Quantifying Land Cover Change in Dryland Environments using Convolutional Neural Networks and Remote Sensing Data

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Program: MSc by Research
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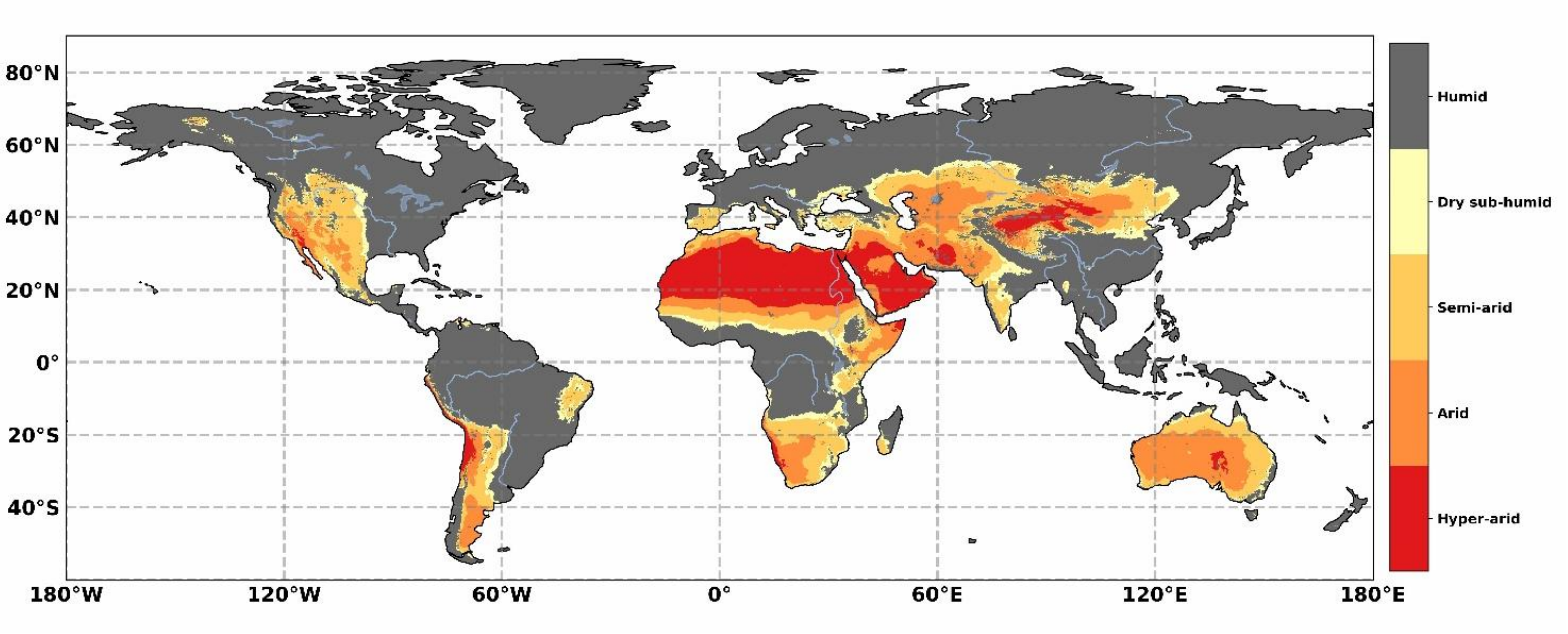
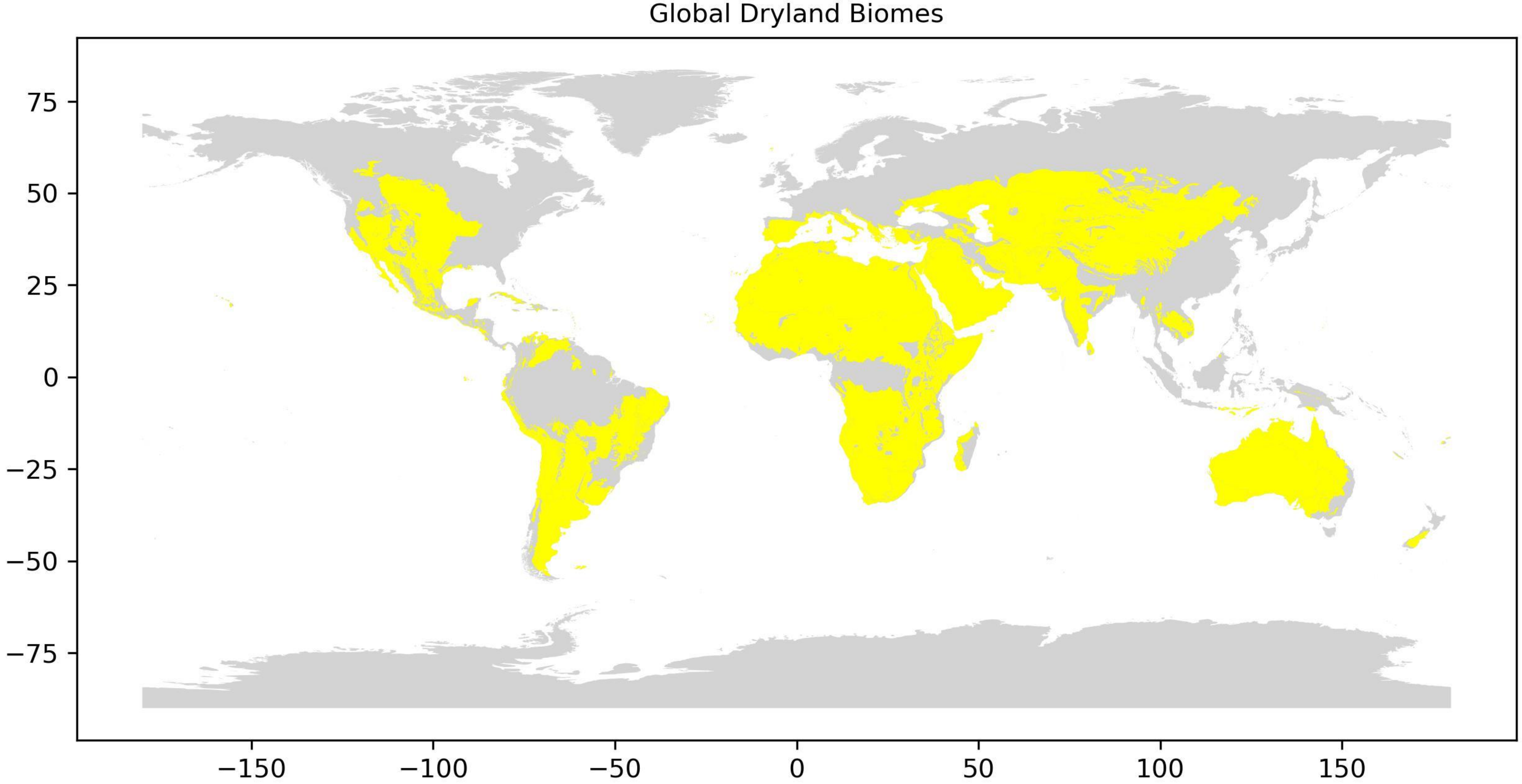
Period of Study: 24 months on a part-time basis. End Aug 2026

Drylands - Aridity Index



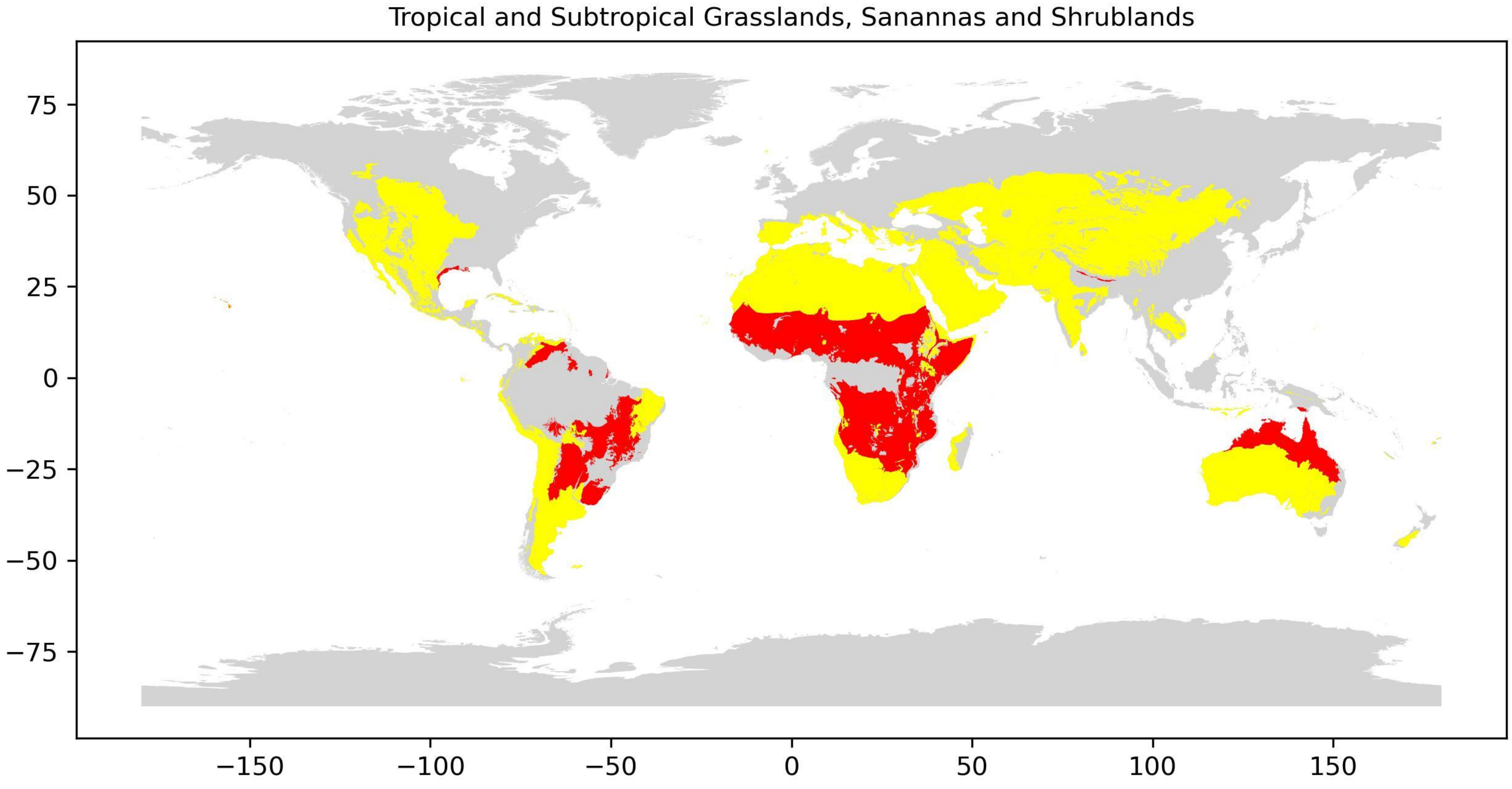
Ratio of annual precipitation to potential evapotranspiration; Hyper-Arid < 0.05, Arid = 0.05-0.2, Semiarid = 0.2-0.5, Dry Subhumid = 0.5-0.65. Arid regions receive less than 250 mm of precipitation per year. Semi-Arid regions receive 250-500 mm per year (Dryland regions of the world, Shukla *et al.* 2019).

Drylands - Biome



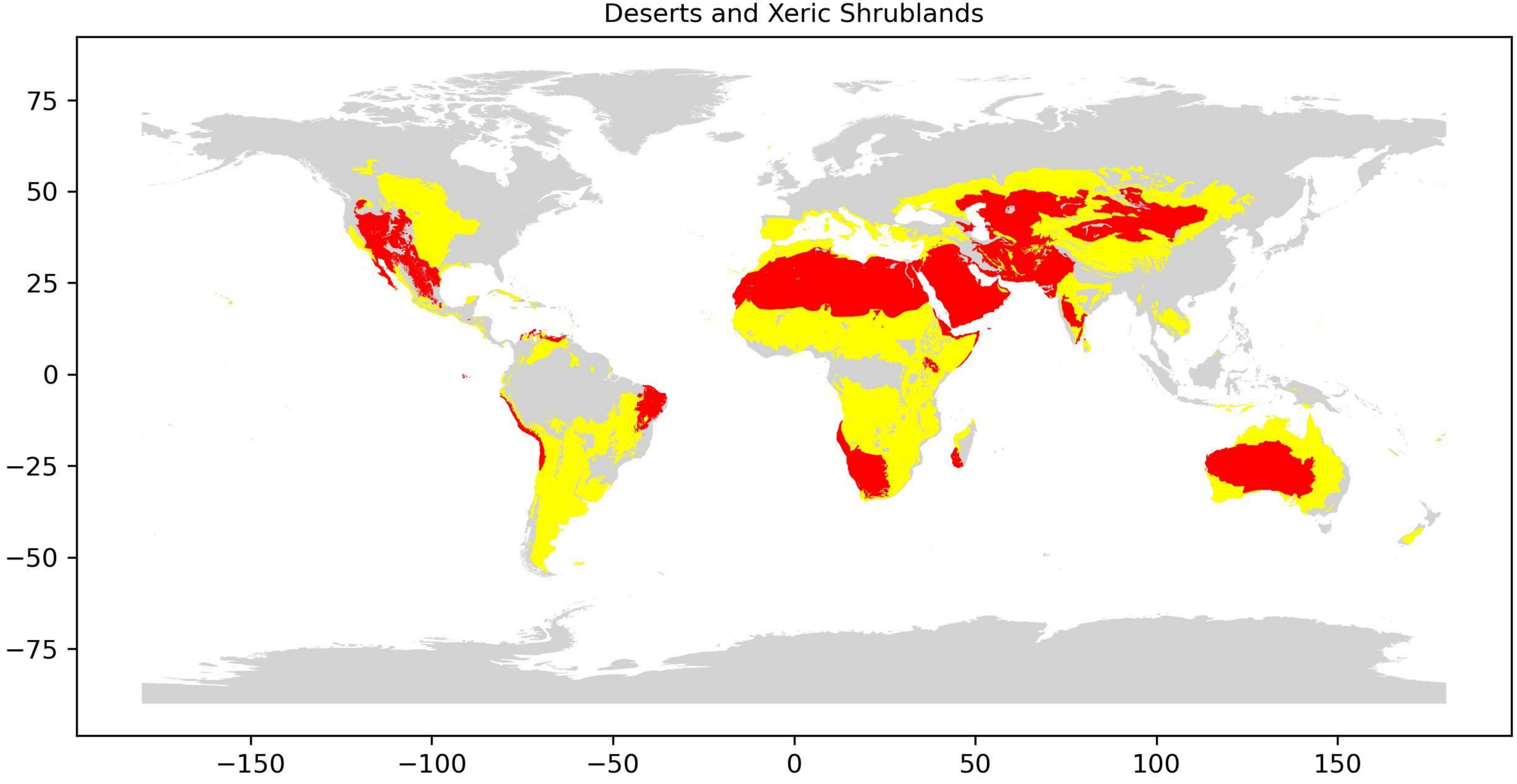
A large geographical area characterized by its specific climate (temperature and rainfall) **and** the types of plants and animals that live there. From Terrestrial Ecosystems of the World (WWF, Olson et al. 2001).

Drylands - Biome



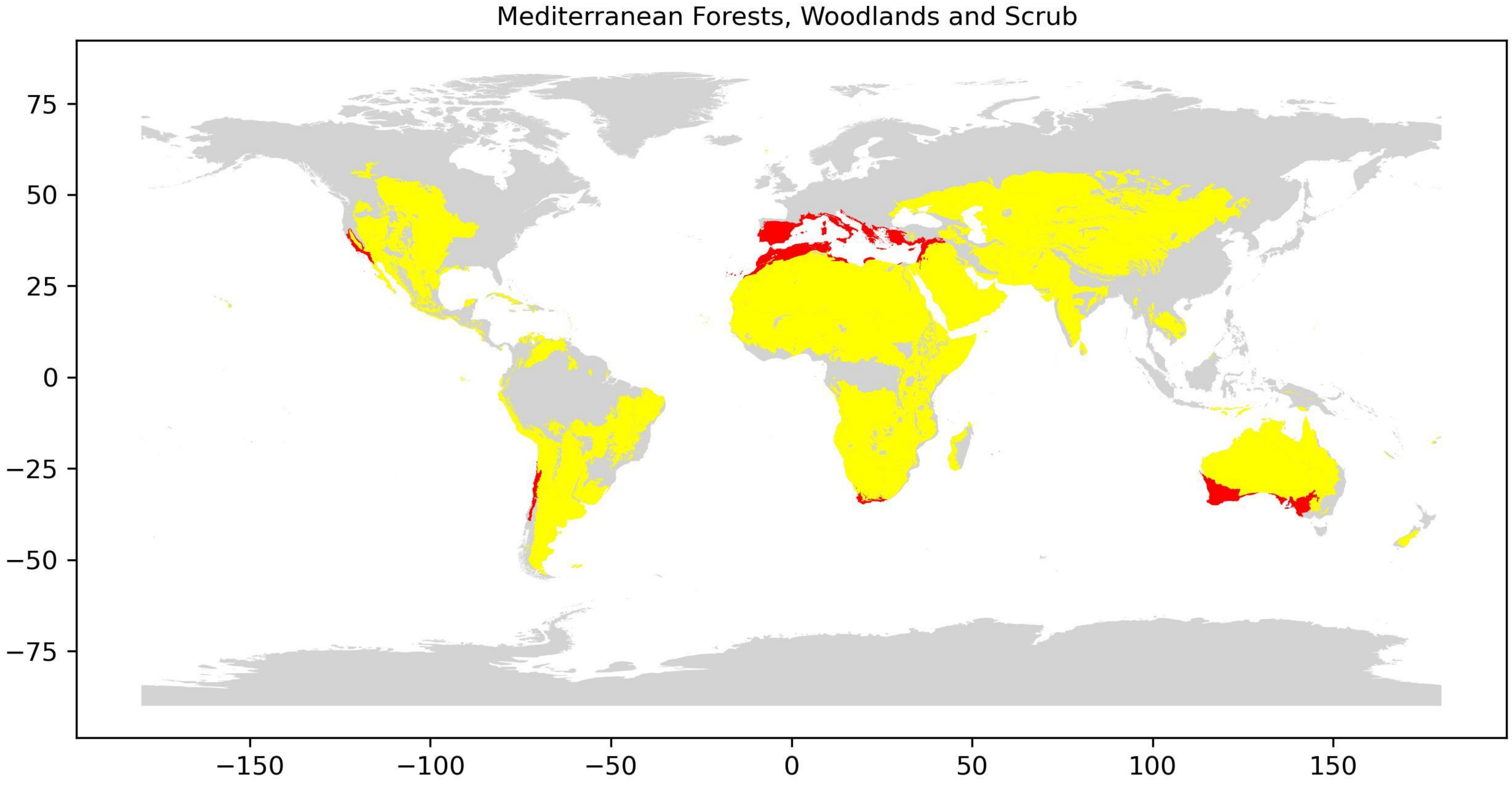
Terrestrial Ecosystems of the World (WWF, Olson et al. 2001).

Drylands - Biome



Terrestrial Ecosystems of the World (WWF, Olson et al. 2001).

Drylands- Biome

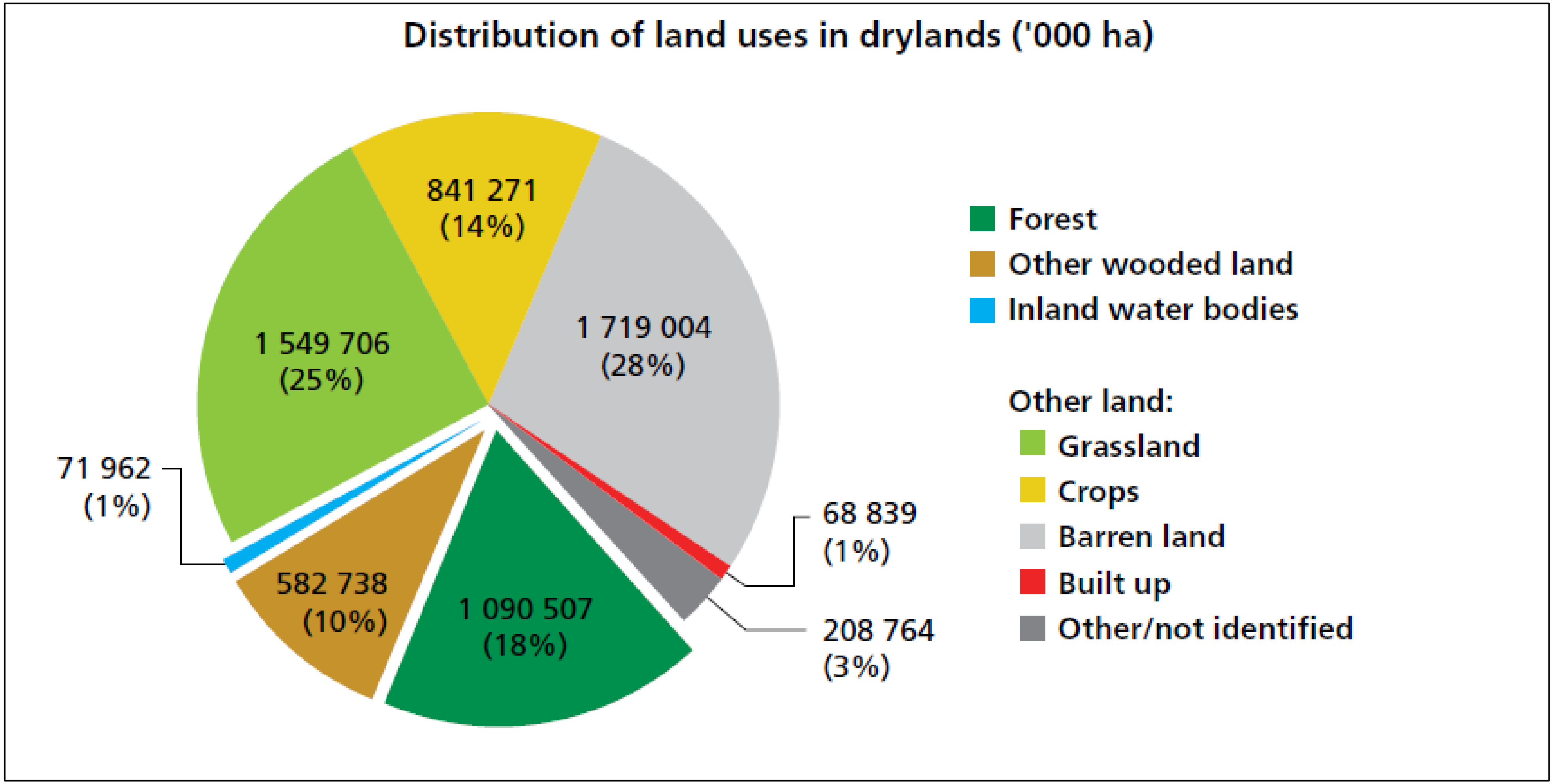


Terrestrial Ecosystems of the World (WWF, Olson et al. 2001).

Why are drylands important?

- Drylands cover approximately 46% of the world’s land surface and are home to 3 billion people (~40% global population).
- They support 50% of the world's livestock, 44% of the world's cultivated land.
- Fragile ecosystems are susceptible to drought, land degradation, land-use change (**agriculture**, urbanisation), deforestation and desertification.

Dryland Land Use



Land use in global drylands. (FAO, 2019. Trees, forests, and land use in drylands: The first global assessment).

Monitoring drylands

- Landcover classification specifically for **dryland environments** is relatively rare.
- Drylands are under-studied because they are often considered “marginal” and of low economic value.
- They are difficult to assess with traditional remote sensing techniques.

- High seasonal variation in vegetation greenness.
- Subtle differences between Grassland, Savanna, Baren, Shrubland, Dry Forest.

CNNs and Land Cover Classification

- Traditional methods have relied on Vegetation Indices or spectral analysis of satellite images.
- Convolutional Neural Networks applied to satellite imagery can be a very effective method of Land Cover Classification, providing sufficient high quality, labelled, training data is available.
- I used Python/Pytorch in a Jupyter Notebook environment.
- Models run locally on my laptop CPU or Google Colab with GPU.
- Use Sentinel-2 satellite images from ESA. 10 m spatial resolution. Full coverage from July 2017 when Sentinel-2B was operational.

Patch Convolution Neural Network

- A traditional CNN will classify a whole image as either 'dog' or 'cat' etc.
- For land cover classification we want to classify each pixel of an image.
- To achieve this I applied a patch methodology with a small CNN.
- In this method small labelled patches of the satellite image (e.g. 5 x 5 pixels with 4-10 channels) are used as the input for training the CNN.
- A 3x3 or 2x2 kernel is moved across the patch during the convolution. We do not use any pooling or padding.
- The output is fed into a SoftMax layer. When the patch is classified, the classification is given to the central pixel of the patch.

Labelled Landcover Data

- Several global landcover training datasets exist. **Hand-labelled by human observers** using Google Earth images or aerial photographs.
- One of the most recent is the Global Land Cover Estimation (GLanCE) dataset from Stanimirova et al. (2023) which is a compilation of a dozen global datasets between 1984 and 2020.
- For dryland Biomes there are 216,000 samples between 2018 and 2020.
- The Level1 classes are Water, Built, Barren, Trees, Shrub, Herbaceous.
- Filter GLanCE data points from specific dryland biome using Geopandas.

Training

- I filtered the GLanCE samples per dryland biome
- Extracted Sentinel-2 images for each sample (10 x 5 x 5)
- I trained a CNN on each biome individually, and one model with all biomes.
- I investigated changing CNN architecture and hyperparameters including; L2 regularisation, dropout regularisation, batch size, learning rate, model depth, model width, activation functions, and data normalisation.

Sentinel-2 Patch Extraction

- Each GLanCE sample has lat/lon, date, landcover classification
- Use Geemap in Jupyter Notebook to pull Sentinel-2 data from Google Earth Engine.
- Sentinel-2B satellite launched in March 2017 not fully operational until July 2017. Full Sentinel-2 coverage in GEE from late 2017.
- Data of extraction matches glance sample date (no month)
- Chose images with less than 50% cloud cover – then median
- I want green images but not cloudy. Wet season = clouds !

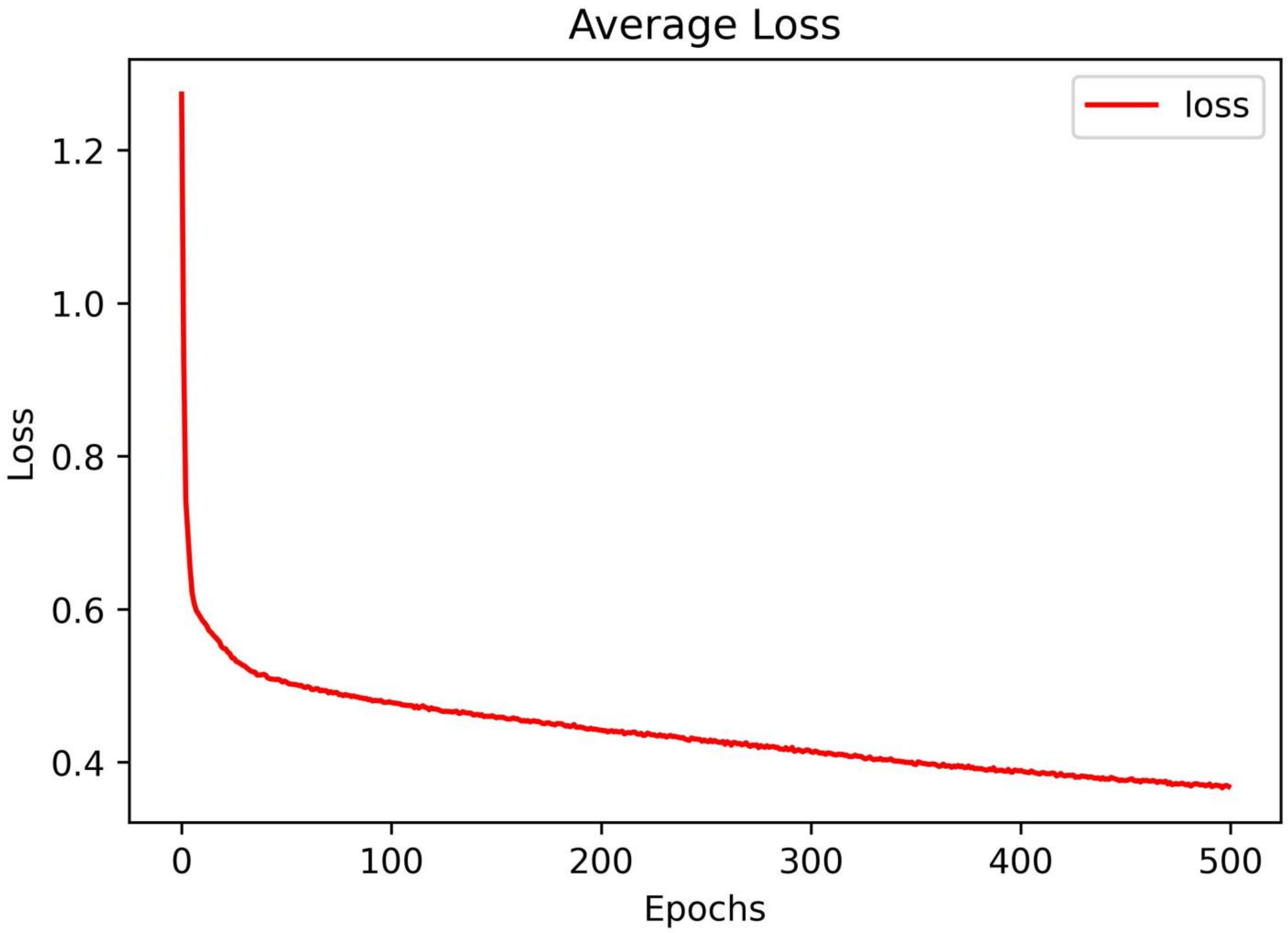
First Results

Level 1	Biome 2	Biome 7	Biome 8	Biome 10	Biome 12	Biome 13	All
Water	3020	9088	551	2560	156	378	15753
Developed	251	837	647	126	1066	760	3687
Barren	111	1353	450	1245	205	6879	10243
Trees	13443	23357	1427	2804	14186	1059	56276
Shrub	401	12279	510	455	2020	6141	21806
Herb	11127	42383	16796	17304	9373	11411	108394
Total	28353	89297	20381	24494	27006	26628	216159
Model Accuracy	88%	88%	89%	89%	85%	74%	82%
million sqkm	3.01	20.18	10.10	5.19	3.22	27.89	69.59
samples / 100 sqkm	0.94	0.44	0.20	0.47	0.84	0.10	0.31

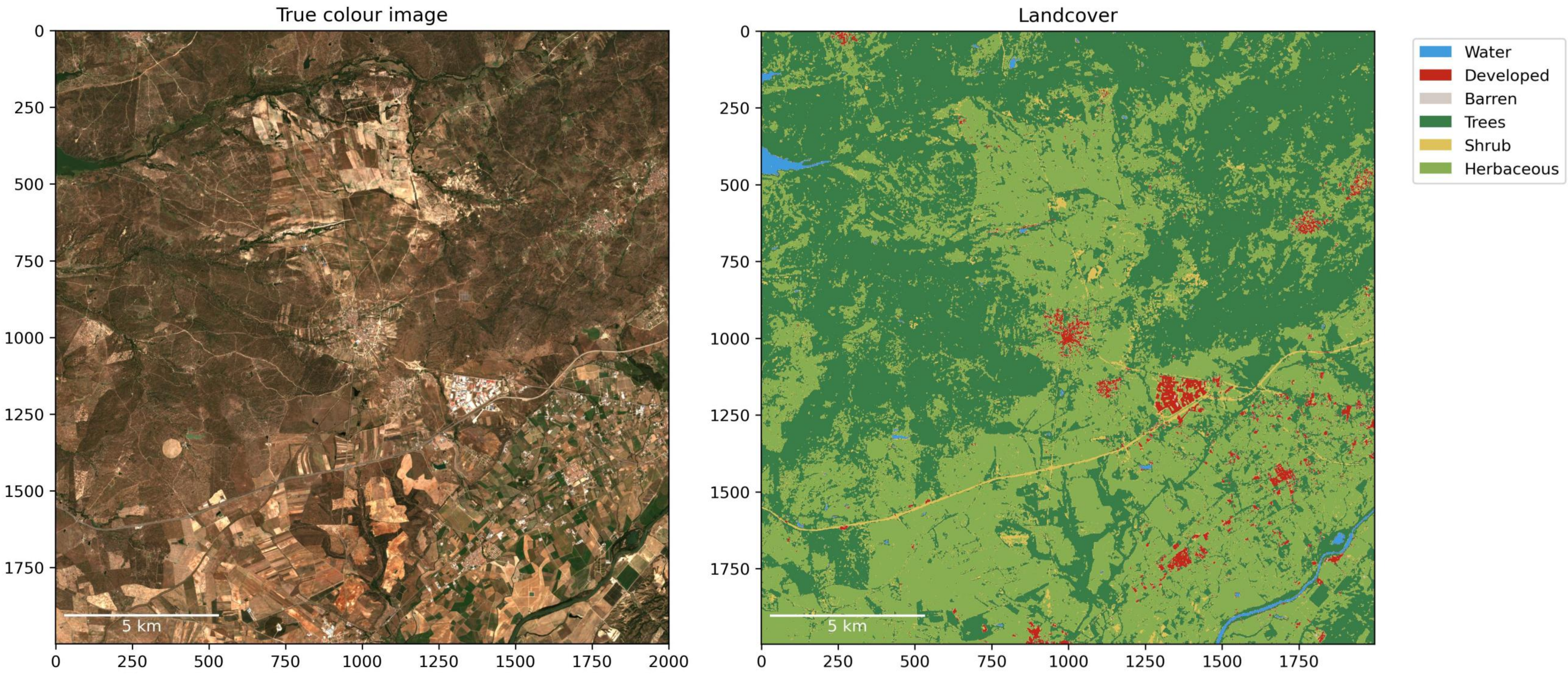
GLanCE Sample Percentages

Level 1	Biome 2	Biome 7	Biome 8	Biome 10	Biome 12	Biome 13	All
Water	10.7%	10.2%	2.7%	10.5%	0.6%	1.4%	7.3%
Developed	0.9%	0.9%	3.2%	0.5%	3.9%	2.9%	1.7%
Barren	0.4%	1.5%	2.2%	5.1%	0.8%	25.8%	4.7%
Trees	47.4%	26.2%	7.0%	11.4%	52.5%	4.0%	26.0%
Shrub	1.4%	13.8%	2.5%	1.9%	7.5%	23.1%	10.1%
Herb	39.2%	47.5%	82.4%	70.6%	34.7%	42.9%	50.1%
Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Biome-12 Loss Curve

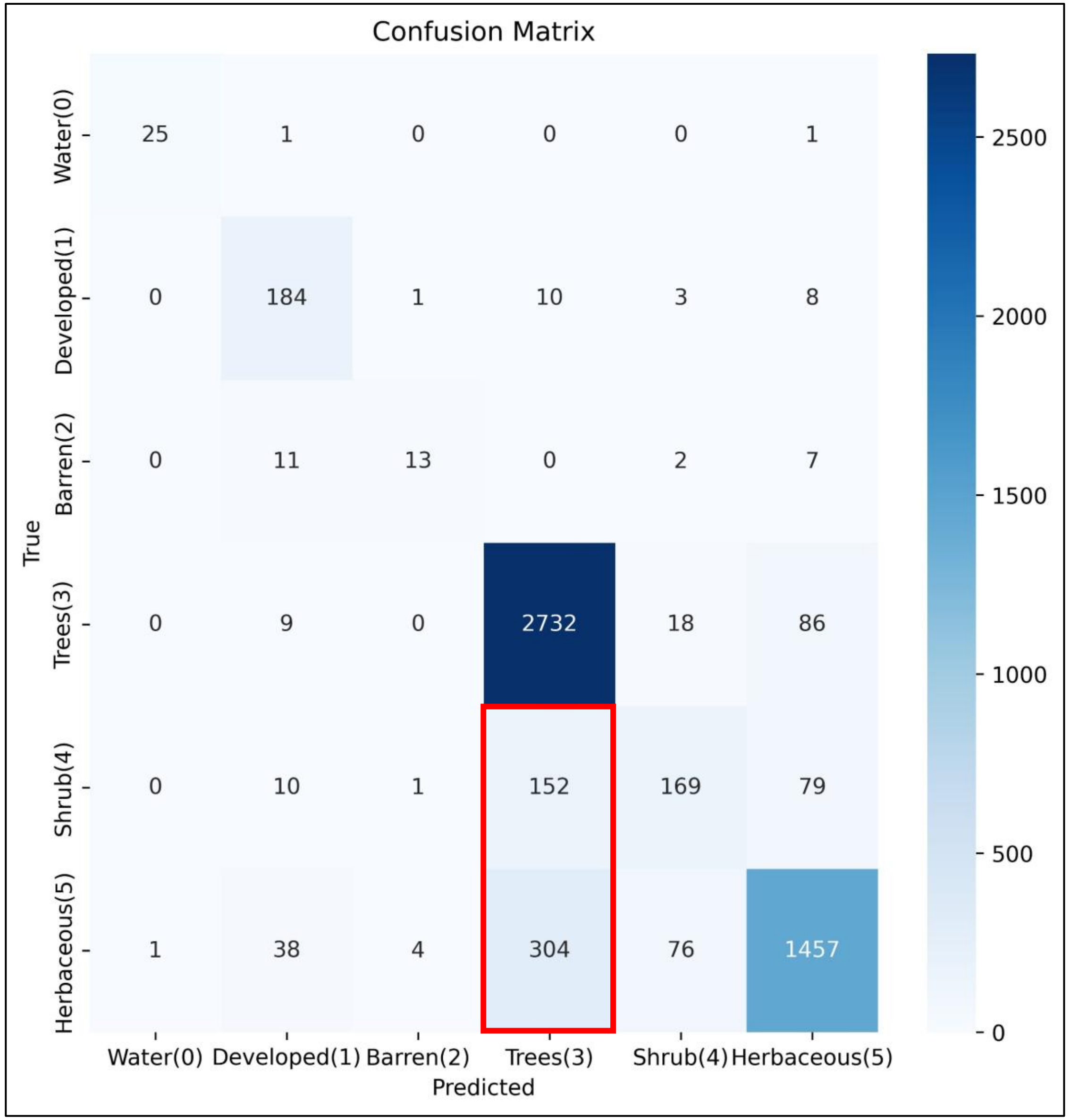


Inference – Mediterranean

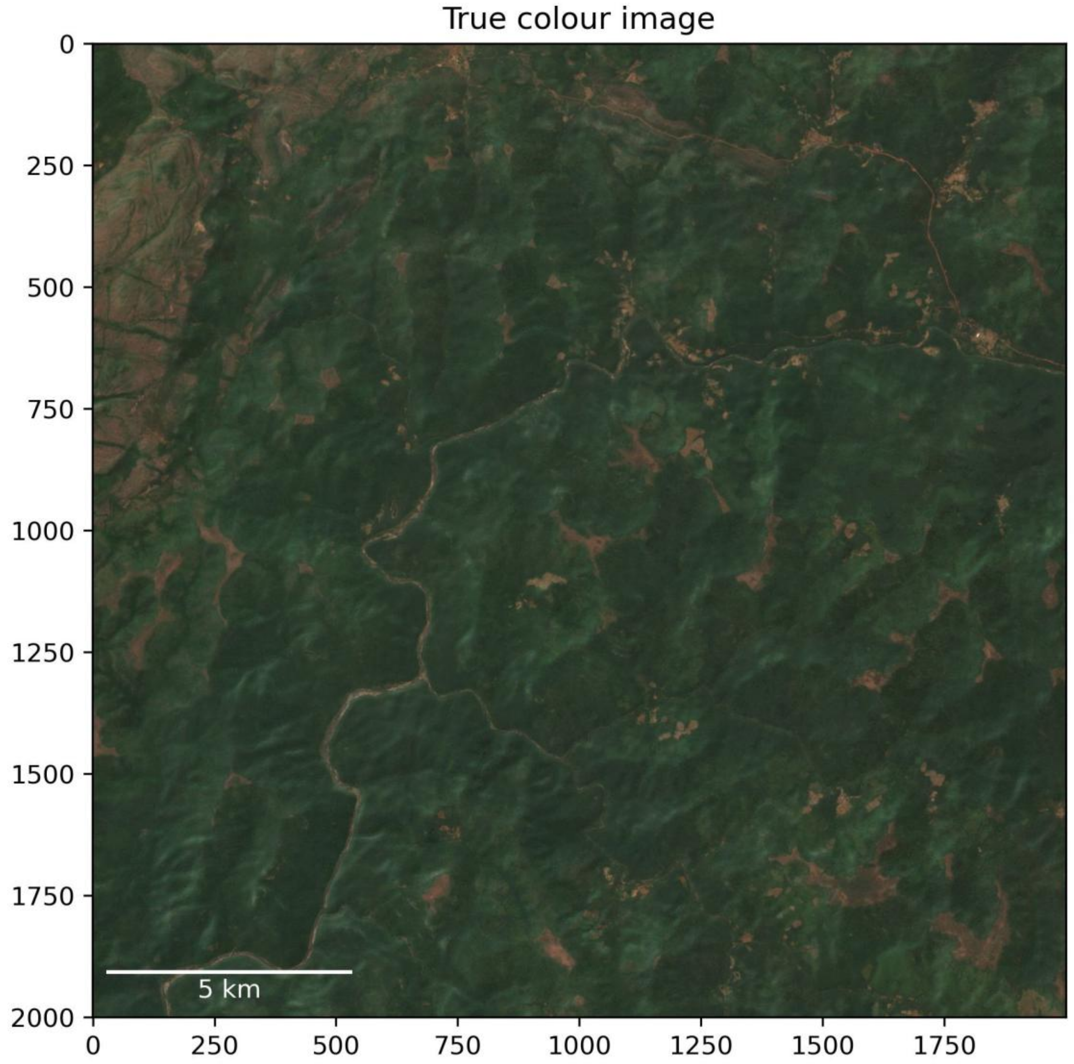


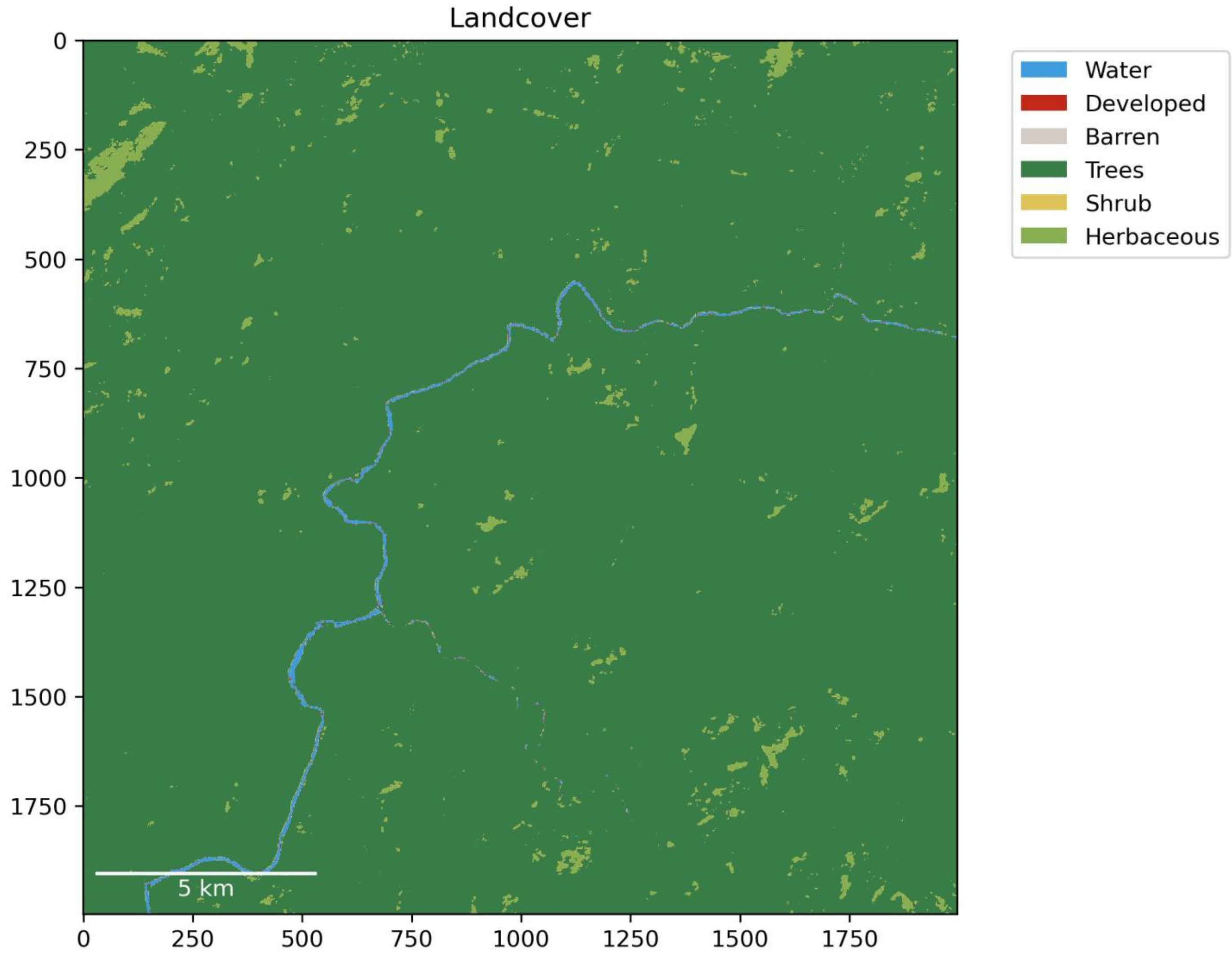
Velada, Central Spain. Biome-12 Mediterranean

Biome-12 Confusion Matrix



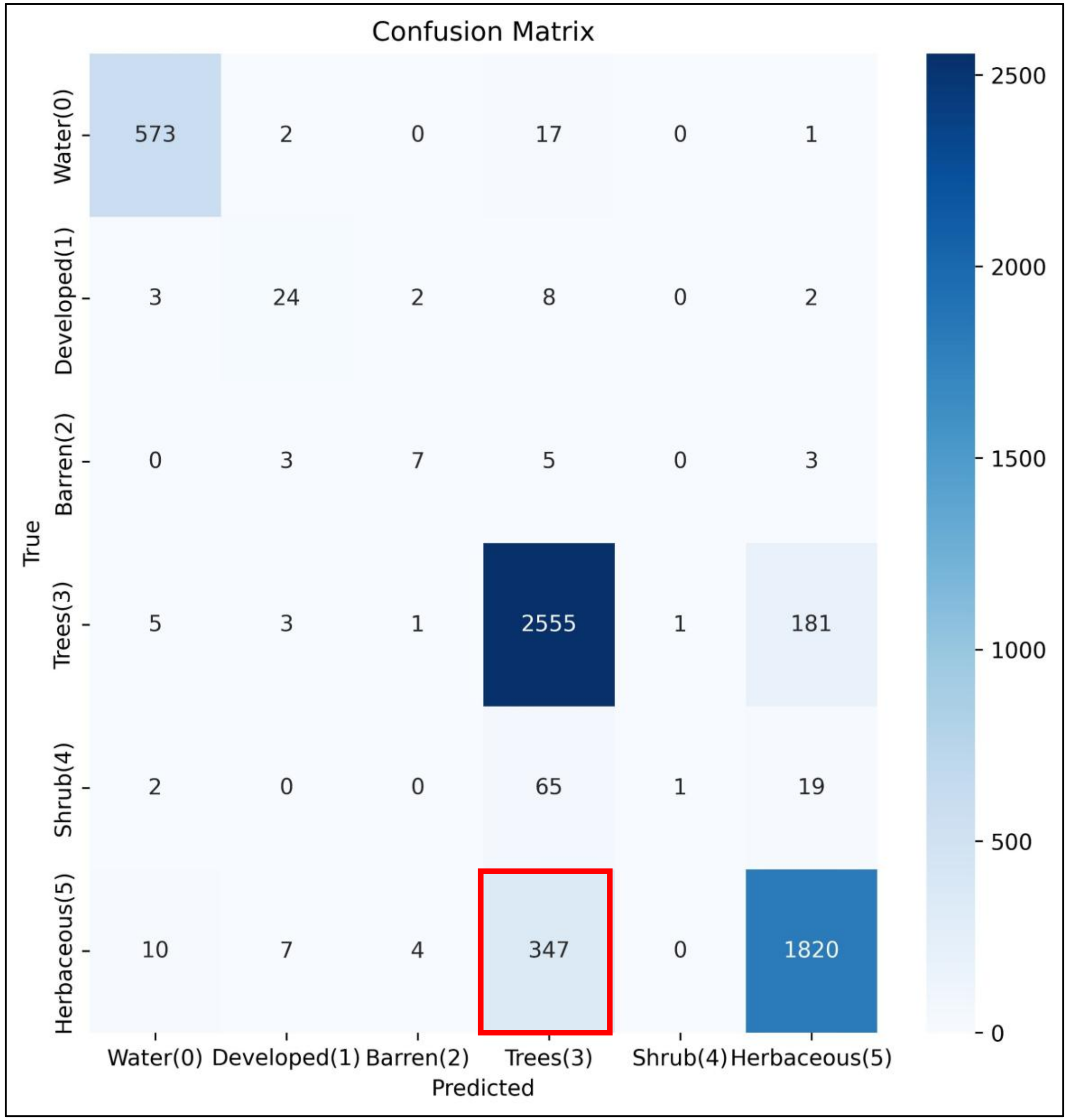
Inference – Dry Broadleaf Forests



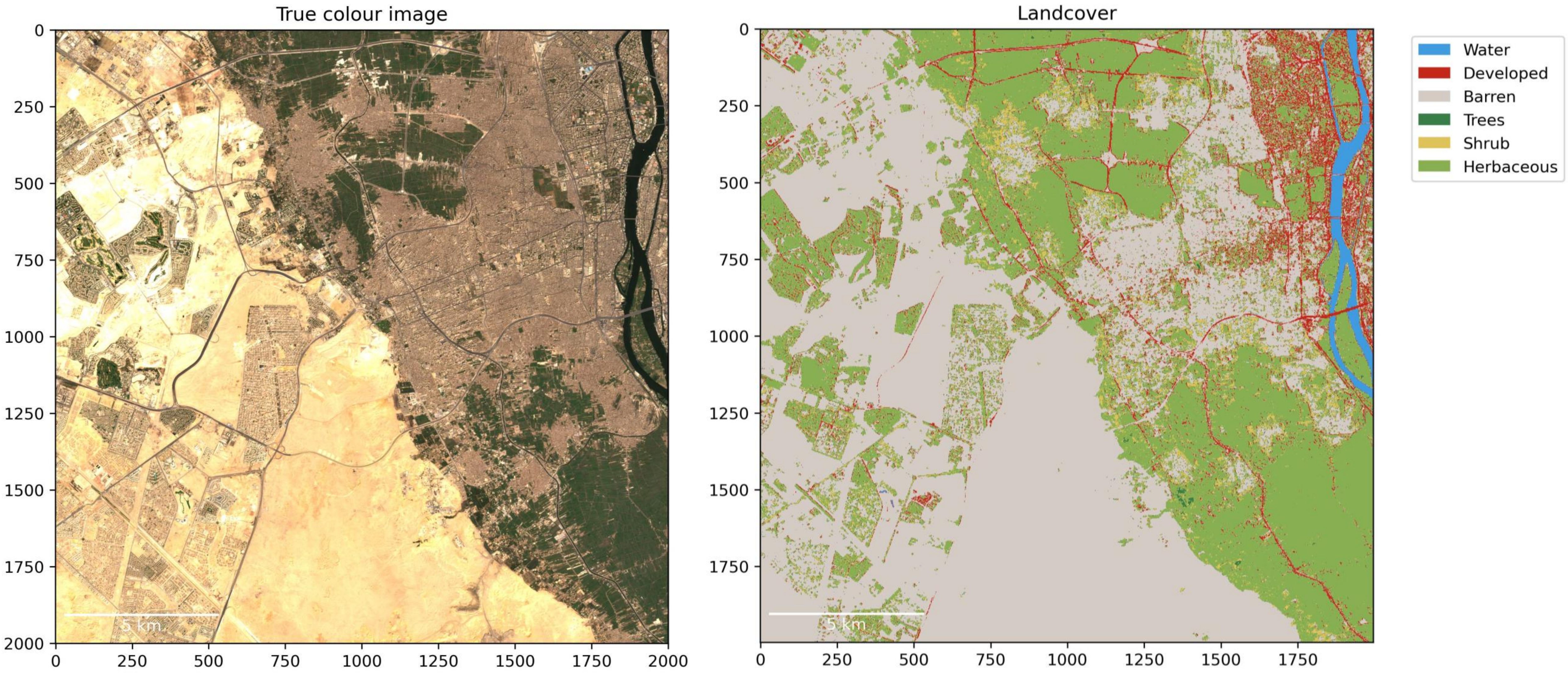


Markud, India. Biome-2 Tropical and Subtropical Dry Broadleaf Forests

Biome-2 Confusion Matrix

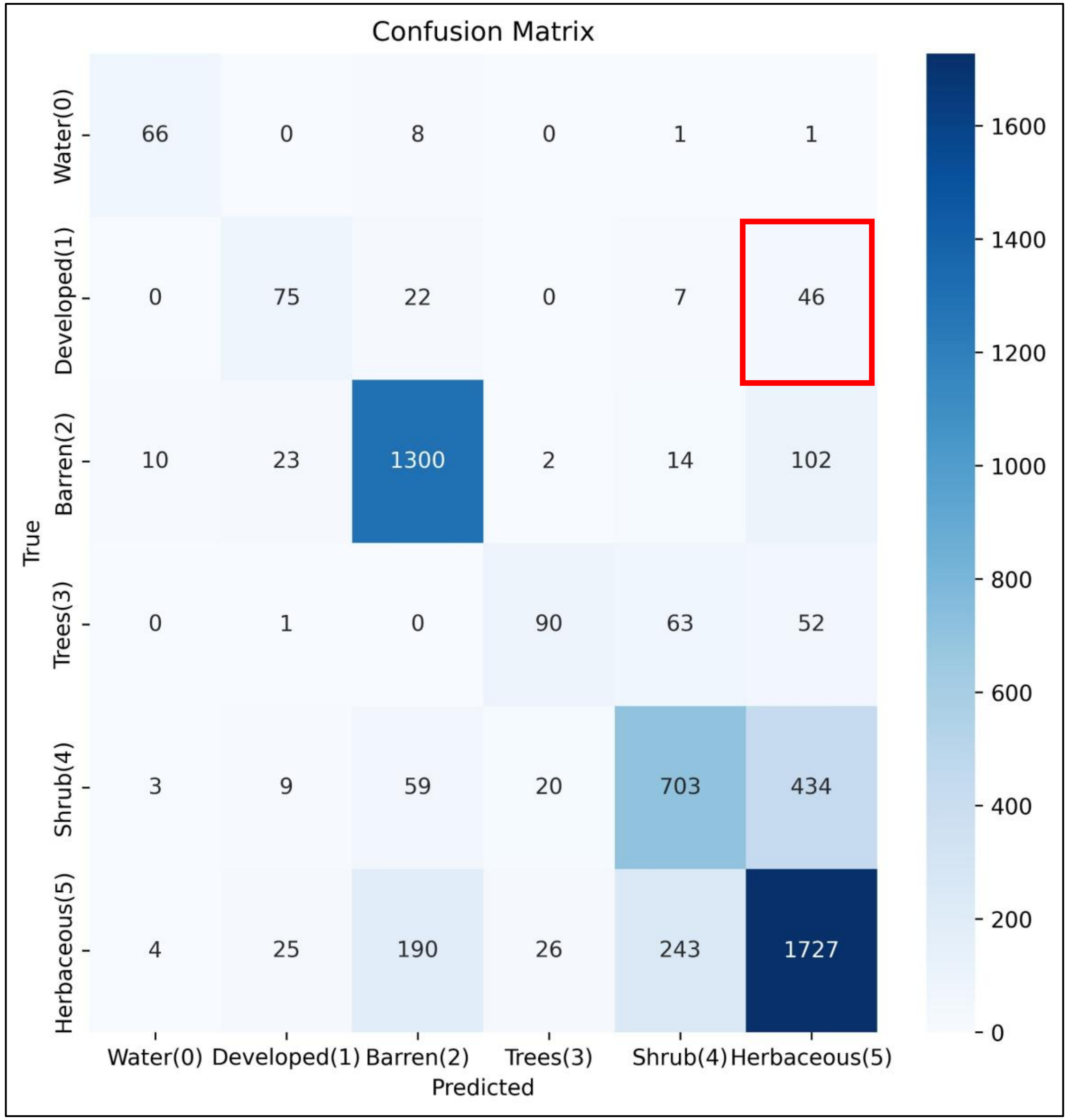


Inference – Deserts and Xeric Shrublands

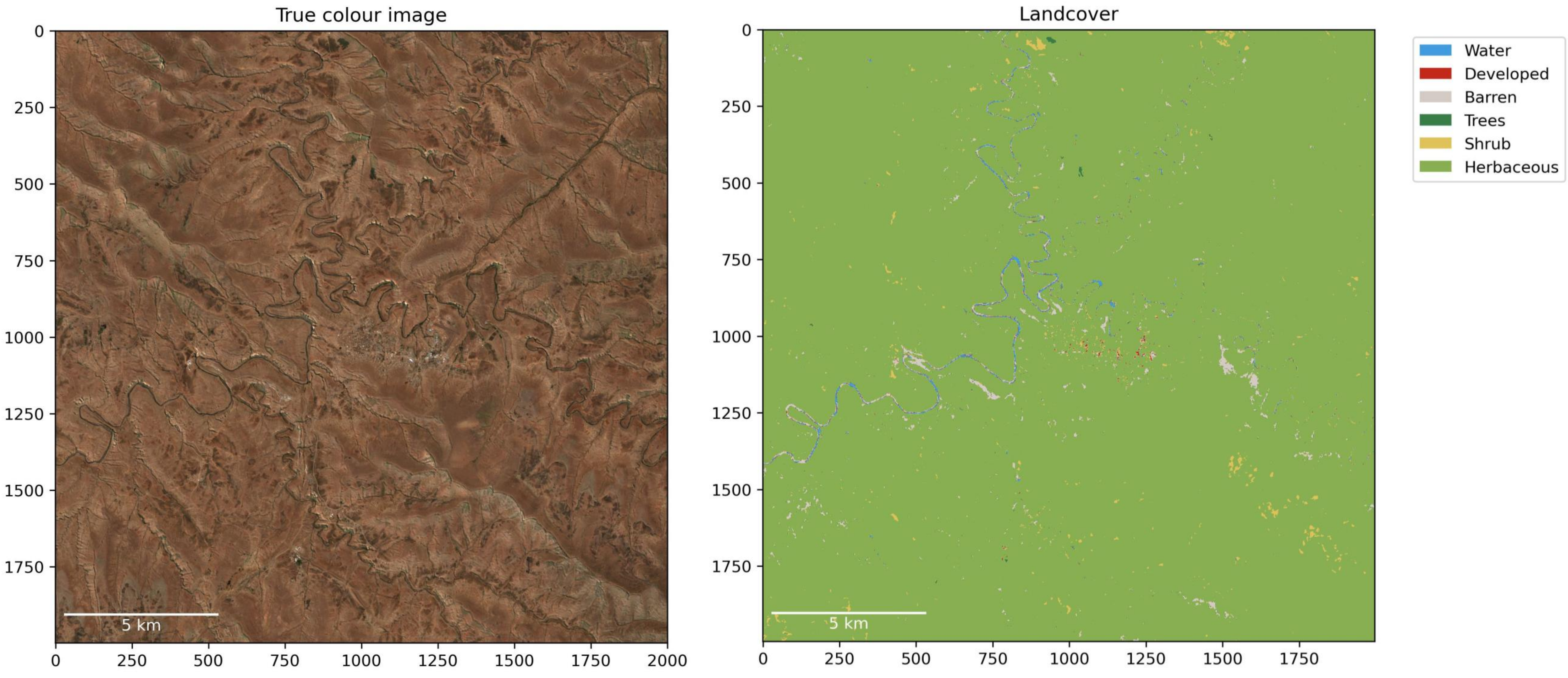


Pyramids, Egypt. Biome-13 Deserts and Xeric Shrublands

Biome-13 Confusion Matrix



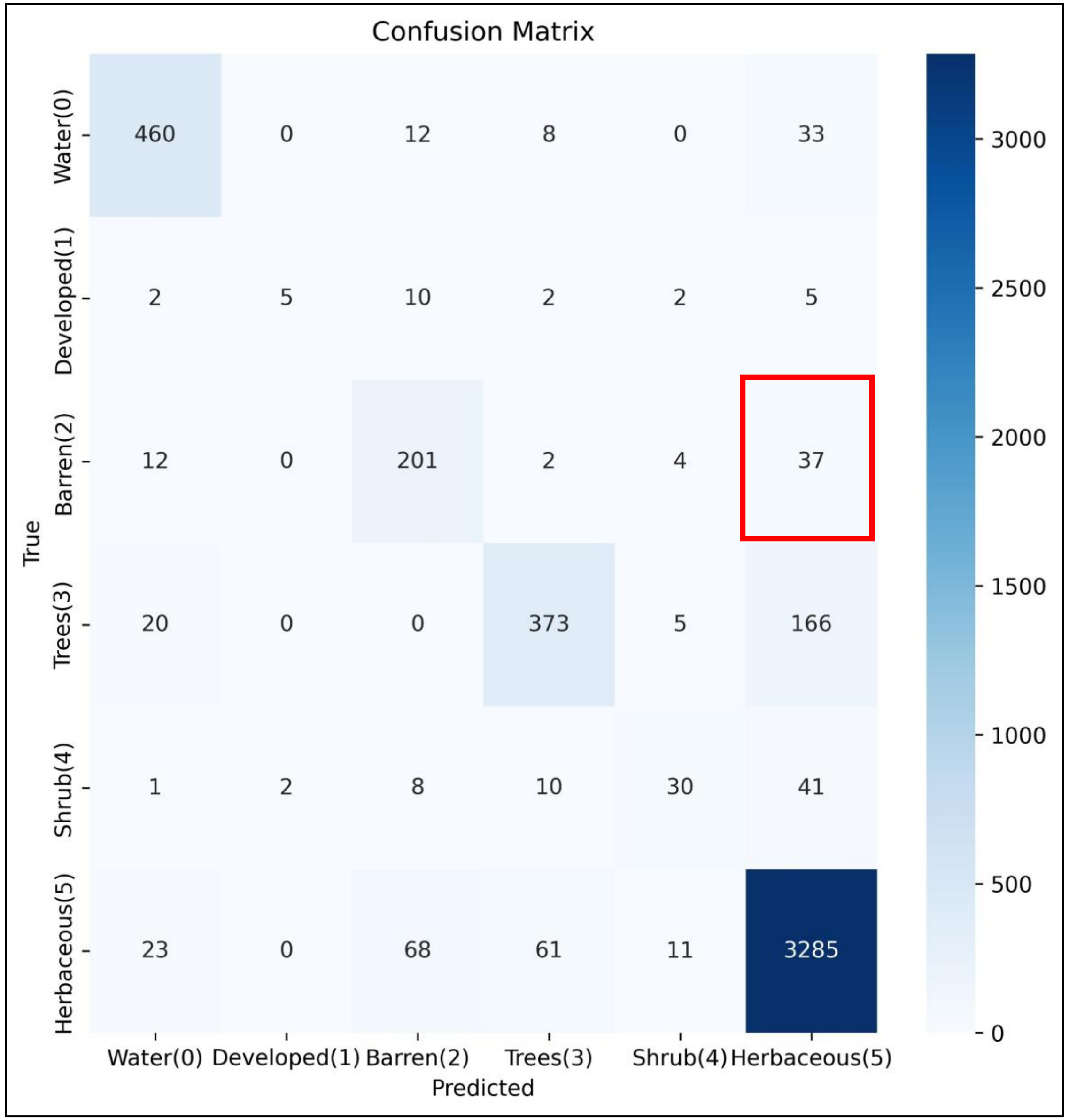
Inference – Montane



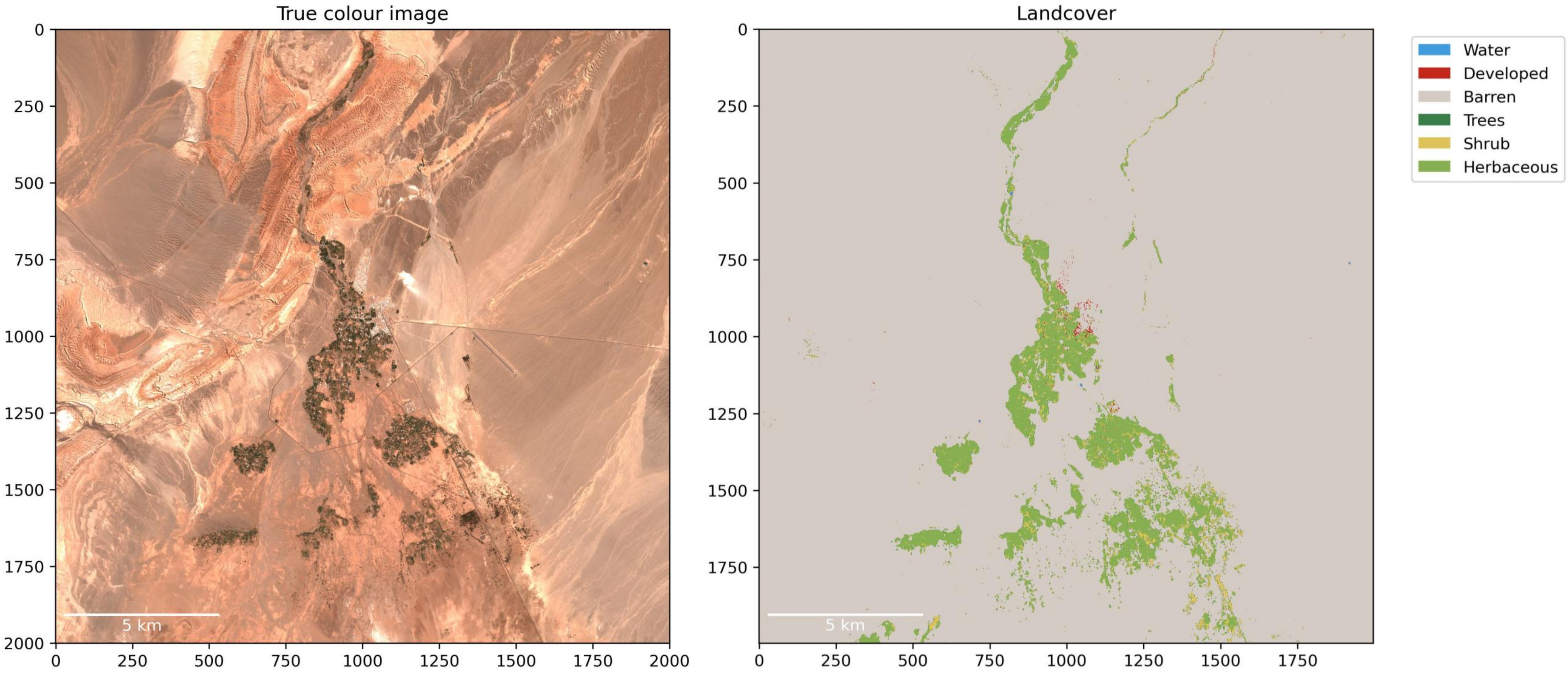
Mokhotlong, Lesotho, Southern Africa. Biome-10 Montane Grasslands and Shrublands

Biome-10 Confusion Matrix

Maybe Lesotho is not typical of global montane environments ?



Inference – Montane



San Pedro, Chile. Biome-10 Montane Grasslands and Shrublands

Sample Distribution

Uneven number of samples per landcover class!

- Augmentation of Barren and Developed samples
- Flipping and rotation could increase x5
- …or get more samples
- Reduce the number of ‘herbaceous’ samples

Other Improvements

- Try 4/5 bands only. 10 bands might dilute the learning ?
- RGB + NIR (10 m) + SWIR1 (20m)
- Use Level-2 classes (Herbaceous -> Grass and Agriculture)
- Tanh rather than leaky RELU activation
- Cloudy Pixels and time of year ?
- Is it OK to use median image of the year ? Representative ?

…then

1. Compare my predicted landcover classes with global landcover models (e.g. ESA World Cover map, Dynamic World, ESRI).
2. Calculate landcover change over multi-year time period. Sentinel-2A launched in June 2015, so would be possible to compare 2016 to 2020 to 2024.
3. Take a look at ERA-5 dataset of global precipitation data (from ECMWF). Does this explain changes in Landcover seen in (2).

Extra Slides

Level 2	Biome 2	Biome 7	Biome 8	Biome 10	Biome 12	Biome 13	All
Water	3020	9088	551	2560	156	378	15753
Developed	251	837	647	126	1066	760	3687
Barren	97	541	315	427	174	2750	4304
Trees	583	1643	358	128	14018	338	17068
Shrub	401	12279	510	455	2020	6141	21806
Grass	2744	30638	10679	14140	3156	8565	69922
Agriculture	858	7622	5444	1281	6041	2754	24000
Undefined	20399	26649	1877	5377	375	4942	59619
Total	28353	89297	20381	24494	27006	26628	216159
Total Defined	**7954**	**62648**	**18504**	**19117**	**26631**	**21686**	**156540**
Model Accuracy	0%	0%	0%	0%	0%	0%	0%
million sqkm	3.01	20.18	10.1	5.19	3.22	27.89	69.59
samples / 100 sqkm	0.26	0.31	0.18	0.37	0.83	0.08	0.22

Level 2	Biome 2	Biome 7	Biome 8	Biome 10	Biome 12	Biome 13	All
Water	38.0%	14.5%	3.0%	13.4%	0.6%	1.7%	10.1%
Developed	3.2%	1.3%	3.5%	0.7%	4.0%	3.5%	2.4%
Barren	1.2%	0.9%	1.7%	2.2%	0.7%	12.7%	2.7%
Trees	7.3%	2.6%	1.9%	0.7%	52.6%	1.6%	10.9%
Shrub	5.0%	19.6%	2.8%	2.4%	7.6%	28.3%	13.9%
Grass	34.5%	48.9%	57.7%	74.0%	11.9%	39.5%	44.7%
Agriculture	10.8%	12.2%	29.4%	6.7%	22.7%	12.7%	15.3%
Total Defined	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Sentinel-2 bands	Sentinel-2A		Sentinel-2B		
	Central wavelength (nm)	Bandwidth (nm)	Central wavelength (nm)	Bandwidth (nm)	Spatial resolution (m)
Band 1 – Coastal aerosol	442.7	21	442.2	21	60
Band 2 – Blue	492.4	66	492.1	66	10
Band 3 – Green	559.8	36	559.0	36	10
Band 4 – Red	664.6	31	664.9	31	10
Band 5 – Vegetation red edge	704.1	15	703.8	16	20
Band 6 – Vegetation red edge	740.5	15	739.1	15	20
Band 7 – Vegetation red edge	782.8	20	779.7	20	20
Band 8 – NIR	832.8	106	832.9	106	10
Band 8A – Narrow NIR	864.7	21	864.0	22	20
Band 9 – Water vapour	945.1	20	943.2	21	60
Band 10 – SWIR – Cirrus	1373.5	31	1376.9	30	60
Band 11 – SWIR	1613.7	91	1610.4	94	20
Band 12 – SWIR	2202.4	175	2185.7	185	20