Rock and Soil Classification Using Thermal and SAR Data in Deep Learning Models

P5 – Javier Martínez Martínez

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Co-Reader:

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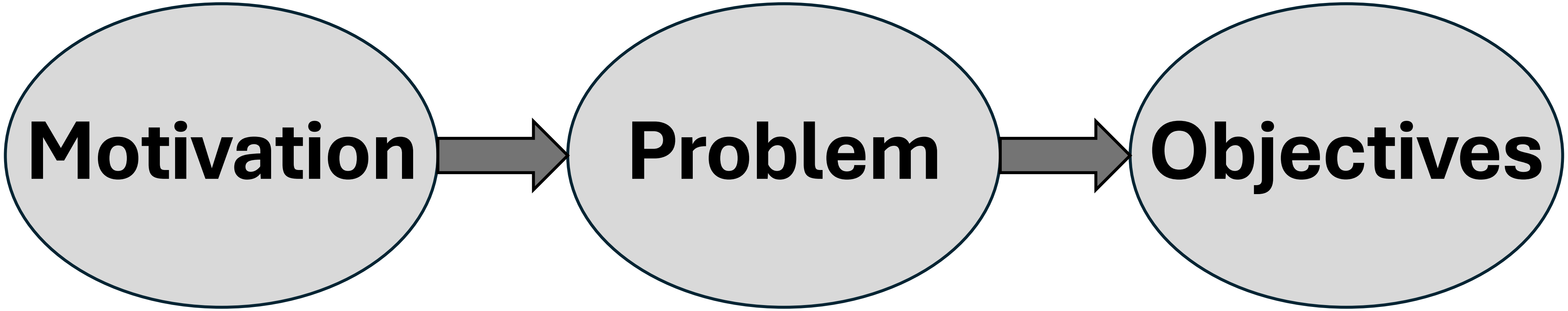
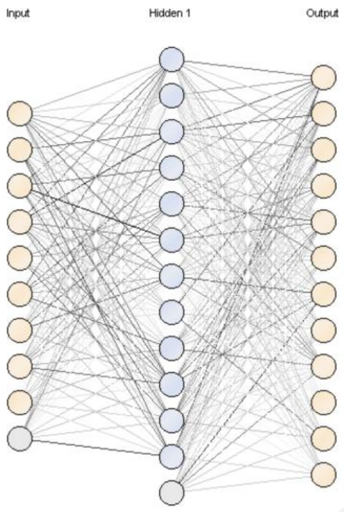
Agenda

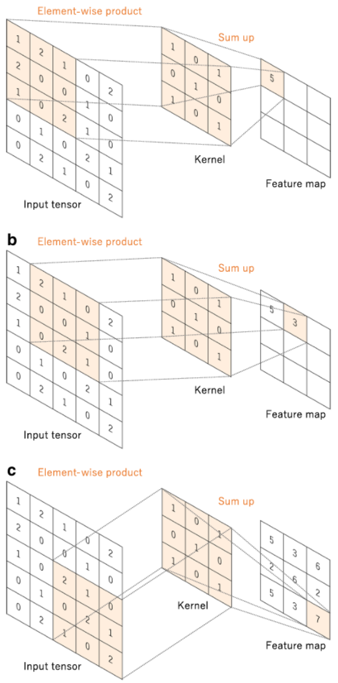
Introduction

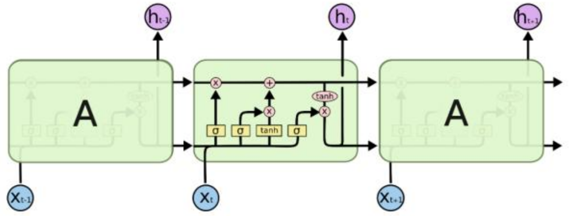

Motivation
Problem
Objectives

Theoretical Background

- **Thermal imagery –** emissivity and LST
- **SAR –** VV and VH
- **NDVI –** additional information
- **CNN –** extracting spatial features
- **ConvLSTM –** obtaining spatio-temporal dependencies







Hypotheses & Research Questions

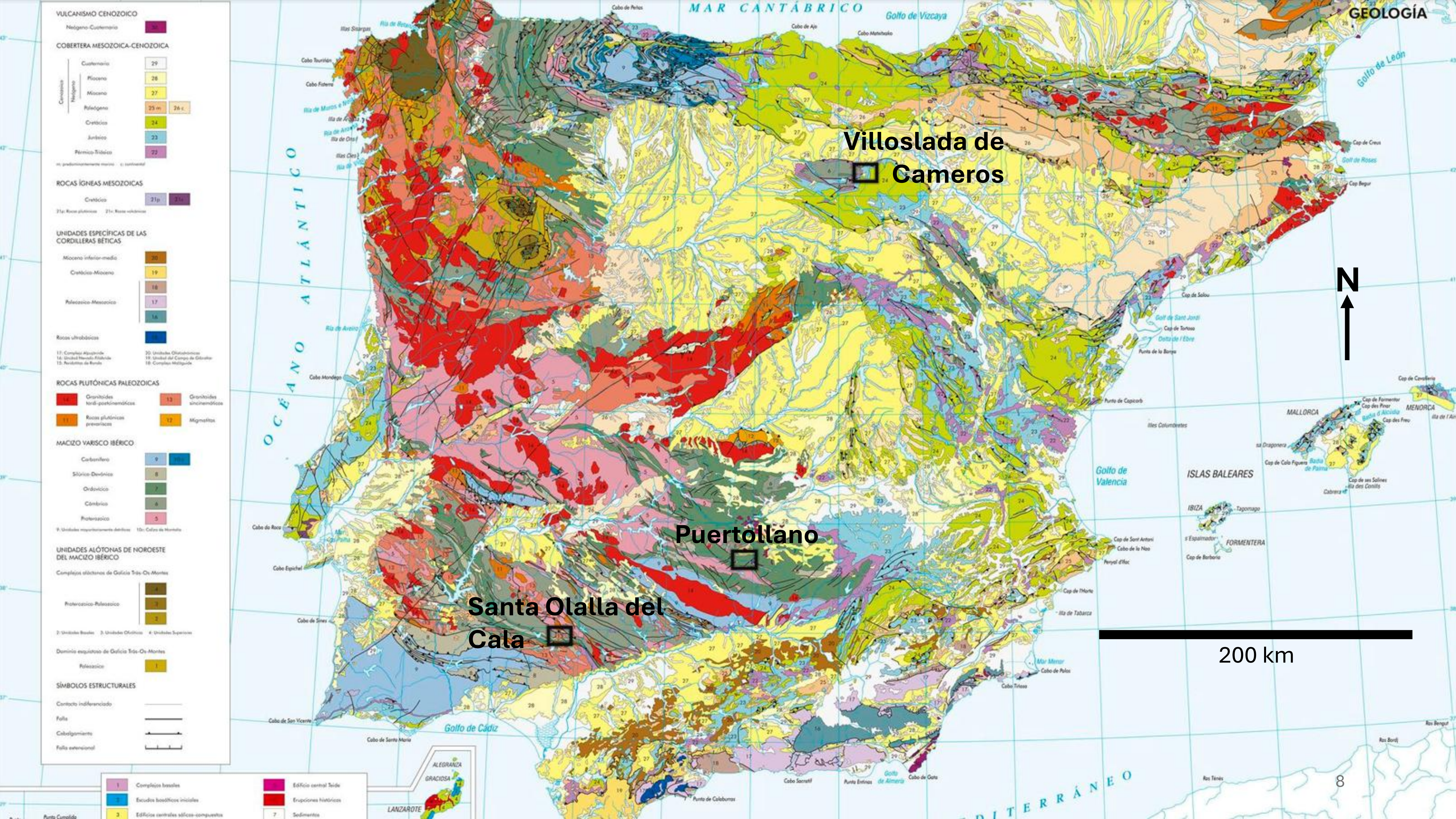
Hypotheses:

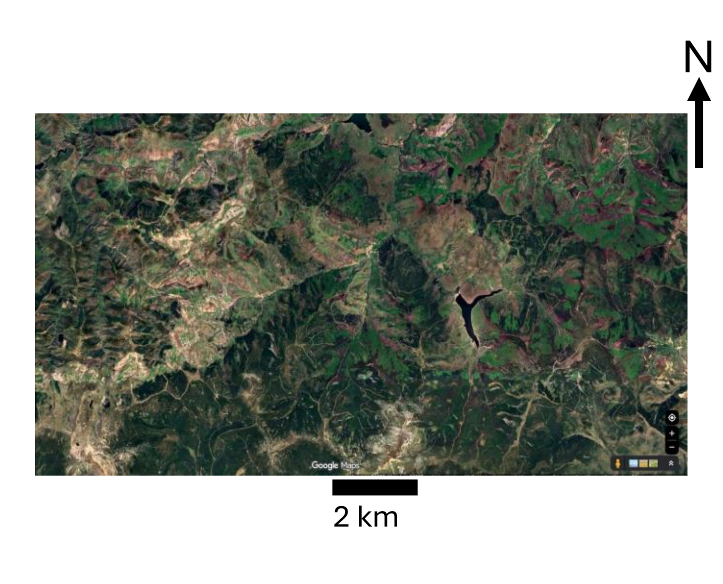
- Clay soils gain heat slowly throughout the day but retain heat longer due to its higher moisture content and fine-grained texture.
- Sandy soils gain heat quickly throughout the day but loose it rapidly given its lower moisture content and coarse-grained texture.

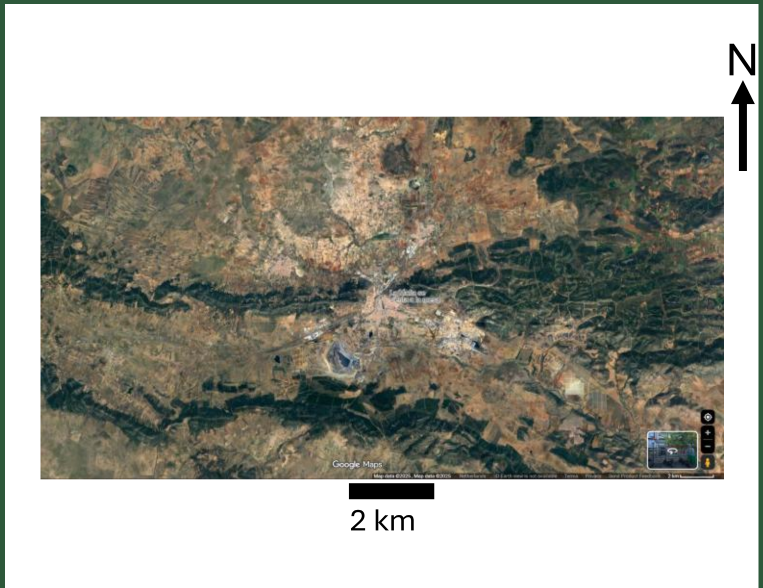
Research questions:

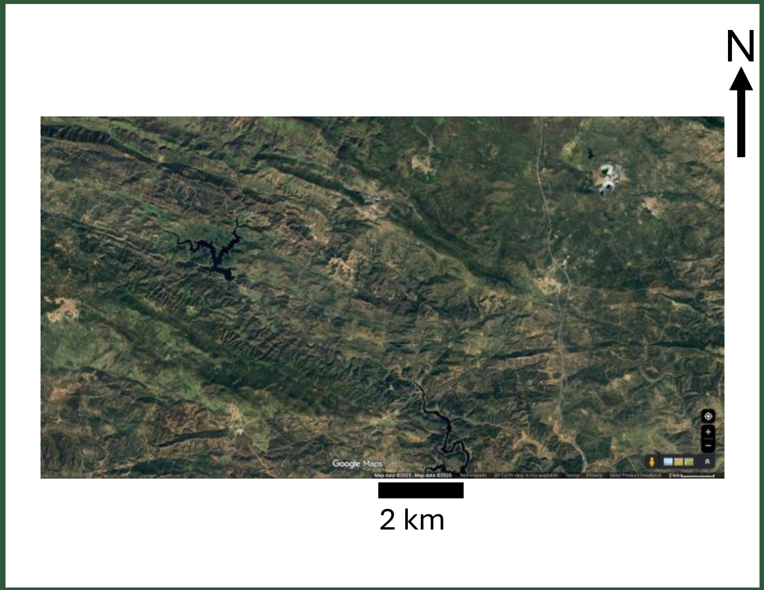
- To what extent can CNN and Recurrent Neural Network (RNN) deep learning methods help identify/detect different soil/rock types with thermal imagery?
- How does the model deal with very similar rock/soil attributes?
- How do temporal factors (diurnal and seasonal changes) affect the classification performance?
- If other types of data are included (SAR), does the performance/outcomes improve?

Methodology


GEOLOGÍA
VULCANISMO CENOZOICO
Neógeno-Cuaternario
COBERTERA MESOZOICA-CENOZOICA
Cuaternario
Plioceno
Mioceno
Paleógeno
Cretácico
Jurásico
Pérmico-Triásico
ROCAS ÍGNEAS MESOZOICAS
Cretácico
UNIDADES ESPECÍFICAS DE LAS CORDILLERAS BÉTICAS
Mioceno inferior-medio
Cretácico-Mioceno
Paleozoico-Mesozoico
Rocas ultrabásicas
ROCAS PLUTÓNICAS PALEOZOICAS
Granitoides tardi-postcinemáticos
Granitoides sincinemáticos
Rocas plutónicas prevariscas
Migmatitas
MACIZO VARISCO IBÉRICO
Carbonífero
Silúrico-Devónico
Ordovícico
Cámbrico
Proterozoico
UNIDADES ALÓCTONAS DE NOROESTE DEL MACIZO IBÉRICO
Complejos alóctonos de Galicia Trás-Os-Montes
Proterozoico-Paleozoico
Dominio esquistoso de Galicia Trás-Os-Montes
Paleozoico
SÍMBOLOS ESTRUCTURALES
Contacto indiferenciado
Falla
Cabalgamiento
Falla extensional
MAR CANTÁBRICO
Golfo de Vizcaya
OCÉANO ATLÁNTICO
Golfo de León
Villoslada de Cameros
Puertollano
Santa Olalla del Cala
N
200 km
MALLORCA
MENORCA
ISLAS BALEARES
IBIZA
FORMENTERA
Golfo de Valencia
Golfo de Cádiz
MEDITERRÁNEO



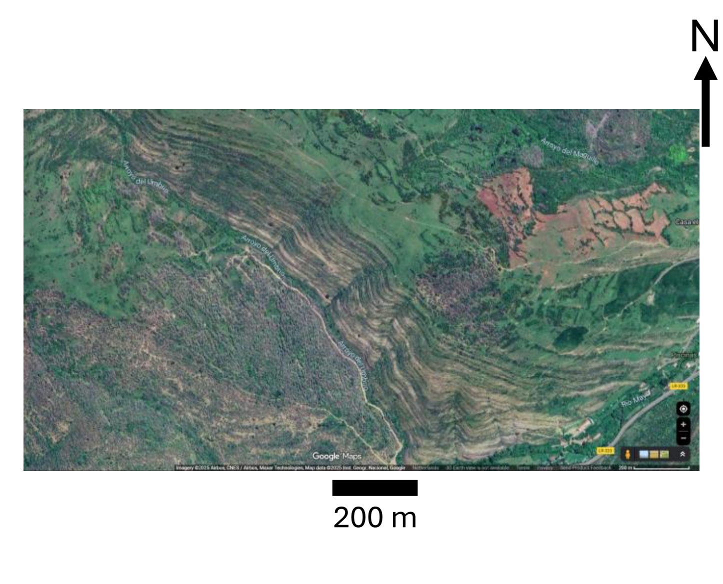


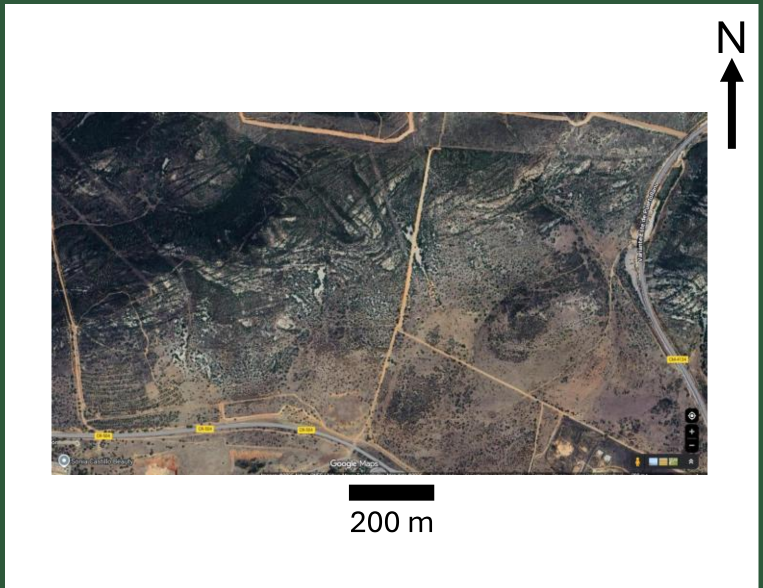


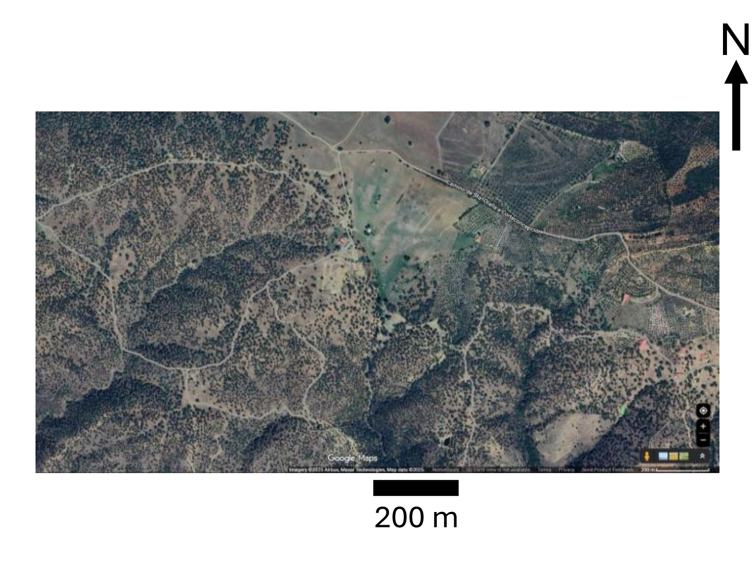
Villoslada de Cameros

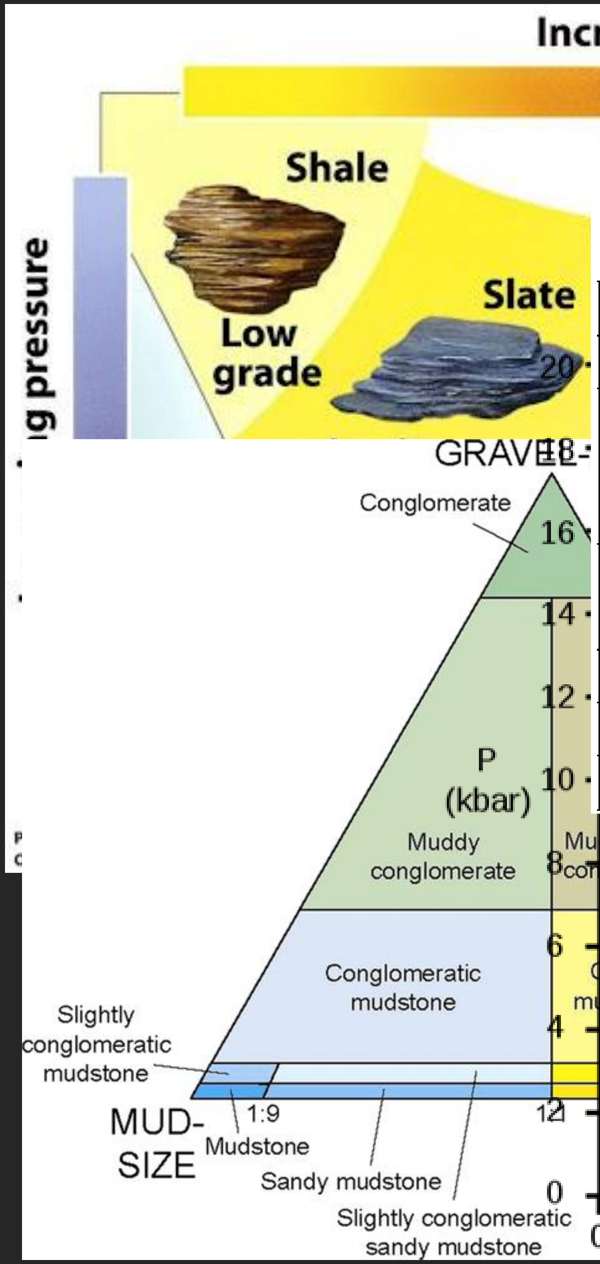
Puertollano

Santa Olalla del Cala



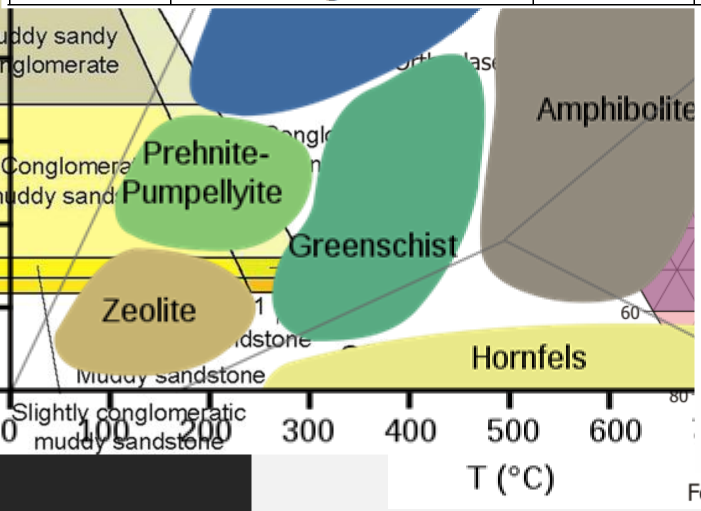


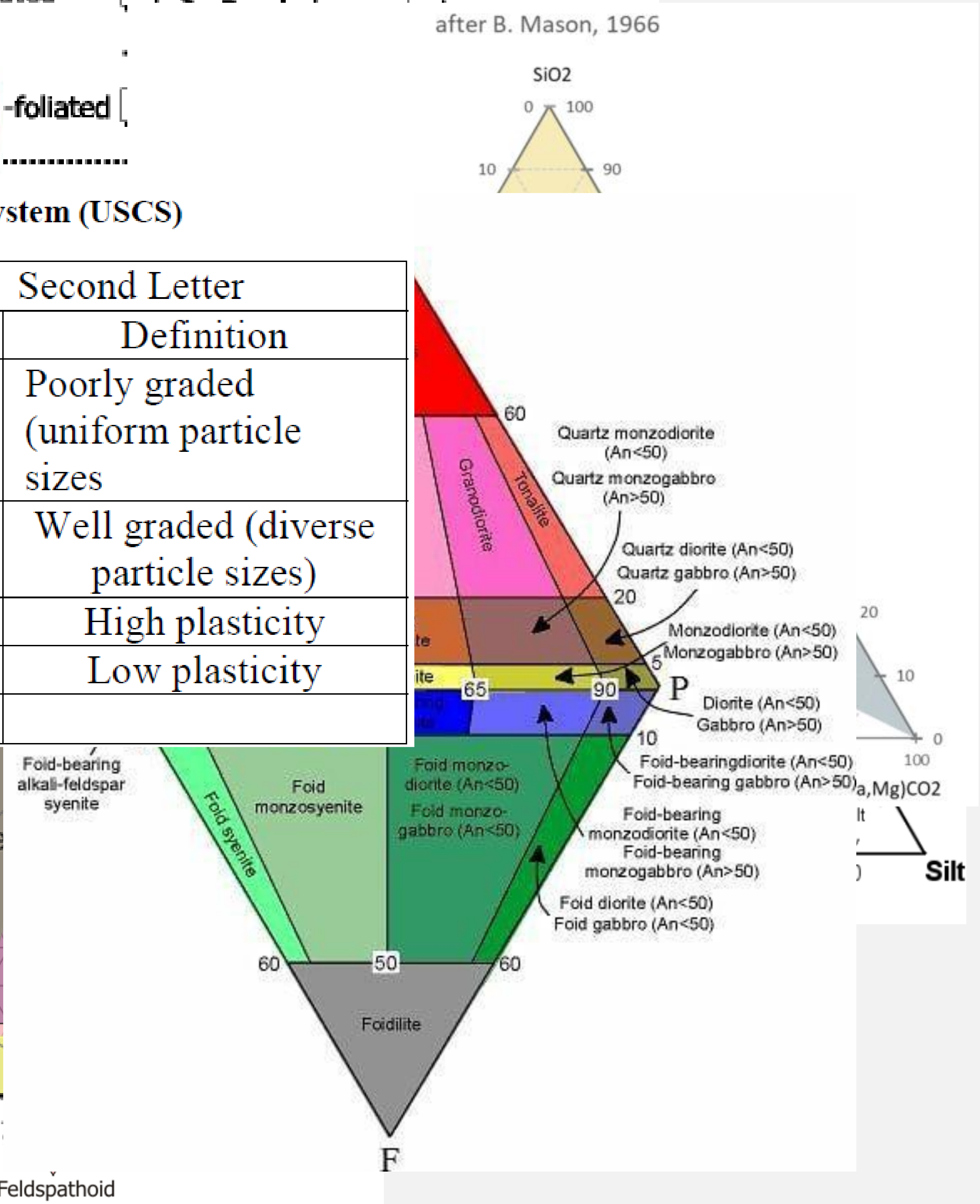


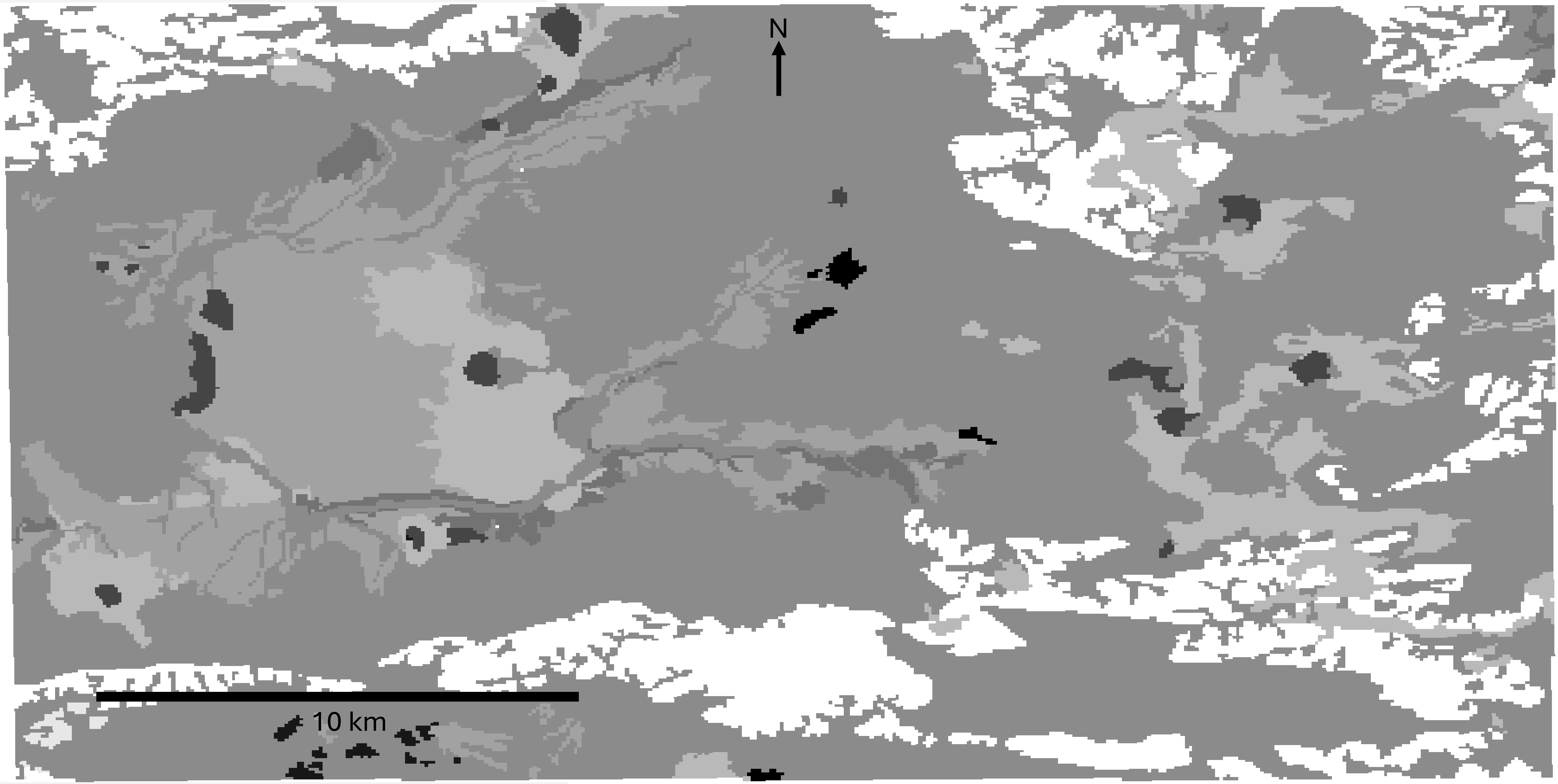


Unified Soil Classification System (USCS)

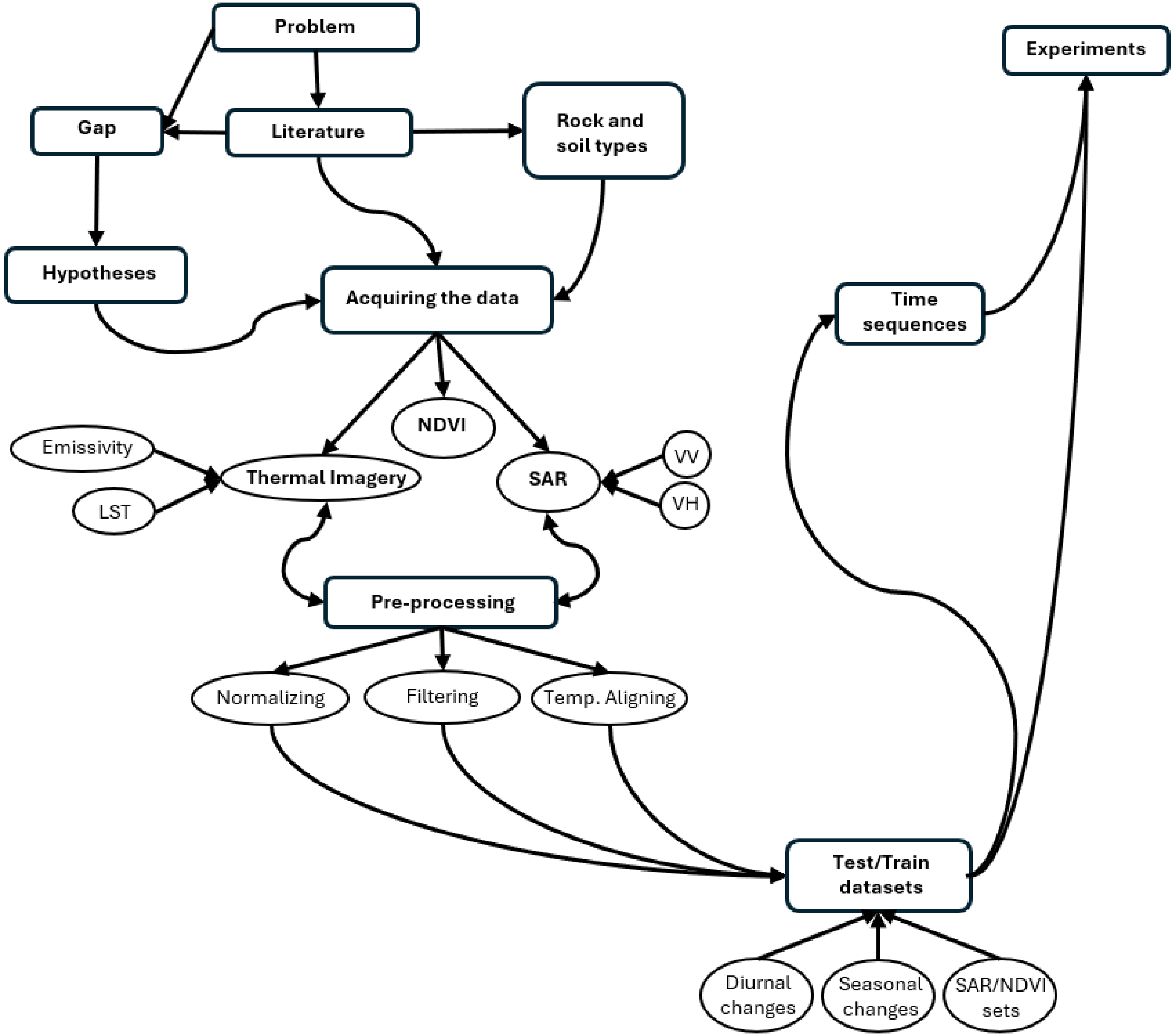
First and/or second letters		Second Letter	
Letter	Definition	Letter	Definition
G	gravel	P	Poorly graded (uniform particle sizes
S	sand	W	Well graded (diverse particle sizes)
M	silt	H	High plasticity
C	clay	L	Low plasticity
O	organic		

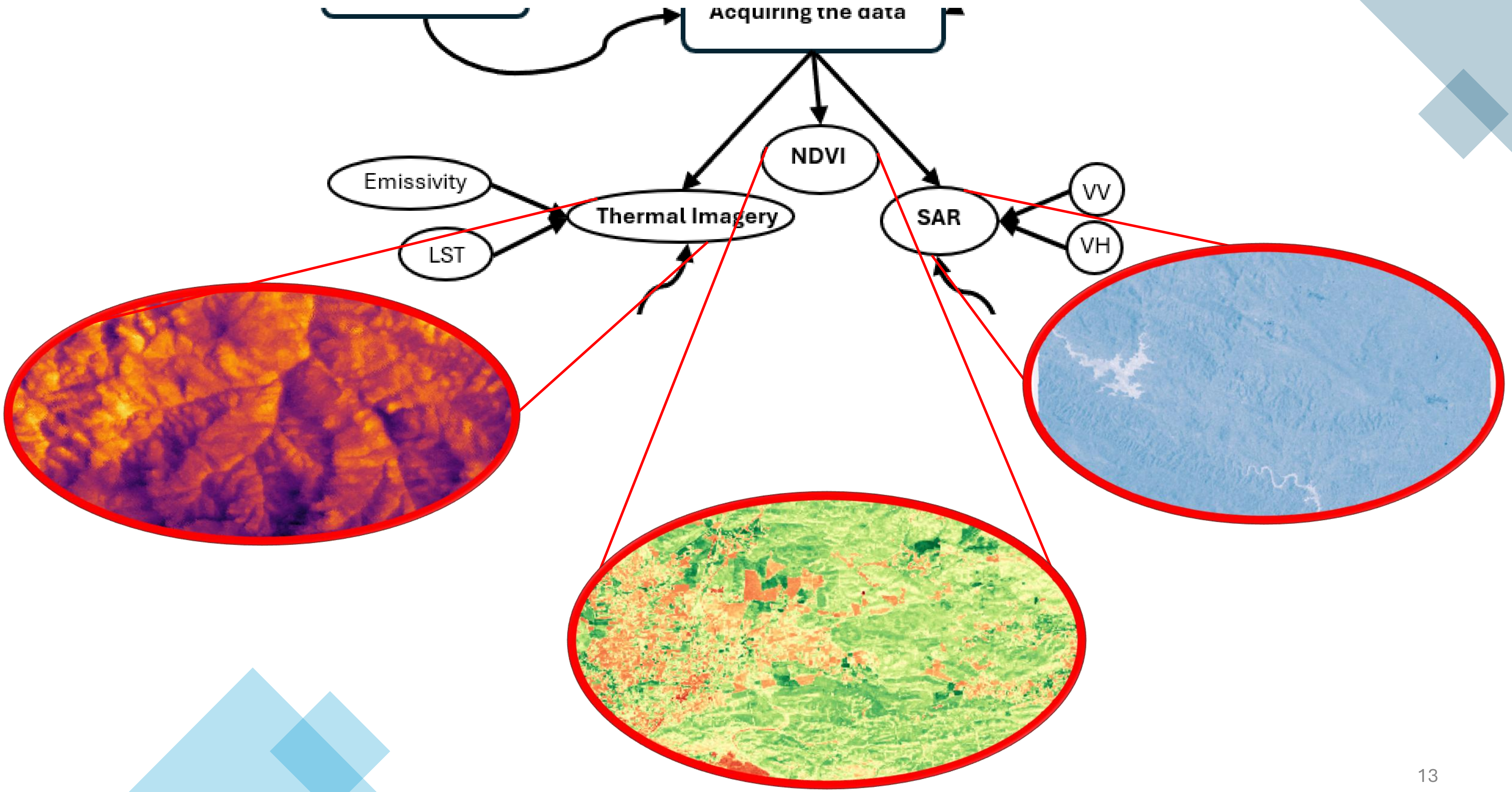


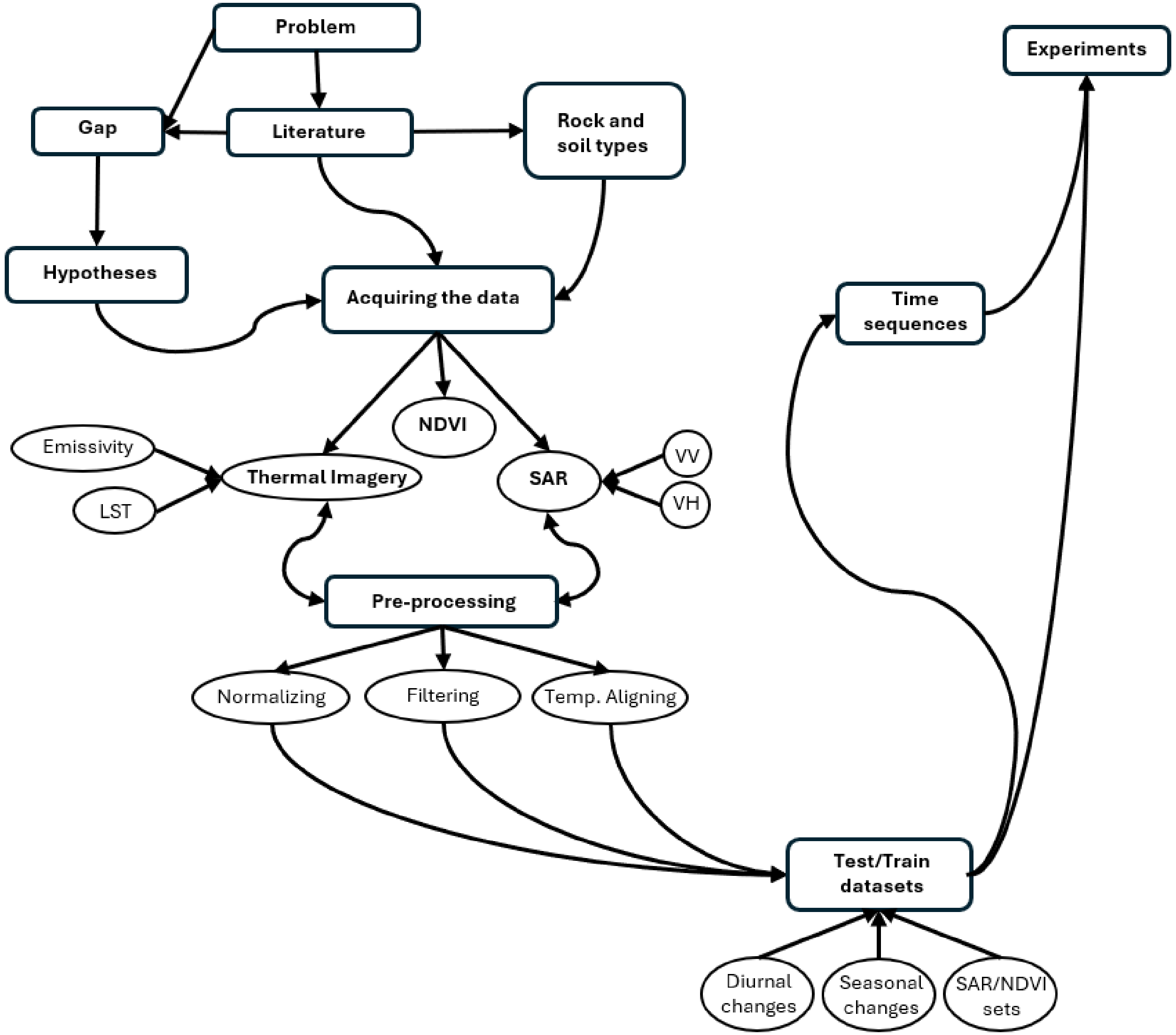



N
10 km

Pre-Processing stage

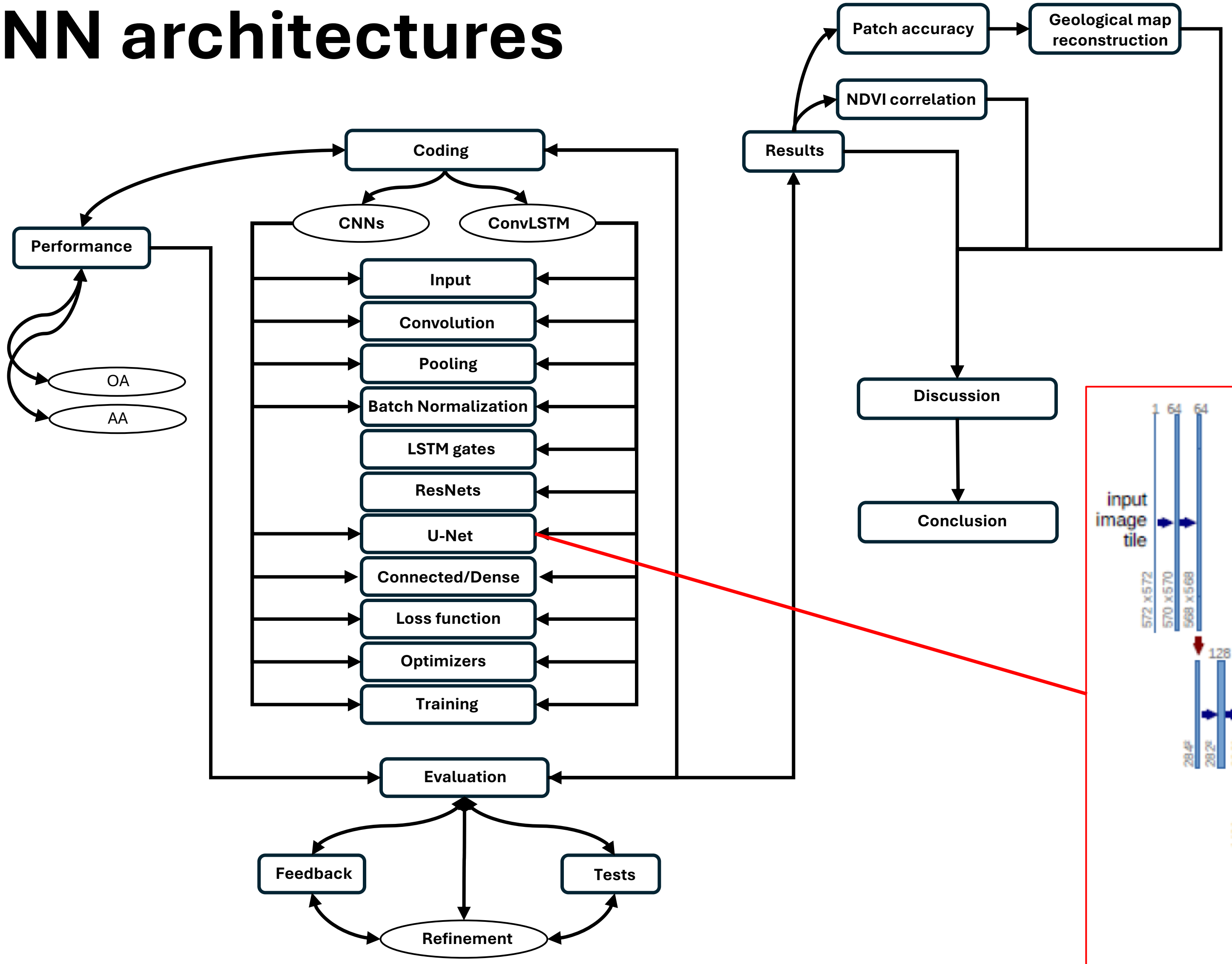



Acquiring the data
NDVI
Emissivity
Thermal Imagery
LST
SAR
VV
VH

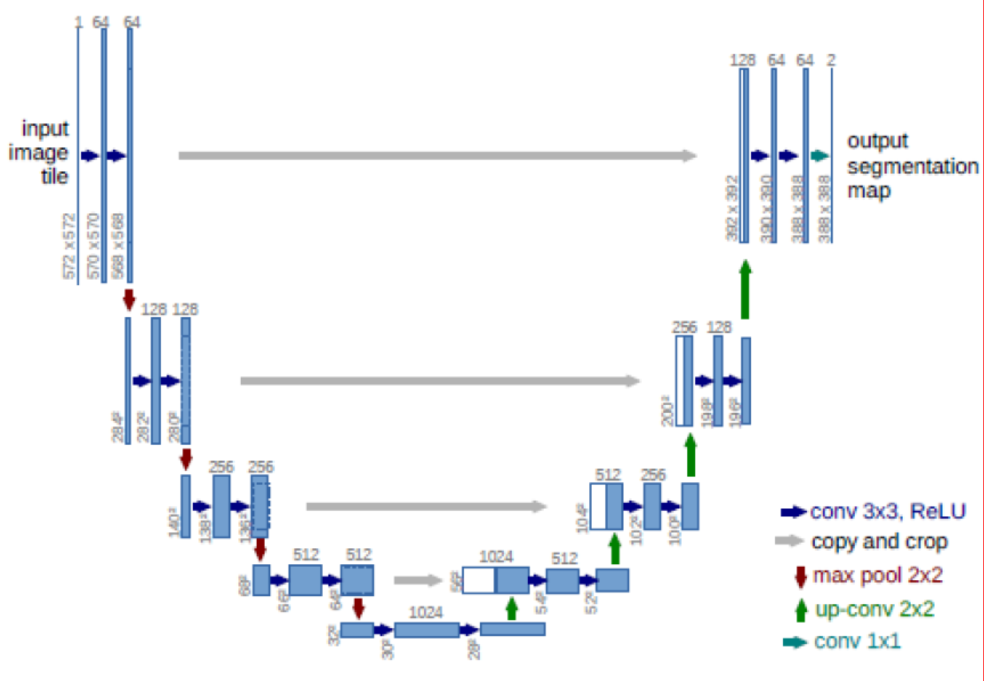


Problem
Gap
Literature
Rock and soil types
Experiments
Hypotheses
Acquiring the data
Time sequences
NDVI
Emissivity
Thermal Imagery
SAR
VV
VH
LST
Pre-processing
Normalizing
Filtering
Temp. Aligning
Test/Train datasets
Diurnal changes
Seasonal changes
SAR/NDVI sets

NN architectures

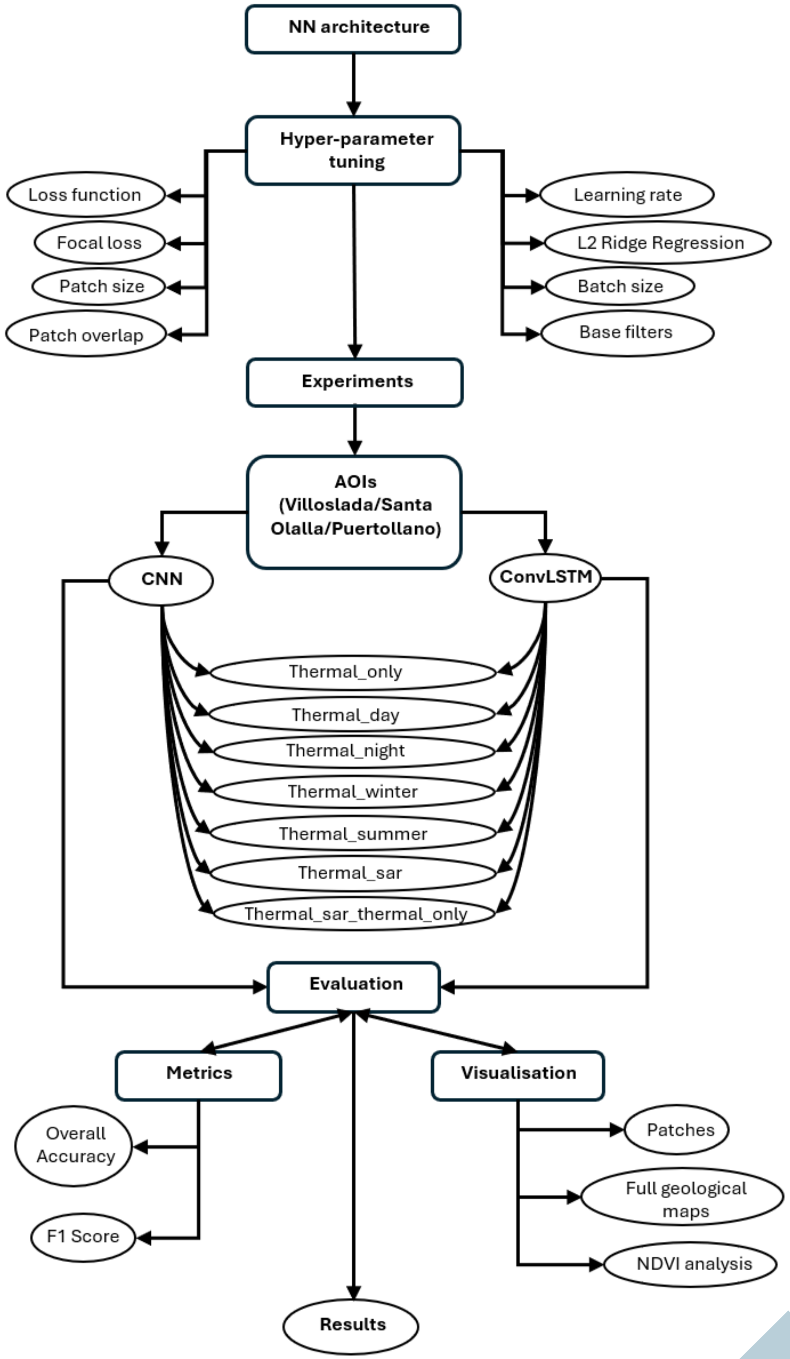


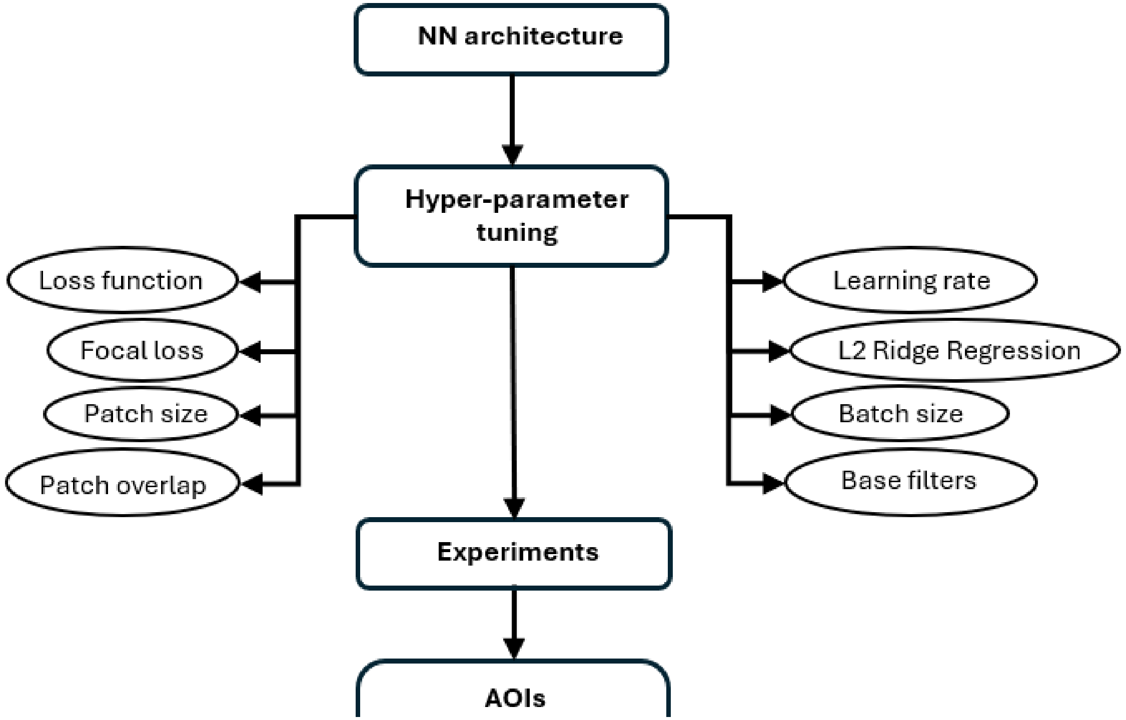
CNN vs. ConvLSTM



Source: Ronneberger et al. (2015)

Training and Parametrisation


NN architecture
Hyper-parameter tuning
Loss function
Focal loss
Patch size
Patch overlap
Learning rate
L2 Ridge Regression
Batch size
Base filters
Experiments
AOIs (Villoslada/Santa Olalla/Puertollano)
CNN
ConvLSTM
Thermal_only
Thermal_day
Thermal_night
Thermal_winter
Thermal_summer
Thermal_sar
Thermal_sar_thermal_only
Evaluation
Metrics
Visualisation
Overall Accuracy
F1 Score
Patches
Full geological maps
NDVI analysis
Results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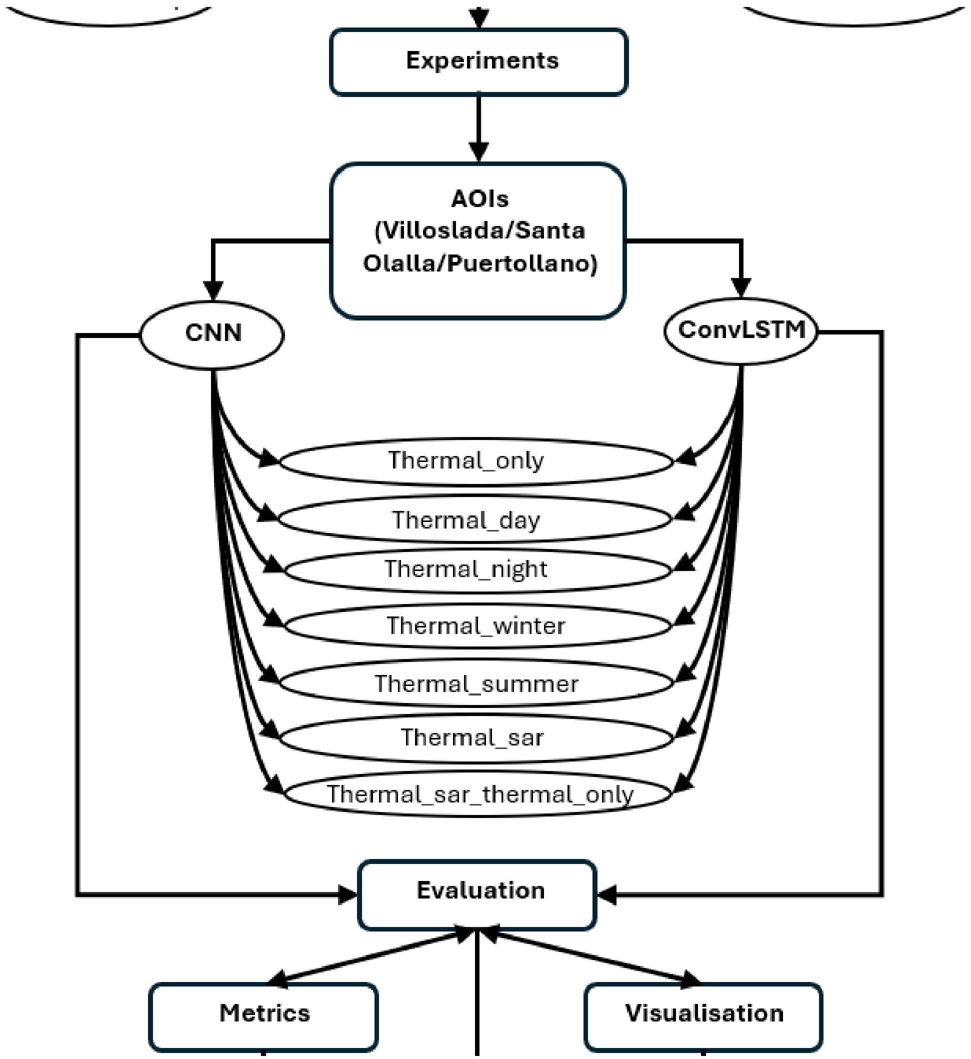
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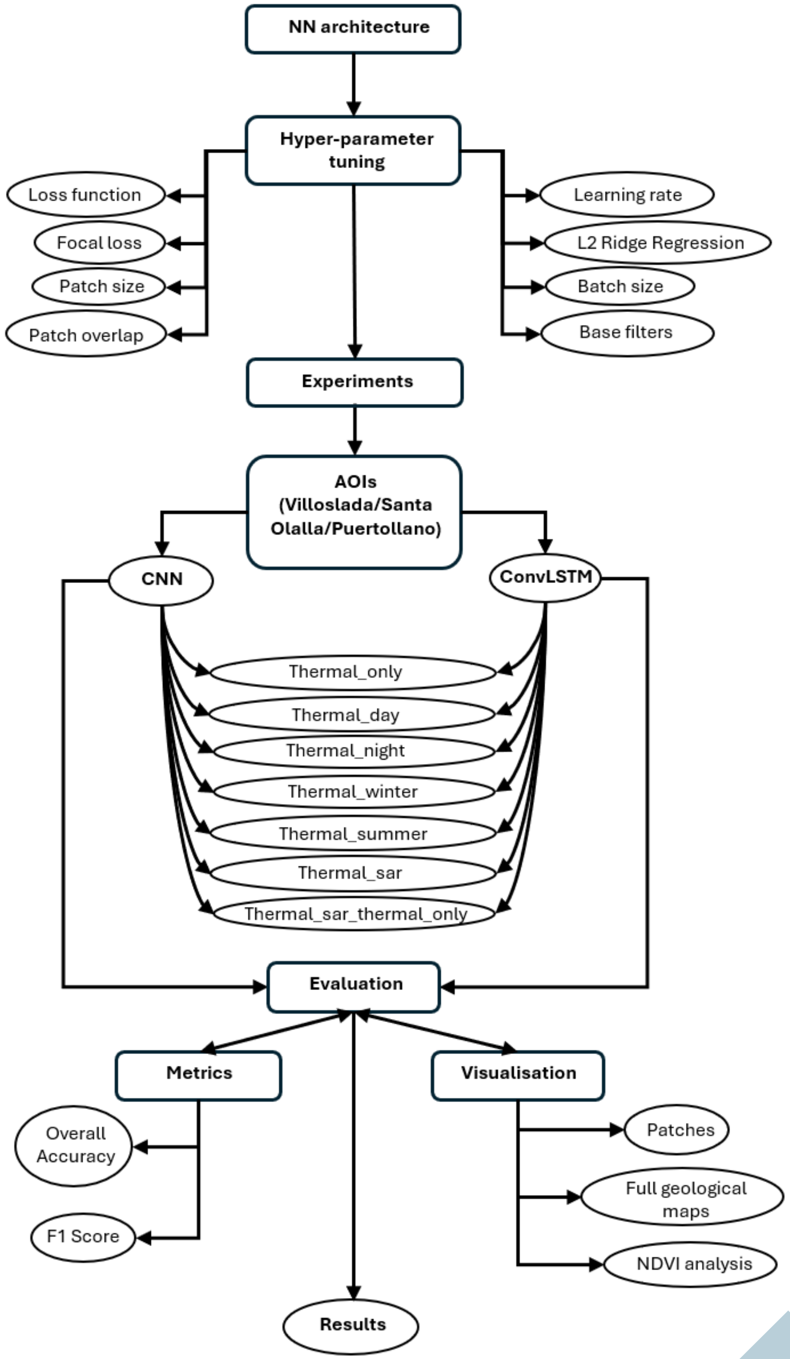
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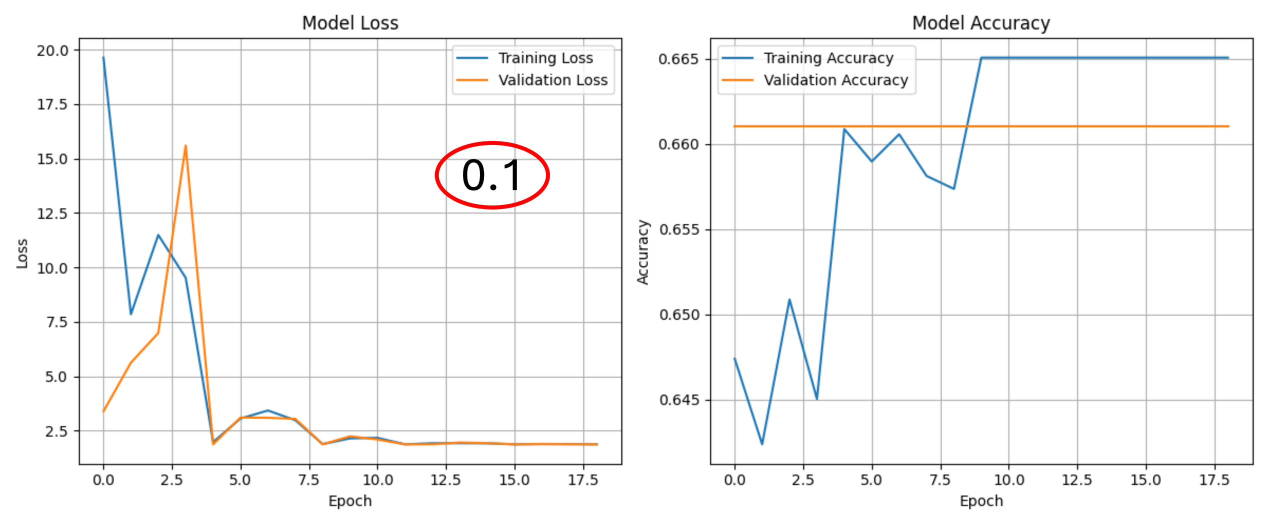
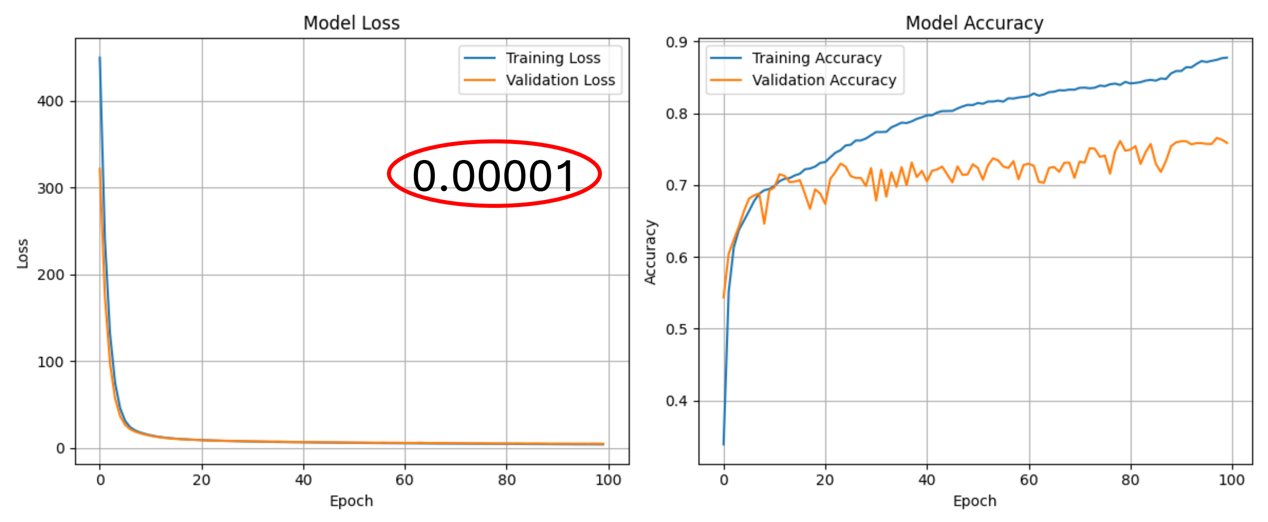
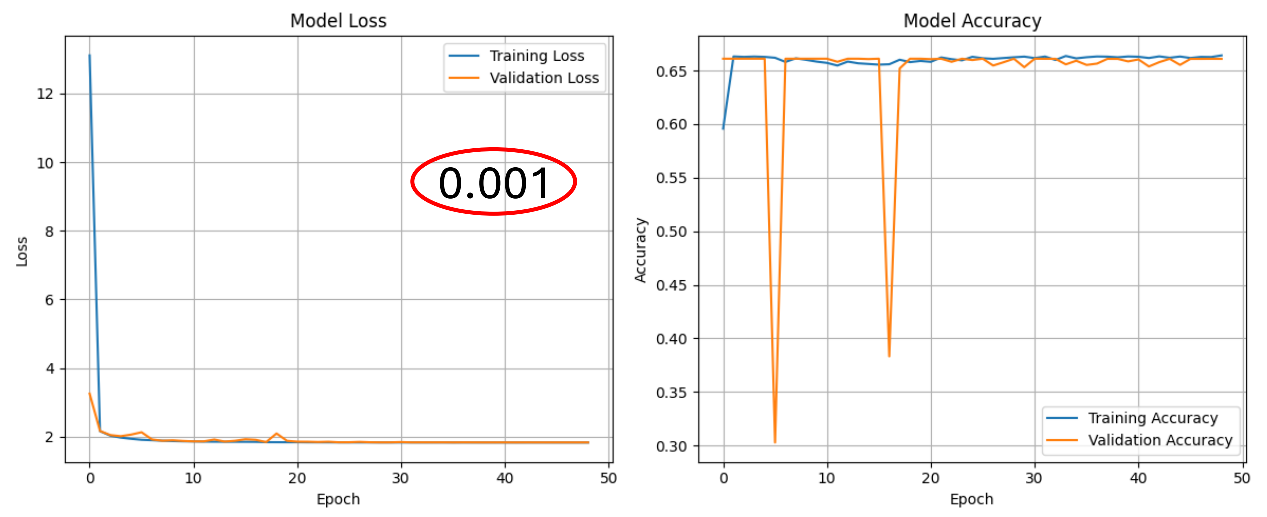
Learning rate

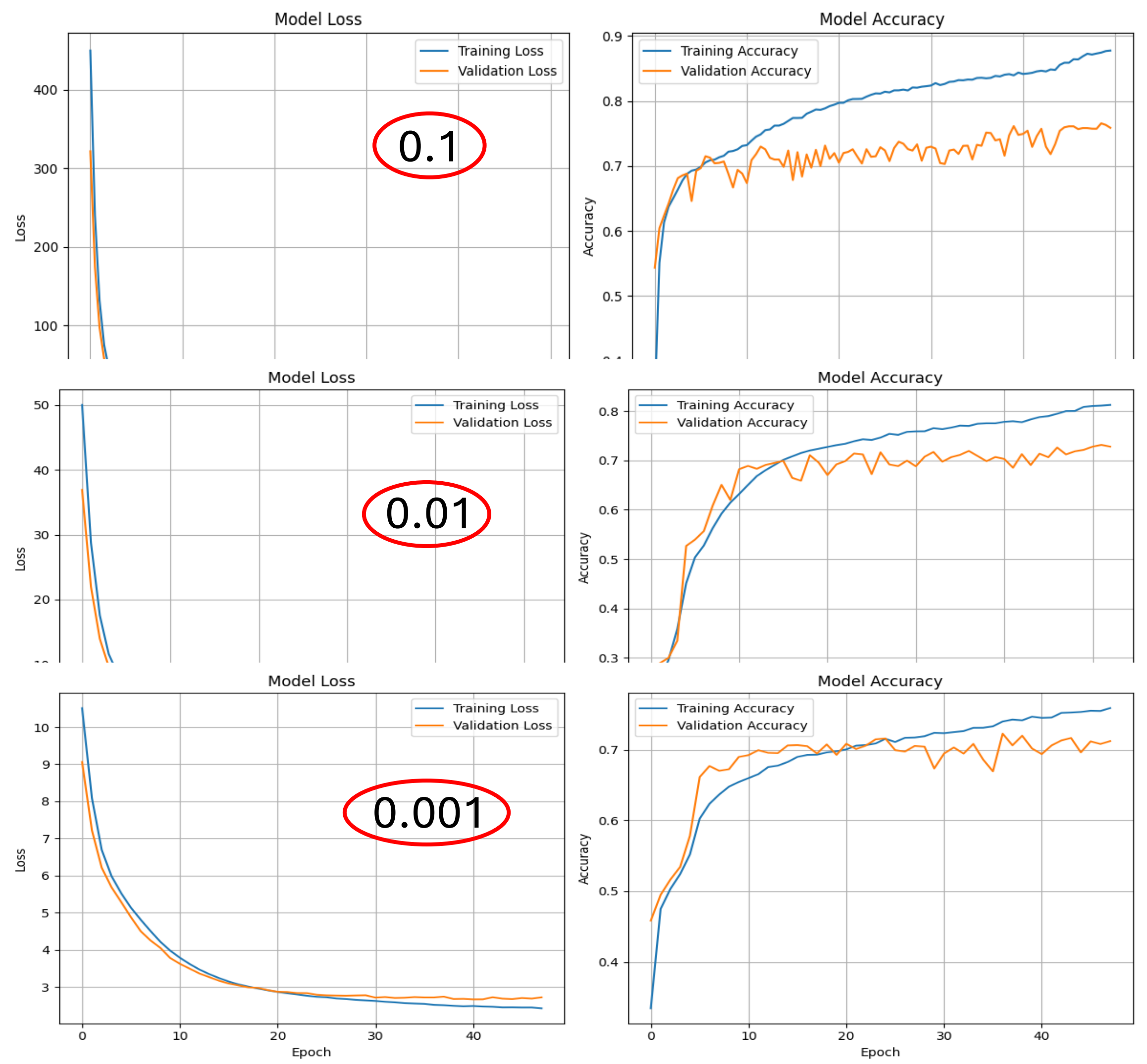


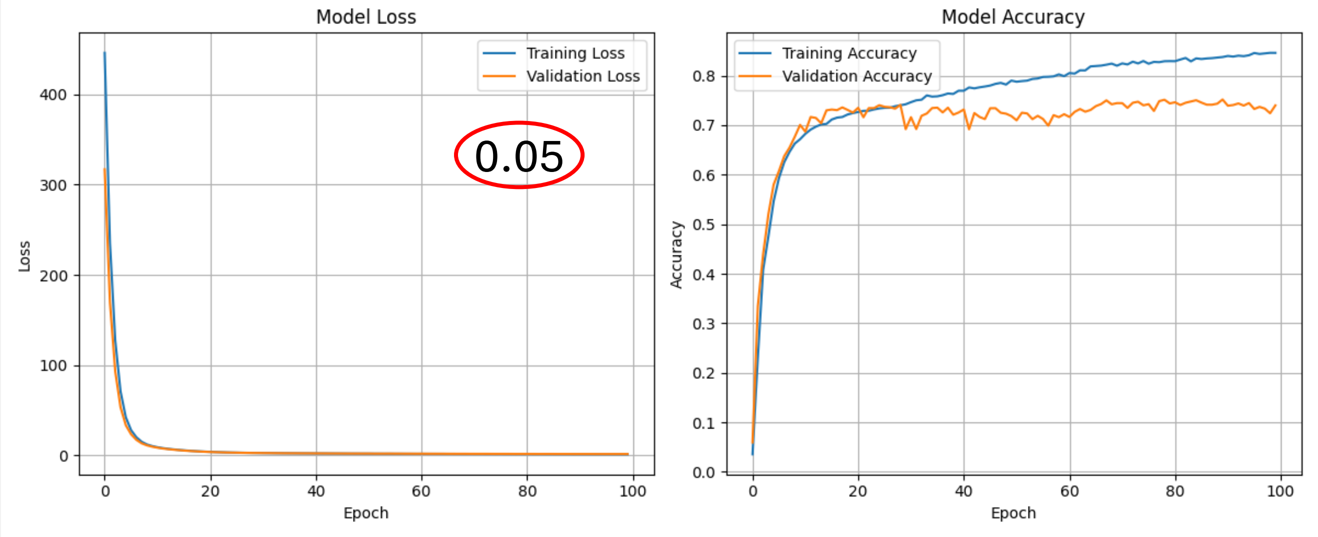




- Amount of parameter adjustment per step
- Higher values produce oscillating loss functions and fluctuating accuracy
- Lower rates produce more stable loss functions
- If too low, learning becomes too slow

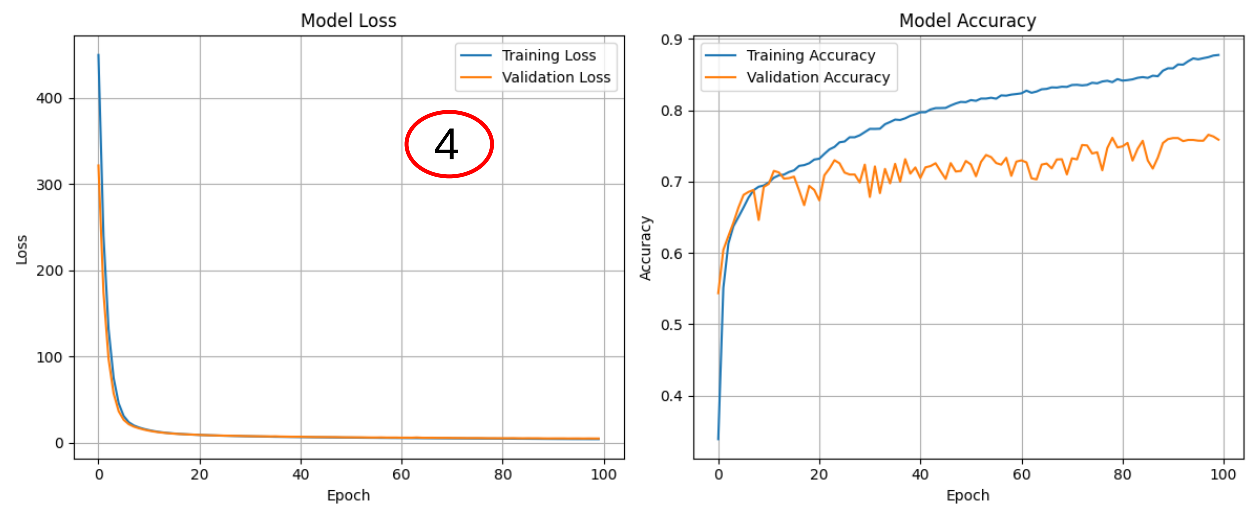
L2 Ridge Regression

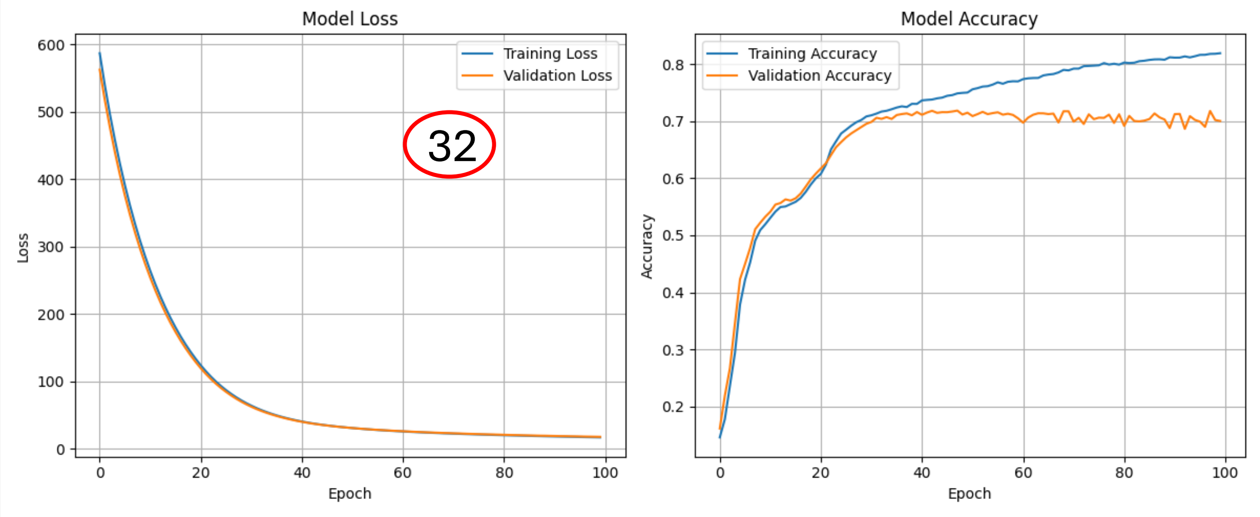


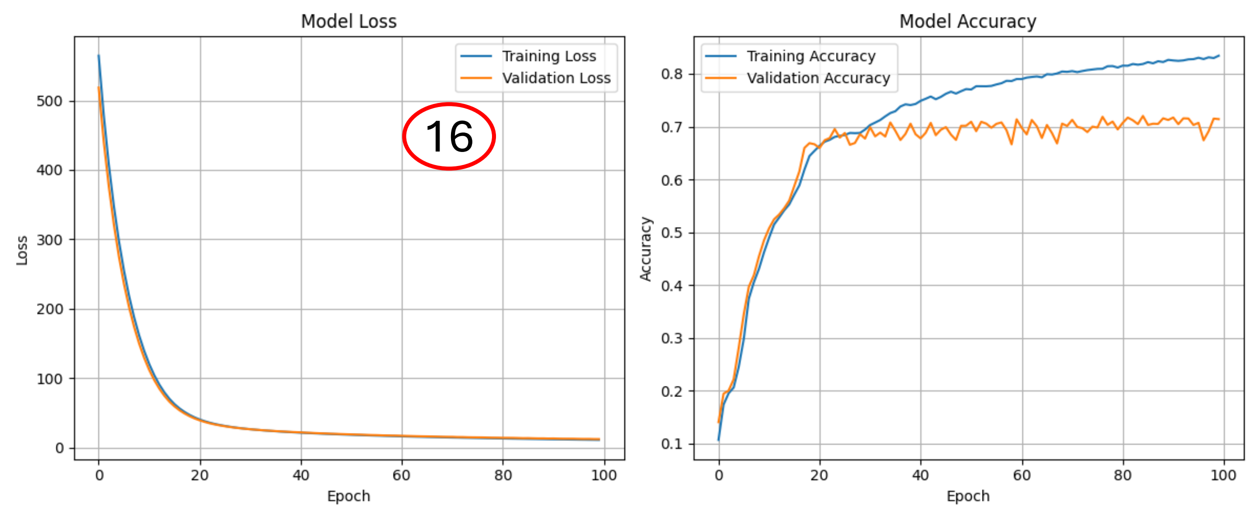


- Added penalty as complexity increases
- Prevents overfitting by avoiding weights becoming too big
- Higher L2 factor, higher initial loss function value
- An intermediate value provides balance between reducing overfitting and accuracy

Batch Size

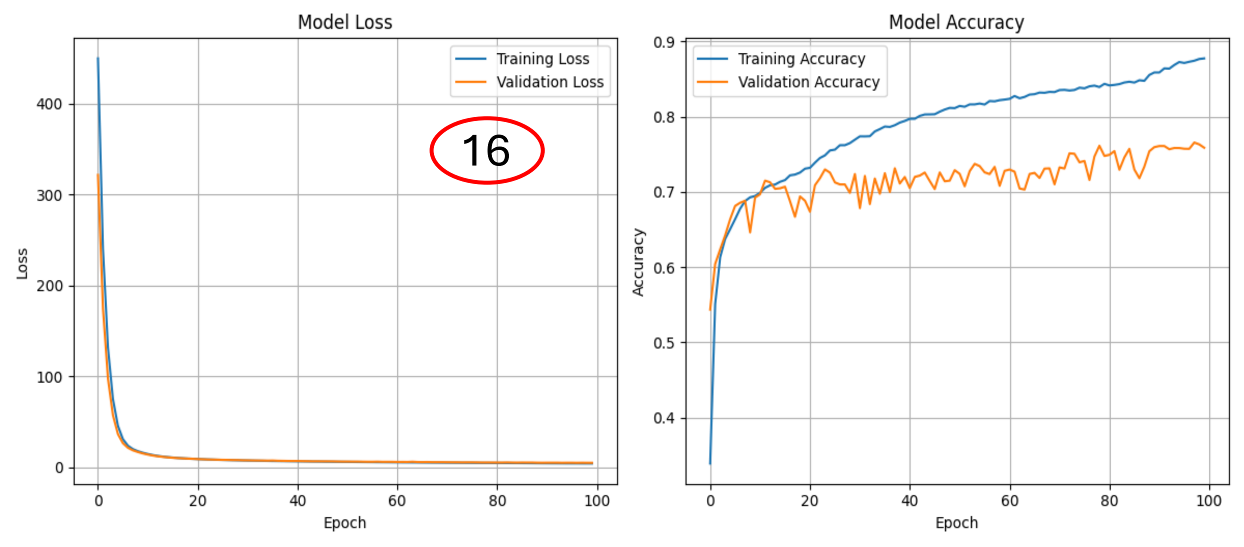


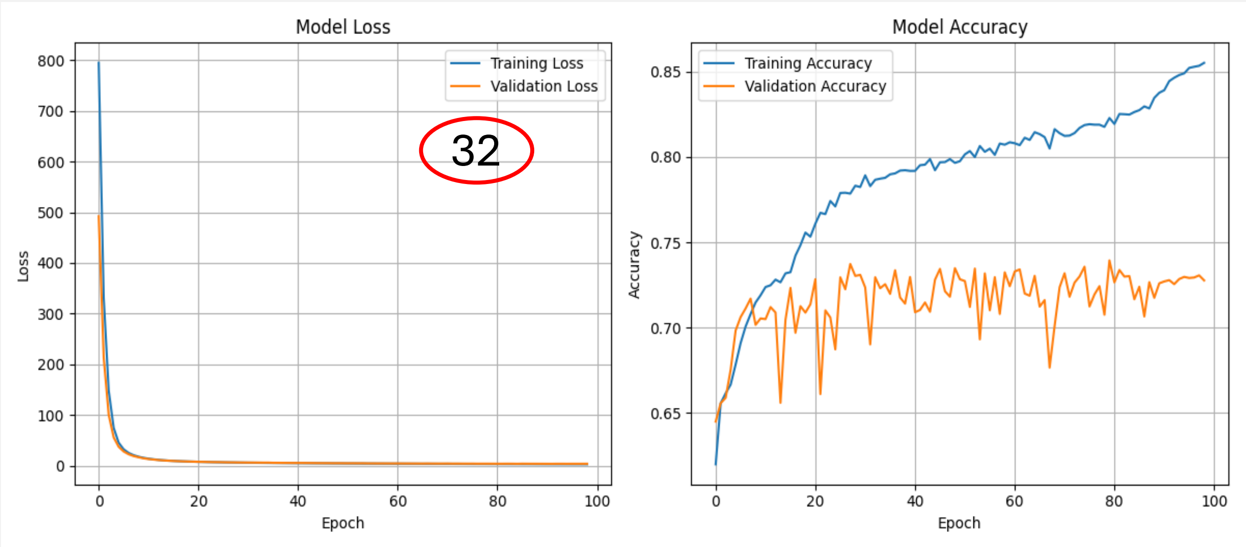




- Subsets of data used at the same time
- Larger sizes produce smoother losses
- Smaller sizes produce slightly more fluctuations
- With smaller sizes, model learns finer details in one go

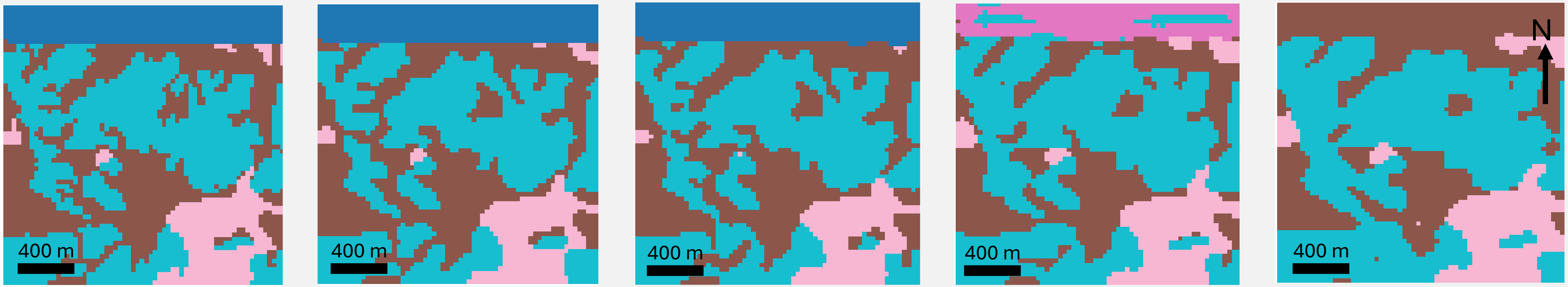
Filters





- Initial number of filters used for convolutional layers
- A higher number of filters exponentially increases computational time
- Higher number also presented higher overfitting

Loss function



Ground truth **SparseCategoricalCrossentropy()** **Equal custom values** **Slightly higher custom values** **Higher custom values**

- The error between the model’s output and the ground truth
- Important to deal with class imbalances
- Customizing weights aids in dealing with minority classes

Table 1. Comparison of model performance across different weighting strategies

Model Setting	Accuracy	Loss	F1
SparseCategoricalCrossentropy	0.698	2.60	0.654
Equal values	0.692	2.52	0.651
Slightly higher (rare classes)	0.619	5.38	0.594
Higher (rare classes)	0.487	8.83	0.482

Optuna & Final configuration

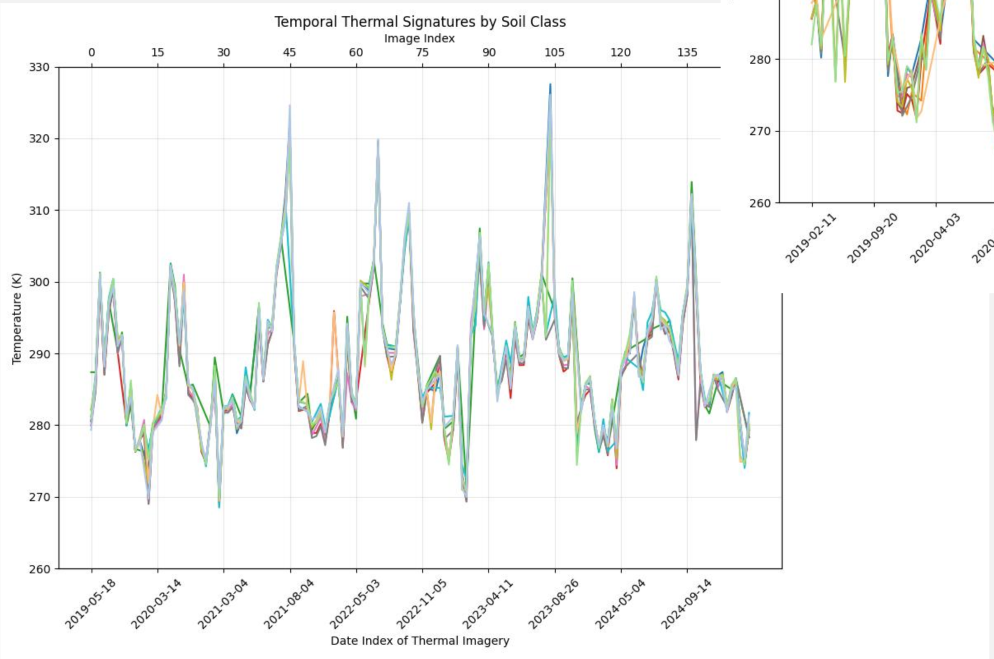
Table 2. **Comparison of accuracies for different hyperparameter configurations**

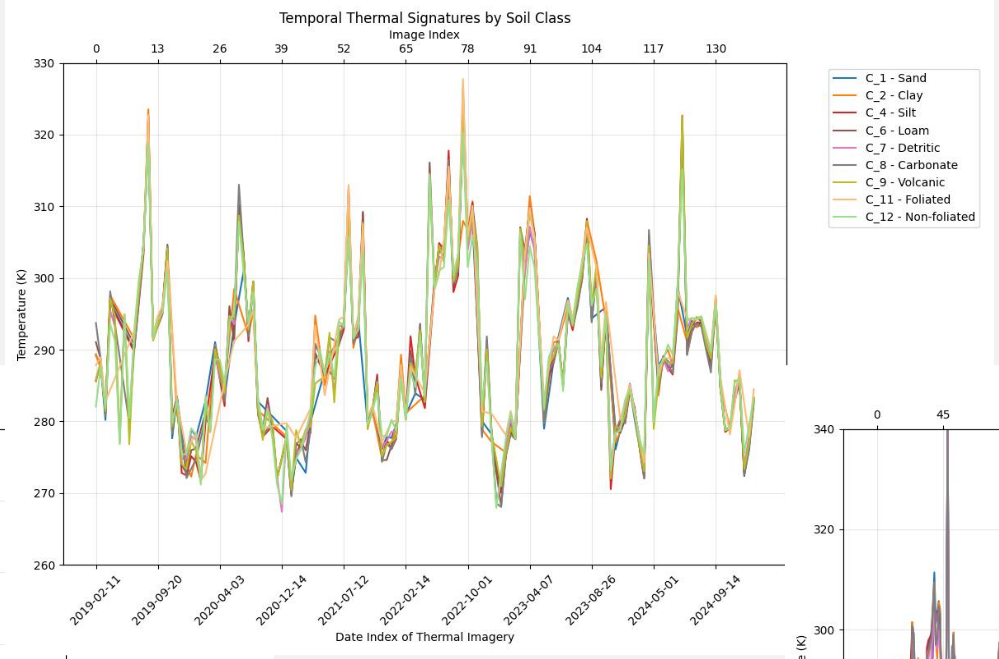
Parameter	Setting	Accuracy
Optuna (final model)	—	0.7289
L2 factor		
	0.1	0.8045
	0.05	0.7328
	0.01	0.7457
	0.001	0.7289
Learning rate		
	0.1	0.6690
	0.001	0.6708
	0.00001	0.8045
Batch size		
	4	0.8045
	16	0.7324
	32	0.7220
Filters base		
	16	0.8045
	32	0.7492

Results

Thermal signatures

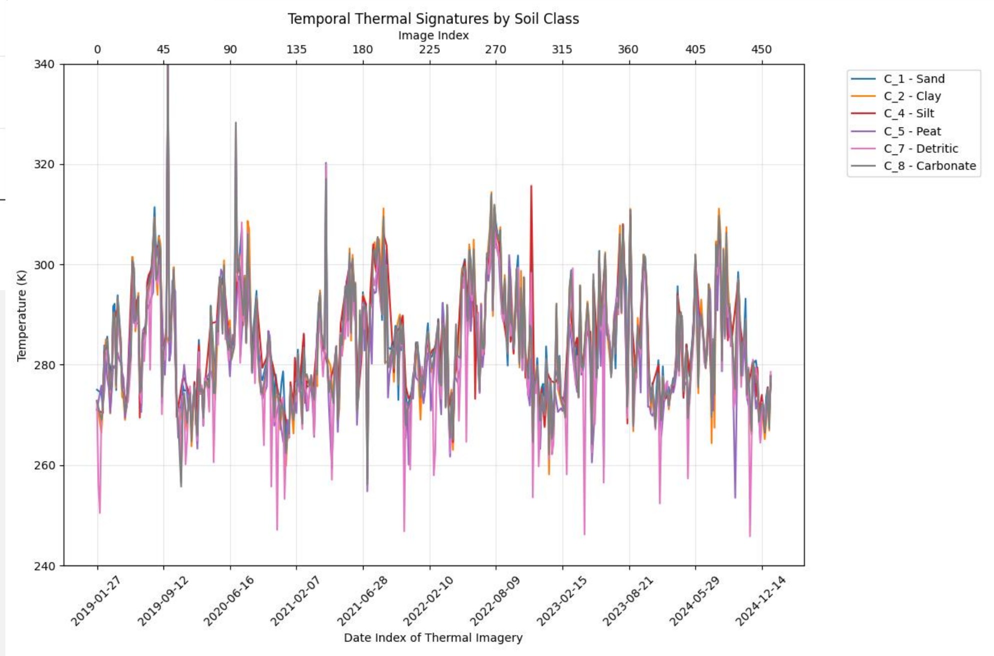
Santa Olalla



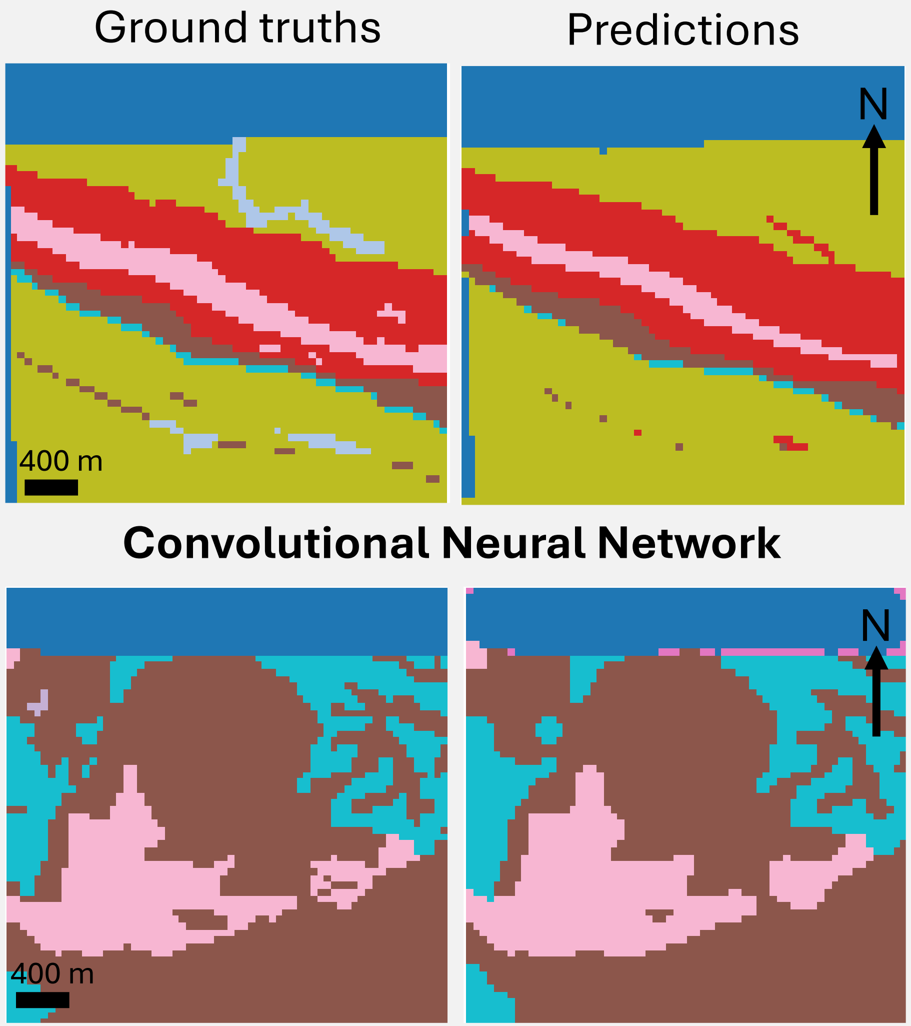


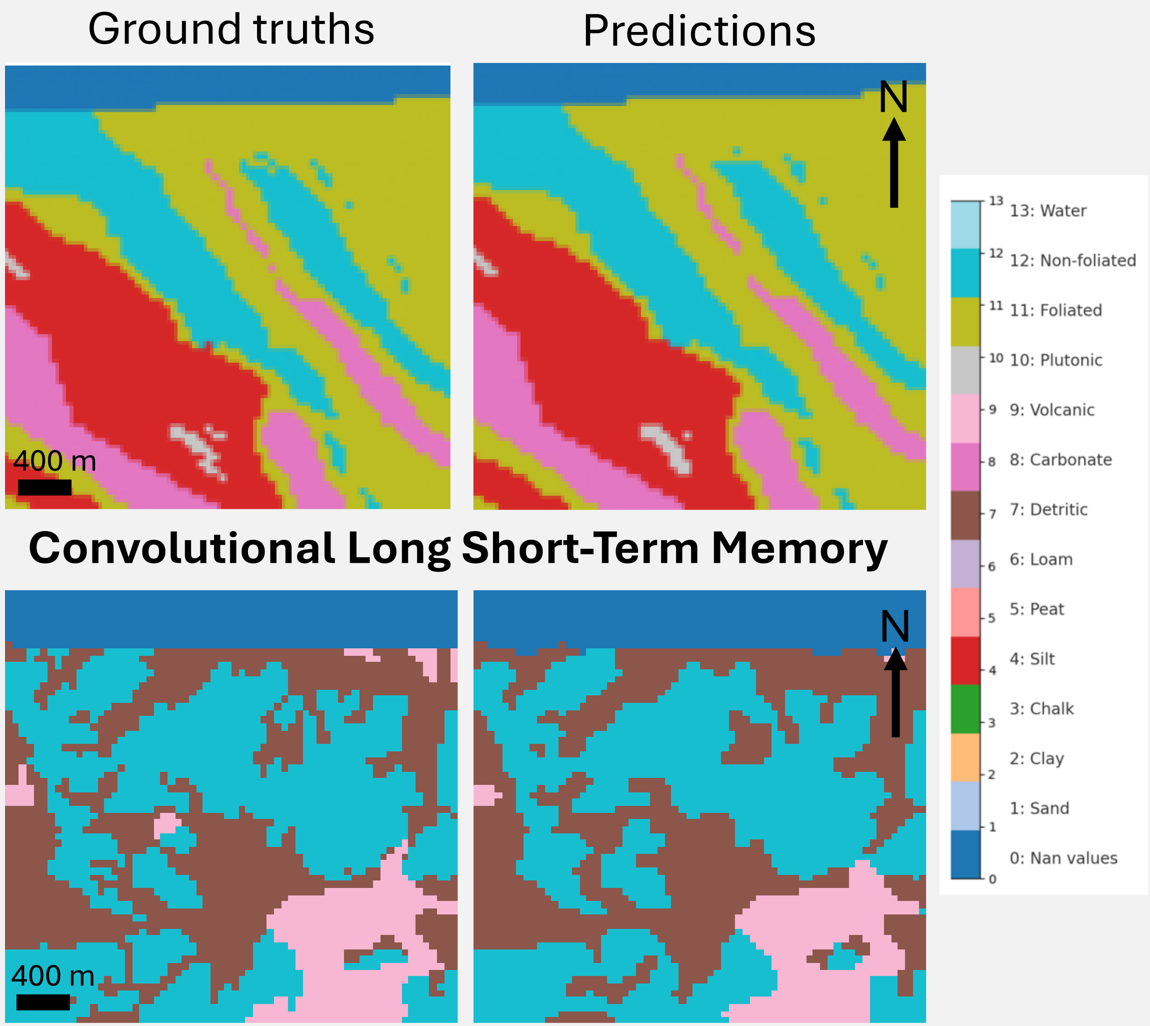
Puertollano

Villoslada

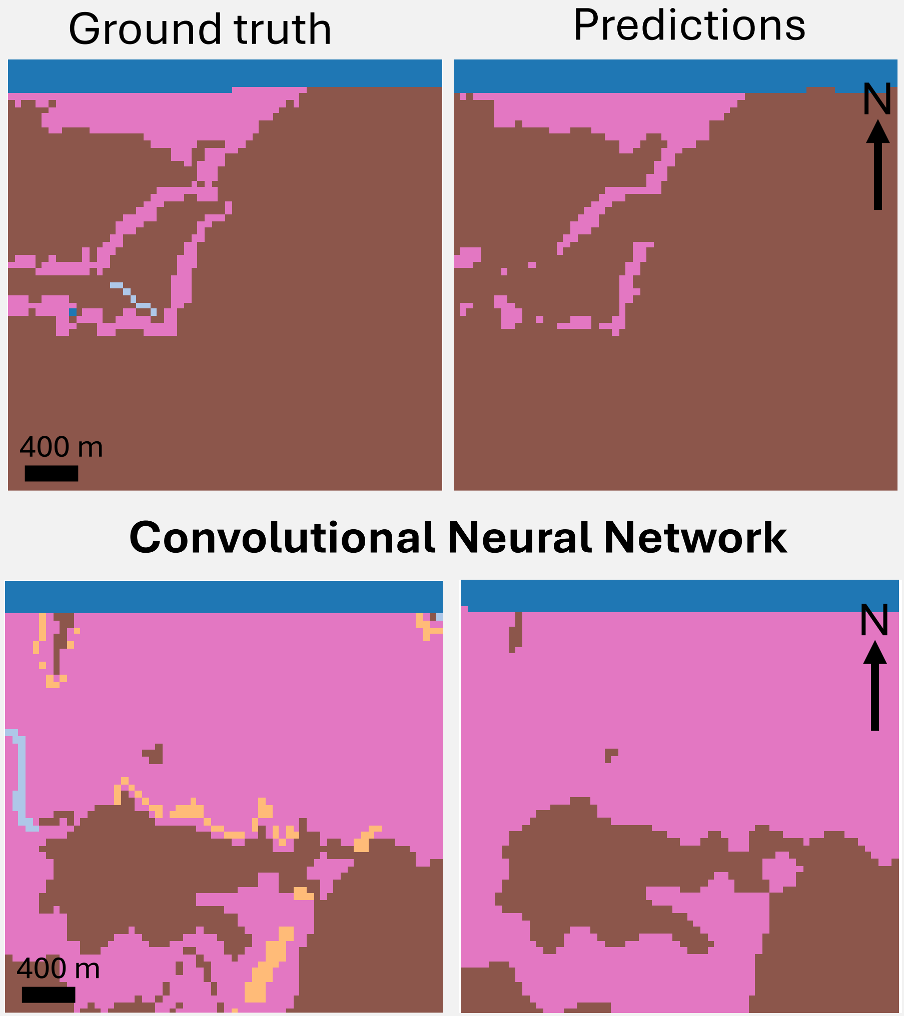


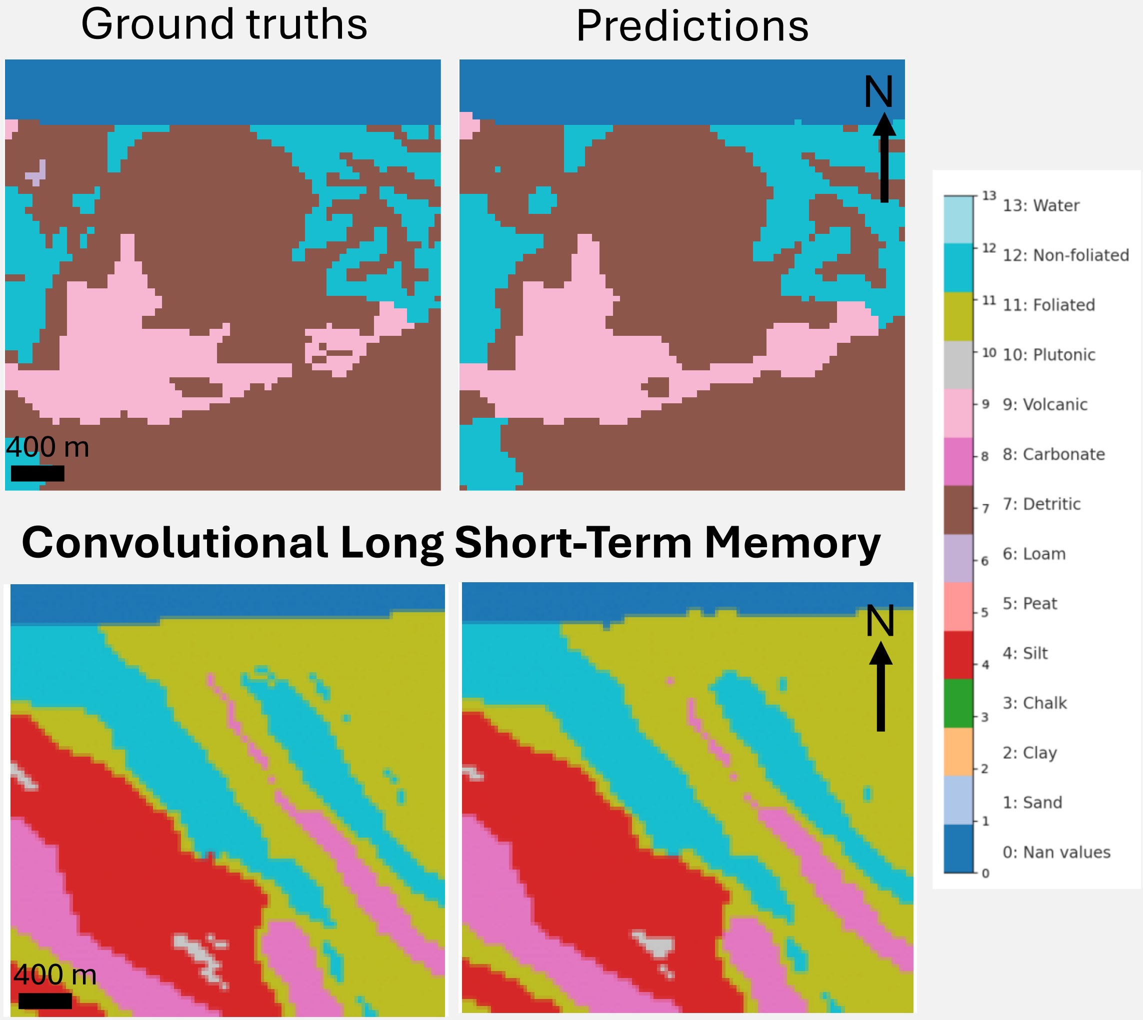
Thermal only



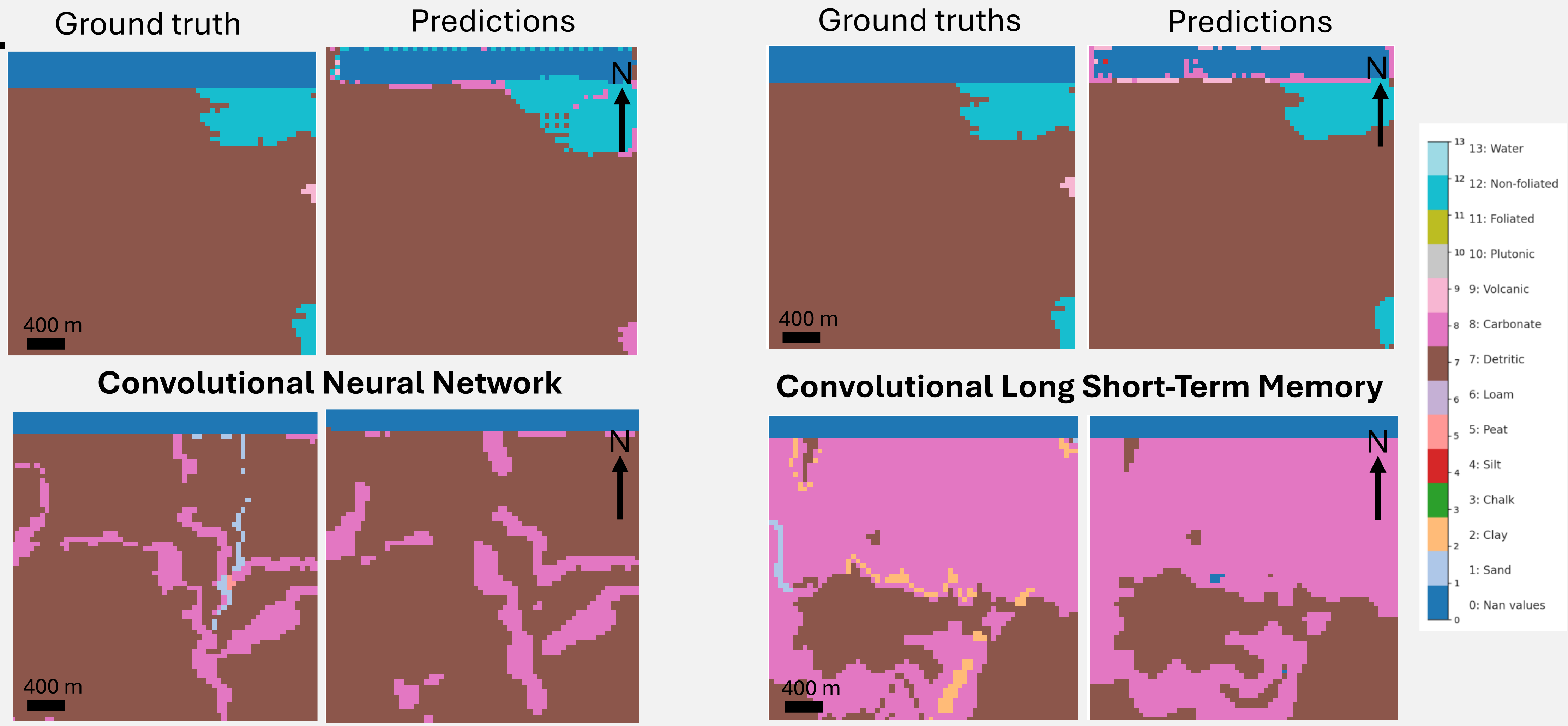


Diurnal experiments - Day

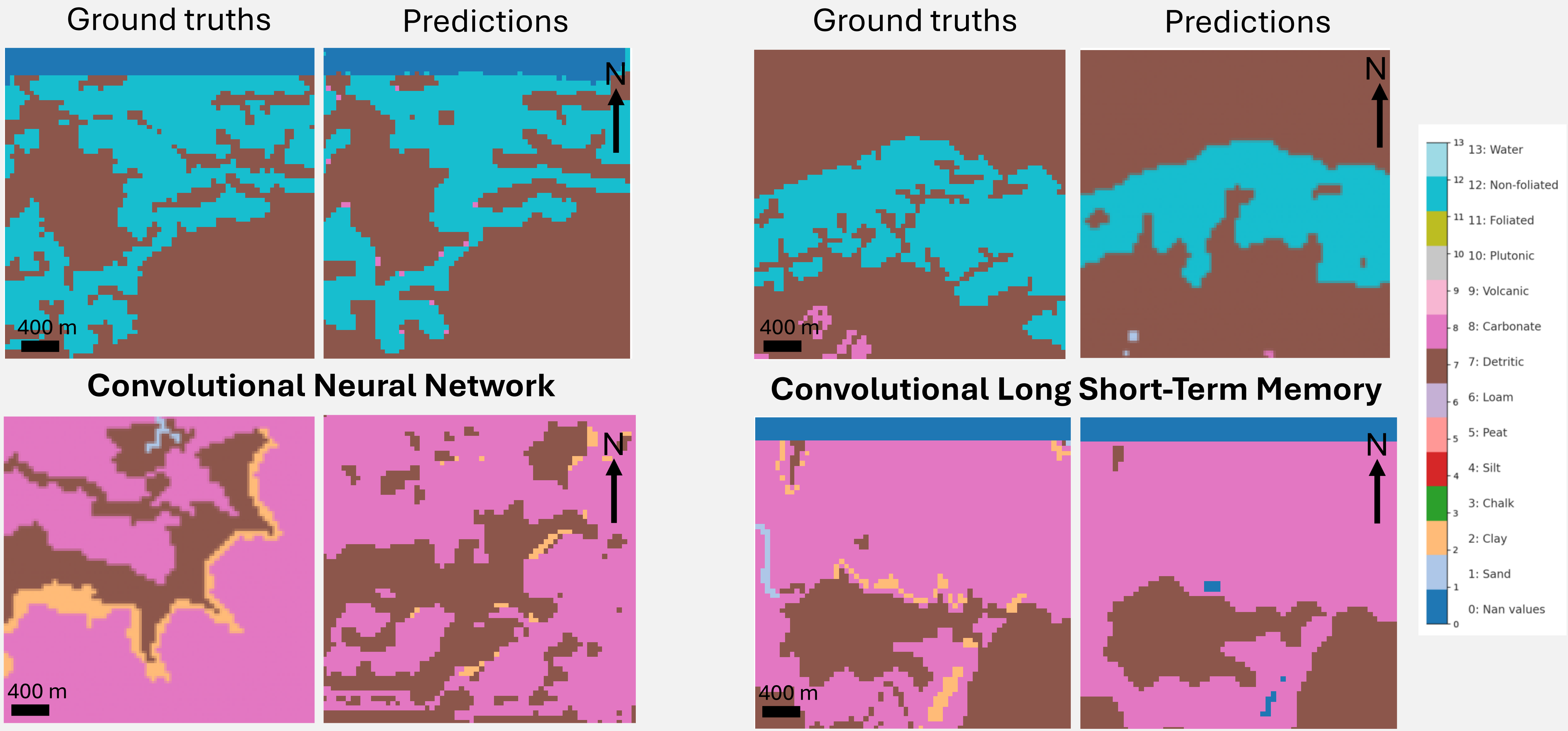




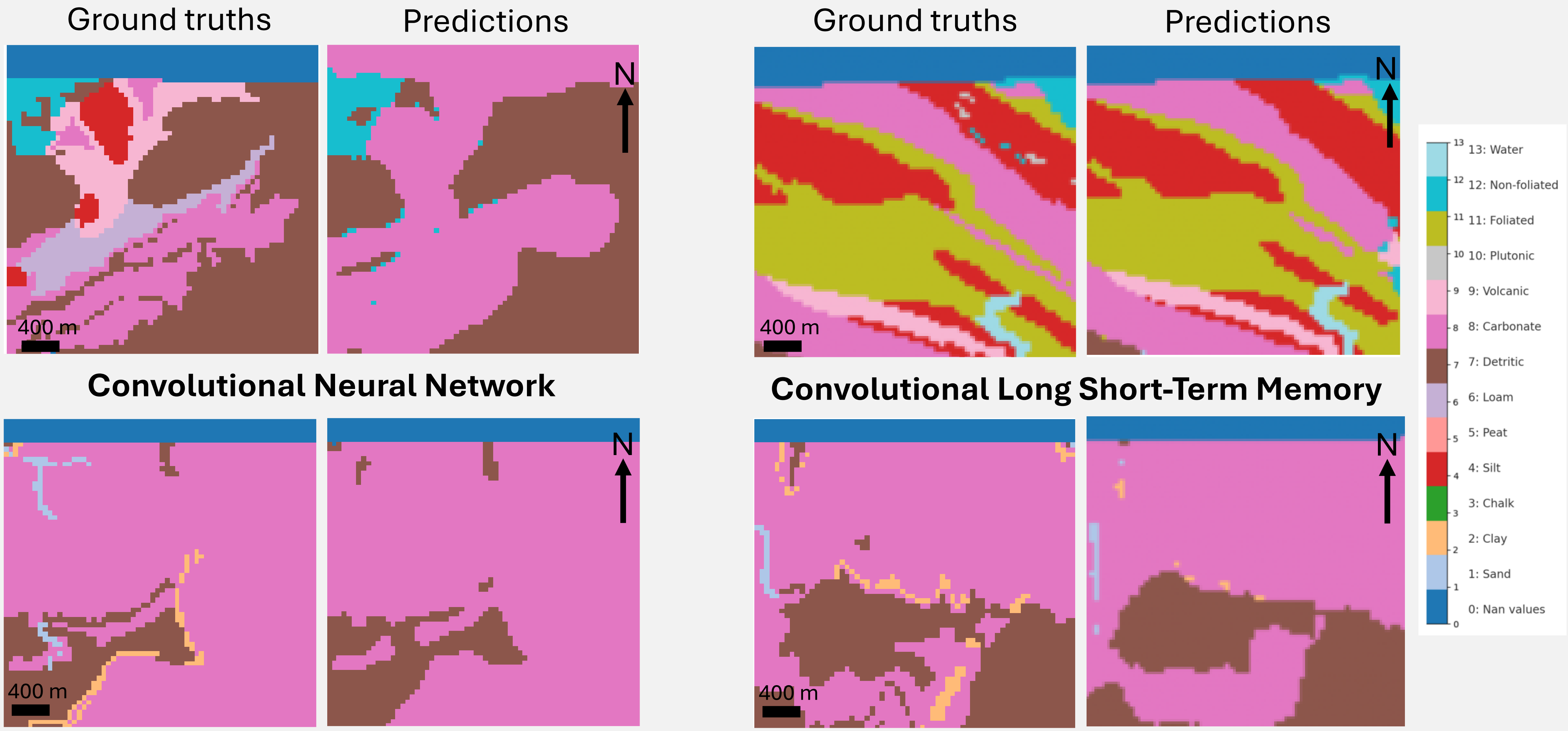
Diurnal experiments - Night



Seasonal experiments - Winter



Seasonal experiments - Summer



Complementary data - SAR

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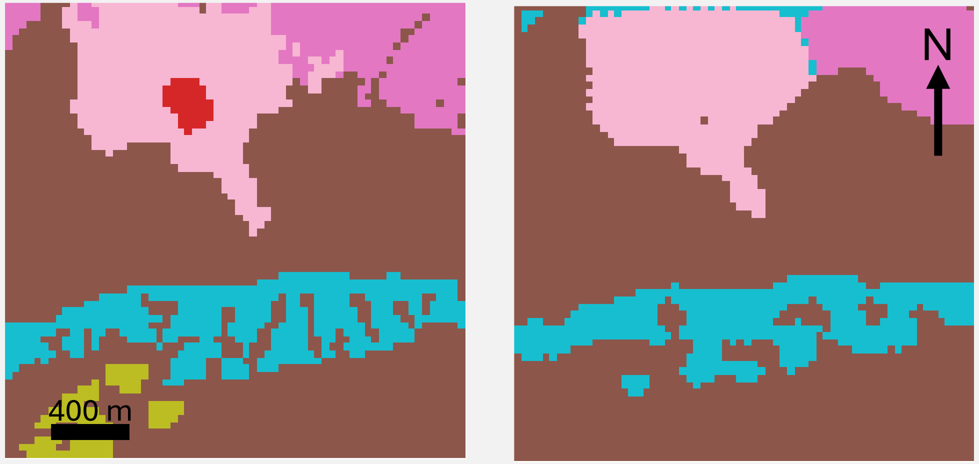
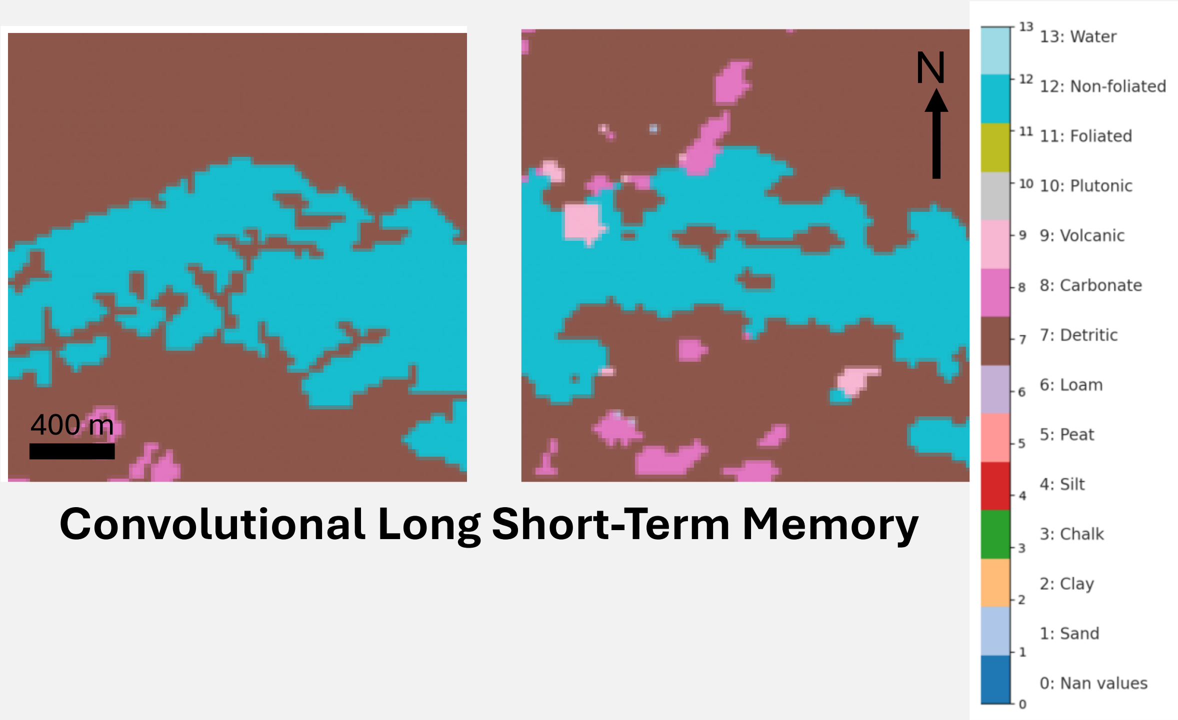


Convolutional Neural Network



Convolutional Long Short-Term Memory

Table 3. Accuracy and F1 scores for Thermal data type

Region / Model	Accuracy	F1 score
Puertollano CNN	0.7128	0.6739
Puertollano ConvLSTM	0.7090	0.7299
Santa Olalla CNN	0.7443	0.6694
Santa Olalla ConvLSTM	0.8106	0.7881
Villoslada CNN	0.7576	0.5156
Villoslada ConvLSTM	0.7759	0.6952

Table 4. Accuracy and F1 scores for Day data type

Region / Model	Accuracy	F1 score
Puertollano CNN	0.6532	0.4580
Puertollano ConvLSTM	0.5804	0.5811
Santa Olalla CNN	0.5793	0.3915
Santa Olalla ConvLSTM	0.7691	0.7607
Villoslada CNN	0.7280	0.4102
Villoslada ConvLSTM	0.7424	0.6871

Table 5. Accuracy and F1 scores for Night data type

Region / Model	Accuracy	F1 score
Puertollano CNN	0.6587	0.5510
Puertollano ConvLSTM	0.6255	0.4029
Santa Olalla CNN	0.5918	0.2396
Santa Olalla ConvLSTM	0.5548	0.3538
Villoslada CNN	0.7206	0.5943
Villoslada ConvLSTM	0.7185	0.4064

Table 6. Accuracy and F1 scores for Winter data type

Region / Model	Accuracy	F1 score
Puertollano CNN	0.6820	0.6004
Puertollano ConvLSTM	0.6786	0.3512
Santa Olalla CNN	0.6203	0.4504
Santa Olalla ConvLSTM	0.5748	0.3054
Villoslada CNN	0.7417	0.6159
Villoslada ConvLSTM	0.7347	0.6021

Table 7. Accuracy and F1 scores for Summer data type

Region / Model	Accuracy	F1 score
Puertollano CNN	0.6873	0.5709
Puertollano ConvLSTM	0.7337	0.5652
Santa Olalla CNN	0.6400	0.5945
Santa Olalla ConvLSTM	0.8016	0.7761
Villoslada CNN	0.7407	0.5975
Villoslada ConvLSTM	0.7130	0.6886

Table 8. Accuracy and F1 scores for SAR data type

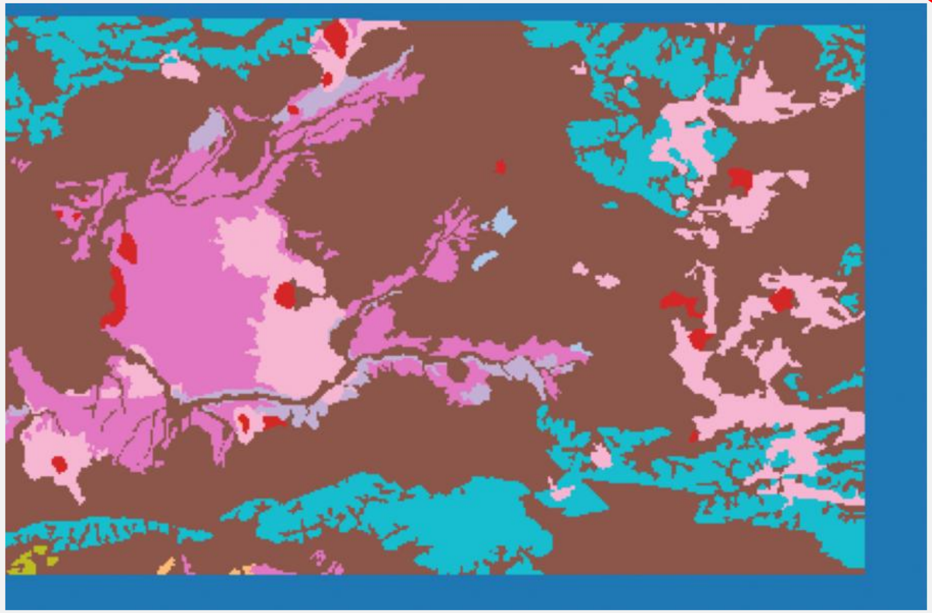
Region / Model	Accuracy	F1 score
Puertollano CNN	0.6472	0.4429
Puertollano ConvLSTM	0.5814	0.4699
Santa Olalla CNN	0.5701	0.4668
Santa Olalla ConvLSTM	0.5072	0.3455
Villoslada CNN	0.7010	0.5901
Villoslada ConvLSTM	0.6319	0.4355

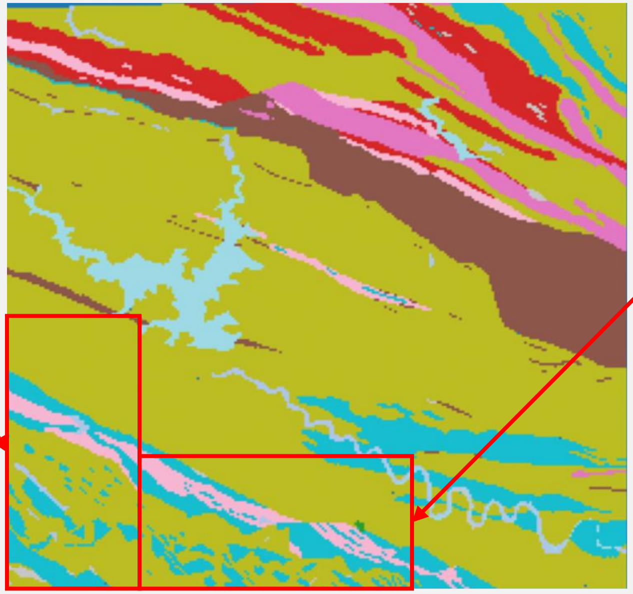
Further experimentation

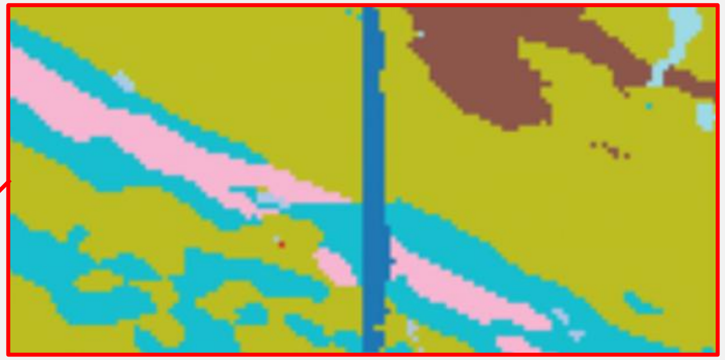
- Patch discontinuities
- Geological map reconstruction
- Overfitting
- NDVI data
- Confidence vs. Vegetation

Geological map reconstruction

Puertollano







Santa Olalla

Villoslada

Final configurations

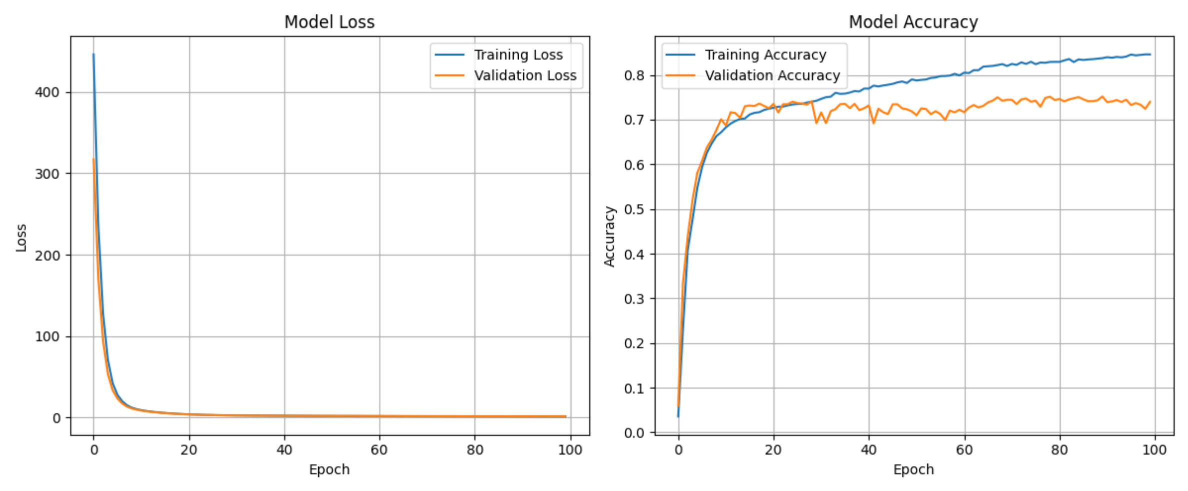
Table 11. Final configuration of parameters for CNN and ConvLSTM models

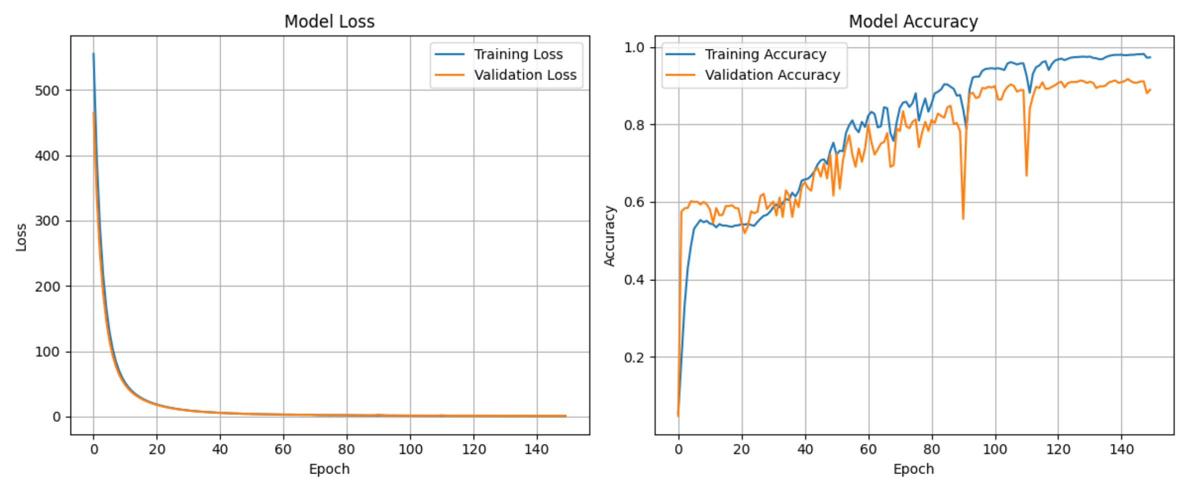
Parameter	Value
L2 Regularization	0.05
Learning Rate (CNN)	0.00001
Learning Rate (ConvLSTM)	0.0001
Batch Size	4
Base Filters	16
Patch Size	64/128 pixels
Patch Overlap	50%
Loss Function	Custom + Focal Loss
Epoch Count	150

Table 12. Class weights assigned for each geological region to address class imbalance

Geological Class	Puertollano	Santa Olalla	Villoslada
NaNs (Background)	1.5	1.5	1.0
Sand	10.0	8.0	3.5
Clay	10.0	1.0	2.5
Chalk	1.0	8.0	1.0
Silt	7.5	4.0	4.0
Peat	1.0	1.0	5.0
Loam	4.0	1.0	1.0
Detritic	1.0	2.5	1.0
Carbonate	1.5	3.0	2.0
Volcanic	3.0	3.0	1.0
Plutonic	1.0	3.0	1.0
Foliated	15.0	1.0	1.0
Non-Foliated	2.5	4.0	1.0
Water	1.0	4.0	1.0

Further experimentation





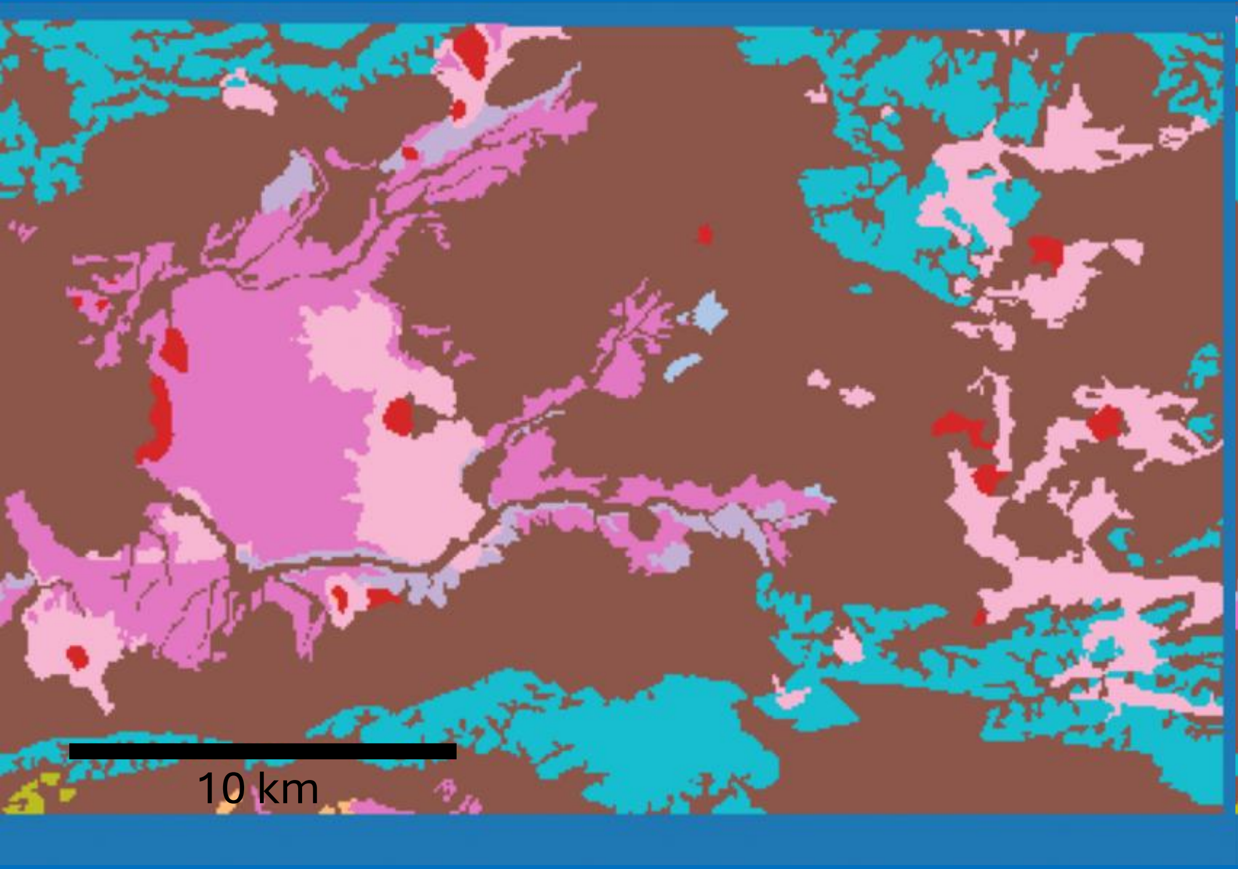
Accuracy and F1 scores of initial Thermal data tests

Region / Model	Accuracy	F1 score
Puertollano CNN	0.7128	0.6739
Puertollano ConvLSTM	0.7090	0.7299
Santa Olalla CNN	0.7443	0.6694
Santa Olalla ConvLSTM	0.8106	0.7881
Villoslada CNN	0.7576	0.5156
Villoslada ConvLSTM	0.7759	0.6952

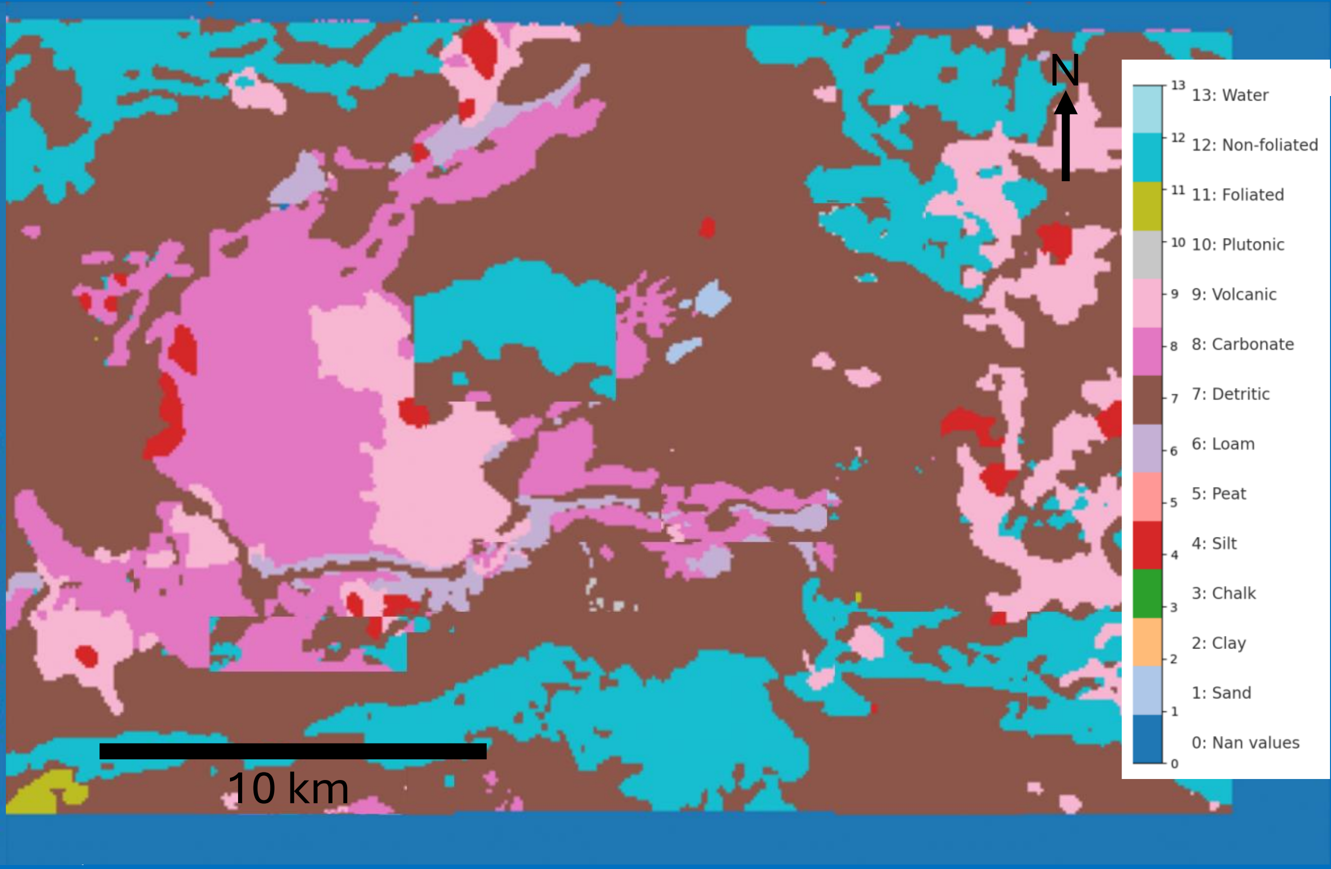
Accuracy and F1 score for final Thermal data tests

Region / Model	Accuracy	F1 score
Puertollano CNN	0.8220	0.7148
Puertollano ConvLSTM	0.9632	0.8499
Santa Olalla CNN	0.8673	0.6093
Santa Olalla ConvLSTM	0.9577	0.8018
Villoslada CNN	0.9252	0.7522
Villoslada ConvLSTM	0.9210	0.7926

Puertollano

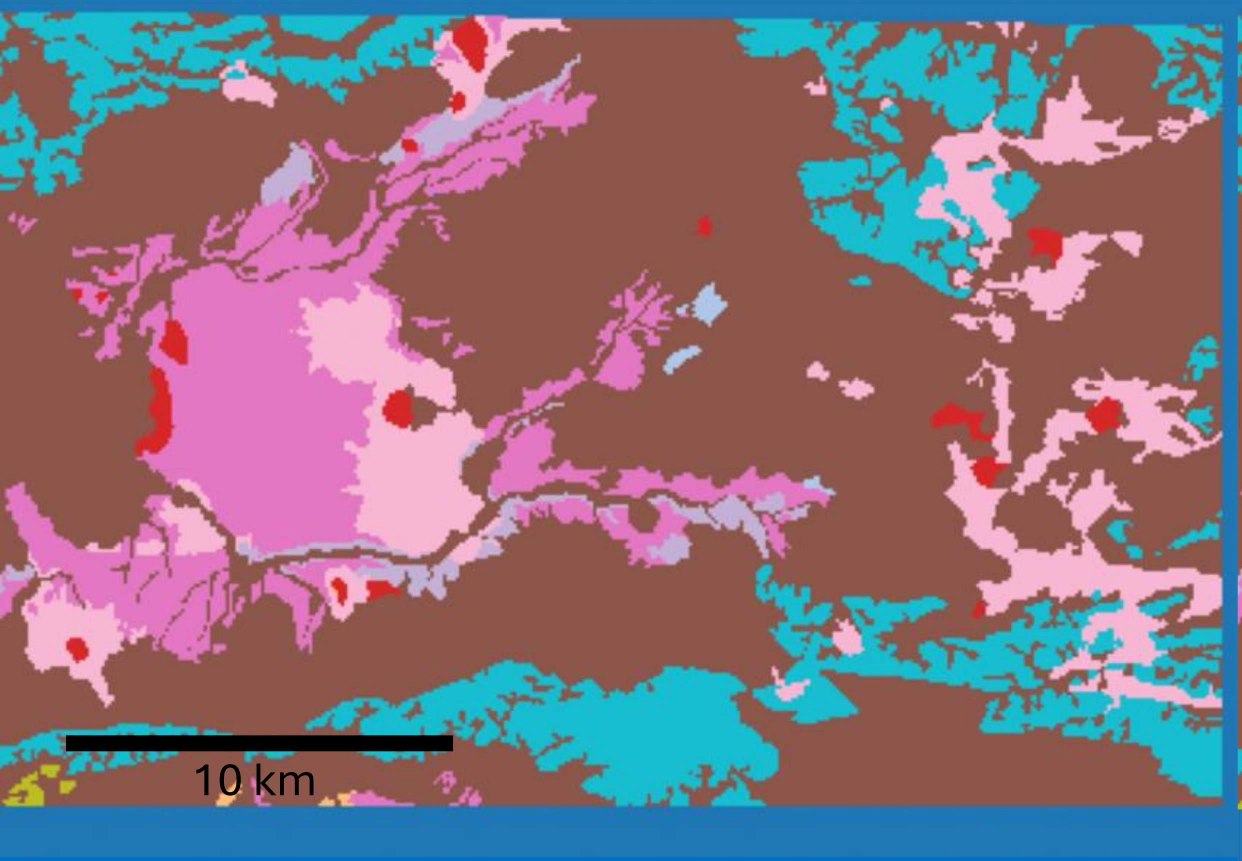


Ground truth

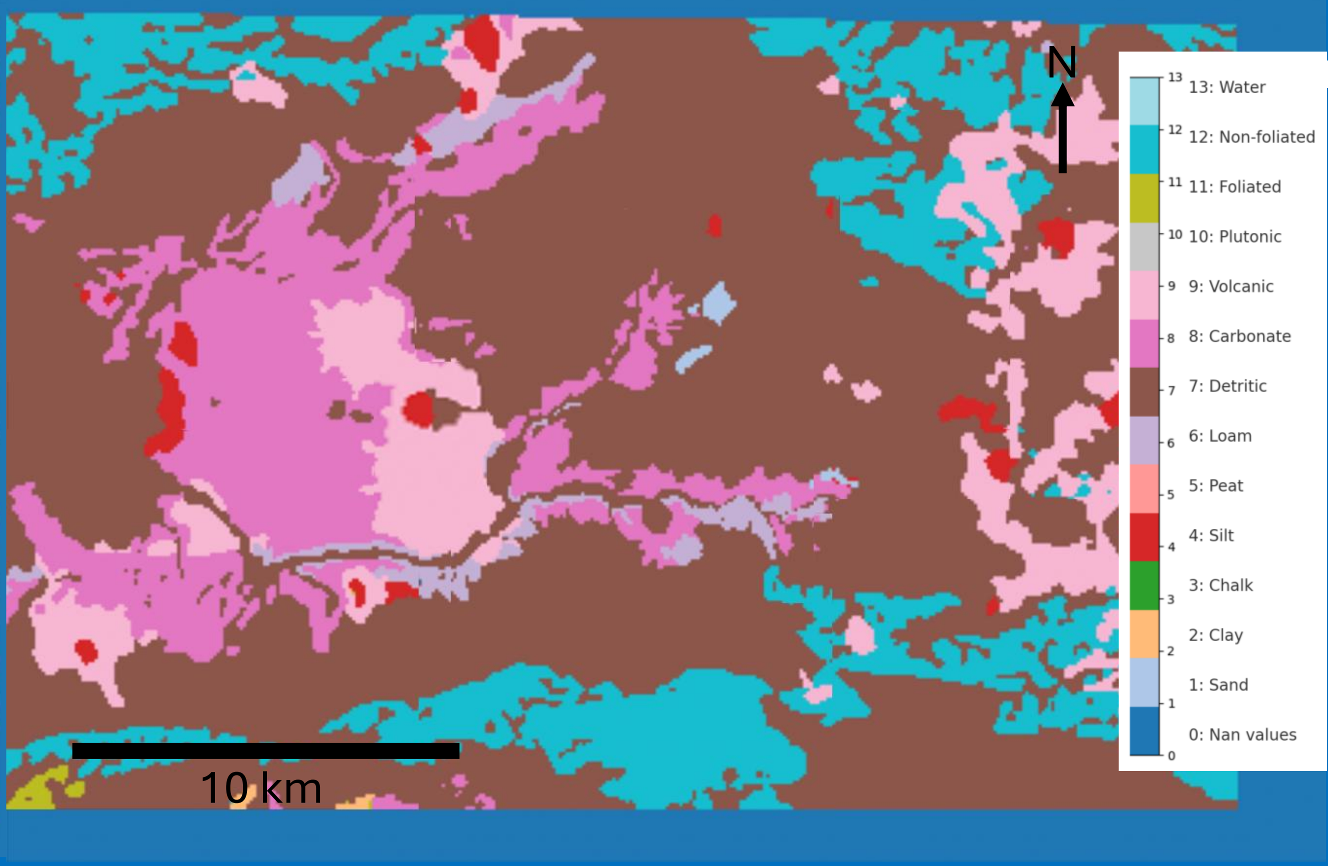


CNN

Puertollano

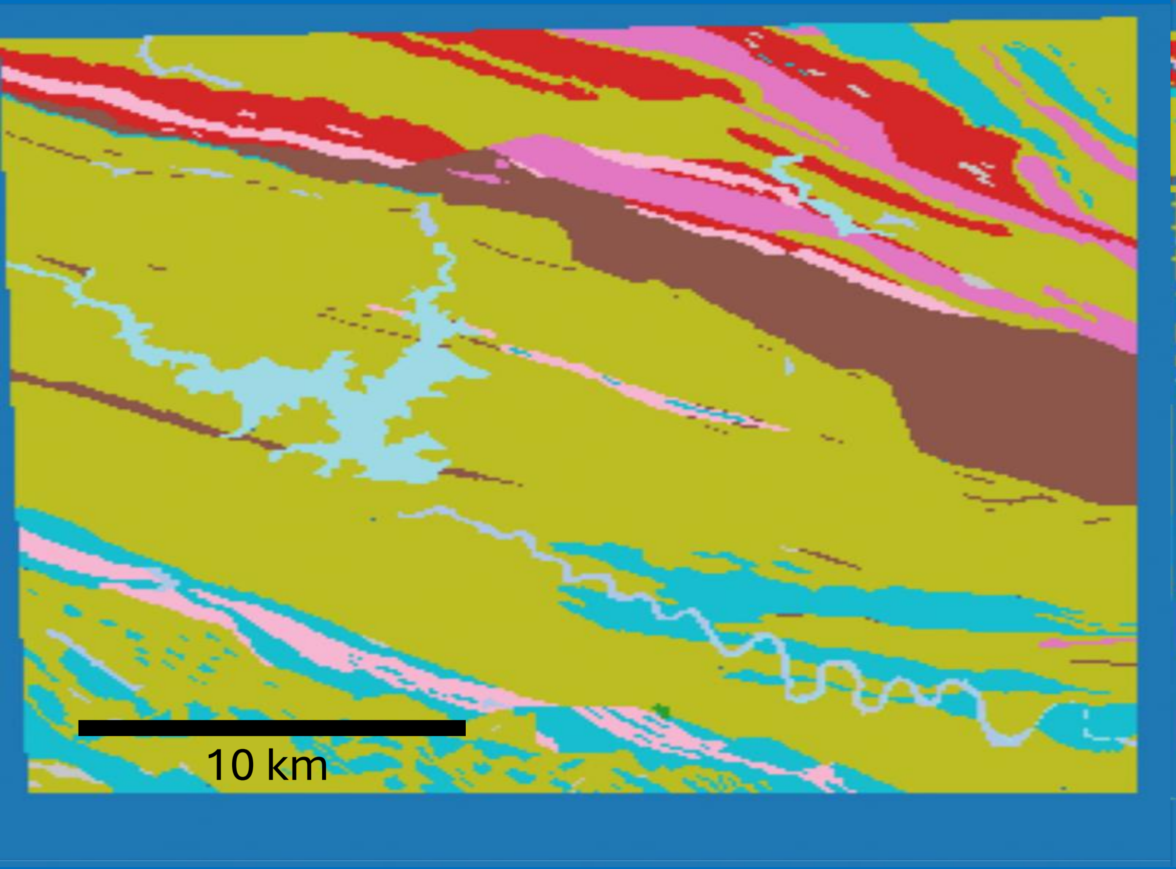


Ground truth

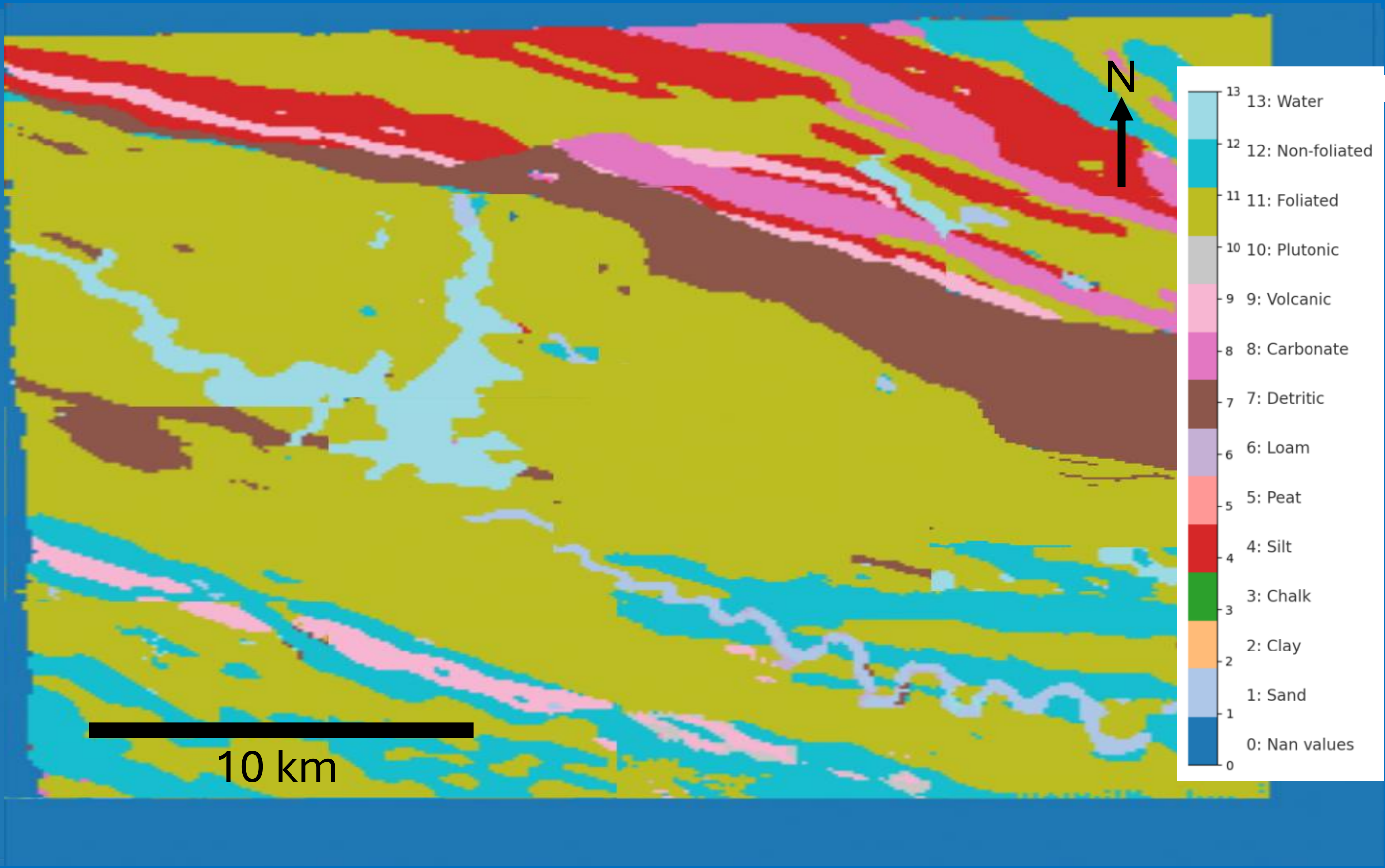


ConvLSTM

Santa Olalla del Cala

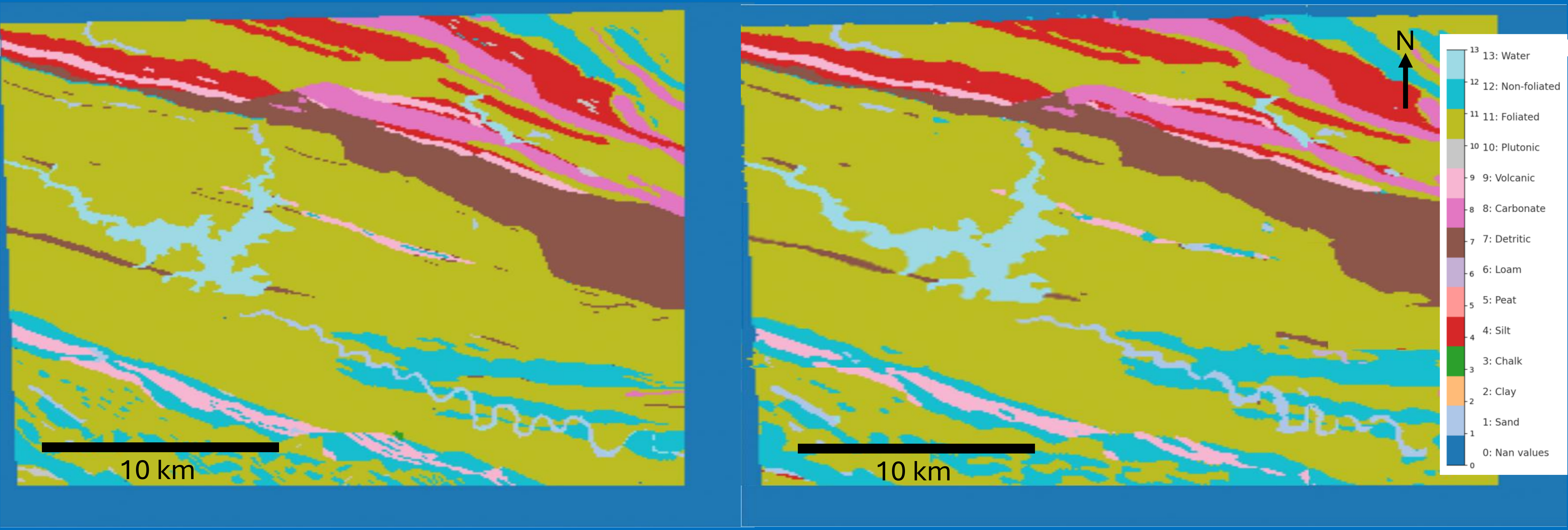


Ground truth



CNN

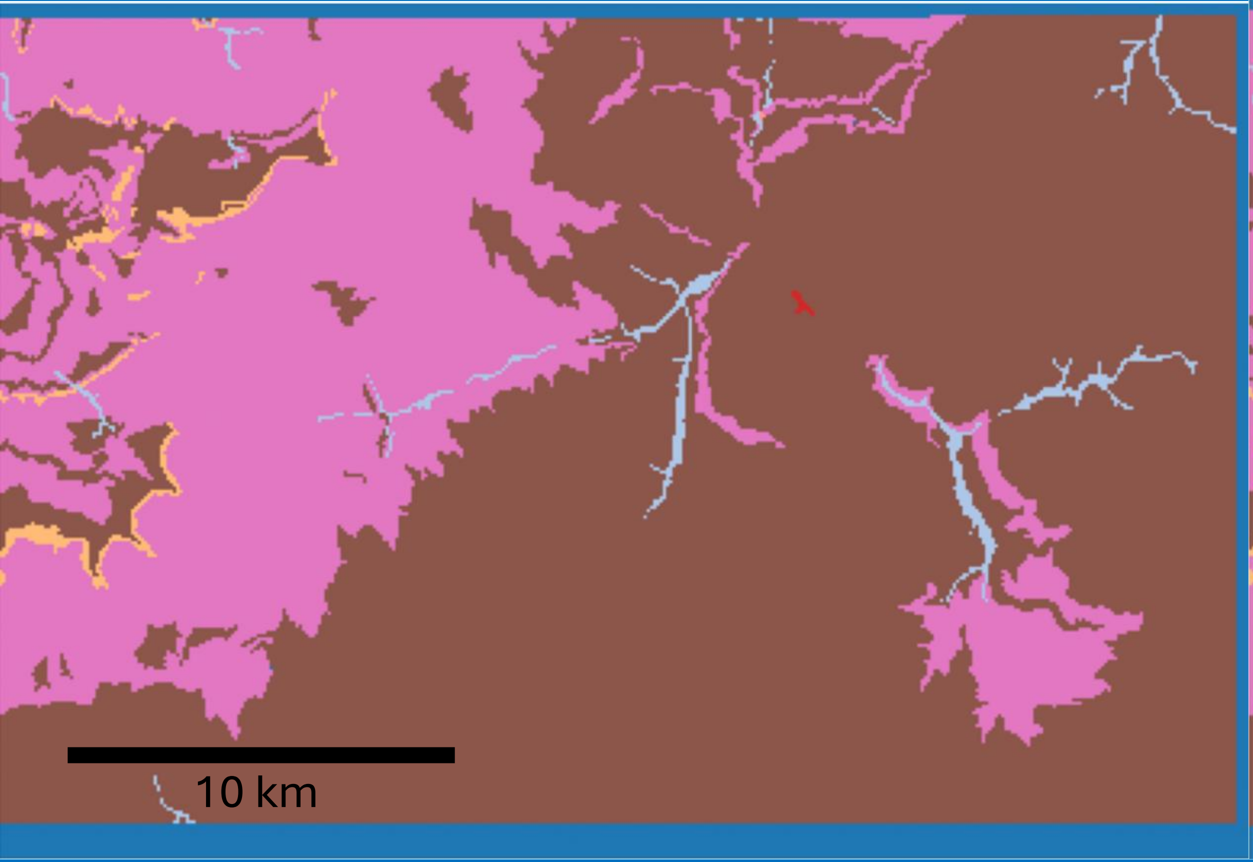
Santa Olalla del Cala



Ground truth

ConvLSTM

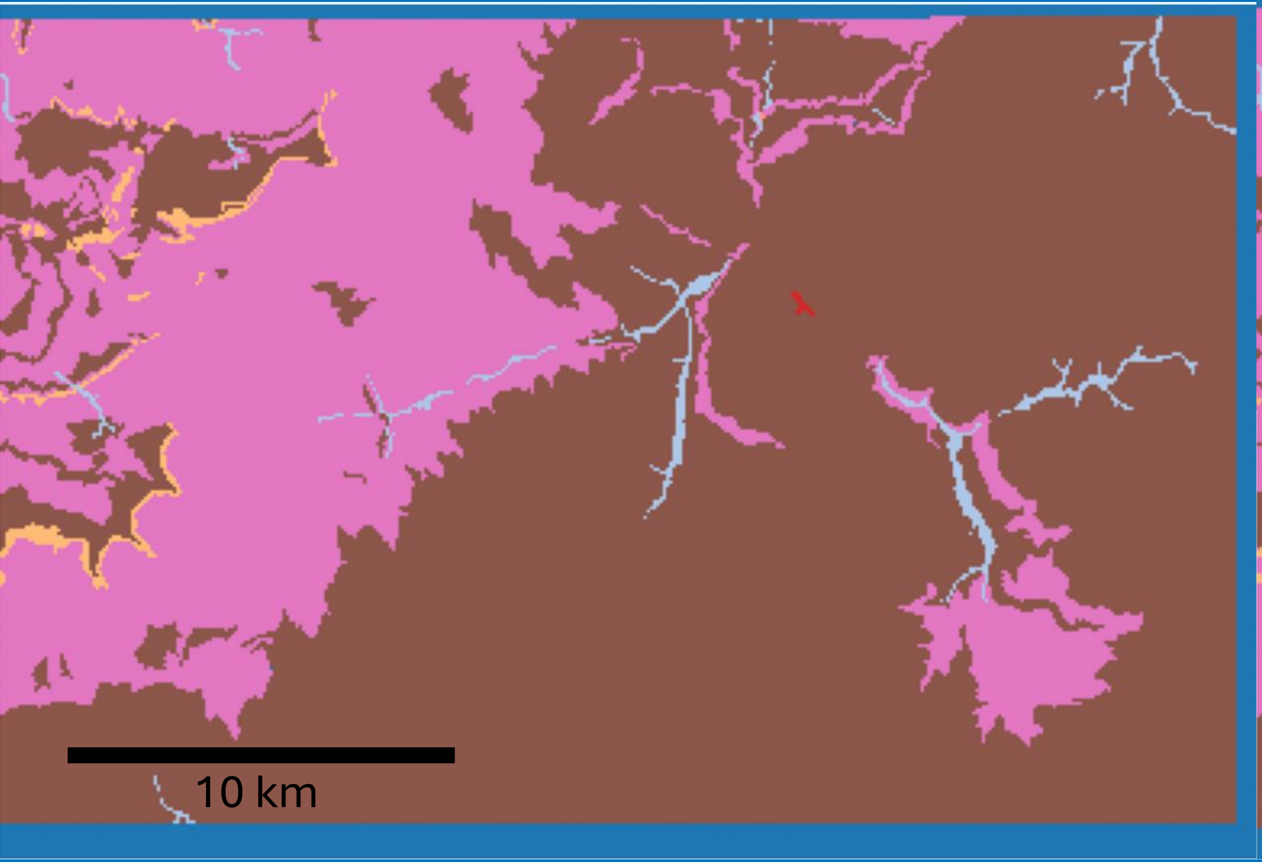
Villoslada de Cameros



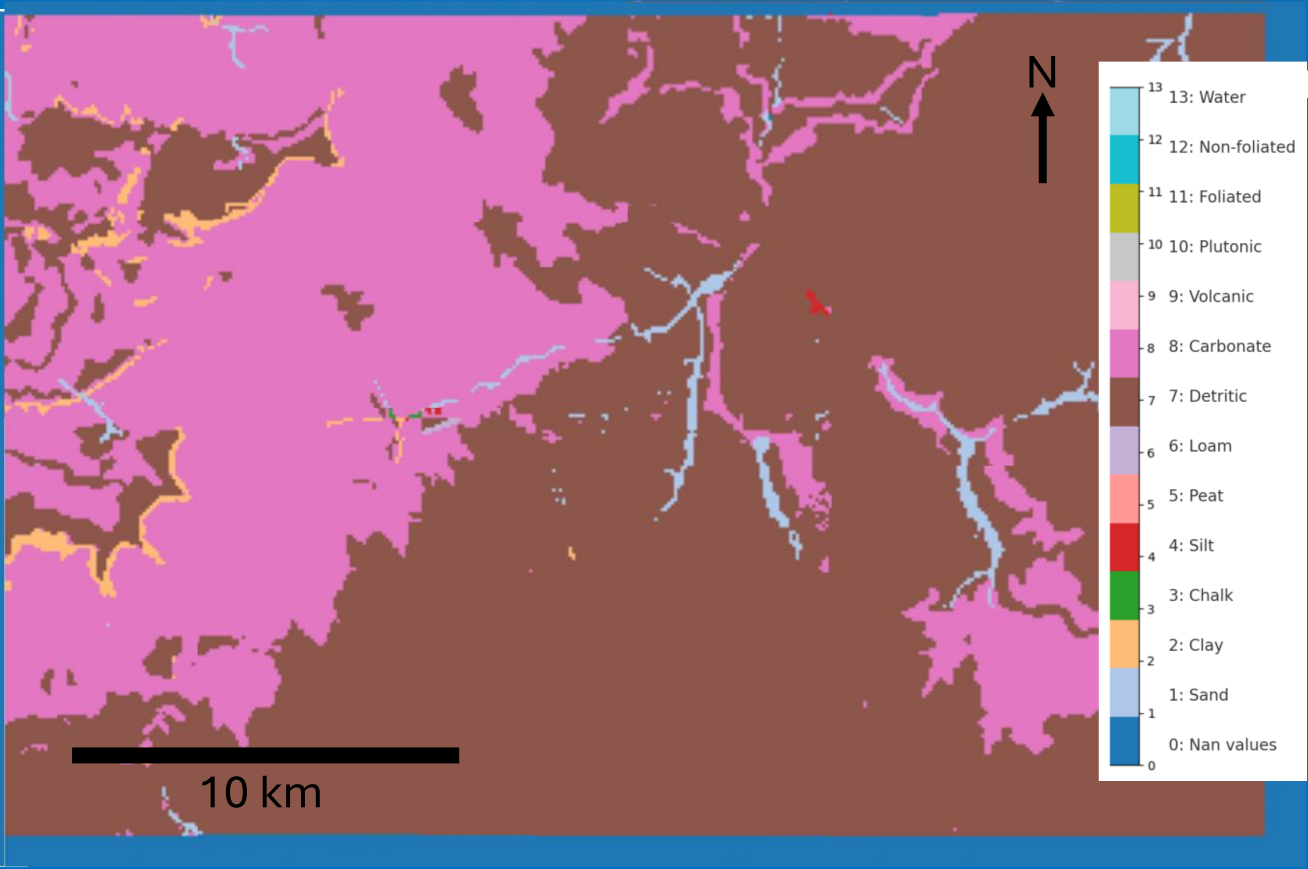
Ground truth

CNN

Villoslada de Cameros



Ground truth



ConvLSTM

Complementary data - NDVI

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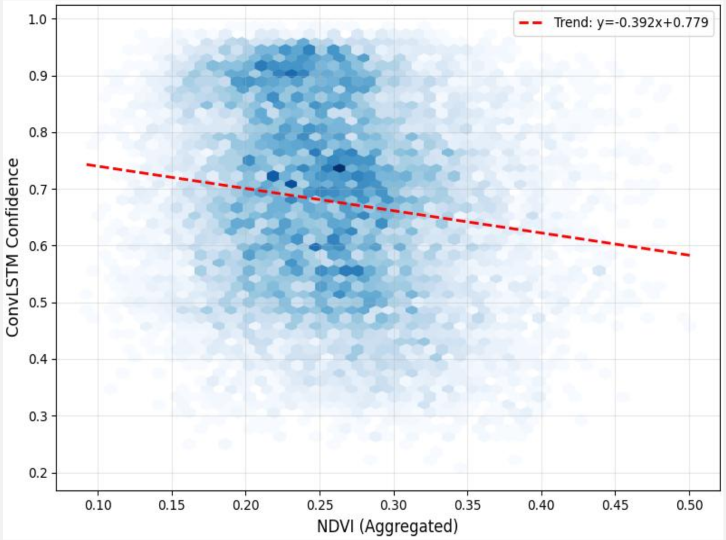
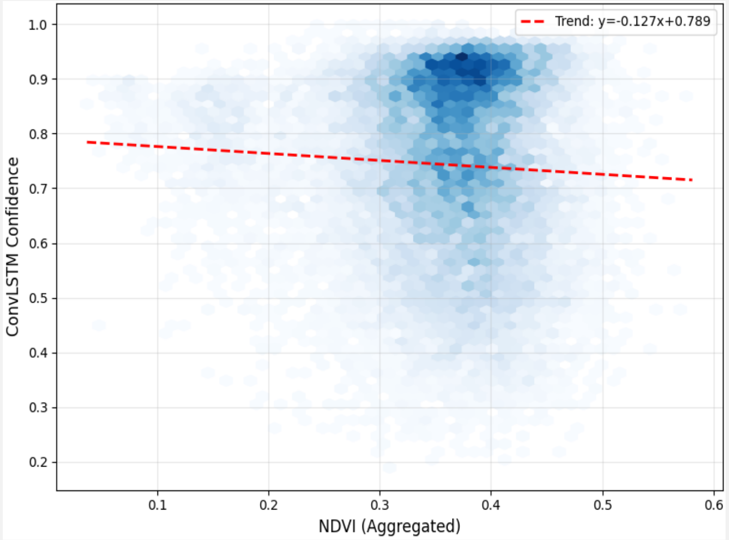
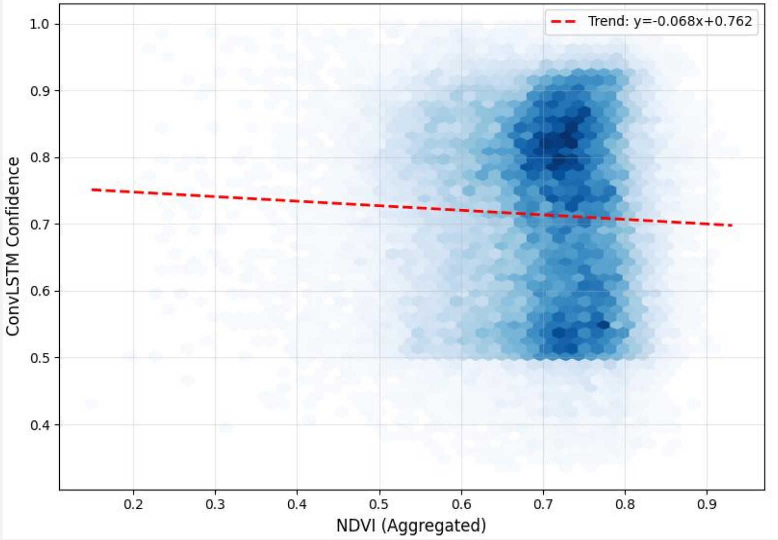


Puertollano

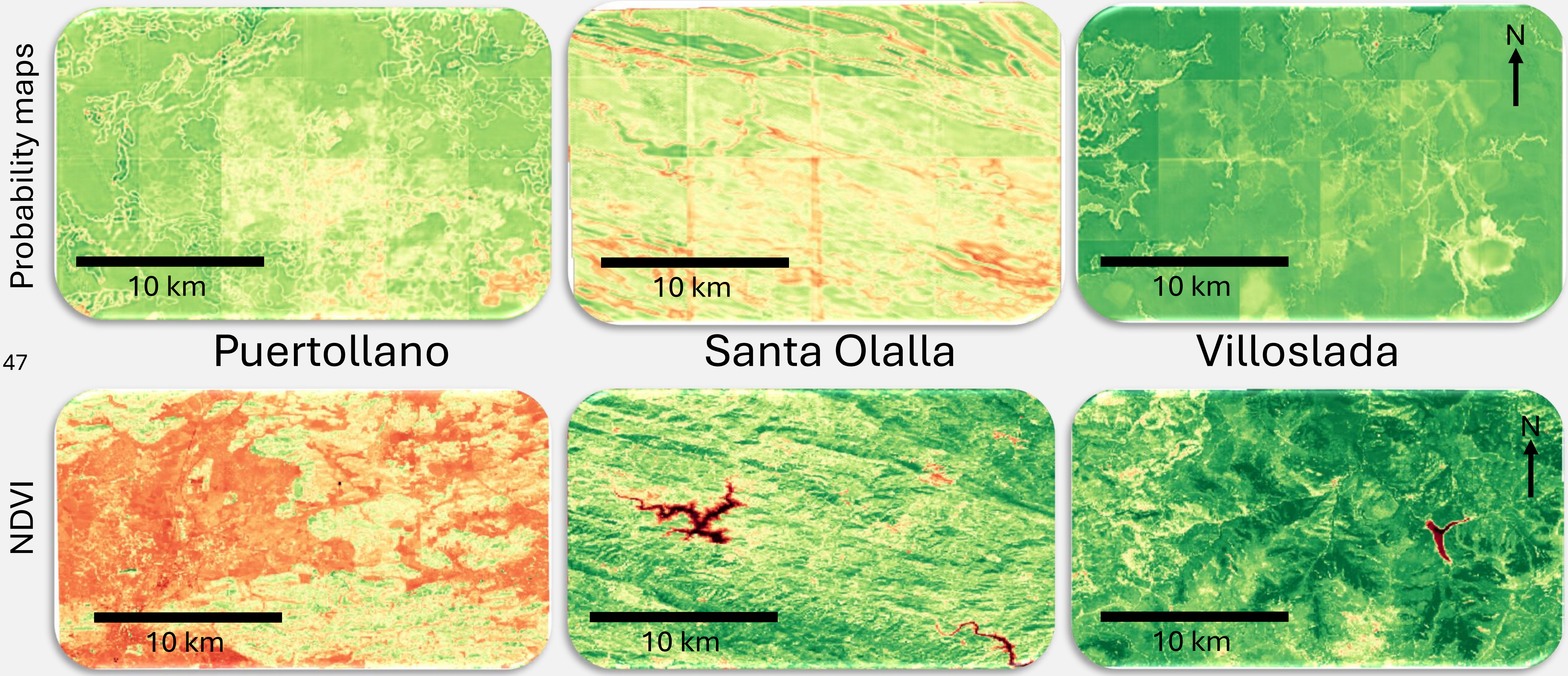


Santa Olalla



Villoslada

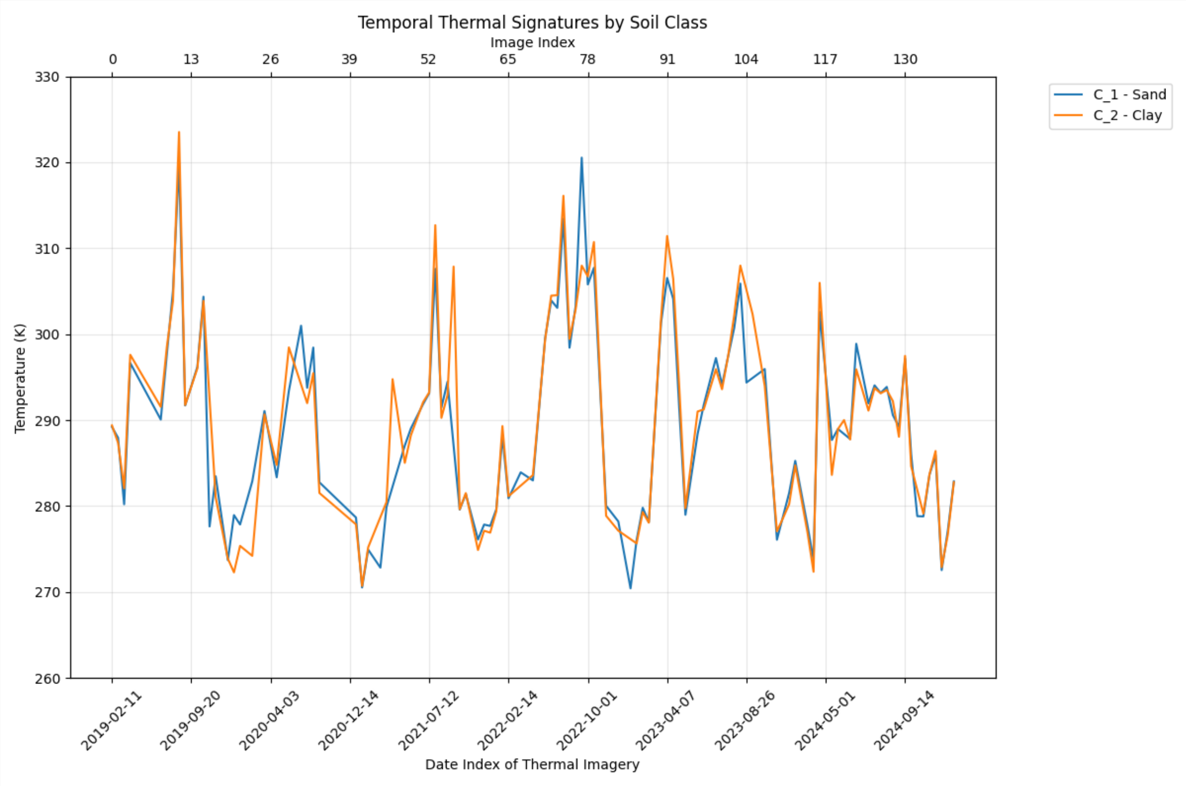
Complementary data – NDVI



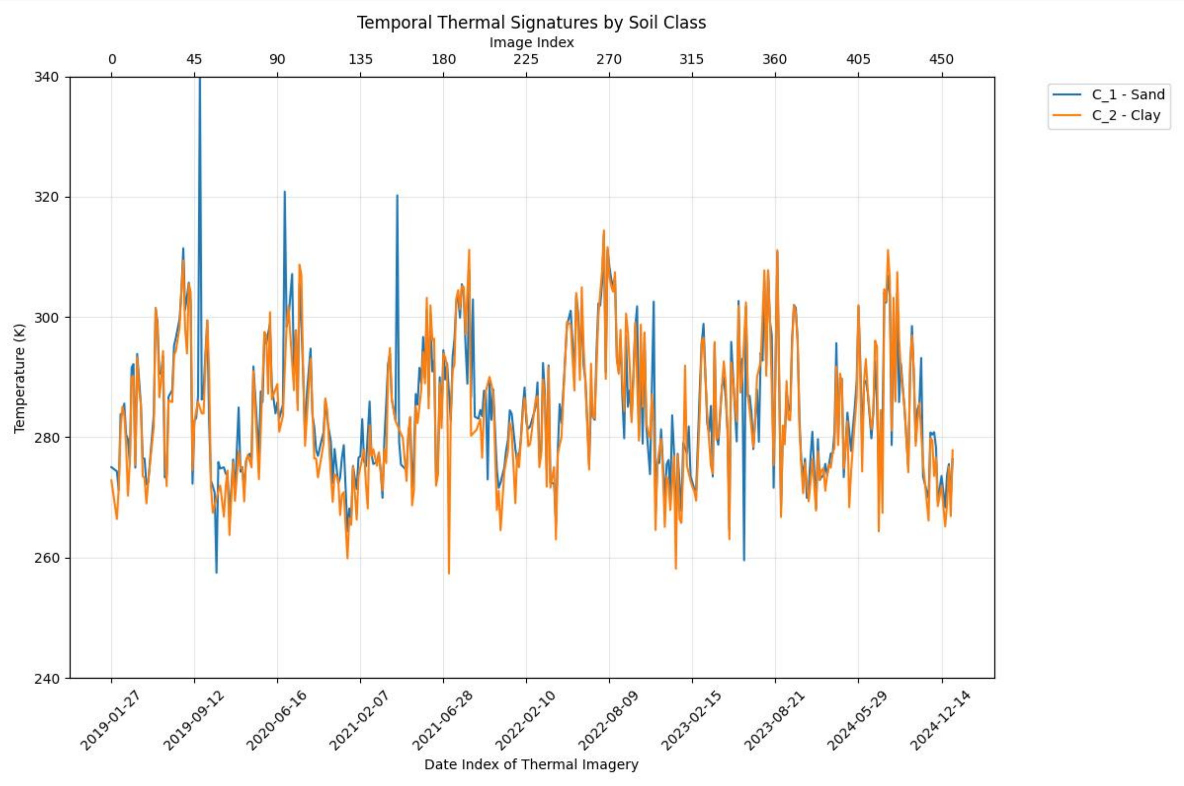
Discussion and Conclusions

<u>CLAY</u> soils gain <u>heat slowly</u> throughout the day but <u>retain heat longer</u> due to its higher moisture content and fine-grained texture

<u>SANDY</u> soils gain <u>heat quickly</u> throughout the day but <u>loose it rapidly</u> given its lower moisture content and coarse-grained texture



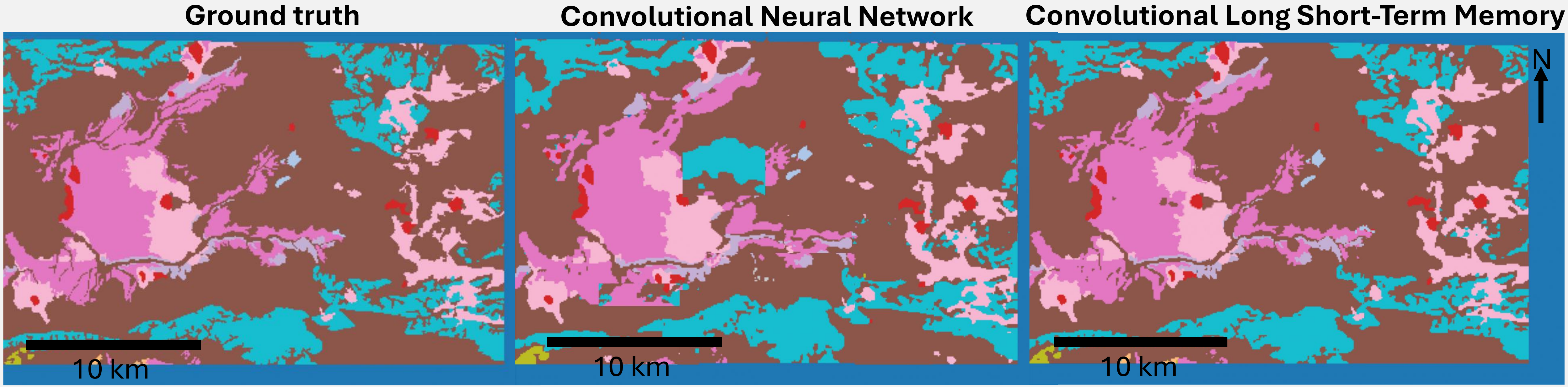
Puertollano



Villoslada

To what extent can Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) deep learning methods help identify/detect different soil/rock types with thermal imagery?

- Both models demonstrate clear ability to perform rock and soil segmentation
- CNN was computationally more efficient with faster training times
- ConvLSTM was more accurate overall and included minority classes



How does the model deal with very similar rock/soil attributes?

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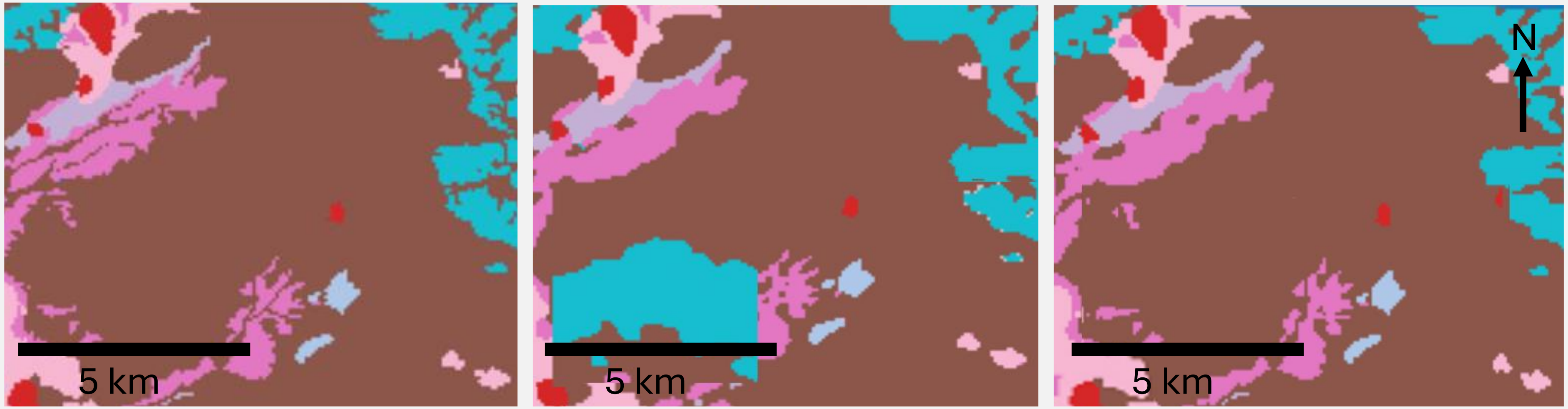
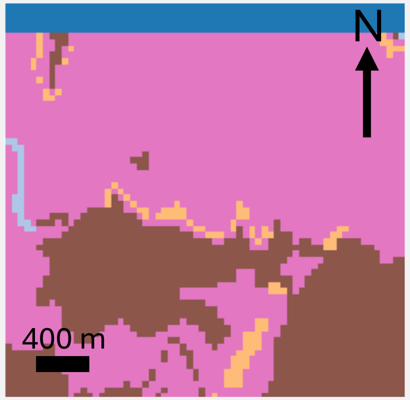


Ground truth **Convolutional Neural Network** **Convolutional Long Short-Term Memory**

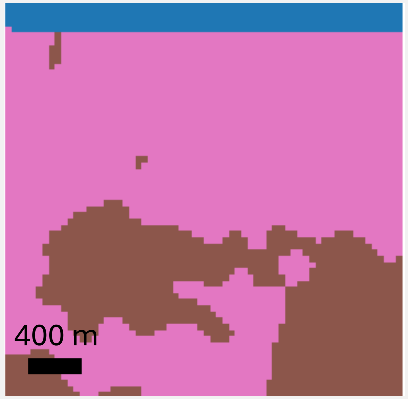
- Minority classes tend to be well represented, especially in ConvLSTM
- Detritic rocks are well differentiated from sands, silts and other soils

How do temporal factors (diurnal and seasonal changes) affect the classification performance?

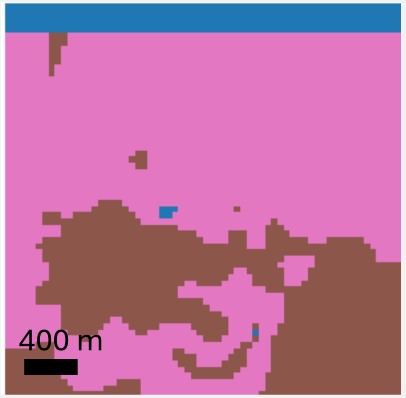
Ground truth



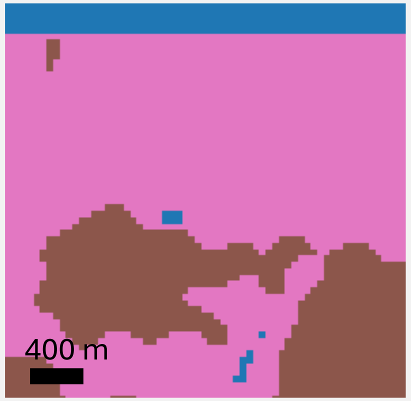
- Optimal timing for data collection is more location-dependent
- Summer proved to be the best subset due to reduced vegetation and clearer atmospheric conditions



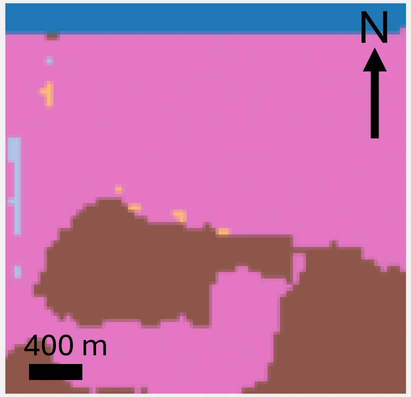
Day



Night



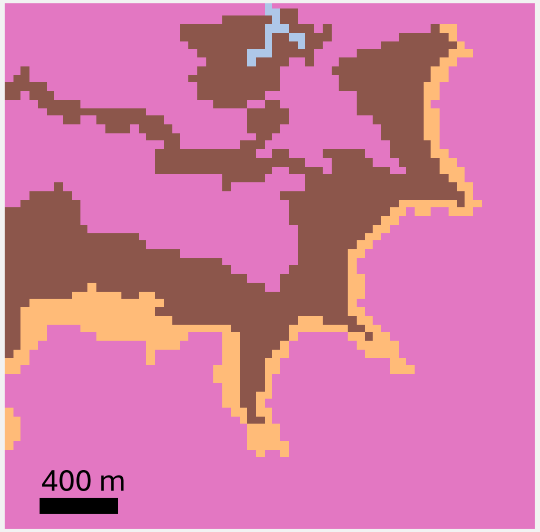
Winter



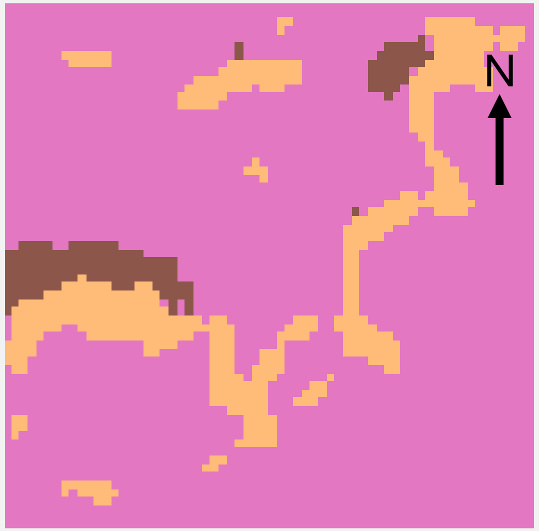
Summer

If other types of data are included (SAR), does the performance/outcomes improve?

- Managed to enhance the representation of minority classes during core experiments
- Clay seemed to be the most benefited one
- Can become important complementary information



Ground truth



Prediction CNN

Conclusions

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- Sand and Clay behaved as expected in the hypotheses
- Vegetation has a higher influence on thermal signatures than anticipated
- Both models can perform a valid classification process
- Temporal memory mechanisms provide advantages for geological segmentation
- Seasonal impact seemed higher than diurnal dynamics
- Models performed better with day and summer datasets
- Villoslada de Cameros presented the most consistent results
- SAR improved minority class representation and demonstrated its value as complementary data
- A higher number of aligned dates with thermal data will provide further insights
- NDVI revealed how vegetation distribution has more impact than density alone
- Scalability could be enhanced in future work

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Thank you for watching