Yield prediction in winter wheat using machine learning; improving implemented farm management tool

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Yield prognosis in winter wheat



The Objectives

The objectives of this study were to:

- 1) Increase the accuracy and robustness of the yield prediction model in winter wheat by adding more data and new features to the model.
- 2) Implement the new model in the web-based management tool CropManager used by Danish Farmers.

Goal: Mean Absolute Error (MAE) < 1 t ha⁻¹



Materials and methods





OTTET A

Data layers used for modelling

- 1) Yield maps from combine harvesters of farmers
- 2) Satellit data (L1C Sentinel data)
- 3) Terrain Elevation (The Danish Terrain Elevation model)
- 4) Weather data (DMI)
- 5) Soil texture
- 6) Crop variety
- 7) Crop rotation



Distribution of yield data

Year	Yield data						
	Number of fields	Number of farmers	Hectare	Pixels ¹	Avg. yield, t ha ⁻¹		
2016	33	7	289	28,898	10.4 (1.8)		
2017	95	15	856	85,611	9.6 (2.2)		
2018	35	6	356	35,580	6.8 (1.5)		
2019	26	5	221	22,062	7.2 (1.3)		
2020	29	4	233	23,322	7.3 (1.6)		
2021	69	5	984	98,356	7.9 (1.3)		
Sum:	287		2,938	293,829			

1) Pixels of 10 x 10 m.



Models

791 features in the model

ML algorithm:

Gradient Boosting Regressor

Prediction dates:

April 6th, May 4th, June 1st and July 27th

The prediction performance:

 $MAE = \sum_{i=1}^{n} \frac{|h_i - p_i|}{n}$ *h* is the measured yield, *p* predicted yield and *n* the number of observations R²

4 model experiments: varies in prediction date, features, number of observation and spilt of data between training and validation.



Results

Promilleafgiftsfonden for landbrug



Experiments	Prediction date	Features	Observations	Split of data
1	April 6 th May 4 th June 1 st July 27 th	All	293,829 pixels	Field level (approx. 40 fields in validation data)



Experiments	Prediction date	Features	Observations	Split of data	MAE, t ha ⁻¹ Validation	R ²
	April 6 th		293,829 pixels	Field level (approx. 40 fields in validation data)	0.67	0.74
1	A dth	All			0.62	0.79
	May 4 ^{°°} June 1 st				0.59	0.82
	July 27 th				0.56	0.83



Experiments	Prediction date	Features	Observations	Split of data	MAE, t ha ⁻¹ Validation	R ²
	April 6 th				0.67	0.74
1	ha, ath	All	293,829 pixels	Field level (approx. 40 fields in validation data)	0.62	0.79
1	June 1 st	2			0.59	0.82
	July 27 th				in 0.62 0. 0.59 0. 0.56 0.	0.83
2	July 27 th	Aggregated to field level + feature elimination	287 fields	Field level (approx. 40 fields in validation data)		



Experiments	Prediction date	Features	Observations	Split of data	MAE, t ha ⁻¹ Validation	R ²
	April 6 th				0.67	0.74
1	Name ath	All	293,829 pixels	Field level (approx. 40 fields in validation data) 0.59	0.62	0.79
	June 1 st				0.59	0.82
	July 27 th				0.59 0	0.83
2	July 27 th	Aggregated to field level + feature elimination	287 fields	Field level (approx. 40 fields in validation data)	0.41	0.91



Experiments	Prediction date	Features	Observations	Split of data	MAE, t ha ⁻¹ Validation	R ²
	April 6 th				0.67	0.74
Experiments F	NA Ath	All	293.829 pixels	Field level (approx. 40 fields in	0.62	0.79
	June 1 st			validation data)	0.59	0.82
	July 27 th				0.56	0.83
2	July 27 th	Aggregated to field level + feature elimination	287 fields	Field level (approx. 40 fields in validation data)	0.41	0.91
1 2 3	May 4 th	Aggregated to field level	00 7 (1 1 1	Cross-validation with vears as		
	July 27 th	+ feature elimination	287 fields	fold		



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Experiments I	NA Ath	All	293.829 pixels	Field level (approx. 40 fields in	0.62	0.79
	May 4			validation data)	0.59	0.82
	July 27 th				0.56	0.83
2	July 27 th	Aggregated to field level + feature elimination	287 fields	Field level (approx. 40 fields in validation data)	0.41	0.91
1 2 3	May 4 th Aggregated to field level	007 (111)	Cross-validation with years as	0.90	0.69	
3	July 27 th	+ feature elimination		fold	0.88	0.68



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	April 6 th		203 829 nivels		0.67	0.74
1	a th	ΔΙΙ		Field level (approx. 40 fields in validation data)	0.62	0.79
Experiments F	May 4 th June 1 st	2			0.59	0.82
	July 27 th				0.56	0.83
2	July 27 th	Aggregated to field level + feature elimination	287 fields	Field level (approx. 40 fields in validation data)	0.41	0.91
2	May 4 th	Aggregated to field level		Cross-validation with years as	0.90	0.69
3	July 27 th	+ feature elimination		fold	0.88	0.68
	May 4 th	Aggregated to field level		Cross-validation with years as		
4	July 27 th	+ feature elimination	195 fields	fold (only data collected in 2022)		



Experiments	Prediction date	Features	Observations	Split of data	MAE, t ha ⁻¹ Validation	R ²	
	April 6 th	April 6 th	April 6 th			0.67	0.74
1	n ath	All	203 820 pixola	Field level (approx. 40 fields in	0.62	0.79	
	May 4" June 1 st			validation data)	0.59	0.82	
	July 27 th				0.56	0.83	
2	July 27 th	Aggregated to field level + feature elimination	287 fields	Field level (approx. 40 fields in validation data)	0.41	0.91	
2	May 4 th	Aggregated to field level		Cross-validation with years as	0.90	0.69	
3	July 27 th	+ feature elimination		fold	0.88	0.68	
	May 4 th	Aggregated to field level	195 fields	Cross-validation with years as	0.65	0.72	
4	July 27 th	+ feature elimination		fold (only data collected in 2022)	0.55	0.80	



Yield prediction at field level



Conclusion

- We were able to predict winter wheat yield on field level with a MAE of 0.65 and 0.55 t ha⁻¹ on May 4th and July 27th respectively when cross-validating with years.
- The prediction accuracy on May 4th (field level) is acceptable to regulate nitrogen application to crop demand in third application in growth stage 37 (BBCH).
- The models are incorporated into CropManager used by Danish farmers.



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