Crop Type Mapping with Sentinel-2 Satellite Imagery and Artificial Intelligence

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Introduction

IRTA

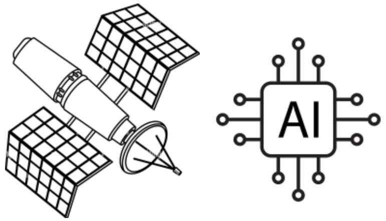
Why we need crop maps?

Does we have enough water to satisfy the <u>agricultural water demand</u>?

$$ET_c = ET_0 * K_c$$

Meteo

Crop type



Irrigation system

DUN SIGPAG

Generalitat de Catalunya
Departament d'Acció Climàtica, Alimentació i Agenda Rural

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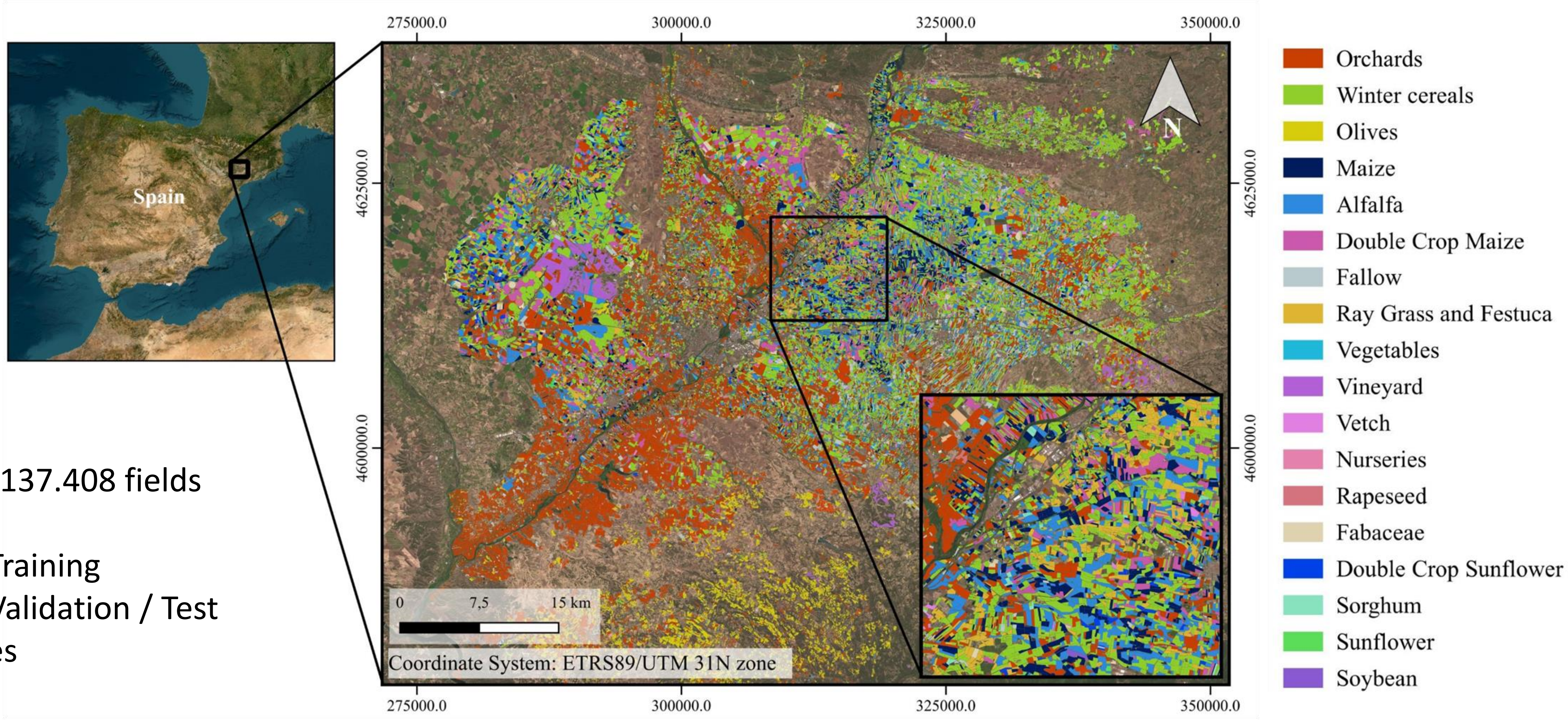
Methodology

IRTA

Region of study and Dataset



- Regions:
  - Lleida: 137.408 fields
- Years:
  - 2022: Training
  - 2023: Validation / Test
- 18 categories

Methodology

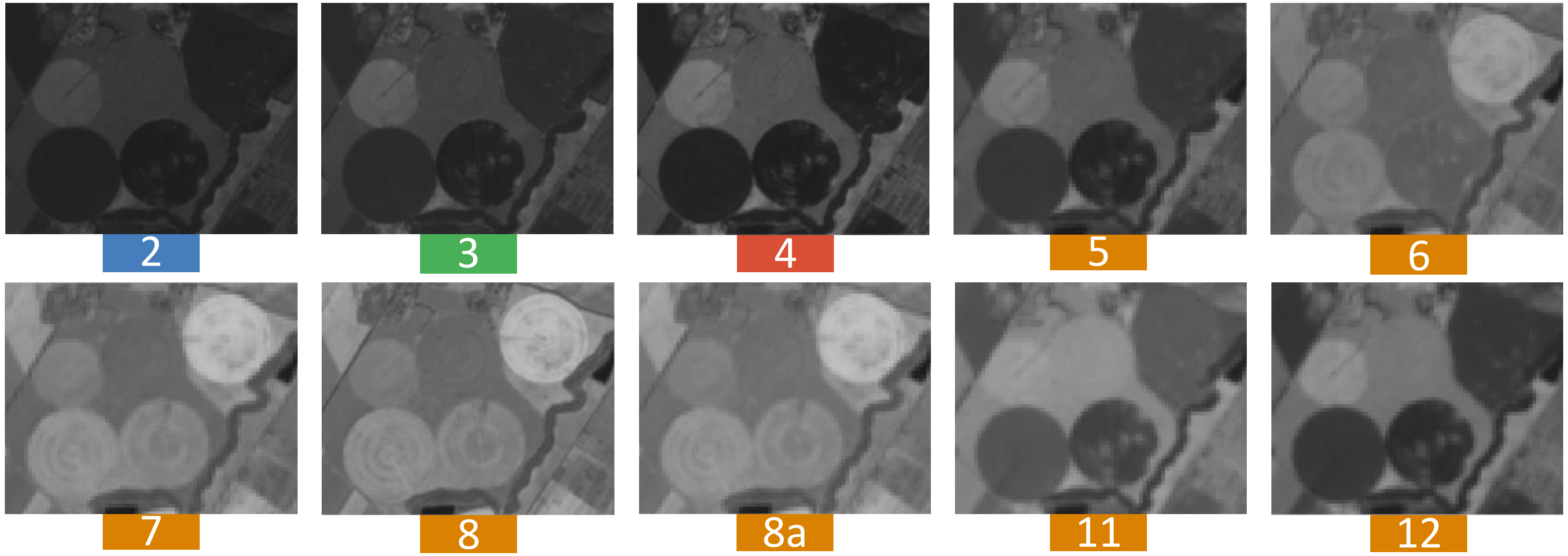
Data acquisition

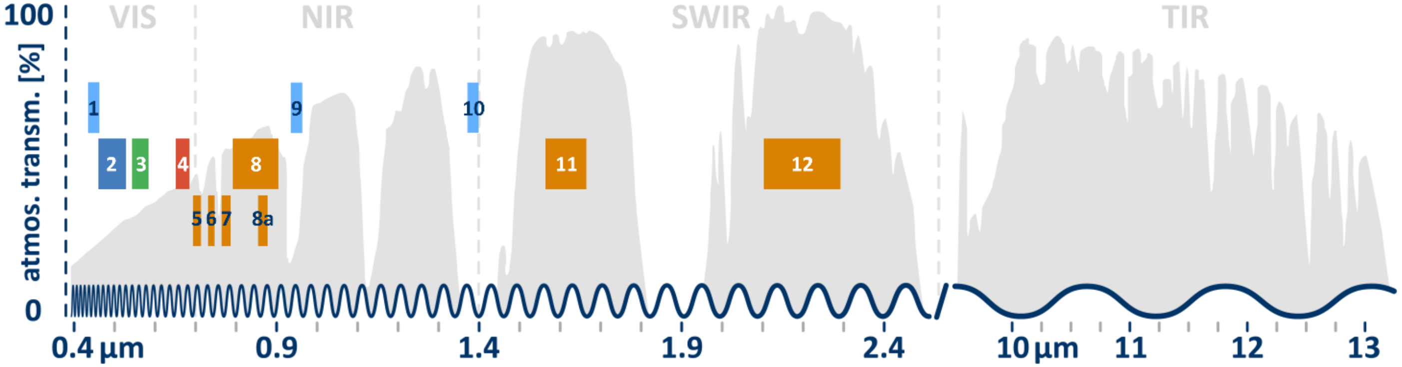
Methodology

IRTA

Data acquisition

BAND	SPECTRAL	WAVELEN. [μm]	GEOM. [m]	SENSOR
1	aerosols	0.429 – 0.457	60	MSI
2	blue	0.451 – 0.539	10	MSI
3	green	0.538 – 0.585	10	MSI
4	red	0.641 – 0.689	10	MSI
5	red edge	0.695 – 0.715	20	MSI
6	red edge	0.731 – 0.749	20	MSI
7	red edge	0.769 – 0.797	20	MSI
8	NIR	0.784 – 0.900	10	MSI
8a	narrow NIR	0.855 – 0.875	20	MSI
9	water vapour	0.935 – 0.955	60	MSI
10	SWIR cirrus	1.365 – 1.385	60	MSI
11	SWIR	1.565 – 1.655	20	MSI
12	SWIR	2.100 – 2.280	20	MSI



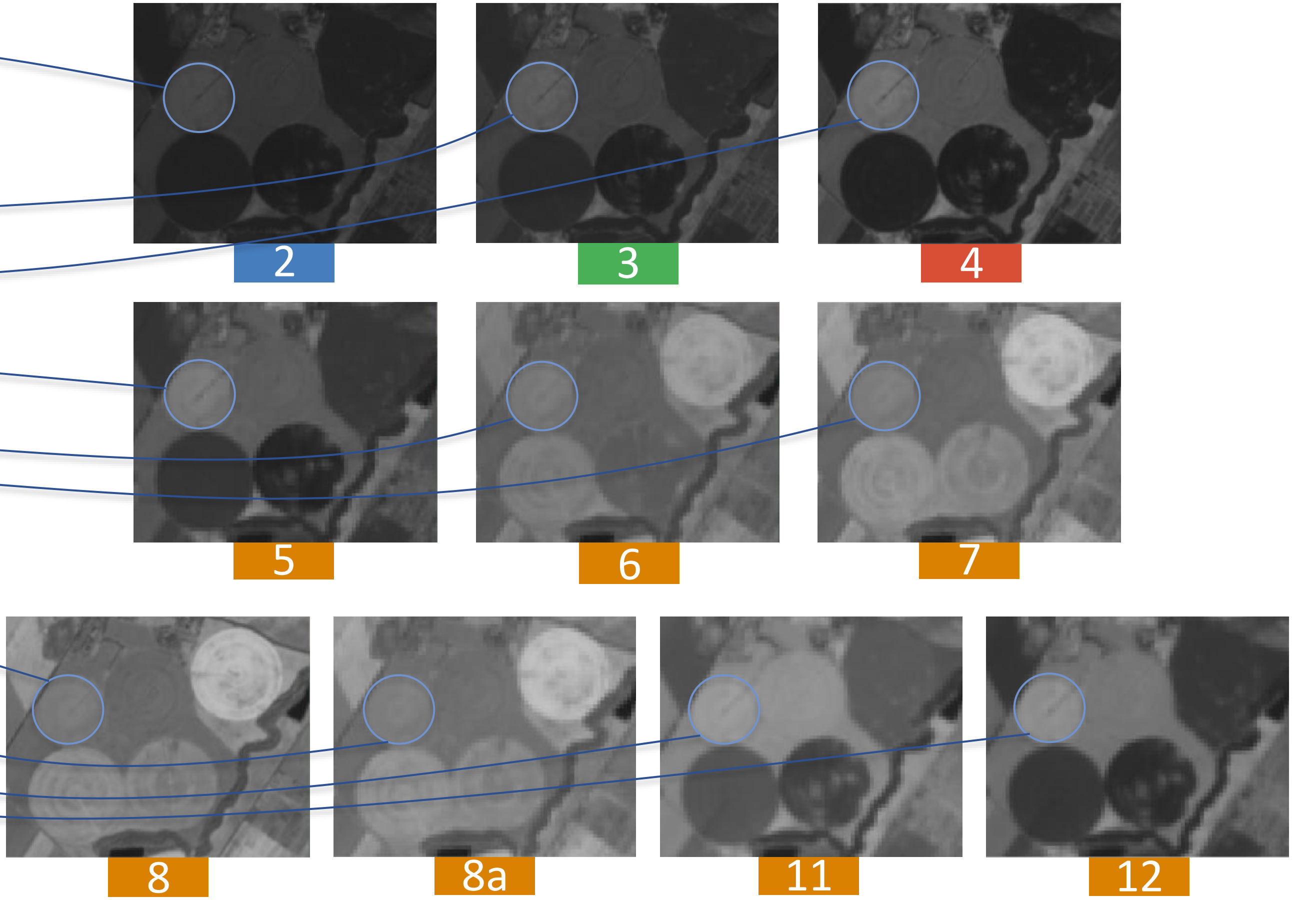


https://blogs.fu-berlin.de/reseda/sentinel-2/

Methodology

Crop spectral response

2	0.27
3	0.35
4	0.43
5	0.46
6	0.47
7	0.49
8	0.48
8a	0.49
11	0.59
12	0.54



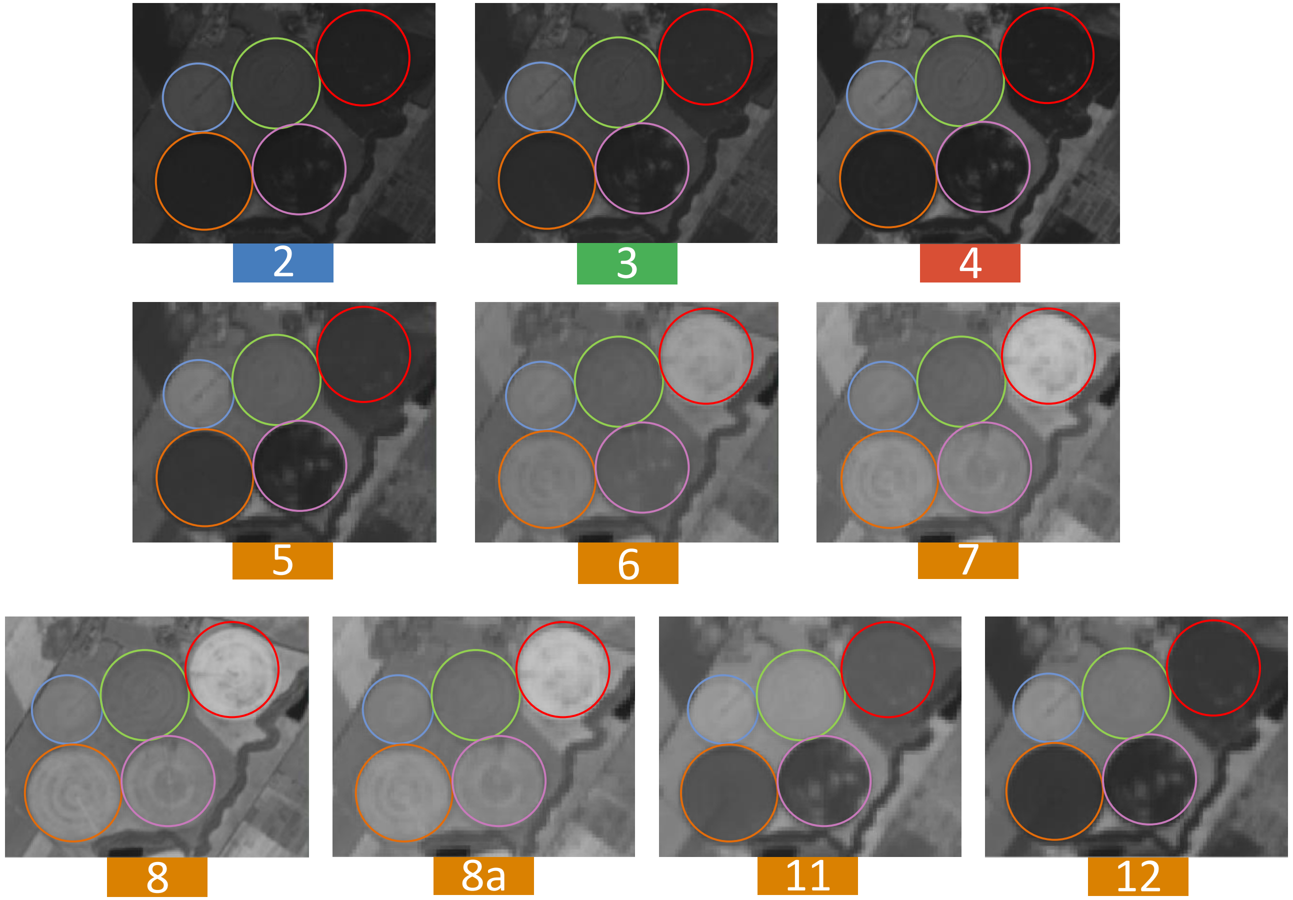
Methodology

IRTA

Crop spectral response

Date: 09/07/2023

2	0.27	0.13	0.13	0.22	0.13
3	0.35	0.17	0.15	0.26	0.17
4	0.43	0.14	0.15	0.32	0.13
5	0.46	0.22	0.15	0.36	0.22
6	0.47	0.48	0.18	0.37	0.59
7	0.49	0.55	0.37	0.40	0.71
8	0.48	0.54	0.51	0.41	0.69
8a	0.49	0.56	0.50	0.44	0.71
11	0.59	0.33	0.31	0.57	0.36
12	0.54	0.22	0.22	0.46	0.22



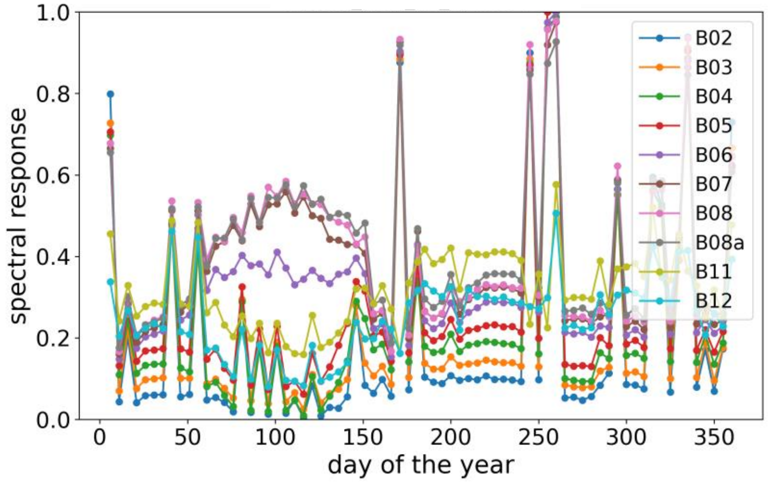
Methodology

IRTA

Full year spectral time series

Temporal Series
Sentinel 2

Band	01/01/2023	04/06/2023	09/07/2023	14/06/2023	31/12/2023
2	0.48	0.34	0.27	0.85	0.31
3	0.47	0.38	0.35	0.82	0.40
4	0.51	0.45	0.43	0.84	0.47
5	0.48	0.48	0.46	0.86	0.44
6	0.45	0.49	0.47	0.89	0.45
7	0.51	0.51	0.49	0.88	0.48
8	0.52	0.52	0.48	0.85	0.51
8a	0.45	0.47	0.49	0.88	0.53
11	0.39	0.60	0.59	0.84	0.57
12	0.34	0.58	0.54	0.87	0.56

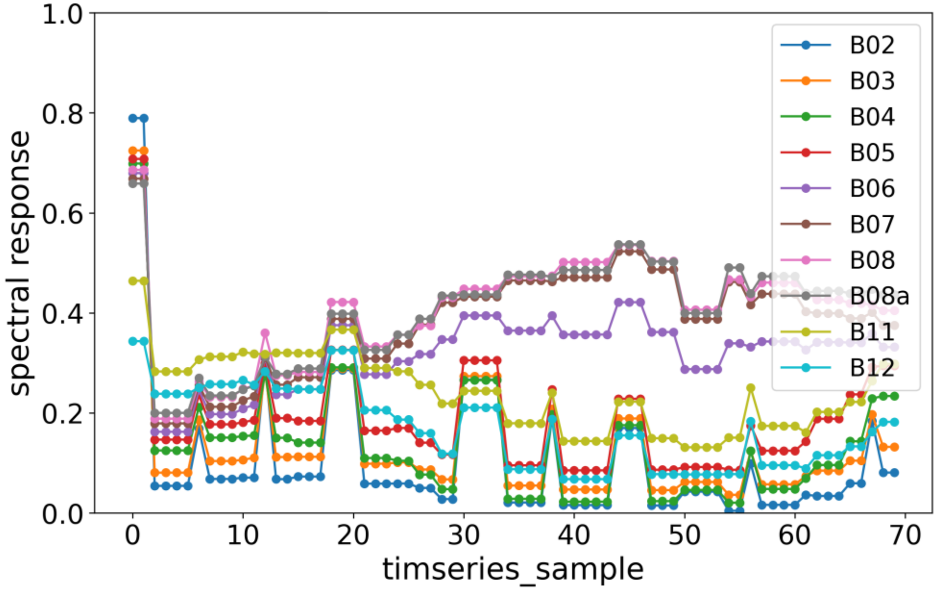


Methodology

Input data organization

Method 1 – Baseline*

column_id	1	2	3	4	5	6		65	66	67	68	69	70
B02 (Blue)	0.79	0.79	0.05	0.05	0.05	0.17	...	0.06	0.06	0.18	0.18	0.08	0.08
B03 (Green)	0.72	0.72	0.08	0.08	0.08	0.19	...	0.10	0.10	0.20	0.20	0.13	0.13
B04 (Red)	0.70	0.70	0.13	0.13	0.13	0.21	...	0.14	0.14	0.23	0.23	0.23	0.23
B05 (Red edge)	0.71	0.71	0.15	0.15	0.15	0.24	...	0.24	0.24	0.29	0.29	0.29	0.29
B06 (Red edge)	0.68	0.68	0.16	0.16	0.16	0.25	...	0.34	0.34	0.36	0.36	0.33	0.33
B07 (Red edge)	0.67	0.67	0.18	0.18	0.18	0.26	...	0.39	0.39	0.40	0.40	0.38	0.38
B08 (NIR)	0.69	0.69	0.19	0.19	0.19	0.26	...	0.42	0.42	0.42	0.42	0.40	0.40
B08a (Narrow NIR)	0.66	0.66	0.20	0.20	0.20	0.27	...	0.44	0.44	0.45	0.45	0.44	0.44
B11 (SWIR)	0.46	0.46	0.28	0.28	0.28	0.31	...	0.22	0.22	0.26	0.26	0.30	0.30
B12 (SWIR)	0.34	0.34	0.24	0.24	0.24	0.25	...	0.13	0.13	0.16	0.16	0.18	0.18
DOY	5	5	10	10	10	15		140	140	145	145	150	150



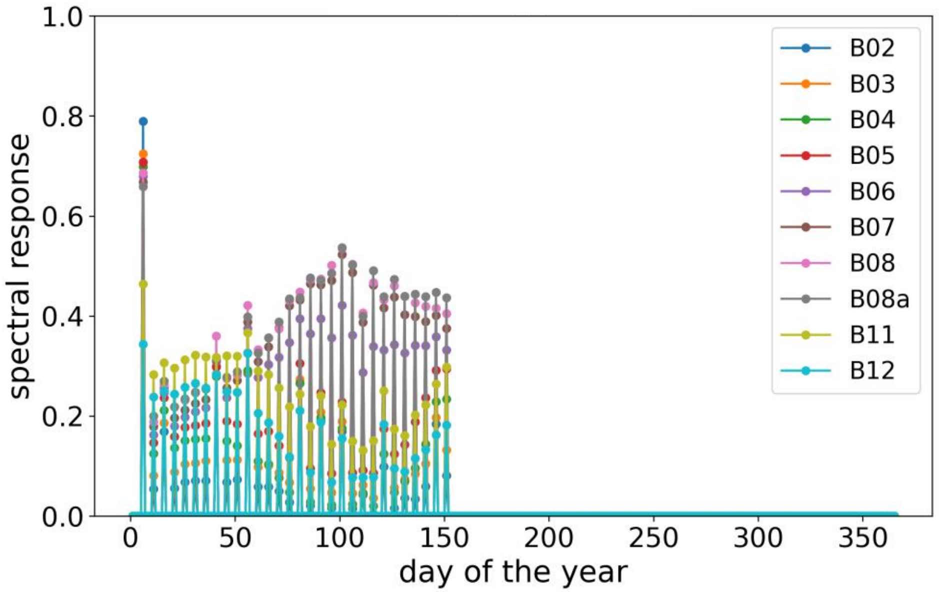
* M. Rußwurm, M. Körner, Self-attention for raw optical Satellite Time Series Classification, *ISPRS Journal of Photogrammetry and Remote Sensing* 169 (2020) 421–435. https://doi.org/10.1016/j.isprsjprs.2020.06.006.

Methodology

Input data organization

Method 2 – Sparse Current Year

column_id	1	2	3	4	5	6	7	8	9	10		143	144	145	146	147	148	149	150	151		365
B02 (Blue)	0	0	0	0	0.79	0	0	0	0	0.05	...	0	0	0.18	0	0	0	0	0.08	0	...	0
B03 (Green)	0	0	0	0	0.72	0	0	0	0	0.08	...	0	0	0.20	0	0	0	0	0.13	0	...	0
B04 (Red)	0	0	0	0	0.70	0	0	0	0	0.13	...	0	0	0.23	0	0	0	0	0.23	0	...	0
B05 (Red edge)	0	0	0	0	0.71	0	0	0	0	0.15	...	0	0	0.29	0	0	0	0	0.29	0	...	0
B06 (Red edge)	0	0	0	0	0.68	0	0	0	0	0.16	...	0	0	0.36	0	0	0	0	0.33	0	...	0
B07 (Red edge)	0	0	0	0	0.67	0	0	0	0	0.18	...	0	0	0.40	0	0	0	0	0.38	0	...	0
B08 (NIR)	0	0	0	0	0.69	0	0	0	0	0.19	...	0	0	0.42	0	0	0	0	0.40	0	...	0
B08a (Narrow NIR)	0	0	0	0	0.66	0	0	0	0	0.20	...	0	0	0.45	0	0	0	0	0.44	0	...	0
B11 (SWIR)	0	0	0	0	0.46	0	0	0	0	0.28	...	0	0	0.26	0	0	0	0	0.30	0	...	0
B12 (SWIR)	0	0	0	0	0.34	0	0	0	0	0.24	...	0	0	0.16	0	0	0	0	0.18	0	...	0
DOY	1	2	3	4	5	6	7	8	9	10		143	144	145	146	147	148	149	150	151		365

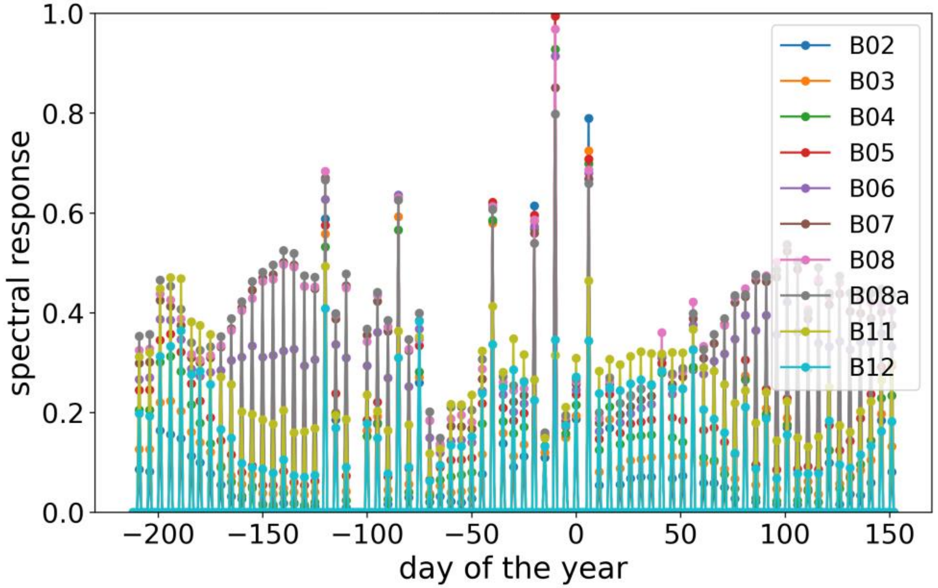


Methodology

Input data organization

Method 3 – Sparse Multi-Year

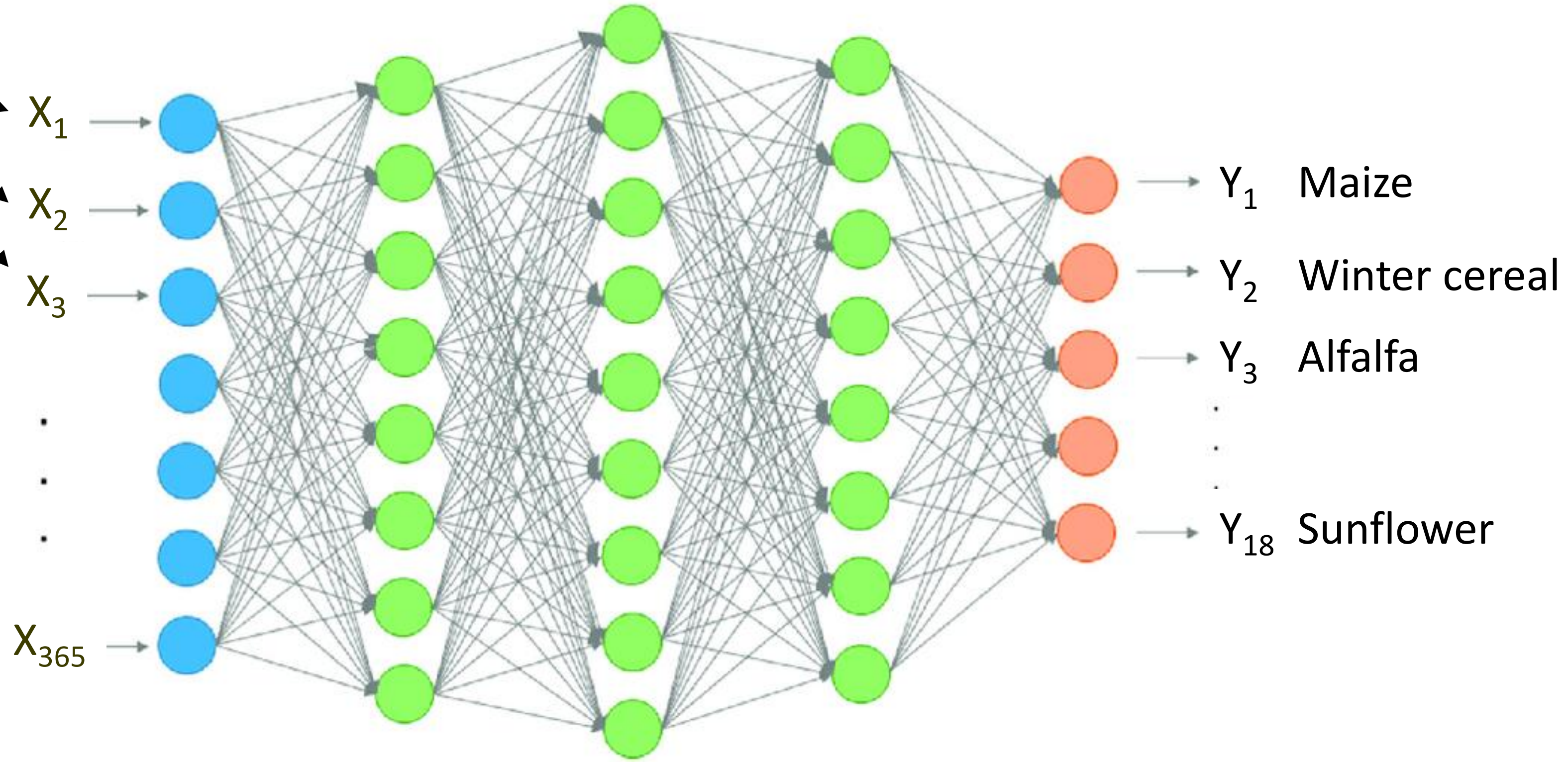
column_id	1	2	3	4	5	6	7	8	9		220	221	222	223	224	225		360	361	362	363	364	365
B02 (Blue)	0	0	0	0.09	0	0	0	0	0.08	...	0.79	0	0	0	0	0.05	...	0.18	0	0	0	0	0.08
B03 (Green)	0	0	0	0.13	0	0	0	0	0.13	...	0.72	0	0	0	0	0.08	...	0.20	0	0	0	0	0.13
B04 (Red)	0	0	0	0.21	0	0	0	0	0.20	...	0.70	0	0	0	0	0.13	...	0.23	0	0	0	0	0.23
B05 (Red edge)	0	0	0	0.24	0	0	0	0	0.25	...	0.71	0	0	0	0	0.15	...	0.29	0	0	0	0	0.29
B06 (Red edge)	0	0	0	0.27	0	0	0	0	0.27	...	0.68	0	0	0	0	0.16	...	0.36	0	0	0	0	0.33
B07 (Red edge)	0	0	0	0.30	0	0	0	0	0.30	...	0.67	0	0	0	0	0.18	...	0.40	0	0	0	0	0.38
B08 (NIR)	0	0	0	0.33	0	0	0	0	0.33	...	0.69	0	0	0	0	0.19	...	0.42	0	0	0	0	0.40
B08a (Narrow NIR)	0	0	0	0.35	0	0	0	0	0.36	...	0.66	0	0	0	0	0.20	...	0.45	0	0	0	0	0.44
B11 (SWIR)	0	0	0	0.31	0	0	0	0	0.32	...	0.46	0	0	0	0	0.28	...	0.26	0	0	0	0	0.30
B12 (SWIR)	0	0	0	0.20	0	0	0	0	0.19	...	0.34	0	0	0	0	0.24	...	0.16	0	0	0	0	0.18
DOY	-213	-212	-211	-210	-209	-208	-207	-206	-205	4	5	6	7	8	9	10	144	145	146	147	148	149	150



Methodology

Algorithm

column_id	1	2	3	4	5	6	7	8	9		220	221	222	223	224	225		360	361	362	363	364	365
B02 (Blue)	0	0	0	0.09	0	0	0	0	0.08	...	0.79	0	0	0	0	0.05	...	0.18	0	0	0	0	0.08
B03 (Green)	0	0	0	0.13	0	0	0	0	0.13	...	0.72	0	0	0	0	0.08	...	0.20	0	0	0	0	0.13
B04 (Red)	0	0	0	0.21	0	0	0	0	0.20	...	0.70	0	0	0	0	0.13	...	0.23	0	0	0	0	0.23
B05 (Red edge)	0	0	0	0.24	0	0	0	0	0.25	...	0.71	0	0	0	0	0.15	...	0.29	0	0	0	0	0.29
B06 (Red edge)	0	0	0	0.27	0	0	0	0	0.27	...	0.68	0	0	0	0	0.16	...	0.36	0	0	0	0	0.33
B07 (Red edge)	0	0	0	0.30	0	0	0	0	0.30	...	0.67	0	0	0	0	0.18	...	0.40	0	0	0	0	0.38
B08 (NIR)	0	0	0	0.33	0	0	0	0	0.33	...	0.69	0	0	0	0	0.19	...	0.42	0	0	0	0	0.40
B08a (Narrow NIR)	0	0	0	0.35	0	0	0	0	0.36	...	0.66	0	0	0	0	0.20	...	0.45	0	0	0	0	0.44
B11 (SWIR)	0	0	0	0.31	0	0	0	0	0.32	...	0.46	0	0	0	0	0.28	...	0.26	0	0	0	0	0.30
B12 (SWIR)	0	0	0	0.20	0	0	0	0	0.19	...	0.34	0	0	0	0	0.24	...	0.16	0	0	0	0	0.18
DOY	-213	-212	-211	-210	-209	-208	-207	-206	-205	4	5	6	7	8	9	10	144	145	146	147	148	149	150



- Random Forest
- MSResNet
- TempCNN
- OmniScaleCNN

CNN

- StarRNN
- LSTM

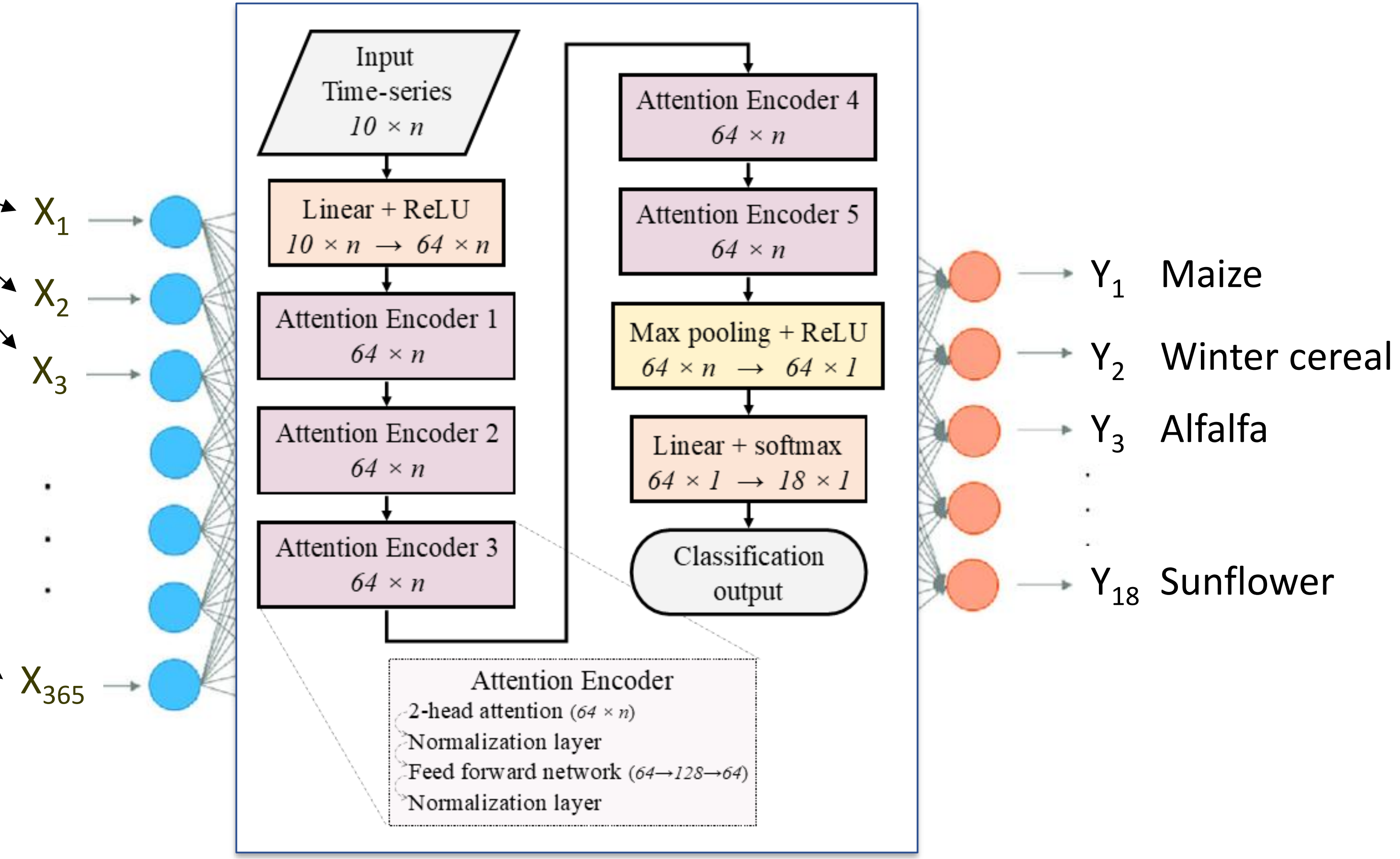
RNN

- Transformer

Methodology

Algorithm

column_id	1	2	3	4	5	6	7	8	9		220	221	222	223	224	225		360	361	362	363	364	365
B02 (Blue)	0	0	0	0.09	0	0	0	0	0.08	...	0.79	0	0	0	0	0.05	...	0.18	0	0	0	0	0.08
B03 (Green)	0	0	0	0.13	0	0	0	0	0.13	...	0.72	0	0	0	0	0.08	...	0.20	0	0	0	0	0.13
B04 (Red)	0	0	0	0.21	0	0	0	0	0.20	...	0.70	0	0	0	0	0.13	...	0.23	0	0	0	0	0.23
B05 (Red edge)	0	0	0	0.24	0	0	0	0	0.25	...	0.71	0	0	0	0	0.15	...	0.29	0	0	0	0	0.29
B06 (Red edge)	0	0	0	0.27	0	0	0	0	0.27	...	0.68	0	0	0	0	0.16	...	0.36	0	0	0	0	0.33
B07 (Red edge)	0	0	0	0.30	0	0	0	0	0.30	...	0.67	0	0	0	0	0.18	...	0.40	0	0	0	0	0.38
B08 (NIR)	0	0	0	0.33	0	0	0	0	0.33	...	0.69	0	0	0	0	0.19	...	0.42	0	0	0	0	0.40
B08a (Narrow NIR)	0	0	0	0.35	0	0	0	0	0.36	...	0.66	0	0	0	0	0.20	...	0.45	0	0	0	0	0.44
B11 (SWIR)	0	0	0	0.31	0	0	0	0	0.32	...	0.46	0	0	0	0	0.28	...	0.26	0	0	0	0	0.30
B12 (SWIR)	0	0	0	0.20	0	0	0	0	0.19	...	0.34	0	0	0	0	0.24	...	0.16	0	0	0	0	0.18
DOY	-213	-212	-211	-210	-209	-208	-207	-206	-205	4	5	6	7	8	9	10	144	145	146	147	148	149	150



- Random Forest
- MSResNet
- TempCNN
- OmniScaleCNN

CNN

- StarRNN
- LSTM

RNN

- Transformer

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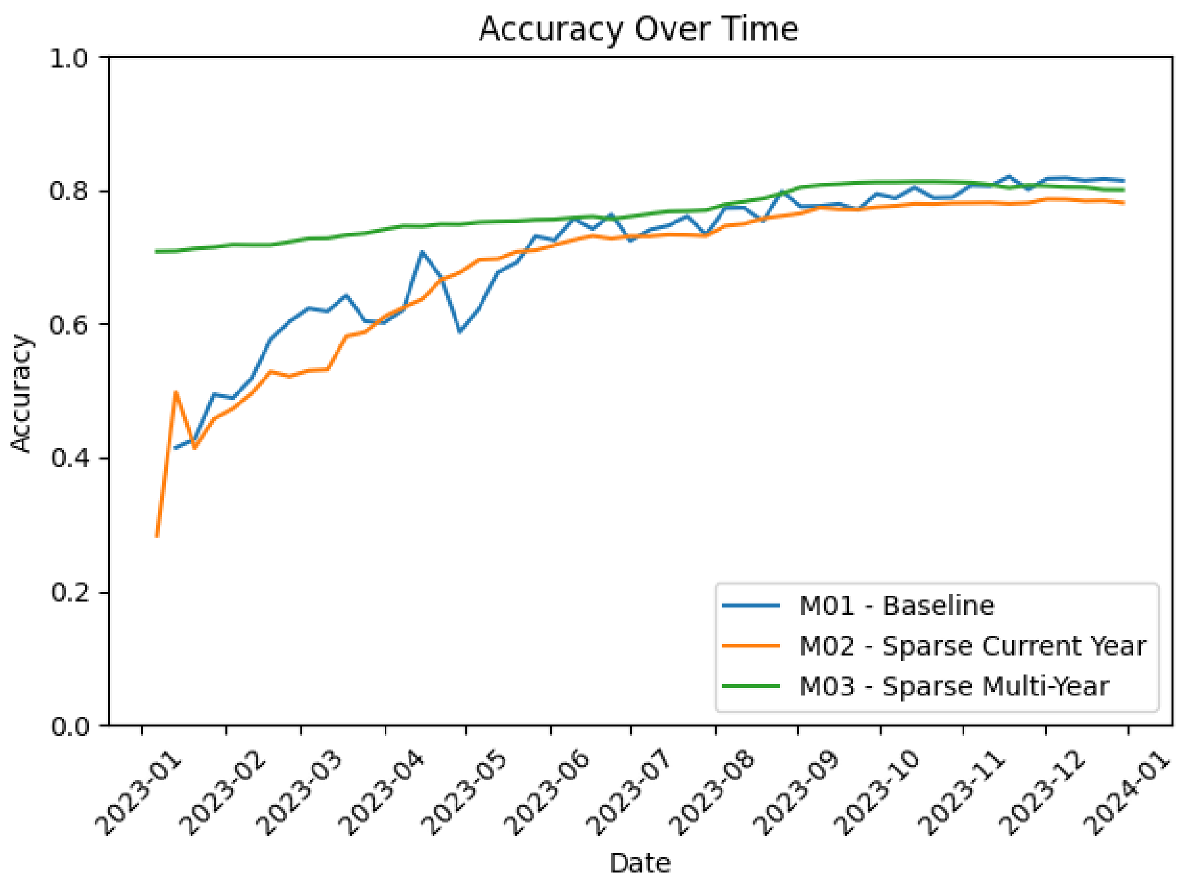
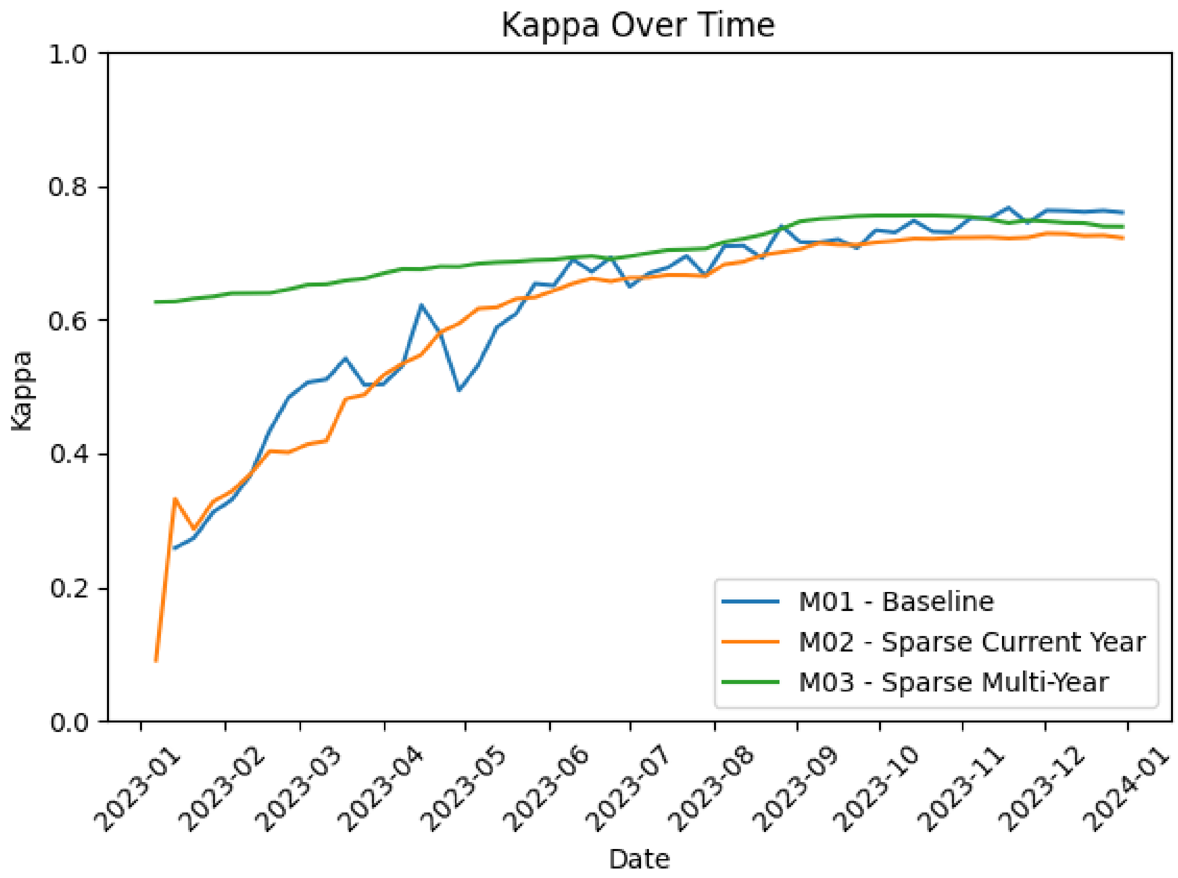
Results

Overall accuracy over time





Results

IRTA

Intra-class evaluation

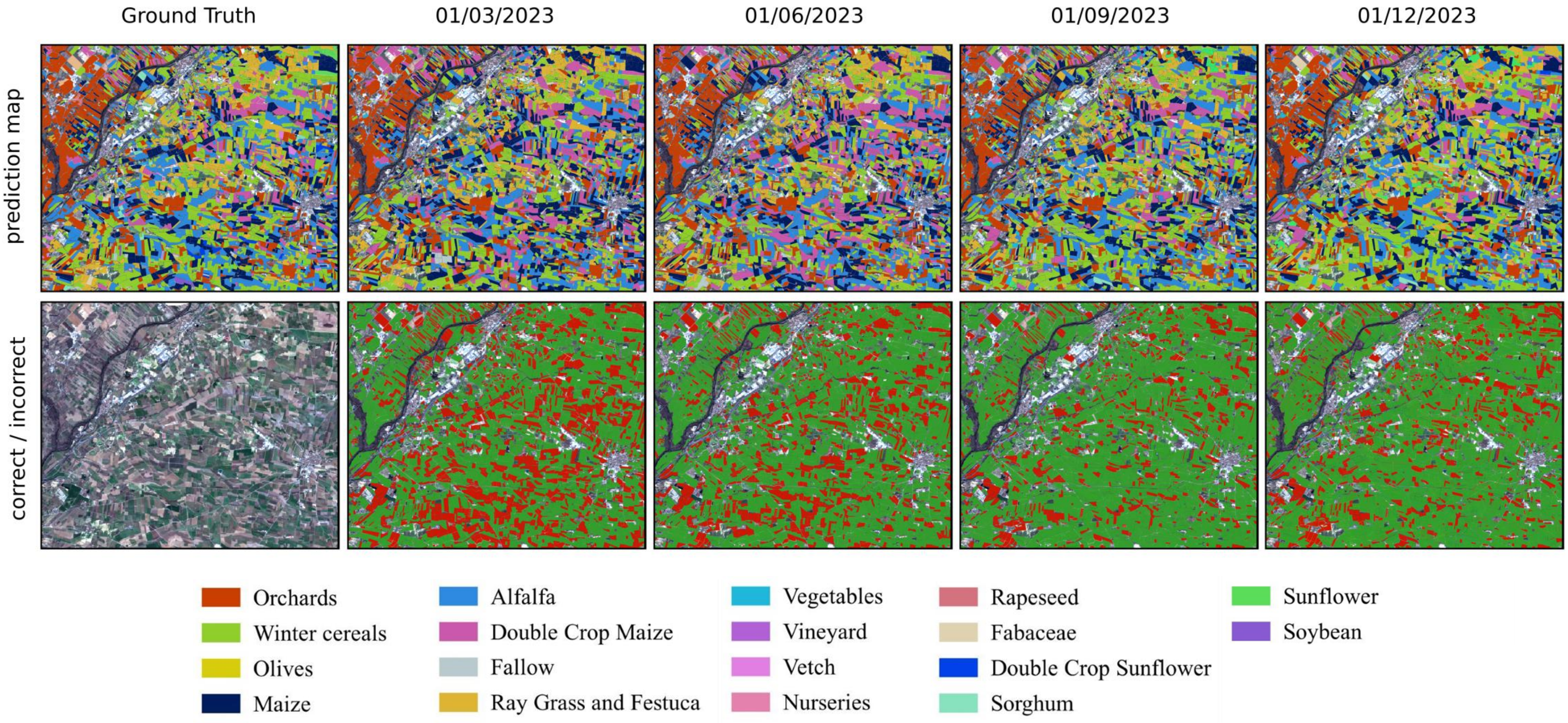
	% of samples	F1-score 03/23	06/23	09/23	12/23
Orchards	39.76	0.71	0.72	0.65	0.61
Winter cereals	15.9	0.41	0.56	0.57	0.56
Olives	11.49	0.8	0.72	0.72	0.67
Maize	9.55	0.39	0.57	0.9	0.89
Alfalfa	5.87	0.71	0.83	0.86	0.88
Double Crop Maize	4.73	0.59	0.64	0.81	0.88
Fallow	4.61	0.06	0.16	0.29	0.38
Ray Grass and Festuca	2.75	0.65	0.85	0.72	0.67
Vegetables	2.57	0.68	0.54	0.48	0.45
Vineyard	1.5	0.88	0.79	0.71	0.62
Vetch	0.29	0	0	0.55	0
Nurseries	0.23	0.18	0.1	0.19	0.1
Rapeseed	0.21	0.84	0.86	0.82	0.69
Fabaceae	0.2	0	0	0.5	0
Double Crop Sunflower	0.18	0.03	0.03	0.23	0.32
Sorghum	0.06	0	0	0.1	0.06
Sunflower	0.06	0	0	0.14	0.07
Soybean	0.04	0	0	0	0

CM at 01/09/2023

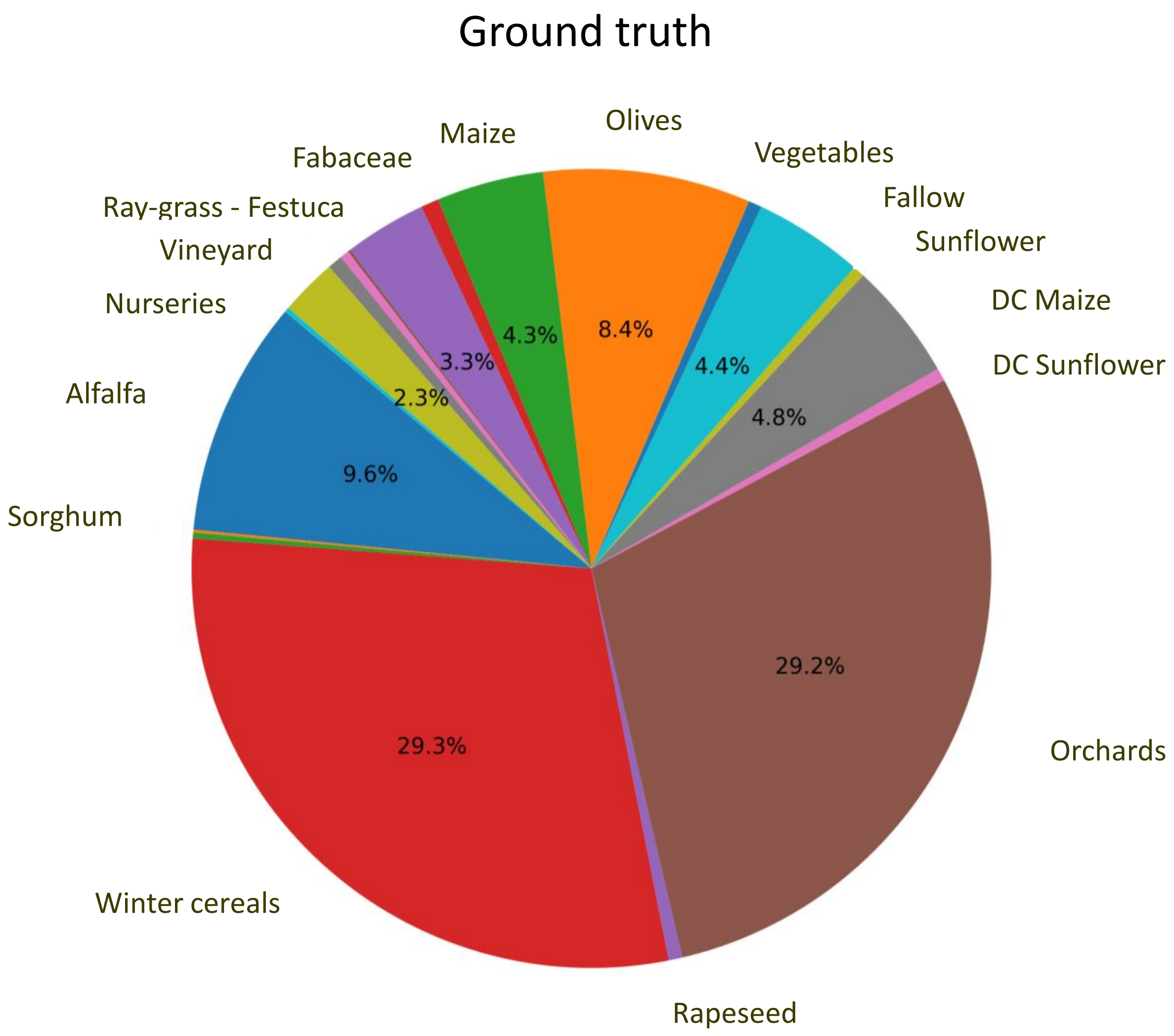
Actual \ Predicted	Orchards	Winter cereals	Olives	Maize	Alfalfa	Double Crop Maize	Fallow	Ray Grass and Festuca	Vegetables	Vineyard	Vetch	Nurseries	Rapeseed	Fabaceae	Double Crop Sunflower	Sorghum	Sunflower	Soybean
Orchards	0.89	0.01	0.05	0.00	0.00	0.00	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Winter cereals	0.02	0.86	0.00	0.01	0.01	0.06	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Olives	0.07	0.00	0.89	0.00	0.00	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Maize	0.02	0.06	0.00	0.80	0.01	0.04	0.05	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Alfalfa	0.06	0.02	0.00	0.01	0.84	0.00	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Double Crop Maize	0.01	0.28	0.00	0.04	0.00	0.63	0.00	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Fallow	0.20	0.10	0.05	0.09	0.01	0.00	0.45	0.01	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Ray Grass and Festuca	0.13	0.08	0.01	0.01	0.04	0.03	0.03	0.65	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Vegetables	0.18	0.08	0.07	0.00	0.03	0.02	0.13	0.01	0.43	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Vineyard	0.35	0.00	0.05	0.00	0.00	0.00	0.04	0.00	0.10	0.46	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Vetch	0.08	0.50	0.00	0.01	0.01	0.10	0.05	0.13	0.03	0.00	0.07	0.00	0.01	0.00	0.00	0.02	0.00	0.00
Nurseries	0.48	0.04	0.09	0.01	0.02	0.00	0.09	0.01	0.23	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00
Rapeseed	0.02	0.11	0.00	0.00	0.01	0.02	0.04	0.02	0.07	0.00	0.00	0.00	0.69	0.00	0.01	0.00	0.00	0.00
Fabaceae	0.09	0.44	0.00	0.03	0.02	0.09	0.10	0.02	0.04	0.00	0.03	0.00	0.01	0.10	0.00	0.02	0.00	0.00
Double Crop Sunflower	0.00	0.65	0.00	0.02	0.03	0.15	0.02	0.00	0.05	0.00	0.00	0.00	0.01	0.00	0.07	0.01	0.00	0.00
Sorghum	0.05	0.18	0.00	0.18	0.03	0.04	0.07	0.10	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00
Sunflower	0.06	0.09	0.00	0.08	0.13	0.01	0.20	0.02	0.36	0.00	0.01	0.00	0.00	0.00	0.00	0.02	0.02	0.00
Soybean	0.09	0.19	0.01	0.16	0.05	0.02	0.17	0.02	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.01	0.00

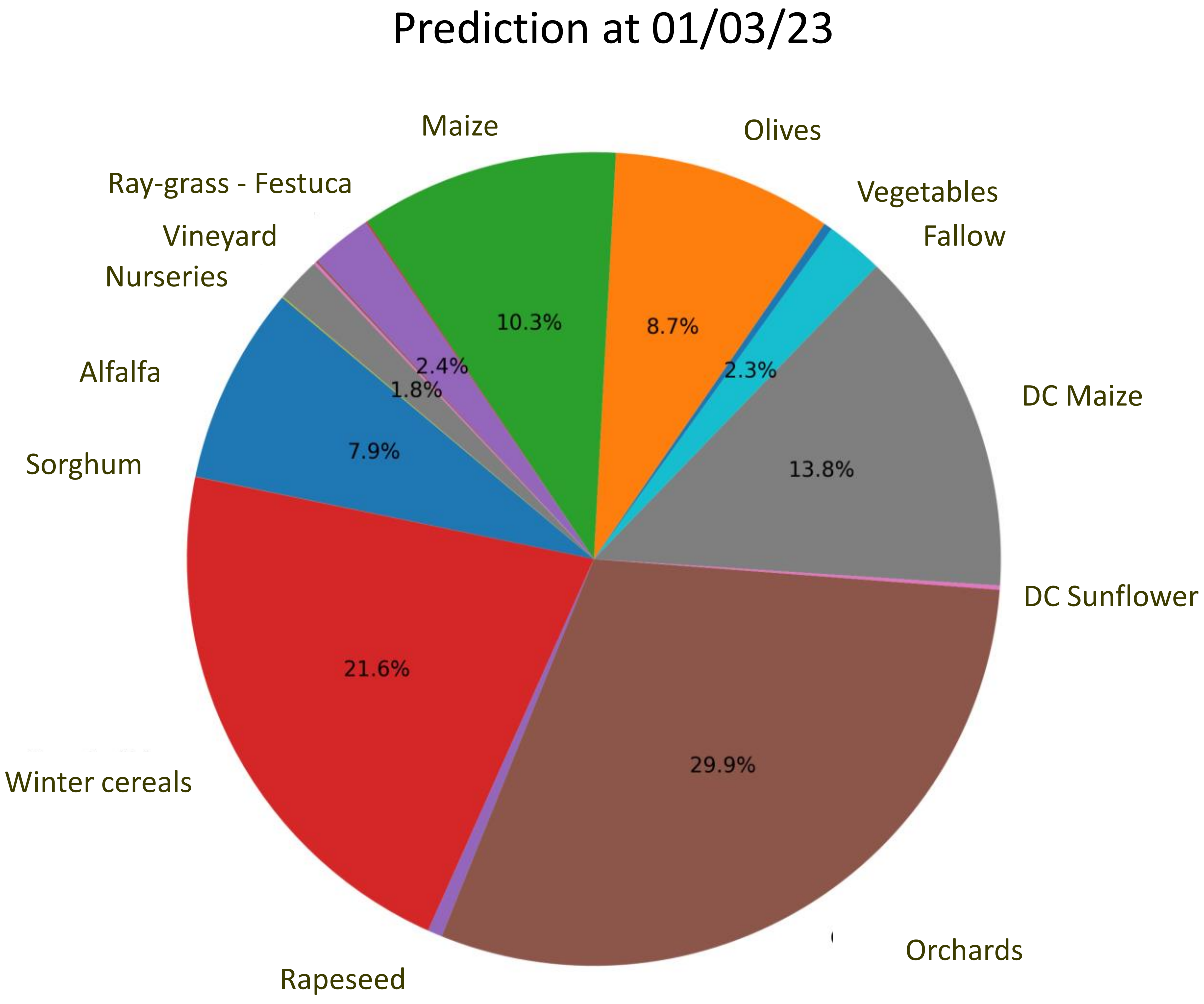
Results

Qualitative results



Results

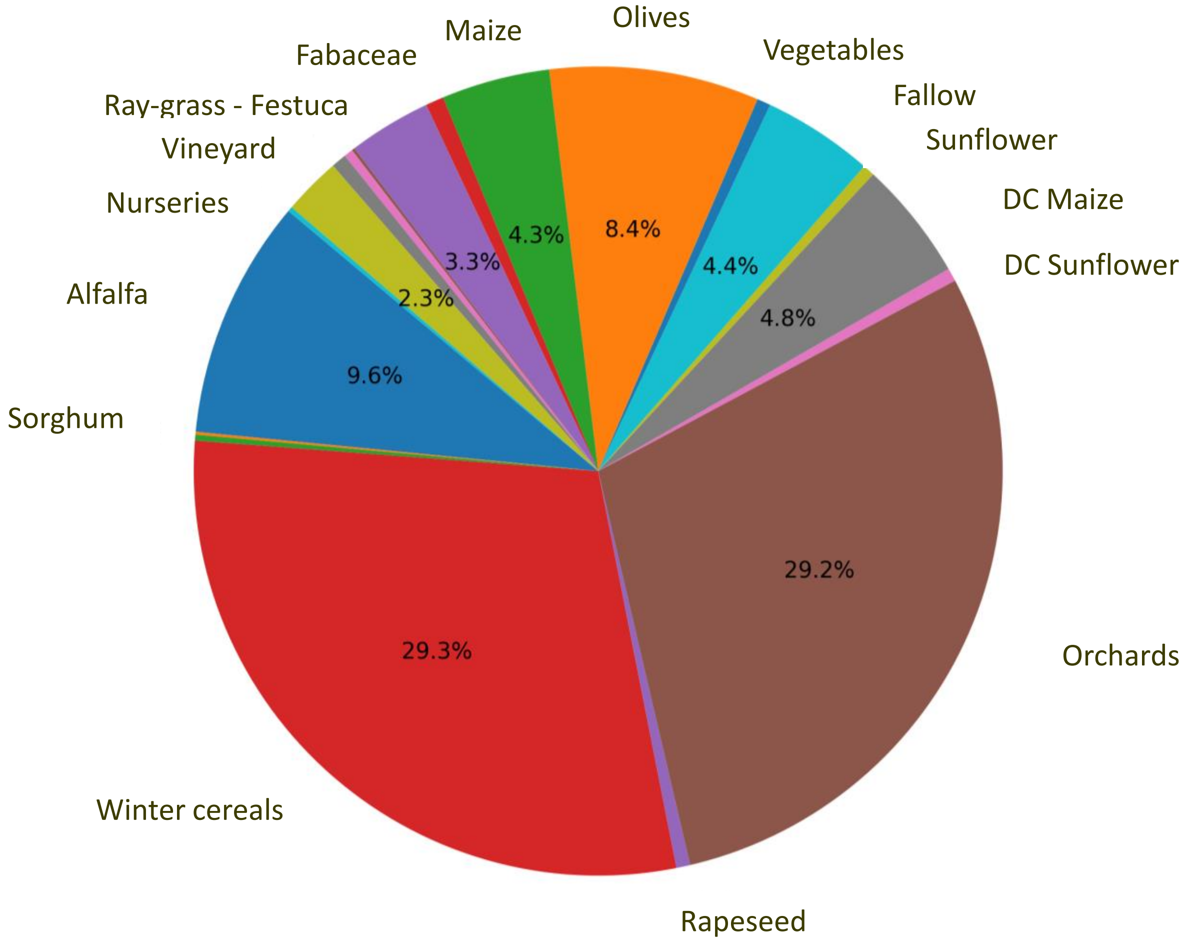

Ground truth
Maize
Olives
Fabaceae
Vegetables
Ray-grass - Festuca
Fallow
Vineyard
Sunflower
Nurseries
DC Maize
DC Sunflower
Alfalfa
Sorghum
Orchards
Winter cereals
Rapeseed
4.3%
8.4%
3.3%
4.4%
2.3%
4.8%
9.6%
29.2%
29.3%


Prediction at 01/03/23
Maize
Olives
Ray-grass - Festuca
Vegetables
Vineyard
Fallow
Nurseries
Alfalfa
DC Maize
Sorghum
DC Sunflower
Winter cereals
Orchards
Rapeseed
10.3%
8.7%
2.4%
1.8%
2.3%
7.9%
13.8%
21.6%
29.9%

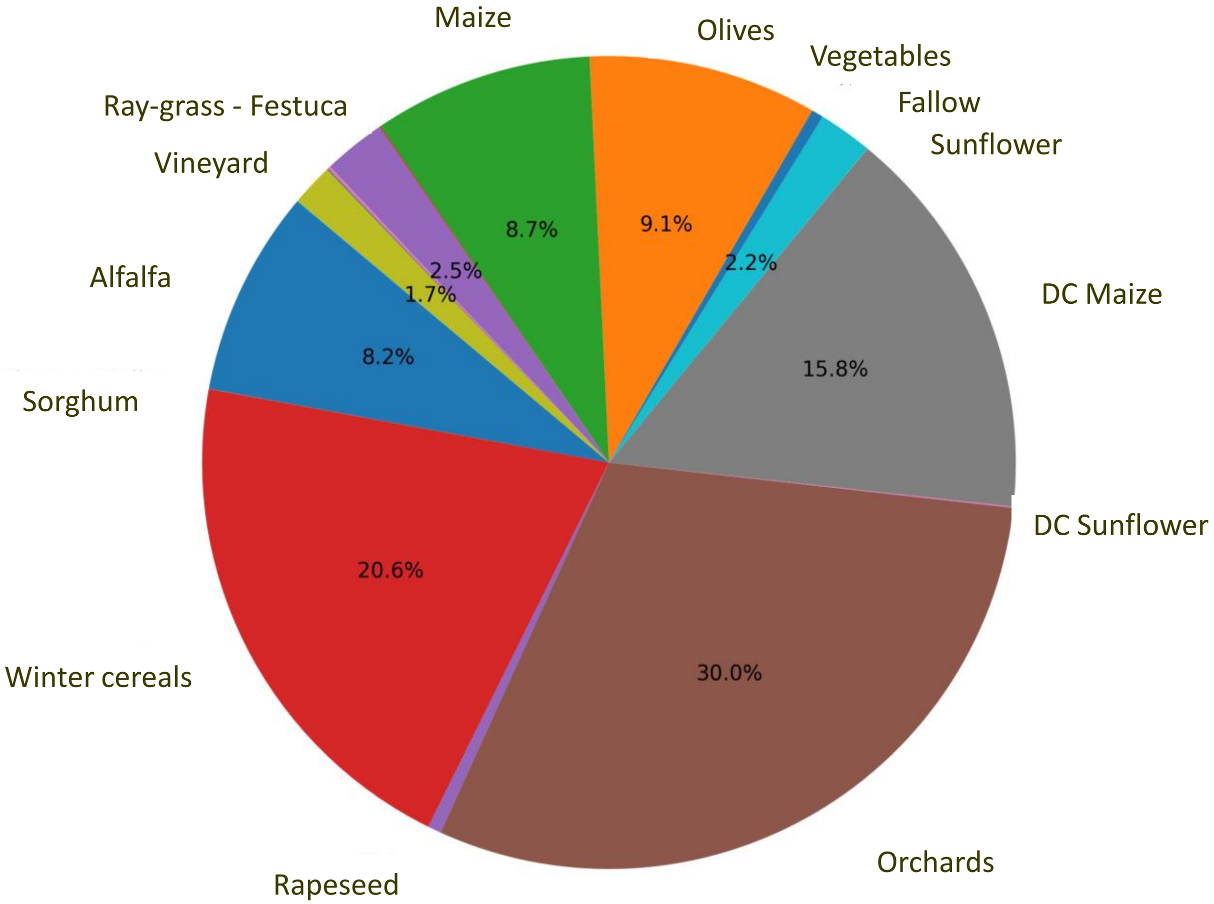
Results

IRTA

Ground truth

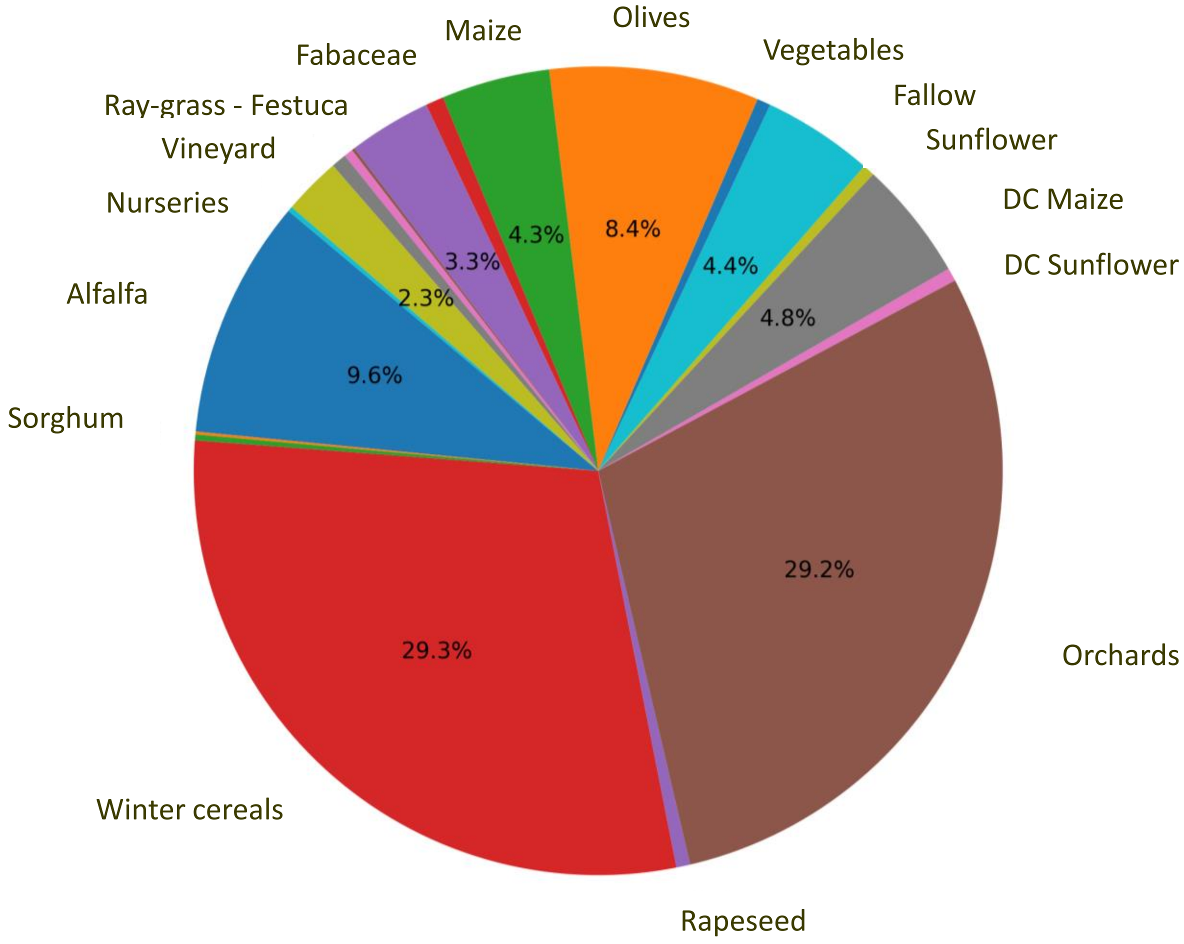


Prediction at 01/06/23

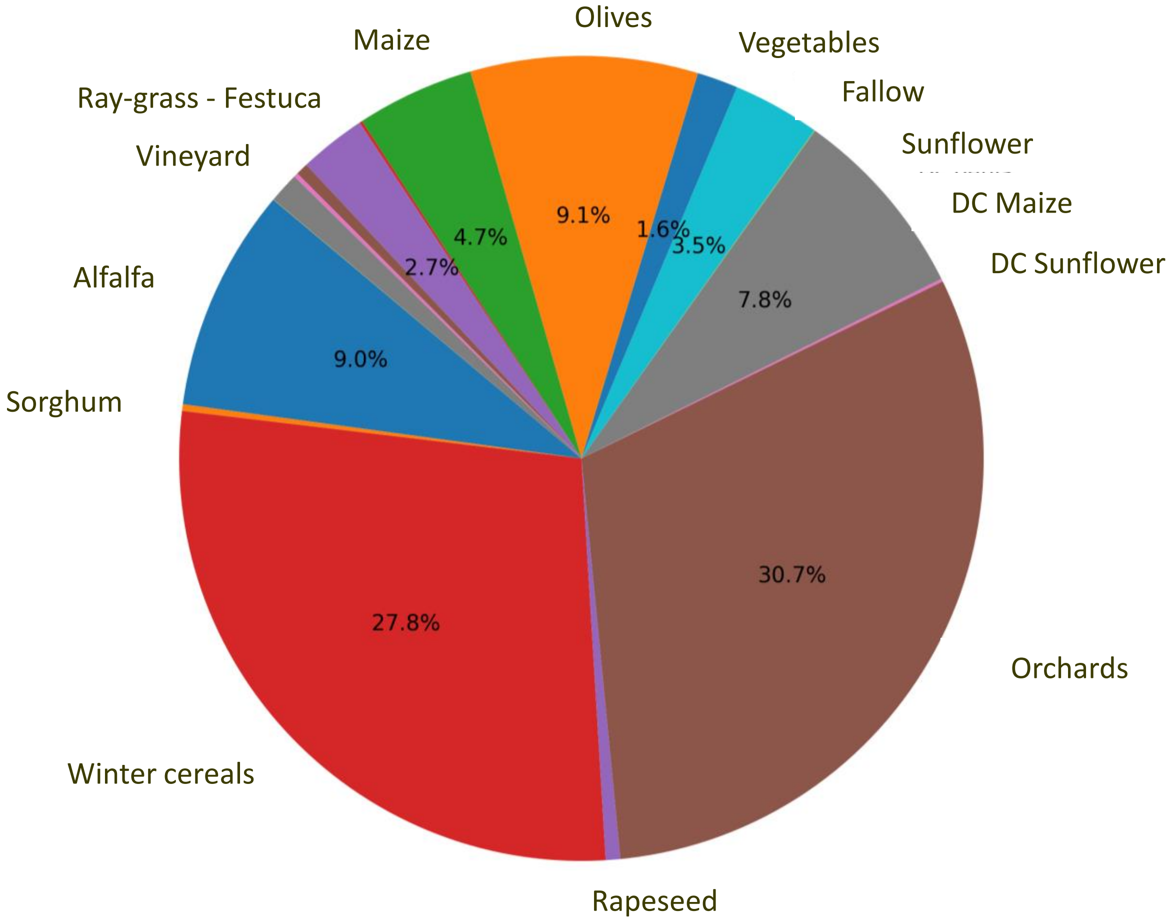


Results

Ground truth

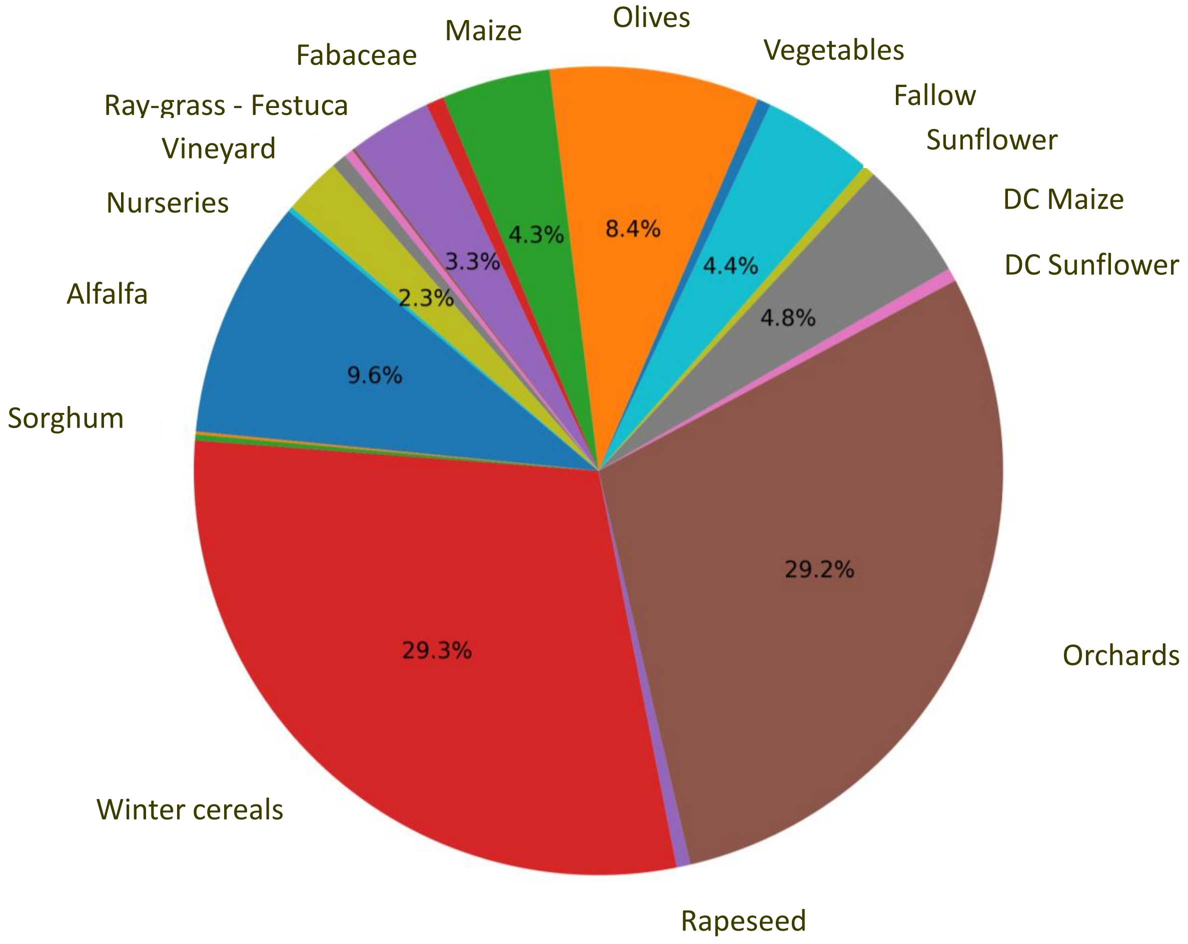


Prediction at 01/09/23

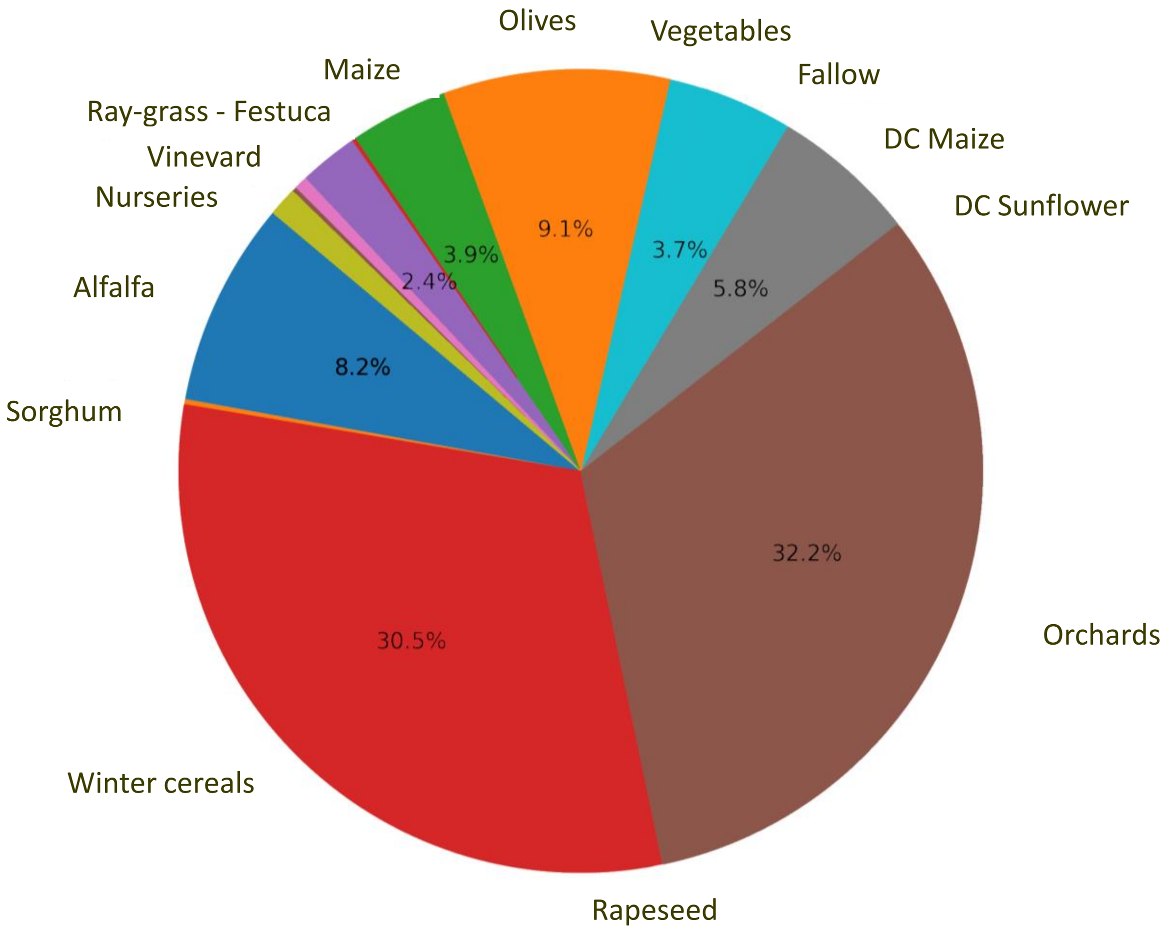


Results

Ground truth



Prediction at 01/12/23



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Conclusions

- The study successfully demonstrated the **effectiveness of spectral time-series from satellite images for crop type classification** using **transformer encoder architectures**.
- Using spectral **data from the previous year** improved the classification performance at early stages.
- **Single-model training** approach (used in M02 and M03) showed **more stable** and less noisy performance compared to incremental learning (M01).
- Classification **accuracy increased progressively throughout the year**, starting at 0.70 and reaching 0.81.
- The study highlights the persistent **challenge of classifying underrepresented crop classes**, where performance remains low due to imbalanced datasets.
- **Future research** should focus on improving classification for these underrepresented crops and explore the integration of additional data sources, such as weather and soil data, to enhance model accuracy and robustness.

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Thank you for your attention!

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