PHENOTYPING OF HERBAGE SEED FIELD PLOTS USING UAV-MOUNTED SENSOR SYSTEM

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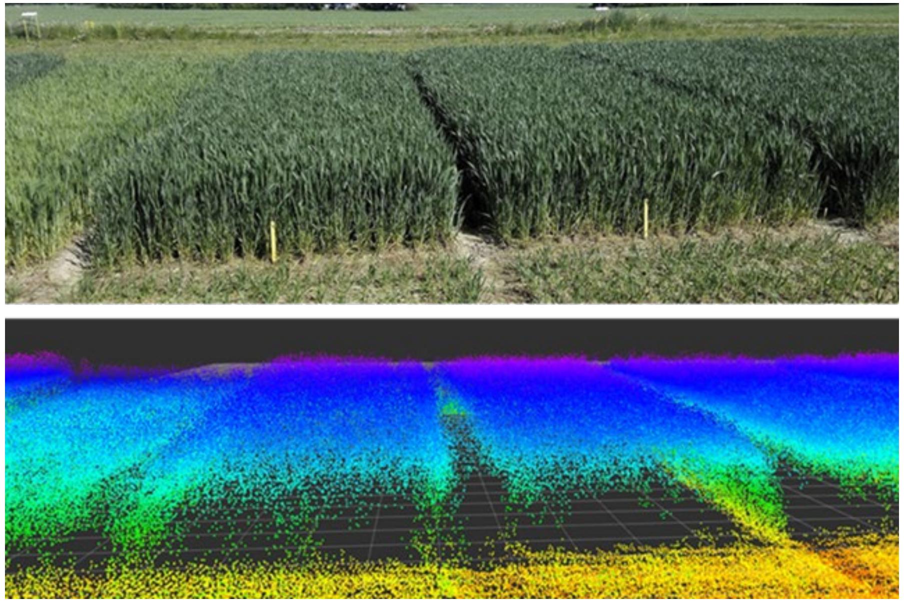
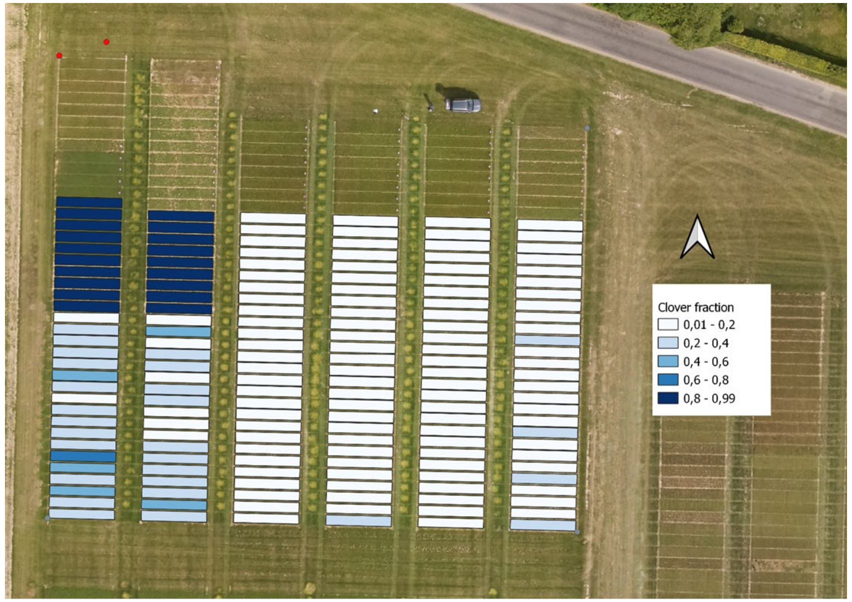
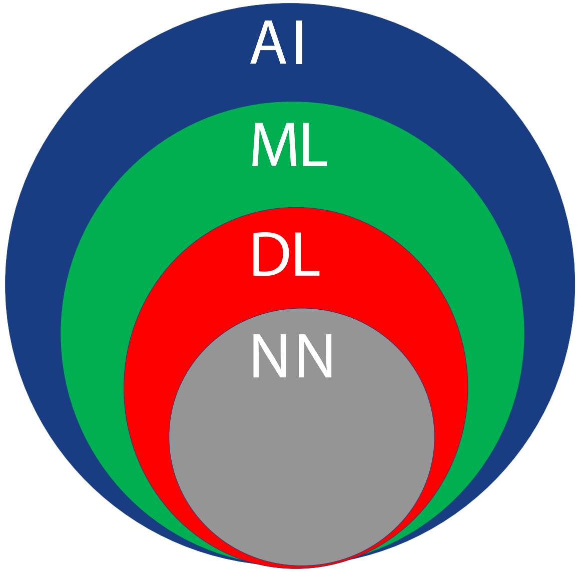
WHY PHENOTYPING

We have used phenotyping for years, but the use and implementation of sensors and AI have made agriculture interesting for some students, engineers, etc.







Phenotyping with a focus on the prediction of %N, N uptake in kg ha^{-1} and dry matter production in tons ha^{-1}.

DATA

eBee UAV mounted sequoia camera with four monochrome sensors: green (550 nm ± 20 nm), red (660 nm ± 20 nm), red-edge (735 nm ± 5 nm) and near-infrared (790 nm ± 20 nm).

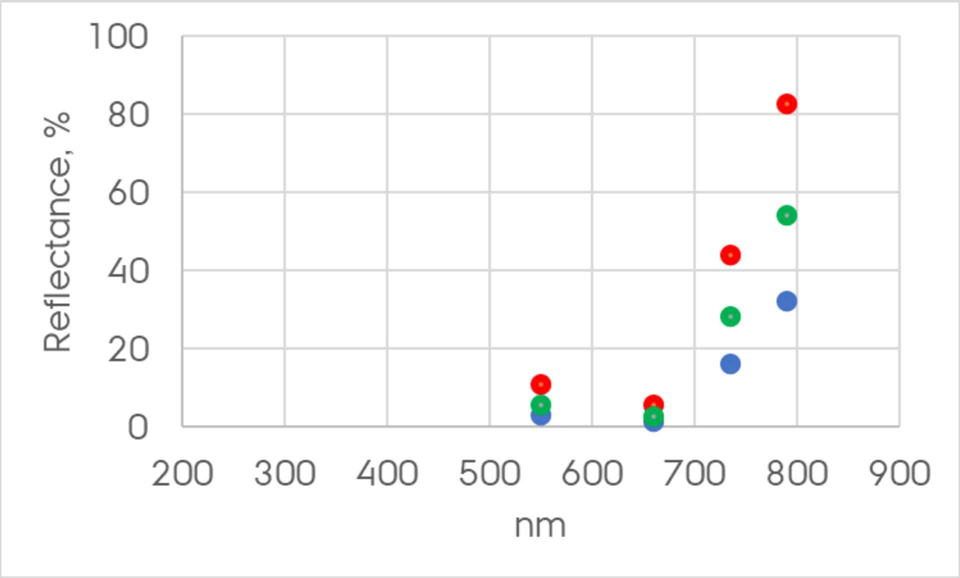
- Eighteen different crop indices were calculated Weather data was growing degree days, precipitation, and global radiation.
- A total of 4 (narrow bands) + 18 (crop index) + 9 (weather data) = 31 variables

Variable	N	Average	Minimum	Maximum
%N, % in DM	1024	2.72	0.21	5.40
DM, tons ha^{-1}	1024	5.23	0.66	15.8
Kg N, kg ha^{-1}	1024	133	10	373

UNDERSTANDING CROP INDEX

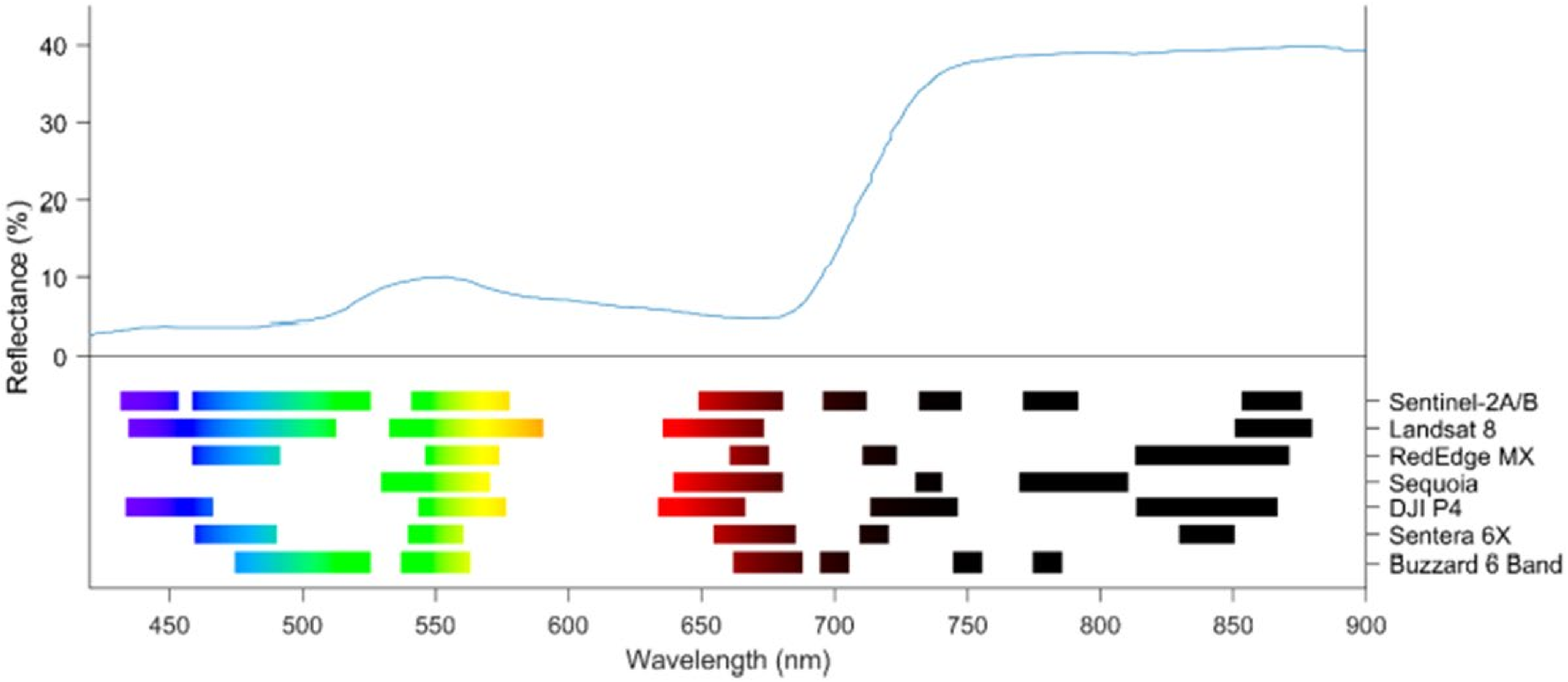
	nm	Minimum	Maximum	Average
Green	550	2.92	11.0	5.78
Red	660	1.30	5.58	2.61
Rededge	735	16.4	44	28
NIR	790	32	83	54

550 measurements



NDVI=(NIR-Red)/(NIR+Red)
NDRE=(NIR-Rededge)/(NIR+Rededge)
Rededge chlorophyll index CIrededge=(NIR/rededge)-1

DIFFERENCES BETWEEN CAMERAS



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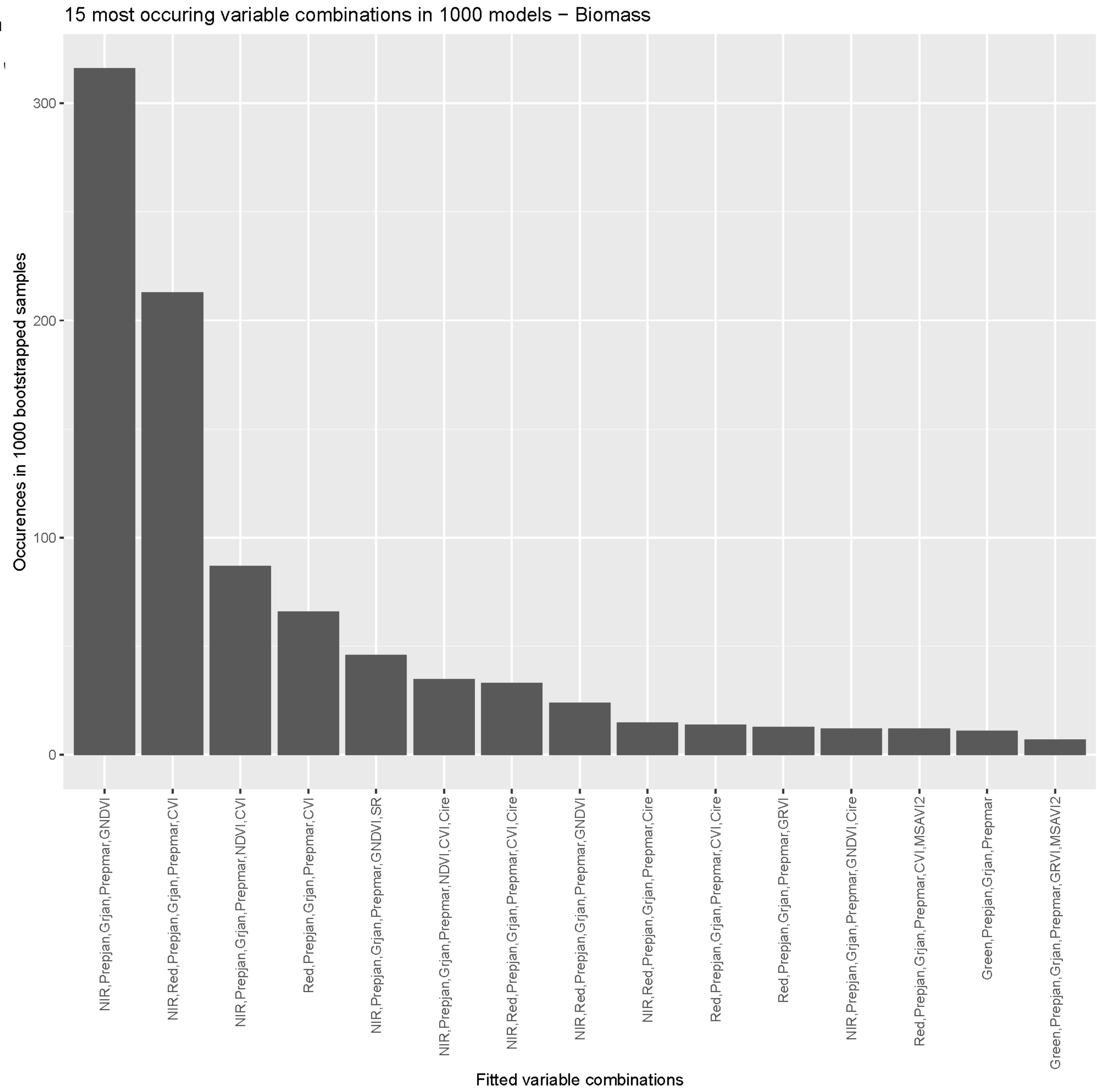
RESULTS

Variable	Model	Training set			Validation set		Test set	
		#PC	R^2	RMSEC	R^2	RMSECV	R^2	RMSEP
%N	SVM	747	0.85	0.28	0.78	0.35	0.75	0.36
Kg N	SVM	654	0.70	26	0.57	31	0.52	33
DM	SVM	597	0.82	0.99	0.73	1.2	0.75	1.12

ADVANCED RESULT

The best results were obtained with a combination of weather and sensor data.



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PHENOTYPING GRASS-CLOVER ALGORITHM

RGB image

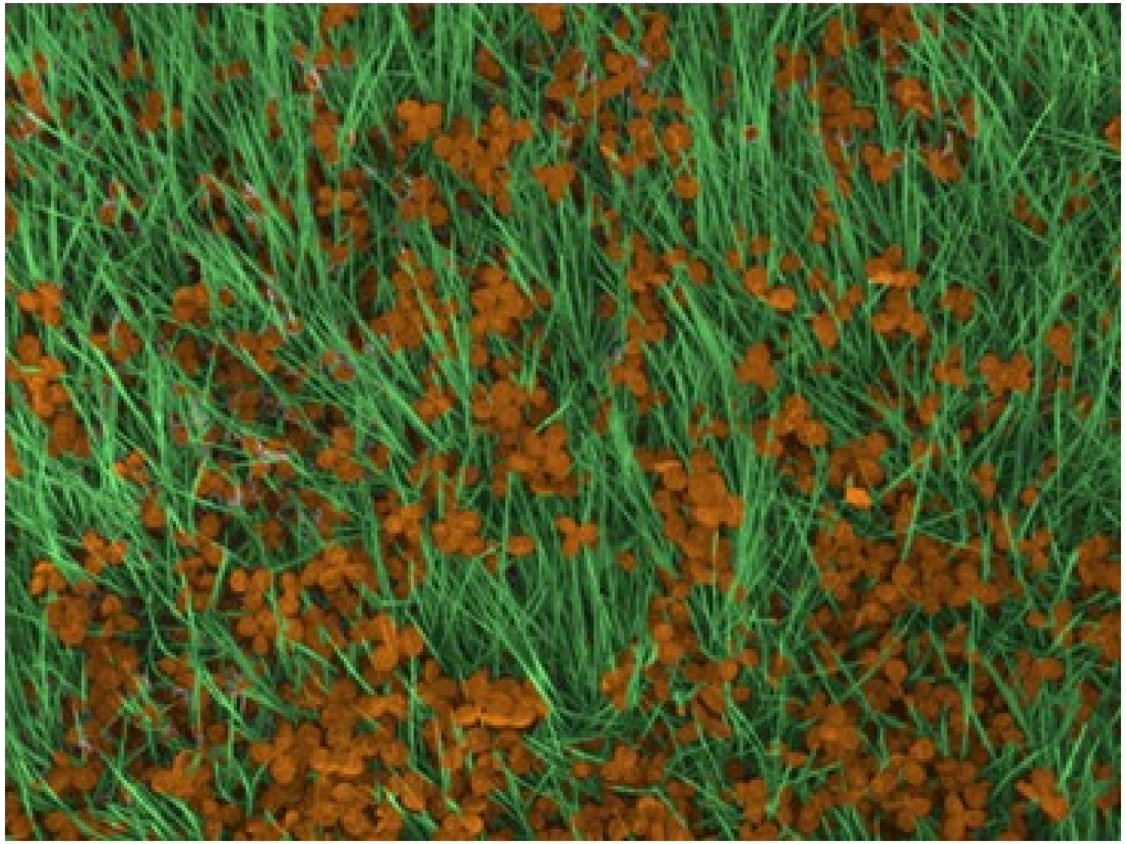


Image after grass-clover Deep Learning algorithm

CONCLUSION AND TAKE HOME MESSAGES

Is an error in dry matter production of ~1.12 tons ha^{-1} satisfying? this can only be answered by the farmer.

We suggest that local models for specific fields, species, and/or areas are developed to reduce the error that undisputedly will be part of a global model.

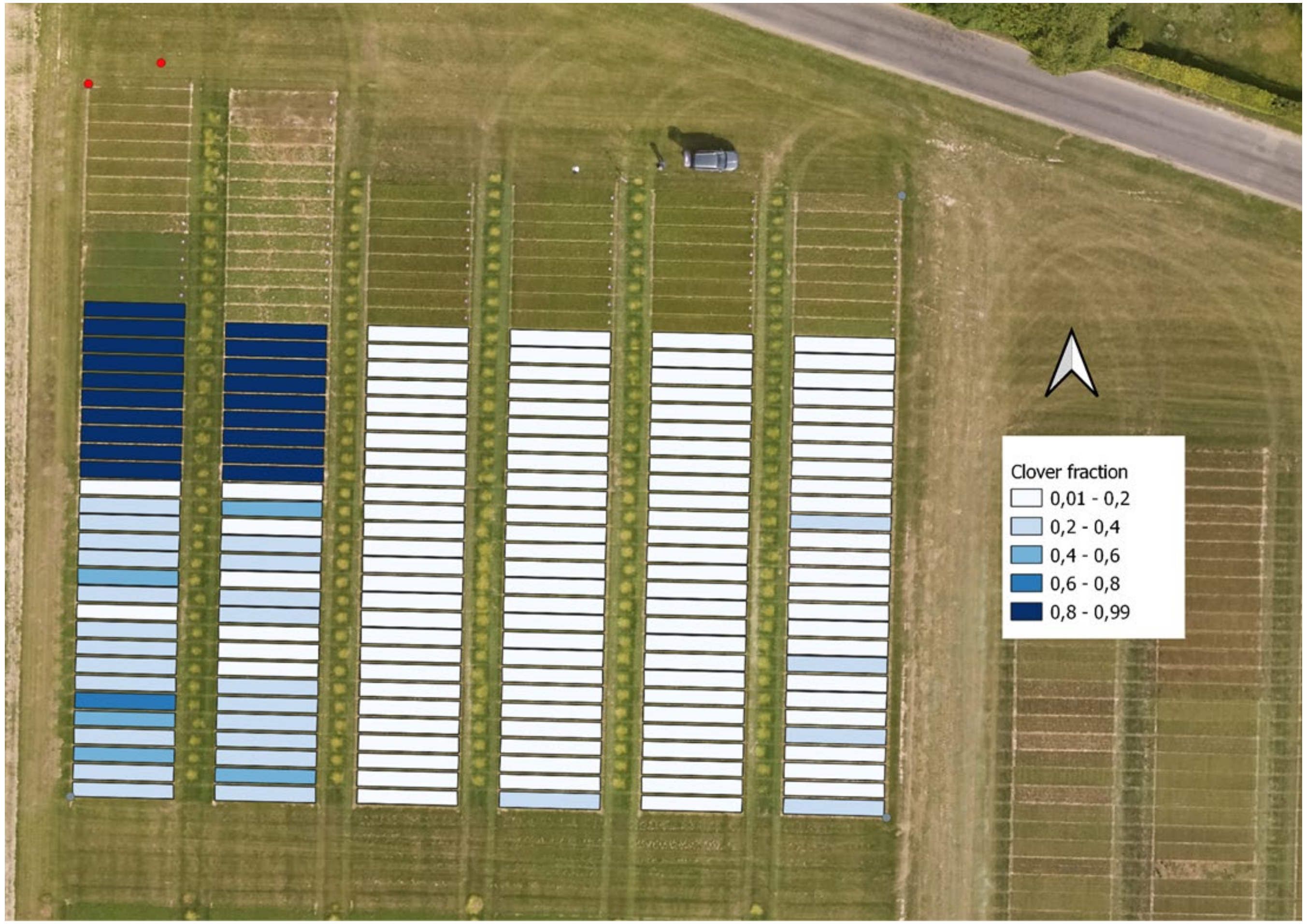
CLOVER-GRASS FRACTION

Sensor:

- MicaSense RedEdge MX

Analysis:

- Semantic segmentation using FCN-8 trained on UAV images[1]
- Pseudo RGB image created using only red channel (668 nm)
- $clover\ fraction = \frac{\#\{clover\ pixels\}}{\#\{clover\ pixels\} + \#\{grass\ pixels\}}$
- $grass\ fraction = \frac{\#\{clover\ pixels\}}{\#\{clover\ pixels\} + \#\{grass\ pixels\}}$



[1] Larsen et al. (2018). *Autonomous mapping of grass-clover ratio based on unmanned aerial vehicles and convolutional neural networks* . In preceedings of International Conference on Precision Agriculture.

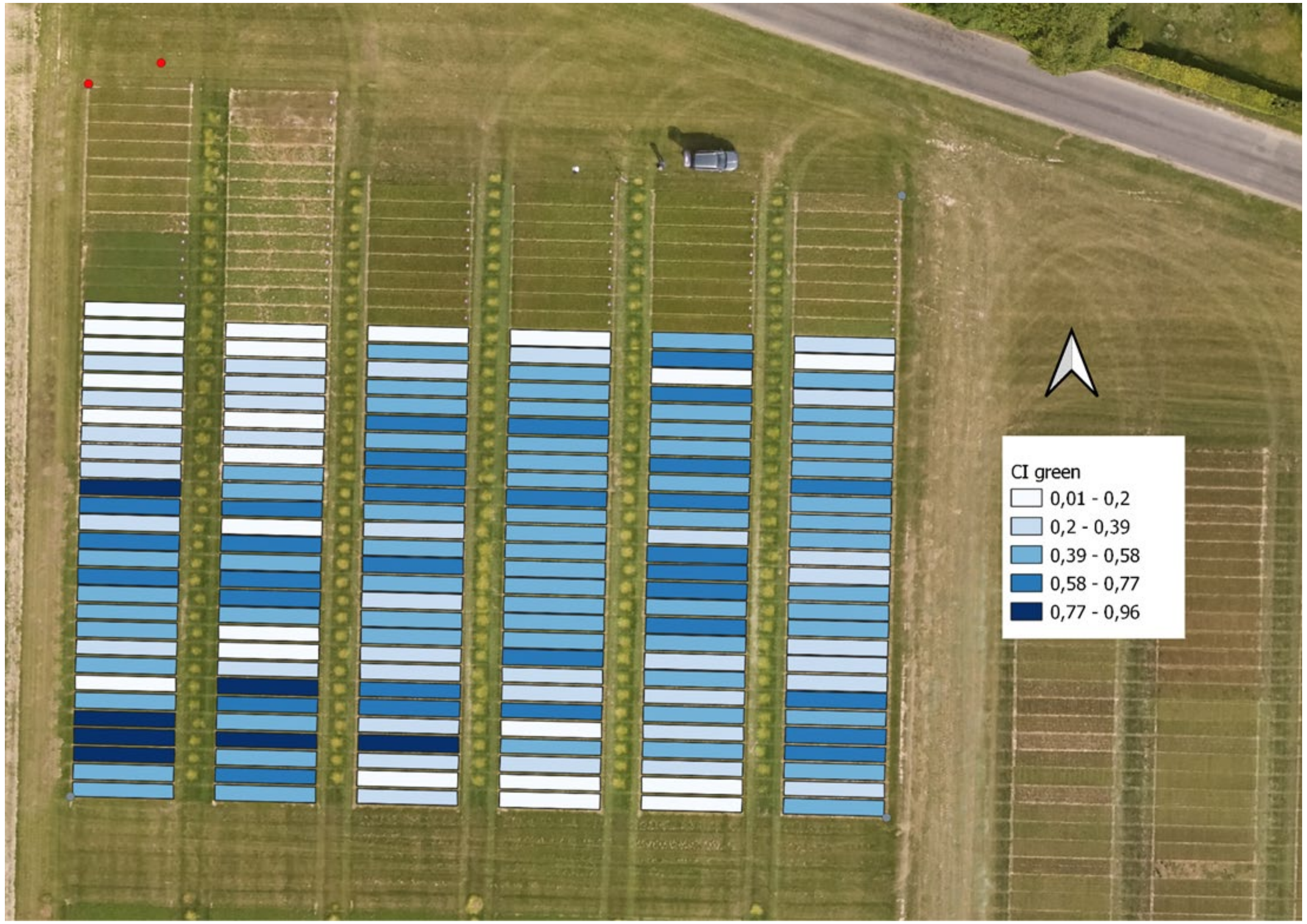
VEGETATION INDICES

Sensor:

- MicaSense RedEdge MX

Analysis:

- Normalized difference vegetation index:
  - $NDVI = \frac{NIR - red}{NIR + red}$
- Normalized difference red edge index:
  - $NDRE = \frac{NIR - red\ edge}{NIR + red\ edge}$
- Green Chlorophyll Index:
  - $CI_{green} = \frac{NIR}{green} - 1$
- Red-Edge Chlorophyll Index:
  - $CI_{red\ edge} = \frac{NIR}{red\ edge} - 1$



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