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SESSION 5 – DECISION MAKING AND INNOVATION SUPPORT

Decision making and innovation support

Process-Based Detection of Drought Stress at Scale: Insights from Silage Maize and Winter Wheat Dynamics in Germany

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Keywords: drought stress threshold, transpiration deficit, crop resilience, recovery, MONICA

Introduction

Drought remains one of the most crucial threats to agricultural productivity, with its timing and severity causing profound impacts on crop development and yield (Zhang et al., 2023; Fuad-Hassan et al., 2008). Large-scale, crop-specific assessments of drought stress timing and severity remain scarce, particularly those linked to yield-determining processes (Riedesel et al., 2023); yet the need to accurately detect when and how major crops experience water deficits on this scale is growing, as tailored coping strategies must be developed. Building on this research gap, this study uses an indicator derived from a process-based agro-ecosystem model to investigate the spatio-temporal dynamics of drought stress. The study employs the daily transpiration deficit (T_{def}) as the ratio of actual to potential transpiration relative to a defined drought stress threshold (DST) for silage maize and winter wheat across Germany. The analysis spans diverse soil and climatic conditions, offering insights into how stress timing, severity and recovery potential have historically influenced yields. By characterising the stress patterns across growth stages and linking them to final yield outcomes, we aim to uncover critical windows of vulnerability and resilience, and to develop a crop-specific drought assessment framework which can be applied in a digital-twin environment to enable scenario-based exploration of climate, management, and policy interventions.

Materials and Methods

To assess drought stress and crop development dynamics, we employed the MONICA crop model (http://monica.agrosystem-models.com/; Nendel et al., 2011), which simulates daily physiological processes with stage-specific parameters. The model was applied at a 100 x 100 m^2 grid to simulate conditions across three German federal states: Brandenburg (2005-2022), North Rhine-Westphalia (2019-2023), and Lower Saxony (2021-2023). Simulations were conducted under two scenarios: i) water-limited, and ii) non-stressed (control), to compare crop responses under water-limited and optimal moisture conditions for winter wheat and silage maize. Daily weather inputs, such as minimum and maximum temperature, global radiation, wind speed, relative humidity, and precipitation, were used to drive the simulations. Model outputs include daily values for T_{def}, across different crop development stages (Table 1). A T_{def} value of 1.0 reflects no deficiency for the crop and values below DST signal the onset of physiological drought stress. The observed district-level (NUTS3) yield data were incorporated for drought impacts and crop resilience analysis. To investigate how the timing and severity of drought events interact with crop-specific sensitivity during different growth stages to influence yield variability, we applied mixed-effects statistical models.

Table 1. Description of the development stages 1 to 6 for winter wheat and 1 to 7 for silage maize in MONICA.

Stage	Winter wheat	Silage Maize
1	Sowing to Emergence	Sowing to Emergence
2	Emergence to Double ridge	Emergence to Shooting
3	Double ridge to Flowering	Shooting to Tasselling
4	Flowering to Grain filling	Tasselling to Flowering
5	Grain Filling	Flowering to Grain filling
6	Senescence	Grain filling
7	-	Senescence

Results and Discussion

The mixed-effects models for silage maize and winter wheat reveal that drought stress during reproductive stages significantly reduces yield, although the timing and severity differ between crops (Figure 1). Despite the high number of dry days during the early stages, i.e., stage 2, drought had little effect on yield, likely due to low crop water demand and crops having recovered later through compensatory growth. For winter wheat, stress during stage 4 (Flowering to Grain filling) was the only stage with a statistically significant negative effect on yield (Estimate = - 0.084, t = - 3.73), highlighting its sensitivity during this narrow window (Figure 1b). On the other hand, maize showed a broader vulnerability: stress during stage 3 (Shooting to Tasselling) and especially stage 4 (Tasselling to Flowering) had strong negative impacts (Estimate = - 0.257 and - 0.728, respectively), reflecting the crop's dependence on water for successful pollination and kernel set. Random effects in both models underscore the influence of spatial and temporal variability, with maize showing particularly high variation across regions (SD = 7.10) and years (SD = 3.73). These findings suggest that while wheat's drought sensitivity is concentrated around flowering, maize requires sufficient water supply across a wider developmental window during dry conditions. Moreover, the positive association between T_{def} and yield ratio (actual over potential yield) in both crops (data not shown) supports the use of T_{def} as a reliable physiological marker of drought resilience.

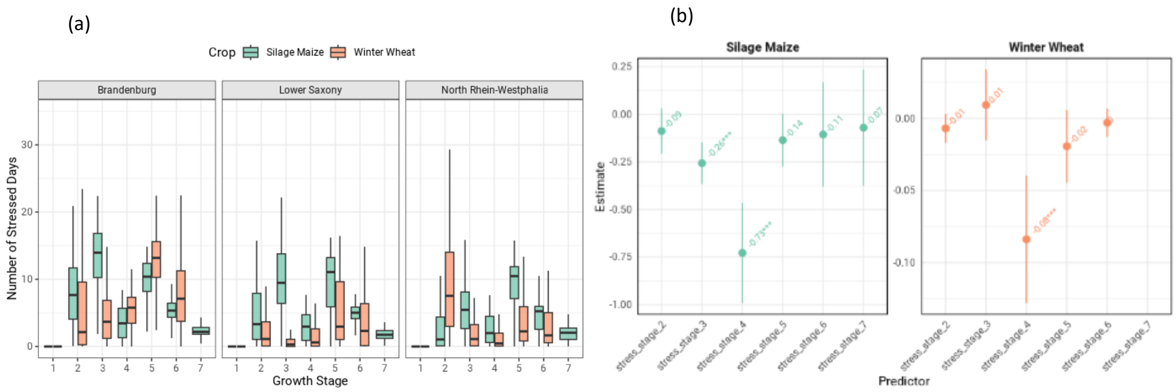

Figure 1. (a) Distribution of drought stress events across crop growth stages for silage maize and winter wheat and (b) effect of drought stress at different growth stages on crop yield.

Conclusions

Understanding drought-induced stress and crop resilience is fundamental to improving model-based assessments of agricultural productivity under climate variability. While the current drought monitoring tools rely on meteorological and soil moisture conditions, our framework uses crop-specific signals to identify periods of prolonged stress which disrupt physiological processes for each development stage or, conversely, to detect when adequate water availability restores normal crop growth. Beyond retrospective analysis, such process-based assessment of drought stress also provides the foundation for digital twin applications in agriculture, where crop models can be coupled with Earth observation data to explore what-if scenarios. By linking physiological stress dynamics with yield outcomes, these simulations enable users to test the implications of alternative climate trajectories, management practices, or policy interventions, thereby enhancing the ability to anticipate risks and support resilience-oriented decision making at scale.

Acknowledgements

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Hybrid ML_Hi-sAFe_LCA framework for climate-smart agroforestry decision support

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Keywords: Agroforestry, Hi-sAFe, machine learning, life cycle assessment, decision support system.

Introduction

Agroforestry systems (AFS) as the intentional integration of trees into cropping systems—encompasses diverse indigenous, traditional, and modern farming practices (Terasaki Hart et al. 2023; Nair 1991). It provides multiple agronomic, environmental, and socio-economic benefits, including improved soil health, climate resilience, and biodiversity (Beillouin et al. 2019; Beillouin et al. 2021). As a nature-based solution, agroforestry sequesters carbon and reduces greenhouse gas (GHG) emissions, supporting both climate mitigation and adaptation (Griscom et al. 2017). However, trees may also introduce competition for light, water, and nutrients, potentially reducing crop yields if not well managed (Gibson et al. 2011). Therefore, optimized site-specific agroforestry design is essential to balance trade-offs and harness synergies (Blaser et al. 2018).

Materials and Methods Calibri pt 10

This study presents a hybrid framework that integrates process-based models (PBMs), machine learning (ML), and life cycle assessment (LCA) into a decision support system (DSS) for designing and evaluating agroforestry systems. Multi-scenario simulations with the 3D PBM Hi-sAFe were conducted for maize–poplar alley cropping across 16 configurations varying in latitude (30–60°) and tree row orientation (0–135°). Outputs included crop yields (4.3–8.1 t ha^{-1}), N_2O emissions (1.6–9.4 kg N ha^{-1}), and land equivalent ratios (LER consistently >1, up to 1.29), highlighting agroforestry's potential to improve land-use efficiency. These data were used to train supervised ML algorithms (Random Forest, ANN, XGBoost). Feature attribution (SHAP) identified temperature, distance from tree strips, and intercepted radiation as primary predictors of yield and N_2O dynamics.

To address data scarcity, Long Short-Term Memory (LSTM) and TrAdaBoost-LSTM models were employed for spatiotemporal gap-filling and forecasting of microclimate variables.

Results and Discussion

This integration reduces computational costs of repeated simulations while enabling accurate predictions in data-limited settings. Model outputs were coupled with LCA workflows to calculate sustainability indicators (CO_2-equivalent emissions, nitrogen footprints, soil organic carbon changes, and water-use efficiency). These were incorporated into a web-based DSS that allows expert and non-expert users to explore alternative agroforestry designs, evaluate trade-offs, and assess national-scale greenhouse gas mitigation potential (Figure 1).

A Germany-wide application illustrates the significant contribution of agroforestry to climate-smart land management. This hybrid PBM–ML–LCA approach represents, to our knowledge, the first operational DSS for agroforestry, combining scientific robustness with practical usability. It demonstrates that agroforestry can surpass monocultures in productivity and sustainability when site-specific optimization is applied, providing a scalable foundation for policy support and decision-making under climate change.

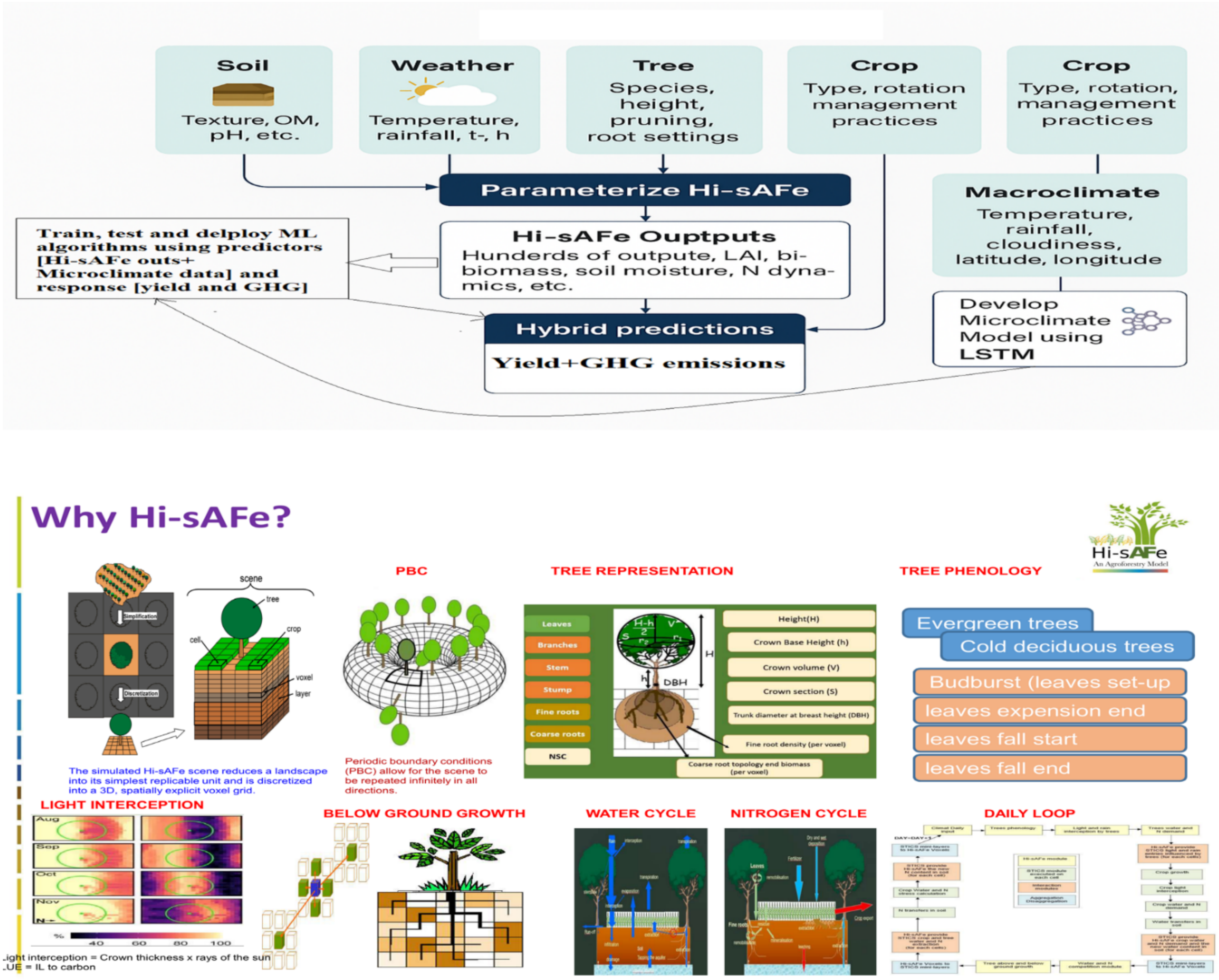

Figure 1. Integrated representation of the hybrid crop modeling workflow. (A) Input data (soil, weather, trees, crops, macroclimate) processed through the Hi-sAFe model to simulate tree–crop interactions, generate multi-scenario outputs, and feed machine learning models (RF, ANN, LSTM) for yield and greenhouse gas predictions. (B) Mechanistic structure of the Hi-sAFe process-based model, showing its 3D voxel grid representation with periodic boundary conditions, tree phenology dynamics, light interception, water and nitrogen cycling, and below-ground growth processes that drive daily simulation outputs.

Conclusions

Results show that agroforestry can surpass monocultures in land-use efficiency, but context-specific optimization is essential. Future work should expand to diverse environments, species, and longer timeframes to fully capture long-term resilience. This framework provides a scalable foundation for operational, climate-smart agroforestry planning and policy support.

Acknowledgements

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A potato digital twin for decision support

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Keywords: potato crop growth model; digital-twin

Introduction

Farm size in Europe and around the world is growing, which means any individual farmer is managing areas of >50 ha and tens to hundreds of fields. Crop growth models can help forecast yields and simulate possible effects of additional irrigation/fertilizer application. However crop growth models do not model all processes ongoing in the field, for example pests and diseases can reduce LAI and soil compaction can limit rooting depth. A digital twin uses in-season observations of modelled state variables (LAI, soil moisture) to correct/adjust the model states. Although much further testing is needed, one may expect superior accuracy of a digital-twin compared with a classical crop growth model. To date, most digital-twins in the agricultural domain have been limited to the “predictive” type (Verdouw et al. 2021), i.e. for accurate yield forecasting. For decision support for farmers an additional element is needed, the element of scenarios:

- What yield if from today onwards I do not apply extra irrigation/fertilizer? (baseline scenario)
- What yield if from today onwards I do apply extra irrigation and/or fertilizer?
- Is the yield gain worth the extra cost of irrigation/fertilizer?

A digital-twin that on top of forecasting addresses these questions is sometimes called a “prescriptive” type (Verdouw et al. 2021). Although strictly these scenarios are not prescriptive. These scenario’s do not prescribe the farmer what to do. Farmers can use these scenarios in combination with farmgate prices and costs of irrigation to decide if a net profit can be made. Only if the yield gain is sufficiently large, farmgate prices high and costs low, only then it will be financially profitable to apply extra irrigation. Here for one of the first times we present such a “prescriptive” digital-twin.

Materials and Methods

A potato digital-twin was constructed using the DFF/NMODCOM modelling platform (van Evert et al 2021), with the Tipstar potato crop growth model (van Oort et al 2024). We modelled the Van den Borne potato farm, a large Dutch/Belgian farm with annually more than 200 potato fields. Location, cultivar, planting date, fertilizer applications and irrigation applications were obtained through the Van den Borne business administration system, retrieved through an automated data connection to the farmmaps platform (Been et al 2023). Location specific weather, soil and satellite observations were provided by the farmmaps platform. Forecasts were made using ensembles of (1) 2025 weather till the prediction date, (2) the 14 days weather forecasts and (3) weather of a past year. For data assimilation the Ensemble Kalman filter was used. Simulations were automatically run on a daily basis for the 200 fields, each field being simulated 3*30*4 times, for 3 randomly sampled of model parameter sets, 30 years of historical weather and 4 crop management scenarios. In visualisations for individual fields forecasting uncertainty was visualised as a plume with median and confidence interval. For farm level summaries (shown below) we present median values. Forecasts were presented for 3 modelled variables: water stress, nitrogen stress and yield.

Results and Discussion

Figure 1 shows the 14 August 2025 forecast. It shows forecasted drought and nitrogen deficit, for the date on which the simulations were made and for the immediate future (7 days after). Figure 1 shows the baseline scenario with crop management as applied so far and no future additional irrigation/fertilizer. The figure shows which fields are already under water stress or risk running out of water in the very near future. Figure 2 shows scenarios:

1. if from today onwards extra nitrogen were applied without extra irrigation, impact on yield would be zero so there is no need for extra fertilizer application;
2. if from today onwards extra irrigation were applied without extra fertilizer, some yield gain is still possible. At this stage in the growing season in mid August the crop is already senescing therefore possible yield gain is relatively small.

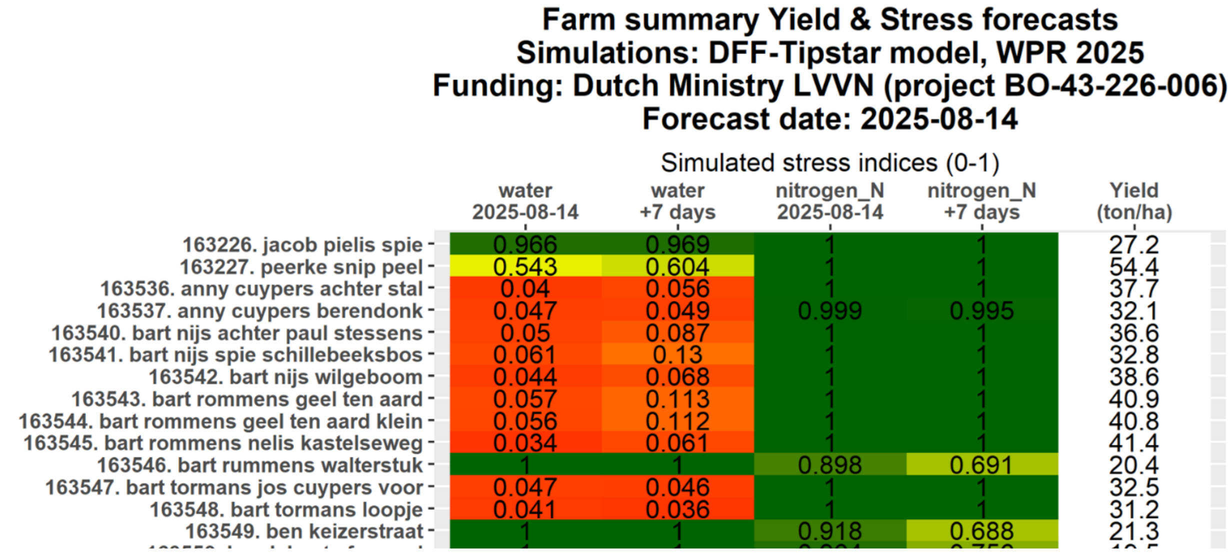

Figure 1. Example forecasts by a predictive digital-twin. Left column: crop field names. Middle coloured columns: simulated stressindex as crop water/nitrogen demand divided by soil water/nitrogen supply. Right column: yield forecast in the scenario with from the simulation date onwards (2025-08-14) no extra irrigation/fertilizer applied.

	Scenarios: from today (2025-08-14) onwards			
Crop field	zero extra irrigation zero extra fertilizer	zero extra irrigation + extra fertilizer	irrigation if needed zero extra fertilizer	irrigation if needed + extra fertilizer
163226. jacob pielis spie	27	27	30	30
163227. peerke snip peel	54	54	64	65
163536. anny cuypers achter stal	38	38	38	38
163537. anny cuypers berendonk	32	32	35	38
163540. bart nijs achter paul stessens	37	37	44	47
163541. bart nijs spie schillebeeksbos	33	33	33	36
163542. bart nijs wilgeboom	39	39	46	47
163543. bart rommens geel ten aard	41	41	41	45

Figure 2. A prescriptive digital-twin builds upon Figure 1 and additionally shows what yield gains are still possible if from the simulation date onwards (2025-08-14) extra irrigation/fertilizer were applied.

Conclusions

This work presents an operational digital twin for decision support in potato farming. The digital-twin can simulate "what-if" scenarios for prioritising and deciding in which out of many fields to apply extra irrigation and fertilizer.

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Near-daily 10-m LAI maps for farmers by combining crop growth model simulations and Planet's Biomass Proxy remote sensing product

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Keywords: precision agriculture, model fusion, remote sensing, crop model integration, model-data integration, leaf area index

Introduction

Farmers increasingly rely on optical satellite-based maps to apply crop protection as well as fertilizer products at variable rates in response to heterogeneous crop growth conditions in the field. Prolonged cloud coverage, however, severely affects the timely provision of these map products, forcing the farmers to either rely on potentially outdated maps that do not reflect the current crop stand variability in the field, or recede to flat rate applications altogether.

The cloud-free vegetation monitoring product 'Biomass Proxy' (BP) from the Planet Labs PBC (San Francisco, California, USA) addresses this problem of prolonged cloud coverage by integrating cloud-resistant synthetic aperture radar (SAR) images (Sentinel-1) and high spatial-resolution multispectral images (Sentinel-2 and PlanetScope) (Planet Labs Inc., 2025). While the BP product provides near-daily raster maps at 10-m resolution, it is a relative measure of aboveground crop biomass in value ranges between 0 and 1 (Burger et al., 2024, Guillevic et al., 2024), rather than absolute leaf area index (LAI) values which are critical to many precision-agriculture practices.

The variable rate application (VRA) advisor integrated into BASF Digital Farming's software tool xarvio Field Manager® issues field-scale recommendations on number of application zones based on field heterogeneity as well as recommendations on product rates. These recommendations are based on absolute LAI values. This study aims to use the LAI development estimated by a dynamic crop growth model to elevate the Biomass Proxy map from a daily-available product indicating relative differences in aboveground crop biomass to a daily-available product that indicates within-field absolute differences in crop LAI, hereby allowing the xarvio Field Manager® to reliably offer maps in its VRA advisor at high temporal resolution.

Materials and Methods

We used the LINTUL5 model implemented in the modeling framework SIMPLACE (see Enders et al., 2023 for a detailed overview over the framework) to simulate daily LAI development in fifty winter wheat and winter barley fields across Germany, planted in autumn 2024 and harvested in summer 2025. Similar to the Weighted Mean approach presented in Tewes et al. (2020), a model ensemble was generated that simulated different LAI development trajectories from sowing date until the acquisition date of the BP map to be converted, by perturbing a set of parameters including the relative increase in LAI during juvenile stage, soil water content at simulation start and maximal rooting depth, among others.

LAI maps derived from Sentinel-2 multispectral imagery acquired prior to the BP acquisition date were used to filter ensemble runs that best represent the satellite-estimated LAI development over time for quantiles 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9 (with q 0.9 assumed to represent optimal plant growth, and q 0.1 to represent restricted plant growth).

Pixel values for the same quantiles were extracted from the BP maps. A linear regression model was created by relating the respective quantile LAI values extracted from the crop growth model runs on the day of the BP acquisition to the BP quantile values themselves. Subsequently the regression model was used to convert the BP values into LAI estimates. To examine the effects of Sentinel-2 image unavailability on the ensemble filtering, images were withheld for periods of 10, 15, and 20 days before the BP acquisition date. For each field, the most recent Sentinel-2-derived LAI maps were selected for March (LAI values ranging from 0.8 to 1.5), April (values between 2 and 5), and May (values between 2 and 6). These LAI values were then compared with those obtained from the corresponding converted BP maps. We evaluated the number of predicted LAI values within ±0.5 and ±1 of the observed LAI, and noted instances where our method overpredicted LAI, potentially leading to slightly higher product rates.

Results and Discussion

The primary outcomes of this model fusion approach are summarized below, focusing on the agreement between the converted Biomass Proxy-derived LAI values and the reference LAI values from Sentinel-2 images (Table 1). Our evaluation highlights both the robustness and limitations of the crop growth model-based conversion methodology under varying scenarios of Sentinel-2 image availability prior to the BP acquisition date.

The proportion of predicted LAI values falling within ±0.5 and ±1 of the observed LAI was generally high when recent Sentinel-2-derived LAI maps were available, particularly during the main phases of crop development in spring. However, as the gap between the last available Sentinel-2 image and the BP acquisition date increased, prediction accuracy tended to decrease, underscoring the importance of frequent multispectral observations for optimal ensemble member selection. Notably, the method demonstrated resilience in scenarios with limited Sentinel-2 LAI data, with only a moderate decline in accuracy even when Sentinel-2 data were withheld for up to 20 days.

Furthermore, our analysis identified certain instances where the approach overpredicted LAI values, which could result in recommendations for higher-than-necessary input rates. Additional refinement of the ensemble filtering process or integration of ancillary data sources may further enhance reliability.

While these findings demonstrate promising alignment between converted and observed LAI values under various data availability scenarios, the impact of the uncertainty range of LAI predictions on VRA advisor logic remains to be tested.

Table 1. Results for LAI Quantile Values Comparison

Scenario, where no S2 LAI image prior the conversion data is available for…	Quantile	Within range ± 0.5 LAI (%) for images end of…			Within Range ± 1 LAI (%) for images end of…			LAI Pred > LAI Obs (%) for images end of…		
		March	April	May	March	April	May	March	April	May
10 days	0.1	100	51	64	100	85	82	58	61	42
	0.5	96	51	53	98	86	92	52	33	34
	0.9	90	48	39	100	77	69	52	24	21
15 days	0.1	100	44	59	100	85	81	57	53	40
	0.5	95	50	50	97	80	88	53	30	34
	0.9	87	47	41	100	76	75	53	23	20
20 days	0.1	100	46	64	100	85	80	55	55	40
	0.5	95	50	56	97	80	80	55	32	36
	0.9	85	47	43	100	73	65	55	26	26

Conclusions

Our results highlight the benefits of integrating satellite observation-based data like the Biomass Proxy and process-based crop growth models in producing near-daily and high-resolution images of leaf area index (LAI), a key enabler for farmers to achieve precision agriculture practices even under cloud covered periods during the season. For farmers, this synergy allows the variability in crops within a field—driven by differences in soil, weather, or management—to be identified and addressed in near real-time to react appropriate to this very different management areas.

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Bridging the Gap: Integrating Remote Sensing Data with a Coupled Crop-Radiative Transfer Model for Improved Agricultural Decision Support

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Keywords: Particle filter, Radiative transfer model, Crop-radiative transfer models coupling, sensitivity analysis.

Introduction

Crop models are vital decision-support tools, but their outputs are subject to inherent uncertainty. A significant challenge is bridging the gap between their simulated outputs and the physical quantities measured by remote sensing (RS) instrument2. This gap can be addressed by coupling crop models with radiative transfer models (RTMs), which simulate the interaction of radiation with crops. This study developed and tested a comprehensive coupling scheme between the DSSAT-CROPGRO crop model and the SCOPE-RTMo RTM for processing tomatoes to investigate the propagation of RS data uncertainty and enhance model predictions**.**

Materials and Methods

The research involved three stages: model coupling, a synthetic data assimilation (DA) experiment, and a real-world DA experiment. The coupling scheme linked DSSAT-CROPGRO state variables, such as Leaf Area Index (LAI) and specific leaf area, to RTMo parameters like leaf chlorophyll and dry matter content. A global sensitivity analysis (GSA) was conducted to identify the most influential crop model parameters on simulated reflectance at different growth stages.

In a synthetic experiment, the coupled model's performance was evaluated using a sensitivity-based particle filter (PF), testing different levels of simulated measurement noise. For the real-life experiment, high-resolution multispectral imagery from a UAV was assimilated into the model for processing tomatoes grown under varying irrigation and fertilization levels. A novel approach was implemented to account for the row crop's non-homogeneous surface by creating a weighted-average reflectance spectrum from vegetation and soil pixels. The PF performance was evaluated by comparing simulated LAI and yield against field measurements

Results and Discussion

The GSA revealed that parameters influencing crop growth rate had a greater impact on simulated LAI and yield variance than phenology-related parameters. In the synthetic experiment, a decrease in measurement noise led to improved parameter convergence and lower uncertainty in model outputs. The real-life experiment demonstrated that the DA scheme significantly improved normalized root mean square error (NRMSE) for LAI from 59% to 42% and for yield from 64% to 35%. The best performance was achieved by excluding the most water-stressed treatments from the DA process, resulting in an NRMSE of 34% for LAI and 16% for yield. This highlights the model's limitations in accurately simulating severe water stress. The study also found that dynamically updating key RTM parameters via the coupling scheme, such as leaf inclination angle distribution (LIDF) and dry matter content (Cdm), was crucial for accurate predictions

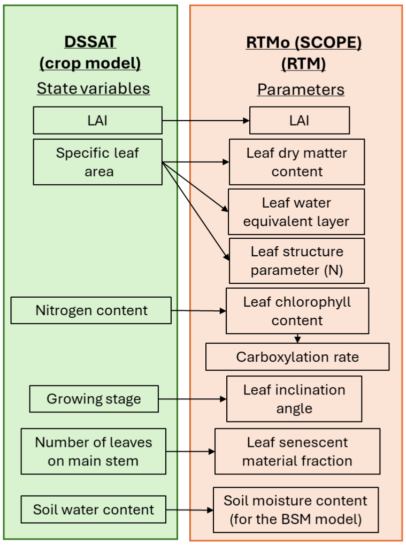

Figure 1. Coupling Scheme

Conclusions

Coupling a crop model with a radiative transfer model and assimilating RS data using a sensitivity-based particle filter is an effective approach for reducing the uncertainty of crop model predictions. Our results show that this framework can successfully improve estimations of LAI and final yield for processing tomatoes. We identified that parameters related to crop growth rate contribute most to model uncertainty, making their accurate calibration a priority for future research. While the framework performed well under low to moderate stress conditions, its accuracy in simulating severe stress needs further improvement. The methodology and findings can guide future research in developing robust tools for digital agriculture and agricultural decision-making.

Acknowledgements

This work was supported by the Chief Scientist of the Israel Ministry of Agriculture, Project 20-21-0010. In addition, the work received support from Action CA17134 SENSECO (Optical synergies for spatiotemporal sensing of scalable ecophysiological traits) and Action CA22136 PANGEOS (Pan-European Network of Green Deal Agriculture and Forestry Earth Observation Science) funded by COST (European cooperation in Science and Technology, www.cost.eu(accessed on June 16, 2025). Amit Weinman received financial support from the Gerald Stanhill Scholarship fund of the Volcani International Partnerships.

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Combining process-based modelling and remote sensing to quantify state-scale groundwater extraction for irrigation in Brandenburg, Germany

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Keywords: Agroecosystem Model, Earth Observation, Crop yields

Introduction

Climate change is already affecting groundwater levels in Germany (Wunsch et al., 2022), and the decline in groundwater levels is also becoming increasingly apparent in the state of Brandenburg (Donheiser et al., 2022), with far-reaching consequences for the state's water supply. In view of this prospect, the authorities in Berlin and Brandenburg are working hard to record current water consumption and identify opportunities for water conservation. While drinking water consumption and water abstraction for this supply are well monitored in the region, there is little knowledge about groundwater use for other purposes, including irrigation of fields. Remote sensing offers the possibility of identifying water bodies from the air, including water hidden in the soil's pore system, commonly referred to as soil moisture. The identification of fields that contain significantly more soil moisture than neighboring fields indicates that a field may have been irrigated (Zappa et al., 2021). Based on this theory, Ghazaryan et al. (2025) created the first map of a larger area in Central Europe identifying individual irrigated fields.

Materials and Methods

We use MONICA (Nendel et al. 2011), a mechanistic, one-dimensional, dynamic simulation model for processes in the soil-plant-atmosphere continuum. It aims to simulate the integrated effects of weather, soil and crop management on plant growth and yield formation, as well as related processes in the soil, including water and nutrient use, changes in carbon stocks and greenhouse gas emissions. To this end, MONICA is equipped with a virtual automatic irrigation system to simulate different irrigation strategies. We first tested whether MONICA reproduces the response of wheat to soil moisture deficits well. To do this, we used 106 combinations of location and year from irrigation and rain exclusion experiments across Central Europe. We then used MONICA to simulate wheat production spatially explicitly for arable land in Brandenburg, applying virtual irrigation to all fields and crops previously identified as irrigated (Ghazaryan et al. 2025). Assuming that irrigation always follows an optimal rather than a deficit water supply strategy, the applied irrigation amounts were added up.

Results and Discussion

Application of the MONICA model to Brandenburg shows that—assuming optimal water supply—a total of approximately 17.7 million m³ of water per year has been used on average to irrigate the four most water-intensive crops: wheat (3.5 million m³), silage maize (11.8 million m³) sugar beet (1.1 million m³) and potato (1.3 million m³) on an average of 12,802 ha (2005–2022). The irrigated areas thus achieved an average yield increase of 53% for wheat, 106% for silage maize, 17% for sugar beet and 37% for potato, with water use of 2.5 million m³ in 2007 yielding only a 9% increase in wheat yield, and 5.2 million m³ in 2022 yielding a 119% increase (Fig. 1). The situation was very similar for silage maize, where water use of 3.8 million m³ yielded an additional yield of 29%, while in 2018, 42.2 million m³ yielded an additional yield of 171%. In that year, the proportion of irrigated silage-maize area rose from an average of

3.6% to 8.5%. The identification of irrigated potato fields was not satisfying (2,139 ha in 2022 vs. 6,500 ha reported), leading to potential underestimation of applied irrigation amounts for potatoes. In contrast, irrigated sugar beet fields were overestimated (1,320 ha vs. 600 ha), with respective consequences for the assessment. Irrigated field vegetable production is missing so far.

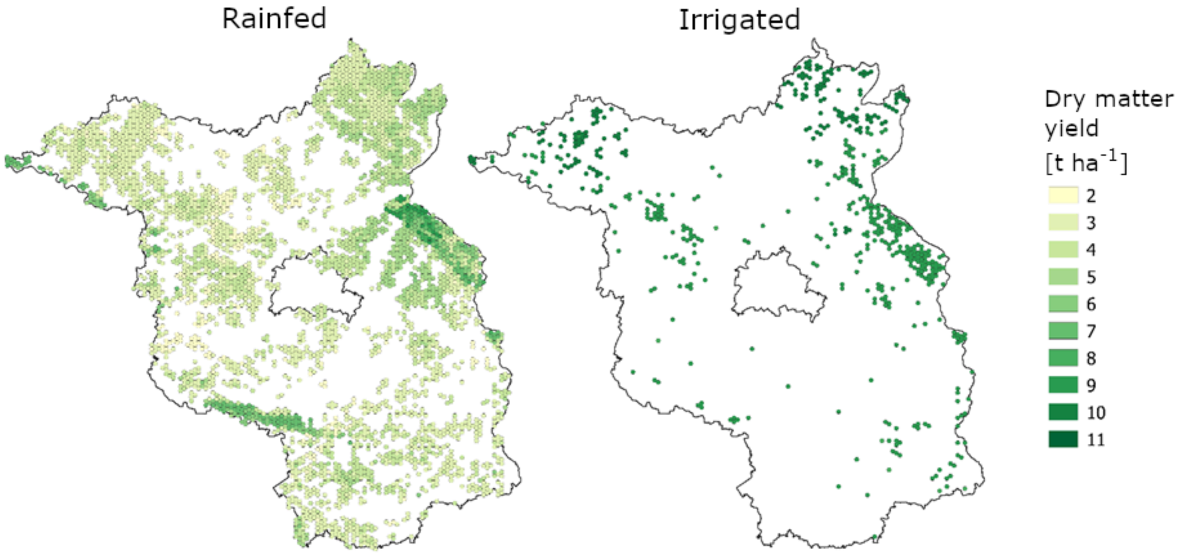

Figure 1. Simulation of dry matter yields of winter wheat in Brandenburg in 2022 on fields with (right) and without (left) additional irrigation.

Table 1. Area under irrigation and irrigation water consumption in Brandenburg, Germany

	Irrigated area [ha]	**Irrigated area Share [%]**	**Average irrigation rate [mm/season]**	**Maximum irrigation rate [mm/season]**	**Average yield boost [%]**	**Total amount of water used [million m³]**
Silage maize	5,771	3.6	195	264	+106	11.8
Winter wheat	3,861	2.6	91	132	+53	3.5
Sugar beet	1,390	18.0	78	154	+18	1.1
Potato	1,780	18.5	68	115	+37	1.3

Conclusions

The presented methodology provides for the first time an observation-based assessment of the irrigation water consumption as an alternative to the meter readings of registered groundwater consumers. Comparing both, the simulated water consumption comes out much higher than the registered one, indicating that some of the water extraction bypasses the official registration process and the related compensation payment. However, the inability of the method to identify deficit irrigation limits its reliance and the potential to replace the registration approach.

Acknowledgements

The authors acknowledge the careful plausibility check of Lambertus Monninkhoff of Berliner Wasserbetriebe, Berlin, Germany.

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Hybrid Training for the Prediction of Fungi on Winter Wheat

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Keywords: Detection, MachineLearning, Forecasting, Classification, Septoria

Introduction

Fungal diseases pose a significant threat to global food production, causing considerable yield losses and economic harm (Chai et al. 2022). Early and accurate prediction of the risk of fungal infection in crops such as winter wheat can enable targeted interventions, reducing the dependency on excessive fungicide use, thereby improving both profitability and sustainability.

Materials and Methods

We propose a hybrid machine learning approach (von Bloh et al. 2024), utilizing a combination of real word infection data and simulated infection risk data provided by ISIP, to train a long short-term memory (LSTM) (Hochreiter and Schmidhuber 1997) model. This will enable the prediction of future fungi infection risk based on past and future weather conditions. To achieve this hybrid, approach the model is pretrained with a large amount of synthetic data and then finetuned for the specific task on real world data. The predictions consider Septoria Tritici, Brown Rust, Yellow Rust, Powdery Mildew and DTR on winter wheat.

Results and Discussion

Figure 1 shows an exemplary fungi incidence prediction for a single location. Performance metrics for all considered fungus types and simulated years can be found in Table 1.

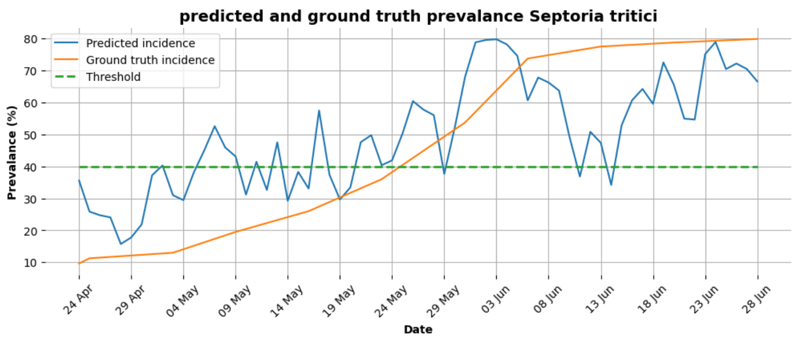

Figure 1. Predicted and measured incidence for Septoria tritici

Building on ISIP models enables the base model to capture fundamental infection patterns, while fine-tuning yields continuous forecasts for threshold-based assessments, supporting more accurate long-term models that can be easily extended with additional data sources. Since the simulation was based on infection risk, whereas the real word dataset contained measured incidence, aligning one set of prediction with the other was inherently imperfect, which is expected to negatively impact the accuracy.

Table 1. F1-Scores for the predicted incidence on the analyzed fungus types

	Septoria	Brown Rust	Yellow Rust	Mildew	DTR
LSTM	29.24	31.05	26.77	21.04	16.62

Despite the imperfect alignment, pretraining the model using simulated data shows to positively impact overall predictive performance.

Conclusions

The performance metrics show that the proposed methodology achieves significant predictive accuracy on unseen data. This demonstrates that the use of simulated data can mitigate the limitations caused by the lack of real-world training data. Additionally, we establish that a model pretrained on risk classification can be fine-tuned to produce continuous outputs.

Acknowledgements

We would like to thank HORSCH Maschinen GmbH, Bavarian State Research Center for Agriculture (LfL), ISIP e.V and ZEPP. for the very good collaboration throughout this project.

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A parsimonious mechanistic crop model for decision support in herbaceous perennial crops: A case study on Asparagus

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Keywords Calibri: mechanistic crop model; carbohydrate allocation; perennial crops; decision support; *Asparagus officinalis*

Introduction

Understanding plant–environment interactions is a major challenge in ecology and is essential for predicting the impacts of agronomic practices and climate change on perennial crop production. While numerous models have been developed for annual crops and major perennials, herbaceous perennials remain largely unmodeled, and the mechanisms regulating growth and carbohydrate storage in these crops are poorly characterized in agronomic context (Samraoui, 2025). The study focuses on *Asparagus officinalis*, a perennial crop harvested for its young shoots, characterized by high variability in yield and for which growth modeling remains a challenge (Drost 2023, Graefe 2010). In collaboration with a French producers' organization, this study addresses the crop's specific agronomic challenges in the context of this local setting, where scientific knowledge on the species remains limited.

Materials and Methods

We developed a parsimonious mechanistic crop model based on fundamental biological principles, (Thornley, 1990) simulating the trade-off between growth and storage in herbaceous perennial plants. Ecophysiological assumptions were developed and translated into mathematical form using existing knowledge of the species and insights from the scientific literature. The model is teleonomic, assuming that plants adjust their shoot-to-reserve carbohydrate ratio in response to environmental conditions and management practices, minimizing it under stress and optimizing it under favourable conditions. Model parameters are initially calibrated and tested using published literature. Participatory protocols are implemented across multiple sites in France in order to get first original data for model validation, including daily harvest measurements on different plots and monitoring of soil and air temperatures under various mulching practices.

Results and Discussion

Model simulations are consistent with published literature data and with the first original data collected. The model is intended to predict plant responses to different cultivation strategies, climate scenarios, and potential increases in plant–pest interactions associated with reduced pesticide use.

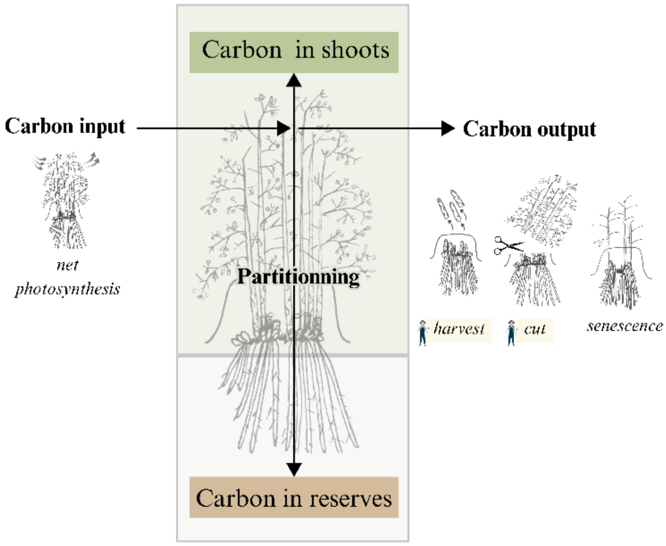

Figure (a) presents a simplified representation of the conceptual model.

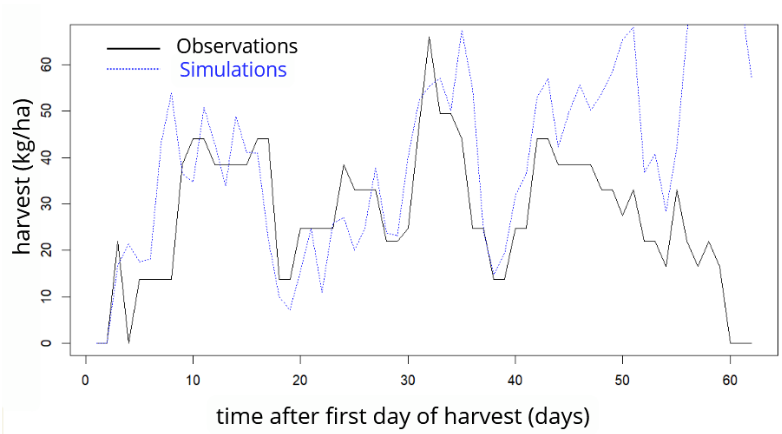

Figure (b) shows a preliminary comparison between observations from a producer (daily yield per hectare in 2025) and simulations from the model based on temperatures measured on the plot, with analysis still ongoing and further validation required.

Conclusion

By capturing the dynamic balance between growth and storage, our model aims to provide insights into the ecophysiology and resilience of *Asparagus officinalis* under variable environmental conditions and agricultural practices.

Acknowledgements

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On farm weekly grass growth prediction in Ireland, from the farm to national television

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Keywords: MoSt GG, forecast, decision-support tool, climate adaptation

Introduction

Ireland's temperate oceanic climate, with mild summers and winters, supports a long growing season and a grass-based agriculture where more than 80% of the agricultural area is under grass or conserved forage. Managing grass and grazing animals requires a good anticipation of the impact of weather variability. PastureBase Ireland (PBI, Hanrahan et al., 2017) is a decision-support tool developed by Teagasc to help farmers better manage their grass. However, all the tools in PBI represent the current or past situation but do not provide information about the future. To address this gap, a national grass-growth prediction program began in 2019 to produce localised grass growth forecasts for farmers. Since 2020, the predictions have been shown each Sunday on national television, and since 2025 they have been available directly within PBI.

Materials and Methods

The project started in 2018 after a challenging grass-growing year with a cold spring and a summer drought, highlighting the need to know when and if grass growth will recover. Predictions initially covered 30 farms and later expanded to 84 predominantly commercial dairy farms distributed across Ireland. The model used is the Moorepark-St Giles Grass Growth model (MoSt GG; Ruelle et al., 2018; Bonnard et al., 2025), a mechanistic model that accounts for weather, soil type, and management to predict primarily grass growth, grass nitrogen content, water and all N fluxes on a daily time step. Meteorological data are provided daily by Met Éireann (modelled data, historical and forecasted) and, where available, on-farm weather stations. Management inputs originate from PBI and include paddock area, grazing and cutting dates, and fertiliser applications (amount and timing). Each paddock is represented individually. Paddock-level predictions are aggregated to farm means for individualised 7-day outlooks, and then to county means for regional situational awareness. Figure 1A shows an example of farm-level outputs and the location of the different participating farms

Results and Discussion

Weekly maps are sent directly to participating farmers via WhatsApp (Figure 1A) and are also available within PBI. Additional dissemination formats have been created to improve the usefulness of the predictions. A current growth map is generated weekly, showing national grass growth, variability between and within regions, and comparisons with previous years (Figure 1C). A simplified county-level forecast is also produced (Figure 1D). These simplified maps are available on the PBI website and disseminated to government agencies, agri-business, and agricultural media (Farmer's Journal, Grass10 newsletter). Since August 2020, county-level predictions have been broadcast every Sunday on RTÉ One during the "Weekly Meteorological Farming Forecast" (Figure 1B).

Farmer feedback has been very positive. The predictions help them identify surpluses or deficits of grass earlier, supporting timely decisions such as whether extra feed is needed. The predictions are most valuable when they differ from farmer expectations, as this can indicate rapid weather changes, the onset of drought, or nitrogen deficiencies.

The main limitation is uncertainty around local rainfall amounts, which strongly influence grass growth. To address this, the program has begun installing weather stations on participating farms to improve accuracy, especially in time of water deficit an increasingly important step in the context of climate change.

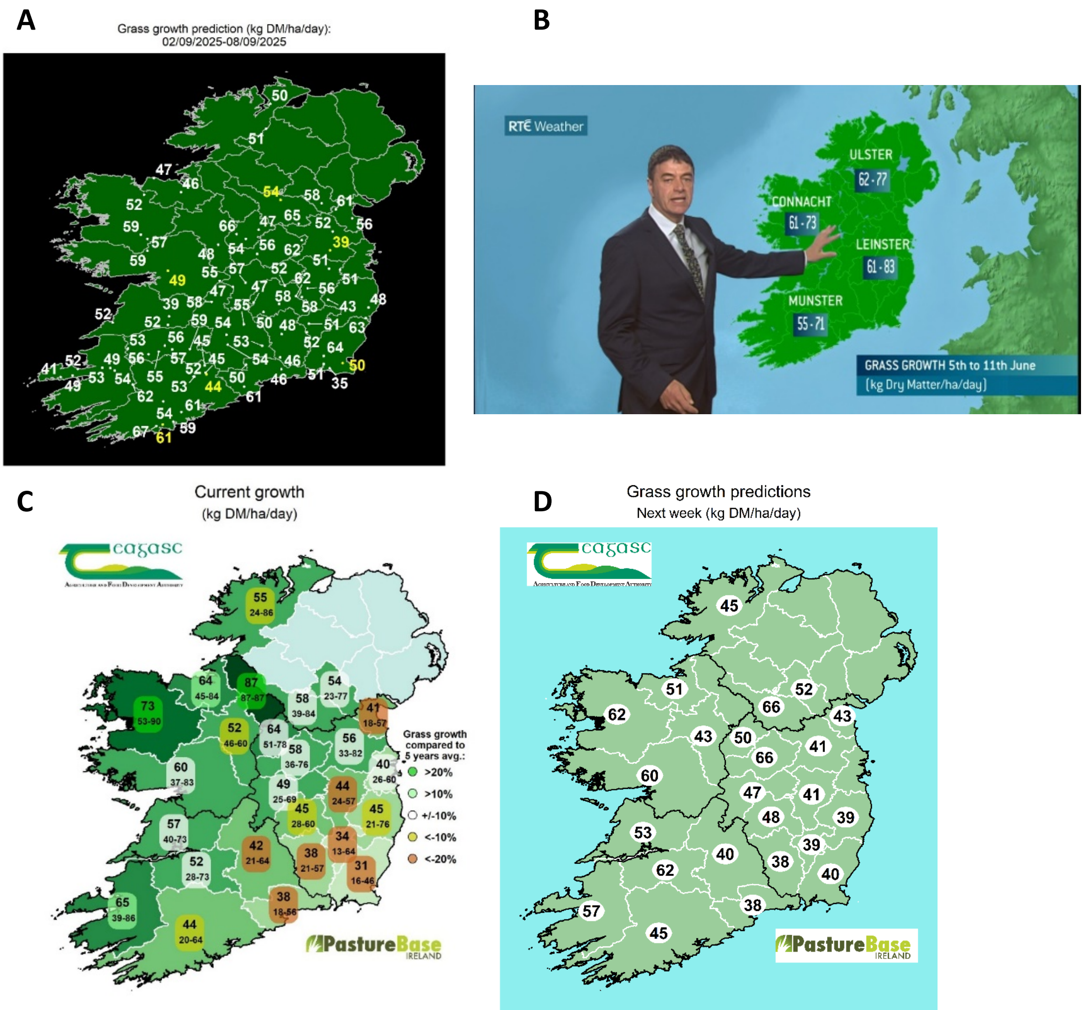

Figure 1. Grass-growth forecasting and dissemination in Ireland: (A) Individual farm-level predictions (kg DM ha^{-1} day^{-1}); (B) RTÉ One 'Weekly Meteorological Farming Forecast' featuring county-level outputs; (C) Current growth map from PastureBase Ireland; (D) County-level forecast for the following week.

Acknowledgements

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Predicting BBCH crop growth stages across the EU for regulation of pesticide application

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Keywords: phenology, crop model, sowing date rules

Introduction

EU Regulation requires environmental risk assessments (ERA) for non-target organisms exposed to active substances in plant protection products. To advance the ERA of pesticides effectively, it is important to have accurate prediction of crop phenology spatially across the EU. Therefore, the present study aims to enhance pesticide risk assessment for non-target organisms by precisely mapping crop development stages (BBCH[1]) across the EU by developing predictive models of crop sowing dates as well as calibrated models of crop phenology.

Materials and Methods

We did an extensive data collection and curation from public sources like C2D2 (Hughes et al., 2023), PEP725 (Templ et al., 2018), and TEMPO (Maury et al., 2023), alongside literature, creating a harmonized database of over 1.2 million phenological observations. Comparisons revealed C2D2's broad spatial coverage across Europe, while PEP725 concentrated in Central Europe and TEMPO in France. C2D2 and TEMPO offered observations across various growth stages, unlike PEP725 which focused on sowing, emergence, and harvest. A model for spatially predicting sowing dates was developed using a temperature-driven rule, supplemented by a median rule for regions where management practices (like irrigation) heavily influence planting, as seen with maize in Southern Europe. The WOFOST cropping system model's phenological sub-model was used to simulate phenology. It predicts crop development through a dimensionless development stage(DVS) variable which is 0 at crop emergence and reaches 1.0 at anthesis and 2.0 at maturity. The model accounts for temperature as well as photoperiod and vernalization for winter crops. The temperature sum requirements to anthesis (TSUM1) and maturity (TSUM2) were calibrated using observed sowing, flowering and maturity dates from the datasets mentioned above. Observations were pooled by defining agroecological zones with similar agroclimatic conditions and all observations in an agroecological zones where used jointly to estimate the TSUM1 and TSUM2 parameters. Next, the intermediate BBCH stages were connected to the DVS scale as defined by WOFOST. Finally, the calibrated model was used to predict development stages based on the predicted sowing dates over the entire European 10x10 km grid in order to have wall-to-wall predictions of all BBCH development stages.

Results and Discussion

The phenological model of WOFOST was calibrated with good results for 8 crops including spring barley, potato, sunflower, maize, winter-wheat, winter-rye, winter-rapeseed and winter-barley. In all 8 cases WOFOST was successful in predicting crop phenology after calibration. Figure 1 shows the results for spring barley for all agroecological zones across Europe. Moreover, it was demonstrated that intermediate crop development stages could be successfully linked to the WOFOST DVS scale for development. Figure 2 demonstrates the relationship between observed BBCH

[1] https://en.wikipedia.org/wiki/BBCH-scale

stages and the WOFOST DVS scale. As expected, BBCH stages do not correspond to single points on the WOFOST DVS scalebut show a certain range and are partly overlapping as well.

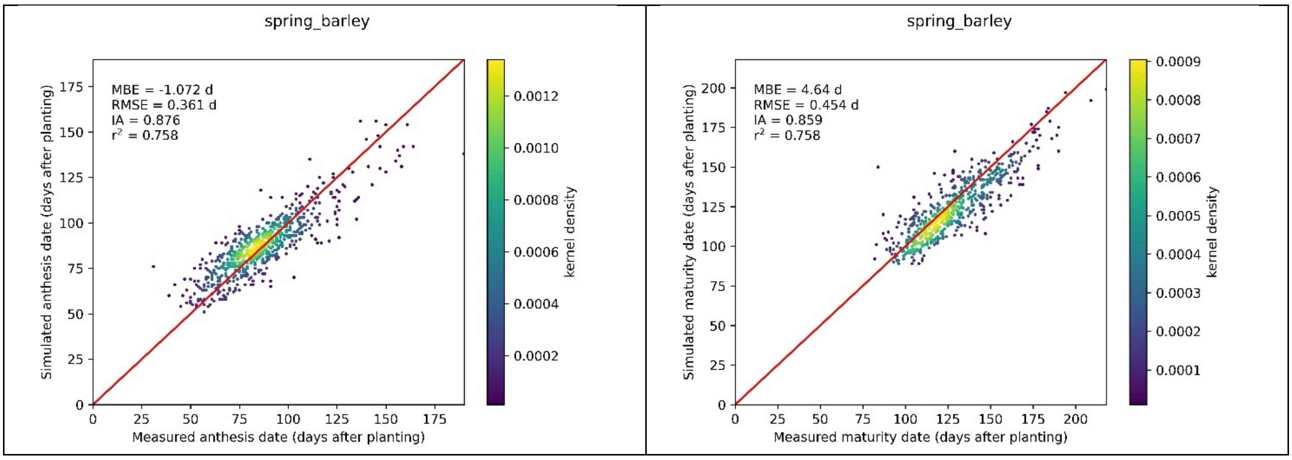

Figure 1. Calibrated and predicted days to anthesis (left) and days to maturity (right) for spring barley.

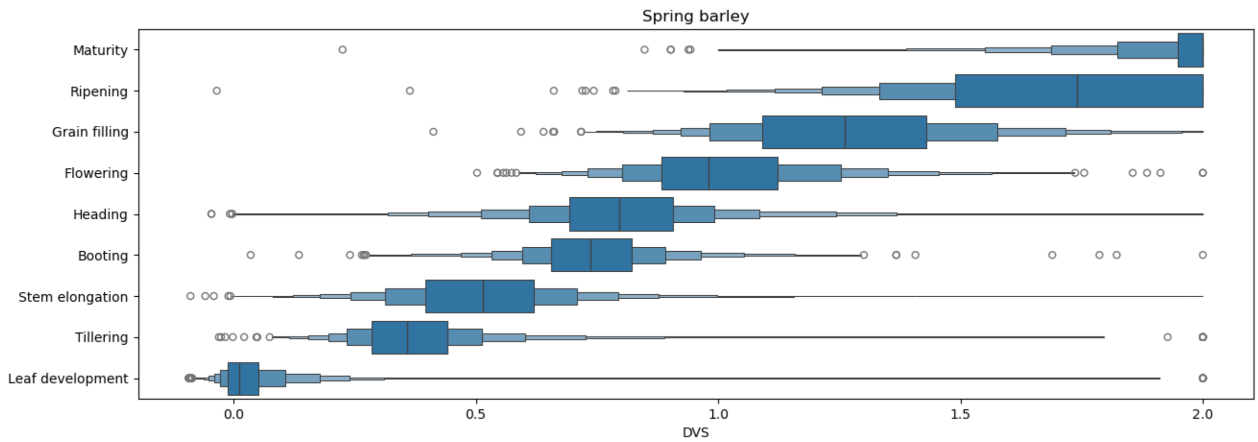

Figure 2 Relationship between WOFOST DVS values (x axis) and BBCH stages (y axis) for spring barley.

Conclusions

In conclusion, the project successfully established a comprehensive phenology database and robust modeling framework. This provides valuable, precise spatio-temporal information on crop development, significantly improving environmental risk assessment for pesticides in the EU regulatory context. In the near future, the developed spatial model for predicting sowing dates as well as the calibrated parameters will be made available as an open data product which facilitates application of the WOFOST model as well.

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Leveraging GenAI for crop simulation model applications

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Keywords: parameterization; decision-making; large language model

Introduction

Process-based crop simulation models, such as the Decision Support System for Agrotechnology Transfer (DSSAT; www.DSSAT.net), have become integral to agricultural systems research and as decision-making tools (Hoogenboom et al., 2019). Despite their wide potential, the large-scale implementation of crop models within the research community as well as among broader agricultural communities is constrained by challenges in model parameterization and model input setup. Accurate simulations require detailed site-specific information, including planting dates, planting density, fertilization strategies, irrigation regimes and cultivar-specific information. Obtaining these inputs is often time-consuming and technically challenging as such data are fragmented across heterogeneous sources. Moreover, even after assembling all the required model inputs, an additional challenge lies in encoding them into the correct formats and structures required by crop models. A minor deviation in the format and structure can break the model run. Thus, parameterization of crop model inputs and file setup have become the primary limitation to the wider adoption of crop simulation modeling for both research purposes and in the field decision-making purposes. The objective of this study is to design and evaluate a workflow that integrates generative artificial intelligence (GenAI) with a process-based crop model to automate the parameterization and creation of required crop model inputs and setup files thereby enabling scalable model applications.

Materials and Methods

We have proposed an approach that leverages GenAI within the DSSAT-Pythia framework (Fig. 1) (Joshi et al., 2025). DSSAT-Pythia provides a scalable framework for running DSSAT crop models across multiple spatial-temporal scales. GenAI offers a powerful solution by generating, inferring, assembling, and harmonizing the required environmental, genotype and crop-management specific parameters, significantly reducing the dependence on manual data collection and preparation. With contextual engineering, we have tailored GenAI to provide crop model parameter sets for specific locations and growing seasons. This capability has enabled efficient and automated parameterization considerably reducing the technical threshold required to configure and execute the model simulations.

Results and Discussion

In this study, we demonstrate the workflow through a case study of historical and near-real-time maize simulations for the Trans Nzoia region of Kenya. Our results highlight both the opportunities and challenges of integrating GenAI with DSSAT-Pythia for spatial model applications and up-scaling model usage beyond the experts. Since GenAI can hallucinate and make mistakes, we also present the necessity of a human-in-the-loop approach where careful review and evaluation of model inputs are integral to the workflow. We propose procedures for quality-checking of model parameters to ensure that input data, file setup and simulation outputs are precise.

Conclusions

The workflow presented in this study focuses on the maize simulations in Kenya. However, the proposed framework is broadly applicable and scalable to other crops, regions, and other modeling scenarios. This study shows promising results in machine-human teaming with GenAI for upscaling crop simulation model applications.

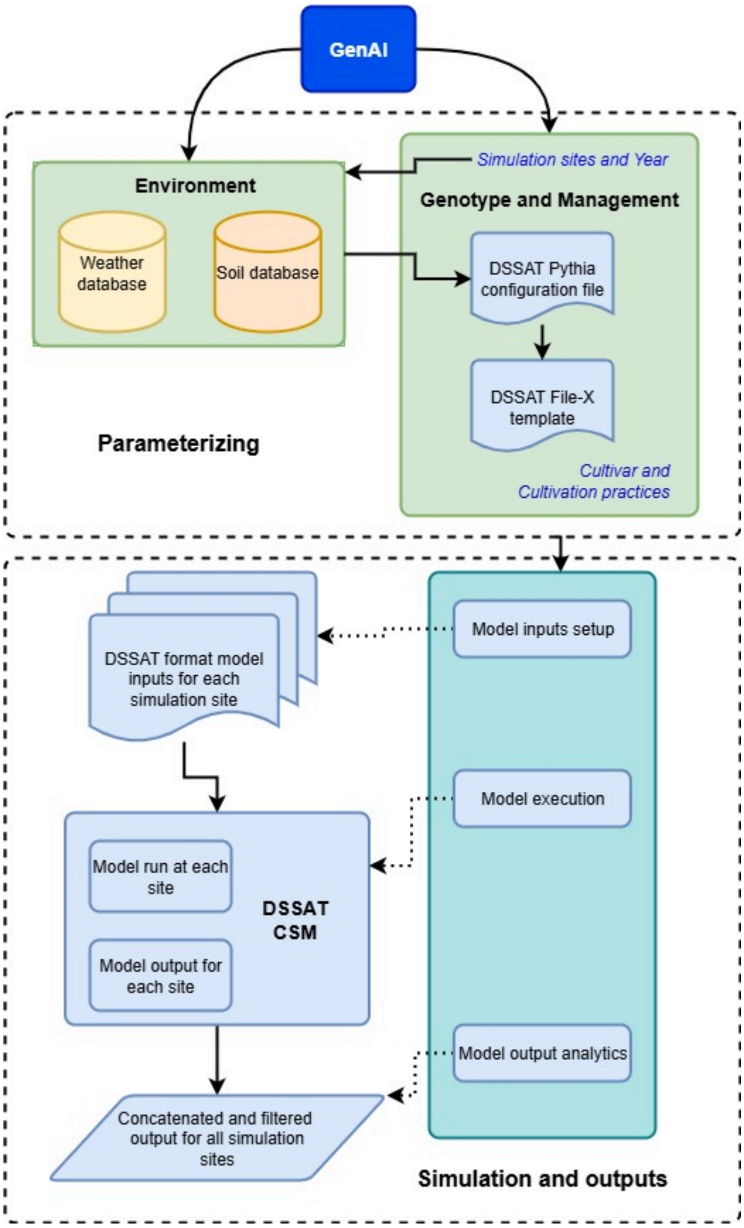

Figure 1. Workflow demonstrating a scalable framework to integrate Generative Artificial Intelligence (GenAI) in parameterizing, setting up files and execution of the DSSAT-Pythia crop simulation model.

Acknowledgements

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Enabling farmers' innovation with models: A framework for mobilizing crop models into participatory approaches.

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Keywords: DSSAT, soil fertility management, contextualization of knowledge, sub-Saharan Africa, smallholder farming.

Introduction

Contextualization of generic scientific knowledge into context-specific farmer knowledge is a necessary but a challenging step in farmers' innovation process. While working together, farmers and researchers may have a different understanding and representation of specific agronomical questions. Crop models can act as an interface during participatory projects to help communicating on complex problems by providing contextualized examples. Given the diversity of practices and indicators relevant to farmers, we argue for the development of a carefully co-designed basket of options. This basket would integrate practices selected by farmers, modelled within specific contexts described by them. Effects of these practices will be translated into indicators they propose and use, thereby allowing each farmer to identify options suited to their own situation.

This work proposes a framework to use crop models to assist decision making and innovation by simulating a large number of scenarios based on farmers' descriptions of their environment, practices own indicators.

Materials and Methods

Drawing inspiration from the concept of a boundary object to structure the exchange of information and knowledge between farmers' and researchers' worlds, we developed a framework composed of 6 Actions (A1 to A6) divided in three phases (Figure 1). This framework facilitates the use of crop models in participatory research by simulating change in practices within "baskets of contextualized options", thus allowing to cover a diversity of practices and environments to approximate farmers' contexts.

To test the framework, three workshops and individual discussions were proposed throughout 2022 to a group of 15 farmers (six women and nine men of all ages) from Arbollé, region Nord of Burkina Faso (12° 50′ 40″ N, 2° 02′ 18″ W). In this area of Sudano-Sahelian climate, rainfed cropping systems include sorghum, pearl millet, cowpea and groundnut with the primary purpose of producing staple food with important challenges regarding nutrient management.

The identification of the agronomical question, the characterization of the system under consideration and the management options to consider provided the basis for adequate crop model selection by researchers (in this case DSSAT V4.7). Based on the description of the management options and the environments made by farmers, the researchers then, used the models to simulate the Management × Environment (MxE) combinations required to assess the potential of farmers' innnovation. Communication tools were generated to present and discuss the main results of the modelling work with farmers.

Results and Discussion

During the testing of the framework on soil fertility management for sorghum production in Arbollé, both farmers and researchers shared knowledge on the drivers of cropping system performance. Despite some necessary approximations, farmers' descriptions of their environment and management practices, complemented by literature, were sufficient to parametrize the model. By matching the main farmer-proposed indicators to the main model outputs, we were able to constitute a basket of option with quantified examples of crop performance under contrasting scenarios. Discussions with farmers started by finding the MxE combination that best matched their own field experience and served as baseline. Then, practices changes were explored and discussed taking the baseline as reference to explain the influence of the change made on various indicators. By confronting the baseline to their own knowledge, farmers could critically receive and discuss the alternative practices and their impact.

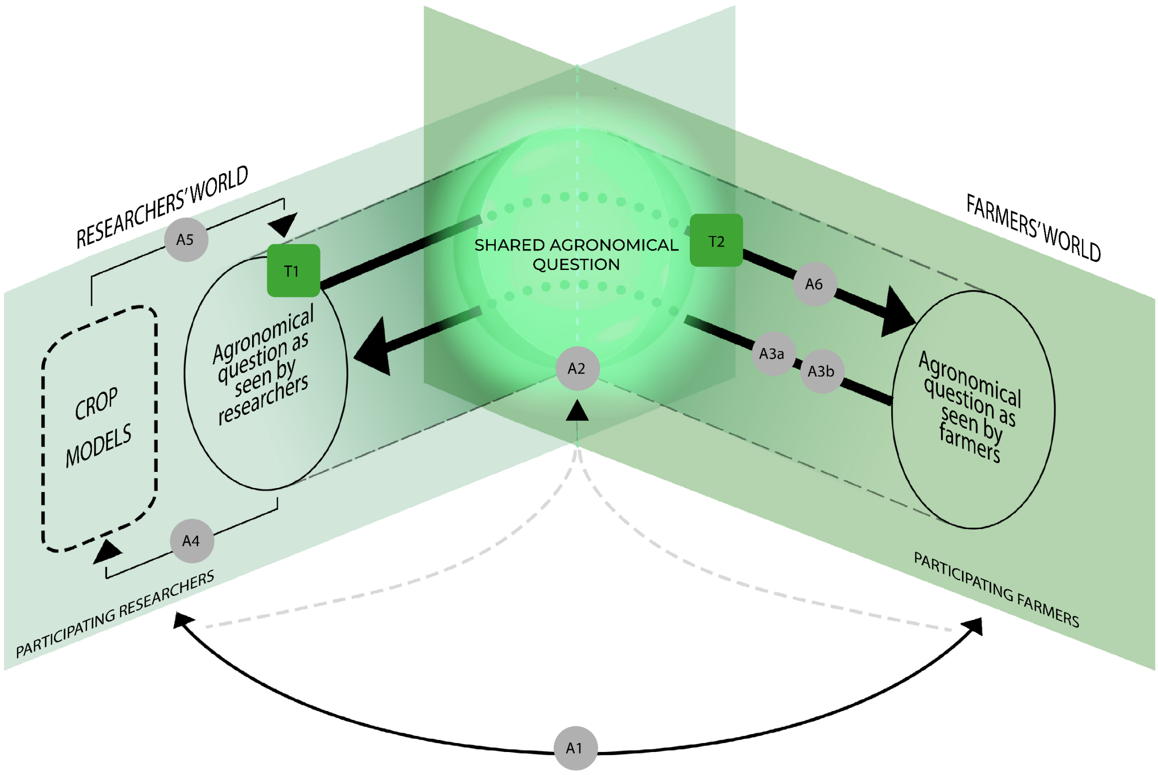

Figure 1. Schematic representation of the framework to use crop models in participatory approaches with farmers. The framework is composed of 6 Actions (A1 to A6, grey circles) divided in three phases. Phase I - Reaching out to farmers' world: A1 – Project initialization, A2 – Identification of the agronomical question, A3 – Characterization of the environments, the management options (A3a) and the indicators to describe the system under consideration (A3b); Phase II - Within researchers' world: A4 – Crop model parametrization, A5 – Translation of model outputs into farmer-proposed indicators; Phase III - Back to the farmers' world: A6 – Exploration of contextualized management options with farmers. The problem to be explored is represented in its shared ill-structured form at the intersection of farmers' and researchers' worlds, while it is more specific within each world. T1, is a first communication tool gathering contextualized management options whose effects are quantified through a crop model and described through farmer-proposed indicators. T2, the 'summary handout' is a second communication tool that substantiates the management options considered by farmers and is offered to them.

Conclusions

The framework formalized in this work serves as a basis for a powerful process for researchers to better communicate and share knowledge on key concepts with farmers during innovation processes, while using crop models. It raised questions on how to appropriately use crop model outputs to produce proxies to farmer-proposed indicators. Although tested with soil fertility management questions, this method could help in addressing a wider variety of issues or in combination with other activities, such as agronomic experiments.

Acknowledgements

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Agricultural systems modelling and stakeholder engagement: A review of approaches and impact in Sub-Saharan African

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Keywords: Climate change adaptation, Sub-Saharan Africa, participatory approaches

Introduction

Agricultural systems in Sub-Saharan Africa (SSA) face persistent threats from climate variability, soil degradation, and resource constraints, with profound implications for food security and rural livelihoods. Crop and farm system models have been widely applied to explore climate change impacts and adaptation strategies, as well as options for nutrient management (Webber et al., 2014). Yet their actual contributions to positive change remain insufficiently assessed (Steger et al., 2021). This study systematically reviews how crop and farm system models have been applied in SSA, with particular attention to the role of stakeholder engagement and the translation of modelling outcomes into practice.

Materials and Methods

We conducted a systematic literature review in Web of Science and Scopus, using the keywords "system model," "positive change," and "Sub-Saharan Africa" with their synonyms. After screening and expert validation, 71 studies were retained and coded for modelling approach, problem type, stakeholder participation and diversity, and analysing study intended and achieved outcomes.

Results and discussion

Across the 71 studies, climate change adaptation emerged as the dominant problem type, followed by nutrient and water management, with relatively fewer addressing resource conservation. Crop system models (n=42) predominated, typically applied for prediction and forecasting, relying mainly on biophysical data. Farm system models were fewer but more often used for decision support, integrating socio-economic as well as biophysical information.

Figure 1 shows a gap between the intended and achieved purposes of modelling studies. Prediction and forecasting aligned most closely with outcomes, while decision support and social learning were rarely realized. Importantly, these gaps varied with the mode of stakeholder participation: consultation-focused studies produced technically sound but underutilized outputs, collaborative approaches improved contextual relevance, and co-developed models fostered trust and uptake by embedding local knowledge (Sempore et al., 2016) into design and validation. This demonstrates that the degree of stakeholder engagement strongly influences whether models advance beyond scientific understanding toward actionable decision support.

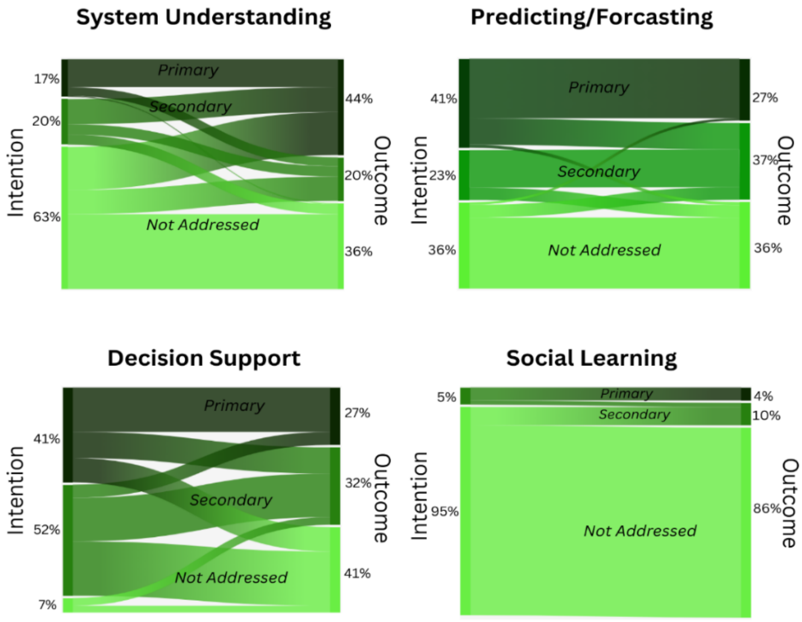

Figure 1. Percentage of papers with a primary or secondary purpose and outcomes for each category of system understanding, predicting & forecasting, decision support and social learning

Conclusions

The impact of agricultural modelling in SSA depends less on technical capacity than on participatory design. Crop models are vital for forecasting, while farm system models better support decision-making when inclusively developed. To drive resilient and equitable transformation, models must move beyond technical forecasting and be co-produced as participatory, context-sensitive tools that link science with local realities.

Acknowledgements

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Optimizing nomadic beekeeping management through integrated phenological models and short-term weather forecasts

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Keywords: DSS, flowering onset, foraging constraints, phenological models, weather forecasts

Introduction

In Italy, apiculture is an important component of national agriculture. Monofloral honeys constitute a distinctive and valuable asset, although their yields exhibit high interannual variability driven by weather fluctuations that affect both the phenology of melliferous plants and bee foraging activity. Consequently, timely information on flowering onset and weather conditions limiting bee activity is essential to optimize apiary management, favor nomadic beekeeping and maximize honey production. Although phenological models are commonly applied to predict the flowering of woody species, their use for herbaceous plants remains limited, and integration with short-term weather forecasts for predicting melliferous flora phenology is rare (Chuine et al. 2013; Alilla et al. 2022). The objective of this study is thus to apply a set of phenological models on short-term weather forecasts for improving beekeeping management and honey production during the season. In detail, we calibrated and validated four temperature-driven phenological models (GDD, UNIFORC, UNICHILL, BRIN) for both herbaceous (sulla, sainfoin, clover) and woody species (black locust, chestnut, linden) in Tuscany, Italy. The best-performing models were combined with 16-day weather forecasts to predict species-specific flowering onset and foraging windows, incorporating temperature, rainfall, and wind thresholds that constrain bee activity and potential honey production.

Materials and Methods

This study was conducted in Tuscany (central Italy), focusing on three herbaceous forage species—sulla (*Hedysarum coronarium* L., SU), sainfoin (*Onobrychis viciifolia* L., SA), and clover (*Trifolium* spp., CL)—and three woody species—black locust (*Robinia pseudoacacia* L., BL), chestnut (*Castanea sativa* Mill., CH), and linden (*Tilia* sp., LI)—important for monofloral honey production. Phenological data were obtained from expert observations, the Italian Phenological Network (IPHEN), and online databases (PEP, GBIF, iNaturalist, and ARPAT), defining flowering onset as 10% of flowers open (BBCH 61) for SU, SA, CL, BL, and LI, and full flowering (BBCH 65) for CH. The dataset included 239 records from 103 sites (2000–2024), with an independent 2025 dataset (93 records) used for model validation. Meteorological data (air maximum and minimum temperature, precipitation, wind speed) were collected from the nearest SIR (Servizio Idrologico Regionale) stations and complemented with 16-day forecasts from OpenWeatherMap at 500 m resolution.

Four phenological models (GDD, UNIFORC-forcing; UNICHILL, BRIN-chilling-forcing) were applied to estimate flowering onset, with all models used for woody species and only forcing models for herbaceous species. Models were calibrated and validated using Phenological Modeling Platform (PMP v5.5; Chuine et al., 2013) on 5 calibration and 5 validation datasets obtained by randomly splitting observed flowering data (60% calibration, 40% validation). A multi-criteria decision-making framework, integrating Compromise Programming with the Entropy Weights Method, was employed to identify the optimal input set and, within it, the most accurate model based on statistical metrics (r, RMSE, AIC) computed during calibration and validation.

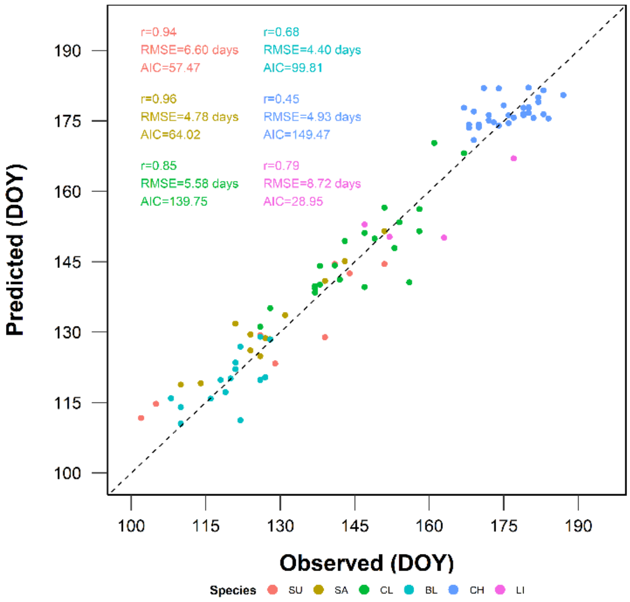
Acronym	*Set*	*Model*	T_b	t_0	$Chill_{req}$	$Forc_{req}$	*a*	*b*	*c*	*d*	*e*
SU	5	UNIFORC	-	2.98	55.72	-	-	-	-	-0.66	11.26
SA	1	UNIFORC	-	79.01	35.32	-	-	-	-	-0.86	10.10
CL	1	GDD	4.37	93.10	523.95	-	-	-	-	-	-
BL	2	UNICHILL	-	244*	193.49	32.54	0.15	14.37	27.40	-0.86	11.22
CH	1	UNICHILL	-	244*	261.22	20.73	0.24	10.45	28.70	-0.15	18.64
LI	4	UNIFORC	-	96.42	47.87	-	-	-	-	-0.80	13.60

**Referred to the year preceding the year in which flowering occurs*

The selected models were then applied to the 2025 dataset using 16-day forecasts to predict flowering onset at the relevant meteorological stations, and the number of suitable foraging days was estimated for each species using thresholds for temperature (20–30 °C), rainfall (<4 mm), and wind speed (<2.8 m s^{-1}) within the predicted flowering window (Czekońska et al. 2023; Vincze et al. 2024).

Results and Discussion

Table 1. Average parameter values of base temperature threshold (T_b; °C), starting day (t_0, DOY), chilling requirement ($Chill_{req}$; CU), forcing requirement ($Forc_{req}$; FU for UNIFORC and °C d^{-1} for GDD), and empirical parameters (a-e) for each combination of herbaceous (SU, SA, and CL) and woody species (BL, CH, and LI), best set and best model selected.



Across calibration **(Tab. 1)** and validation **(Fig. 1)**, UNIFORC provided the most accurate predictions for SU, SA and LI ($\bar{r}$ = 0.92, $\overline{RMSE}$ = 5.18 days, $\overline{AIC}$ = 61.19), followed by UNICHILL for BL and CH ($\bar{r}$ = 0.63, $\overline{RMSE}$ = 4.54 days, $\overline{AIC}$ = 153.50), and GDD for CL ($\bar{r}$ = 0.86, $\overline{RMSE}$ = 5.19 days, $\overline{AIC}$ = 169.35). These results confirm that forcing-based models effectively capture flowering dynamics in Mediterranean herbaceous species, where dormancy is minimal during winter, while chilling-forcing models remain useful for some woody species, even if the role of dormancy still should well evaluate. For this reason, although our results align with previous studies (Alilla et al. 2022; Kim and Jung 2022), comprehensive datasets combining field observations with experimental tests on bud exposure to varying cold periods are needed in order to assess the actual contribution of dormancy in melliferous species. Integrating phenological models with 16-day weather forecasts allowed prediction of flowering onset 10–14 days in advance and reliable estimation of optimal foraging days. This highlighted that early-flowering species at low elevations are more sensitive to cold, rainfall limits bee activity across all altitudes, and wind increasingly constrains foraging at higher elevations, as also reported by Messeri et al (2024) and Zola (2024).

Conclusions

This study demonstrates that integrating phenological models with short-term weather forecasts enables early prediction of flowering onset, providing actionable guidance for beekeeping and forage management. Future decision-support systems could combine hourly environmental data with field observations provided by beekeepers to refine models in real-time and optimize honey and crop production under Mediterranean climate variability.

Figure 1. Comparison between observed and simulated flowering dates (DOY) across herbaceous (SU, SA, and CL) and woody species (BL, CH, and LI) using the best-selected set and model. The dashed line represents the 1:1 reference line.

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Integrating forecasted weather conditions into data-driven models for wheat yield forecasts before harvest

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Keywords: Yield variability; Weather extremes; Machine learning; Climate change

Introduction

Wheat yield variability is projected to increase under climate change, driven by droughts, heat waves, and compound stresses (Liu et al., 2021). Reliable in-season yield forecasts are therefore essential for farmers, policymakers, and humanitarian organizations to anticipate supply shocks, stabilize markets, and plan effective responses (Funk et al., 2019). The challenges of in-season forecasts are the unknown growth conditions for the remainder of the crop season from the forecast date to harvest. These conditions can be provided from weather or climate forecast models. While the application of forecasted weather conditions within process-based crop models has been widely studied, the systematic use of forecasted weather data in data-driven yield forecasting remains underdeveloped. The overarching aim of this study is to develop and evaluate wheat yield forecasting models that integrate forecasted weather data in order to improve their timeliness, accuracy, and practical utility. Building on this motivation, the study investigates four central research questions. First, it examines whether multi-model ensembles provide an advantage over climatology or single-model forecasts in predicting wheat yields. Second, it explores how the composition of such ensembles, specifically, the number and selection of models, influences forecast performance. Third, it evaluates the relative importance of forecasted weather data compared to other predictors, such as soil properties or vegetation indices, in machine learning-based crop yield models. Finally, it considers whether shorter lead times can improve the predictive skill and usefulness of yield forecasts for agricultural decision-making.

Materials and Methods

This study develops and evaluates data-driven models that link meteorological and ancillary input data to wheat yield outcomes across major production systems in Brazil, Argentina, the United States, and the European Union. The core focus lies on the use of forecasted weather data, derived from seasonal and subseasonal climate prediction systems, which are bias-corrected and aggregated to match observed or reanalysis weather records. These forecasts are combined with vegetation indices (NDVI, fAPAR) and soil properties to forecast end-of-season yield statistics on (sub-)national level. Three modeling approaches are applied. Ridge regression offers an interpretable linear benchmark that relates aggregated weather anomalies to yield variability. Long Short-Term Memory (LSTM) networks exploit sequential dependencies, capturing how evolving weather and vegetation dynamics across the growing season affect yield formation. Gaussian Process Regression (GPR) provides a flexible non-parametric alternative, well suited for nonlinear relationships and heterogeneous regional data. Model skill is assessed using a range of complementary metrics, including RMSE, MAE, R^2, and ROC scores.

Results and Discussion

Our study shows that wheat yield forecasts with multi-model ensembles (MMEs) provide more consistent performance than single-model forecasts or climatology benchmarks. MMEs of three models (ECMWF, Météo-France, and NASA) delivered the best performance in Argentina, where national yields could be forecast skillfully one month before harvest.

In Brazil, MMEs reduced errors relative to climatology and showed less variability across months, providing a practical tool for planning in a country heavily reliant on wheat imports. In the U.S. Great Plains, machine learning models that incorporated forecasted seasonal climate data (especially in April–May) improved predictive skill by up to 10% during critical stages such as booting and heading, demonstrating that forecasts, even with horizons as short as two weeks, can meaningfully support decision-making. A key highlight of this work is the evaluation of the added value of four-week weather forecasts into the official EU MARS Crop Yield Forecasting System through the new MARS+Forecast framework. When assuming a perfect four-week weather forecast based on reanalysis data (MARS+Perfect), MARS forecasts would theoretically be improved in 16 countries, covering 60% of EU wheat area and 55% of wheat production. Figure 1 illustrates these country-level performance differences, highlighting where MARS+Perfect provided the greatest added value. Taken together, the results highlight that small MMEs (around three models) and the targeted use of subseasonal forecasts around crucial development stages can enhance the timeliness and accuracy of wheat yield forecasting across diverse agro-climatic regions. Improvements in weather forecast skill, are likely to translate directly into agricultural value, but only if yield models are designed to account for the specific properties of forecast data. For instance, forecast skill often declines at higher spatial resolution, so aligning forecast resolution with crop modeling scales is critical to avoid spurious errors. Likewise, building yield models that explicitly consider the strengths and weaknesses of weather forecasts (e.g. biases, ensemble spread, and temporal aggregation) can improve robustness. The results also underscore the value of short-term forecasts, especially during sensitive growth stages, where even two-week lead times can aid operational decision-making. Looking ahead, advances in AI-based forecasting systems provide promising opportunities to strengthen the use of forecasted weather data within data-driven crop yield models.

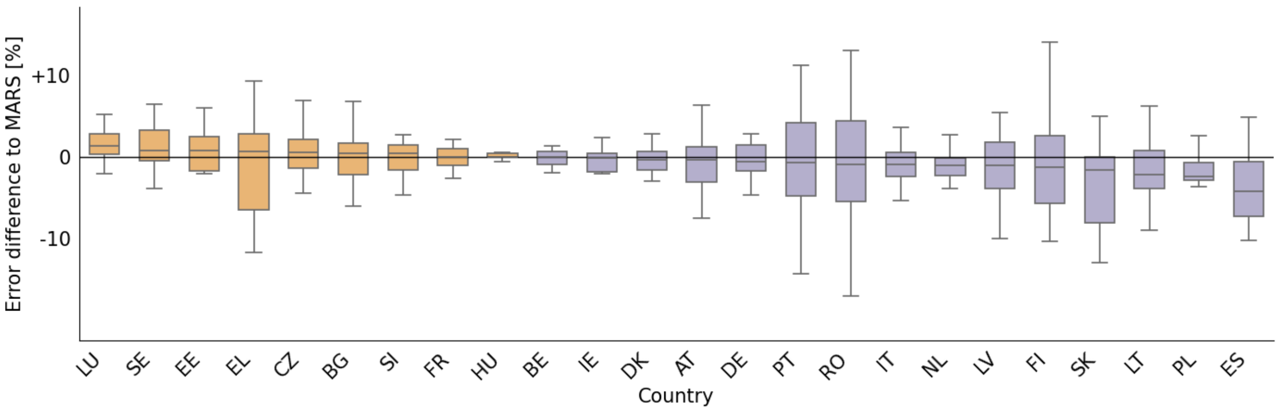

Figure 1. Performance comparison of MARS and MARS+Perfect across EU countries. The MARS Crop Yield Forecasting System is the operational EU framework that combines process-based crop model outputs, satellite vegetation indicators, and gridded meteorological data within an analyst-guided statistical approach. In May, during a critical stage of wheat development, MARS issues its first forecast based on observed data. Our extension, MARS+Perfect, incorporates theoretical always-correct four-week weather outlooks of temperature and precipitation after the May publication date, providing a quantitative way to assess the potential added value of subseasonal weather information. The figure shows the distribution of annual performance differences between MARS+Perfect and MARS at the country level. Each boxplot depicts the range and median of yearly error differences, with a vertical line at zero indicating equal performance. Purple boxplots denote countries where MARS+Perfect outperformed MARS in more than half of the years (median < 0), while orange boxplots denote the opposite (median ≥ 0).

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Integration of crop models, agronomic knowledge and technology for the success of decision making in crop management

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Keywords: decision support systems, resilient cropping systems, resource management.

Introduction

Decision Support Systems (DSS) in agriculture are digital tools that can integrate different technologies to assist farmers, agricultural professionals, and decision-makers in taking informed decisions. These systems use data, models, and algorithms to provide insights, predictions, and recommendations that can optimize agricultural practices. The goal is to improve resource management, sustainability, and profitability in farming operations by promoting more sustainable, adaptive, and resilient cropping systems. Although several alternatives are available for agricultural stakeholders, adoption is still low, with one of the main obstacles being convincing farmers and technicians that a DSS can address their specific needs, even if it has been developed in a different agronomical context.

Materials and Methods

Horta's DSSs are based on key aspects that enable them to face the challenges of convincing farmers of the trustability and robustness of the DSSs, especially to enter into new contexts (countries/environments/agricultural practices) or to respond to climate change. These key aspects are: i) deep agronomic and biological knowledge, based on continuous experimental trials, controlled environmental experiments, and agronomical expertise ii) mechanistic process-based modelling framework, iii) use of historical and real-time data from different sources (proximal/remote, automatic/manual, territorial/site-specific) related to weather, soil, plant and crop operations and vi) flexibility/customization of stakeholders needs.

All key aspects of crop management are considered by integrating models and functionalities related to: crop growth, biotic stresses (diseases, pests and weeds control), abiotic stresses (irrigation, temperature and physiopathologies), nutrition, soil and carbon management, production (yield and quality), and sustainability.

Results and Discussion

Thanks to these features, Horta's DSS are actively used by thousands of farmers and advisors, as well as cooperatives and agri-food industries on 16 crops (arable, fruit and vegetables) in 12 Countries. Benefits of using the DSSs for decision making in crop management were measured in different pilot projects and some practical examples are described:

1. water management is a very important aspect for tomato agri-food industry; by using Horta's Tomato DSS, that includes a water balance model, 20% reduction in water consumption was demonstrated. Other aspects were improved (optimization of disease control and fuel use) that converge in an average reduction of carbon emissions by 25% (CO_2eq t/t) (on farm field trials 2016-2024).
2. for durum wheat management a fundamental aspect is the correct distribution of nitrogen; Horta's Wheat DSS includes a nutrition balance model that, integrated with satellite remote sensing of vegetation indexes, optimize precision applications of nitrogen, both amount and spatial distribution (variable rate applications). Within the project ADP4durum (funded by Apulia Region, Italy) a saving of 40% of N kg/ha was achieved. Moreover, long term on-farm trials (2012-2022) carried out in collaboration with Barilla Industry, demonstrated improvements in crop management both on production and quality (increase of 4,5% in yield and of 3,2% in protein content) and on sustainability (reduction of carbon emissions by 12% CO_2eq t/t).

3. in viticulture, diseases and pests are the major factor that may affect yield and quality, and a high number of plant protection products are applied during the season. In addition to grape production, grape growers play a fundamental role in safeguarding the agricultural land of large hilly areas which are subject to erosion and loss of organic matter. Within the EU funded project PLOUTOS, 15 grape growers adopted Horta's Grape DSS and inter-row grassing and were able to generate and certify around 10 Carbon Credits/ha/year.
4. within the EU LIFE AGRESTIC project and follow-ups, Efficient Cropping Systems (improved crop rotations with cover crops, reduced tillage and use of Horta's DSS) were tested over several cropping seasons (2020-2025). Decrease in fuel consumption, use of nitrogen fertilizers, number of phytosanitary treatments, number of irrigation and volume of water, as well as sowing densities, was demonstrated and resulted in an overall decrease of carbon footprint of 37%.

Conclusions

Integration of different technologies and multidisciplinary knowledge is key for the development of successful digital farming tools. The real-world examples described above demonstrate how the combination of process-based models, agronomic knowledge and technology within Horta's DSS have shaped and supported decisions by agricultural stakeholders. The results obtained on farm trials have provided measurable benefits in all sustainability pillars, although the best metric for the evaluation of such tools is the constant increasing in adoption and high renewal rate by users.

FLORSYS: a mechanistic model bridging scientists, advisors and farmers for designing agroecological weed management

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Keywords: 3D individual-based, ecological intensification, cropping system design, crop ideotypes, data mining

Introduction

Arable weeds are essential for biodiversity and highly damaging to crop production. So far, no non-chemical curative weed-control option used alone is as efficient as herbicides. Because their seeds survive for several years in the soil, weeds must be managed at the rotation scale to limit damage to the current and following crops. Weed management must therefore undergo a major paradigm shift, from a single highly efficient cropping technique (i.e., herbicides) to a combination of multiple, partially efficient, and interacting techniques. This shift requires a change of perspective from cure to prevention, from chemical suppression to biological and mechanical regulation, from single-minded control to reconciling damage and benefits resulting from weeds. To make these new weed-management strategies efficient and acceptable to farmers, they must be adapted to the pedoclimatic conditions, production contexts and socio-economic specificities of their farms.

The objective of this paper was to demonstrate how a mechanistic process-based model was developed and used to co-design crop ideotypes and cropping systems for weed management, thus bridging the gap between research on biophysical processes and agroecological weed management in real-life farms.

Materials and Methods

The methodology comprises three steps: (1) experiments in controlled conditions, experimental stations and farmers' fields to understand biophysical processes that drive weed dynamics and impacts in agroecosystems, in relation to cropping techniques, (2) synthesize this knowledge into simulation models and decision-support systems to produce emergent knowledge on agroecological levers, (3) design cropping systems and crop ideotypes adapted to different goals and local contexts.

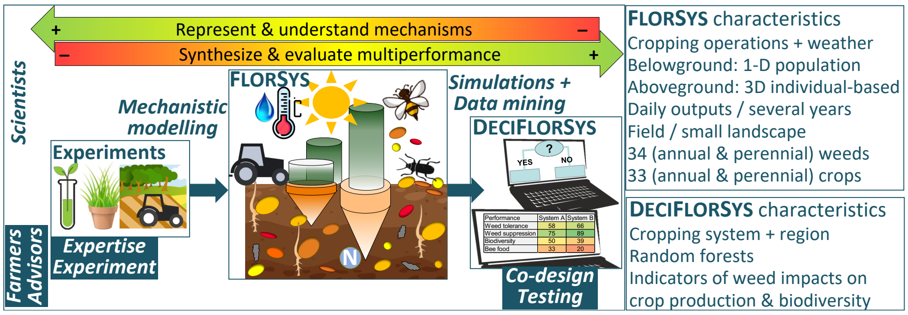

Figure 1. The modelling chain linking experiments, mechanistic modelling and decision-support systems for designing agroecological weed management strategies and the role of scientists, advisors and farmers (Colbach et al, 2021).

These steps were conducted with farmers and advisors to ensure the operational nature and adoption of weed management strategies. Step 1 uses mechanistic modelling to translate experimental results into equations and parameters for the FlorSys simulation model (Figure 1). Step 2 uses FlorSys simulations and data mining to co-design decision support systems. Step 3 uses these tools to evaluate and design crop ideotypes and cropping systems for agroecological weed management, with increasing degrees of farmer implication: (1) define the objective of the simulation study, (2) provide farm practices for simulations via surveys and agricultural databases (DEPHY), (3) propose prototypes for simulations, (4) iteratively design cropping-systems in participatory workshops. Latin Hypercube Sampling (LHS) was used to determine simulation plans, machine learning (classification and regression trees, random forests) to build decision trees and meta-models, and optimisation algorithms to identify solutions reconciling contrasting objectives and constraints.

Results and Discussion

The FLORSYS model to synthesize knowledge in a virtual experimental field. The FLORSYS simulation model started twenty years ago as a research tool (Colbach et al., 2021). Its inputs list all cultural operations in detail over several years, together with daily weather data (past or future), soil characteristics and a regional weed species pool. The 3D individual-based multispecies model simulates biophysical processes that are essential for non-chemical crop management and biological weed regulation. To tailor FlorSys to stakeholders' requirements and to simplify the multi-criteria comparison of cropping systems, the detailed model outputs were aggregated into indicators of crop production and weed impacts on crop production and biodiversity, together with advisors and farmers. FLORSYS has evolved over time to account for stakeholders' questions and the changing context, recently adding (1) processes such as plant–plant competition for water (to include tropical conditions and climate change), weed seed predation and vegetative reproduction of perennial weeds (which increase in conservation agriculture), (2) species and varieties to evaluate crop diversification, (3) innovative management techniques (e.g., topping, agroecological infrastructures).

Use FlorSys to co-design decision support systems. FlorSys was used as a virtual farm-field network, simulating thousands of cropping systems with different soils and weather records. The simulation outputs were used to check and improve existing decision-support systems, e.g., whether OdERA (https://www.agro-transfert-rt.org/outils/odera/) was fit for climate change. But FlorSys's importance for making process-scale knowledge available to different stakeholders was best illustrated with the development of DeciFlorSys. This faster and easier-to-use metamodel was built from FlorSys simulations using machine learning techniques. DeciFlorSys was co-designed with farmers and crop advisors via surveys and participatory workshops testing successive versions to identify (1) key functions, applications and input/output formats, and (2) how to shift stakeholders' weed perception from eradication (focusing on weed abundance) to agroecological management (based on weed impacts).

Co-design cropping systems and crop ideotypes. The ideotypes and ideal systems identified from simulations based on LHS plans and optimization algorithms were often very different from existing varieties and cropping systems. Key techniques and rules for combining them were identified, showing that the best 0-herbicide systems with well-timed false-seed-bed operations and occasional mouldboard ploughing had a weed-caused yield loss of only 4%. These results and rules were then used to accompany farmers in participatory workshops to design new cropping systems.

Conclusions

FlorSys complements field experiments and local expertise via long-term simulations with different climate scenarios, disentangling the effects of correlated practices and predicting the effects of interacting techniques as well as giving access to difficult-to-measure state variables on soil, crops and weeds needed to understand how the agroecosystem functions. The benefits, crop ideotypes and optimal agroecological cropping systems depended on the production contexts and the scale (field vs farm vs landscape, year vs rotation) at which objectives should be reconciled. Flexible rules are thus required to account for local specificities as well as models to establish these rules.

Acknowledgements

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Applying Digital Twins and Geospatial Cyber-Infrastructure to Agricultural Policy and Practice

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Keywords: Geospatial DSS, process-based modelling, nitrate fate, pesticide fate, what-if modelling

Introduction

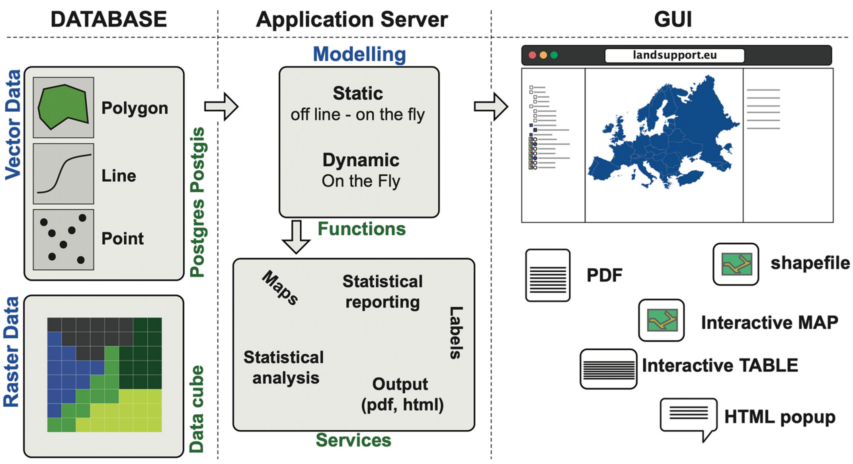
At present, there is a clear tension between the increasing environmental demands placed on agriculture and the need to maintain farmers' presence and incomes in rural areas (e.g., EU Green Deal, CAP). We argue that addressing these competing challenges requires the development and use of user-friendly, freely available, web-based operational tools. Such tools do not provide a single "solution," but rather a set of "options" from which users can choose. In this way, they can both support the implementation of environmental and agricultural policies and empower stakeholders to take concrete actions toward environmental sustainability.

Our proposed solution is a network of Digital Twins and databases designed to support decision-making in agriculture, forestry, environmental management, and land-use policy. The LANDSUPPORT platform is a free, web-based Geospatial Cyber-Infrastructure, strongly grounded in process-based modelling, that integrates 15 macro-tools. In this contribution, we present evidence from five agriculture-related tools.

Main elements of the digital twin:

Figure 1 illustrates the three tiers of the LANDSUPPORT geospatial cyber-infrastructure:

Figure 1. Main elements of the LANDSUPPORT geospatial DSS



Agriculture-related tools

The agriculture-related tools of the LANDSUPPORT platform applied at both national and regional scale.

i. Climate resilience agriculture: Supports the development of robust knowledge for informed decision-making and enhances the climate resilience of agriculture and forestry; contributes to LULUCF reporting.
ii. Best practices: Gives clear results about the production and the environmental impact in a given area in what-if scenarios of field management.
iii. Nitrate and Pesticide: Simulates nitrate and pesticide balances under different management scenario, assisting in reducing leaching in farming systems.
iv. Ecosystem services: Quantifies ES and resilience to climate change, enabling the simulation and evaluation of alternative agri-environmental and climate scenarios.
v. Soil health: Assessing a bundle of key ecosystem services using a process-based modelling approach, providing a foundation for assessing potential soil health status.

Conclusions

We argue that robust operational Spatial Decision Support Systems (S-DSS) represent a critical step toward transforming data availability into concrete actions for sustainable agricultural management. This can be achieved by ensuring:

(i) a user-friendly GUI that conceals underlying complexity;
(ii) implementation of the concept of land and soil multifunctionality;
(iii) adaptability to diverse user needs;
(iv) incorporation of “what-if” modelling to empower decision-making;
(v) low-cost transferability of the approach to new regions; and

integration of bottom-up contributions from users.

A Virtual Agricultural Innovations Laboratory (AVAIL) – Crop Model Data Assimilation and Machine Learning for Innovations in Iowa

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Innovation, Iowa Corn, DSSAT, machine learning, digital twin, data assimilation, decision support

Abstract

NASA's A Virtual Agricultural Innovations Laboratory (AVAIL) project responds to farmer and agricultural sector stakeholders clamoring for decision support tools that will help them meet current and future challenges in food systems. In particular, our outreach has indicated that interested parties can be overwhelmed by the firehose of remote sensing products, ground datasets, weather datasets, crop models, and data-driven (machine learning) models that each offer a differing perspective on agricultural systems. AVAIL is a technological framework developed to link together these different perspectives using process-based crop models (DSSAT and APSIM) as a basis for rectifying observational discrepancies and allowing farmers to answer "what if?" questions that go beyond the observed experience (Figure 1). These include the ability to revisit previous disasters (e.g., floods, droughts, insect outbreaks, windstorms, heat waves) to explore whether alternative seeds or management could have alleviated damages, as well as to explore risks of similar (or more severe) disasters striking in the future. The AVAIL team is also engaging with farmers and commodity groups to explore and prioritization of seed genetics and management options that can meet a variety of farmer goals, including higher resource efficiency, yield stability, productivity increases, improved sustainability, adherence to policy requirements, and higher net farm returns. With the AVAIL system these innovative farming systems can be analyzed under normal and adverse conditions, as well as in diverse regions to explore geographic viability.

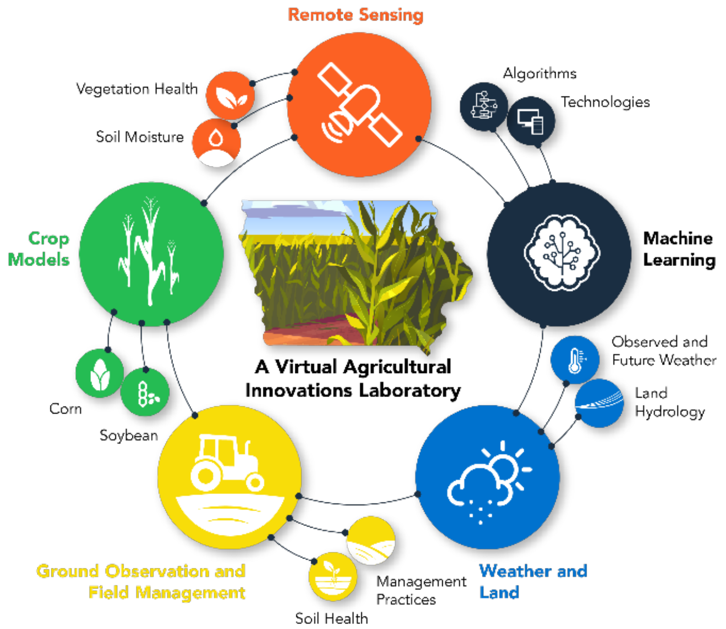

Figure 1. Components of the AVAIL system

We will describe the ambition and early progress of AVAIL, including advances in balanced DSSAT within-season data assimilation, bias-adjustment of satellite and ground datasets, high-resolution configuration across heterogeneous landscapes, and initial tests of innovative strategies. We will also describe plans for scaling this work to other regions and farming systems within AgMIP, as well as the potential transfer of crop model components into other process-based models that will open up new doors in multi-model analysis and decision support for innovation.

Acknowledgements

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Biomass and Yield Estimation of Rice-Wheat Cropping System Using UAV-based Machine Learning Algorithms and DSSAT Crop Model

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Keywords: Irrigation Methods, and ML Algorithms

Introduction

India is the second largest producer of wheat and rice crops with a production of 101.29 Mt and 175.58 Mt, respectively (Dey and Dinesh, 2020). Wheat is cultivated in the winter months when rainfall is limited, which highlights the need for efficient irrigation water management. Due to the continuous submergence of paddy crops, it requires three times higher water than other cereal crops (Rao et al., 2019; Ashfaq et al., 2020). Considering the growing competition for water resources, there is a need to explore novel methods for enhancing water use efficiency in irrigated paddy fields. Unmanned Aerial Vehicle (UAV)-remote sensing and crop modeling are useful tools to study the spatial variability of crop growth and crop response to different water levels and irrigation scenarios (Dar et al., 2017; Rathore et al., 2017). UAV remote sensing enables high-frequency, plot-scale observations of canopy structure and vigor, while process-based crop models such as Decision Support System for Agrotechnology Transfer (DSSAT) capture genotype-environment-management interactions across seasons. This study integrates UAV-derived vegetation indices with machine-learning (ML) algorithms and DSSAT simulations to (i) quantify biomass and yield response of rice under alternate wetting and drying (AWD) and wheat under different irrigation methods (drip, sprinkler and flood) with variable rates of crop evapotranspiration (100%, 75%, 50% and 0% rainfed treatment), and (ii) compare the performance of ensemble ML against DSSAT for yield estimation across two seasons of the rice-wheat cropping system in Roorkee, India.

Materials and Methods

The field experiments were conducted at the Demonstration Farm of the Department of Water Resources Development and Management (WRD&M), Indian Institute of Technology (IIT) Roorkee, Uttarakhand, India, during the *Rabi* (November–April) season for the wheat crop and the *Kharif* (June–October) season for the rice crop for two years. Weather data including rainfall, minimum temperature, maximum temperature, relative humidity, wind speed, solar radiation, and pan evaporation were collected from the Agromet Observatory installed at the IIT Roorkee campus. The Q6 UAV (IdeaForge Pvt. Ltd., Mumbai, India) was used for data collection at different growth stages of the rice-wheat cropping system. Vegetation indices (e.g. Normalized Difference Vegetation Index), gray-level co-occurrence matrix (GLCM) textural features, and biophysical properties (LAI and plant height) were estimated from the image processing. Machine learning (ML) algorithms, viz. Support Vector Machine (SVM), XGBoost, Adaboost, Gradient Boosting Decision Tree (GBDT), and Random Forest were developed using the UAV-based imagery and used for the biomass and yield estimation of the rice-wheat cropping system. The ML models were ensembled with Random forest as a meta learner and the other four models as base models. Hyperparameters were tuned with cross-validated grid search. Biomass and yield were also simulated using the DSSAT crop modeling for the two-year field experiment data. The efficacy of the DSSAT model and ML algorithms was compared for the biomass and yield simulation. The Model performance was evaluated with the coefficient of determination (R^2), Kling–Gupta efficiency (KGE), normalized root mean squared error (NRMSE), and percent bias (PBIAS).

Results and Discussion

The biomass and yield results obtained from the different ML algorithms and the DSSAT crop model were compared. The ensemble ML approach using UAV-derived spectral, textural, and biophysical features delivered the strongest predictive performance for plot-scale yield estimation. During the training process of the ensemble random forest model, it performed better with a higher KGE (0.91) and a lower value of NRMSE (0.033), and a minimal PBIAS of 0.13%. The ensemble random forest model performed better during the testing process of the rice yield estimation (R^2 = 0.60, KGE = 0.71, PBIAS = −2.26%, NRMSE = 0.136). For wheat yield estimation, training results were similar with strong model performance (R^2 = 0.8137, KGE = 0.83, PBIAS = 1.36%, NRMSE = 0.470). The stacked model (RF meta-learner) achieved strong goodness-of-fit with low error metrics in both training and testing, outperforming individual learners for rice and wheat yield estimation. These findings indicate that fusing high-resolution UAV features with an ensemble ML framework yields accurate, spatially-varied predictions suitable for plot-level decision support. The improvements in KGE and NRMSE, together with low absolute bias, underscore the model's ability to capture both correlation structure and magnitude of yields.

Conclusions

The findings demonstrate that combining UAV-derived spectral, textural, and biophysical features with an ensemble machine learning framework offers the most accurate plot-scale yield estimation for the rice-wheat cropping system, outperforming individual learners and a stand-alone process model. The DSSAT model added mechanistic insight into genotype-environment-management interactions, clarifying seasonal dynamics that purely data-driven ML models treat as a black box. The UAV-ML and DSSAT workflow captured both the fine-scale spatial variability needed for site-specific field decisions and the process understanding needed for generalization across the seasons. This integrated workflow supports the UN Sustainable Development Goals (SDGs)—specifically SDG 2 (Zero Hunger) and SDG 6 (Clean Water and Sanitation).

Acknowledgements

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Potential of seasonal rainfall forecast to improve yields in sub-Saharan Africa: a proof of concept

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Keywords: Climate information services, crop management, smallholder farmer, rainfed crop, crop modelling

Introduction

Smallholder farmers in Sub-Saharan Africa largely rely on rainfed agriculture. As a result, their crop productivity is highly vulnerable to the impacts of climate change and variability. Providing access to climate information services is therefore seen as a critical way to help these farmers adapt their crop management and reduce climate-related risks. Although research has extensively explored the factors that drive the adoption of these services, their actual impact on crop productivity has received little attention (Nyoni et al., 2024). Using a modelling approach over five study sites, the objective of our research was to determine if optimal sowing date, based on a perfect rainfall forecast knowledge, can significantly improve yields and lower their variability compared to farmer practices informed with lower levels of climate information. We also aim to assess whether this potential value of rainfall forecast is consistent across different locations.

Materials and Methods

We used five study sites in sub-Saharan Africa (Benin, Ethiopia, Ghana, Mali, and Rwanda) with contrasted climate. These sites were selected due to the availability of historical daily climate data series spanning from 1980 to 2010 and the extensive work on model calibration and validation that has been priorly conducted at these locations (Falconnier et al., 2020). Using the ACME crop modelling framework (Giner et al., 2024) that includes the three crop models STICS, DSSAT and CELSIUS, we simulated water-limited maize yield with a 10-day sowing date interval for each year of the climate data series. We then extracted contrasting sowing dates corresponding to three levels of climate information, namely (i) sd_20, the sowing date of a "average" farmer following basic extension recommendation of 20 mm rainfall cumulated over two days to identify the onset of the rainy season; (ii) sd_avg, the sowing date of an "informed" farmer who would have access to the sowing date leading to maximum simulated water-limited yield, averaged across 30 years of historical weather data, and would applied that exact same sowing date every year; and (iii) sd_opt, the sowing date of a "clairvoyant" farmer who would have access to perfect weather forecast to determine the sowing date that leads to the highest simulated water-limited yield each year. Yield gain was then calculated as the percentage difference between the simulated yield from the informed and clairvoyant farmer relative to the one of the average farmer.

Results and Discussion

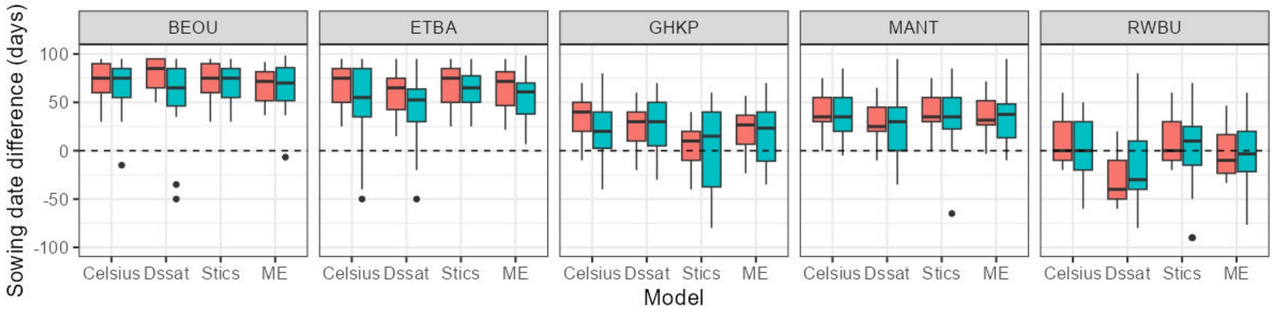

Figure 1. Boxplot distribution of the sowing date difference comparing average farmer's strategy (sd_20) to the informed (sd_avg, red) and clairvoyant farmer's (sd_opt, blue) strategies for each location and each model over 30 simulated cropping seasons. ME is the mean of the three models ensemble.

Our simulations indicate considerable variation in sowing date difference across sites and models when comparing three levels of climate information knowledge. Benin (BEOU) and Ethiopia (ETBA) exhibit consistently large positive median differences (up to 80 days). In contrast, Ghana (GHKP) and Rwanda (RWBU) show smaller median differences, even displaying negative median differences. For both informed and clairvoyant farmer strategies, the median sowing date differences are often comparable for a given site-model combination. But the variance of the clairvoyant strategy is always larger.

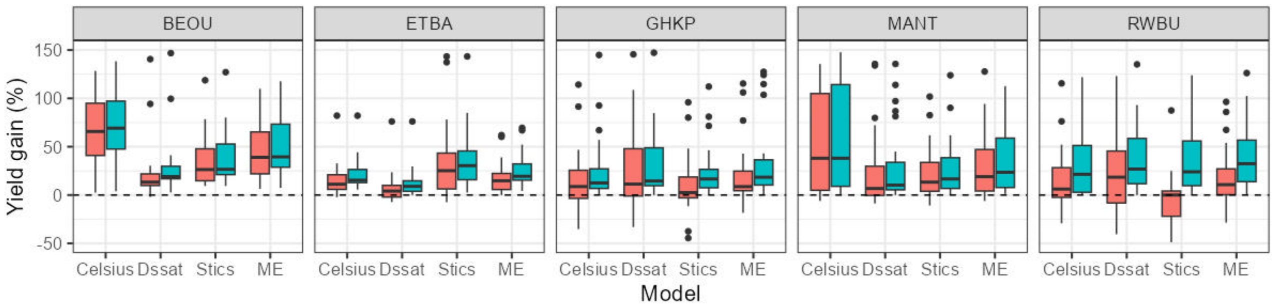

Figure 1. Boxplot distribution of the yield gain comparing average farmer's strategy (sd_20) to the informed (sd_avg, red) and clairvoyant farmer's (sd_opt, blue) strategies for each location and each model over 30 simulated cropping seasons. ME is the mean of the three models ensemble.

These variations in sowing dates differences translate into a considerable variation in yield gain. The median yield gain ranges from approximately 0% to 70%, varying by site and crop model. In most cases, median yield gain is very similar for both informed and clairvoyant farmer strategies. But in few cases, informed strategy leads to very low yield gain or even yield losses. It demonstrates that the value of optimising the sowing date is highly dependent on local climatic regimes and the baseline practice, implying that investment in high-skill seasonal climate prediction should be strategically targeted toward highly variable and sensitive regions. The results also indicate that each model simulates water stress differently. Hence, improving climate forecast should go hand in hand with improving crop models' accuracy to develop robust decision support tools for farmers.

Conclusions

Our study presents a highly promising proof of concept, demonstrating the power of our modeling approach to explore the complex interaction between sowing dates, rainfall variability, and soil conditions. This framework provides critical insights into the value of developing more accurate weather forecasts, particularly for identifying and targeting regions where the timing of planting has the most significant impact on yields. The results also highlight the need for continued research into improving crop models' accuracy. The next step will be to investigate the interactions with fertilization strategies. The cost-efficiency of the modelling approach makes it a scalable solution, opening the door for its application across larger regions, for multiple staple crops, to support sustainable farming practices on a broader scale.

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Assimilation of Remotely Sensed Data into the DSSAT-CSM model

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Keywords: remote sensing, direct assimilation, CROPGRO, vegetation index, DSSAT-RS

Introduction

Crop growth models are powerful tools for assisting decision-making processes in agriculture. However, reliable estimation of crop development and in-season yield forecasting remains a challenge, especially under current weather conditions. Remote sensing (RS) technologies can provide both temporal and spatial data for vegetation indices to estimate the current leaf area index (LAI), which can be used to improve crop modeling predictions (Richetti et al., 2019). Integrating RS data into crop models can ultimately strengthen decision-making by enabling growers to better manage weather risks, adapt their practices, and optimize resource use (Zhuang et al., 2024). The overall goal of this project was to develop a remote sensing module for integration into the Cropping System Model (CSM) of the Decision Support System for Agrotechnology Transfer (DSSAT; Hoogenboom et al., 2019; Hoogenboom et al., 2024) to assimilate remotely sensed LAI (RSLAI) and enable in-season forecasting of crop yield.

Materials and Methods

The DSSAT-RS module was developed in Fortran within the DSSAT-CSM source code. This module updates crop model state variables based on RSLAI estimates by proportionally adjusting the plant growth parameter through a novel approach named direct assimilation. To enable interaction with crop growth models during runtime, DSSAT-RS leverages the default DSSAT time-series data file. The DSSAT-RS was coupled with the CSM-CROPGRO, a model designed for simulating grain legumes, through internal calls within the main subroutine of the crop model (Figure 1A).

Model performance was evaluated based on soybean experiments conducted in Teresina, Piaui, Brazil, in 2019 (Figueiredo Moura da Silva et al., 2024). The experiment included two treatments, one with no nitrogen applied (0 kg ha^{-1}) and another with 1000 kg ha^{-1} of nitrogen, both under irrigation restricted to 50% of the crop water requirements. High-resolution satellite imagery, obtained from Planet Labs' PlanetScope (https://www.planet.com) during the growing season, was used to estimate LAI derived from the Normalized Difference Vegetation Index (NDVI).

Model outputs were compared against field measurements of LAI and grain weight collected throughout the growing season. Furthermore, the performance of the novel assimilation method was assessed against the uncoupled model and other RS assimilation techniques used in the literature, such as linear interpolation and Kalman filtering.

Results and Discussion

The coupling of the DSSAT-RS module with the CSM-CROPGRO-Soybean model improved performance across both water-limited treatments. A total of 28 satellite images were collected for the experimental site during the 2019 soybean growing season. The default model underestimated both LAI and grain yield compared with the field data. All remote sensing assimilation approaches consistently outperformed the default simulation. The direct assimilation method was the most effective at capturing both LAI trajectories and grain weight accumulation for the treatments with a 0 kg N ha^{-1} (Figure 1B I) and 1000 kg N ha^{-1} application rate (Figure 1B II).

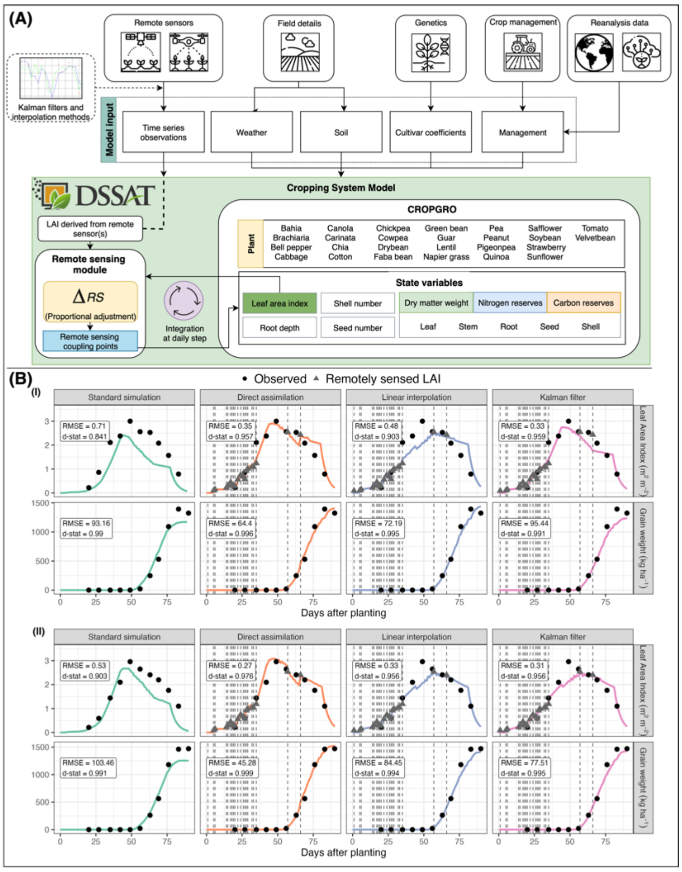

Figure 1. Diagram representing the integration of the remote sensing module and the CROPGRO model within the DSSAT-CSM (a) and the coupled model outputs for the soybean experiment conducted in Teresina, Piaui, Brazil, in 2019 (B) with two water-limited treatments with 0 kg N ha^{-1} (I) and 1000 kg N ha^{-1} applied (II).

Conclusions

Integrating remote sensing data into dynamic crop growth models significantly improves the precision and reliability of yield predictions. The DSSAT-RS module coupled with the CSM-CROPGRO model and evaluated for soybean grown under contrasting conditions, improved the predictions for crop growth and final yield predictions. This new module in DSSAT provides a robust framework for integrating RS data into the DSSAT-CSM and the use of the novel direct assimilation method for in-season forecasting.

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MLDNDC: A machine learning-based surrogate model for the optimisation of cropping systems in Denmark

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Keywords: sustainable agriculture, crop yield, soil organic carbon, greenhouse gas emissions, multi-objective approach

Introduction

Optimising cropping systems is critical for increasing agricultural productivity while reducing environmental impacts. In Denmark, where agriculture covers more than 55% of the total land area (Hansen et al., 2025), improving management practices is both necessary and urgent. Process-based models such as Landscape Denitrification Decomposition (LDNDC) (Haas et al., 2013) are widely used for scenario analysis, but their computational demands limit their application at the national scale, where thousands of management combinations must be tested within defined decision boundaries.

Materials and Methods

To address this challenge, we developed MLDNDC, a machine learning–based surrogate model of LDNDC. The surrogate predicts key agro-environmental outcomes including crop yield, nitrous oxide (N_2O) emissions, nitrate leaching (NO_3^-), and soil organic carbon (SOC) changes at national scale in Denmark. Synthetic datasets generated with LDNDC were used to train several machine learning algorithms within a single task learning framework, extended through a custom function for multi-task inference, enabling simultaneous optimisation of multiple outputs.

Results and Discussion

The surrogate model substantially reduced computational costs and processing time, while retaining high predictive accuracy across all variables. Coupled with the NSGA-II optimisation algorithm (Deb et al., 2002), MLDNDC enabled efficient exploration of trade-offs between productivity and environmental objectives.

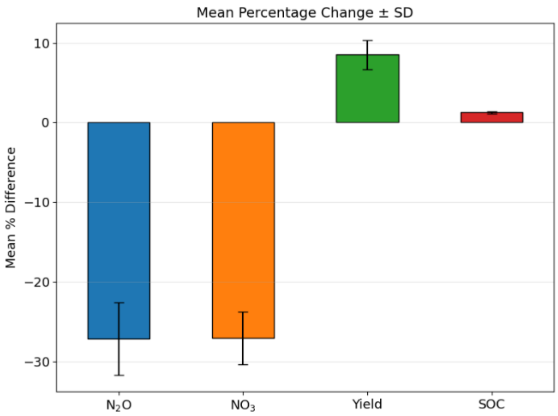

Figure 1. Mean percentage change (± SD) in N_2O emissions, NO_3^- leaching, crop yield, and soil organic carbon (SOC) under optimized management scenarios in Denmark. Reductions are shown for N_2O and NO_3^-, while increases are shown for yield and SOC.

Optimizing cropping systems in Denmark can enhance crop yields by up to 10%, increase soil organic carbon stocks by more than 3%, and reduce N_2O emissions and NO_3^- leaching by up to 27% and 25%, respectively. Optimizing cropping systems in Denmark demonstrates clear potential for advancing both productivity and environmental sustainability. The projected increase in crop yields by up to 10% highlights how improved management can help meet growing food demands without expanding cultivated land. At the same time, the enhancement of soil organic carbon stocks by more than 3% contributes to long-term soil fertility and carbon sequestration, supporting climate change mitigation goals. Importantly, reductions of up to 27% in N_2O emissions and 25% in NO_3^- leaching indicate that optimized practices can substantially decrease agriculture's contribution to greenhouse gas emissions and water pollution. Together, these outcomes suggest that targeted management interventions can simultaneously deliver agronomic, environmental, and climate benefits, aligning with Denmark's green transition objectives.

Conclusions

This methodology demonstrates the potential of machine learning-based surrogates to replace computationally intensive process-based models for national-scale optimisation. By facilitating rapid scenario testing, MLDNDC provides a scalable and practical decision-support tool for advancing sustainable agricultural management and policy development.

Acknowledgements

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Forecasting End-of-Season Winter Wheat Yields Across Germany Using an Enhanced Temporal Fusion Transformer

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Keywords: Deep learning, Crop yield, Crop phenology, Remote Sensing.

Introduction

Accurate crop yield forecasting is crucial for agricultural planning, food security, and policy. It aids farmers in resource optimization, market stabilization, and government preparedness. Since yield data is only available post-season, early prediction methods are essential. This study uses a modified Temporal Fusion Transformer (TFT), a state-of-the-art deep learning model for time series forecasting (Junankar et al., 2023). The TFT offers high predictive accuracy and interpretability, identifying key factors influencing yields (e.g., weather, environment, management practices). This is valuable for precision agriculture. We forecast German winter wheat yields using the TFT. The model integrated static data (soil, landscape), historical yields, and dynamic climate data (temperature, rainfall). The TFT captured temporal dependencies and prioritized features, providing reliable, interpretable forecasts pre-harvest. This demonstrates advanced deep learning's potential for data-driven agricultural decision-making, offering transparent insights into yield drivers.

Materials and Methods

In this study, we modified the Temporal Fusion Transformer (TFT) to improve high-resolution winter wheat yield forecasting across Germany. The model flexibly integrates static covariates both real-valued (soil quality, topography) and categorical (soil type)- enhancing spatial heterogeneity capture. Germany was divided into 2.5 km hexagonal grids, with NUTS-3 yields downscaled using EVI as a spatial proxy. Time-varying inputs included daily ERA5-Land climate variables (temperature, precipitation, radiation) and ECMWF seasonal forecasts for future weather during the growing season. Phenology data defined biologically relevant growth windows; data outside sowing-to-harvest were masked, focusing the model on active growth periods. Training used 70% of the growing period as input and 30% as forecast horizon, enabling accurate end-of-season predictions before harvest. This phenology-aligned, spatially detailed, and interpretability-focused TFT framework advances reliable and actionable crop yield forecasting across Germany.

Results and Discussion

The modified Temporal Fusion Transformer (TFT) demonstrated strong and consistent performance in forecasting end-of-season winter wheat yields across Germany. Compared to traditional machine learning models such as Random Forests and Support Vector Machines, as well as standard deep learning approaches like LSTMs, the TFT consistently provided higher predictive accuracy and robustness (Vijayasuganthi et al., 2025). Its architecture is particularly effective in capturing complex temporal dependencies, non-linear relationships, and interactions between static and dynamic predictors, making it well-suited for time series–based crop yield forecasting. A key strength of the TFT lies in its interpretability. Static covariates, including soil quality and landscape features, were also important, highlighting the critical role of spatial heterogeneity in shaping crop productivity. The phenology-informed data alignment and the structured division of the growing period into input and forecasting windows further enhanced model performance. By focusing exclusively on biologically relevant growth stages and masking non-growth periods, the TFT was able to learn from meaningful temporal patterns while generating reliable end-of-season forecasts well before harvest. This capability is crucial for supporting timely farm-level interventions, market planning, and national policy decisions.

These findings align with advances in smart farming and hybrid modeling, where integrating data-driven models with process-based or remote sensing data improves yield prediction, resource efficiency, and decision-making (Yang et al., 2025). Hybrid models combining crop growth parameters and vegetation indices with attention-based architectures emphasize physiological and spectral features as key predictors, while morphological traits contribute less, highlighting the TFT's capacity to capture growth stage–specific environmental and management effects. This study confirms that Transformer-based models offer superior accuracy, robustness, and interpretability versus traditional machine learning and standard deep learning. By integrating static and dynamic inputs and accounting for phenology, the TFT provides a scalable, practical framework for data-driven decisions from farm management to regional and national planning.

Conclusions

By integrating static factors, historical yield data, and dynamic climate and vegetation inputs, and by aligning predictions with phenology, the TFT effectively captures spatial and temporal variability in crop growth. Overall, the approach highlights the potential of attention-based deep learning architectures to support data-driven, precision agriculture and strategic agricultural planning.

Acknowledgements

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Real-time crop modelling APIs for optimizing agricultural decisions

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Keywords: relative yield, abiotic stress, decision-making, optimal application windows, biologicals

Introduction

Modern agriculture faces increasing challenges from climate variability associated with climate change and the need for precise resource management (Lobell et al., 2011; Ray et al., 2015). In many regions, heat stress during sensitive crop growth stages can result in substantial yield losses, while unpredictable weather patterns make it challenging for growers to intervene effectively (Zhao et al., 2017). Traditionally, such decisions rely on field scouting, historical averages, or single-source data, which often fail to capture the dynamic interactions between weather, soil, and crop physiology. Crop models have emerged as tools to support agricultural decision-making, providing data-driven insights that enhance productivity while optimizing inputs used by growers (Boote et al., 2013).

Materials and Methods

This study presents the development and application of three integrated models developed as APIs (Application Programming Interface) designed to support growers through comprehensive crop modelling capabilities. The integrated modelling capabilities include (1) the Relative Yield model for prediction and benchmarking; (2) the Growth Stage Prediction model for phenological forecasting (Soler et al., 2007); (3) the Abiotic Stress model for environmental stress assessment (Mittler, 2006; Suzuki et al., 2014). Model calibration was performed using genotype-specific parameters derived from multiple field trials across different geographical regions. Crop-specific coefficients were calibrated using field trial data with cross-validation techniques to ensure model accuracy across diverse environmental conditions and management practices (Wallach et al., 2018). Collectively, these APIs integrate weather data, soil characteristics, and crop-specific parameters to enable data-driven decisions across diverse geographies and temporal scales.

Results and Discussion

This integration provides real-time assessment of crop conditions for individual fields and alerts growers when interventions are needed. To demonstrate practical applications, we present two distinct use cases. For rice production in India and Pakistan, the tool enables smart application timing of biological products to mitigate heat stress during critical growth periods (Jagadish et al., 2015; Coast et al., 2015). These integrated models assist identifying optimal application windows by combining real-time growth stage predictions with diurnal and nocturnal temperature stress indices, allowing growers to proactively protect yield during vulnerable developmental phases. For corn production in Brazil, the model provides in-season relative yield predictions from planting to physiological maturity, with stable predictions approximately 35–40 days before physiological maturity, enabling informed harvest planning and sales decisions (Mourtzinis et al., 2015; Basso et al., 2013).

Conclusions

These models, coupled with visualization capabilities, illustrate how advanced crop modelling can be effectively translated into practical decision support tools, bridging the gap between scientific research and on-farm application for both technical and non-technical users (Rose et al., 2016; Antle et al., 2017).

Acknowledgements

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When properly instructed, ChatGPT can provide accurate and site-specific irrigation decisions

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Keywords: Large Language Models; Prompt engineering; Artificial Intelligence.

Introduction

Large Language Models (LLMs) are rapidly evolving and are increasingly adopted in many different fields to write or summarise text and computer code. Thanks to the chain of thought and prompt refinement techniques, they show reasoning and quantitative capabilities that allow them to accomplish tasks well beyond simply analysing and writing text (Wei et al., 2022; Feng et al., 2023). Therefore, it is likely that LLMs will be increasingly used for decision support, including in agriculture. LLMs could be fed with real-time data (from sensors, models, or weather forecasts) and suggest the timing and rate of application of water, fertilisers, and pesticides. The literature already reports tests of LLMs making irrigation and nitrogen decisions. In some cases, the LLM was trained via reinforced learning to improve answer quality (e.g. Wu et al., 2024). Here, we wanted to verify the hypothesis that LLMs have a basic capacity to suggest proper decisions in irrigation management without specific training, thus providing support to farmers and advisors who cannot train them.

Materials and Methods

The irrigation case study used for the test involved maize (*Zea mays* L.) cultivation at Bushland (TX, USA). We first used a cropping system mechanistic daily time step model to simulate soil water content and irrigation demand during a growing season. The model is a simplified version of CropSystVB (Bechini and Stöckle, 2007). The inputs of this model are crop parameters (used to simulate crop development, canopy cover, and crop transpiration), soil sand and clay concentration (used to calculate the parameters of the water retention curve, and the soil water content at field capacity and permanent wilting point), and daily weather data (rainfall, air temperature, air humidity, global solar radiation, and wind speed). The model simulates crop development, green canopy cover, crop height, root depth, biomass growth, crop transpiration, soil evaporation, and soil water content for 0.1-m layers. Irrigation is scheduled when the soil available water drops below user-provided maximum allowable depletion (MAD), which triggers the model to refill to field capacity the portion of the soil profile occupied by roots. We applied this model for daily simulations in 2018, on three soil textures (loamy sand, loam, and clay loam), and three levels of maximum allowable depletion (0.4, 0.5, or 0.6) to generate many irrigation scheduling conditions (1386 combinations based on 154 days, three soils, and three MAD). We then submitted a prompt to ChatGPT 4. The prompt included soil type, water content of 0.3-m soil layers (as could be provided by sensors), and green canopy ground cover that could be obtained from remotely derived NDVI. We added, as "weather forecast", the daily values of reference evapotranspiration (ET_0) and the rainfall for the next seven days and provided the desired maximum allowable depletion. We finally asked ChatGPT to indicate, based on this information, when and how much irrigation would be needed in the next seven days. The prompt was submitted manually (for a few selected cases) and automatically (with batch runs using APIs, for all irrigation scheduling conditions). ChatGPT outputs were compared with the irrigation amounts calculated by the model, considered as a benchmark. The prompt was adjusted to reach a satisfactory version of it after the first manual and automatic tests.

Results and Discussion

ChatGPT reasoning was appropriate, and almost completely correct, with the first manual attempt. It used a soil water balance approach, by estimating field capacity, wilting point and total available water for the specific soil type, then calculated the current soil water depletion (based on actual water storage), actual crop evapotranspiration (ET_c) for the next seven days, and finally, after comparing the actual with the maximum allowable depletion, it calculated the irrigation required. ET_c was always calculated correctly as k_c ET_o, using appropriate values of k_c, derived from the green canopy cover. The application of the water balance was conceptually sound, adding rainfall and subtracting ET_c. However, initially, ChatGPT frequently failed (not irrigating when needed, or strongly understimating the amount), either because sometimes it confounded the concepts of soil water content and plant available water, or because it decided only to restore the anticipated ET_c, not refilling the soil profile to field capacity. Therefore, one change to the prompt included the explicit request to refill the soil to field capacity. This draws our first conclusion: the specificity of the question matters. The fewer things that are given for granted in the prompt, the better the LLM will work.

We also noted that it is useful and important to ask ChatGPT to provide the reasoning it followed, the calculation steps, and all the sources used, allowing the user to understand what was done, and apparently forcing the LLM to check more thoroughly the solution to be presented. Another difficulty that arises during the optimization of the prompt is that the answers of a LLM are stochastic, not deterministic. Therefore, outputs can vary from test to test. This variability is influenced by LLM's parameters such as temperature, which controls the degree of randomness in the model's responses: a lower temperature tends to produce more consistent, deterministic-like answers, while a higher temperature increases diversity and creativity, at the cost of reproducibility.Our optimized version of the prompt with example data is: "You are an irrigation engineer. There is a corn crop in a field at Bushland (TX) in the year 2018. The soil type is loam, with a volumetric field capacity of 0.260 and a permanent wilting point of 0.118 m^3/m^3. The green canopy cover is 0.87. The volumetric soil water content (m^3/m^3) in the 0-30 cm soil layer is 0.177, in the 30-60 cm layer is 0.193, in the 60-90 cm layer is 0.210, in the 90-120 cm layer is 0.227, and in the 120-150 cm layer is 0.245. In the next seven days, weather forecasts predict 7.41, 7.55, 8.16, 8.73, 6.66, 5.06, and 6.7 mm/d of reference crop evapotranspiration, and 0, 17.48, 0, 0, 0, 0, 0 mm/d of precipitation. Based on this information, determine if irrigation to refill the 150-cm soil profile to field capacity is needed in the next seven days if the maximum allowable depletion for this crop is 0.5. Provide the day (1 through 7) and the amount in mm of irrigation if needed. Explain the reasoning and give details of the calculation steps". Figure 1 shows some example results.

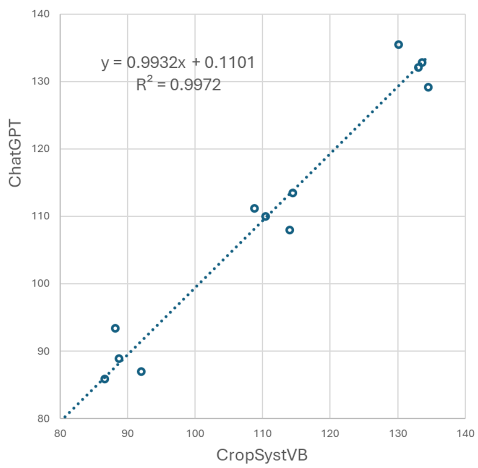

Figure 1. Example results of ChatGPT irrigation decisions (on the Y-axis) for a loam soil with a field capacity of 0.26 $m^3 m^{-3}$ and a wilting point of 0.12 $m^3 m^{-3}$, compared with the results of a dynamic mechanistic crop model (CropSystVB), on the X-axis. The graph shows that ChatGPT irrigations were mostly applied on the same day as predicted by CropSystVB, with a few exceptions with one-day difference. In addition to the data shown in the Figure, there are six data points with both ChatGPT and CropSystVB showing zero irrigation.

Conclusions

If properly prompted, the performance of ChatGPT in identifying dates and amounts of irrigation events was satisfactory. This approach has the potential to be used by anyone and anywhere with good sensors and access to weather forecasting.

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A model-based decision support framework for optimizing cultivar choice. A case study on *Pisum sativum* L.

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Keywords: Ideotypes, Sensitivity analysis, STICS crop model, Similarity, Yield stability.

Introduction

Cultivar choice is a crucial decision-making process for farmers and technicians, paving the road for a successful cropping season. Crop models can effectively support the selection of the most suitable cultivar for a given climatic, edaphic, and managment context to maximize yields and profitability, as they enable the rapid exploration of a wide range of agro-climatic conditions that would be difficult to capture with traditional methods (e.g., multi-environment trials). The latter indeed, being limited in space and time, often fail to properly characterize genotype (G) × environment (E) × management (M) interactions (Cooper at al., 2021). By using pea (*Pisum sativum* L.) in Northern Italy as a case study, we show how crop models combined with spatial exploration of climate and soil features can be used to investigate cultivar responses under different environments, providing context-specific rankings of available genotypes to support decisions on cultivar choice.

Materials and Methods

The study focused on the Emilia-Romagna region, one of the most relevant pea cultivation area in Italy. An agro-climatic zonation was carried out by considering the two main sowing windows and intersecting climate and soil data. The results are 24 homogeneous agro-climatic contexts for which the analysis was performed. Field trials - involving one of the most important company for canned vegetables in Europe (Conserve Italia Soc. Coop. Agricola) – were carried out to parameterize the crop model STICS (Brisson et al., 2009) for the study area and to derive distributions of functional traits related to phenology, canopy structure, biomass partitioning, and photosynthesis for 20 *Pisum sativum L.* modern cultivars. Variance-based global sensitivity analysis was run for each agroclimatic context to design ideotypes that maximize yield and its stability (Ravasi et al., 2020). The similarity between the phenotypic profiles of the 20 pea cultivars and the context-specific ideotypes was then evaluated through the weighted Euclidean distance method (Carvalho et al., 2002) adapted to *in-silico* analysis by Paleari et al. (2020), providing context-specific ranking of cultivars to drive cultivar choice (Fig. 1).

Results and Discussion

Sensitivity analysis highlighted the key role of radiation use efficiency during the reproductive phase and grain filling duration under humid climate conditions – being the crop not irrigated - whereas phenological traits involved with earliness (thermal time to first pod) played a crucial role for yield and its stability regardless of the conditions explored. This heterogeneity in traits relevance reflected on the ideotypes designed and, thus, on the most promising cultivars for a given agro-climatic context. As shown in Fig. 1 indeed, a clear re-ranking of cultivars was found according to the conditions explored, with some cultivars being ranked first in drier climates (e.g., cv. Belvedere) while placed in 11th position under more humid contexts.

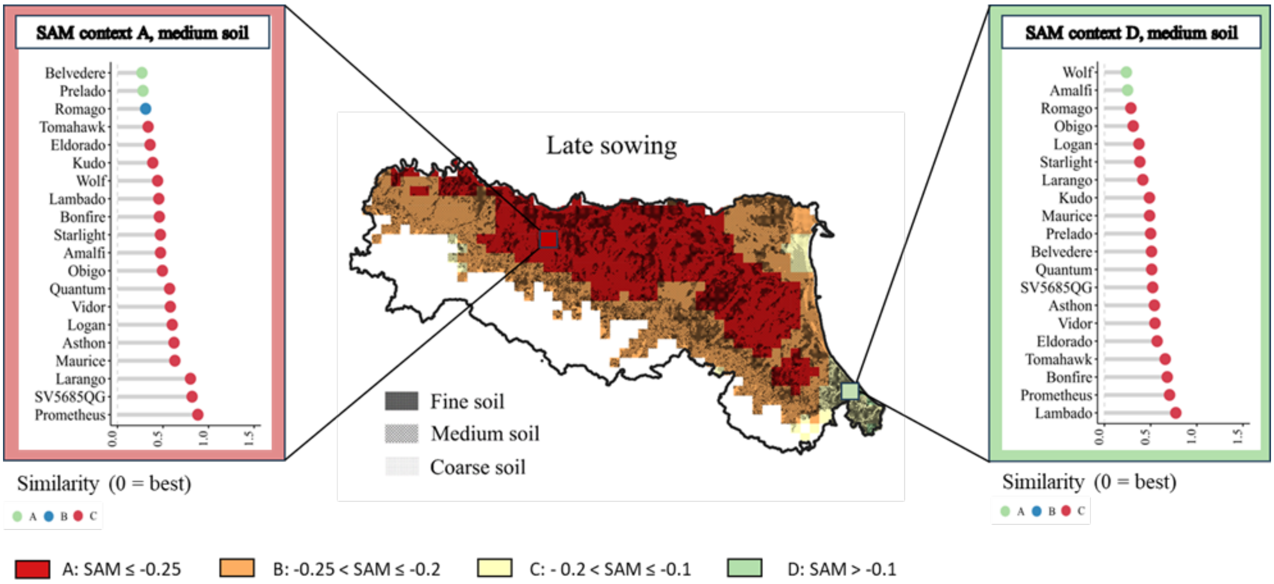

Figure 1. Central panel: example of the agro-climatic characterization of the study area obtained by clustering the Syntetic Agroclimatic Index (SAM, normalized difference of rainfall and reference evapotranspiration during the cropping season) calculated for late sowings. Negative SAM values indicate dry climates while positive values highlight humid conditions. Left and right panels show two examples of cultivar ranking obrained for different conditions, humid (right panel) and dry (left panel). In the ranking, green points indicate recommended, blue represents second-choice varieties, and red highlights less suitable varieties.

Conclusions

This study highlighted the relevance of decision support tools for cultivar choice explicitly accounting for G × E × M, even in relatively small areas as that investigated in this study. A clear re-ranking of cultivars was indeed observed while changing agro-climatic conditions. The simple methodology used to derive the cultivar phenotypic profiles allows to easily extend the framework to other pea cultivars, making the system easily adapted to new cultivar release.

Acknowledgements

The authors gratefully acknowledge Daniele Piva and Caterina Vanni (Conserve Italia Soc. Coop. Agricola) for supporting field trials, and the Ministero dell'Università e della Ricerca, FSE -REACT EU PON 'RICERCA E INNOVAZIONE' for partly funding this study.

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Data model for a digital twin of a field supporting interchangeable modelling approaches

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Keywords: smart farming, decision support

Introduction

Digital twins present real-world objects as their virtual entities and can provide decision support in various tasks in agriculture. We developed a digital twin for optimal field management. It simulates the impact of different management options, e.g., on yield and grain quality, and is linked, e.g., to farm management information systems, weather data interfaces, ISOBUS task files, and remote sensing data sources.

The aim of this study was to create an open-source data model interface for the digital twin. The data model increases flexibility by enabling the same interface to the digital twin, regardless of the modelling approach within it. The NGSI-LD specification for presenting virtual digital twin entities and providing standardized communication (ETSI, 2021) was followed to build a documented data model. A use case was created to demonstrate the use of the digital twin via the data model.

Materials and Methods

Management of the digital twin data via the NGSI-LD real-time interface was implemented with the FIWARE open-source context-broker (FIWARE, 2021). Semantic interoperability was ensured by using ICASA vocabulary with required extensions. A data model was published as part of the open-source farmingpy Python package (https://github.com/TwinYields/farmingpy/tree/datamodel). Figure 1 presents the data flows through the data model.

The use case presented a digital twin of a spring wheat field in Jokioinen, Finland, in growing season 2024. WOFOST with soil nitrogen and carbon balance module SNOMIN (Berghuijs et al., 2024) was used as a crop model in the use case. The input data included farm management, ISOBUS task, weather, remote sensing, crop, and soil data.

Results and Discussion

The data model was feasible for implementing the digital twin to a new use case and for providing input data for WOFOST crop model. The data model is built in a way that the modelling approach can be changed. However, a script for a data format conversion from the data model format to a model-specific format needs to be created for each new model. New models might require extensions to input entities of the data model. NGSI-LD data model enables extensions without breaking compatibility with old versions.

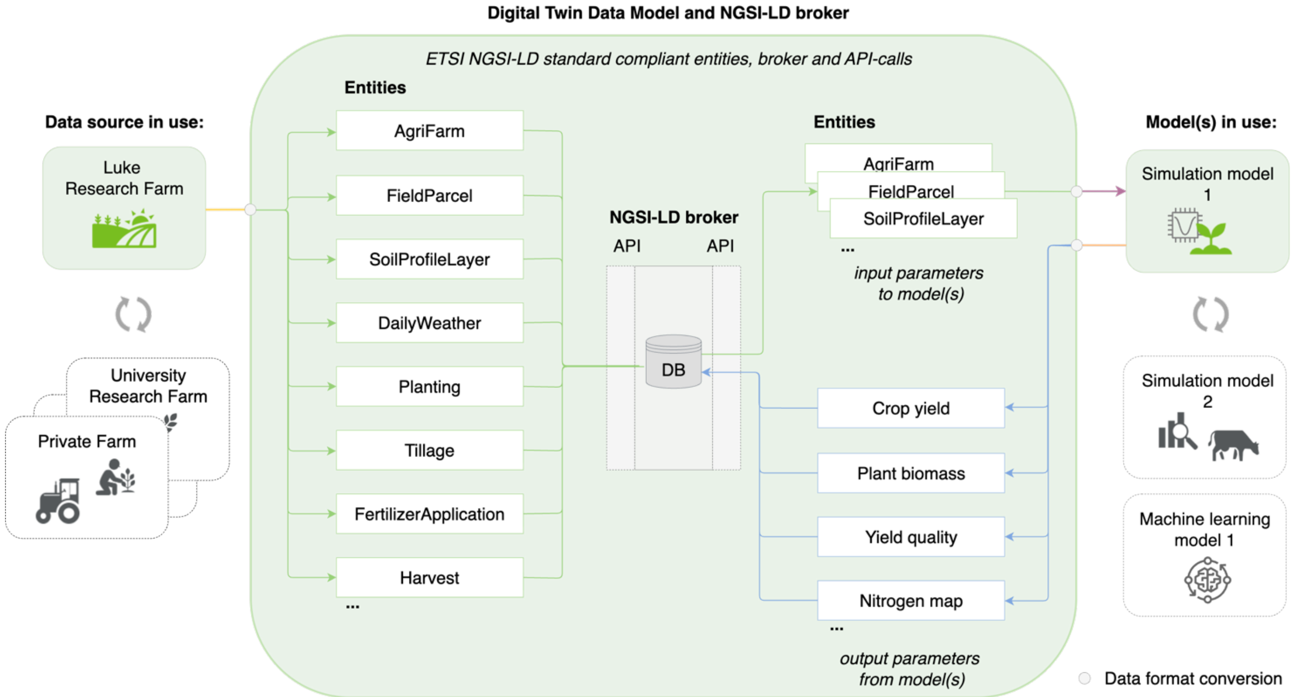

Figure 1. Data flow via the digital twin data model between data sources and models

Conclusions

The NGSI-LD data model provides a documented interface for the digital twin and improves flexibility with modelling approaches. The next steps could include testing the digital twin with data flows from a real farm via the context-broker or comparing multiple modelling approaches.

Acknowledgements

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Remote Sensing Meets Crop Models: Improving Potato Yield Simulations under Diverse Management

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Keywords: Crop Growth Models, Remote Sensing, Data Assimilation, Uncertainty Reduction, Accuracy Increment.

Introduction

Crop growth models are essential tools for assessing food security and developing adaptation strategies in response to global change. However, their predictive capacity is often constrained by the limited availability of reliable site-specific input parameters and the associated high uncertainty. Remote sensing offers a unique opportunity to overcome these limitations by providing spatially and temporally explicit observations that can be integrated into crop models. Yet, systematic assessments of how remotely sensed traits can improve simulations across crop growth models and management practices remain scarce. This study presents a collaborative effort initiated through an international hackathon organised by the Pan-European Network of Green Deal Agriculture and Forestry Earth Observation Science (PANGEOS) European Cooperation in Science and Technology (COST) action, bringing together a multidisciplinary group of researchers to evaluate the added value of remote sensing in crop model calibration and prediction.

Materials and Methods

The data used for this work resulted from an experiment conducted in the Netherlands on potatoes grown at two sites with different soil types. At each site, six different management practices and three genotypes were present, resulting in 42 plots per site and a total of 84 plots. Among the management practices, three nitrogen fertilisation levels and two irrigation levels were examined. During the growing season, measurements of leaf area index (LAI), chlorophyll content, dry mass of different organs, and canopy reflectance were collected. These observations provide a unique dataset for linking field measurements with remote sensing retrievals and crop model performance.

The canopy reflectance is used for LAI, chlorophyll content and dry mass retrieval using two approaches: inversion of the Soil Canopy Observation of Photosynthesis and Energy fluxes (SCOPE) radiative transfer model and machine learning, both with explicit propagation of uncertainties from the measurements to the parameters. The derived parameters are then used to calibrate seven widely used crop growth models, evaluated in three modes: (i) standard settings without calibration, (ii) calibration based on field measurements, and (iii) calibration based on remote sensing retrievals. This systematic comparison enables us to quantify the degree to which remote sensing information can improve the accuracy of yield estimation and reduce the uncertainty of simulations across sites, varieties, and management regimes.

Results and Discussion

The expected outcomes of this ongoing work are twofold. First, we anticipate that integrating remotely sensed parameters will reduce the discrepancies between simulated and observed crop performance compared to uncalibrated models. Second, we expect that the explicit accounting of uncertainty in remote sensing retrievals will provide a more robust framework for evaluating model reliability. By testing this hypothesis, the study provides a rigorous basis for advancing the integration of remote sensing into crop growth modelling and contributes to the broader goal of improving yield forecasts for food security under global change.

Conclusions

The combination of unique experimental data, state-of-the-art remote sensing retrievals, and a diverse set of crop models provides a strong foundation for advancing the science of crop growth prediction. Beyond methodological innovation, the work highlights the potential of collaborative initiatives such as hackathons to accelerate the testing and adoption of novel approaches in agricultural modelling. The findings are relevant not only to potato systems in Western Europe but also to broader applications where reliable and scalable yield predictions are crucial for agricultural planning and policy support.

Acknowledgements

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VISTAA - Virtual Intelligent Simulation Tool for Agriculture Advisor

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Keywords AI, DSSAT, Nutrient Management

Introduction

Nitrogen (N) is one of the most critical inputs for crop production, directly affecting yield potential and profitability. Yet, inefficiencies in its management lead to reduced productivity and environmental externalities, including nitrate leaching and greenhouse gas emissions (Jones et al., 2003). Decision support systems (DSS) and crop growth models (CGMs) such as DSSAT and APSIMX simulate genotype × environment × management (G×E×M) interactions, providing insights into biomass accumulation, N dynamics, and water use efficiency. Despite their strengths, adoption remains limited due to complex parameterization, data requirements, and steep learning curves. To address these barriers, we developed the Virtual Intelligent Simulation Tool for Agriculture Advisor (VISTAA), a proof-of-concept system integrating conversational AI with DSSAT (Hoogenboom et al., 2019) simulations. VISTAA allows users to pose natural language questions (e.g., “What is the best nitrogen dose for my location?”), automatically configures model inputs, and returns transparent, reproducible recommendations. This approach lowers barriers to model use and demonstrates the potential of AI-driven interfaces in advancing climate-smart agriculture (Shaikh et al., 2025).

Materials and Methods

The VISTAA architecture combines a large language model (LLM) with DSSAT to create an interactive decision support pipeline. The LLM interprets user queries, extracts essential parameters (e.g., location, cultivar, management), and guides the dialogue until sufficient data is collected for simulation. For prototyping, Meta’s Llama 3 8B Instruct was deployed locally on the University of Florida’s HiPerGator supercomputer using two NVIDIA A100 GPUs, balancing accuracy with low latency. Running locally avoided reliance on external APIs and preserved user privacy (Tian et al., 2025).

To scale simulations, the backend leverages MPI-based parallelization on HiPerGator, enabling millions of possible G×E×M scenarios for a selected environment. This parallel structure accelerates response time while maintaining a continuous connection with the user. The backend is built with FastAPI, enabling communication between the front end, the LLM inference engine (vLLM), and DSSAT. Inputs such as weather, soil profiles, and genetic coefficients are automatically assembled. Outputs—including yield, Nitrogen balance, and efficiency indicators—are stored alongside user queries in a MongoDB database. The front end, prototyped in Figma and implemented in React, allows users to review past conversations, download outputs, and visualize results (Fig 1).

Results and Discussion

The prototype successfully demonstrated end-to-end conversational decision support: from user query to DSSAT simulation and result reporting. VISTAA generated nitrogen management scenarios, producing recommendations for optimal dose, planting window, and expected yield outcomes (Fig 1). Early testing showed that conversational interfaces reduce the technical barrier for non-expert users, who otherwise face challenges in formatting DSSAT inputs. Moreover, the audit trail of dialogue provides transparency, enabling users to review parameter choices and replicate simulations.

Parallel execution on HiPerGator using MPI further enabled efficient exploration of millions of possible G×E×M scenarios, significantly reducing turnaround time while maintaining continuous interaction with the user. Limitations include crop coverage (currently corn only simulated on CEREZ-Maize model), absence of dynamic integration with remote sensing datasets, and limited validation of automatically extracted parameters. Future work will extend coverage to additional crops and more calibrated genotypes, building on the current set of G2F lines and commercial hybrids already available in the system.

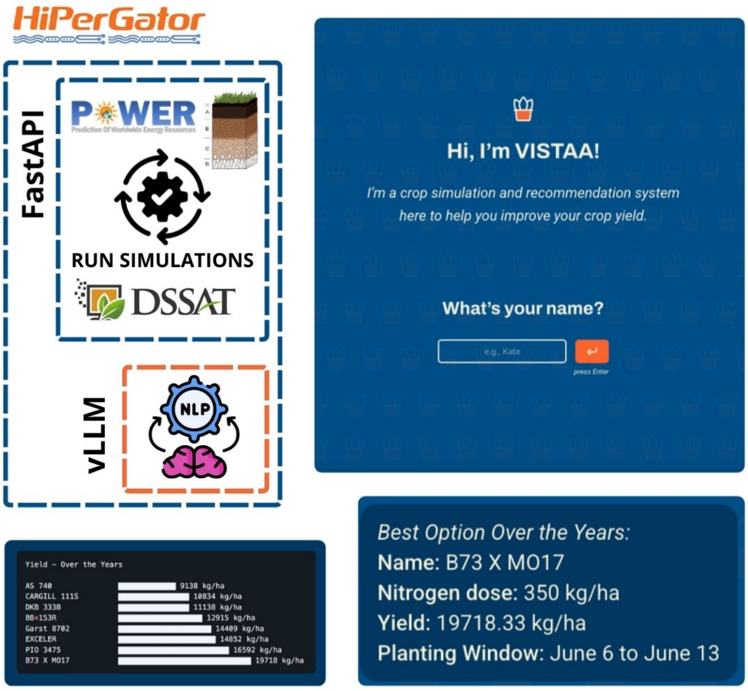

Figure 1. Prototype of the Virtual Intelligent Simulation Tool for Agriculture Advisor (VISTAA). The left panel illustrates the system architecture, where a large language model (LLM) interfaces with DSSAT simulations via a FastAPI backend, integrating weather (NASA POWER), soil, and genotype data on the HiPerGator supercomputer. The right panel shows the user-facing prototype, enabling conversational interaction through a natural language interface and returning nitrogen-efficient management recommendations, including optimal dose, planting window, and expected yield outcomes.

Conclusions

VISTAA demonstrates the feasibility of combining LLM-driven natural language interfaces with DSSAT simulations to deliver accessible, nitrogen-efficient management recommendations. By lowering barriers to model adoption and ensuring reproducibility, this approach represents a step toward AI-enabled, climate-smart agriculture.

Acknowledgements

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Expanding the Generic Disease Model for multi-disease, multi-cycle, and user-defined applications

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Keywords: phytopathology, DSSAT, crop simulation, resilience, epidemiology

Introduction

Crop diseases threaten food security by limiting quality and supply. While chemical control of biotic stress is effective, overreliance contributes to dependence. To improve efficiency, modeling is a necessary tool to put in the hands of stakeholders. The Generic Disease Model (GDM) simulates disease dynamics in cropping systems (Pavan & Fernandes, 2009). Originally developed as a standalone module, the GDM has been incorporated into the Decision Support System for Agrotechnology Transfer (www.DSSAT.net, Hoogenboom et al., 2019). The GDM provides a flexible structure that integrates environmental, host, and pathogen variables. Key strengths of the model include integration of environmental and physiological data, flexibility across cropping systems, and scalability for regional forecasting.

Despite its strengths, the GDM still has notable limitations. In past research, the model could not previously simulate multiple diseases concurrently. Another limitation is that it does not support varying disease cyclicity. These both limit analysis of disease interactions, which often play a role in crop health (Tatineni et al., 2022). Improvements to input flexibility are key because of disease variability. Enhancing the GDM is of paramount importance considering the crops studied are both essential and vulnerable. This is only compounded by climate change impacts on yields (Pequeno et al., 2024). By addressing these gaps, the GDM can evolve into a more powerful tool for sustainable disease management. In this study, the GDM is improved in flexibility and acessibility.

Materials and Methods

The modifications to the GDM are designed to increase parameterizability to new scenarios, diseases, and crops. Multiple diseases are now simultaneously simulatable. Input files were converted from a fixed width format to the YAML specification which allows comments, optional inputs, and improved readability. The use of flexible equations allows for adaptability to various disease cases. The model architecture was redesigned to accomodate both monocyclic and polycyclic diseases to ensure that the model remains applicable in various cases. Figure 1 shows how the seasonal init step has been modified, the disease loop has been created for handling multiple infections, and the coupling is clearly an input from a configuration file.

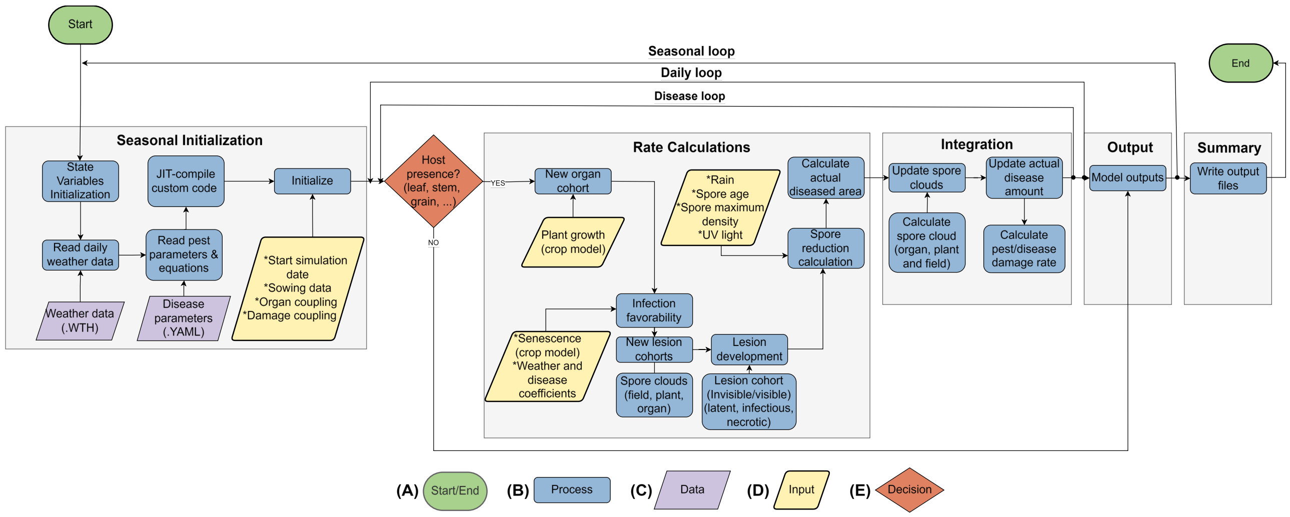

Figure 2. GDM process diagram.

Results and Discussion

The improved GDM is used to simulate fungal diseases of wheat impacting South Brazil. Model predictive accuracy is measured with RMSE, while flexibility changes are evaluated by user experience. The new version of the GDM is more accessible to those without inherent knowledge of phytopathology. Because biotic stress is so often ignored in modeling software, these improvements are key to the refinement of yield estimates. This work can significantly impact agricultural productivity and stability, further strengthening food security and economic resilience, as well as potentially yielding evidence for mechanistic interactions that govern the spread and impact of crop diseases.

Conclusions

These GDM modifications make results more accessible and widely applicable. The user is exposed to fewer endpoints and more safeguards make errors less common. Because of this improved flexibility, it can now be applied to biotic challenges around the world, not just in the scenario studied. These improvements make the GDM a valuable tool to be used by crop modelers and phytopathologists alike.

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Keywords: site-specific; maturity duration; low-input systems; crop modeling; yield stability

Introduction

Heterogeneity of soil properties within landscapes cultivated by smallholders is a common feature in the semi-arid regions of Sub-Saharan Africa (Chivenge et al., 2022). Low farmer yields are common due to the low inherent fertility of the soils, translating not only into variable yields, but also a low response to fertilizers reported as a disincentive for investing in fertilizers (MacCarthy et al., 2025). This situation is further compounded by increasing soil degradation and poor soil management, which handicap sustainable agricultural production. Thus, soil-plant specific management is hypothesized as a prerequisite for sustained crop production across these landscapes.

Materials and Methods

This study used the Agricultural Production Systems sIMulator (APSIM) to quantify the impacts of fertility management, planting windows, and cultivar maturity duration on maize performance Tolon, Savelugu, and Mion districts in Northern Ghana. Fertility treatments included control (no inputs), sole manure, sole inorganic fertilizer, and combination of manure and inorganic fertilizer. Two maize maturity classes; intermediate (Obatanpa) and extra-early (Abontem) were evaluated across staggered planting dates set every two weeks from 15 May to 30 July. Model performance was assessed using on-station trials and farm-level experiments in 19 farmer fields within similar environments. Treatment preferences were assessed through questionnaires on social indicators and productivity (grain yield, Interannual standard deviation, coefficient of variation (CV) and Yield stability (SYI)) evaluated using multiple-year grain yield simulations (1984–2024), and a score for each indicator was generated.

Results and Discussion

For productivity, relative to the control, sole manure increased yields by about 154%, while sole inorganic fertilizer raised yields by 140%. The combined application of manure and inorganic fertilizer provided the largest benefits, increasing yields by 238% (Fig. 1) while improving stability indicators. Early sowing increased grain yield by up to 9% and improved SYI compared to late sowing in all locations. Intermediate-maturity maize (Obatanpa) was superior to the extra-early variety as evident across all fertility treatments and locations. Integrated soil fertility and early planting increased yields between 129% at the fertile site (Mion) and 296% at the low-fertility site (Tolon), with the moderately fertile site (Savelugu) showing intermediate gains (246%). Yield stability was highest at the fertile site and lowest at the low-fertility site. In terms of social indicators, the sole use of inorganic fertilizer was the preferred treatment for the Savelugu and Mion sites based on mean scores from the social indicators.

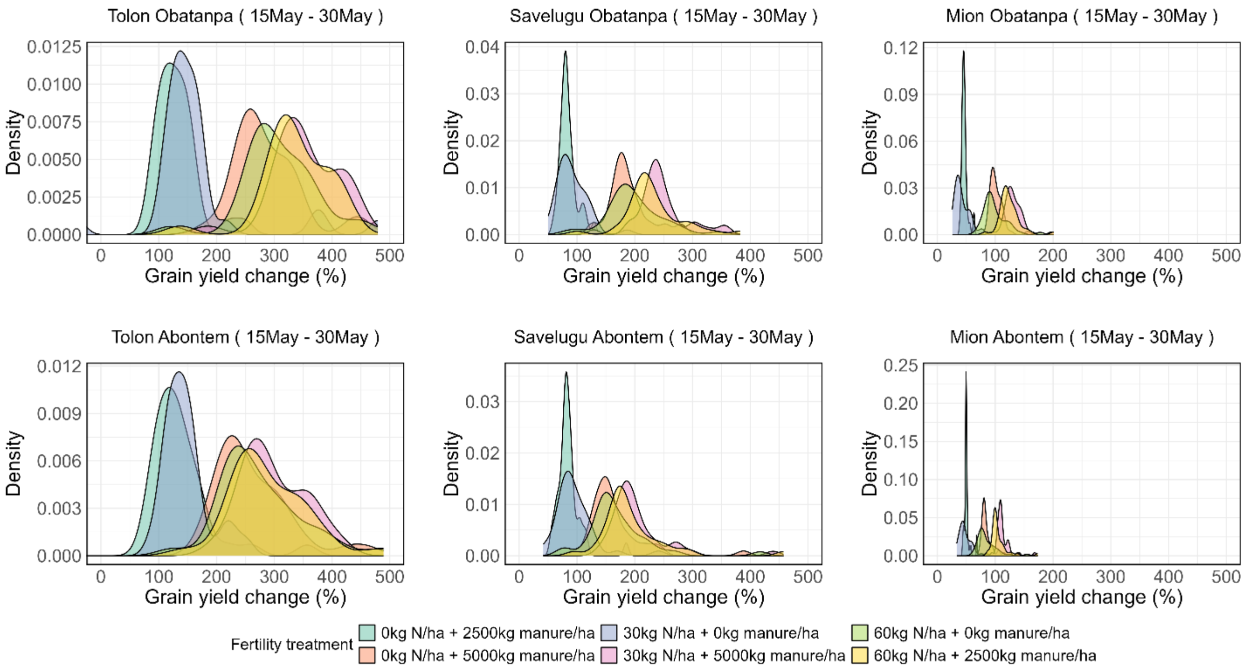

Figure 1. Yield gain from different fertility treatments relative to Control

Conclusions

These initial findings confirm that maize yield and stability are enhanced when both organic and inorganic fertilizers are applied early in the season using intermediate maturity cultivars across locations, with the largest relative improvements recorded in low-fertility landscapes. Grain yields will further be used to compute scores for environmental impact (nitrogen use efficiency, NUE), and economic returns (cost–benefit). Scores from all pillars will be combined into a composite index to assess each treatment's potential for sustainable maize production, providing a holistic, site-specific, climate-smart intensification strategy.

Acknowledgements

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Growing Smarter: Hybrid Models for Crop Yield Prediction

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Keywords: Hybrid machine learning; Process-based models; Crop yield; Climate extremes; Synthetic data

Introduction

Accurate yield forecasts at field scale are critical for resilient food systems under climate change (Bracho-Mujica et al., 2024; Asseng et al., 2015). Purely data-driven machine learning (ML) approaches often suffer from limited agricultural data (Weersink et al., 2018), while process-based crop models, despite their strong biophysical foundations, lack generalization and adaptability (Lobell and Asseng, 2017; Wallach et al., 2021). To overcome these limitations, we propose a hybrid framework that transfers domain knowledge from the process-based DSSAT-Nwheat crop model (Jones et al., 2003) into ML algorithms, combining the interpretability of simulation models with the flexibility of ML.

Materials and Methods

We developed a knowledge-informed hybrid ML system using >75,000 wheat field trial observations across Germany (2005–2021) combined with synthetic data generated from DSSAT-Nwheat. Synthetic samples included observed, historical, and climate projection weather scenarios (CDC, 2018; Jeffrey et al., 2013) to expand the distribution space. Neural networks and random forests were benchmarked against site-mean yield baselines and pure DSSAT simulations.

Results and Discussion

Neural networks enhanced with DSSAT-simulated features outperformed both data-centric and process-based baselines, reducing RMSE by up to 8% compared to pure ML models and >10% compared to site-mean benchmarks. The strongest gains originated from synthetic samples generated under hot and dry climate extremes (Shahhosseini et al., 2021; Kallenberg et al., 2023), confirming that diversity rather than size of synthetic data drives improvements. While random forests did not benefit from hybridization, neural networks successfully learned generalized growth rules transferable across diverse cultivars and sites (Maestrini et al., 2022).

Conclusions

Our results highlight that integrating process-based domain knowledge with ML significantly improves wheat yield predictions, especially under extreme climate conditions. The approach demonstrates that hybrid models can enhance robustness in data-scarce environments, offering a scalable pathway to strengthen climate adaptation and food security (Asseng et al., 2015; Lobell et al., 2020). Future work should explore generative models to expand fine-grained weather and crop datasets, further advancing hybrid learning for agricultural applications.

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Machine Learning–Enhanced Crop Modeling with Multidimensional Data Assimilation for Agricultural Decision Support

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Keywords: AVAIL, AgLIS, Iowa, Digital Twin, Central Assimilation Module

Introduction

Integrated model-data approaches are increasingly critical for precision agricultural decision support. Process-based crop models, such as the Decision Support System for Agrotechnology Transfer (DSSAT), provide valuable insights into crop growth dynamics and enable yield prediction under defined environmental and management conditions. At the same time, data assimilation techniques allow observational data to be incorporated into models, constraining uncertainty and reducing model drift. Despite these advantages, assimilating heterogeneous datasets into crop models remains a major challenge, particularly given the diversity of sources and scales in today's data-rich era (Montzka et al., 2012). This research supports the NASA A Virtual Agricultural Innovations Laboratory (AVAIL) and Agricultural Land Information System (AgLIS) programs, which aims to facilitate the adoption of Earth observation data, Earth system models, and agricultural modeling tools to inform real-world farming decisions.

Materials and Methods

Initial model cultivar parameters and management practices were derived from Iowa field trials involving a corn-soybean rotation with winter rye cover cropping (Chatterjee et al., 2025). To refine parameter selection, crop model outputs were integrated with machine learning using the XGBoost model. This approach identified parameter combinations that minimized Root Mean Squared Error (RMSE) relative to USDA NASS county-level yield averages, and also identified parameter combinations to maximize simulated yield under the observed weather conditions. We developed a Central Assimilation Module within DSSAT which enables the integration of multidimensional datasets, including remote sensing products, field-based observations, and management records, into the modeling framework. In addition, DSSAT was coupled with NASA's Land Information System (LIS) (Kumar et al., 2006) to improve the representation of hydrological processes. The coupled system was implemented at a fine spatial resolution of 30 meters across the state of Iowa, providing the capacity for high-resolution simulations.

Results and Discussion

The integrated DSSAT-CAM model successfully assimilated diverse data streams into the crop model, enhancing the realism and adaptability of simulations. The 30-meter resolution implementation enabled spatially detailed forecasts of crop growth and yield (Figure 1), while also capturing hydrological dynamics relevant to agricultural production. The framework demonstrated robust functionality in handling heterogeneous datasets and effectively linking observational inputs with process-based simulations. This study highlights the potential of combining crop modeling with advanced data assimilation and hydrological coupling to improve agricultural forecasting. The Central Assimilation Module extends DSSAT's capability to leverage multidimensional data sources, reducing uncertainty and enhancing predictive accuracy. By integrating with NASA's LIS, the system further strengthens the representation of water-related processes that are essential for understanding crop performance under variable conditions.

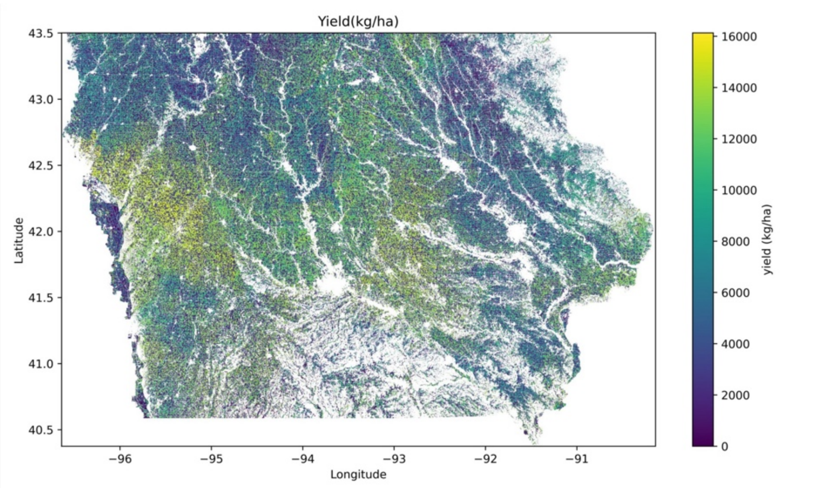

Figure 1. Spatial pattern of 20-year-mean corn yield in Iowa at 30-meter resolution.

Conclusions

The integration of process-based modeling, data assimilation, machine learning, and hydrological coupling offers a powerful and transferable framework to advance precision agriculture in a changing climate. The successful application in Iowa demonstrates the framework's scalability and relevance for climate adaptation strategies, with implications for agricultural decision support both regionally and globally.

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Drought stress monitoring for climate resilience: maize monocrop vs. intercrop in western Kenya

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Keywords: drought/stress monitoring, Sentinel-2, stress indices, maize, intercropping.

Introduction

Smallholder farming systems in sub-Saharan Africa are highly diverse and sensitive to climate variability. Western Kenya is dominated by maize-based systems that are either monocropped or intercropped. In practice, maize is often intercropped with legumes such as beans, groundnuts, or cowpeas to improve soil fertility, manage pests, and support food security, making resilience assessment highly relevant. While MODIS-derived drought indices are widely applied at regional scales (Chakraborty and Sehgal, 2010), coarse resolution limits suitability for field-level analysis and climate resilience planning. Sentinel-2 provides an opportunity to capture vegetation biotic and abiotic stresses at field scale (Segarra et al., 2020). However, methodologies are required to (*i*) identify mono- vs inter- crop, and *(ii*) transform spectral vegetation indices into high resolution stress indicators. Accordingly, we develop and test a framework to compare stress dynamics between maize monocrop and maize intercrop, and to identify which system shows greater resilience to climate variability. The ongoing work is orienting results towards near-real-time system-specific agri-advisories, through collaboration with iShamba.

Materials and Methods

We analyzed two seasons (2021, 2023). To make stress estimates crop-type specific, we produced maize monocrop vs intercrop maps through a three-step supervised Random Forest approach: (*i*) cropland vs natural vegetation, (*ii*) maize vs other crops, (*iii*) monocrop vs intercrop maize. Inputs for the classification methodology contained vegetation indices-based Sentinel-2 with Sentinel-1 bands.

Three vegetation indices were used to classify monthly stress during the long rains: (*i*) Vegetation Condition Index (VCI), which is based on NDVI; (*ii*) Moisture Condition Index (MCI), which is based on NDMI; and (*iii*) GNDVI, the basic of the Greenness Condition Index (GCI) for chlorophyll-related stress, sensitive to nutrient and pest pressures. A pixel-based ensemble (ENS) classification aggregated the three indices into four stress categories (Healthy, Moderate, Severe, Extreme) using the majority vote method. Stress dynamics, for the long rainy season, were compared between maize monocrop and intercrop using the resulting crop-map. An Intercrop Advantage Score (IAS) was then defined and derived by summarizing differences in Stress Scores (Δ) and their consistency across months to quantify resilience advantage. IAS measures the relative benefit, in terms of reduced stress, of intercrop vs monocrop.

Results and Discussion

The classification methodology achieved adequate overall accuracy OA for 2021 (Step 1: 0.96, Step 2, 0.87, Step 3: 0.77) and slightly better OA for 2023 (Step 1: 0.97, Step 2: 0.87, Step 3: 0.80). These results show that the used method allows the separation between maize monocrop and intercrop systems with acceptable reliability considering the small and irregular fields (Figure 1).

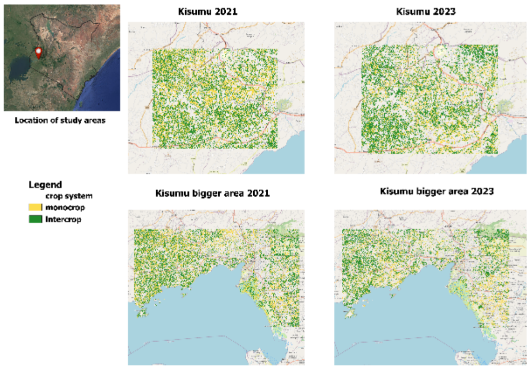

Figure 1. Comparison of maize monocrop and intercrop classification results for Kisumu and the larger study area in 2021 and 2023.

The Intercrop Advantage Score (IAS) was assessed (Figure 2), and intercompared with the individual indices, in two study areas, with the objective of evaluating how intercrop resilience varies with meteorological conditions. Across both areas and years (2021 and 2023), intercrop consistently outperformed monocrop. In 2021, the advantage was moderate and of similar amplitude in both areas, with IAS values across indices generally in the range of 1 to +2. In 2023 the larger area showed a markedly stronger intercrop advantage, with IAS values exceeding +5 for several indices and consistency reaching 100%. These resilience patterns may be partly explained by agronomic factors, as intercropping improves canopy cover, soil fertility, and pest management, while monocrops remain more vulnerable under stress.

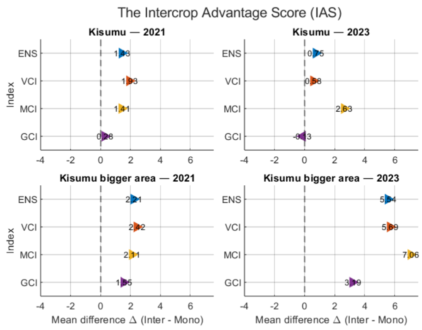

Figure 2. Intercrop Advantage Score (IAS) across vegetation indices for Kisumu and the larger study area in 2021 and 2023.

Conclusions

Our results demonstrate the utility of integrating Sentinel-2 and Sentinel-1 data into a three-step classification to generate crop-type maps that enable cropping-system-specific drought stress monitoring. We conclude the talk by discussing why and how the benefit of resilience varies with climate regime, and the implications for operational agro-advisory. These insights highlight the role of intercropping as a climate-smart practice, with potential to strengthen resilience strategies for smallholder farmers

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