A simulation of variable rate nitrogen application in winter wheat with soil and sensor information

- An economic feasibility study

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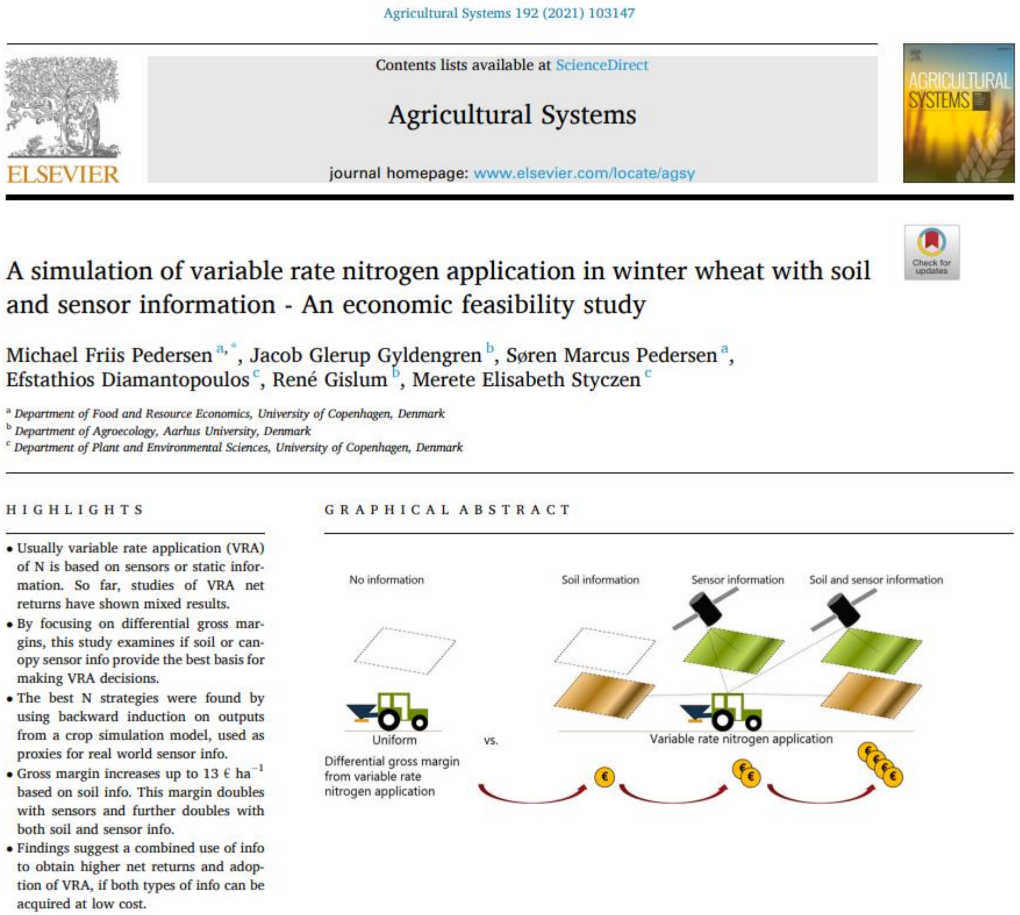
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HIGHLIGHTS

- Usually variable rate application (VRA) of N is based on sensors or static information. So far, studies of VRA net returns have shown mixed results.
- By focusing on differential gross margins, this study examines if soil or canopy sensor info provide the best basis for making VRA decisions.
- The best N strategies were found by using backward induction on outputs from a crop simulation model, used as proxies for real world sensor info.
- Gross margin increases up to 13 € ha^{-1} based on soil info. This margin doubles with sensors and further doubles with both soil and sensor info.
- Findings suggest a combined use of info to obtain higher net returns and adoption of VRA, if both types of info can be acquired at low cost.

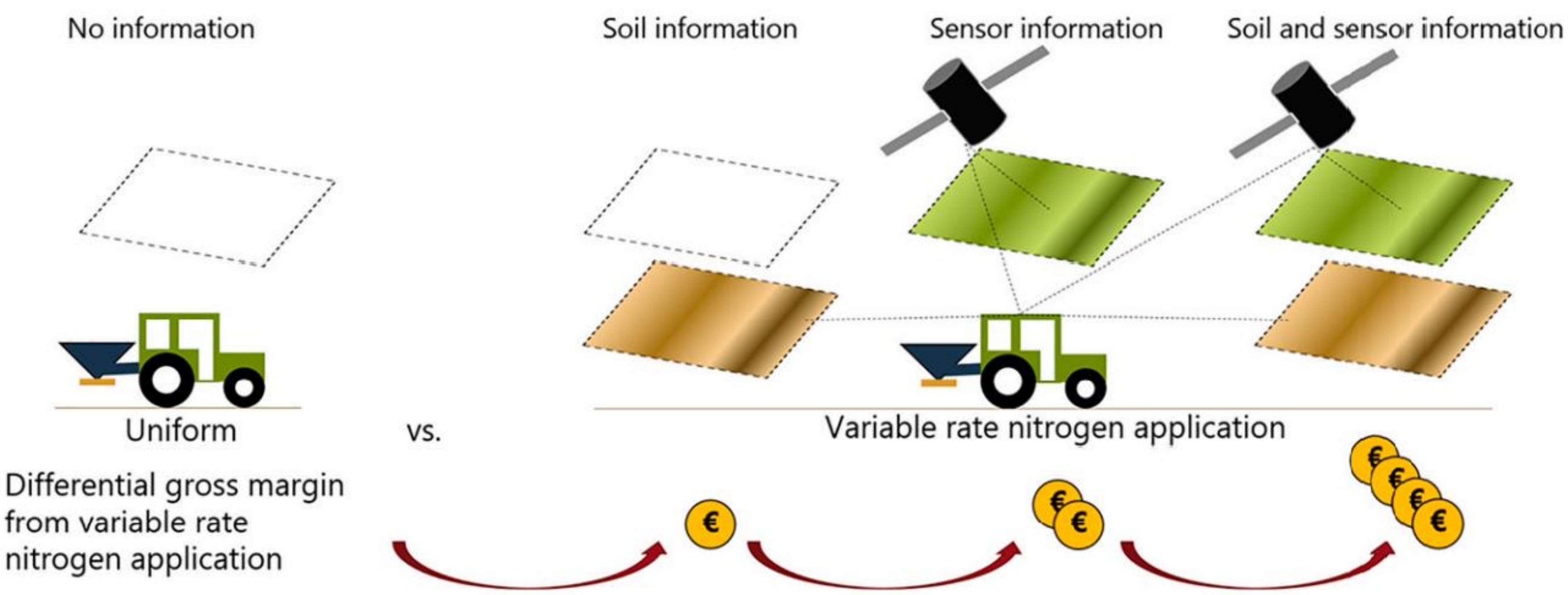
GRAPHICAL ABSTRACT

Research questions

- Will information about the crop canopy obtained before N application have the potential to improve the gross margin per hectare?
- Will sensor information and management zone (soil profile) information to a large extent capture the same in-field variation?
- Will sensor information and management zone (soil profile) information together create an additive or synergistic effect, where the combined effect is the sum of the individual effects or larger than the sum of the individual effects?

What we did – and what we found

GRAPHICAL ABSTRACT



How we did it

- Step 1 - Agroecosystem modelling using the DAISY model
  - Five-year crop rotation on six soil profiles found in a heterogeneous sandy loam field.

    Spring Barley →

    Winter Wheat (WW-SB) →

    Winter Rape (WR) →

    Winter Wheat (WW-WR) →

    Winter Wheat (WW-WW) + Oil Seed Radish (N catch crop).

  - A range of management descriptions (16 N strategies) was setup and simulations were made using 5 × 500 years of synthetic weather data with each crop in a five-year rotation set at the first year of the five parallel simulations.

  - Result in a total of 240.000 (5 rotation offsets x 500 years × 16 N strategies x 6 soil types) yield simulations of which 144.000 were simulations of winter wheat

Simple N management "decision tree" in basic DAISY setup vs. Dynamic N management decision tree

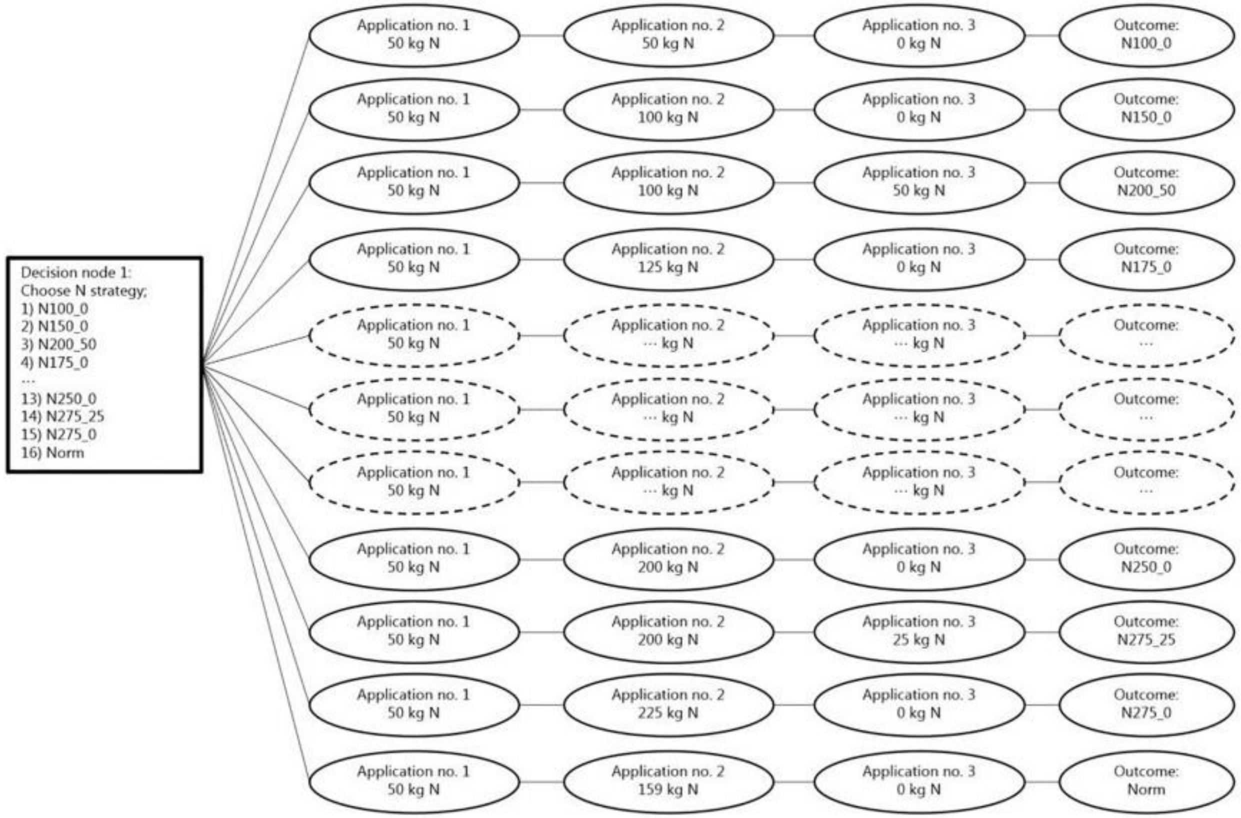


Fig. 1. Illustration of the simple N management 'decision tree' in the basic DAISY setup, with an indication of kg N per hectare for application no. 1–3.

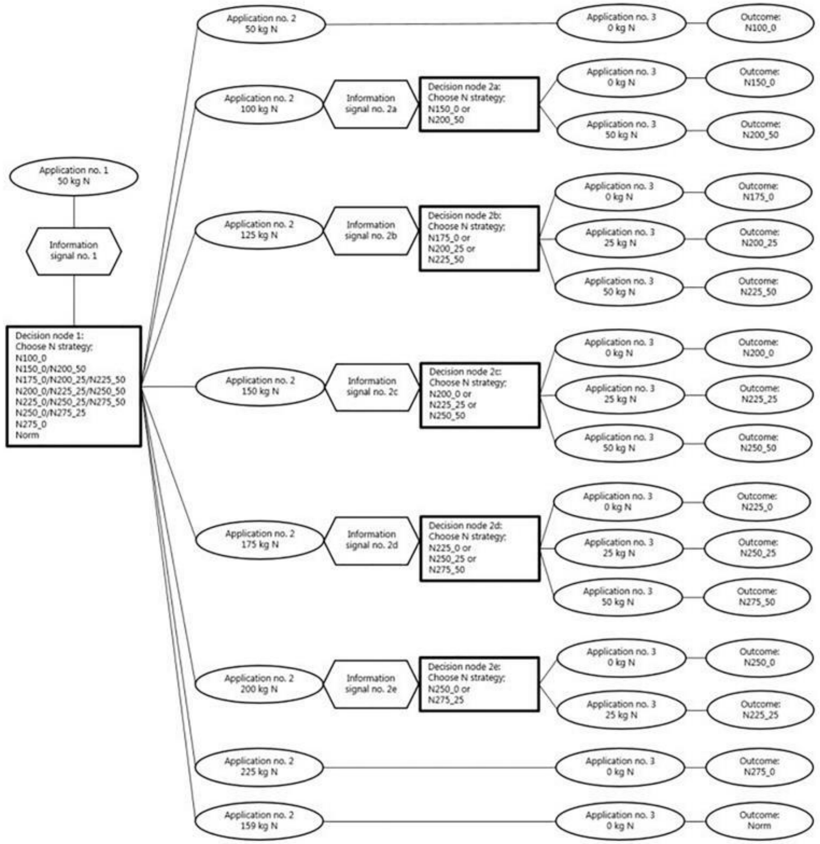


Fig. 2. Illustration of a dynamic N management decision tree influenced by information received during the growth season, with an indication of kg N per hectare for application no. 1–3.

N is applied regardless growth conditions (weather)*

*DAISY does have some dynamics regarding the timing of N application

N management decision tree influenced by information received during the growth season like in a real world VRA case

How we did it

- Step 2 – Analysis of DAISY output
  - Simulated growth variables were used as proxies for a ‘dynamic’ canopy sensor information system.
  - The differential gross margin was then calculated for a range (18) of price relations between fertilizer (model input) and wheat yield (model output), including wheat price adjustments according to protein content.
  - From regressions and backward induction analysis, the N application that maximizes the expected grain revenue minus fertilizer expenditure was estimated for four information cases

    - Case 1) uniform application without information,
    - Case 2) variable rate fertilization based on soil information,
    - Case 3) variable rate fertilization based on canopy sensor information and finally
    - Case 4) variable rate fertilization based on a combination of soil and canopy sensor information.

Summary results – soil type distribution as case field

Summary results, differential gross margin and average annual grain revenue minus fertilizer expenditure over all prior crops for situations reflecting the case field in Kalundborg, Denmark, wheat price 0.16 € kg^{-1}, protein adj. Price 0.40 € kg^{-1}, N fertilizer 1.25 € kg^{-1}.

	No soil profile information	Soil profile information
No sensor information	Uniform N-application. Grain revenue minus fertilizer expenditure 1412.59 € ha^{-1}	VRA with management zones based in soil profiles. Grain revenue minus fertilizer expenditure 1419.71 € ha^{-1} Differential gross margin from VRA 7.12 € ha^{-1}
Sensor information	VRA based on 'dynamic' sensor information. Grain revenue minus fertilizer expenditure 1428.37 € ha^{-1} Differential gross margin from VRA 15.78 € ha^{-1}	VRA based on sensor information and soil profiles. Grain revenue minus fertilizer expenditure 1447.11 € ha^{-1} Differential gross margin from VRA 34.52 € ha^{-1}

Summary results – different soil type distribution

Summary results, differential gross margin and average annual grain revenue minus fertilizer expenditure over all prior crops for the a priori soil distribution, wheat price 0.16 € kg^{-1}, protein adjustment price 0.40 € kg^{-1}, N fertilizer 1.25 € kg^{-1}.

	No soil profile information	Soil profile information
No sensor information	Uniform N-application. Grain revenue minus fertilizer expenditure 1392.51 € ha^{-1}	VRA with management zones based on soil profiles. Grain revenue minus fertilizer expenditure 1398.78 € ha^{-1} Differential gross margin from VRA 6.27 € ha^{-1}
Sensor information	VRA based on 'dynamic' sensor information. Grain revenue minus fertilizer expenditure 1427.12 € ha^{-1} Differential gross margin from VRA 17.05 € ha^{-1}	VRA based on sensor information and soil profiles. Grain revenue minus fertilizer expenditure 1409.56 € ha^{-1} Differential gross margin from VRA 34.61 € ha^{-1}

Conclusion

We analysed if soil or sensor information is the most valuable information to use for VRA using DAISY.

We found a synergistic effect between the two information types with important implications for the development of crop models and variable rate technologies for farmers in the future.

However, it is important to notice that values from vegetation indices are dependent of which platforms are used (we use DAISY output as proxies for this) and the fact that we have not considered what the optimum time for obtaining sensor information actually is.

The result is sensitive to the level of in-field variation, as the economic potential of VRA from heterogeneous fields is higher compared with homogeneous fields.

Thank you for listening

Questions?

DAISY model setup - N scenarios

Table 2
N application strategies.

N-strategy (ID) \ Time \ #of N application			1. Application March 1st - March 25th Kg N ha^{-1}	2. Application + 30 days (March 31st - April 24th) Kg N ha^{-1}	3. Application + 30 days (April 30th - May 24th) Kg N ha^{-1}
1	N100_0		50	50	0
2	N150_0			100	0
3	N200_50				50
4	N175_0			125	0
5	N200_25				25
6	N225_50				50
7	N200_0			150	0
8	N225_25				25
9	N250_50				50
10	N225_0			175	0
11	N250_25				25
12	N275_50				50
13	N250_0			200	0
14	N275_25				25
15	N275_0			225	0
16	Norm	WW-SB	50	159	0
		WW-WW	50	159	0
		WW-WR	50	136	0

Regression analysis made in all decision nodes to determine best N strategy given signal (DAISY output as proxies for a 'dynamic' canopy sensor information system)

$$\begin{aligned}
\text{Differential Gross Margin} \equiv & \left(\text{Grain revenue minus fertilizer expenditure}_{\text{N applicaton i}} - \text{Grain revenue minus fertilizer expenditure}_{\text{N application j}}\right) \\
& \approx \text{b}_1\text{Nleaf} + \text{b}_2\ \text{LeafAI} + \text{b}_3\text{Height} + \text{b}_4\ \text{AccPhotoSyntesis} + \text{b}_5\text{Nleaf}^2 + \text{b}_6\ \text{LeafAI}^2 + \text{b}_7\text{Height}^2 + \text{b}_8\ \text{AccPhotoSyntesis}^2 \\
& + \text{b}_9\text{Nleaf*LeafAI} + \text{b}_{10}\text{Nleaf*Height} + \text{pb}_{11}\text{Nleaf*AccPhotoSyntesis} + \text{b}_{12}\ \text{LeafAI*Height} \\
& + \text{b}_{13}\ \text{LeafAI*AccPhotoSyntesis} + \text{b}_{14}\text{Height*AccPhotoSyntesis}
\end{aligned}$$

Two different soil type distributions used

Soil profile description and relative area distribution at Kalundborg case field (Gyldengren, 2019) and a priori assumption.

Profile	Description	Soil distribution, Kalundborg case field, pct.	A priori soil profile distribution, pct.
Profile 1	Well drained sandy loam	28.2	30
Profile 2	Poorly drained sandy loam	13.5	10
Profile 3	Depression	13.9	10
Profile 4	Sandy loam with sandy subsoil	34.7	30
Profile 5	Sandy soil	0.8	10
Profile 6	Hill shoulder	8.9	10
All	Total	100.0	100