Del 2: Slutrapport Target-N

1 Introduction

The European Union (EU, 2016), Intergovernmental Panel on Climate Change (Smith et al., 2016) and Exponential Roadmap to meet the Paris Agreement (Falk et al., 2018) all regard precision agriculture, including site-specific optimisation of nitrogen (N) rates, as part of the solution in environmentally and economically sustainable food production. When N rates are not adapted site-specifically, this results in financial losses and risks of negative environmental impact, e.g. N leaching (Delin & Stenberg, 2014) and N volatilisation (Balafoutis et al., 2017).

Data from the European Sentinel-2 satellites can be accessed free of charge in the CropSAT decision support system (DSS) (developed in collaboration between SLU, Hushållningssällskapet and DataVäxt AB, with support from Stiftelsen Lantbruksforskning, Agroväst and Greppa Näringen; Söderström et al., 2017).
In systems such as CropSAT, there is an existing efficient data flow from satellite image to the end-user in the tractor. In 2022, CropSAT had >20,000 unique users in Sweden and internationally (according to Google Analytics provided by Dataväxt AB). Consequently, such DSS has the potential to influence practical crop production.

However, before the Target-N project, there was no openly available models for predicting the supplementary N rate from spectral data. The objective of this project was therefore to develop such models between multispectral reflectance measurements in winter wheat (*Triticum aestivum* L.) and spring barley (*Hordeum vulgare* L.) and the optimal N rate, for use in satellite image based DSSs aimed at practical precision agriculture.

The main hypothesis for the Target-N project is that optimal N supplemental N rate to winter wheat and malting barley can be predicted from multispectral remote sensing data with sufficiently high accuracy, at a relevant stage of crop development, for implementation in a DSS for precision agriculture.

2 Materials and methods

2.1 Data collection

To develop the N rate models we used data collected in field trials by a sensor mounted on a drone. The models were transferred to satellite imagery and made available to end-users in the CropSAT DSS[1]. The drone sensor used was a nine-band camera (MAIA; Eoptis Srl, Italy) with wavelengths spectrally identical to nine of the bands of Sentinel-2 (in the spectral range 400-900 nm). Hence, this facilitates the transfer of an algorithm from the drone sensor (with cm-pixles) to the satellite image (with 10-20 m pixels – too

[1] The implementation was not part of the present project, but was realised within a related project (Formas; project 2019-02280).

large for use in field trials). A brief description of the methods are given below; more details are found in Piikki et al. (2022).

Remote sensing data were collected in 12 winter wheat trials (series L7-150; *Kvävebehov hos olika höstvetesorter*) and malting barley trials (L7-426; *Kvävebehov hos olika maltkornsorter*) over the years 2019-2021 (the originally planned field trial series were L3-2299 (N strategy in winter wheat) and L3-2302 (N strategy in malting barley) but the winter wheat series was cancelled just before the project started). Data was collected in all trials, except trials in Västerås (too close to airport) and in Visby (for practical reasons). Flights with the drone were done in three crop developmental stages: DC 31-32, DC 37-39 and DC 69-73 (scale by Zadoks et al., 1974).

Before each flight, one set of four 50 cm × 50 cm reflectance plates with known reflectance values (2%, 9%, 23%, and 44%; Mosaic Mill Oy, Vantaa, Finland) were placed along each of the short edges of the trial. When necessary, these plates were placed on racks to avoid shading by the crop. The UGCS ground control software (SPH Engineering, Latvia) was used for route planning, so that images overlapped by at least 80% along and between flight lines. One image per band was collected, at frequency 1 Hz, 80 m above ground level and flight speed 5 m s^{-1}. Each flight took around 10 min and was carried out in as uniform light conditions as possible, e.g. avoiding cloud shadows. For practical reasons, time of day differed between the flights, with sun elevation varying between 35 and 53 degrees.

2.2 Drone sensor data preparation

The drone was equipped with an incoming light sensor that continuously recorded ambient light for each band of the camera, data used by the software for radiometric correction. After data collection, geometrically and radiometrically corrected nine-band tif-images were generated. The geometrically corrected images were stitched to orthomosaic raster images by the Solvi web application (https://solvi.ag; Solvi AB, Sweden). Polygons of the plots were generated in the Solvi application, and all data were downloaded and further processed in ArcGIS Desktop (version 10.8; ESRI Inc., CA, USA). The median digital number (DN) of all raster cells within each trial plot (avoiding approximately 0.2–0.3 m along the edges of the plots) was extracted, and paired with agronomic data (yield [kg per ha 85% dry matter] and crude protein content [% of dry matter]) from the Nordic Field Trial Database (NFTS).

2.3 Modelling

For the modelling, only cultivars tested all three years were included (winter wheat: Etana, Hallfreda, Informer, Julius and RGT Reform; spring barley: Ellinor, KWS_Irina, Laureate and RGT Planet). Six trials were excluded from the analyses. In wheat it was the trials in Tommarp 2019 (too progressed crop development at remote sensing) and in Alnarp 2019 (abnormal yield in zero-plots; 10 tonnes ha^{-1}) and in barley it was the trials in Kristianstad 2019, in Mulltorp 2019, in Logården 2020 and in Ekebyborna 2020 (unsuccessful data collection in all cases). Modelling was done in two steps:

1. Optimal N rate per trial and cultivar (ONR) was determined through dose-response relationships (yield as a function of total N rate over the season – a cubic function for malting barley and a monotone increasing function for wheat were selected

based on best fit to observed data). This was meant to represent the field average optimal N rate and models were developed to predict ONR from combinations of yield potential (in this study: yield in max-plots), N uptake in zero-plots, N uptake in max-plots, cultivar and geographic region.

2. The optimal supplemental N rates in the different N treatments (Nreq) were computed by subtracting the N rate given earlier in the season from the ONR. Any negative remaining N requirements were set to zero. This was meant to represent the optimal supplemental N rate in different parts of a field with different N status of the crop. The supplemental rate was expressed relative to the median for the trial and cultivar in question ($Nreq_r$) and was modelled as a linear function from different remote sensing-based vegetation indices (VIs; for equations see Piikki et al., 2022). Also the VIs were expressed relative to the median for the trial and cultivar (VI_r)

Dose-response models for crude protein concentrations (CP) were parameterized and used to determine the N rate required to reach target CP (11.5% for bread wheat and 10.5% for malting barley), Any positive difference between this N rate and the ONR is the recommended protein addition.

In order to assess how well the models would work in new site-years, evaluation was done by a cross-validation strategy where one entire trial was left out at a time. The Nash-Sutcliffe modelling efficiency (E) and the mean absolute error (MAE) were used to quantify model performance. All modelling was carried, using the R software (R Core Team, 2021). The model type was linear regression.

3 Results and discussion

Yield in zero-plots and max-plots of the trials and optimal N rates are presented in Table 1. It can be noted that the yields in zero-plots, especially in winter wheat is relatively high in most trials. As a consequence, the optimal N rates were relatively low.

Correlation coefficients between pairs of variables are presented in Figure 1. The correlation coefficients are computed per cultivar, based on one value pair per trial, and then averaged for all trials. The correlations largely follows what can be expected:

- Correlations between one chosen VI, the chlorophyll index (CI), and ONR are generally stronger than correlations between CI and the N rate required to reach the target CP (pONR), which may indicate that the latter would be more difficult to model from this index.
- Correlations between CI or yield with ONR are most often stronger for winter wheat than for malting barley, indicating that it will be more difficult to use remote sensing methods for determination of optimal N rate (using this VI) in spring barley.
- In winter wheat, correlations between CI and ONR are generally stronger at end of stem elongation than at earlier and later occasions, while for spring barley correlations are stronger the later the measurement. DC 37-39 is however more relevant for supplemental fertilization.
- In both crops, the negative relationship between CI in DC 37-39 and ONR are strongest in zero-plots but declines (and in some cases turn positive) with increasing N rate and the positive relationship between yield and ONR is strongest

in max-plots and weakens (and turns negative) with decreasing N rate. This indicates that zero-plots are better than any fertilized plots as a proxy for soil N supply by mineralization and that max-plots are better than any less fertilized plots as a proxy for non-N-limited yield potential.

Table 1. Descriptive statistics (trial mean ± standard deviation between cultivars) of yield in zero-plots, yield in max-plots and optimal N rate.

Site	**Year**	**Region**	**Yield in zero-plots (kg ha^{-1})**	**Yield in max-plots (kg ha^{-1})**	**Optimal N rate (kg ha^{-1})**
Malting barley					
Flo	2019	West	2593+144	5113+129	105+11
L. Böslid	2019	South	5839+237	6910+228	53+4
L. Uppåkra	2019	East	4643+261	5660+391	51+2
Motala	2019	East	5168+292	6973+285	81+16
L. Böslid	2020	West	2379+150	7003+201	168+12
Kristianstad	2020	South	4962+146	9391+218	176+19
Borrby	2021	South	4057+46	6367+173	115+19
Motala	2021	East	3633+149	6786+680	117+11
Örebro	2021	East	3934+373	5886+358	114+33
N. Vånga	2021	West	3883+93	7232+365	133+39
Winter wheat					
Linköping	2019	East	6422+482	9861+488	126+9
St. Markie	2019	South	4421+278	8443+366	112+10
Linkoping	2020	East	6949+401	10637+349	202+19
Flo	2020	West	2319+91	9647+348	206+5
Brantevik	2020	South	4838+171	12594+437	222+12
Lund	2020	South	4485+362	9889+253	162+7
Brantevik	2021	South	6020+180	10043+583	137+15
L. Böslid	2021	West	4150+268	9771+427	167+22
Salstad	2021	West	4658+216	9556+530	140+18
Vreta kloster	2021	East	6468+360	9108+504	121+7

Table 2. Correlation coefficients between x and y. ONR = optimal N rate (ONR) with respect to yield; pONR= ONR with respect to protein; ci = chlorophyll index. For both crops n = 10 trials, and correlation coefficients with an absolute value ≥0.55 are statistically significant at the p-level 0.05.

Nrate (kg ha^{-1})	**x=CI**						**x=Grain yield**	
	DC31-32		**DC37-39**		**DC69-73**		**Harvest**	
	y=ONR	**y=pONR**	**y=ONR**	**y=pONR**	**y=ONR**	**y=pONR**	**y=ONR**	**y=pONR**
Winter wheat								
0	-0.64	-0.18	**-0.77**	-0.60	-0.52	-0.19	-0.41	-0.29
80	-0.44	-0.21	-0.70	-0.59	-0.50	-0.08	-0.01	-0.03
140	-0.20	-0.10	-0.50	-0.48	-0.24	0.11	0.68	0.41
200	-0.17	-0.05	-0.46	-0.38	-0.11	0.3	0.84	0.59
260	-0.10	-0.05	-0.40	-0.36	0.02	0.32	0.81	0.46
320	-0.05	-0.04	-0.36	-0.37	-0.02	0.27	**0.86**	0.51
Spring barley								
0	0.16	0.37	**-0.23**	0.06	-0.52	-0.10	-0.44	-0.43
54	0.26	0.50	0.00	0.36	-0.30	0.25	-0.18	-0.10
98	0.32	0.42	0.24	0.43	-0.09	0.46	0.19	0.06
145	0.22	0.34	0.22	0.42	0.10	0.62	0.48	0.22
189	0.18	0.36	0.21	0.43	0.25	0.76	**0.54**	0.24

Reflectance spectra

Reflectance spectra from the remote sensing in DC 37-39 are presented in Figure 1. The correlations between band reflectance values and remaining N requirement differ between crops. For wheat, the correlation was always stronger with the remaining N requirement than with N rate applied earlier in the season but this was not the case for barley (Figure 1e and f.). For wheat, the red-edge inflection occured at a longer wavelength than in barley. Consequently, it was band 6 that had the weakest correlation with the N management and the N status of the crop in wheat, while in barley band 5 had the weakest correlation (in the red-edge region) with these variables.

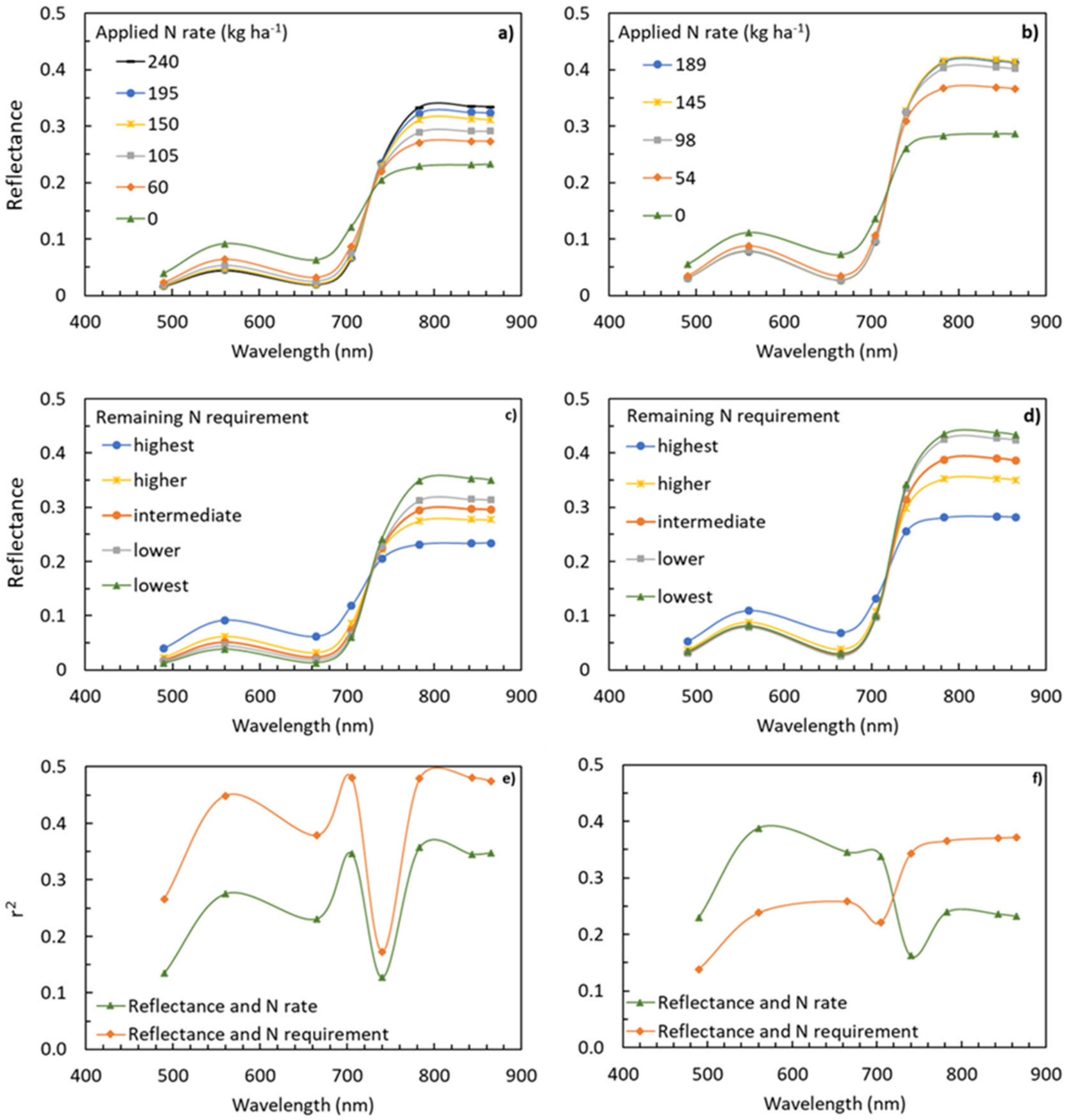

Figure 1. Reflectance spectra (a-d) from the remote sensing in DC 37-39 and coefficients of determinations (e-f) for different wavebands in wheat (a, c, e) and in barley (b, d, f). Symbols show centre wavelengths of bands. In e and f, N rate is the N rate applied earlier in the season and N requirement is the remaining N requirement.

3.1 Model evaluation results

In the modelling of ONR from all combinations or predictor variables, there was a similar pattern in both crops; yield potential was the variable that improved models the most, followed by N uptake in zero-plots. N uptake in max-plots sometimes improved and sometimes deteriorated the models, while cultivar was relatively unimportant and region often made the models perform worse (results not shown). Based on this, the combination of yield potential and N uptake in zero-plots was considered practical and functional for modelling of ONR in DC 37-39. The ONR model worked relatively well for wheat, but for barley, it was less reliable (Table 3.). Also for prediction $Nreq_r$, models generally perform better in wheat than barley (Figure 2.). In both crops, several of the multispectral indices perform about equally well, and markedly better than RGB indices. The NDVI however, which is a commonly used proxy for biomass, did not perform as well as many other multispectral indices. The supplemental N rate computed as the sum of the mean N rate and the relative N rate had an MAE of 17 kg N ha^{-1} in winter wheat and 20 kg N ha^{-1} in spring barley (Table 3).

Table 3. Evaluation statistics for predictions of optimal N rate (ONR) relative remaining N requirement ($Nreq_r$), and the sum of the two, the supplemental N rate (Nreq). E = Nash-Sutcliffe modelling efficiency and MAE= mean absolute error.

Evaluation	Winter wheat		Spring barley	
	E	MAE (kg N ha^{-1})	E	MAE (kg N ha^{-1})
ONR predictions based on N uptake in zero-plots and yield potential	0.74	17	0.27	30
$Nreq_r$ predictions based on best VI (wheat $d_{74}r_6$; barley $NDRE_{75}$)	0.76	15	0.66	12
Nreq computation (sum of the two predictions above)	0.74	17	0.48	20

3.2 Model equations

The model for prediction of field average ONR is presented in Equation 1, and the corresponding model for barley is presented in Equation 2. Yield potential (15% water content) is expressed in tonnes ha^{-1} and N uptake in zero-plots is expressed in kg ha^{-1}. For wheat, N uptake in zero-plots is computed from CI by a model developed by Wolters et al. (2021). The same model was applied for barley, but as it was not developed and tested for this crop, the values should not be interpreted as absolute values of N uptake.

ONR = -2.27 × N uptake in zero-plot + 19.8 × yield potential + 43.1 Eq. 1

ONR = -2.15 × N uptake in zero-plot + 22.3 × yield potential + 26.4 Eq. 2

Note that the yield potential is the yield in plots with the trial maximum N rate. This wheat yield is on average 0.608 tonnes ha^{-1} larger than the yield at ONR and the corresponding value for barley is 0.153 tonnes ha^{-1}, so if one wants to compute ONR from a target yield at optimal fertilization, these values should be added to that target yield.

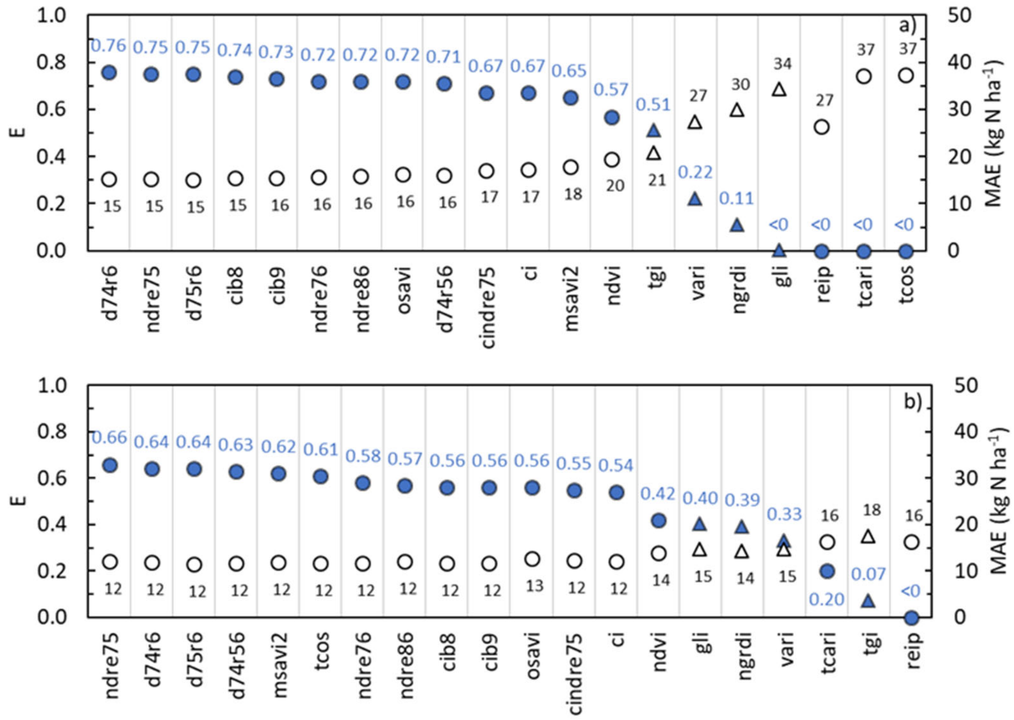

Figure 2. Evaluation metrics for prediction of relative N rate based on relative vegetation indices (for VI equations, see Piikki et al., 2022) in a) winter wheat and b) spring barley. E = Nash-Sutcliffe modelling efficiency (filled symbols) and MAE= mean absolute error (open symbols). Circles show multispectral indices, while triangles show RGB-indices.

The equations for computation of relative N rate (Nreqr) in wheat based on relative values of the best RGB index and the best multispectral index are presented in Equations 3-4 and the corresponding equations for barley are presented in Equations 5-6. The average N rates to add to reach target CP is 24 kg N ha^{-1} for wheat, which may be somewhat high compared to current practice. For barley a target CP of 10.5 % is reached at ONR.

$$Nreq_r = 73.4 \times TGI_r + 1.38 \quad \text{Eq. 3}$$

$$Nreq_r = -391 \times d_{74}r_{6r} + 2.22 \quad \text{Eq. 4}$$

$$Nreq_r = -633 \times GLI_r + 0.95 \quad \text{Eq. 5}$$

$$Nreq_r = -566 \times NDRE_{75r} -3.79 \quad \text{Eq. 6}$$

3.3 Proposed implementation of the Target-N modelling framework

Models from the present project are made available for practical application, e.g. in a DSS. Models can then be applied as follows:

1. Predict field mean ONR for the season based on an assessment of yield potential and N uptake in zero-plots. Alternatively, the ONR can be determined based on user expert knowledge.
2. Subtract the rate of N given earlier in the season.

3. Predict the $Nreq_r$ within the field (the N rate to add to or subtract from the median rate, in different parts of the field) based on Sentinel-2 data (VIs relative to the field median)
4. Sum the predicted ONR and the predicted $Nreq_r$ for every raster cell in the field.
5. Optional: add a tabulated N rate to reach the protein target for bread quality (winter wheat).
6. Modify the prescription map by setting boundary conditions (minimum and maximum N rates), adjusting the median N rate, and/or delineating areas in which a new custom N rate is set.

3.4 Implementation in a decision support system

So far, models have been implemented in the CropSAT DSS (Dataväxt AB, Sweden) for precision agriculture (Figure 3). Since 2021, users can choose to provide a mean N rate for the field and the increase or decrease in different parts of the field was generated based on models from the present project. In 2023, the plan is that also the mean N rate will be proposed based on models from the present project. In addition, because yield potential is known to often vary substantially within fields a spatially variable target yield based on models by Söderström et al. (2021) could be used. The latter is an extension of the present project and is presented here for information.

Figure 3. Models from the project has been implemented in the free-to-use CropSAT application for generation of prescription files for site-specific management.

3.5 Opportunities and remaining challenges

Implementation of remote sensing-based prediction models of optimal supplemental N rate in a DSS, has the potential to enable wide adoption of precision N management, which in turn may improve better efficiency in the use of N fertilizers and thereby reducing risks for negative environmental impact. In the continued effort to streamline a functional DSS with continuous model updating, the following challenges may need to be considered (text with some modification from Piikki et al., 2022).

Designing national field trial series to produce data for model calibration. National field trials are usually carried out in locations with relatively favourable conditions for crop growth and may not be representative for areas with poorer cropping conditions.

Devloping recommendations for on-farm experiments (OFEs) to produce data for model application. Guides are needed on how to design OFE (number, size and locations of zero- or max-plots) to use interactively with this type of models.

Handling yield-limiting factors other than nitrogen. An option is to use homogeneous zones to reduce other variation than soil N supply. An alternative option could be to work with spatially continuous data on yield potential.

Handling model sensitivity to crop developmental stage. Models for absolute optimal supplemental N rates are more sensitive to crop development than relative rates (as modelled in the present study) and would require provision of accurate enough predictions of crop developmental stage.

Optimising N rate with respect to multiple goals. A procedure that simultaneously optimise N rate with respect to profit, grain protein goals, nutrient use efficiency and risks for lodging and N leaching or volatilization remains (to our knowledge) to be developed.

Growth conditions in the remainder of the season are unknown at the time of supplemental fertilisation. This is a (perhaps forever-unavoidable) source of uncertainty in supplemental N rate decisions.

Ensuring robust models. Development of functioning models at sites and years other than those used for model parameterisation needs extensive datasets for calibration, plus a validation approach that assesses model performance for new sites and years.

Ensuring up-to-date models. Modelling frameworks can be general, but model parameters are specific for cultivars etc. and would need to be updated for new cultivars, sensors and geographical areas.

Transferring models between sensor platforms. Successful transfer of models from one sensor platform to another (here from drone to satellite) requires knowledge on platform-transfer functions. Research on this is ongoing as a continuation of this project.

4 Conclusions

We have developed the Target-N algorithms for variable-rate application of supplementary N in winter wheat and spring barley based on remote sensing data during the stem elongation. It consists of a two-step approach – first the field average total N requirement is estimated from yield potential and N uptake in zero-plots (and optionally max-plots). Then, the rate of N previously applied is subtracted to determine the optimal supplemental N rate; secondly, this field average supplemental N rate is distributed and varied within the field based on the best-performing vegetation index that can be acquired from a satellite image. The project exemplifies an efficient and quick pathway through which results from crop field trials can be transferred to end-users, via drones to satellite image based decision support systems, for development of digital agricultural solutions. Further research challenges are presented, which aims at facilitating implementation of this type of projects even more.

5 Practical use and recommendations

Implementation of remote sensing-based prediction models of optimal supplemental N rate in a DSS, has the potential to enable better adaptation of N rates to local optima, which in turn may improve better N fertilizer use efficiency and reduced risks for the environment. However, one need to keep in mind that even if there are remaining challenges in designing prescription files for VRA of supplemental N, a uniform supplemental N rate may still be less correct. Our recommendation is to use the presently presented models, but always be aware that a prediction should be regarded as decision support rather than the true optimum. Therefore, in DSSs for precision agriculture where this type of algorithms are presented for end-users, it is important to include interactive functions to facilitate adjustments of model outputs based on user needs, experiences, and knowledge of local conditions.

6 References

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Wolters, S., Söderström, M., et al. (2021). Precision Agriculture, 22(4), 1263-1283.
Zadoks, J. C., Chang, T. T., et al. (1974). Weed research, 14(6), 415-421.

Del 3: Resultatförmedling

I Tabell 1 redovisas den resultatförmedling som genomförts i projektet.

Tabell 1. Genomförd resultatförmedling

Vetenskapliga publiceringar	Piikki, K., Söderström, M., & Stadig, H. (2022). Remote sensing and on-farm experiments for determining in-season nitrogen rates in winter wheat–Options for implementation, model accuracy and remaining challenges. Field Crops Research, 289, 108742. https://doi.org/10.1016/j.fcr.2022.108742
	Persson K., Söderström, M., Stadig H. & Martinsson J. (2023). Target-N: Sentinel-2 based nitrogen optimisation in Swedish winter wheat production. Abstract accepterat för muntlig presentation på European Conference on Precision Agriculture, Bologna, Italien 2023.
Muntlig kommunikation	Presentation på Ämneskommitté växtnärings möte i Linköping (2019-11-27).
	Presentation på Växjö möte (2022-12-14). Target-N: kvävekomplettering med fjärranalys.
	Presentation på regional växtodlingskonferens i Uddevalla (2023-01-11). Target-N: kvävekomplettering med fjärranalys.
	Presentation på ett nordeuropeiskt möte med fokus på kväveoptimering i stråsäd, som organiserades av SEGES i Köpenhamn (2019-11-29).
	Demonstration på Borgeby Fältdagar (2022). Dataväxt visade hur modeller från projektet implementerats i CropSAT.
	Presentation på webinarium arrangerat av Jordbruksverket (2022-08-28). Precisionsodlingsteknik i spannmål och vall.
	Presentation på N-workshop om precisionsodling och rådgivning, där Seges (Danmark), SLU, Agroväst, Dataväxt och Yara deltog (2021-11-17), Skara.
Studentarbete	Inget studentarbete har varit kopplat till projektet.
Övriga publiceringar	Pressmeddelande SLU: https://www.slu.se/ew-nyheter/2021/5/enklare-godsla-ratt-med-ny-algoritm-for-automatisk-kvavefordelning/

Övriga publiceringar	Projektbeskrivning på SLUs hemsida för LADS: https://www.slu.se/lads
	Artikel i Lantbrukets affärer, nr 6, 2022: Smart algoritm för tilläggsgödsling
	Lantbruksnytt Webb-TV-inslag: https://lantbruksnytt.se/tv/program/2021-05-07/
	Greppa-nyhet: https://greppa.nu/vara-tjanster/nyheter/arkiv---nyheter/2021-05-28-nya-funktioner-i-cropsat
	SLF-nyhet: https://www.lantbruksforskning.se/aktuellt/nyheter/battre-godsling-med-ny-algoritm-automatisk-kvavefo/
	Registrering av varumärket Target-N (samt -Y och -P) inom EU (reg. no 018583997).

Innovationspris

Baserat på data insamlade i detta projekt har modeller för skördekartering utvecklats. Modellerna har implementerats i CropSAT för att tillhandahålla möjlighet till skördekartering för alla. Innovationen har tilldelats följande pris:

Skara och Sparbanken Skaraborgs innovationspris 2021 från SLU (75 000 SEK) för Target-Y (skördekartering via satellit). Pristagare: M Söderström (SLU), K. Piikki (SLU), H. Stadig (Hushållningssällskapet) och J. Martinsson (Dataväxt AB).

Övriga publikationer baserade på data från projektet

Data som samlats in i detta projekt (DC69-73) har även nyttjats i andra projekt och genererat följande vetenskapliga publikationer:

Söderström M., Piikki K., & Stadig, H. (2021). Yield maps for everyone - scaling drone models for satellite-based decision support. In Precision Agriculture '21: Wageningen Academic Publishers, Wageningen, the Netherlands. p. 911–918. https://doi.org/10.3920/978-90-8686-916-9_109

Wolters, S. (2022). Towards synthesis for nitrogen fertilisation using a decision support system. Acta Agriculturae Sueciae 2022:59. Doctoral thesis available at: https://pub.epsilon.slu.se/28958/ (Accessed: October 19, 2022).

Wolters, S., Söderström, M., Piikki, K., Börjesson T., & Pettersson, C.G. (2022). Predicting grain protein concentration in winter wheat (Triticum aestivum L.) based on unpiloted aerial vehicle multispectral optical remote sensing. Acta Agriculturae Scandinavica, Section B — Soil & Plant Science, 72(1), 788-802. https://doi.org/10.1080/09064710.2022.2085165.