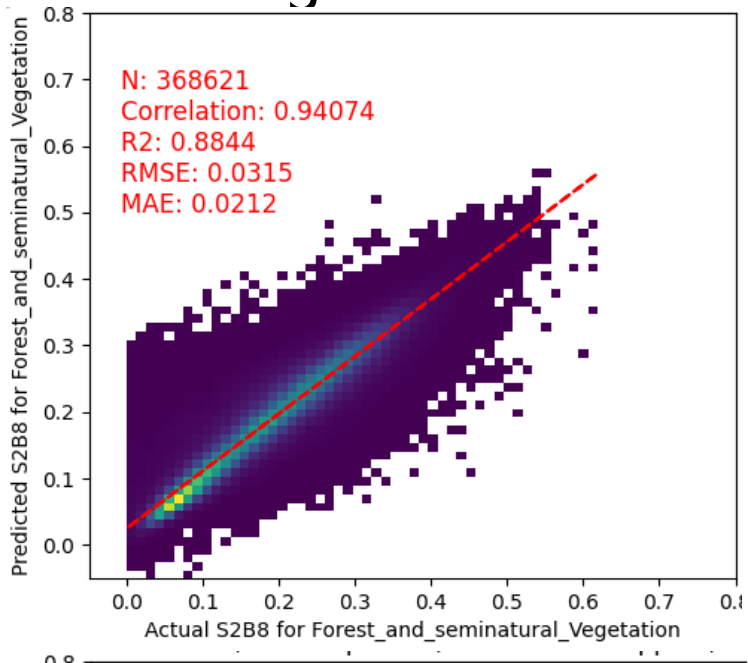
Explanatory variables
- Elevation
- LC type
- Geo-coordinates
- Temperature
- Relative Humidity
- Solar Radiation
- Total precipitation
- Time information

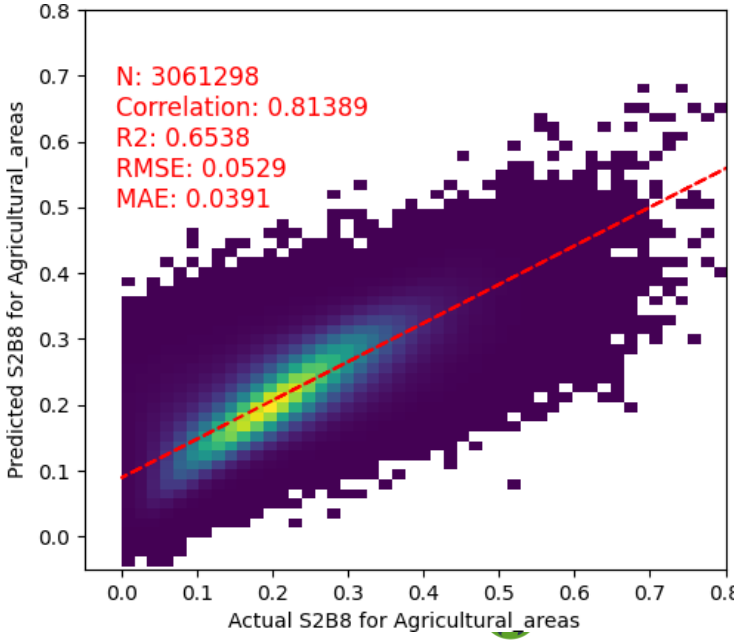
Model Building| Training | validation | gap filling

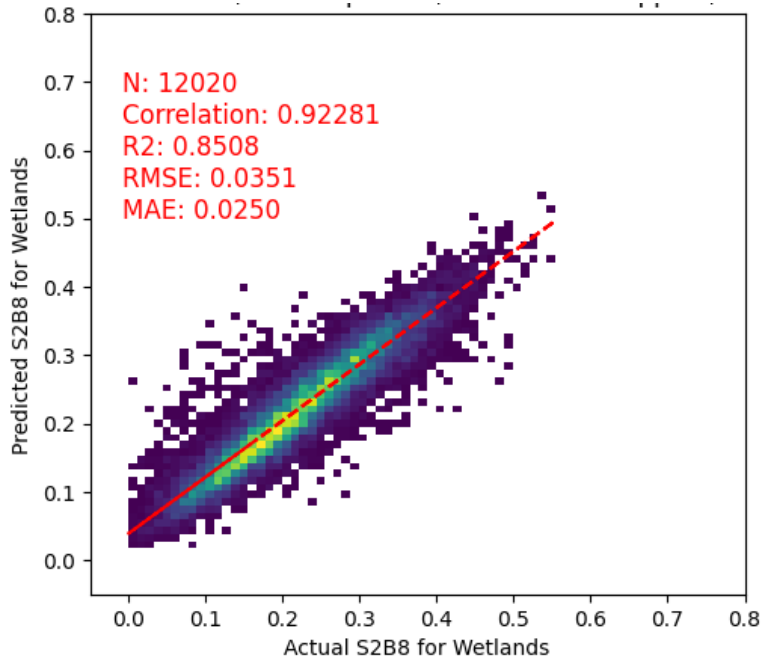
Simplified L2 Product Prototype Processor(SL2P)

Vegetation products (LAI, fAPAR and CCC)



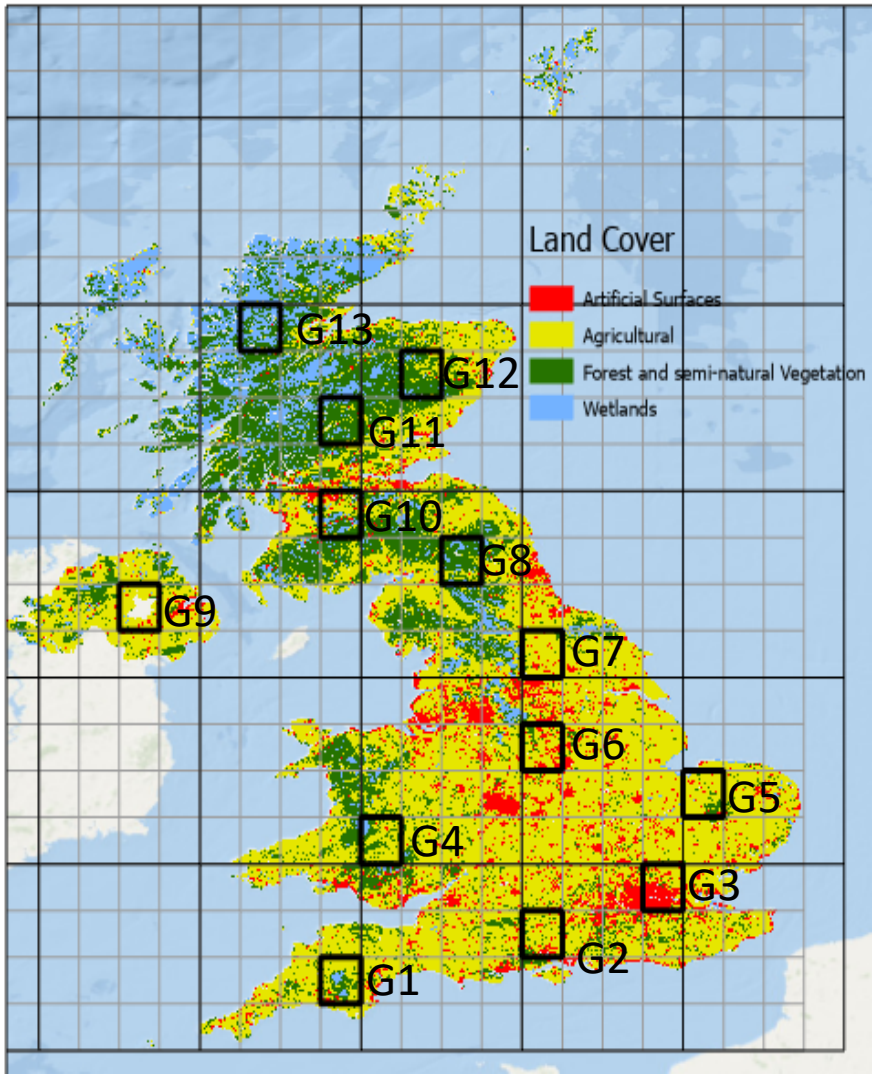


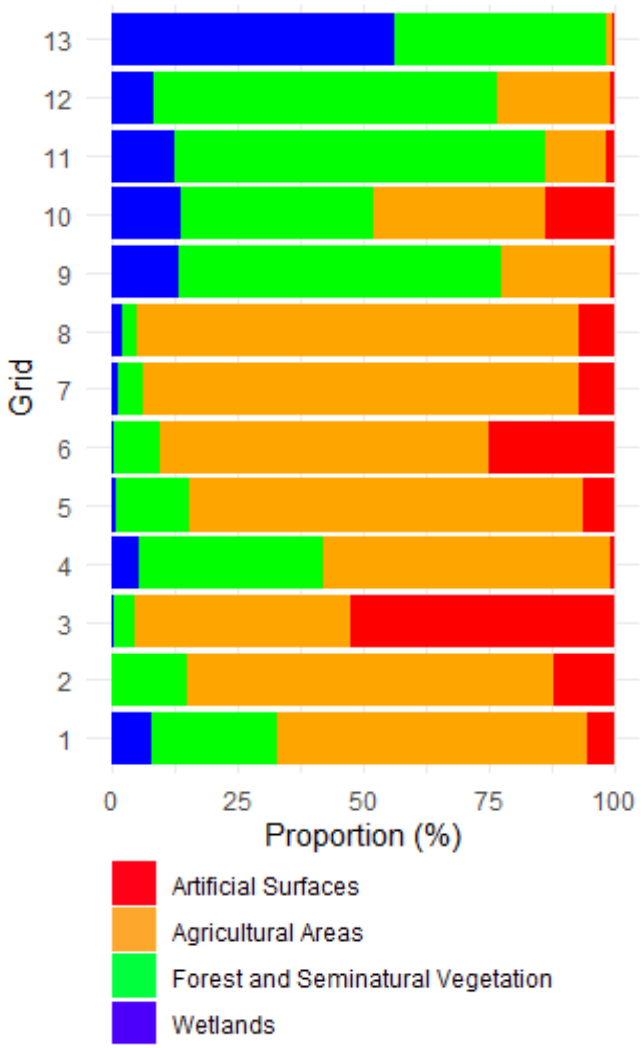




EARTH OBSERVATION CLIMATE INFORMATION SERVICE

Adopted approach





Experimental group:
4 major in 2° Latitude interval

50 × 50 km experimental sites

Land cover specific Model

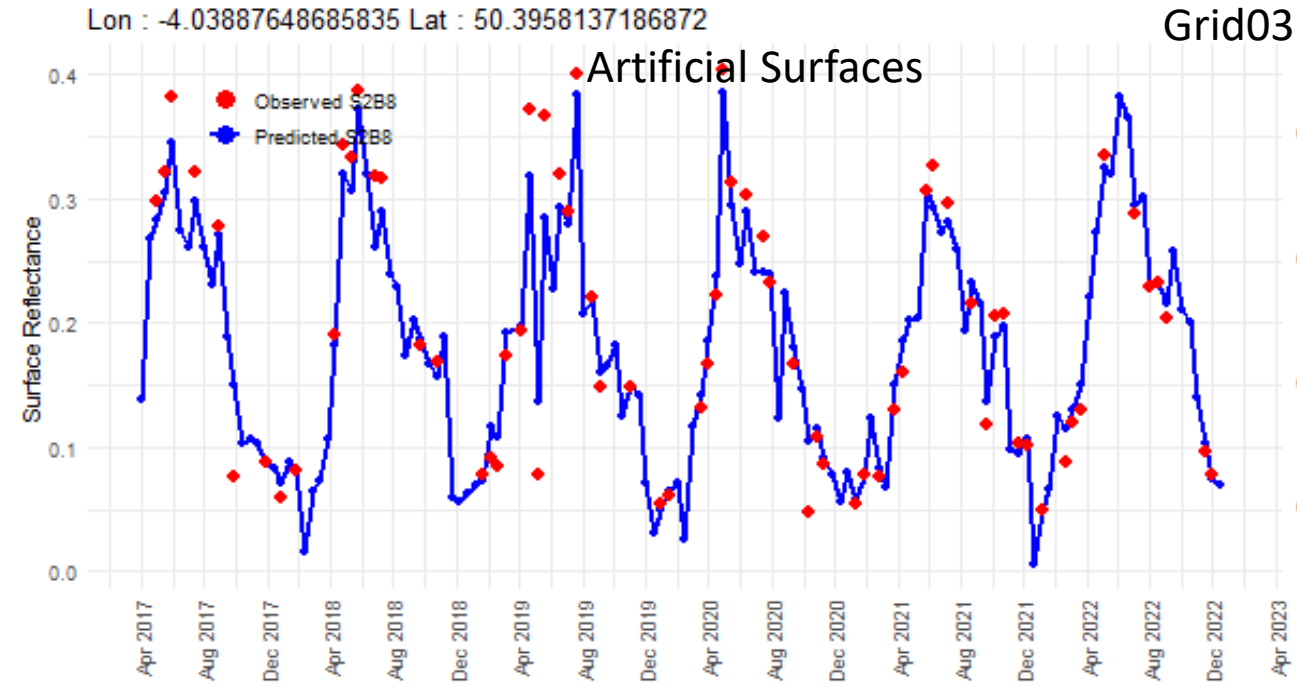
Modelling and Ensemble prediction over 2° Lat zones

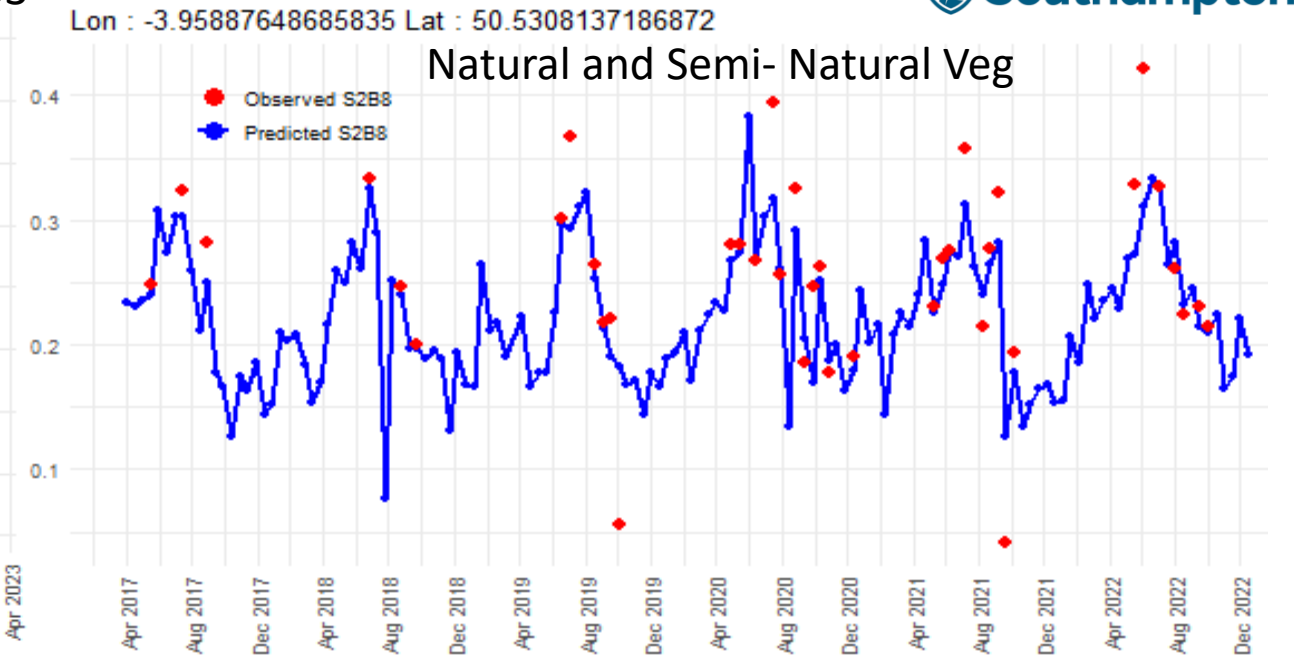
Simplified L2 Product Prototype Processor(SL2P)

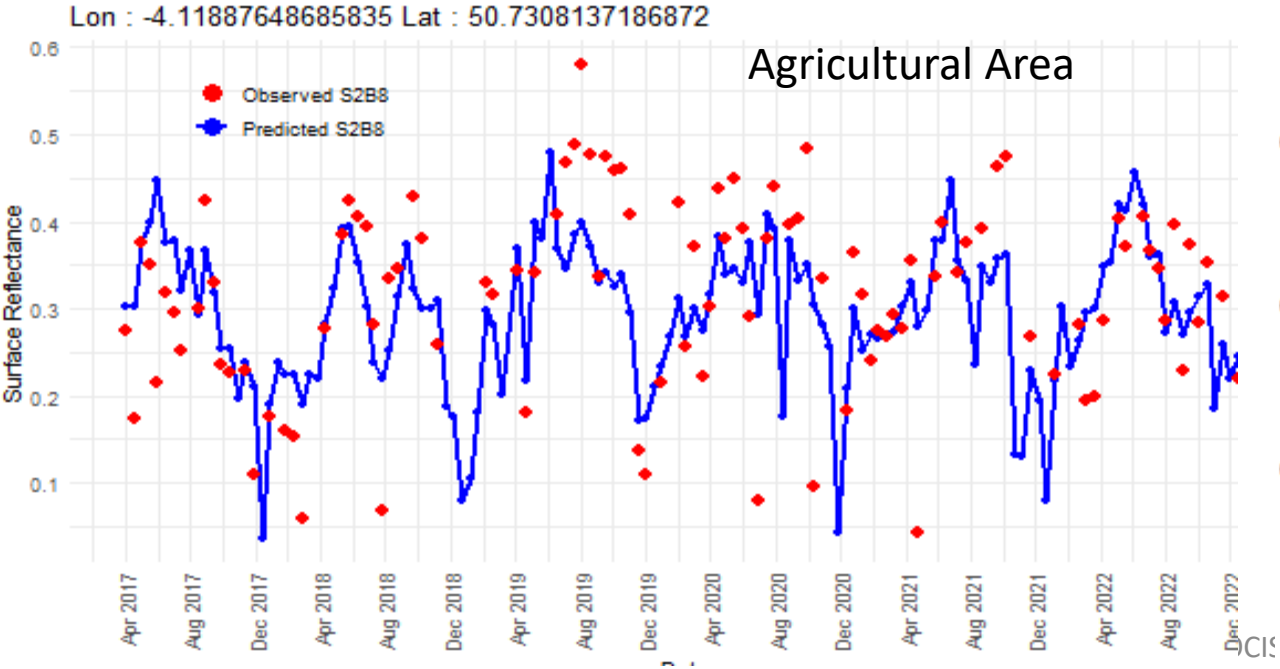
Vegetation products (LAI, fAPAR and CCC)

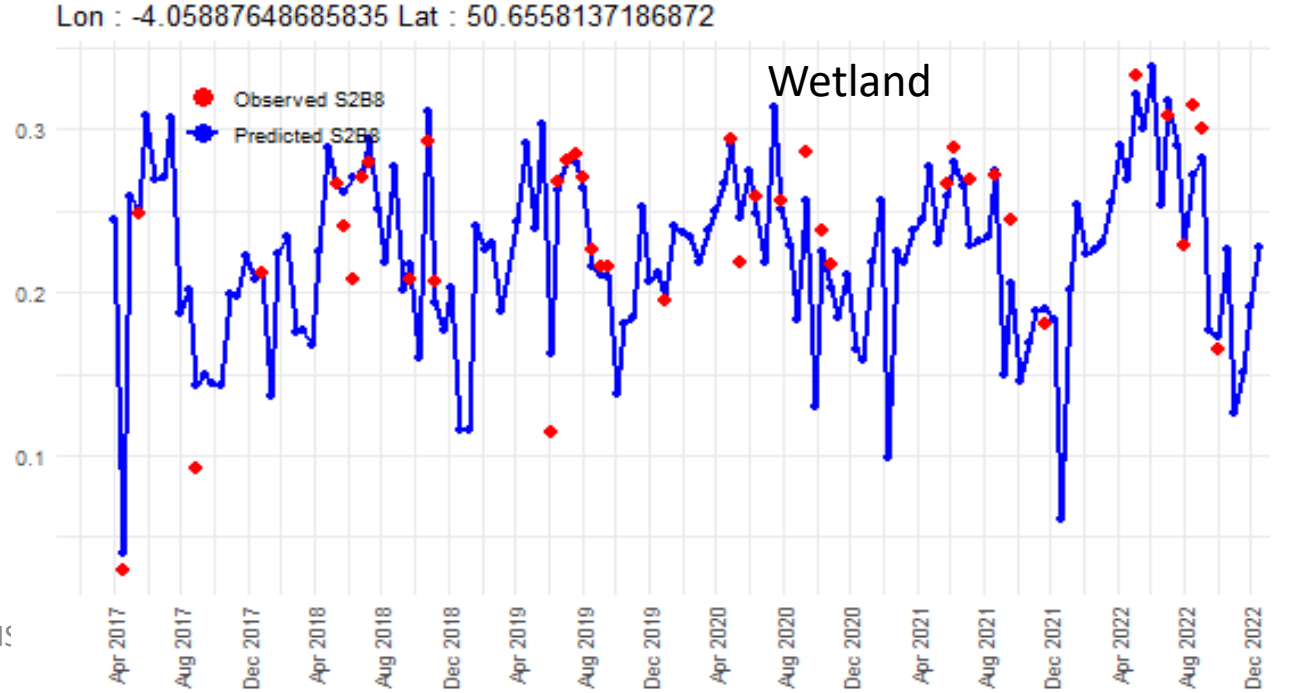
Numbers of points for every grids: 309692

Grid03


Lon : -4.03887648685835 Lat : 50.3958137186872
Artificial Surfaces
Observed S2B8
Predicted S2B8
Surface Reflectance
0.0
0.1
0.2
0.3
0.4
Apr 2017
Aug 2017
Dec 2017
Apr 2018
Aug 2018
Dec 2018
Apr 2019
Aug 2019
Dec 2019
Apr 2020
Aug 2020
Dec 2020
Apr 2021
Aug 2021
Dec 2021
Apr 2022
Aug 2022
Dec 2022
Apr 2023


Lon : -3.95887648685835 Lat : 50.5308137186872
Natural and Semi- Natural Veg
Observed S2B8
Predicted S2B8
0.1
0.2
0.3
0.4
Apr 2017
Aug 2017
Dec 2017
Apr 2018
Aug 2018
Dec 2018
Apr 2019
Aug 2019
Dec 2019
Apr 2020
Aug 2020
Dec 2020
Apr 2021
Aug 2021
Dec 2021
Apr 2022
Aug 2022
Dec 2022


Lon : -4.11887648685835 Lat : 50.7308137186872
Agricultural Area
Observed S2B8
Predicted S2B8
Surface Reflectance
0.1
0.2
0.3
0.4
0.5
0.6
Apr 2017
Aug 2017
Dec 2017
Apr 2018
Aug 2018
Dec 2018
Apr 2019
Aug 2019
Dec 2019
Apr 2020
Aug 2020
Dec 2020
Apr 2021
Aug 2021
Dec 2021
Apr 2022
Aug 2022


Lon : -4.05887648685835 Lat : 50.6558137186872
Wetland
Observed S2B8
Predicted S2B8
0.1
0.2
0.3
Apr 2017
Aug 2017
Dec 2017
Apr 2018
Aug 2018
Dec 2018
Apr 2019
Aug 2019
Dec 2019
Apr 2020
Aug 2020
Dec 2020
Apr 2021
Aug 2021
Dec 2021
Apr 2022
Aug 2022
Dec 2022