COMPASS INFORMATICS
TRACSIS
Information and Location Insights

Grazing detection in Ireland

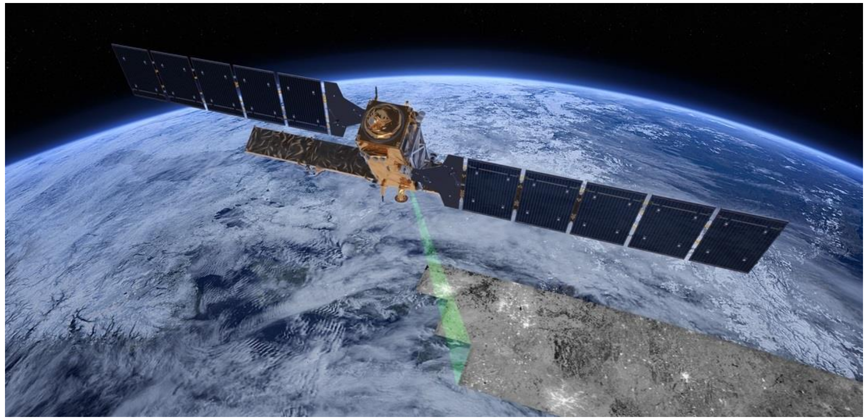
A study using Deep Learning and Sentinel-1 time series

07 / 09 / 2023

Adriaan Keurhorst – Earth Observation Specialist - HubCAP

Context – Sentinel-1 and Sentinel-2

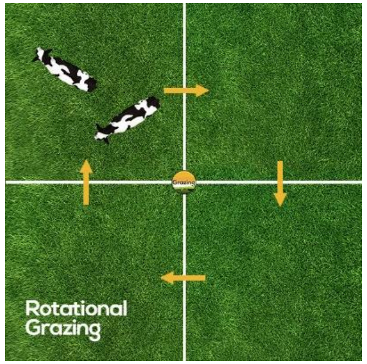
- Sentinel-1
  - A pair of radar satellites – Sentinel-1A and Sentinel-1B
  - Revisit time of 6 days
  - Spatial resolution of 10 metres
  - Advantage – can see through clouds
- Sentinel-2
  - A pair of optical satellites – Sentinel-2A and Sentinel-2B
  - Revisit time of 5 days
  - Maximum spatial resolution of 10 metres
  - Advantage – lots of information stored in the spectral bands

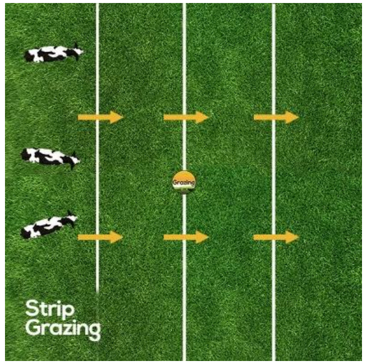


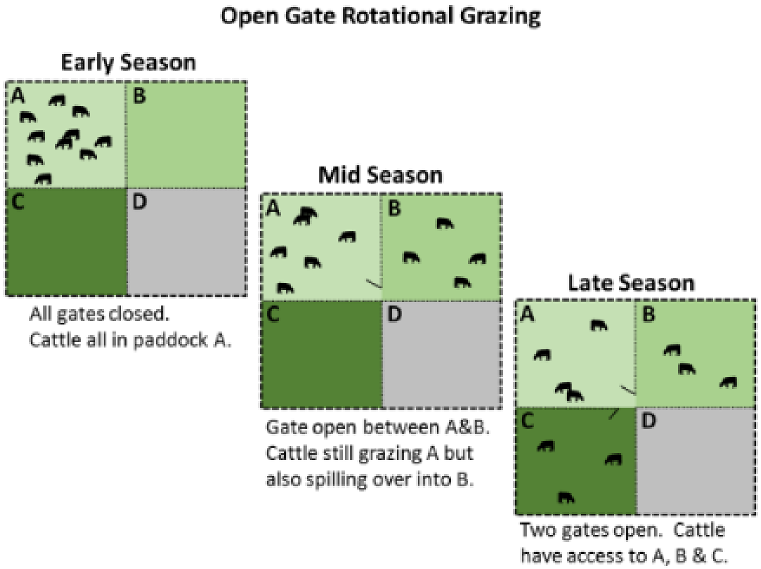
https://sentinels.copernicus.eu/web/sentinel/missions

Context – Grazing

- Intensive grazing vs. extensive grazing







Presentation structure

1. Problem statement
2. Data and methodology
3. Model design
4. Output
5. Results and statistics
6. Improvements

Problem statement – Has parcel X been grazed over the past year?

- Detect grazing using Sentinel-1
- Why Sentinel-1?
- Literature suggests coherence and backscatter data have potential
  - VV Coherence increases after grazing event
  - Backscatter increases after grazing event
- Challenges
  - Grazing is notoriously difficult to detect using Sentinel-1
    - Signal too noisy
  - Solution? Deep learning

Data

- Open-source platforms
  - Python
  - QGIS
  - Sen4CAP

- Signals – Open source
  - Sentinel-1 time-series

- Labels
  - Daily grazing observations

Signals – how to retrieve them?

- Sen4CAP – European Space Agency project to provide stakeholders with Sentinel-1 and Sentinel-2 derived information
- Open source
- Upload shapefiles of parcels
- Get a time-series for a given parcel
    - VV Coherence, VV Backscatter and VH backscatter

sen4cap
common agricultural policy

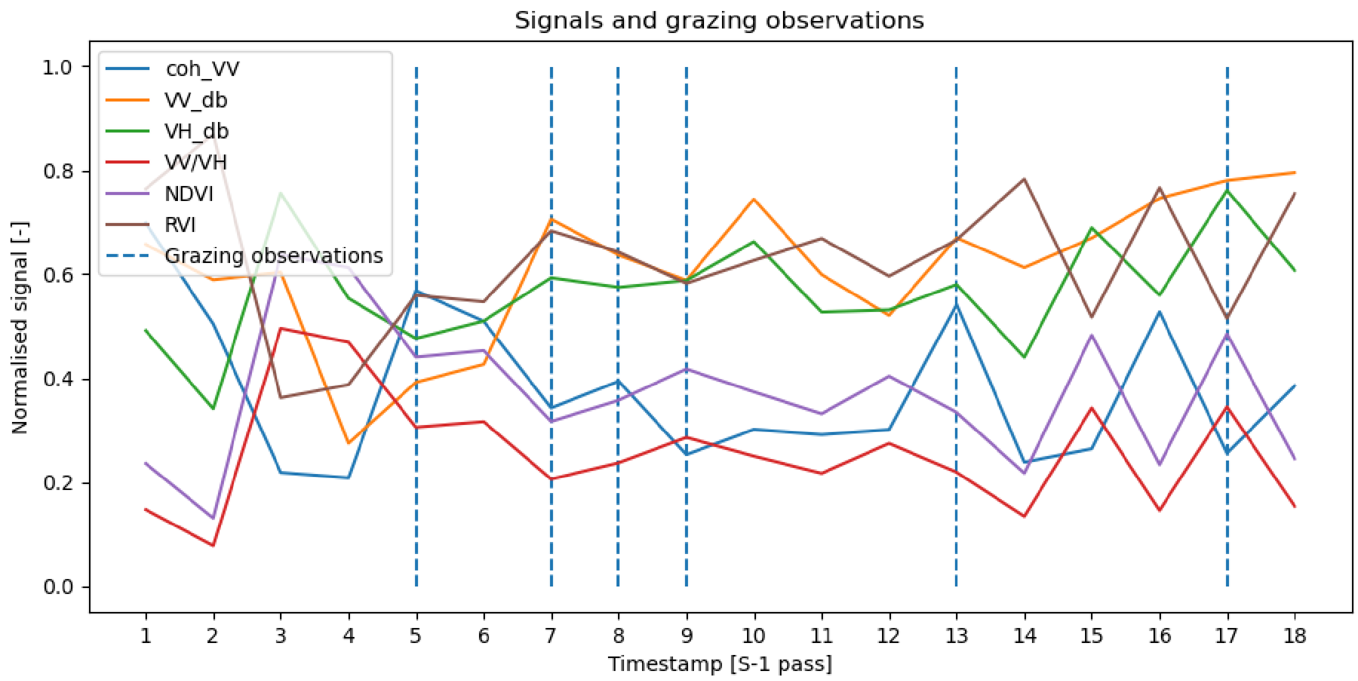
Signal and label data used

<u>Signal data</u>

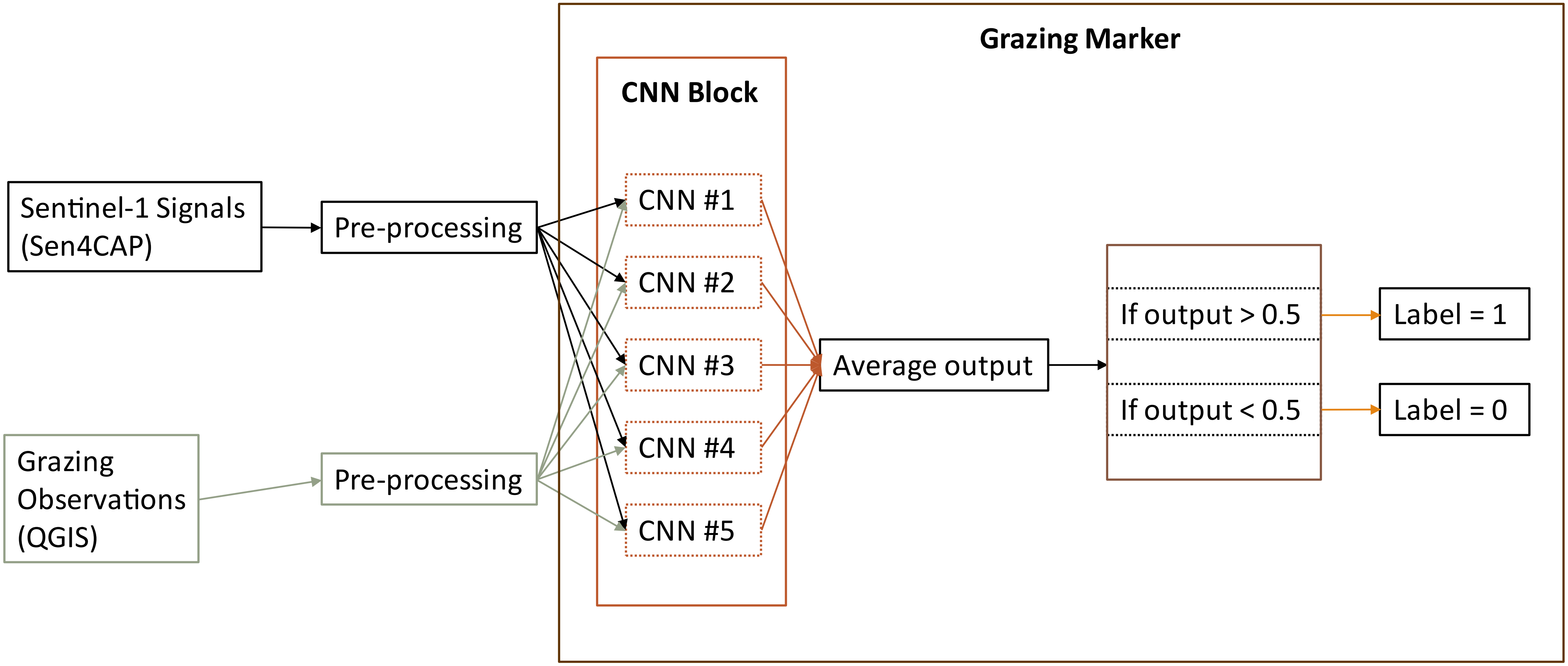
- 2022 Sentinel-1A data between March 1st to November 30th
    - VV Coherence
    - VV Backscatter
    - VH Backscatter
    - Ratio of VV_backscatter/VH_backscatter
    - Normalised Difference of backscatter bands
    - Radar Vegetation Index

<u>Label data</u>

- 2022 daily grazing observations
    - Training: 72%
    - Validation: 8%
    - Testing: 20%



Workflow



Grazing Marker
CNN Block
Sentinel-1 Signals (Sen4CAP)
Pre-processing
Grazing Observations (QGIS)
Pre-processing
CNN #1
CNN #2
CNN #3
CNN #4
CNN #5
Average output
If output > 0.5
If output < 0.5
Label = 1
Label = 0

Output

Timestamp

Parcels

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
0	0.06823	0.02007	0.02631	0.01959	0.01024	0.00983	0.02842	0.15362	0.21896	0.80104	0.64620	0.38884	0.07321	0.41191	0.51618	0.00033	0.16781	0.34997
1	0.71322	0.14622	0.70541	0.07324	0.88115	0.14202	0.68647	0.43168	0.31596	0.24602	0.48822	0.14064	0.15770	0.41234	0.39172	0.00081	0.18967	0.41877
2	0.08024	0.82277	0.15430	0.73190	0.42372	0.76793	0.34609	0.61420	0.23256	0.74943	0.33766	0.29121	0.09300	0.36998	0.41658	0.00051	0.10732	0.35964
3	0.23641	0.39964	0.15304	0.44514	0.12571	0.29361	0.38855	0.34894	0.46642	0.57835	0.30721	0.25092	0.56897	0.23351	0.14280	0.00070	0.08260	0.01466
4	0.03977	0.41219	0.29721	0.39816	0.43536	0.47092	0.58671	0.37201	0.70416	0.29603	0.61258	0.32947	0.16355	0.51837	0.14091	0.00016	0.17327	0.09607
5	0.03040	0.84060	0.41416	0.09279	0.76790	0.03759	0.77649	0.07991	0.81635	0.26563	0.02026	0.00956	0.00609	0.00680	0.00885	0.00018	0.01321	0.03078
6	0.06287	0.77765	0.08114	0.48495	0.15381	0.77926	0.18374	0.63182	0.51031	0.43215	0.33851	0.51304	0.53488	0.38341	0.46814	0.00047	0.06976	0.11966
7	0.18575	0.07758	0.12585	0.38761	0.41101	0.57995	0.41517	0.56571	0.57738	0.44335	0.20544	0.38327	0.61862	0.20794	0.38430	0.00016	0.37101	0.11997
8	0.15826	0.05968	0.12603	0.23604	0.14058	0.24278	0.12803	0.50844	0.21515	0.64912	0.52188	0.55179	0.18405	0.41956	0.60043	0.00033	0.07319	0.70877
9	0.83933	0.07331	0.00393	0.06562	0.02241	0.03381	0.11149	0.58994	0.77308	0.70373	0.10981	0.65764	0.72090	0.04488	0.41370	0.00046	0.03352	0.02717
10	0.67685	0.05454	0.02189	0.01859	0.03876	0.01058	0.12954	0.33469	0.16901	0.59251	0.45424	0.44604	0.03667	0.52966	0.21121	0.00039	0.29860	0.07259

```
y_pred_labels[y_pred > 0.5] = 1
y_pred_labels[y_pred < 0.5] = 0
```

Y predicted

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
0	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000	1.00000	0.00000	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000
1	1.00000	0.00000	1.00000	0.00000	1.00000	0.00000	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
2	0.00000	1.00000	0.00000	1.00000	0.00000	1.00000	0.00000	1.00000	0.00000	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
3	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000
4	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000	0.00000	1.00000	0.00000	1.00000	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000	0.00000
5	0.00000	1.00000	0.00000	0.00000	1.00000	0.00000	1.00000	0.00000	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
6	0.00000	1.00000	0.00000	0.00000	0.00000	1.00000	0.00000	1.00000	1.00000	0.00000	0.00000	1.00000	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000
7	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000	0.00000	1.00000	1.00000	0.00000	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000
8	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000	0.00000	1.00000	1.00000	1.00000	0.00000	0.00000	1.00000	0.00000	0.00000	1.00000
9	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000	1.00000	1.00000	0.00000	1.00000	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000
10	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000	0.00000

Y test

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
0	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000	1.00000	0.00000	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000
1	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
2	0.00000	1.00000	0.00000	1.00000	0.00000	1.00000	0.00000	1.00000	0.00000	1.00000	0.00000	1.00000	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000
3	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
4	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000	0.00000	1.00000	0.00000	1.00000	1.00000	1.00000	0.00000	0.00000	0.00000	0.00000
5	0.00000	1.00000	0.00000	0.00000	1.00000	0.00000	1.00000	0.00000	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
6	0.00000	1.00000	0.00000	0.00000	0.00000	1.00000	0.00000	0.00000	1.00000	0.00000	1.00000	0.00000	1.00000	0.00000	1.00000	0.00000	0.00000	0.00000
7	0.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	0.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
8	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
9	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000	1.00000	1.00000	0.00000	1.00000	1.00000	0.00000	1.00000	0.00000	0.00000	0.00000
10	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000	0.00000	1.00000	0.00000	1.00000	0.00000	0.00000	0.00000	0.00000

Results

- Recap of objective: Has parcel X been grazed over the past year?

Grazing marker results	Stats	Testing set 1	Testing set 2	Test on both
Grazed	Precision	100%	92%	74%
	Recall	98%	74%	94%
	F-1	99%	81%	83%

Confusion matrices

Testing set 1		Predicted	
		Not grazed	Grazed
TRUE	Not grazed	1	0
	Grazed	1	60

Testing set 2		Predicted	
		Not grazed	Grazed
TRUE	Not grazed	2	3
	Grazed	12	33

Testing on both		Predicted	
		Not grazed	Grazed
TRUE	Not grazed	5	33
	Grazed	6	94

Digging deeper into the results

- Event level statistics – when did a grazing event take place?

Testing set 1	Stats	Testing set 1
Grazed	Precision	46%
	Recall	44%
	F-1	45%
Not grazed	Precision	79%
	Recall	81%
	F-1	80%

Testing set 1		Predicted	
		Not grazed	Grazed
TRUE	Not grazed	794	192
	Grazed	213	165

Improvements to event level statistics

- Hyperparameter optimisation
- Increasing information from signals
- Creating a pre-marker grassland classification
- Including more training data

Increasing information from signals

- Feature selection
- Pixel based classification
- Deep learning to link Sentinel-1 backscatter values to NDVI
    - What is NDVI?
        - Sentinel-2 derived vegetation index
    - Why?
        - NDVI is best for grazing detection
    - How?
        - Sentinel-1 as input dataset
        - NDVI as target dataset
        - CNN to perform classification task

https://www.mdpi.com/2072-4292/11/12/1441
https://www.mdpi.com/2072-4292/14/11/2600

Creating pre-marker grassland classification

- Should the marker be picking up grazing in parcels where it's nearly impossible?
    - Mountainous areas?
    - Boggy areas?
- Grassland classification could be used to create weights to different types of pastures

Increasing amount of training data

- More training data typically yields better results
- Including more years in the training set
- Including weather events
  - Precipitation/drought affects radar signals
  - Precipitation/drought affects livestock going out to graze
- Increasing the spatial variability of training data
  - Location transferability typically low in ML/DL models

Issues

- Sentinel-1B is offline
  - 12-day temporal resolution – what if grazing has occurred on the 13th day?
- Radar signal is very noisy
- Very difficult/impossible to detect 1 cow grazing a field