A digital twin for arable crops and for grass

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Abstract.

There is an opportunity to use process-based cropping systems models (CSMs) to support tactical farm management decisions, by monitoring the status of the farm, by predicting what will happen in the next few weeks, and by exploring scenarios. In practice, the responses of a CSM will deviate more and more from reality as time progresses because the model is an abstraction of the real system and only approximates the responses of the real system. This limitation may be overcome by using the CSM as a digital twin. A digital twin (DT) is a model of a specific physical object, that is kept synchronized by using real-time observations on that object. In this paper we present the Digital Future Farm (DFF), a digital twin for arable and dairy farming. The DFF comprises access to data sources (e.g. weather, soils, farm management, remote sensing), a suite of models, and utilities for data assimilation and visualization of simulation results. The working of the DFF is demonstrated with examples from a multi-year experiment and from a commercial potato farm. In addition to a CSM, the DFF is also demonstrated to work with a summary model for potato growth. Initial experiences indicate that the DFF produces information that is helpful to farmers but it is difficult to evaluate the performance of the DFF in quantitative terms because of variability between years, fields, and the lack of availability of on-farm data. The most immediate contribution of the DFF is to provide farmers with a ranking of their fields according to how urgently they need an intervention. Experiences with the DFF have helped to formulate further research questions.

Keywords.
process-based model, nitrogen, fertilization, irrigation, data assimilation, Kalman filter, machine learning, recursive neural network (RNN).

Introduction

There is a huge opportunity for the application of process-based cropping systems models (CSMs) to support farm management decisions. A properly calibrated and initialized CSM can support farm management in at least three ways.

- Monitor - Which of my fields has insufficient soil water and/or nitrogen?
- Predict - Is there enough water and/or nitrogen for the coming week?
- Explore scenarios - Alternative schedules for irrigation and/or nitrogen (given limited resources)

In practice, no matter how well calibrated and initialized, the responses of a CSM will deviate more and more from the reality on the farm as time progresses. This is to be expected because a CSM is a model, i.e. an abstraction of the real system, and as such only approximates the responses of the real system. However much this deviation may be expected, it is not what farmers, the intended users of CSM-based predictions, expect. When a model deviates from reality, trust in the model is diminished.

A simulation will deviate from reality because some processes may not be modeled in all detail, and some processes may not be included at all. For example, in crop models, the response to extreme temperatures may not be modelled in great detail, and the response to diseases is typically not modelled at all. However, even if all relevant processes are included in the model, imperfect calibration of some parameters may still lead to deviations.

The above limitations may be overcome by using a CSM as a digital twin. A digital twin (DT) is a model of a specific physical object, that is kept synchronized by using real-time observations on that object (Grieves, 2014). DTs are widely used in engineering and the concept has recently started to receive attention in agriculture (Pylianidis et al., 2021, Van Evert et al., 2021).

In this paper we describe the Digital Future Farm (DFF), a digital twin for arable crops and grass. We show some applications and discuss research questions that arise from these applications.

Digital Future Farm (DFF) – technical overview

MODCOM

The DFF is a digital twin for arable farming and dairy farming (Knibbe et al., 2022, Van Evert et al., 2021). DFF can work with different models to represent arable and dairy farms. DFF can also work with different models to represent e.g. potato or grass. This is achieved by using a generic simulation framework, to link models, data sources, and utilities.

The MODCOM simulation framework (Hillyer et al., 2003) allows linking of sub-models and handles numerical integration, events, and communication between sub-models. MODCOM can be considered to be an implementation of the Discrete Event System Specification (DEVS) (Zeigler et al., 2000). Specifically the DFF uses NModcom (Van Evert and Lamaker, 2007), which is the C# version of the original C++ implementation. NModcom has inspired both SIMPLACE (Enders et al., 2010) and BioMa (Donatelli et al., 2012). NModcom is available as open-source at https://github.com/nmdcom/NModcom .

Models

Selected models currently available in DFF are listed in Table 1. Most models are written in C#, the language in which the MODCOM framework is written. Some models are written in other languages and are linked to the DFF using one of the available cross-language interoperability mechanisms.

Table 1. Selection of models available in DFF

Model	Purpose	Language and linking method	Reference
Dairy cow	Dairy cow	C#	Zom (2014)
Silage	Fodder conservation	C#	Schils et al. (2007)

SNOMIN	Soil organic matter	C#	Berghuijs et al. (2024)
Tipstar	Potato	C#	van Oort et al. (2024)
TipstaRNN	Potato	C#, C++	Boersma et al. (2024)
Grass2007	Grass	Delphi, via COM	Vellinga et al. (2004)
SWAP	Soil water	Fortran, via DLL	Kroes et al. (2017)
WOFOST	Arable crops	Python, via IronPython	De Wit et al. (2019)

Farmmaps

A model is only useful if it can be supplied with input data. Unfortunately, accessing input data for commercial farms, at scale, is much more challenging than collecting model input in the setting of a scientific experiment. The DFF addresses this challenge by leveraging Farmmaps (Been et al., 2023).

Farmmaps is a cloud-based data and service platform for precision agriculture. It provides basic apps and services (e.g. weather data, soils data, satellite data) as well as specific applications. The DFF accesses several data sources that are available through Farmmaps.

A central concept in Farmmaps is “crop field” which represents the growing of a crop on a given field during a defined period of time. Associated with the crop field is a geo-located polygon that indicates the spatial extent of the field. This polygon can be drawn by hand but users typically take advantage of the link that Farmmaps provides to an existing data source such as the EU-mandated Land Parcel Identification System (European Court of Auditors, 2016).

For each crop field, Farmmaps provides soil physical data either from BOFEK database (Heinen et al., 2021; only The Netherlands) or from SoilGrids[1] (global coverage). Weather data (current, historic, and 14-day forecasts) are obtained from a commercial provider. Satellite imagery is obtained from SentinelHub[2] and other providers. Drone imagery, if available, can be uploaded by users and will then be linked to the relevant crop fields.

Field operations such as tillage, sowing, irrigating, fertilizing, harvesting, and grazing can be recorded for a crop field. This data can either be entered by the user or it can be retrieved from the user’s (commercial) Farm Management Information System (FMIS).

Data assimilation

Data assimilation is a term that denotes the use of observations to make simulations match better with the modelled system. Three main methods of data assimilation are distinguished, namely forcing (where observations replace one or more state variables that would otherwise be simulated, calibration (where model parameters are adjusted), and filtering (where observations and simulations are combined into a new, optimal estimation of the state of the system) (e.g. Jin et al., 2018, Jindo et al., 2023). Filtering takes into account the uncertainty in observations as well as the uncertainty in simulation results. The most well-known filtering method is the Kalman filter. This cannot be used directly with a CSM, however, an alternative formulation, the Ensemble Kalman Filter (EnKF), can be used. The DFF uses an EnKF implementation originally proposed by (De Wit et al., 2012, De Wit and van Diepen, 2007).

Utilities

The DFF includes a Postgresql[3] database to collect input and store simulation output. This facilitates the generation of graphics that visualize simulation results and compare these with observations.

DFF applications

The DFF is currently being used in several contexts.

[1] https://www.isric.org/explore/soilgrids
[2] https://www.sentinel-hub.com/
[3] https://www.postgresql.org/

Farm of the Future

Farm of the Future (FOTF[4]) is an initiative in which farmers and Wageningen University & Research work together to develop solutions to the challenges faced by agriculture in the Netherlands, drawing on the expertise and practice of both organic and mainstream agriculture.

Specifically, the FOTF aims to bring more diversity to the farm, through more crops in the rotation, a wider range of crops and cultivars, and different spatial arrangements: crops are grown in strips (3 or 15 m wide). This is expected to lead to greater biodiversity in the field and thus better suppression of pests and diseases. The experiment is at farm scale, and field operations are entered into a commercial farm management information system. The DFF is used to monitor the status of crops and soil and to support e.g. decisions on side dressing N in potatoes. Simulations for a number of crops are run daily (Figure 1, Figure 2), observations of LAI from Sentinel-2 are assimilated into the model, and the results are available in a dedicated section on the project's website and are updated every day[5].

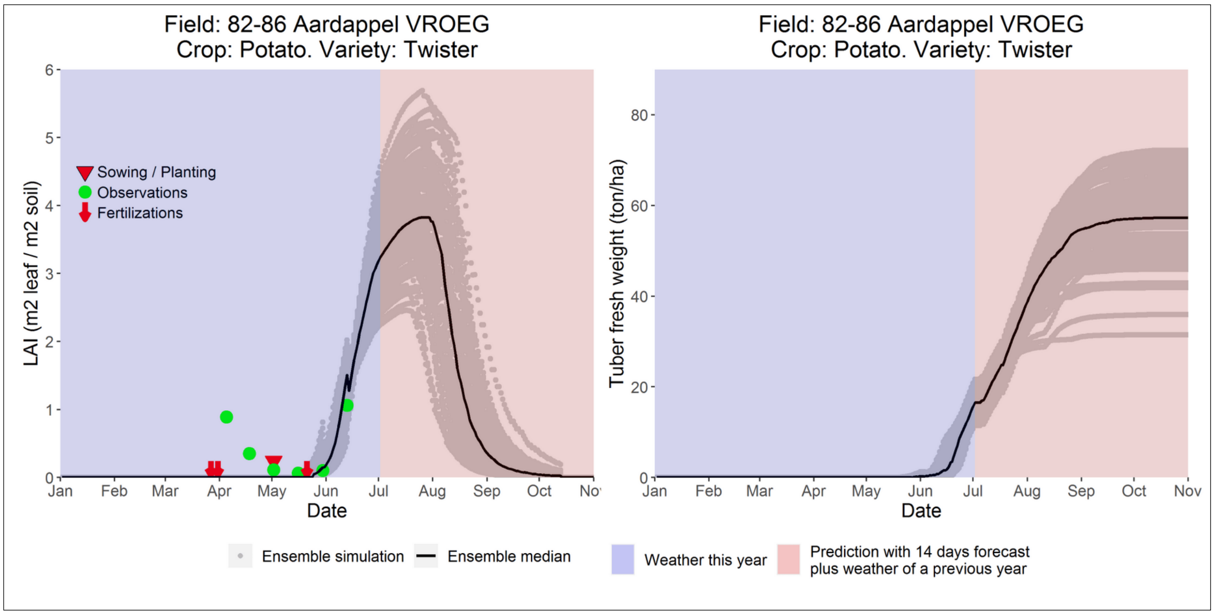

Figure 1. Simulation output from the DFF. Left panel: LAI; right panel: tuber weight. This simulation was made on 3 July 2024. In both panels, the purplish background indicates the period from the beginning of the year to 3 July; during this period observed weather was used. The pinkish background indicates the future: from 3 to 20 July a weather forecast is used, while from 21 July to the end of the year historic weather from a previous year is used. Grey dots represent 30 different simulation curves (the "ensemble"), each made with slightly different values for a selected set of parameters, to represent the uncertainty in the prediction. In addition, each of the 30 curves uses a different historic year for the period from 21 July to the end of the year. The solid black line is the median of the ensemble, it represents the best estimate of the state of the system. Green dots indicate drone-based observations of LAI. Each time a LAI observation is available, the simulations are adjusted using the Ensemble Kalman filter.

[4] https://farmofthefuture.nl/en/

[5] https://farmofthefuture.nl/data-precisietechnologie/gewasgroeimodellen/

forecast date: 2024-06-25

	Simulated stress indices (0-1) water 2024-06-25	water +7 days	nitrogen 2024-06-25	nitrogen +7 days	final yield (ton/ha)
01. Potato, Cammeo, 174-178 Aardappel LAAT	1	1	0.253	0.42	35.1
02. Potato, Cammeo, 164-168 Aardappel LAAT	1	1	0.25	0.422	35.1
03. Potato, Cammeo, 154-158 Aardappel LAAT	1	1	0.253	0.422	35.1
04. Potato, Cammeo, 144-148 Aardappel LAAT	1	1	0.254	0.424	35.1
05. Potato, Cammeo, 53 Aardappel LAAT	1	1	0.203	0.337	32.6
06. Potato, Cammeo, 45 Aardappel LAAT	1	1	0.241	0.395	35.4
07. Potato, Cammeo, 37 Aardappel LAAT	1	1	0.242	0.4	35.3
08. Potato, Cammeo, 28 Aardappel LAAT	1	1	0.242	0.391	35.5
09. Potato, Cammeo, 20 Aardappel LAAT	1	1	0.295	0.507	35.3
10. Potato, Cammeo, 12 Aardappel LAAT	1	1	0.294	0.506	35.3
11. Potato, Cammeo, 4 Aardappel LAAT	1	1	0.293	0.491	35.7
12. Potato, Twister, 92-96 Aardappel VROEG	1	1	0.275	0.459	33.1
13. Potato, Twister, 82-86 Aardappel VROEG	1	1	0.273	0.455	33.2
14. Potato, Twister, 72-76 Aardappel VROEG	1	1	0.275	0.459	33.2
15. Potato, Twister, 62-66 Aardappel VROEG	1	1	0.277	0.46	33.2
16. Potato, Twister, 57 Aardappel VROEG	1	1	0.272	0.455	33.3
17. Potato, Twister, 49 Aardappel VROEG	1	1	0.269	0.451	33.3
18. Potato, Twister, 41 Aardappel VROEG	1	1	0.28	0.444	33.7
19. Potato, Twister, 32 Aardappel VROEG	1	1	0.271	0.452	33.2
20. Potato, Twister, 24 Aardappel VROEG	1	1	0.326	0.537	33.6
21. Potato, Twister, 16 Aardappel VROEG	1	1	0.326	0.537	33.6
22. Potato, Twister, 8 Aardappel VROEG	1	1	0.325	0.549	33.2

forecast date: 2024-06-26

	Simulated growth conditions (1=very good) water 2024-06-26	water +7 days	nitrogen 2024-06-26	nitrogen +7 days	final yield (ton/ha)
01. Potato, Cammeo, 174-178 Aardappel LAAT	1	1	1	1	64.1
02. Potato, Cammeo, 164-168 Aardappel LAAT	1	1	1	1	63.7
03. Potato, Cammeo, 154-158 Aardappel LAAT	1	1	1	1	63.8
04. Potato, Cammeo, 144-148 Aardappel LAAT	1	1	1	1	63.8
05. Potato, Cammeo, 53 Aardappel LAAT	1	1	1	1	63.5
06. Potato, Cammeo, 45 Aardappel LAAT	1	1	1	1	63.6
07. Potato, Cammeo, 37 Aardappel LAAT	1	1	1	1	63.7
08. Potato, Cammeo, 28 Aardappel LAAT	1	1	1	1	63.5
09. Potato, Cammeo, 20 Aardappel LAAT	1	1	1	1	57.6
10. Potato, Cammeo, 12 Aardappel LAAT	1	1	1	1	57.6
11. Potato, Cammeo, 4 Aardappel LAAT	1	1	1	0.928	42.1
12. Potato, Twister, 92-96 Aardappel VROEG	1	1	1	1	56.8
13. Potato, Twister, 82-86 Aardappel VROEG	1	1	1	1	56.9
14. Potato, Twister, 72-76 Aardappel VROEG	1	1	1	1	56.5
15. Potato, Twister, 62-66 Aardappel VROEG	1	1	1	1	56.8
16. Potato, Twister, 57 Aardappel VROEG	1	1	1	1	56.9
17. Potato, Twister, 49 Aardappel VROEG	1	1	1	1	56.5
18. Potato, Twister, 41 Aardappel VROEG	1	1	1	0.944	42.7
19. Potato, Twister, 32 Aardappel VROEG	1	1	1	1	56.8
20. Potato, Twister, 24 Aardappel VROEG	1	1	1	1	48.7
21. Potato, Twister, 16 Aardappel VROEG	1	1	1	1	49.3
22. Potato, Twister, 8 Aardappel VROEG	1	1	1	1	49.2

Figure 2. Warnings generated for potato strips at Farm of the Future. Left panel: simulation results on 25 June, before application of N sidedress: supply of soil water is sufficient on this day and is projected to be sufficient one week into the future; nitrogen supply is insufficient on this day and is projected to be still insufficient one week into the future. Also shown is projected final fresh tuber yield. Right panel: simulation results on 26 June, after application of N sidedress.

Assimilation of soil water data

In addition to measurements of aboveground biomass and/or LAI, remote sensing can provide an estimate of (top) soil water content. This may reduce the uncertainty related to the availability of water. Correcting soil moisture is important because this is a large source of uncertainty: precipitation is the most spatially heterogenous of weather data and the amount of irrigation is often not recorded by farmers.

We used top soil water content retrieved from passive satellite microwave measurements as provided by Planet[6]. Microwave measurements are transformed to soil water content (resolution 100x100 meter) (De Jeu et al., 2014, Owe et al., 2008, Owe et al., 2001).

The assimilation of data within the season corrected both LAI and topsoil moisture model estimates downward (Figure 3). This resulted in lower light interception and higher water stress. As a result the final yield estimate of the model + data assimilation was corrected to a lower value, which is closer to the final observed yield.

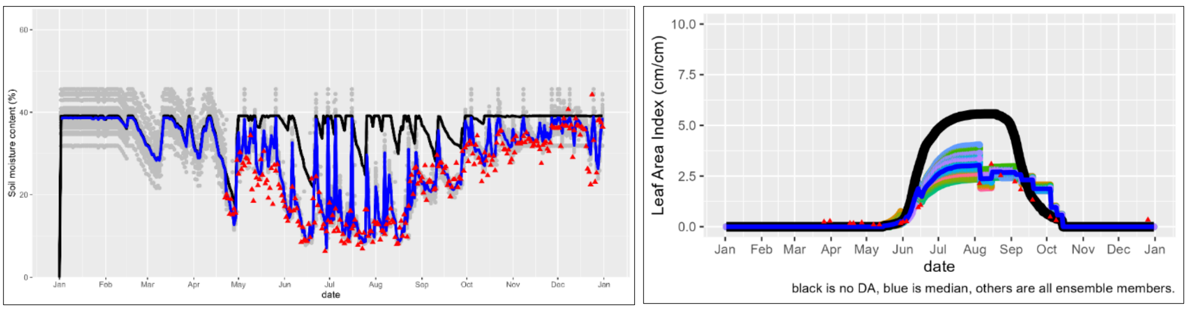

Figure 3. Assimilation of remotely sensed top soil water content. Data are for one of the potato strips in FOTF in 2022. Left panel: The black solid line represents simulated soil water content 0-5 cm without data assimilation. Red triangle symbols represent remotely sensed soil water content. Grey dots represents individual simulations of the Kalman filter ensemble. Blue solid line is the median of the ensemble simulation; this represents the best estimate (observation + model). Right panel: The black solid line represents simulated LAI without data assimilation. Red triangles represent LAI measurements from drone imagery. Blue solid line is the median of the ensemble simulation (individual ensemble simulation are shown in various colours).

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[6] https://www.planet.com/

Commercial potato farm

Van den Borne Aardappelen is a commercial farm which grows approx. 500 ha of potatoes each year[7]. The farm is located in the south of The Netherlands on shallow, coarse sandy soil. The variation in texture, soil organic matter, and profile depth between fields is relatively large which poses management challenges.

Van den Borne have been pro-active in documenting their operations since approx. 2010, including farm management, yields, soil analyses, and in-season crop growth measurements. This has led to several research reports (Mulders et al., 2024, Mulders et al., 2021, Van Evert et al., 2019, Yan et al., 2015). Nevertheless it has been a challenge to connect the proprietary databases in real-time to CSMs. Recently Van den Borne have switched to a commercial FMIS and this has made it possible to simulate crop growth in real-time (Figure 4). The next step will be to evaluate the setup for the remaining approx. 150 fields and rank them in the same way as the FOTF fields in Figure 2.

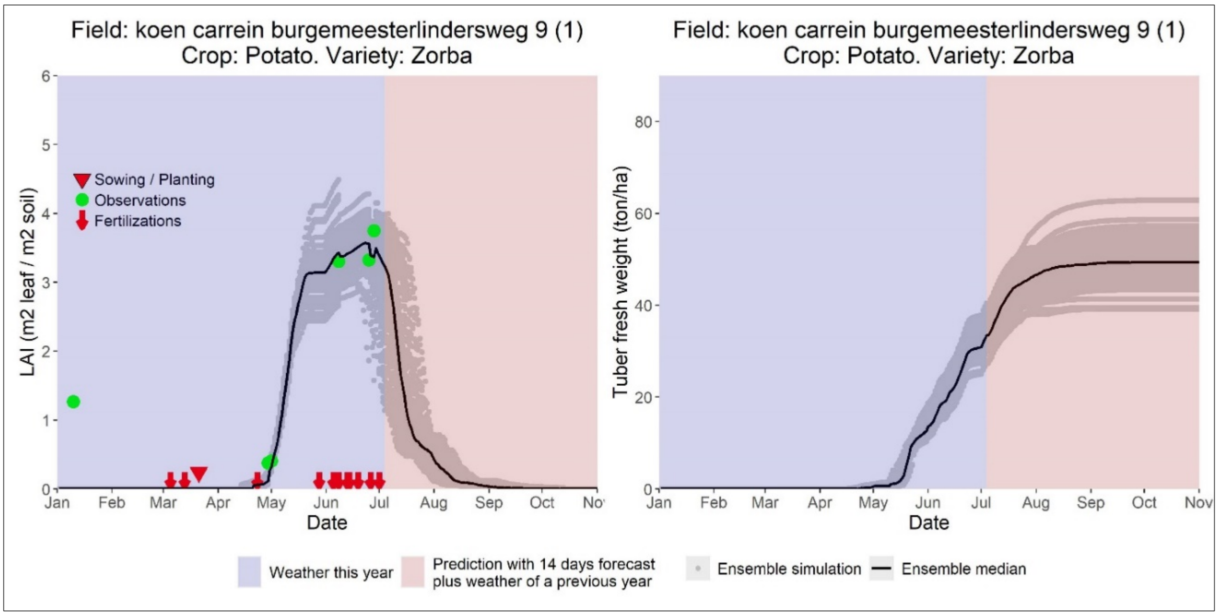

Figure 4. Visualization of the digital twin on a commercial field of potatoes. Simulation with Tipstar; results for 3 July 2024. Symbols and colors as in Figure 1, but LAI observations are estimated from Sentinel-2 imagery.

Maize and soybeans in Serbia

In an on-farm experiment in Čenej, Vojvodina (Serbia), soil conditions and the growth of soybean and maize were monitored in 2023 (Kopanja et al., 2024). LAI was measured both destructively, with an LI-3100C leaf area meter (Licor, Lincoln NE, USA), and remotely, with imagery from Sentinel-2. For the latter, the formulate given by Gaso et al. (2021) was used to convert images to LAI. This resulted in a discrepancy between LAI measured destructively and LAI estimated from remote sensing.

Simulation results for maize are shown in Figure 5. Early simulated LAI deviates much from observed LAI because the emergence date was modeled inaccurately. The Ensemble Kalman filter partially corrected the wrong emergence date estimation from the model. Simulation of soybean corresponded closely to reality (Figure 6) and filtering resulted only in small adjustments to the simulation.

[7] https://www.vandenborneaardappelen.com/

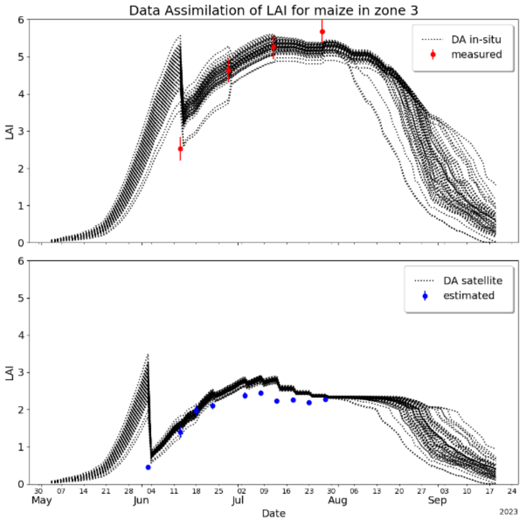

Figure 5. Data assimilation of in-situ LAI (upper) and satellite LAI (lower) for maize.

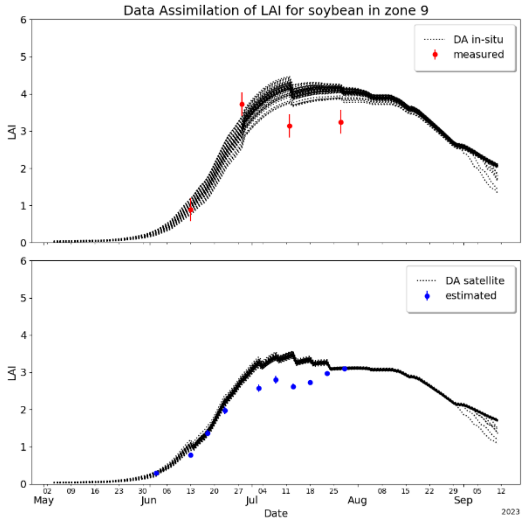

Figure 6. Data assimilation of in-situ LAI (upper) and satellite LAI (lower) for soybean.

Working with a digital twin

In this section some observations are made about working with a digital twin in agriculture, based on experiences to date.

Emergence

The date of emergence of an annual crop such as potato, maize, or soybean, is an important determinant of growth and final yield. Unfortunately the date of emergence is rarely observed in practice. That means that date of emergence has to be modelled, for example as taking place a certain number of days or degree-days after sowing or planting (which most farmers do record). Emergence is a complex process that cannot be modeled accurately; relying on an emergence model may well result in a simulation that deviates significantly from reality.

It is tempting to use filtering to correct for an inaccurately simulated date of emergence as was done in Curnel et al. (2011) as well as in Figure 5 above. However, this is fundamentally incorrect and may have unintended consequences. First, if uncertainty about one parameter (date of emergence) is addressed by varying one or more completely unrelated parameters, then the simulation may deviate in areas where it was performing well before the variation was imposed. Second, if an incorrect date of emergence is used, development events such as flowering and maturity, which are linked to the moment of emergence, will likely be mis-estimated.

It is preferable to estimate the date of emergence from observations, for example by iteration or by direct estimation. In the iterative method, the date of emergence is by trial and error until a certain criterion is minimized, for example RMSE between simulated and measured LAI during the first few weeks after emergence (Maas, 1993). In the direct method, measurements of LAI during the first few weeks after emergence are used to estimate the date of emergence by regression and extrapolation (Figure 7).

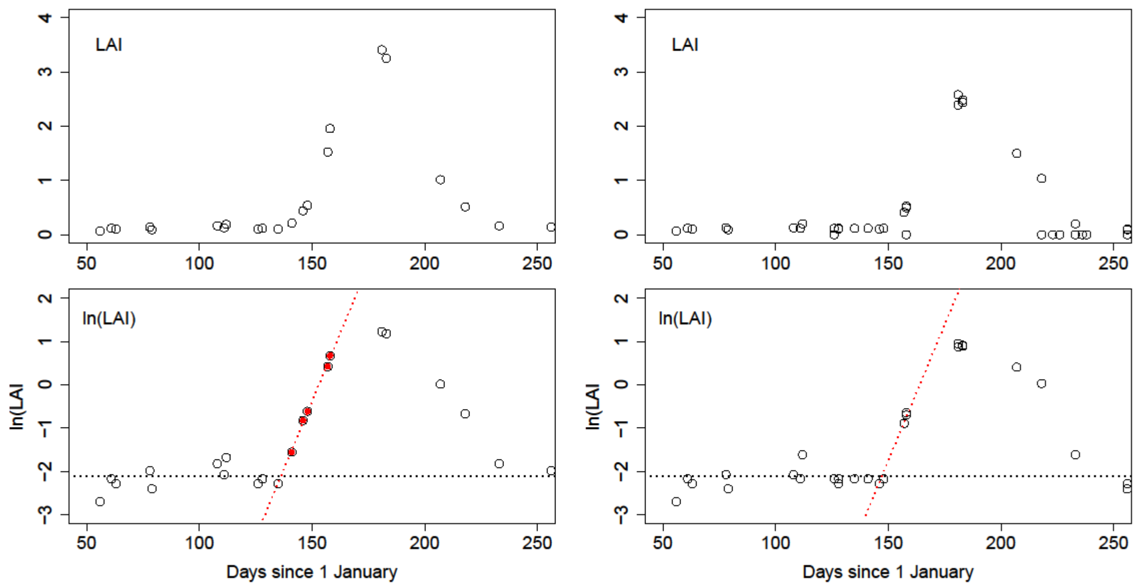

Figure 7. Estimation of emergence date of potatoes. Top row: LAI estimated from satellite for two different fields with potato. The general shape of the LAI curve over time is similar in both cases but the top-left panel has more frequent measurements than the top-right panel. Bottom row: logarithmic transformation of the data in the top row, which highlights the exponential phase of canopy expansion. In the bottom-left panel there are sufficient measurements to estimate the date of emergence via linear regression. In the bottom-right panel, there are insufficient measurements for a linear regression; however, the slope of the regression line is conservative and by using the slope from the bottom-left panel the date of emergence can still be determined.

Summary models

The models described above are process-based models, i.e. models in which the equations reflect the (bio-)physics of the modeled system. But in many engineering disciplines it is common to use summary (or: meta) models based on the output of process-based models. This has also been done in agriculture (e.g. Hack-ten Broeke et al., 2016, Maestrini et al., 2022).

The DFF is being used to explore the use of a summary model. A new model, TipstaRNN, was created by (Boersma et al., 2024). Potential growth of potato was simulated with Tipstar, a process-based model, for many hundreds of combinations of location, year, and planting date. A recurrent neural network (RNN) was trained on the simulation output to predict the daily rate of increase of LAI and fresh tuber weight (TW). The RNN has a history of 10 days and is able to reproduce the output of the original process-based model.

The new model, TipstaRNN, was constructed and trained using the CasADi open-source tool for nonlinear optimization and algorithmic differentiation (Andersson et al., 2019). The trained RNN was exported as C++ code, compiled into a DLL, and wrapped with C# into a MODCOM component model for inclusion in the DFF.

TipstaRNN predicts the rate of increase of LAI and TW on a given day based on the weather of that day and on LAI and TW of the 10 previous days. This poses a challenge for the initialization of the model. We have chosen to address this as follows. For the first 10 days following emergence, TW stays constant - this is reasonable because tubers are not growing yet. On the day of emergence, LAI is initialized with a value which reflects the number of stems and the initial LAI per stem. During the 10 days following emergence, LAI increases exponentially with a relative growth rate that is a function of average daily temperature – this is how many CSMs simulate early leaf growth.

With a process-based model, we can create an ensemble by varying some of the parameters of the model, taking into account the uncertainty that exists about their true value. TipstaRNN does not have parameters that lend themselves to this treatment, instead we create an ensemble by adding, at each time step, some white noise to the predictions of the model. A result is shown in Figure 8.

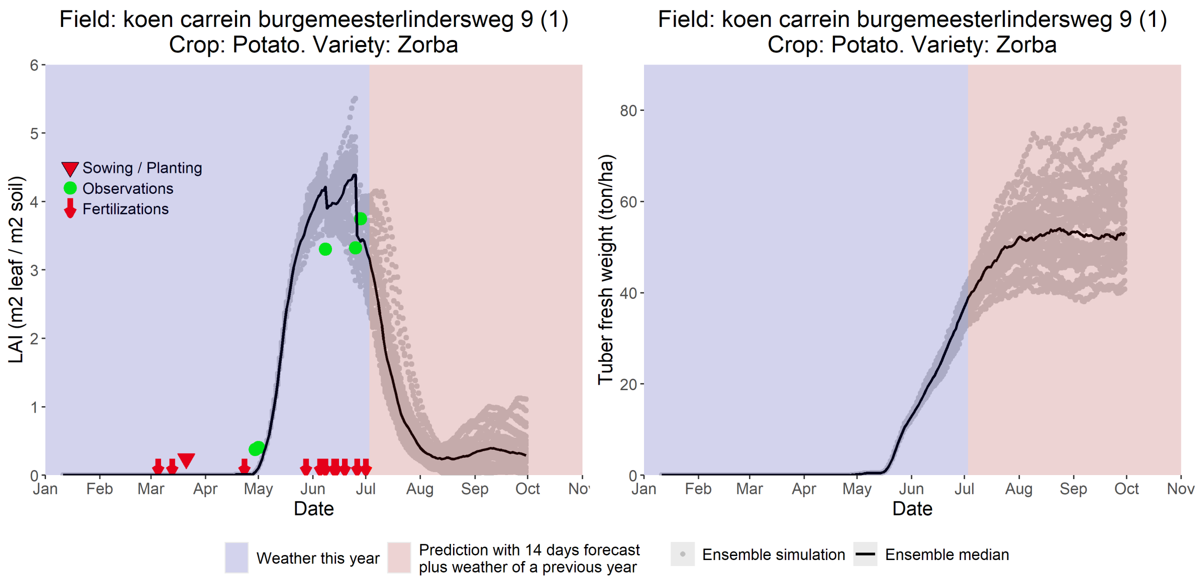

Figure 8. Visualization of the digital twin on a commercial field of potatoes. Simulation with TipstaRNN; results for 3 July 2024. Symbols, colours and data as in Figure 4.

Discussion

Data assimilation

CSMs can in principle be used to support decision making in precision agriculture. They can be used to monitor the state of crops, soils, and livestock on the farm, to predict future states, and to evaluate alternative management scenarios. However, models are imperfect due to limitations in the model structure and processes, uncertainty about model parameters and initial conditions, as well as uncertainty about the driving variables that the models require. Therefore, the simulated states often diverge from reality and this uncertainty tends to increase with every time-step of the model. When a model is used to forecast the impact of management decisions, this uncertainty has a negative impact on the value of the digital twin.

Data assimilation is a tool to adjust the state of a model whenever observations are available that provide information on the state of the modeled system. Three main methods of data assimilation can be distinguished, namely forcing (where observations replace one or more state variables that would otherwise be simulated), calibration (where model parameters are adjusted), and filtering (where observations and simulations are combined into a new, optimal estimation of the state of the system) (e.g. Jin et al., 2018, Jindo et al., 2023).

<u>Forcing</u> is not a method that we have considered for the DFF. Clearly this could be useful in a situation where a model is missing and where frequent, accurate and precise measurements are available.

<u>Calibration</u> is the appropriate method to use if there is reason to believe that local information can be used to derive better parameter values. It is perhaps useful to differentiate between parameters that are intrinsic to the model (e.g. radiation use efficiency, minimum nitrogen concentration of plant organs, specific leaf area) and parameters that initialize the state of the model (soil water content at start of simulation, but also date of emergence).

Intrinsic parameters describe processes in a way that is not dependent on any individual experiment or farm field. It is highly unlikely that using information from an individual experiment or farm field will lead to better estimates for these parameters than the combined information from the large number of experiments that were used to estimate these parameters in the first place. Trying to estimate these parameters with local information would indeed be a cumbersome way of curve fitting (De Wit, 1970).

Parameters that initialize the state of the system are best estimated from local information. A relevant parameter of this kind is date of emergence. Estimate either by direct measurement as advocated above, or by trial-and-error (Maas, 1993).

Soil hydrological parameters describe the soil in a particular location and should therefore also be calibrated. Especially useful if data from several years is available, so that effects of the weather and different crops can be separated from the influence of soil (Riepma, 2019, Van Evert et al., 2018, Van Evert et al., 2019)

Filtering is the method to use when the model has been calibrated as well as possible but it still deviates from reality. The Kalman filter is the original method but it can only be applied to linear systems with Normal uncertainty estimation (REF). The Ensemble Kalman filter approximates this situation by representing uncertainty with an ensemble consisting of dozens or hundreds of model instances.

If a CSM is used, each of the ensemble members is parameterized slightly differently. A typical CSM has hundreds of parameters. Some of these have a large influence on model results and are probably best left alone. Others may either have well-known values or do not have a large influence on the model. We have opted to select a small number of parameters to which the model is sensitive, and where it is hard to determine an exact value. Examples are leaf area at emergence, relative growth rate of leaf area, maximum leaf age, maximum rate of photosynthesis, specific leaf area, and maximum root depth.

In selecting parameters to create variability in ensemble, one must take into account that some parameters add variation in the ensemble only in the first half of the growing season and others only in the second half. For example, relative growth rate of leaf area affects the simulation during the exponential growth phase, while the maximum leaf age parameter has an effect only when leaves start dying (Figure 5 in Knibbe et al., 2022).

If a summary model is used, variation is introduced by adding white noise to the ensemble members. We have not yet explored the effect of using white noise to introduce variation in a CSM ensemble (possibly in addition to varying some parameters).

Models for digital twin

So far we have mainly used process-based models in the DFF. However, in engineering it is common to derive summary models from mechanistic models and use the summary model in operational digital twins. Benefits of summary model in this context include that the summary model may run faster than a process-based model due to its simpler structure, and that it may have fewer tunable parameters which makes it easier to calibrate it to a specific environment.

In addition to process-based and summary models one may think of a third type of model, namely simple process-based models. A simple, process based model aims to capture the most important responses but does not aim to be exhaustive. For crop growth, the major responses would be to light, temperature, and water; SIMPLE (Zhao et al., 2019) and LINTUL POTATO DSS (Haverkort et al., 2015) are examples of simple models that describe these processes at a basic level. LinFert is a simple model that focuses on the availability of N (Van Evert et al., 2006). An overview of the three kinds of models is given in Table 2.

CSMs such as WOFOST and Tipstar are very fast and then the speed of a summary model such as TipstaRNN does not seem to be a large advantage; however, Linfert is much faster than the CSM from which it was derived.

TipstaRNN works quite well in the (limited) experience we have gained with it in 2024. However it should be noted that TipstaRNN currently only simulates potential growth, which goes a long way to explaining its behaviour in the current year which is characterized by high precipitation. Another point is that TipstaRNN is specific to one maturity class. This is not a problem because the model can easily be trained for other maturity classes. However, this limitation of the summary model must be kept in mind when its performance is compared with the performance of a CSM.

A CSM may be expected to have realistic responses over a longer period of time into the future than a summary model. It is tempting to think that this may be not so important in the context of a digital twin. A digital twin is driven by frequent observations on the modeled system. Thus in principle the model of the digital twin can be very simple without impacting the performance of the digital twin. And indeed, measurements of soil water content with an electronic, buried instrument, or based on remote sensing, may be available on a daily basis. But most other measurements on crops, such as remotely sensed leaf area, are available far less frequently and are also less accurate. This means that the model must be able to simulate realistically over longer intervals and must therefore represent the real system with greater degree than would be the case if observations are available every day.

During filtering, the state of the model is adjusted repeatedly by the filter. For a CSM, this may lead to incoherent state of the model, i.e. a state that the model would not have reached via time steps (De Wit, 2007). When the model corrects a root/shoot ratio or reimposes a minimum nitrogen concentration, this may lead to unrealistic, transient behaviour. It can be expected that a summary model is less susceptible to this kind of problem.

Table 2. Three broad categories of models that can be used in an agricultural digital twin.

	Process-based models	Simple models	Statistical models
Definition	Describe processes as realistic as we know how	Describe processes such that the main responses are captured	Black-box model, resulting from training (fitting) a model on combinations of input and output
Examples	Tipstar, WOFOST, DSSAT, APSIM, SWAP	SWB, SIMPLE, LINFERT	TipstaRNN
Pro's	Many processes, realistic description of processes	Main responses are described in realistic manner When internal consistency is disturbed, model still provides reasonable responses.	Always approximately right (when used in the environment in which the model was trained)
Con's	Potential to derail if not properly calibrated Not all processed included When internal consistency is disturbed, unrealistic transient responses may occur.	Not able to reproduce subtle interactions such as limited N uptake from dry soil	Strictly limited to the environment in which the model was trained No parameters that can be modified to create an ensemble, so must add white noise to model predictions

How to evaluate the benefit of a digital twin?

CSMs have been used to simulate all kinds of scenarios related to farm management, such as selection of crops and cultivars, planting dates, soil organic matter management, fertilization strategy, and irrigation strategy. For these kinds of studies it is not strictly necessary that simulation results are exactly the same as observed results because the interest is primarily in differences between strategies. However, the purpose of the DFF is to support operational and tactical farm management decisions and then it ís important that simulation results match closely with reality. A digital twin closes the gap between simulation and reality by updating the state of the model in real-time.

This leads to the question: how much better is a simulation with DT compared to a simulation with a model that is not adjusted in real-time. In turn this leads to the question: how should we make this comparison. It is fully expected that including real-time observations gives "better" predictions. How much better will depend on many factors: how well does the simulation model represent the relevant processes, and how well is it calibrated (including initialization) to the local situation. Some of the factors will differ between years and between fields. In some years, crop growth will be determined strongly by those processes that are well-represented in the CSM. In other years, processes that are less well represented by important determinants of crop growth. Examples are extreme temperatures, shortage or surplus of water, or poorly controlled pests and/or diseases. A similar reasoning can be followed for individual fields. For example, in fields with a simple hydrology, a CSM will work well, whereas in fields with many stones or complex layering, most CSMs will fail. Another consideration is that an agricultural DT needs forecast weather to simulate beyond today, and that the performance of a DT will thus depend to some extent on the quality of the weather forecast.

A meaningful quantification of the value of a DT has to involve at least several years, a large number of fields, and access to past weather forecasts. Given that the purpose of a DT is to support operational and tactical farm management decisions, the evaluation of its benefit should be done with data from practical farms. Unfortunately, this kind of data is rarely available. Finally, given the practical context, the most relevant metric to evaluate may be the availability of water and nitrogen one week into the future.

Our work currently focuses on making the digital twin operational on commercial farms. We expect that farmers will gain confidence in the model when they see, in real-time, simulations that closely follow satellite-based observations for their own fields. We have found that ranking fields as shown in Figure 2 is helpful to them. Admittedly, producing this graph is low-hanging fruit but we consider it real progress because it provides farmers with useful information.

Summary

The DFF is a digital twin that can be used to monitor arable crops and grass and evaluate irrigation and fertilization scenarios. Links to on-farm data sources have been effectuated and the DFF can make use of several types of models. Initial experiences with the DFF have helped to formulate further research questions but already the DFF is able to support farm management decisions.

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