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Decision making and innovation support

Field-to-Region Production Forecasting for Processing Tomato: An Integrated Model-DSS approach

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Keywords: Agri-food industry, Area production, Crop growth model, Stress models, Crop and Cultivar Parameters.

Introduction

The aim of the present study is to develop, calibrate, and validate a yield prediction model for processing tomato, using data ranging from field experiments to regional assessments.

Crop growth models are essential for food value chains and regional forecasts, as climate change amplifies extremes and interannual variability, heightening uncertainty in yield predictions from year to year (Yin et al., 2025). For agri-food industries, reliable pre-season estimates across cultivars, transplanting windows, and sourcing regions that converge on shared processing facility are essential to forecast processed output, optimize logistics, and anticipate deficits or surpluses. Traditional statistical approaches, constrained by simplified structures and sparse information, inadequately represent spatial heterogeneity in stressors and yield limits, and thus systematically under- or overestimate regional yield gaps (Couëdel et al., 2024). This underscores the need for robust and well-validated crop models, integrated with local data, spatially explicit frameworks, and scalable extrapolation methods.

Materials and Methods

The yield prediction model (Figure 1) is incorporated into Horta S.r.l. processing tomato Decision Support System (DSS) that integrates multiple components to accurately simulate crop growth, water and nitrogen balance, and key diseases development (e.g., late blight). The model uses site-specific, crop, and cultivar parameters alongside weather variables and incorporates field operations such as irrigation, fertilization, and pesticide treatments as factors that moderate the impact of agronomically manageable stresses. This structure enables estimation of yield (t ha^{-1}) and total production (t), supporting scalable, field-specific to regional-level forecasting.

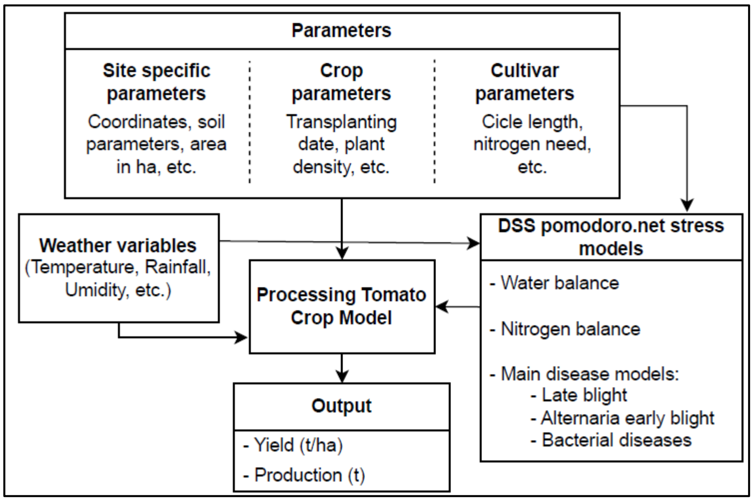

Figure 1. Scheme of the processing tomato crop model linking inputs and stress sub-models to yield and production outputs.

Calibration and validation used multi-year, multi-site datasets. Calibration dataset relied on field-plot trials, including controlled irrigation to impose water-stress gradients, nitrogen-rate contrasts, and disease assessments; in selected years cultivar contrasts quantified genotype-by-stress interactions. In addition to quantitative and qualitative harvest data, specific trials measured in-season biomass partitioning (i.e. roots, stems, leaves and berries at the green, yellow and red stages). Proximal sensing provided crop cover and leaf-area estimates. Table 1 reports locations, years, and survey types. Validation dataset used commercial fields recorded in the processing tomato DSS, with complete records of irrigation, fertilization, and plant protection. Study areas span Italy and abroad over multiple years. Each region-year marketable fresh yield was evaluated by year, cultivar, sowing period (early/mid/late), and their interactions. Parameter uncertainty was analyzed with Generalized Likelihood Uncertainty Estimation (Tan et al., 2019). Parameter estimation used Differential Evolution (Martinez-Ruiz et al., 2021). Model performance was quantified with standard indices, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2).

Table 1. Field-plot trials by location and year. Codes: W=water-stress assessment; N=nitrogen stress assessment; C=cultivar response; P=proximal sensing; B=biomass partitioning sampling; D=disease-stress assessment.

	Ravenna (IT)	**Foggia (IT)**	**Utrera (ES)**
2022	W,N,C,P,B,D	-	-
2023	W,N,C,P,B,D	-	-
2024	W,N,C,P,B,D	-	-
2025	W,N,C,P,B,D	W,N,P	W,N,C

Results, Discussion, and Conclusion

To date, the model has been calibrated and validated with 2022–2024 data; 2025 observations will extend the analysis. Validation on commercial fields yielded MAE < 14 t ha^{-1} between observed and predicted yields, while regional production showed R^2 > 0.80 across year, cultivar, and transplanting period. Because calibration data derive mainly from Ravenna (Italy), performance is expected to improve with 2025 trials in Foggia (Italy) and Utrera (Spain).

Through the DSS for agronomic operations, field technicians can consistently and comprehensively enter important information into the crop model-DSS system, which in turn helps the agro-industry spatialize production at regional level to monitor and guarantee a reliable supply of processed products within the area of interest.

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Journal article

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Python plug-in for water management in DSSAT

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Keywords: crop model, soil water, software tool

Introduction

Various cropping systems that rely on irrigation for higher yields constantly face the challenge of knowing and anticipating how much water at what plant development stage is indeed required by plants. By calculating available soil water spatially according to physical soil properties over time throughout the growing period based on accumulated biomass (plant water demand), water can be managed more efficiently. Crop growth models such as DSSAT can take into account various interactions occurring in plant×environment dynamics on a daily basis (Hogenboom et al., 2024). Based on soil physical properties, layer-based soil water holding limits, including lower limit (LL) and upper limit (DUL), are calculated and define daily plant available water, following the tipping bucket approach with respect to soil drainage factor and saturated hydraulic conductivity (Ritchie 1998). To run a DSSAT simulation, users require daily weather data from the start of the simulation to harvest, as well as soil characteristics and crop management information. To use DSSAT for “real-time” water management, a user can extrapolate historical weather data into the future. Crop model simulations must be evaluated against sensor and biomass measurements to ensure that crop model parametrization is correct. Especially in the case of water management, some simulation outputs can be directly evaluated against soil moisture sensor measurements. The advantage of having sensor measurements is that users can evaluate crop model parametrization of the soil water dynamics (layer-based) and measure current water status in the soil to produce more informed management decisions in “real-time”. This Water Management software tool was developed to enable users to combine DSSAT irrigation algorithms with sensor measurements to estimate “real-time” in-season plant water demand.

Materials and Methods

The DSSAT CROPGRO-Chickpea model (v. 4.8.5, Hogenboom et al., 2024) was used to simulate in-season leaf area index (LAI) and biomass accumulation under German conditions in 2024. The crop model was calibrated and evaluated within other study that is currently under review. In this short study, only part of the results was shown, including LAI, aboveground biomass (tops), grain weight, and soil water simulation at 15 cm depth (second layer in the soil file) for one year.

DSSAT has the capability to determine daily irrigation based on soil water depletion and plant available water according to two methods: growth stage-controlled automatic irrigation and ET-based automatic irrigation. The first method, used in this study, relies on plant×enviornment×management dynamics for calculating irrigation requirements of the plant per growth stage. The volumetric water content (VWC) variable, in combination with a defined soil management depth, is used to determine irrigation at the point when the VWC reaches a lower threshold defined by the user as a percentage of the available water-holding capacity (Lopez et al., 2017).

The Water Management external Python plug-in for DSSAT (test version) was developed to complement the existing DSSAT irrigation method by enabling users to include layer-based soil water sensor measurements in the process of determining irrigation deficits. A user can pass into the DSSAT File-T layer-based soil moisture sensor measurements and calculate VWC Irrigation Deficit (VWC_{IT}) based on field capacity (DUL), permanent wilting point (LL), and different levels of plant available water content percentages (e.g. 50, 60, 70 % etc.) (PAWC) (Eq. 1). The final objective of the tool is to combine model and sensor-based irrigation triggers into one practical irrigation recommendation (work in progress).

$$VWC_{IT} = DUL - [(DUL - LL) * (1 - PAWC)] \quad (1)$$

The current version of the plugin was developed to work with one sensor measurement per soil profile. For this specific study, 15 cm sensor readings were used to evaluate the conceptual framework for two sowing dates in 2024. The plugin was developed to be used as a “real-time” decision tool, enabling users to update weather and utilize future forecasts.

Results and Discussion

The agreement between the CROPGRO-Chickpea simulation and measurements of phenological events, including the onset of flowering, first pod, and first seed, was very good, with average errors of ±0.6 and ±3.3 days, respectively, for the first and second sowing dates. Detailed statistics for LAI, tops, and grain yield dry matter are shown in Table 1. RMSE and d-Stat. of LAI and aboveground biomass indicated good agreement between simulated and measured data for two sowing dates. End of season grain yield was not entirely simulated satisfactory and requires further improvement.

Table 1. CROPGRO-Chickpea evaluation statistics including LAI, tops ang grain weight for two sowing dates.

	15 cm ($cm^3 cm^{-3}$)	LAI	Tops ($kg\ ha^{-1}$)	Grain ($kg\ ha^{-1}$)	15 cm	LAI	Tops	Grain
Sowing date	RMSE				d-Stat.			
30.04.2024	0.03 (125)	0.64 (10)	1272 (11)	845 (7)	0.92	0.94	0.98	0.91
15.05.2024	0.05 (109)	0.61 (9)	377 (9)	734 (6)	0.78	0.95	1.00	0.90

(n) – total number of observations used.

In Figure 1 the Water Management tool interface is shown with preliminary results. The plug-in is already fully functional; however, it requires further testing. Figure 1 (left) shows the tool setup with selected experiment treatment, soil water layer 2 (SW2D), and PAWC 50 % (0.5). In Figure 1 (right), LL (LL2D), DUL (DUL2D), measurements, and VWC_{IT} threshold line (T-2D) are shown. In Figure 1 (right) soil irrigation triggered based on soil sensor measurements is indicated with star-styled markers, for all measurements below VWC_{IT} (T-2D).

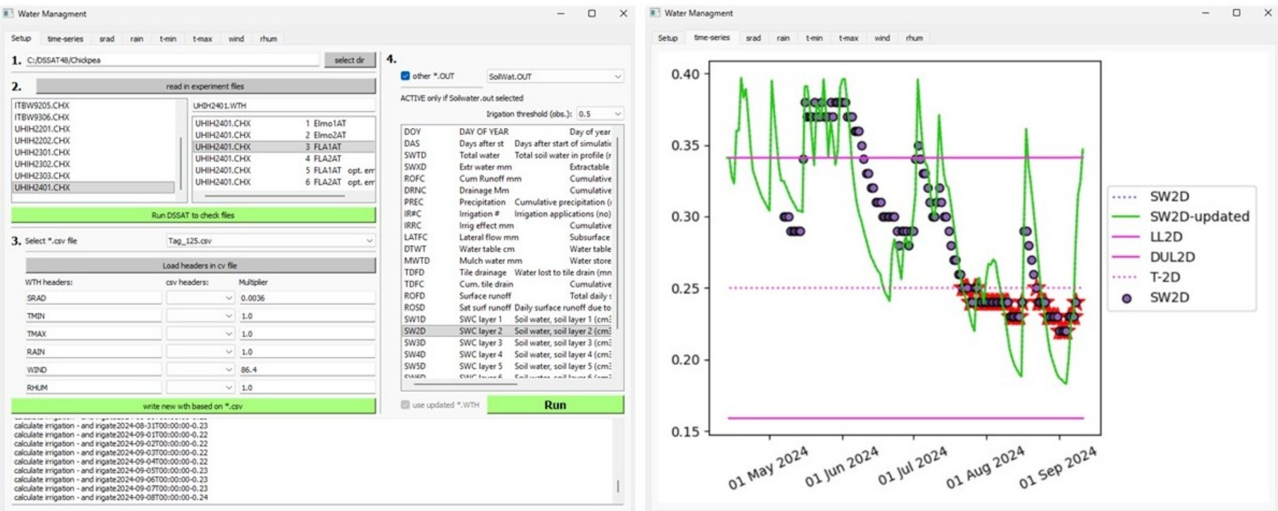

Figure 1. Water Management tool interface (left); simulation output including sensor measurements, LL, DUL and irrigation threshold (T-2D) (right).

The problem with the irrigation trigger in the tool is that it is based on one sensor layer depth. Ideally, the entire root zone soil water depletion should be considered, especially if sensor measurements for multiple depths are available.

Conclusions

For the data presented, the soil water simulation line had a very similar trend to the sensor-based soil water measurements. This is not always the case and can cause serious problems if VWC_{IT} is based on inaccurate LL and DUL. Since soil water content simulation calculated in the model based on soil properties and weather conditions is not always accurate, a combination of crop model-based irrigation recommendation with sensor-based recommendation might offer more realistic values.

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Monitoring Soybean Development through Vegetation Indices: An Approach for Crop Modelling

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Keywords: time series, NDVI, climatic, productivity.

Introduction

According to OECD-FAO (2020), the world population will reach 8.4 billion by 2029, requiring sustainable increases in agricultural productivity. Brazil plays a key role in global food supply, particularly the MATOPIBA region (Maranhão, Tocantins, Piauí, and Bahia), where Western Bahia has recently become important for its soybean expansion (CONAB, 2025). This growth highlights the need for effective tools to monitor agricultural productivity.Traditionally, crop monitoring in Brazil is conducted through field surveys by official agencies which is time-consuming, and costly, while remote sensing enables systematic crop monitoring with vegetation indices that indicate crop vigor.Among the most widely used indices are the NDVI and EVI. Recently, the NDRE has demonstrated advantages for crop monitoring. Given the agricultural expansion in Bahia, this study aimed to evaluate the use of vegetation indices for monitoring soybean development throughout the growing season in Western Bahia, Brazil.

Materials and Methods

The study area was Western Bahia, Brazil, which had 2 million hectares of soybean planted in the 2024/2025 crop season. The methodology was developed to monitor soybean vegetative vigor by comparing current season NDVI values with the historical NDVI and climate time series. First, soybean areas were identified using land use map from MapBiomas (Souza et al, 2020) from 2019 to 2024. Climate data, including precipitation, were obtained from the ECMWF forecast and used to compose a 30-year historical series (1994-2024). NDVI was calculated using monthly Sentinel-2 satellite imagery from 2019 to 2025. Data processing was carried out in Google Earth Engine using Python scripts. NDVI results were analyzed over time using a three scale—stable, warning, and alert—based on the GEOGLAM Crop Monitor methodology (Becker-Reshef et al., 2020).

Results and Discussion

For the 2024/2025 crop season, most municipalities showed NDVI values at or above historical averages, indicating favorable vegetative vigor, particularly in Baianópolis, Cocos, and São Desidério (Figure 1). With the advance of the dry season, precipitation remained low and consistent with historical averages, leading to reduce NDVI due to limited water availability, the end of the harvest, and Brazil's soybean sanitary void. The integration of NDVI and climatic monitoring provides monthly updates on crop vigor, supporting producers in crop development dynamics and adapting to environmetal conditions.

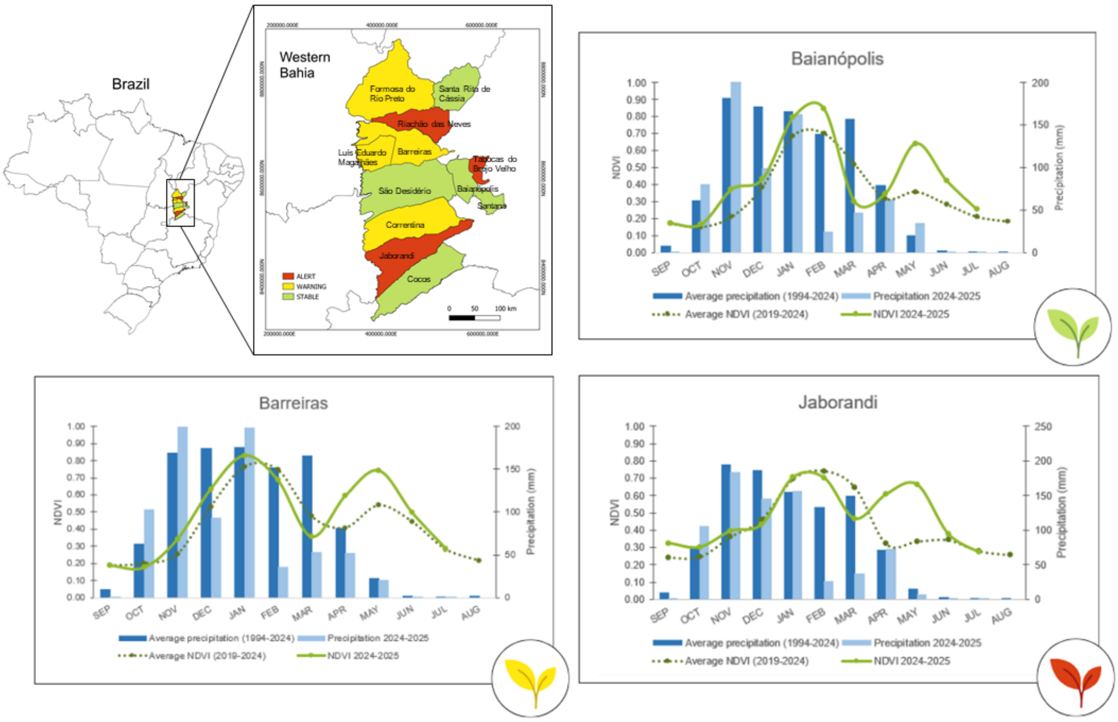

Figure 1. Vegetative vigor map for Western Bahia (green: stable, yellow: warning, red: alert), highlighting Barreiras, Baianópolis, and Jaborandi.

Conclusions

Monitoring soybean crops using time series of satellite imagery and climate data holds significant potential for agricultural planning and strengthening rural extension services. Its informative nature enables the early detection of crop issues such as pests, diseases, or water stress. Therefore, vegetation indices and climatic data are valuable tools for providing real-time insights and supporting timely decision-making in the field.

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Integrating Satellite Data with DSSAT for Soybean Yield Forecasting in Data-Scarce Smallholder Farms of India

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Keywords: DSSAT-CROPGRO; Smallholder farmers; Soybean phenology; Soybean Yield; Semi-Arid regions.

1. Introduction

Crop simulation models like DSSAT (Hoogenboom et al., 2024) have become increasingly important for studying the effects of climate change and supporting agricultural decision-making. However, most research relies on experimental data, which reduces its applicability in real-world situations where data is limited. For example, (Boote et al., 2018) examined how elevated temperatures affect soybean and peanut yields, while (Debnath et al., 2021) applied a quantile mapping technique to estimate rice yield gaps across India's diverse agro-climatic zones. Studies that use real-time data rather than controlled experiments are few and tend to focus on larger farms, which are less representative of typical Indian agriculture. With nearly 89.4 per cent of farming households in India cultivating less than two hectares, farmers are marginal and vulnerable to climate-related crop losses. Calibrating DSSAT for farms under two hectares can therefore support better resource management.

This study applies a quasi-experimental approach using primary data collected from 65 smallholder soybean farmers in Keshegaon, a drought-affected village in Maharashtra, India. The objective is to calibrate the DSSAT-CROPGRO model for soybean cultivation under rainfed conditions with limited available data. Because this research relies on real-time field observations instead of controlled experiments, data gaps remain a challenge. In-depth details of soil analysis, surface texture, drainage depth, etc and difficulty obtaining cloud-free satellite images, present challenges, as soybean is a Kharif crop dependent on the monsoon, making explicit imagery harder to acquire.

The calibration is validated using two indicators: the difference between actual and simulated yields, which provides a measure of the model's accuracy in predicting real-world outcomes, and the comparison between modelled and satellite-observed soybean growth phenology derived from leaf area index (LAI), which ensures the model's ability to replicate the plant's growth stages as observed in the actual plots.

2. Materials and Methods

Keshegaon, a small village in Tuljapur tehsil of Dharashiv (formerly Osmanabad) district in Maharashtra, lies approximately 32 km from the sub-district headquarters of Tuljapur (Ref; Figure 1A, supplementary table S1). We use a structured questionnaire to ensure systematic data collection and capture key aspects of farming operations by including sections on- (a) basic information of the plot (e.g., Land area, GPS Route identification number, previous crop, irrigation type, soil type etc.), (b) management practices (e.g., planting and sowing dates, fertilizer used, tillage operations), and

(c) economic factors (e.g., input costs, labour charges and other associated expenses). The data acquired through this instrument act as inputs to run the DSSAT seasonal models for each plot.

2.1 Data

The average yield of the sample size taken is 1867.92 kg/ha with a median of 1700.55 kg/ha, indicating a slight right skew in the yield distribution. The maximum yield observed within the sample is 5922.37 kg/ha, making it the outlier of the entire sample, while the lowest is 681.26 kg/ha. There is considerable variability among the sampled plots, as suggested by the 821.13 kg/ha standard deviation. Most of the sampled plots fall within the ±1 standard deviation range of 2689.05 kg/ha and 1046.78 kg/ha (Ref; Supplementary table S2)

2.2 Sampling

Keshegaon has 1144 farmers, 409 of whom are small landholding farmers, and 555 of whom are marginal landholding farmers. We could identify 807 farmers from the village's agricultural records based on the beneficiaries of various government schemes. Using a stratified sampling to ensure representation across different landholding categories, our study sample consisted of 75 farmers for farm-level data collection. It was possible to acquire data and details for 68 farmers out of our sample of 75. Further, out of those 68 plots, three experienced complete crop loss primarily due to excessive water stress and waterlogging conditions, leaving us with a sample of 65 farmers for further analysis. These 65 marginal farmers have below 1 hectare of land, and 10 small farmers have 1-2 hectares of farming land.

2.3 Analytical approach

Sentinel-2 image calibration

Using a GPS device, we map the 75 farms, process them in Google Earth Pro, and code them as "routes" to identify and refer to. Simultaneously, we extract the Sentinel-2 images for the crop cycle dates from 1st June 2024 to 30th November 2024. We chose NDVI as the vegetation index and processed the pixel-wise NDVI using GEE and R-Studio. The NDVI was converted to LAI using the LAIr package (Bajocco et al., 2024); as the equation for Sentinel-2 is not available yet, the equation for LANDSAT by "Kross et al., et.al 2015" was used, keeping in consideration that both the satellites have similar sensors.

DSSAT model calibration

The extant literature served as the repository for the mandatory field details such as location longitude, latitude and elevation. The gram panchayat provided Dharashiv's daily weather data. Again, information on some unknown parameters not accessible through primary data was taken from existing literature, while we use arbitrary values for some others. For soil depth, we followed (Shaikh & Birajdar, 2015). Motarjemi et al. (2023), in their research on the effects of drainage conditions on sandy loam soil, mention the water table depth of sandy loam soil to be 200-300 cm. It is a close fit to our location as the soil texture is sandy-loam. Following Nargund et al. (2024), we manually add the data for Genetic coefficients to the soybean cultivar file for JS-335.

For this study, we define an ideal yield difference as less than 100 kg/ha due to the small size of the farms. A default run of all 65 farmers resulted in 4 farmers having the perfect fit of less than 5kg/ha yield difference. We divide the farmers into two groups for Run 2, where 25 are isolated from the remaining 65. Multiple simulations were conducted on these 25 farmers, adjusting various parameters in each run. The farmer was excluded from the list when the model output was less than 100 kg. After completing the simulations for all 25 farmers, the remaining 40 were processed using the optimized values obtained.

We convert the Leaf Area Index (LAI) from the DSSAT simulated results into a phenology curve according to sowing and harvesting dates. After cleaning, we compared it with the LAI obtained from the Sentinel images to include only the dates when both DSSAT and satellite data were available.

3. Results and Discussion

We categorize the results into three groups based on the yield difference: 'Group-A': 0-10 kg/ha yield difference, 'Group-B': 10-20 kg/ha yield difference and 'Group-C': >20 kg/ha yield difference. Eight plots fall within Group A, two fall within Group B, and the remaining fifty-five plots are in Group C. These results indicate the model's performance in predicting soybean yields, with Groups A and B showing the closest predictions.

Actual Yield and Simulated Yield

Route 42 reports an exceptionally high yield at 5922.37 kg/ha with a total production of 3900 kg, making it an extreme case scenario, or an outlier among the samples we analyzed separately. However, the rest of the plots fit the model well. Among all calibrated plots that predicted yields below 100 kg/ha (Table 1), six plots demonstrated near-perfect alignment with observed data, with yield differences of less than 5 kg/ha. The lowest yield difference emerges in Route-80, with an actual 1202.39 kg/ha yield. At the same time, the model simulated 1202 kg/ha, resulting in a yield difference of just 0.39 kg/ha, achieved in the default run itself. It suggests that the farmer's practices on this plot were highly accurate, with management practices aligning with model expectations.

Four plots reported yields lower than the range of the average yield. Meanwhile, six plots reported yields exceeding the average standard deviation range. However, the total production of these plots is higher than some of their yields. When the simulated yield by the model is under the average range but the farmers' reported yield is less than that of the model, it indicates crop loss due to multiple factors. Route 51, for instance, reported a total production of 1200 kg on a 1.76-hectare plot, resulting in an exceptionally low yield of just 681 kg/ha. Some plots have opted for different cultivars such as DS-228, MAUS-612, and KDS-228; they show lower yields as they stand differently from the JS-335. The variation in genetic coefficients associated with these cultivars may not align well with the corresponding management practices.

This series of simulation runs helped identify a set of optimal input values for soybean cultivation in DSSAT under data-scarce conditions. These values, derived from field data, literature references, and iterative calibration, can be reliable defaults when input data are limited or unavailable.

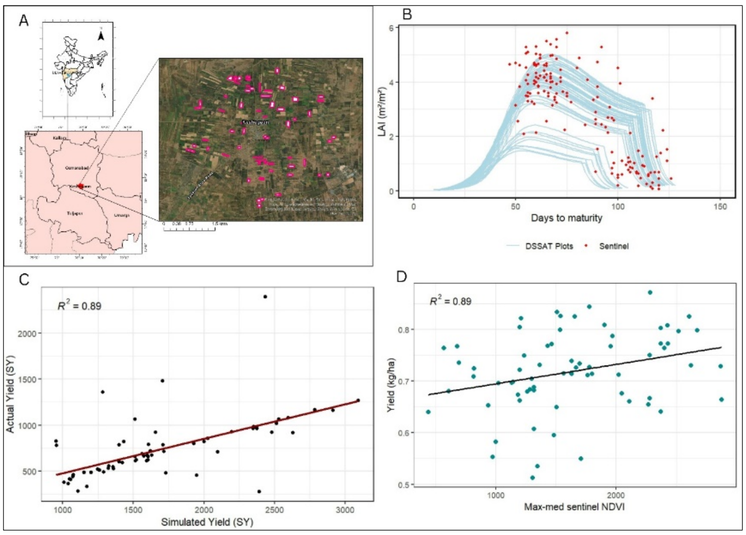

Figure 1: A) Location map of plots in Keshegaon, Maharashtra, created on ArcGIS pro; B) Spaghetti Plot for DSSAT derived soybean phenology with satellite derived LAI for all plots; C) Scatter plot of actual yield reported and simulated yield by DSSAT; and D) Scatter plot of yield reported and max-med sentinel NDVI

Route Number	Area (ha)	Actual Yield (AY) (Kg/ha)	Simulated Yield (SY) (kg/ha)	Yield Difference (AY-SY)
Route - 19	0.69	1514.27	1515.8	-1.53
Route - 63	0.22	1357.34	1357.5	-0.16
Route - 80	0.30	1204.17	1202	2.17
Route -12	0.51	2376.24	2373.5	2.74
Route -70	0.24	2517.20	2514	3.20
Route - 71	0.19	1263.96	1260.5	3.46

Table 1: Plots showing <5 kg/ha yield difference

DSSAT obtained phenology vs satellite phenology

The model correctly captures the basic timing of the crop's phenology, and the satellite data also follows the same pattern (Figure 1 B). However, the model underestimates the maximum LAI compared to the satellite's observed. Contrary to the later stages, the satellite fails to show the initial stages of growth due to the unavailability of images on the sowing to maturity dates. Despite the shortcomings, the DSSAT LAI and satellite-derived LAI show a coefficient of variation of 0.88 (Ref; Supplementary Figure S3).

4. Conclusion

Merging crop models with satellite imagery can offer deeper insights into crop growth, particularly for smaller farms, and improve yield forecasting for better mitigation of crop loss and optimized resource use. By training models with satellite-derived LAI data, simulations can be refined for greater accuracy, providing valuable support to the crop insurance industry where insurers can assess risks, process claims fairly, and expedite payouts following climate-induced crop losses. Together, these efforts can transform agricultural resilience and productivity for smallholder farmers.

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Supplementary Tables and Figure

Table S1:

Basics	
1. Village Name	Keshegaon Taluka
2. District	Dharashiv, Maharashtra
3. Geographical Area	1644.22 hectares
4. Agro-climatic zone	Zone 10 (Southern Plateau and hills region)
5. Total population	4949 (2011 census)
6. Average temperature	21°C - 42°C
7. Average rainfall	50 cm – 100 cm
Agricultural details	
1. Total Cultivable land	1569.30 hectares
2. Rainfed land	1373.25 hectares
3. Total Farmers	1144
4. Large Landholding farmers	180
5. Small Landholding farmers	409
6. Land under Kharif crop	1307.00 hectares
7. Land under Rabi crop	1065.0 hectares

Supplementary Table 1: Details of study area; Keshegaon

Table S2:

Statistic	Value	Notes
Sample Size	65 plots	Final sample after filtering
Average Yield	1867.92 kg/ha	Mean of observed yields
Median Yield	1700.55 kg/ha	Central tendency indicator
Maximum Yield	5922.37 kg/ha	Outlier in the dataset
Minimum Yield	681.26 kg/ha	Lowest yield observed
Standard Deviation	821.13 kg/ha	Indicates variability among plots
±1 Standard Deviation Range	1046.78 – 2689.05 kg/ha	Most plots fall within this range

Supplementary Table 2: Data description

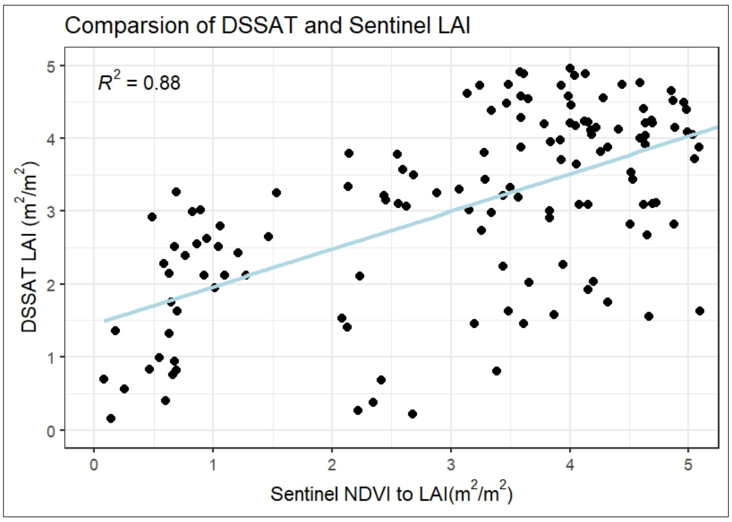

Figure S3: Scatter plot of DSSAT LAI and Sentinel LAI

Integrating and comparing grassland models in GraminR for European yield simulations

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Keywords: ensemble modelling; forage yield; policy support; reproducibility.

Introduction

Process-based models are essential for predicting European grassland dynamics, which have declined since the 1960s due to intensified agriculture and land-use changes. Among these, PaSim simulates long-term biogeochemical fluxes (Graux et al., 2011), GrasProg targets short-term growth dynamics of intensively managed ryegrass swards (Peters et al., 2022) and ModVege incorporates vegetation traits to capture biomass quantity and quality (Jouven et al., 2006). This study integrates these models into GraminR, a new R-based model library developed by Joint Research Centre (JRC), expanding on the LINGRA model available on the Agri4CAST CGMS platform (https://code.europa.eu/agri4cast/lingra). GraminR advances this concept by offering a more flexible and scientifically reproducible framework for ensemble simulations and model evaluation. The overarching objective is to establish a harmonised, interoperable and multi-model simulation framework for European grasslands, facilitating intercomparison, reducing uncertainty and strengthening decision-making for sustainable land management.

Materials and Methods

Model integration was conducted using a modular R-based workflow with standardised input/output handling. GrasProg was re-implemented in R from its original equations, PaSim (Fortran-based) was encapsulated with an R interface and ModVege, already in R, was adapted as a proof of concept by being within the GraminR framework. The system supports dual deployment: standalone (outside GraminR) for local testing, and integrated (within GraminR) for operational use at the JRC. Standardised functions were developed to manage climate data (daily/hourly), soil properties (texture, organic matter, depth), management practices (mowing, grazing, fertilisation) and vegetation traits. An automated reporting tool was implemented for model evaluation, using harmonised European datasets with consistent spatial referencing via the INSPIRE grid (https://inspire.ec.europa.eu). Climate forcing was provided in NetCDF format, and soil data sourced from established databases (Baumann & Escriu, 2019). Model outputs - specifically dry matter yield - were evaluated against independent observations from 12 long-term experimental sites (multiple plots) across Europe: five in France, three in Italy, and one in Greece, Sweden, Switzerland, and the UK. Performance was assessed using global modelling efficiency (EFg), mean absolute error (MAE) and two ensemble-based indicators - multi-model average (MMA) and multi-model median (MMM).

Results and Discussion

This study establishes a reproducible multi-model workflow within GraminR, addressing reproducibility is crucial in process-based modelling, especially when models are recoded or wrapped into new environments. Reproducibility - both methodological and inferential - is ensured through standardised inputs, procedures and outputs, enhancing transparency and scientific rigour. Validation confirmed full consistency between the R-based GrasProg and its original version, and between the R-encapsulated PaSim and its Fortran executable, using both legacy ($\text{PaSim}_{\text{leg}}$) and updated ($\text{PaSim}_{\text{new}}$) configurations. Another key advancement is GraminR's automated evaluation tool, which streamlines input preparation, simulation execution and performance reporting. It provides three core benefits: (1) reproducibility through transparent, shareable and consistent evaluation protocols; (2) scalability for large-scale model intercomparison using harmonised datasets; and (3) operational integration with the Agri4CAST platform for ensemble model evaluation. These developments ensure that models can be evaluated reproducibly, and achieve operational results for agricultural forecasting and policy support. Quantitative evaluation highlights the value of ensemble modelling (Figure 1).

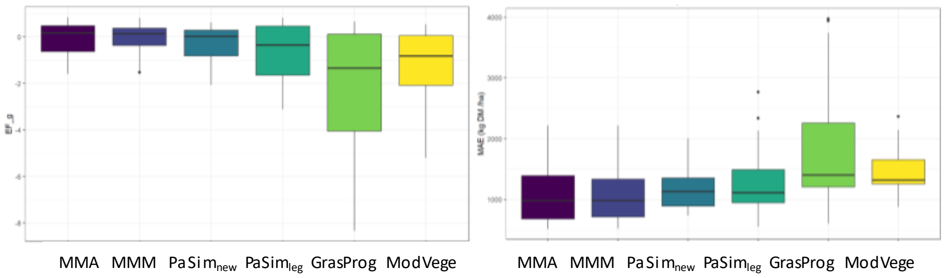

Figure 1. Performance metrics for predicting annual dry matter yield (12 sites). (Left) Global modelling efficiency (EFg). (Right) Mean absolute error (MAE, kg DM ha^{-1}). Model outputs from the model ensemble (mean: MMA; median: MMM) are compared with four model realisations.

Across 12 European sites, MAE ranged from 1184 for PaSim$_{new}$ to 1798 kg DM ha^{-1} yr^{-1} for GrasProg. Ensemble outputs consistently outperformed single models, with MMA of 1088 and MMM of 1104 kg DM ha^{-1} yr^{-1} (Table 1), reducing relative MAE from ~60-70% (individual models) to a more manageable ~50% (model ensemble). Ensemble robustness was further confirmed by fewer sites with EFg<0: ~35% for ensembles versus >70% for GrasProg and ModVege.

Table 1. Model performance indicators across 12 European sites (annual dry matter yield).

Metric	MMA	MMM	PaSim$_{new}$	PaSim$_{leg}$	GrasProg	ModVege
Number of plots	37	37	37	37	34	34
Mean MAE (kg DM ha^{-1})	1088	1104	1184	1286	1798	1465
Mean relative MAE (%)	51.5	53.1	58.1	69.6	68.9	62.1
Mean EFg	-0.0	-0.1	-0.3	-0.7	-2.3	-1.3
Sites with EFg<0 (%)	35.1	37.8	46.0	59.5	70.6	70.6

While the MMM consistently enhanced overall accuracy, each model showed distinct strengths and limitations, e.g.: PaSim is robust but computationally demanding, GrasProg is efficient but ryegrass-specific, ModVege provides detailed vegetation traits but underperforms under drought conditions. This reinforces the value of ensemble approaches for accurate, resilient predictions and informed agricultural policy (Bellocchi, 2023).

Conclusions

GraminR is a major step forward in agroecological modelling as the first interoperable, multi-model framework for grassland simulation within the European Commission's forecasting platform. By recoding GrasProg in R and encapsulating PaSim, it ensures scientific reproducibility and transparency. The integrated reporting tool standardises data and workflows, enabling large-scale, ensemble-based assessments. This approach enhances robustness, reduces prediction errors and leveraged complementary model strengths, ultimately supporting sustainable grassland management evidence-based agricultural and environmental policy in Europe.

Acknowledgements

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Integrating remote sensing and modelling for enhanced wheat management and supply chain logistics

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Keywords: Wheat management, seasonal forecasts, remote sensing, supply chain

Introduction Calibri pt 10

Global food security is increasingly threatened by geopolitical unrest and climate change (FAO, 2024). Within this context, the extent to which we rely on domestic food production or trade as a means of achieving food security needs to be examined. Timely and reliable crop yield forecasts are vital for agricultural sustainability and food security interventions that can help to contribute to this balance. Yield forecasts weeks or even months in advance of harvest are increasingly common using methods including machine learning (ML), statistical and process-based crop-climate models, and remote sensing data (Schauberger et al., 2020).

Most crop yield forecasts operate at lead times of just one to two months, often too short for meaningful post-harvest interventions or on-farm management planning. Only a handful of forecasts extend beyond four months, with these showing limited predictability (Schauberger et al., 2020). In addition, most approaches rely on seasonal climate forecasting, which has proven value in agricultural decision making, although it can be costly and computationally expensive. In the United Kingdom (UK), national scale wheat forecasts are based on surveys and historical data rather than modelled predictions, and forecasting studies are rare compared to other European countries (Schauberger et al., 2020). As a result, post-harvest planning, trade and supply logistics, and within season management decisions such as fertiliser applications are sub-optimally informed.

Materials and Methods Calibri pt 10

We develop a winter wheat yield forecasting system and identify key management decisions that can be supported by the model, as agreed with a UK farmer stakeholder network. The General Large Area Model for annual crops with Satellite remote sensing data (GLAM-Sat) embeds ML algorithms to predict crop development alongside integration of biomass estimated from Normalized Difference Vegetation Index (NDVI) data. A logistical function is used to finish the growing season at different lead times. Through dialogue with stakeholders, we examine the key management and supply chain decisions that can be informed by the model.

Results and Discussion Calibri pt 10

GLAM-Sat shows high skill in reproducing interannual variability of historical yield data when driven by NDVI data for the whole growing season (Figure 1A; R2 0.8). Skill gradually reduces as lead time increases, with R2 0.66 when making an end of season prediction with NDVI data cut off on April 1st (Figure 1B). Skill is generally significant in Eastern regions that grow the most wheat.

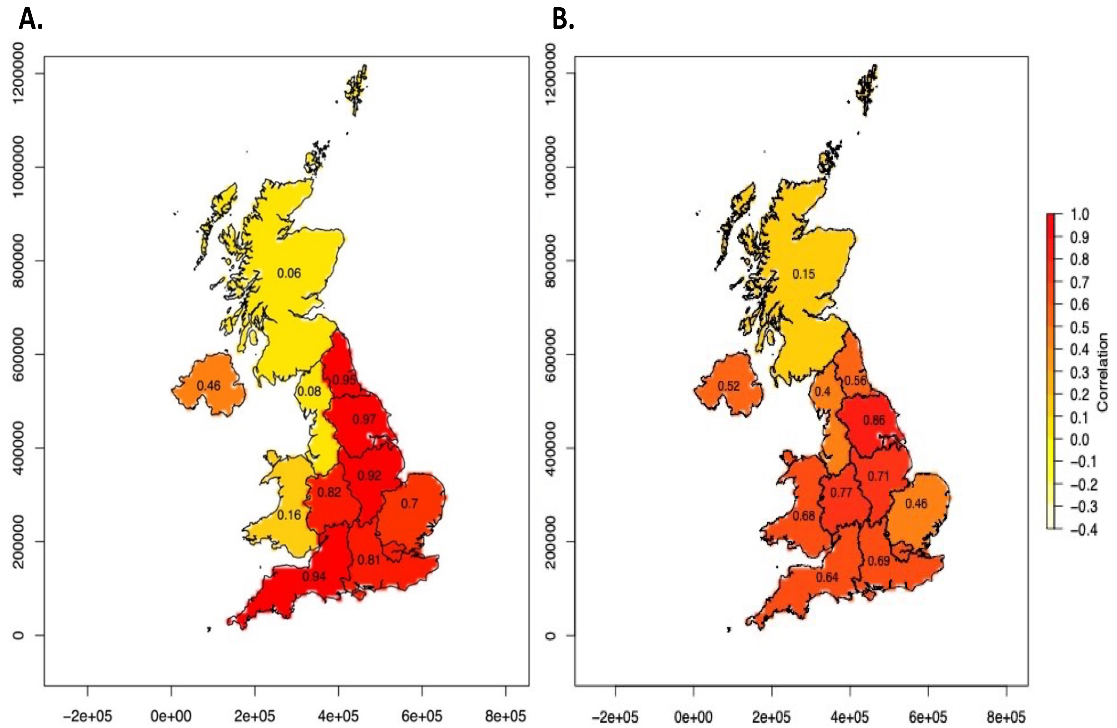

Figure 1. Correlation coefficient between observed and simulated yields. A: data for all of growing season. B: four month lead time, i.e. no NDVI data from April 1st.

Conclusions Calibri pt 10

GLAM-Sat shows skill at lead times of up to four months, and therefore able to inform key UK wheat management decisions as identified by stakeholders. For example, between February and April, nitrogen is applied to maximise yield. In May and June, additional nitrogen is applied to milling wheats to meet protein targets, with needs shaped by yield, soil nitrogen, and markets. Post-harvest planning in the UK can also be successfully informed, with the imports necessary to meet wheat demands estimated and accounted for. Haulage, labour, trading, and storage also hinge on predicted tonnage. Our results principally target UK national institutions such as the UK's Department for Environment, Food and for Rural Affairs, whose information will ultimately aid farmers and actors further down the supply chain - improving the efficiency, environmental outcomes, and profitability of these decisions.

Acknowledgements Calibri pt 8

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References Calibri pt 8

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Adapting and parameterizing the DSSAT Cropping System Model to simulate onion (*Allium cepa* L.) growth and development

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Keywords: Crop modeling, dry matter partitioning, photoperiod sensitivity, onion yield

Introduction

Mechanistic models are increasingly used in digital agriculture to predict crop growth and automatize processes for precision agriculture. DSSAT (Decision Support System Agrotechnology Transfer; www.DSSAT.net) is one of the most powerful and widely applied crop modeling system (Hoogenboom et al., 2019). Its embedded CROPGRO family models have been successfully adapted to more than 27 crops (Boote et al., 2021). Beyond its original development for legumes, CROPGRO was extended to several crops. However, a fully developed DSSAT-Cropping System Model (CSM)-CROPGRO model for onion is still lacking, despite the worldwide interest in such a crop. The current study aimed to adapt and develop CSM-CROPGRO model suited to simulate onion growth and predict N management.

Materials and Methods

The experimental data were obtained from field studies conducted at Oppeano municipality (Verona province), northeastern Italy, during 2021-2025, using varying N rates (138 to 220 kg N/ha). The onion cultivar *Borettana* was used for model testing. Soils were analyzed for key physicochemical properties at the start of each season, and daily weather data were collected from a nearby station. Onion growth traits, biomass, and N concentration in leaves and bulbs were monitored biweekly, and soil N content was measured during the season. The starting template was the species, ecotype, and cultivar files for the CROPGRO-Soybean model in DSSAT v4.8.5 (Hoogenboom et al., 2024). Species-specific parameters were defined based on literature values and measured data in the field (e.g., N content). Model input data included soil characteristics, weather data, and crop management. Experimental time series of growth, N content, and yield at harvest were used to evaluate the model performance. Experimental data from 2023 and 2025 were used for model calibration. Cultivar- and ecotype-specific genetic parameters were optimized against observed growth and yield data using sensitivity analysis.

Results and Discussion

From the CROPGRO-Onion model calibration, species genetic coefficients reflected its specificity, especially the vegetative growth, leaf expansion, and the critical transition to bulb growth. Onion sensitivity to photoperiod governed bulb initiation rather than flowering, highlighting the need for species-specific parameterization to accurately simulate growth and yield. The results showed a close agreement between simulated and observed biomass values (leaves and bulbs, Fig.1.), canopy height, and N concentration in crop tissues, with d-statistics above 0.84 and low RMSE. However, specific leaf area, LAI and the number of leaves per plant require further optimization.

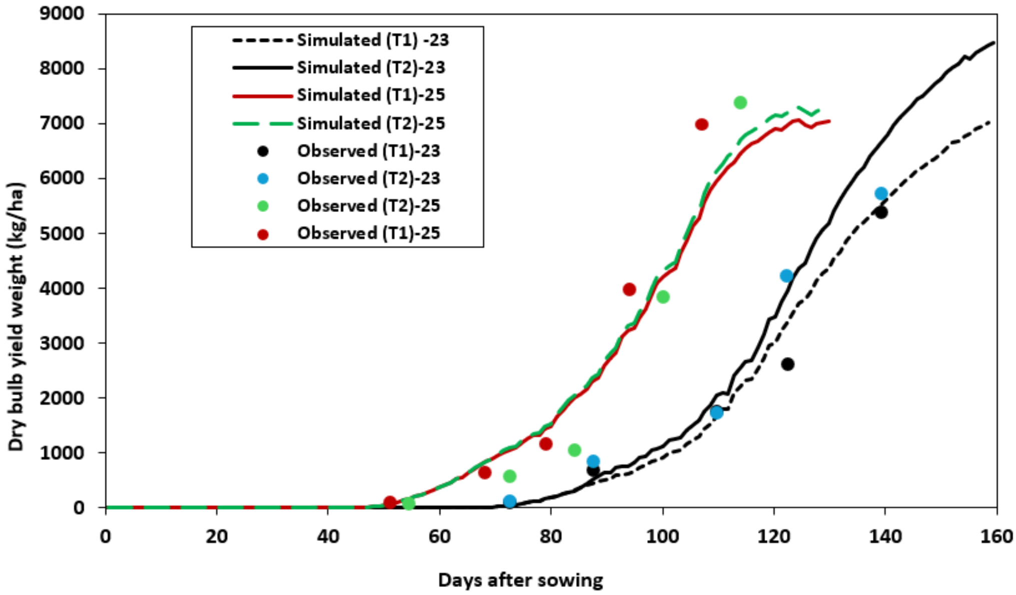

Fig. 1. The red line (simulated) and red points (observed) represent T1 (138 kg N ha^{-1}, 2025), while the green dashed line (simulated) and green points (observed) represent T2 (145 kg N ha^{-1}, 2025). The black solid line (simulated) with blue points (observed) corresponds to T1 (168 kg N ha^{-1}, 2023), and the black dashed line (simulated) with black points (observed) corresponds to T2 (220 kg N ha^{-1}, 2023).

Conclusions

The CSM-CROPGRO model was adapted for Borettana onion by modifying species coefficients and calibrating cultivar and ecotype files, resulting in good agreement, especially for yield and final N uptake. However, improvements are still needed for simulating crop traits such as aboveground biomass growth and LAI to improve N management throughout the crop season.

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Development of Easy Simulator Crop Model (EaSiCroM) for irrigation management in water scarce environments

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Keywords: water scarce agriculture, decision support system, precision agriculture, crop modelling

Introduction

Agriculture in water scarce environments faces critical challenges due to reduced and erratic precipitation patterns and increased competition for limited water resources, severely impacting crop yields and agroecosystem sustainability. Furthermore, precision irrigation is facilitated with real-time simulated forcing from observed plant metrics such as leaf area index and soil moisture, enabling dynamic, spatially resolved irrigation recommendations based on accurate crop and soil statuses (Zucaro et al., 2024; Ahmad and Sohel, 2025) by means of integrated tools as spatial decision support systems (Rinaldi and He, 2014).

The aim of the research is to describe and evaluate a decision support systems developed in a water scares environment and applied to field crops.

Materials and Methods

The Easy Simulator Crop Model (EaSiCroM) decision support system is designed to operationalize irrigation scheduling through simulation of crop growth and soil water interactions, enabling adaptive irrigation based on precise crop water demand. Notably, EaSiCroM's crop growth simulations incorporate the influence of ambient CO_2 concentration alongside irrigation management and water stress, thus integrating environmental and management-driven factors for improved crop water use efficiency estimation.

EaSiCroM accepts user inputs describing crop parameters, soil properties, and meteorological data in standard digital formats. The system simulates crop biomass accumulation and canopy development through empirical sigmoid and beta growth functions, dynamically adjusted for temperature variations and water stress effects as represented by soil water depletion and plant available water values (Garofalo et al., 2020). Users can select from different irrigation triggering mechanisms: fixed irrigation turns, irrigation triggered upon reaching soil water depletion thresholds, or plant available water thresholds.

EaSiCroM supports simultaneous multi-simulation runs covering monoculture, crop rotations, and complex field heterogeneity via plot-specific IDs. The platform allows for long-term simulations and incorporates climate forecasts, supporting both tactical and strategic irrigation approaches in water scarce environments.

Results and Discussion

Preliminary studies conducted using EaSiCroM on selected crops such as tomato and cotton have demonstrated the system's capability to simulate canopy cover development, biomass accumulation, transpiration dynamics, and soil water availability in water scarce agricultural systems. Simulation outputs closely aligned with observed data, confirming that EaSiCroM irrigation scheduling algorithms, triggered by soil water depletion or plant available water levels, optimizes water application and limits wastage. Precision irrigation scenarios, leveraging near-real-time data inputs, effectively capture intra-field spatial variability (Fig. 1), allowing for differential water applications tailored to the needs of sub-plot areas.

These preliminary findings underscore EaSiCroM's potential to sustainably improve water productivity and maintain crop yields under challenging water availability. Its straightforward parameterization, modular design, and accessible user interface promote broad adoption by farmers, advisors, and water resource managers, bridging agronomic research and practical water conservation strategies (Sportelli et al., 2024).

Conclusions

EaSiCroM is a scientifically rigorous and operationally flexible decision support tool fostering sustainable irrigation management within water scarce agricultural systems. Its multi-simulation framework with real-time data integration makes it applicable from precise field-scale management to regional water resource planning. EaSiCroM is freely available at: https://drive.google.com/drive/folders/1E0Fq5Hk_4u0xaCV1ilXixGHEfSvWL4aK?usp=sharing

supporting dissemination of best irrigation practices in water constrained agricultural regions.

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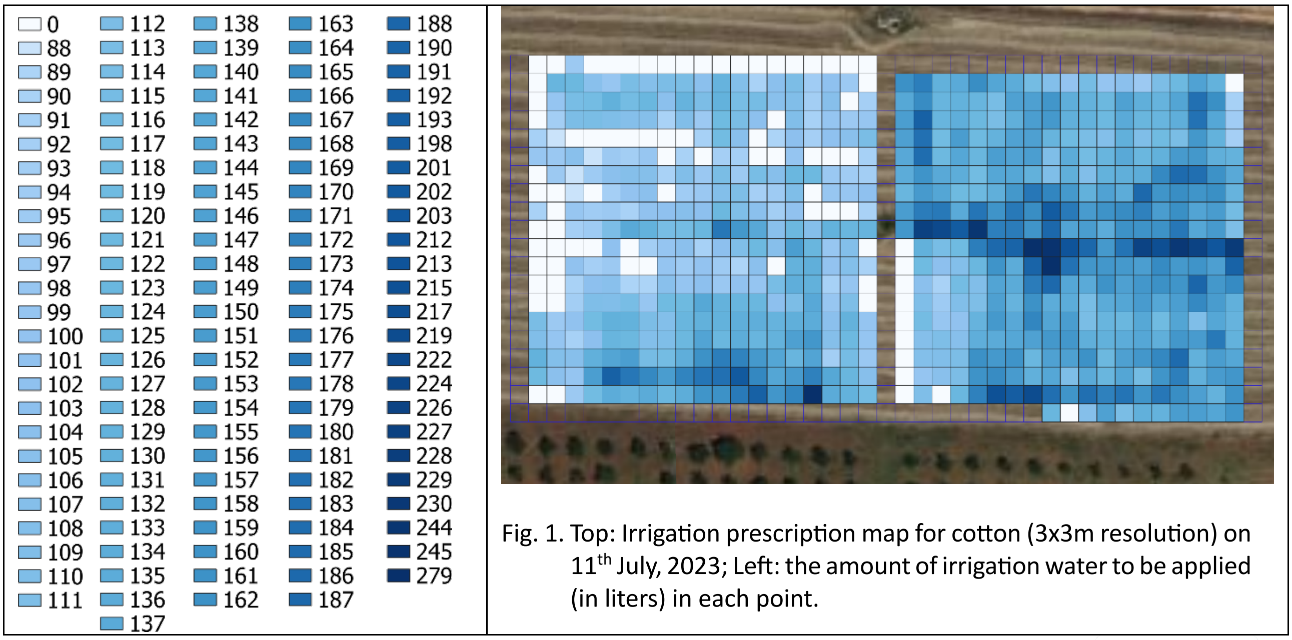

Fig. 1. Top: Irrigation prescription map for cotton (3x3m resolution) on 11th July, 2023; Left: the amount of irrigation water to be applied (in liters) in each point.

Can spatial predictors improve Random Forest predictions? A case study of mapping regional-scale groundwater levels

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Keywords: Machine learning, spatial interpolation, monthly high-resolution groundwater level mapping, Random Forest for Spatial Interpolation

Introduction

Groundwater (GW) is a vital resource for sustaining crop growth, and fluctuations in groundwater levels (GWL) directly affect agroecosystems (Tao et al., 2022). Small shifts in GWL can significantly affect agroecosystems and farm economies, especially under climate change (Shabbir et al., 2023). Therefore, it becomes important to identify the GW depletion hotspots. However, in many regions, GWL data remain limited due to sparse spatial coverage and discontinuous observations (Tsypin et al., 2024). Recent studies show that machine learning techniques can provide useful GWL estimates; however, these approaches often overlook spatial information such as distances and observations from nearby monitoring points. In this study, we examine the added value of including such spatial covariates by applying Random Forest for Spatial Interpolation (RFSI). To assess its performance, we compare the RFSI model against a conventional Random Forest (RF), a spatially adapted Random Forest (RFsp), and a Support Vector Machine (SVM).

Materials and Methods

We used RF, RFsp, SVM and RFSI to predict and map GWLs at 1 km × 1 km resolution in the federal state of Brandenburg, Germany. The RFSI model incorporates covariates accounting for (1) observations at the nearest locations and (2) their distances, enabling spatial context within the RF model. GW head measurements from 1,840 piezometers were available for 2001–2022. We selected wells suitable for analysis, excluding those affected by anthropogenic or extreme climate events. Selection criteria included: (1) data consistency, (2) observational uncertainty (RMSE ≤ 0.25 m) and (3) continuous well functionality.

Results and Discussion

Table 1 shows the Leave-one-out cross-validation (LLOCV) accuracy of the four models. RF performed worst due to limited covariates and its inability to capture residual spatial autocorrelation. RFsp accuracy improved by adding buffer distances but was still less effective than RFSI. RFSI outperformed both RFsp and SVM, likely by better capturing links between GWLs and environmental covariates (Sekulić et al., 2020). This improvement aligns with (Leirvik and Yuan, 2021), who found the mean of the five nearest stations most predictive for interpolating missing surface radiative fluxes. The trained RFSI model was applied to generate continuous, high-resolution (1 km²) monthly GWL maps for 2001–2022, covering unmonitored sites and piezometers with missing data. As shown in Fig. 1, high R^2 values confirm strong agreement between simulated and the observed GWLs across sites since 2016.

Figure 1. RFSI-based monthly groundwater depth estimates (blue line) and historical data gap filling (red dotted line)

Table 1. Model type, performance evaluation, hyper-parameters and computing time.

Model	RMSE (m)	MAE (m)	R^2	ntree	min.node.size	mtry	Sample fraction	Computing time (min)
RF	4.78	2.847	0.563	586	6	1	0.85	60
RFsp	4.51	2.836	0.654	485	3	6	0.65	125
RFSI	3.92	1.866	0.671	250	3	6	0.87	21
SVM	4.56	3.25	0.432	-	-	-	-	350

Conclusions

In this study, we proposed and tested a framework for mapping GWL using observations from the nearest locations along with their distances as additional covariates in a RF model. The resulting gridded GWL database was generated at a 1 km resolution. Our findings show that the RFSI model outperformed conventional ML methods (SVM, RF, and RFsp), with the added spatial covariates significantly improving predictive accuracy and capturing long-term GWL trends. The framework also produced reliable predictions for unmonitored sites and piezometers with missing records. Model performance from 2016 to 2022 highlights the RFSI approach's ability to reconstruct historical estimates using nearby observations and environmental variables.

Acknowledgements

The authors thank the Landesamt für Umwelt Brandenburg for providing mean monthly groundwater level observations for the Federal State of Brandenburg. This research was funded by the German Federal Ministry of Education and Research (BMFTR) through the Multi-modale Datenintegration, domänenspezifische Methoden und KI zur Stärkung der Datenkompetenz in der Agrarforschung (KIKompAg) project.

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Estimating the spatio-temporal variability of the simulated aboveground biomass yield of spring barley in Ireland

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Keywords: Cereals, Crop simulation model, Harvest, Land optimisation**,** Whole-crop

Introduction

The Irish ruminant sector is dependent on a grass-based system. However, fluctuations in the demand for grass silage supplies in recent years have increased interest in supplementary high-yielding forage crops, such as forage maize, despite variable annual yields in recent years (CSO, 2024). The cultivation of small-grain cereals on suitable soils in Ireland often yields among the highest grain yields globally. Hence, whole crop small-grain cereals may serve as a stable buffer forage supply for the ruminant sector. There have been limited studies that facilitate the evaluation of small grain cereals as forage crop options in Ireland. This study aimed to estimate the consistency and spatial variability of potential spring barley aboveground biomass yield using a parsimonious crop simulation model.

Materials and Methods

The Teagasc Spring Barley Yield Potential Crop Growth model is a simple growth and development model which utilises incident intercepted radiation, thermal time and precipitation data to simulate aboveground biomass and grain yield on a daily time step based on benchmark GAI and growth stage (GS) values observed by Kennedy et al. (2017). The aboveground biomass yield at GS 85 was extracted as a representation of whole-crop barley dry matter yield potential. Daily climate data were obtained from seven synoptic weather stations across Ireland from Met Éireann (2009-2023; Fig. 1a). The model was calibrated with observed data from nine multi-environmental experiments. March 15 was selected as the sowing date throughout the evaluated years, and the available water capacity of the soil was 285 mm. Therefore, the simulations represent the consistency of growth and development conditions, independent of factors that influence the sowing time and differences in soil type.

Results and Discussion

The simulated aboveground biomass yield ranged between 11.22 t DM ha^{-1} (Dublin) and 18.29 t DM ha^{-1} (Galway; Fig. 1b). The coefficient of variation (CV) ranged from 4.3% (Donegal) to 10.3% (Carlow). This difference is likely due to Donegal experiencing consistent rainfall and moderate temperatures throughout the period, while the greater variability in Carlow reflects greater interannual fluctuations in incident solar radiation and drought events in the simulation at this site.

For grain yield, the variability was more substantial than that of aboveground biomass yield, ranging from 7.25 to 24.2%. The CV values were greater than 10% for all the sites except Donegal (7.25%). The highest mean simulated grain yield was recorded in Donegal and Cork (9.91 and 9.74 t ha^{-1}), whereas the least was simulated from Carlow (8.32 t ha^{-1}; Fig. 1c). Carlow and Dublin (24.2% and 20.9%) recorded the highest variability as compared to Donegal (7.25%), which recorded the least variability.

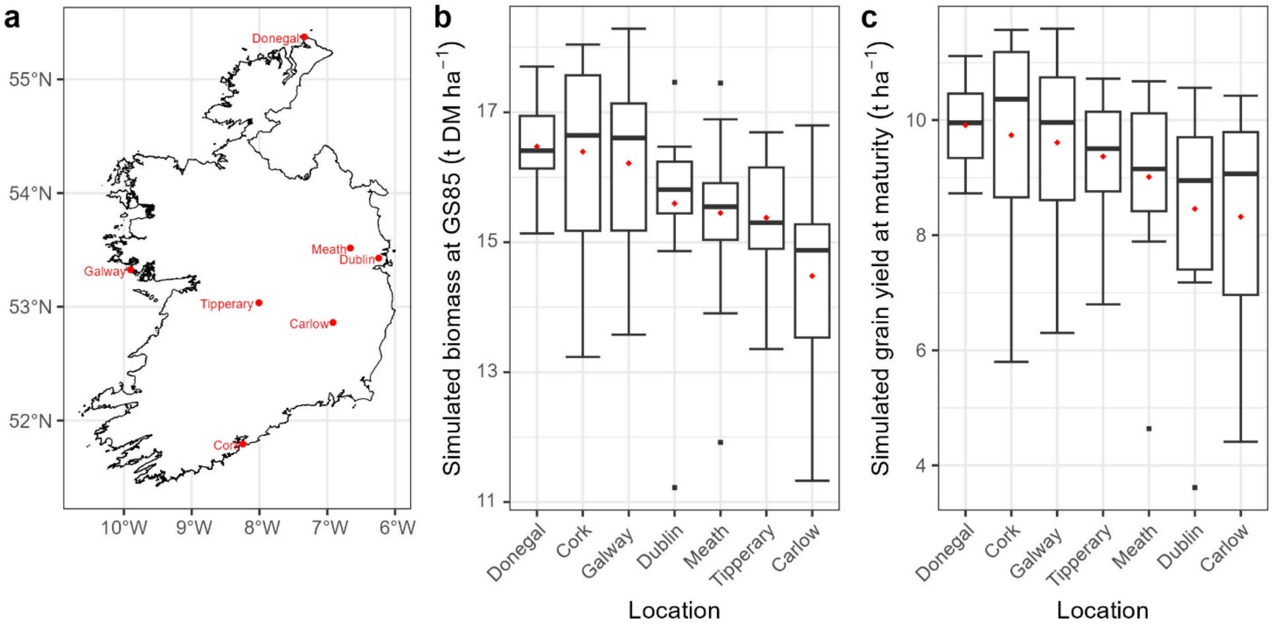

Figure 1. (a) Study sites and spatial variability of simulated spring barley (b) aboveground biomass at GS85, and (c) grain yield at maturity.

Conclusions

Simulation results indicated that the aboveground biomass yield potential exhibited lower interannual variability than the grain yield at a number of evaluated locations in Ireland. Furthermore, the largest mean yield differences between sites tend to reflect the likelihood of drought impact in model simulations, when differences in soil profiles and sowing date were not considered.

Acknowledgements

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Development and first evaluation of a white clover sub-model to extend the Most GG capabilities

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Keywords: white clover, grassland modelling, biological nitrogen fixation

Introduction

Since 2019, the Moorepark St Gilles Grass Growth (MoSt GG) model (Ruelle *et al.,* 2018) has predicted daily on-farm perennial ryegrass (PRG; *Lolium perenne* L.) growth in Ireland using local weather and farmer management data (nitrogen (N) fertiliser application, pre-/post-grazing sward height, rotation length). It simulates N dynamics, including organic and mineral N, N leaching and gaseous emissions. In the last 5 years, white clover (WC; *Trifolium repens* L.)) adoption has increased in Ireland to reduces reliance on synthetic N fertiliser and help improve farm profitability. Given the increasing adoption of PRG-WC based systems, it is essential to adapt the MoSt GG model to accurately predict PRG-WC sward growth.

Materials and Methods

MoSt GG model, developed in C++, is a mechanistic process-based model running at a 2 m^2 scale and a daily time-step. Based on the original PRG model, the new version adds WC biomass dynamics, biological N fixation (BNF) and inter-species competition. While PRG relies on soil mineral N uptake only, WC balances soil N with atmospheric N fixation, which increases as soil mineral N declines (Ledgard *et al*., 2001). The growth and environmental response functions use species-specific parameters with new functions developed for WC N nutrition. The outputs include daily growth, biomass partitioning, N and water dynamics, BNF and sward N content.

Simulations were run over 21 years (2003-2023) of Teagasc Moorepark synoptic weather station data. A heavy (HS) and a free draining (FD) soil were compared. Two sward types were simulated (PRG- only and PRG-WC) under rotational grazing (21- or 30-day interval), with three N fertiliser rates compared (0, 150 or 250 kg N ha^{-1}; 0N, 150N, 250N). Cow number per grazing rotation was automatically adjusted to graze the available biomass (>4 cm) in a day with a fixed intake of 16 kg DM cow^{-1}.

Results and Discussion

Annual herbage yields were always higher for PRG-WC than PRG-only. The yield response on FD soils to addional N fertiliser application was greater for PRG-only than PRG-WC (+21 *vs* +18 kg DM kg N^{-1}; from 0 to 250N), but PRG-WC produced 3 t DM ha^{-1} more than PRG-only at 0 and 150N, with the gap narrowing at 250N. Similar results were observed on HS soils, with higher absolute yields for PRG-WC (Fig. 1C). The model reproduces the benefit of clover at low N and the dimishing return of increasing N fertiliser. The greater PRG N response leads to PRG outcompeting WC, with WC content falling from 24-30% at 0N to 5-18% at 250N, consistent with field data (e. g. Burchill *et al*., 2014). At 150N, PRG-WC yield outperformed PRG yield at 250N by 7% on average, showing the efficiency of BNF as a substiture for N fertiliser. The PRG-WC supported more grazing days, particularly on HS soils, and longer rotations (Fig. 1A). The year-to-year and seasonal variability was well reflected (Fig. 1B), for example, the 2018 summer drought affecting growth. Peak growth was reached earlier for PRG-only swards than PRG-WC swards. The BNF declined as N fertiliser inputs increased (fig. 1D), from 70-81 to 32-48 kg N ha^{-1}, due to a reduced WC content and its simulated inhibition by soil N (Ledgard *et al*., 2001). On HS, PRG-WC produced more despite less WC and BNF than on FD soils. This is partly explained by more N leached in FD soils and lower N mineralisation rate.

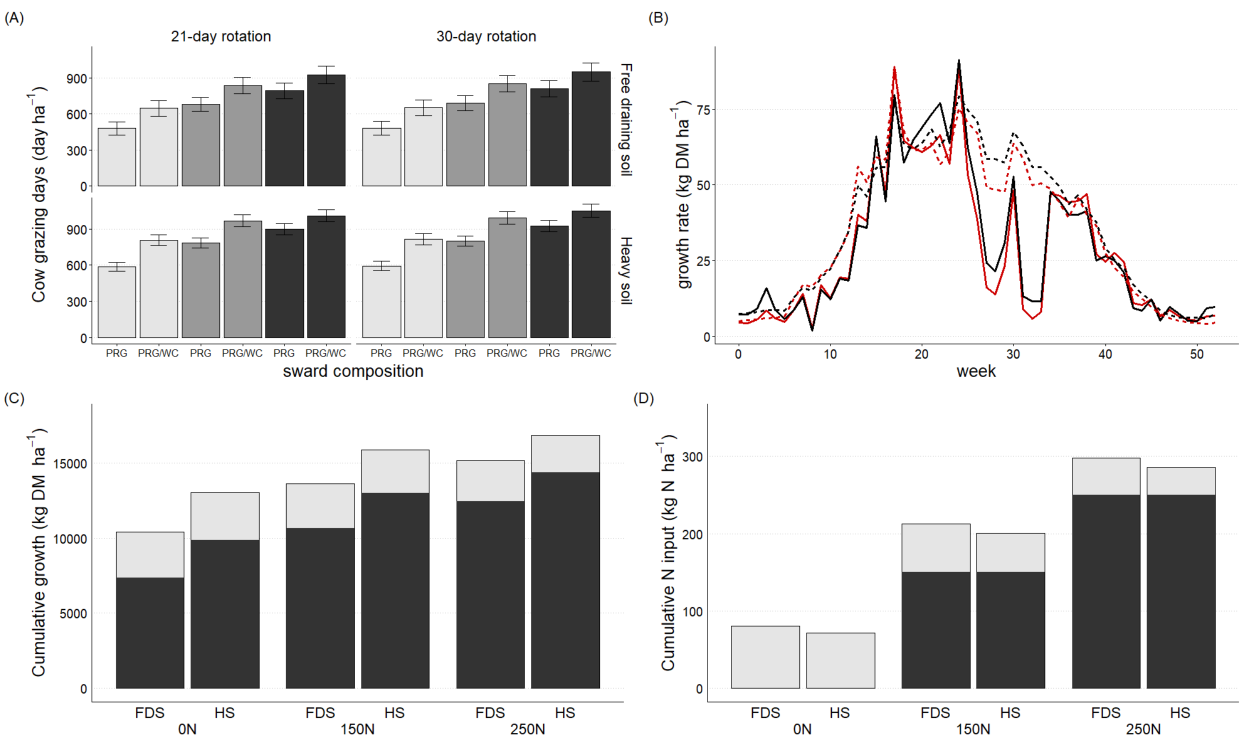

Figure 1 : (A) average annual number of cows grazing days and standard deviation for each treatment combination (light grey is 0N, dark grey is 150N and black is 250N) ; (B) average growth of PRG-WC swards at 150N (black) and PRG swards at 250N (red) for the average of the period (dotted) and in 2018 (summer drought; plain); (C) comparison of cumulative growth on PRG+WC swards (PRG in black, WC in grey); and (D) total N input (N fertiliser (black) + N fixation (grey)) to PRG-WC swards under a 30-day grazing rotation for all combinations of soil types (FDS = free drainins, HS = heavy) and N rates.

Conclusions

A new sub-model was developed for the MoSt GG model to simulate growth on PRG-WC swards. Evaluation shows that it can simulate BNF and predict herbage yield, quality, and seasonality as expected.

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Site-specific nitrogen fertilization from yield predictions using high-resolution soil maps and weather forecast

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Keywords: precision fertilization, nitrogen modeling, crop yield forecasting, high-resolution soil maps

Introduction

Nitrogen (N) fertilization is a key factor in achieving high crop yields, ensuring product quality and maintaining soil fertility. For an economical and environmentally friendly crop production, it is necessary to apply the optimum amount of nitrogen fertilizer in line with the crop's N-demand. In practice, however, determining the optimum fertilizer rate is still a challenge, as numerous influencing factors have to be taken into account, e.g., the targeted crop yield or the content of plant-available mineral nitrogen in the soil. Therefore, this contribution presents a model-based approach for site-specific nitrogen fertilization, which takes into account the variability of crop growth and nitrogen uptake based on sensor-derived soil properties and weather forecast during the growing season.

Materials and Methods

The approach was first developed and tested on a 29-hectare arable field in Brandenburg, Germany, within a crop rotation (winter triticale (*Triticum aestivum*), winter rye (*Secale cereale*), sorghum (*Sorghum bicolor*) and winter triticale) between 2019–2022. Nitrogen uptake was modelled and N-fertilization prescription maps were computed for winter triticale in 2022. For the biomass and grain yield simulation, the "Model for Nitrogen and Carbon Dynamics in Agro-ecosystems" (MONICA) was used (Nendel et al. 2011). High-resolution (10 m) maps of clay, silt, and sand in 20 × 10 cm layers were derived from inverted apparent electrical resistivity (ERa) data collected with the Geophilus multi-sensor platform (Lueck & Ruehlmann, 2013) and calibrated using soil samples taken from 3–5 horizons in 10 representative profiles (Roudsari et al., submitted). Together with soil organic carbon (SOC) maps of the topsoil derived from Sentinel 2 bare soil images (Schröter et al. 2025), the soil texture maps were used to derive soil physical and hydrological parameters (bulk density, pore volume, field capacity and permanent wilting point) by applying pedotransfer functions. Daily weather data (precipitation, temperature, radiation, windspeed and relative air humidity) was taken from the German Meteorological Service (DWD) for historical data and for prognostic data from the European Centre for Medium-Range Weather Forecasts (ECMWF). Modelled soil moisture was validated with soil moisture monitoring data from 2023 and 2024 of the 10 profiles using TDR and PR2 probes (UP Umweltanalytische Produkte GmbH, Cottbus, Germany). The triticale yield forecast was modelled once using the daily documented weather data and once the prognostic weather data. The evaluation of the biomass and yield predictions were compared with harvester monitoring data. Results in the N-requirements and associated costs were compared to a field uniform fertilization strategy.

Results and Discussion

The root mean square error (RMSE) for the 3D clay map was 13.9% (coefficient of determination, $R^2 = 0.52$), for sand 14.1% ($R^2 = 0.71$), for silt 4% ($R^2 = 0.78$), for SOC 0.27% ($R^2 = 0.71$) and for the modelled soil moisture distribution at the survey dates 4 Vol% ($R^2 = 0.75$). The crop yield, N-crop removal and the N-requirement were modelled for the first N fertilization date (1 March 2022), the modelled mean yield of the field was underestimated by only 0.22 t ha^{-1} using the documented daily weather as reference. Using the prognostic weather, the mean yield deviation was 0.86 t ha^{-1}. However, the amplitude of spatial differences was not yet simulated adequately in both predictions. Nevertheless, the prediction of crop yields was used to estimate the expected N removal at the harvest date. While the field uniform fertilization approach resulted in a N quantity of 135 kg N/ha, the quantities calculated using the site-specific approach varied between 40 kg N ha^{-1} in the low-yielding sandy areas and 130 kg N ha^{-1} in the loamy areas having an average of 101 kg N ha^{-1}. The site-specific fertilization resulted in estimated savings of around 51 € kg^{-1} ha^{-1} compared to the "traditional" fertilizer requirements.

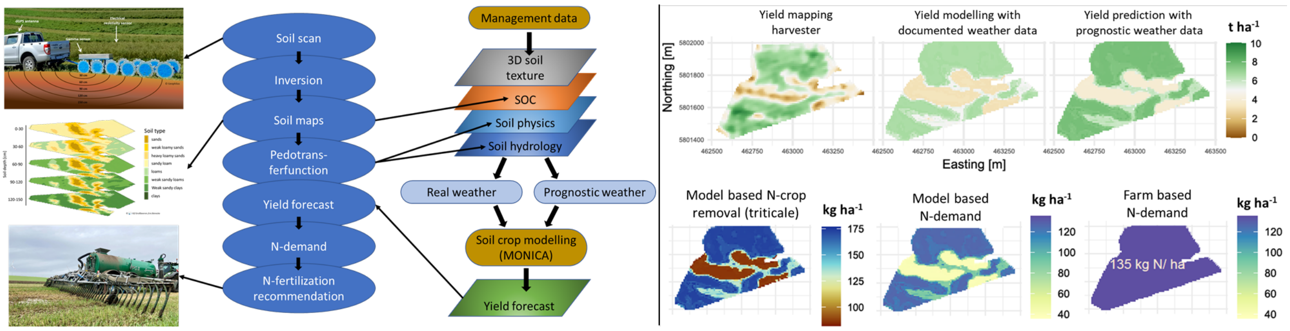

Figure 1. Left: Workflow to determine variable N-fertilization. Right: spatial variability of the original yield harvester monitoring (upper left), modelled yield data based on dicumented weather data (upper middle), modelled yield prediction based on weather prognosis (upper right), N-crop removal of the triticale yield (lower left), model based N-deman (lower middler) and farm based field uniform N-demand (lower right).

Table 1. Overview variability of yield modeling compared to harvester monitoring data (SD = standard deviation).

	Min	Max	Mean	SD
Yield mapping harvester	0.2	10	5.7	1.8
Yield modelling with documented weather data	3	6.7	5.5	1.4
Yield prediction with prognostic weather data	3.7	7.9	6.6	1.5

Conclusions

The developed approach can be used as a decision support for site-specific nitrogen fertilization. However, the need for improved model parameterization and calibration of the underlying soil texture and SOC maps as well as soil moisture modeling is required to address spatial heterogeneity more adequately. Savings in the total fertilizer costs of approx. 25% could be realized as 35 kg ha^{-1} more fertilizer was applied than necessary in the conventional approach.

Acknowledgements

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PastureBase Ireland – Results from Ireland national grassland database and decision support system

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Keywords : Grassland, Decision support, databases, grazing.

Introduction

PastureBase Ireland (PBI) is a web-based grassland management decision support tool that was first developed in 2013 for Irish grassland farmers. The secondary purpose of PBI is to serve as the national grassland database for Irish grassland farmers. PBI is designed to allow grassland farmers to improve their grassland management on farm. It offers farmers 'grassland decision supports' and stores the data from dairy, beef and sheep farmers in a central national database. In 2024, there was over 14,000 farms registered on PBI. Approximately 50% of all pasture covers are now uploaded from the PBI mobile application where users with more than 25 annual covers on PBI use the mobile application for most of their data recording events. There has been a clear, continual increase in grassland measurement on dairy farms over time. The integration of the Moorepark St Gilles (MoSt) grass growth model into PBI started in 2023 and will be rolled out fully in the next years. The objectives of using PBI on grassland farms is to focus on optimising pasture utilisation across all ruminant sectors, improving farm productivity, promoting sustainable grazing practices and supporting evidence-based decision-making on Irish grassland farming. This paper investigates the grassland management performance from a 11 year dataset of a sample of grassland farms (n = 163) taken from the PBI database and describers their performance from 2013 -2024.

Materials and Methods

PastureBase Ireland

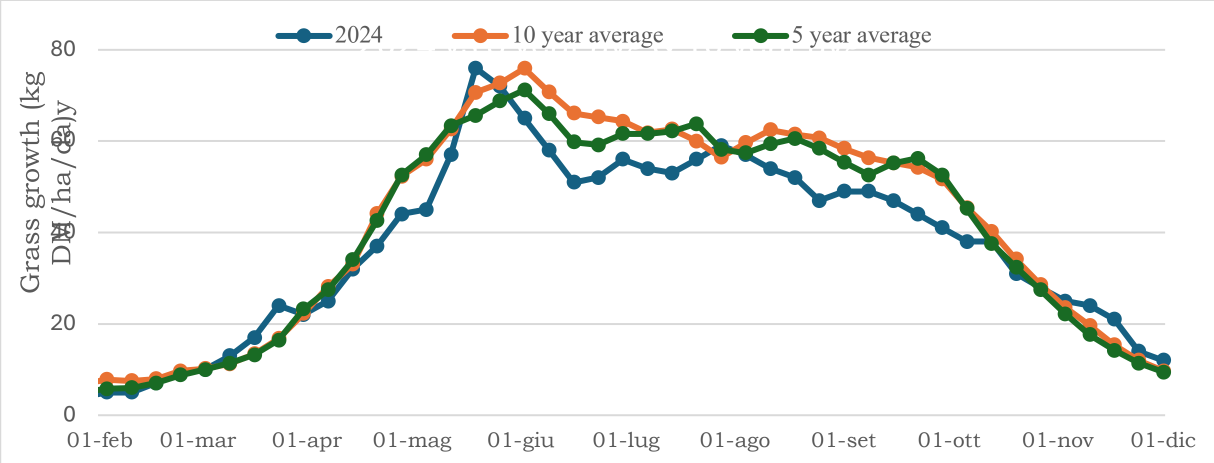
Pasture Base Ireland (PBI) (Hanrahan et al., 2017) has a range of grassland support tools available to farmers to assist in short-, medium- and long-term grassland decisions. Each year there is a growing number of farmers using the application. In 2024, over 142,000 farm covers were recorded, an increase of 43,000 since 2022. There is a clear, and continual increase in grassland measurement across the country, which has been aided by the grassland measurement requirement for farmers with a nitrate's derogation plan. Currently over 2,000 spring/autumn rotation planners are completed in PBI per year. There are over 11 Application program interfaces linked from external Agri industry partners linked to PBI, these include Jenquip plater meter, Grasshopper plate meter, dairy Co-ops, Feed and soil analysis labs etc.

On Irish farms clover is now becoming more popular, due in part to reductions in chemical N allowances on farm. A number of new decision support tools have been developed in PBI to assist strategic decision making regarding nutrient application, including the 'Nitrogen Planner', Nitrogen Cycling calculator. Conserving adequate feed levels for the winter period is a growing challenge for farmers in recent years due to grass growth variability and climate challenges. A key tool has been developed in PBI to allow farmers to quantify fodder supplies on their farms. PBI has developed as an influential software tools that farmers can use to better manage their grassland systems.

Results and Discussion

Grazing management and grass DM production data from 163 farms recording >35 covers on PBI annually over an 11-year period (2014 – 2024), annual pasture growth averaged 13.2 t DM/ha during that period, with 7% variation in DM production (+/- 907 kg DM/ha) between years. Spring pasture DM production had greater variation compared with summer and autumn (Table 1). On average, over the 11 years, spring (Jan – April) pasture DM production was 1.8 (+/- 0.3) t DM/ha, summer (May – July) DM production was 6.2 (+/- 0.5) t DM/ha, and autumn (Aug – Dec) DM production was 5.3 (+/- 0.3) t DM/ha. The average number of days at grass ranged from 274 to 296 days between years, with an overall mean of 285 grazing days.

Figure 1. *Weekly grass growth on PastureBase Ireland dairy farms (2013- 2024)*



Conclusions

PastureBase Ireland is a multi-purpose grassland tool that allows farmers to improve grazing management, fodder security, and nutrient management on the farm. It is an ever-evolving decision support tool. The objective within PBI is to continue to add new features to help farmers' usability of the application and to improve management practices on farm. Future developments that are planned include greater incorporation of the MoSt grass growth model into the application. The future of grassland systems will depend on the ability to increase herbage production within the constraints of reducing chemical N fertiliser inputs. Using available technologies and achieving grazing management targets will be critical to meeting these challenges. PastureBase Ireland may in the future develop as a European grassland database.

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Mapping crop water footprint in the Upper Syr Darya Basin, Central Asia using ACEA model

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Keywords : water consumption, green-blue water, water scarcity, Central Asia

Introduction

The Upper Syr Darya Basin is a critical agricultural region in Central Asia that depends heavily on the Syr Darya River for irrigation, particularly for water-intensive crops such as cotton. Increasing and, at times, excessive pressure on water resources has led to severe shortages, inefficient practices, and widespread water insecurity, as dramatically demonstrated by the environmental collapse and near disappearance of the Aral Sea (Berdimbetov et al., 2020; Gupta, 2020; Hoekstra, 2020; Loodin, 2020). Despite formal transboundary agreements governing water allocation among riparian nations, effective cooperation at multiple governance levels remains highly constrained (Abdolvand et al., 2015). This lack of collaboration hampers data sharing, impedes evidence-based decision-making, and undermines policy development (De Keyser et al., 2023). As agriculture accounts for approximately 90% of total water withdrawals in the region, precise spatial quantification of the crop water footprint, distinguishing between green (rainfed) and blue (irrigated) water use is essential for informed water-resource management. This study aims to quantify the crop water footprint, analyze interannual variability, and identify hotspot areas to support policy interventions.

Materials and Methods

The ACEA crop water productivity model, developed by Mialyk et al. (2022), is implemented in Upper Syr Darya Basin at an enhanced spatial resolution of 5 arc-minutes for the period 2000–2019. ACEA is based on AquaCrop-OSPy v6.1, which mimics the daily crop growth and vertical soil water balance. The model distinguishes, green and blue from capillary rise, and irrigation, enabling precise green-blue water accounting throughout the crop growing season. The model input datasets like climate forcings, CO2 concentration, groundwater table, and crop-specific parameters were consistent with the original setup. The soil layer was updated in the model with Soil Grids data version 2.0 (Poggio et al., 2021) to improve the spatial resolution of soil layer. Model outputs are analysed for the historical period 2000–2019 to capture interannual variability and spatial patterns in crop water use and also computed at the monthly scale.

Results and Discussion

Spatially explicit maps of crop water footprint are expected to reveal significant variation in blue water consumption, especially in cotton irrigation systems across the Upper Syr Darya Basin. The ACEA implementation is anticipated to provide quantitative separation of consumptive green and blue water footprints at high spatial resolution. This capability will help identify areas of inefficient water use and support the development of scenarios to improve irrigation efficiency.

Conclusions

Regional ACEA modeling provides a robust framework to address critical data gaps in quantifying consumptive crop water footprints at high spatial and temporal resolution in the Upper Syr Darya Basin. The process-based approach enables accurate separation of green and blue water consumption components, essential for developing targeted water conservation strategies in this water-scarce region. Results will provide essential insights to optimize water allocation, improve irrigation management efficiency, and guide sustainable agriculture practices, contributing to regional water security.

Acknowledgements

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Real-time detection of situations which need crop model reparameterization for soil nitrogen stock estimation

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Keywords: winter wheat, dynamic model, remote sensing, regression trees, soil nitrogen stock validation.

Introduction

CHN, a crop model developed by Arvalis, simulates daily crop state and its growth forecast at field level. One of the main uses of its outputs is to manage nitrogen fertilization on winter wheat. It is coupled with Sentinel 2 data (Piquemal et al., 2020) and the repeated satellite acquisitions estimate regularly Leaf Area Index and Nitrogen Content, variables used to confirm or correct model simulations during the cropping season.

Deployed at large scale, CHN in certain plots can simulate a wrong estimation of soil nitrogen (SN) stock, variable which play a key role in building nitrogen input advice. The best proxy indicator to identify fields with a wrong estimation of SN stock is the difference between plant nitrogen quantity simulated by CHN and the one measured using satellite data (=ΔQNf) at flowering stage (last date of nitrogen input management). If ΔQNf exceeds 20 kgN ha^{-1} on a field, SN stock needs to be adjusted.

The aim of this study is to build and evaluate a method to predict ΔQNf with indicators calculated at early stages in winter wheat cycle. In campaign, it will be used to flag fields that need SN stock adjustment.

Materials and Methods

259 fields of different trials network located in France are used. They cover all metropolitan area from 2020 to 2024. For each field, we get back CHN outputs with or without using Sentinel 2 data in the model, calculate ΔQNf at flowering stage and tag fields that need SN stock adjustment.

Many indicators describing the discrepancy between model output and sensor data are calculated at three dates in the beginning of crop cycle (for instance, the difference between biomass simulated by CHN and the one calculated with sensor data). Regression trees using CART (Breiman et al., 1984) are built on these predictors to identify thresholds that can separate tagged fields from the others.

Results and Discussion

Table 1 presents the performance on an independent dataset of previous indicators to flag fields with high ΔQNf at flowering stage. Indicators detect 76% of all fields tagged. Nonetheless, some tagged fields are still non detected, and 12 non-tagged fields are detected. This can be linked to low satellite coverage, bad quality acquisitions or specific environmental conditions on these fields.

	Tagged fields (ΔQNf > 20 kg N ha^{-1})	**Non-tagged fields** (ΔQNf < 20 kg N ha^{-1})
Positive Detection	53	12
Negative Detection	16	15

Table 1. Confusion matrix of the indicators used to predict fields which need SN stock adjustment (= tagged fields)

Conclusions

The detection method developed shows great performances to identify fields that need SN stock adjustment. Nevertheless, it is mainly dependent of the coverage and quality of satellite data, especially around the dates used for prediction. Despite the high number of years considered in the study, the question of the stability of indicators and associated threshold from one year to another can be limiting, particularly in case of year with atypic environmental conditions.

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Challenges of applying crop models in Decision Making and Innovation in sub-Saharan Africa

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Abstract

Crop models integrate diverse datasets; weather, soil properties, crop genetics, and management practices - to predict outcomes such as biomass accumulation, phenological stages, and final yields. They enable scenario testing without the high costs of repeated field trials and allow lessons to be transferred across environments. However, in sub-Saharan Africa (SSA), modelling efforts are constrained by data scarcity. This review assesses progress on the use of crop modelling in decision-making and innovation in SSA, highlights persistent challenges, and outlines areas for improvement. Evidence suggests that the limited availability of reliable historical data, particularly at the required temporal resolution, is a key barrier. Moreover, uncertainties in model calibration, climate projections, and management assumptions further limit the reliability of future yield predictions.

Key words: complexity, model coupling, data sources, soil variability, future management

1. Introduction

Crop modeling has high potential to play a crucial role in modernizing agriculture, enabling science based and data-driven decision-making and enabling innovation (Boote et al. 2017; Corbeels et al. 2018). Crop modelling involves the use of mathematical and computational simulations to represent crop growth, development, and yield under varying environmental, genetic, and management conditions. These Crop models are broadly classified into empirical (statistical relationships) and process-based (mechanistic, simulating physiological processes) types. By functioning as virtual laboratories, they allow researchers, policymakers, and farmers to explore scenarios and optimize management strategies without costly or time-intensive field trials. In this paper, I highlight four major areas that need attention for improve model use in decision making and innovation in Africa.

2. Challenges of model application in SSA

2.1 Abstraction vs. complexity: Most models are an abstraction because they are simplified, incomplete representations of complex reality, focusing on specific features while ignoring others to achieve a particular goal or gain understanding. However, SSA has very diverse socio-ecological conditions. This diversity is underpinned by a combination of biophysical factors such as soils and climate, socioeconomic factors such resource ownership and access capital and markets as well as farmers' production orientation (production for cash vs. sustenance). Soil degradation and unpredictable rainfall synergistically constrain food production and the viability of smallholder agriculture in SSA, where 90% of main crop production is under rain-fed conditions. The wide variability of soil and rainfall precludes the widespread use of crop models for decision making and innovation (Challinor et al. 2018).

2.2 Data limitation: Data limitations for crop modeling in Africa stem from a combination of infrastructural, economic, and environmental challenges. Many African regions lack robust data collection systems, with limited weather stations, soil sensors, and satellite coverage providing inconsistent or incomplete data on climate, soil properties, and crop performance (Silva and Giller 2021). Financial constraints and underfunded agricultural research institutions hinder the development and maintenance of comprehensive databases. Additionally, the diversity of smallholder farming systems, coupled with varied agroecological zones, makes standardized data collection difficult. Political instability and poor coordination among governments, NGOs, and research bodies further exacerbate gaps in data sharing and accessibility, limiting the accuracy and applicability of crop models for improving agricultural outcomes.

2.3 Model coupling: Corbeels et al. (2018) assessed the reliability of coupling climate model projections with process-based crop growth models to assess climate change impacts on crop yields and inform specific management-level adaptation strategies. They reported significant uncertainties in such approaches, particularly from global circulation models (GCMs), which are combined with uncertain future management regimes and argued for a more cautious application. Selection of the correct crop model and GCM combination is critical to obtain realistic and reliable results. The use of GCMs in Africa is unreliable due to the coarse spatial resolution and limiting their use in coupling with crop models for climate change prediction (Tanimu et al. 2024)

2.4 Science of translation: A persistent challenge is bridging the gap between model outputs and practical decision-support tools. Participatory modelling, where farmers and other stakeholders are directly involved in the calibration and validation process, is essential for building trust, improving adoption, and ensuring that models generate actionable insights

3. Conclusions

Crop models offer powerful tools for simulating the complex interactions between crops, environments, and management practices. They can guide resource optimization, risk mitigation, and the design of sustainable farming systems. However, in SSA, their potential remains underutilized due to ecological heterogeneity, data scarcity, and the uncertainties inherent in climate–crop coupling. Moving forward, investments are urgently needed in (i) developing models tailored to SSA conditions, (ii) improving GCM resolution and downscaling, (iii) strengthening soil and crop data collection systems, and (iv) embedding participatory approaches to ensure outputs translate into locally relevant, actionable decisions.

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Causal machine learning for fertilizer recommendations: offline bandit policy improves profit in historical evaluation

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Keywords: causal ML; contextual bandit; off-policy evaluation; crop modeling; fertilizer optimization

Introduction

Blanket fertilizer guidelines often misallocate inputs across heterogeneous soils and climates, depressing profitability (Murphy et al., 2024). We aimed to develop and rigorously vet a support-aware, site-specific N–P_2O_5–K_2O recommendation policy learned entirely from historical data, targeting higher expected profit while remaining within empirically supported practice.

Materials and Methods

We used a multi-year agronomic dataset from on-farm maize trials in Chiapas (2012–2018; 4,585 field-seasons) with yield, management (N, P_2O_5, K_2O), soil, topography, and weather features (Trevisan et al., 2022). Yields span 0.1–10.0 Mg ha^{-1}, reflecting high variability typical of smallholder systems.

We trained a stacked surrogate reward model (XGBoost, LightGBM, CatBoost; Ridge meta-learner) using grouped cross validation (CV) by geo-clusters and train-only adaptive action binning to mirror off-policy support.

Policy learning followed a contextual-bandit framing with conservative constraints (ensuring support coverage and utilizing baseline-mixing) to avoid extrapolation beyond observed fertilizer regimes.

Evaluation used a conservative off-policy protocol based on self-normalized doubly robust (SNDR) estimators with cluster-bootstrap confidence intervals and multiple validity gates (mass-in-support ≥0.95, overlap ≥ 95% with $\pi_0(a) \geq 0.1$, acceptable weight distribution/ESS, and uplift lower confidence bound (LCB) > 0), rejecting any year that failed a gate.

Results and Discussion

The surrogate achieved out-of-fold $R^2 \approx 0.59$–0.62 with RMSE ≈ 1.20–1.26 t ha^{-1} in most recent years (2016–2018), indicating strong predictive skill for noisy agronomic outcomes; 2015 was an expected outlier ($R^2 < 0$).

The joint propensity model over 36 N–P_2O_5–K_2O cells was well-calibrated (Test ECE = 0.020) with broad action-space coverage (34/36 cells observed; 28 cells ≥10 samples), supporting reliable weighting.

Applying the conservative OPE gates, five of six evaluation years (2013, 2014, 2016, 2017, 2018) showed statistically significant profit gains over baseline; 2015 failed due to a negative uplift LCB and was rejected. Averaging across accepted years, we achieve a mean profit uplift of ~+5.9%.

To translate these findings into practice, we built a bilingual web app that operationalizes this winning policy: users enter field conditions, and the app recommends optimal N–P_2O_5–K_2O rates, with appropriate guardrails. This implementation demonstrates how conservative, offline-validated policies can be delivered in an interpretable tool for smallholders and extension partners, directly linking our causal ML results to actionable advice.

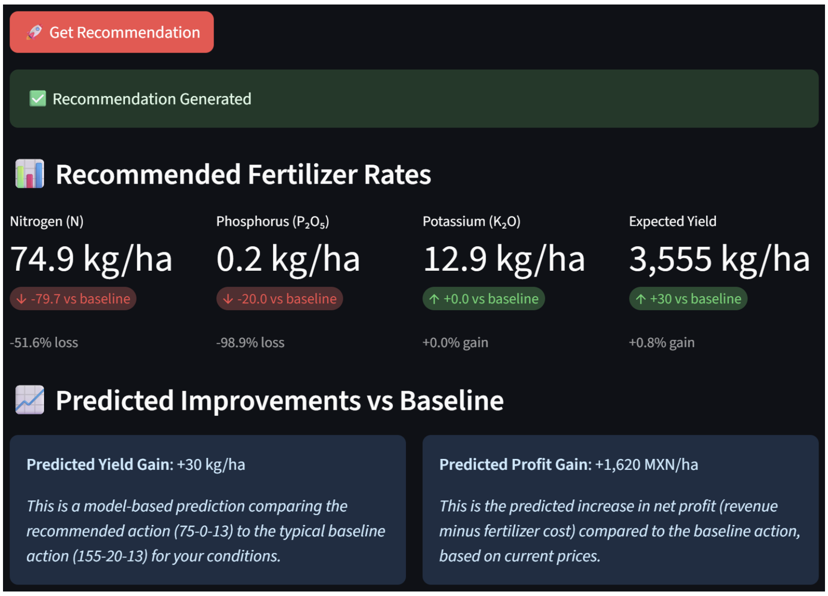

Figure 1. Screenshot of example recommendation in app

Conclusions

Our offline contextual-bandit policy trained on CIMMYT's Chiapas dataset using conservative causal machine learning (ML) methods yields consistent, statistically-validated profit improvements in historical evaluation while honoring strict safety constraints. This offers a practical pathway to deliver site-specific fertilizer advice to smallholders – improving profitability without recommending untested doses – ready for cautious pilot deployment.

Acknowledgements

We thank the farmers and extension partners in Chiapas who contributed to the multi-year on-farm dataset, and the International Maize and Wheat Improvement Center (CIMMYT) for open data access.

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Combining crop modeling and high-resolution data for enviromics to detect high performing and stable cultivars

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Keywords: Crop modeling; Genotype environment interactions; Ecophysiology; Environmental covariates; Envirotyping ; Partial least square regression.

Introduction

The identification of high yielding cultivars performing consistently under heterogeneous soil and climate contexts constitutes a major challenge for the resilience of agricultural systems. Understanding the substantial intra and inter-annual yield variations largely observed across cereal and oilseed crops requires to decipher the environmental factors driving yields and Genotype x Environment Interactions (GEI) for yield (Fekadu et al., 2023; Han et al., 2023). Cropping models combined with emerging approaches characterizing environmental factors and their contribution to GEI can enhance our understanding of the main drivers of GEI within each agricultural territory. Such approaches would enhance varietal recommendations while contributing to a better understanding of cultivar adaptations.

Materials and Methods

To unravel the main factors driving yield as well as GEI and highlight high performing stable genotypes we adapted an approach combining high resolution climatic and pedological data and crop modelling (Bicard et al., 2025; Corlouer et al., 2024; Le Roux et al., 2024). Simulated and observed phenological stages were employed to calculate a wide range of environmental covariates among which critical drivers were selected. To understand diverging and converging patterns of adaptation to increasingly unstable climatic conditions among major crops and support consistent yields at regional level three majors crops with contrasted crop cycles were examined: winter wheat, spring barley and winter rapeseed. Partial least square regression was employed for unbiased selection among often correlated environmental covariates based on a regional varietal trial dataset with 13 to 31 environments and 7 genotypes per species. Patterns among critical environmental covariates driving GEI and their occurrence were further characterized at regional level (Bicard et al., 2025). Finally, genotype yield performance and static and dynamic stability were analyzed via several approaches such as the additive main effects and multiplicative interaction model and the genotype plus genotype-by-environment biplot along with performance and stability indices, notably based on environmental clustering.

Results and Discussion

Important GEI were observed within the regional trial network, with interactions between proposed environmental clusters and genotypes having similar or superior effects on yield compared to genotypic main effects. Higher GEI were observed for wheat and rapeseed than for spring barley for which the genetic pool is more limited. Contrasted critical environmental covariates were selected for the three main crops with varied cropping cycles examined, with several pedological factors retained as key drivers of GEI. Environmental clustering underlined high variability of environments within the Northeastern region of France analyzed with cluster occurrences over 10 years often close to 30%. We observed variations in how genotypes adapt to changing conditions with different profiles with regards to yield performance and consistency. For high performing genotypes, our results reinforce tradeoffs between yield performance and stability. Nonetheless, optimal genotypes with good yield performance and high stability indices were highlighted.

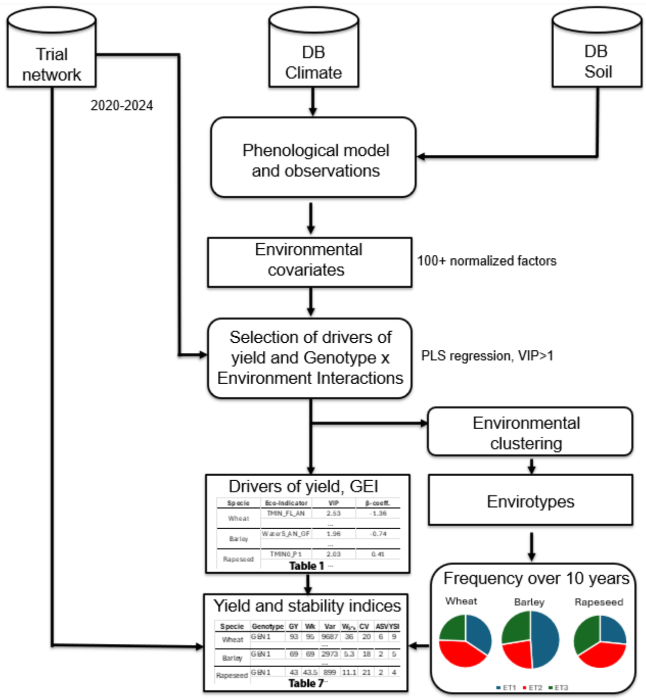

Figure 1: Workflow and outputs of the approach developed

Conclusions

The approach developed allowed to improve knowledge of critical environmental factors driving yield performance and GEI for yield of three important crops at regional level. Even at the regional level and with the limited number of repeated genotypes in the agricultural cooperative trial network analyzed our results underlined large influence of GEI emphasizing the challenges in identifying and deploying high yielding cultivars performing consistently. Critical environmental covariates estimation via crop modelling and high resolution pedoclimatic data could support further explorations of future climate scenarios under climate change and their consequences for genotype performance and stability. The genotypes with high yield stability and medium to high performance highlighted could contribute to stabilizing production in already variable and increasingly heterogenous conditions. The approach developed could contribute to varietal recommendations for farmers while deepening our understanding of genetic resources to better guide breeding strategies.

Acknowledgements

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In-Season Yield Forecasting for Risk Management under Climate Variability with CRAFT

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Keywords: Climate change; climate uncertainty; adaptation; resilience; decision support systems

Introduction

Climate variability and unpredictable extreme weather events have led to disruptions in food production and increases in market prices. The food crises of the 2000s and 2010s, triggered by extreme weather events, underscore the need for swift, timely, and accurate decisions in agricultural production. Therefore, timely and accurate yield and production forecasting is becoming increasingly vital for informed crop management and financial decision-making.

When producers have earlier access to seasonal climate forecasts during the growing season, they can implement more effective management practices to optimize their yields. By utilizing accurate seasonal climate forecasts, in-season yield forecasting enables decision-makers to plan early and estimate production levels and related market prices. The goal of this study was to evaluate the capabilities of the CRAFT spatial in-season yield forecasting system for effective risk management in response to climate uncertainties.

Materials and Methods

Gridded simulations using the Decision Support System for Agrotechnology Transfer (DSSAT) and the CCAFS Regional Agricultural Forecasting Toolbox (CRAFT) were used as a method. The DSSAT is a software application that comprises crop simulation models for over 42 crops, as well as tools to facilitate the effective use of these models (Hoogenboom et al., 2024). To obtain regional and nationwide spatial results, the CRAFT was developed and integrated with DSSAT, which allows field-level simulations. CRAFT is a multi-scale and multi-model gridded framework for forecasting crop production, risk analysis, and climate change impact studies (Shelia et al., 2019; Tesfaye et al., 2023). CRAFT enables spatial yield predictions to be obtained at a five-arcmin resolution using local weather, soil, and crop management data. Wheat, which is widely cultivated across Türkiye, was selected for the study. Areal crop production and crop mask data were obtained from IFPRI's Spatial Allocation Model (SPAM) for 2020 Version 2.0 (IFPRI, 2024). Daily historical weather data were obtained via the NASA POWER web portal in CRAFT version 4.0. The SOILGRID and WISE soil profile databases provided by DSSAT were used for the Türkiye domain.

Results and Discussion

In this study, the CRAFT model was initially calibrated using wheat yield data from the period 2011 to 2023. In the second stage, SST parameter data sets were utilized for forecasting in-season spatial yields for 2024. The Climate Predictability Tool (CPT) (Simon et al., 2025) within the CRAFT model was used to download Sea Surface Temperature (SST) data sets for the region surrounding Türkiye, covering the months of March, April, and May—just prior to the wheat harvest season in the country. Using SST data as a predictor with the CRAFT tool resulted in a 2024 spatial wheat yield estimate with approximately 90% consistency.

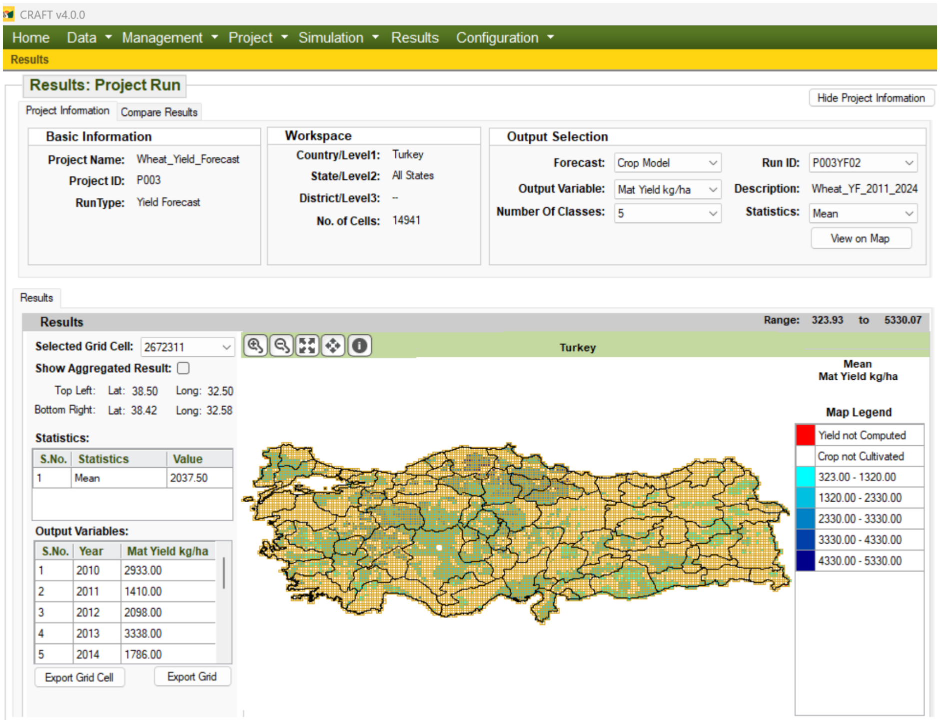

Figure 1. Spatial wheat yield forecast with 3 months prior to harvest time for Türkiye in 2024

Conclusions

The study showed that the CRAFT tool effectively estimate in-season wheat yields across the Türkiye domain area. To improve the accuracy of in-season yield predictions, it is advisable to analyze SST data from various regions that could influence the study area, in addition to examining the specific SST dataset used in the research. Furthermore, incorporating parameters such as precipitation is also recommended. The CRAFT tool can serve as a valuable resource for decision-makers in generating yield estimates prior to final harvest for the current growing season.

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A prototype decision support system integrating climate forecasts, earth observation, and APSIM for pre-sowing risk management

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Keywords : yield forecasting, GCM, remote sensing.

Abstract

Australia's sorghum growers face mounting pressures from climate variability, shifting markets, and production risks, underscoring the need for tools that can reduce uncertainty in pre-sowing decisions. Cultivar and management choices are especially challenging when future climate conditions and initial soil water status are unknown.

We present a prototype decision support framework that integrates seasonal forecasts from ECMWF global circulation models, Sentinel-1 and Sentinel-2 earth observation datasets, and the APSIM crop model into a user-driven platform. Machine learning methods convert remote sensing data into estimates of starting soil water, reducing reliance on sparse climate station networks. These inputs drive APSIM simulations that explicitly evaluate the interactions between genotype (cultivar choice), environment (forecast climate and soil moisture), and management (sowing date, fertilisation, row configuration). This G×E×M framing enables users to benchmark alternative strategies under realistic site and season specific conditions, translating model complexity into practical decision points.

A key innovation is the platform's spatial capability: satellite imagery allows field-scale variability to be incorporated into crop simulations, enabling detection of zones with higher or lower production potential. This supports precision agriculture by guiding input targeting, while also identifying high-risk scenarios—where crop failure is likely—as well as situations where yield potential is under-realised. Together, these insights allow growers to actively manage both climate risks and opportunity gaps.

Still at prototype stage, the system is undergoing advisor feedback, informing an interface that balances usability with modelling sophistication. Early applications suggest the framework narrows decision spaces, sharpens risk awareness, and enhances climate resilience in sorghum systems. This work demonstrates how integrating forecasts, earth observations, and APSIM through a G×E×M lens can generate actionable tools for decision-focused crop modelling.

Acknowledgements

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Frequent flyer: UAV-based crop model calibration

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WOFOST, high-throughput phenotyping, potato, drought, nitrogen

Introduction

The combination of climate change and stricter environmental regulations will lead to the increased exposure of potato (*Solanum tuberosum* spp.) crops to drought and nitrogen stress in the Netherlands. Gaining a better understanding of the response of potato to the combination of both stressors, and the resulting effect on tuber yield, will facilitate adaptation via improved plant breeding and crop management. Crop growth models are an important tool for understanding the interaction between genotype, environment, and management (Tardieu et al., 2018). However, insights remain limited due to the need for genotype-specific parameterisation (ten Den et al., 2022). Combining model calibration (MC) with high-throughput phenotyping shows promise for generating the required parameter sets (Huang et al., 2023). In particular, the development of low-cost UAV-based sensors (RS) offers the potential for high-frequency and high-resolution time-series data for small-plot trials. Yet, the performance and data requirements of calibration methods remain unclear. We aim to identify suitable calibration methods, input traits, and number and timing of observations for generating genotype-specific model parameter sets.

Materials and Methods

In the context of the CropXR programme[1], large-scale field experiments were conducted in two locations in the Netherlands in 2024 and 2025. The treatment factors included irrigation, nitrogen (N), and genotype. True colour, multispectral, and thermal-infrared images were collected weekly from emergence until haulm-killing and processed into “off-the-shelf” traits (e.g., RS-LAI) by a commercial company. There were four (2024) and five (2025) harvests to measure biomass, leaf area, and tissue N-content. WOFOST 8.1 will be used for a model-based analysis of stress-tolerance traits following calibration.

Research Approach

A review of WOFOST state variables and available literature identified leaf area index (LAI), nitrogen nutrition index (NNI), crop water stress index (CWSI), and final tuber dry matter yield as potential observations to use for MC. However, exploratory analysis shows only medium predictive ability of RS-LAI, and no “off-the-shelf” products are available for NNI and CWSI. Preliminary results (figure 1) show that combining RS-traits can improve LAI prediction.

Once LAI, NNI, and CWSI prediction methods are established, a sensitivity analysis will be used to determine WOFOST-parameters to be calibrated under optimal, drought-, and nitrogen-stressed conditions. The ‘24/’25 data will be used to develop the main calibration pipeline and determine Bayesian calibration’s data requirements in terms of observation type (LAI, NNI, CWSI, yield), and number and timing of observations. Additionally, we will explore if the inclusion of hierarchical relationship (e.g., location, year, and genotype) improves parameter uncertainty and yield prediction. After

[1] www.cropxr.org

applying the developed pipeline to the 200 genotypes of the '26/'27 experiments, the calibrated model will be used to identify drought- and nitrogen-stress tolerance strategies and their trade-offs under optimal conditions.

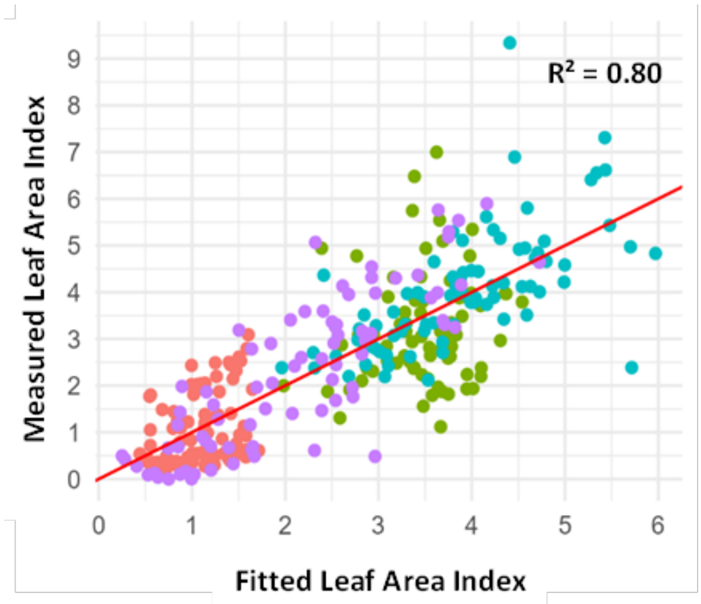

Figure 1. Fitted versus measured leaf area index for a preliminary model using Simple Ratio and Maximum Canopy Height to predict LAI. Different harvest moments are highlighted (red, green, blue, and purple, respectively, for harvests one to four) and the red line indicates the line of equality (y = x).

Acknowledgements

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Adapting the OliveCan process-based model to simulate olive oil yields across Europe.

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Keywords: OliveCan-Lite, Olive oil forecasting, biophysical modelling

Introduction

OliveCan (López-Bernal *et al.*, 2018) is a process-based model that simulates olive oil production under varying climatic and water conditions. It has been applied to assess the impacts of climate change on olive production across Europe (Mairech *et al.*, 2021) and to evaluate cover crop effects on orchard water balance and yield (López-Bernal *et al.*, 2022). OliveCan belongs to the family of mechanistic crop models, i.e. those with a strong biophysical basis (García-Tejera *et al.*, 2024). Such models improve our understanding of crop–environment interactions and physiology but require extensive parameterization and are computationally demanding (Boote *et al.*, 1996; Passioura, 1996). In its current form, OliveCan is therefore unsuitable for large-scale, real-time applications. To overcome this, we developed **OliveCan-Lite**, a streamlined version that reduces simulation time while retaining its biophysical foundation.

Two main simplifications were introduced in OliveCan. First, the canopy is assumed to be perfectly coupled to the atmosphere (Villalobos *et al.*, 2000), i.e. leaf temperature follows air temperature and transpiration depends mainly on stomatal conductance. Second, water stress effects are modelled applying Ritchie (1985) conceptual model, instead of solving equilibrium between leaf water potential and stomatal conductance (García-Tejera et al., 2017). These changes allow analytical solutions for transpiration, reducing computation time. The objective was to evaluate OliveCan-Lite adaptations against experimental yield data.

Materials and Methods

Model performance was tested with data from an orchard experiment in Córdoba, Spain (Iniesta *et al.*, 2009), also used in previous OliveCan assessments (López-Bernal *et al.*, 2018). The trial was conducted from 2004 to 2006 at the Alameda del Obispo Research Station (37.8°N, 4.8°W, 110 m a.s.l.) with 'Arbequina' trees spaced 7 × 3.5 m. The soil was a 2 m sandy loam, with water contents at field capacity and wilting point of 0.23 and 0.07 $m^3 m^{-3}$, respectively (Testi *et al.*, 2004). Weather data were collected from a station 500 m from the orchard. Three irrigation regimes were tested, but only two were simulated: (i) control (C), fully replacing ET demand, and (ii) continuous deficit irrigation (CDI), supplying 25% of C. Regulated deficit irrigation could not be simulated, as OliveCan-Lite does not yet allow irrigation scheduling by date.

Results and Discussion

Simulation time was reduced from 1 minute with OliveCan to 5 seconds with OliveCan-Lite. This efficiency gain did not compromise accuracy, as preliminary results show good agreement between observed and simulated yields under both irrigation regimes (Figure 1). However, significant discrepancies occurred in 2005, an "off" year with low crop load. This suggests that alternate bearing, a key feature of olive production, is still insufficiently represented and requires further model refinement.

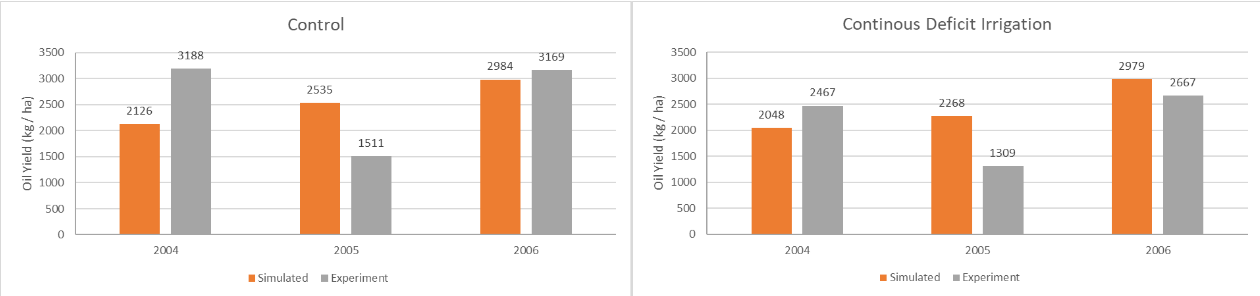

Figure 1. Oil yield comparison between simulated and experimetal data for the Control and the Continuous Deficit Irrigation treatments

Conclusions

OliveCan-Lite represents a first step toward an efficient, large-scale olive oil yield forecasting tool. It maintains the biophysical foundation of OliveCan while achieving a 12-fold reduction in runtime. Further improvements are needed, particularly in simulating alternate bearing, to enhance its predictive capacity across diverse European regions.

Acknowledgements

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Using the critical nitrogen uptake curve to drive nitrogen demand within an in-season decision support system for wheat.

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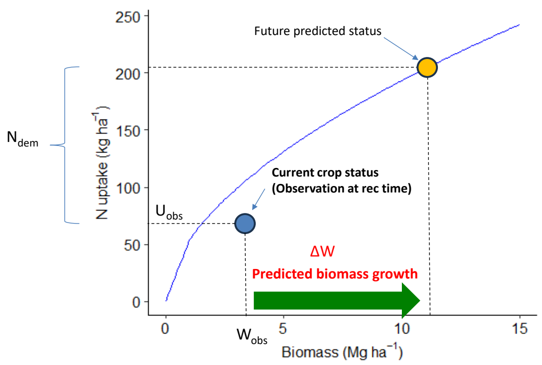
Keywords : Critical nitrogen dilution curve; nitrogen nutrition index; biomass nitrogen allometry; dynamic recommendation; Optifert-N

Introduction

Critical nitrogen dilution curves (CNDCs) are widely used to diagnose the nitrogen nutritional status of crops by estimating the Nitrogen Nutrition Index (NNI) (Justes et al., 1994; Lemaire et al., 2019), which informs fertilization decisions. CNDCs, by design, imply maximum biomass accumulation when NNI = 1, and in most cases, also maximum grain yield. Several studies confirm that maintaining an NNI close to 1 during stem elongation maximizes grain yield (Hoogmoed et al., 2018; Lemaire et al., 2008), while lower values are favorable before stem elongation (Ravier et al., 2017). In-season decision support systems (DSSs) for diagnosing nitrogen needs enable better synchronization of nitrogen demand and supply, reducing losses and maximizing profit. In situ sampling combined with remote sensing and simple models can be scaled to large areas using management practice information readily available from farmers and limited field data, as these are key factors in facilitating farmer adoption. This study explores a novel application of the CNDC by proposing the use of the analogous critical nitrogen absorption curve (Lemaire et al., 2008) to forecast future nitrogen demand, thus enabling in-season estimation of crop nitrogen requirements through an in-season nitrogen mass balance and the estimation of future biomass accumulation. Rather than diagnosing the current nitrogen nutritional status, this prognostic approach predicts future nitrogen needs based on the crop's expected capacity for biomass accumulation, which can be estimated with greater accuracy than nitrogen needs directly.

Materials and Methods

The Optifert-N DSS is based on an in-season nitrogen mass balance that incorporates several components to estimate a recommended nitrogen rate (N_{rec}, kg ha^{-1}) to be applied: residual soil nitrogen from previous fertilization (N_{res}, kg ha^{-1}), projected future nitrogen demand (N_{dem}, kg ha^{-1}), observed accumulated biomass and nitrogen in the crop (W_{obs}, Mg ha^{-1}; U_{obs}, kg ha^{-1}), and estimated nitrogen mineralization (N_{min}, kg ha^{-1}, defined as the nitrogen captured by a zero-N plot, which should be site-specific) (Figure 1). The function GRf(NNI_{obs}) is an empirical relationship derived from observed data, relating the daily growth rate to the NNI in a quadratic-plateau form; however, it can be replaced by any function capable of predicting future crop growth (e.g., derived from remote sensing). NNI_{obj} represents the target NNI, typically set to 1 at anthesis. This procedure can be applied between the jointing and booting stages of wheat development to determine an in-season top-dress fertilization rate.



$$N_{rec} = \frac{N_{dem} - N_{res} - N_{min}}{Ef_r}$$

$$N_{dem} = NNI_{obj} * a * [(\Delta W + W_{obs})^{1-b}] - U_{obs}$$

$$\Delta W = \ GRf(NNI_{obs}) * (t_{anthesis} - t_{obs})$$

$$N_{res} = \max(0\,, N_{soil\ Z0} + N_{fert\ Z0} * Ef_v + N_{fert\ Z22} * Ef_v + N_{fert\ Z30} * Ef_r - U_{obs})$$

$$N_{min} = 120$$

Figure 1. Conceptual diagram and equations of the DSS. With Ef_r=0.6, Ef_v=0.5, a=53.5, b=0.442. $N_{soil\ Z0}$, $N_{fert\ Z0}$, $N_{fert\ Z22}$ and $N_{fert\ Z30}$ are the initial soil nitrogen content at planting (0-60cm depth in kg ha^{-1}), and rates of fertilizer aplcation at planting, Zadoks 22 and 30 respectivelly if aplied.

Results and Discussion

To validate the model, a set of nitrogen response experiments (n = 20) conducted between 2018 and 2020 at INIA La Estanzuela was used. The model was used to determine the recommended nitrogen rate (N_{rec}, kg ha^{-1}) at Zadoks 30 (jointing) through destructive biomass sampling. Estimated biomass at the end of vegetative growth (Zadoks 65) (Figure 2, left) ranged from 4 to 16 Mg ha^{-1}, with a root mean square error (RMSE) of 2.3 Mg ha^{-1}. Plots receiving lower nitrogen rates exhibited lower biomass accumulation (blue) compared to those receiving higher rates (green). To evaluate overall performance and account for residual nitrogen from previous applications, the total nitrogen applied (N_{rec} + previous applications) for each treatment was compared to the site-specific economic optimum nitrogen rate (EONR). The DSS performed well in two out of three years, with an RMSE of 51 kg ha^{-1} and a tendency to underestimate (false lows) rather than overestimate (false highs) nitrogen rate recommendations, likely due to overestimation of nitrogen use efficiencies (Efr, Efv) in years with extreme climatic events.

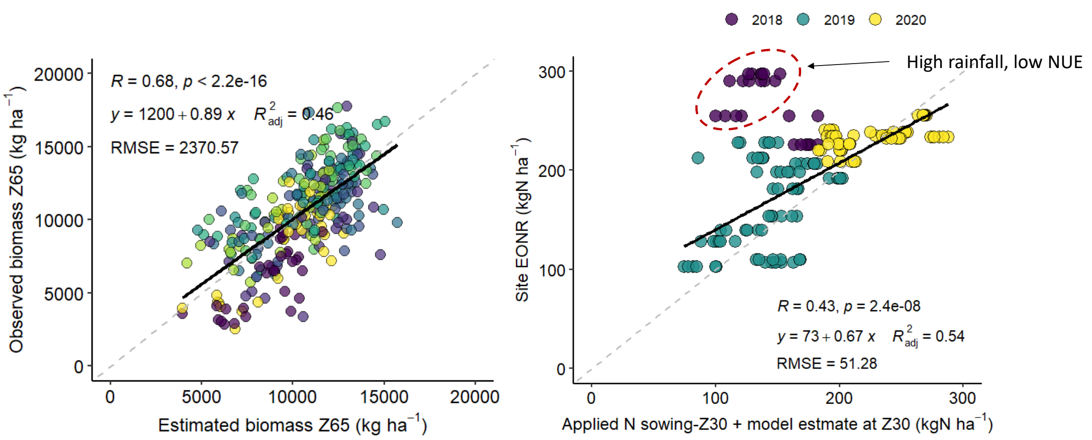


Figure 2. Observed vs estimated biomass (W+ΔW) as estimated by the biomass prediction model (color scale green-yellow-blue form higher to lower N rates respectively) . Biomas estimation (left) and validation of DSS as compared to economic optimum nitrogen rate (EONR) at sites with nitrogen response experiments in three years (right).

Conclusions

Using the critical nitrogen uptake curve to estimate nitrogen demand proved a promising strategy for determining in-season nitrogen applications, enabling the development of simple models that can be integrated into more complex DSSs. The approach achieved a reasonable RMSE and was effective in: 1) avoiding falsely high application rates, 2) reducing nitrogen rates when crop response is limited due to poor crop status at the time of sampling or limited capacity for future growth, and 3) recommending high rates when necessary.

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Assimilation of biophysical variables from Sentinel-2 into the DSSAT model: a calibration approach to wheat yield estimation

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Keywords: DSSAT, wheat, yield, calibration, assimilation.

Introduction

Ensuring food security under climate change and resource constraints requires tools for sustainable intensification of cereal production. The global population, projected to reach 9.7 billion by 2050, will raise food demand by almost 60% (FAO, 2022). Conventional systems based on intensive inputs and uniform practices are insufficient to meet these challenges while preserving sustainability (Casa & Pisante, 2024). Precision agriculture, integrating remote sensing and crop models, offers a pathway to enhance input efficiency and reduce environmental impacts (Cammarano et al., 2023).

Process-based models such as the Decision Support System for Agrotechnology Transfer (DSSAT) simulate crop–environment–management interactions and support decision-making from field to regional scale (Jones et al., 2003; Hoogenboom et al., 2019). Their reliability depends on calibration and assimilation: calibration aligns parameters to local cultivars and conditions, while assimilation corrects model states with external observations, enabling dynamic and spatially explicit yield prediction. Challenges remain, including data needs and calibration complexity, although advances are improving accessibility and robustness (Holzworth et al., 2014; Cammarano et al., 2023).

This study focused on winter wheat (*Triticum aestivum* L.), the world's most important cereal and a staple in Mediterranean cropping systems, where rising temperatures already threaten production (Asseng et al., 2015). The objective was to evaluate DSSAT performance in the Rieti plain (Central Italy), analyzing the effect of calibration and assimilation of biophysical variables measurable via remote sensing.

Materials and Methods

Field trials were carried out in three farms of the Rieti plain (Italy) in 2023–2024, with ten 30×30 m plots across contrasting soils. Phenology was recorded (BBCH), LAI measured with LI-3100C, biomass sampled by quadrats, dried and weighed, while canopy N was determined by a portable near-infrared (NIR) spectrometer and grain yield from harvesting. DSSAT v.4.8.2 was parameterized with local station weather data and regional soil maps supported by field sampling. Calibration of cultivar and ecotype parameters was performed with CroptimizR using a Nelder–Mead simplex algorithm, testing assimilation of LAI, biomass, N, and their combinations.

Results and Discussion

Uncalibrated DSSAT failed to reproduce growth dynamics, underestimating LAI and misrepresenting biomass, resulting in poor yield predictions (R^2 = 0.04). Assimilation under default settings improved correlations (R^2 = 0.71) but increased RMSE. Manual calibration of cultivar and ecotype parameters improved model fidelity, especially for phenology and LAI. When assimilation was applied post-calibration, accuracy improved: assimilating biomass reduced RMSE to 1.8–2.0 t ha^{-1} and raised R^2 above 0.5. Assimilation of LAI or nitrogen alone had limited benefits.

Table 1. Observed yield versus simulated yields with and without assimilation.

Plots	1	2	3	4	5	6	7	8	9	10
HND	2.137	1.817	1.715	2.013	1.651	2.275	2.362	1.439	1.597	1.294
HN%D_def	1.633	1.149	1.373	1.305	1.289	1.237	1.197	1.275	1.312	1.112
HN%D_ass	3	1.813	2.489	1.442	2.241	1.445	1.386	1.842	1.872	1.426

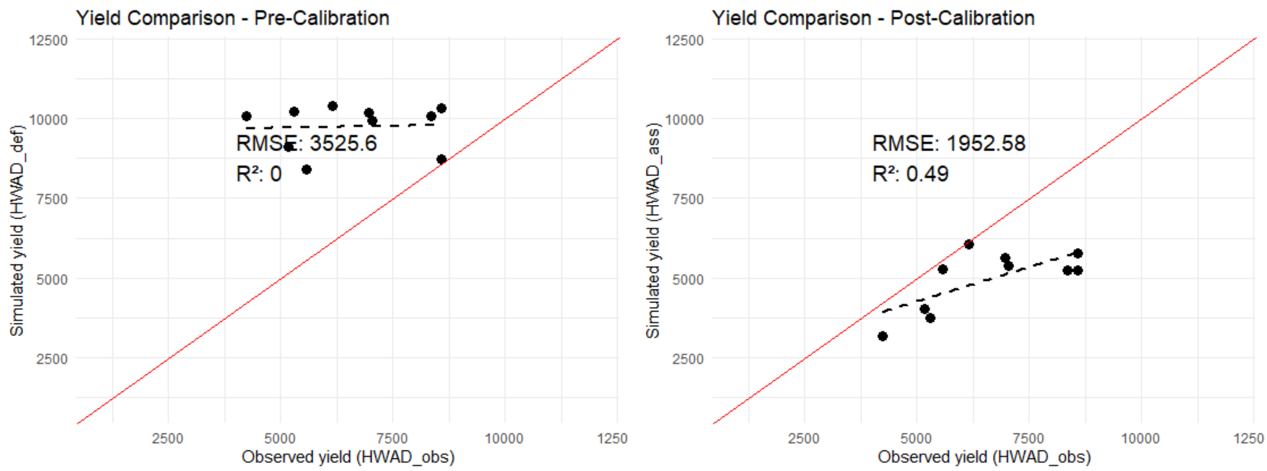

Figure 1. Comparison of yield (HWAD) before and after assimilation of LAI (LAID), aboveground biomass (CWAD), and canopy nitrogen (CNAD): on the left a before assimilation, on the right after assimilation.

Conclusions

Combining calibration and data assimilation maximized the predictive power of DSSAT. Biomass proved to be the most informative assimilated variable. The study shows that calibrated DSSAT supported by assimilation of remote-sensing indicators can generate reliable yield maps and provide decision-support tools for fertilization, irrigation, and harvest planning in Mediterranean wheat systems. The workflow is transferable to other contexts, contributing to resilience and sustainability in global grain production.

Acknowledgements

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Towards EU-wide forecasting of olive yields and production: Database for region-wise model parameterisation

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Keywords: Olive production systems, Mediterranean agriculture, data harmonisation, regional characterization.

Introduction

Olive and olive oil production is a pillar of rural economies in the Mediterranean. The EU produces over 50% of global olives and two-thirds of olive oil, mainly in Spain, Italy, Greece, and Portugal. Yet, inter-annual variability is high, driving price volatility and uncertainty for stakeholders. Timely, accessible forecasts are essential to enhance market transparency, avoid speculation and support decision-making. Within this context, the European Commission, through the Joint Research Centre (JRC), has proposed including olive in the MARS Crop Yield Forecasting System (MCYFS). To anticipate production outcomes, several approaches have been tested: in situ surveys, empirical models including machine learning (Ramos et al., 2025), process-based models (López-Bernal et al., 2018), and aerobiological modelling (Oteros et al., 2014). Each offers advantages and limitations, underscoring the potential of hybrid approaches.

The proposed idealised Olive Yield Forecasting System (Figure 1) follows this path. The present work focuses on the creation of region-specific and gridded datasets to characterise olive production and production systems in the EU's main olive-producing countries. The resulting database is used to parameterise and test an adapted version of the OliveCan model (OliveCan-Lite), which was specifically developed for being integrated into the MCYFS (Garcia-Tejera et al., 2026).

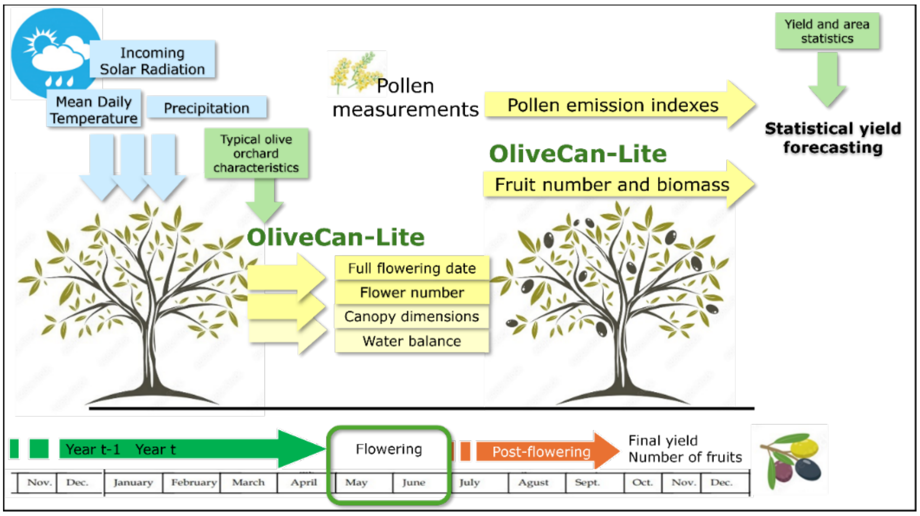

Figure 1. Olive Yield Forecasting System

Materials and methods

To characterize olive production systems in Spain, Portugal, Italy, and Greece, information was collected from multiple sources. Official statistics and reports from national ministries, regional administrations, and producer organizations were combined with evidence from specialized literature and technical documentation. Data collection was carried out at both NUTS3 and grid cell (10 × 10 km) levels, enabling the compilation of historical series together with spatially explicit information. To capture the spatial dimension, parcel-level databases of olive orchards were combined with remote sensing indices such as NDVI and SAVI.

Results and discussion

The characterization generated harmonised datasets at both geographic levels. At NUTS3 level, information includes historical series of area, production, and yields, along with descriptors of orchard typologies, tree density, soil and terrain attributes, irrigation practices, flowering and harvest dates, predominant cultivars, and main pests and diseases. Grid cell level data provide information on the area of olive cultivation and tree canopy cover. These datasets support the parameterisation of OliveCan-Lite and enable cross-country comparisons. Important challenges encountered include the fragmentation of data across administrations (i.e., information dispersed across different levels of regional authorities), the lack of up-to-date information on irrigated areas, and gaps in key variables in some regions (e.g., dates of critical phenological stages and tree density), which had to be estimated through alternative procedures.

Conclusion

The creation of this harmonised database provides the foundation for the first regional-scale statistical models to forecast olive yield and production in the EU's main olive producing countries. We believe that the database will also find applications beyond this goal. After further testing and improvement, it will be made publicly available.

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Using drone imagery as a decision support tool for the detection of disease in perennial ryegrass swards

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Keywords: Crown Rust, greenness, disease score, herbage quality, yield.

Introduction:

Climate change is increasing the incidence of warmer and wetter conditions in Ireland (Nolan & Flanagan, 2020), leading to an increase in fungal diseases, such as Crown Rust (*Puccinia Coronata*). Disease development is also more likely as regulations reduce the nitrogen inputs allowed on grassland farms. The increased stress placed on growing plants during times of soil moisture deficits and low nitrogen can promote fungal spread (Critchett, 1991). Diseases like Crown Rust negatively impact herbage yield and quality, significantly affecting pasture productivity and nutritive quality for grazing cattle (Carr, 1975). Diseases can be visually assessed as the reduction of green in the sward (Kimbeng, 1999). However, disease monitoring can be laborious, and disease may only be noticed when large areas of the sward are already infected. The use of technology driven disease detection could reduce associated labour inputs and decline in sward quality and yield. The difference in greenness can be utilised to inform a decision support tool (DST) that can monitor for disease incidence. The objective of this study was to detect disease incidence in PRG swards using drone imagery, using greenness as a proxy.

Materials and Methods:

The study was carried out on 200 plots containing various perennial ryegrass (PRG, *Lolium perenne)* cultivars in October 2024. Herbage samples were collected from each plot by cutting a 0.25m^2 area within a quadrat using Gardenia hand shears to 4cm. 100g of each sample was oven dried at 90°C for further analysis. Herbage samples were analysed using near infrared spectroscopy for estimation of dry matter digestibility (DMD), and other quality metrics. Disease scoring was assessed visually on each plot by three independent scorers, by calculating the % of the plot infected × % leaf area affected. Drone imagery was captured using a DJI Mavic Series 3 drone. Greenness was quantified by calculating the number of green pixels out of the total area analysed. Statistical analysis was carried out using RStudio and R version 4.4.1.

Results and Discussion:

Regression analysis showed that greenness had a significant negative association with disease score ($p < 0.001$) (Figure 1). Disease score explained ~65% of the variation observed for greenness (R^2=0.647). This impact of disease aligns with the expected reduction of green leaf area and increased dead tissue (Potter, 1987). A relationship was also observed between disease score, greenness and quality traits. DMD was negatively associated with disease score, ($R^2 = 0.52$, $p < 0.001$), and DMD was positively associated with greenness ($R^2 = 0.66$, $p < 0.001$). As disease incidence increased, DMD decreased along with the level of greenness, suggesting that plant greenness can be used to detect disease. This reduction in herbage quality with the incidence of disease can limit animal performance, particularly during autumn when grass growth is slowing (O'Donovan *et al,* 2016). The potential of drone derived imagery for the early detection of disease in PRG could mitigate the negative impacts of disease in pasture-based systems.

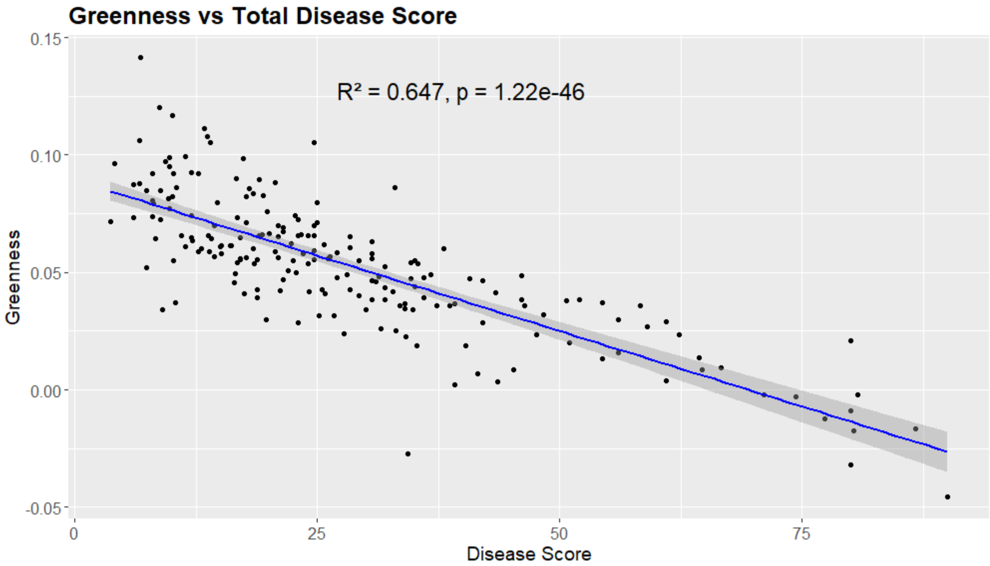

Figure 2: Relationship between greenness and Disease Score. A significant negative linear relationship was observed ($R^2 = 0.65$, $p < 0.001$), with 95% confidence intervals shown.

Conclusion:

The use of greenness derived from imagery has the potential to predict the presence of disease of PRG. As climate induced temperatures increase along with reduced N inputs, monitoring swards for the presence of disease will become more important. Identifying disease using drone imagery will be useful on grassland farms as a DST to reduce the negative impacts of disease including reduction in herbage yield and quality.

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A Digital Twin for Sugar Beet irrigation at a world-wide scale

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Sugar beet (Beta vulgaris L.) is one of the most important sugar-producing crops. With more than 4 bha, it contributes approximately 20% of the world's sugar supply. The more, its cultivation is gaining interest in several countries, due the high revenue, and an high sugar purity. Nonetheless sugar beet is in many countries an irrigated crop and the water management may be a critical factor because of the high susceptibility to a range of foliar and root diseases that may significantly compromise both yield and sugar content, most of them being strongly dependent on the level of humidity – it means that watering could be a dangerous practice.

In irrigation the use of models as Decision Support Systems to estimate water balance is a common practice for decades, but the huge number of parameters make their estimate of water availability not reliable on a large scale - soil maps and weather forecast cannot give information with the due precision. Crop models have been recently embedded in Digital Twins (DTs) where a data assimilation process allowing to progressively adjust parameters, initial conditions and forcing. In this case the model AquacropOS (ver.6) has been rearranged in a Digital Twin architecture, able to work on nation-wide soil maps and weather data, and using . NDVI and NDMI (from Sentinel-2) as proxy variables for cover crop and stress coefficient respectively. New modules have been added to model root and sucrose dynamics.

Two sugar been grown fields have been considered for 2023 and 2024 in the central high-plane of Spain and irrigation schedules from farmers have been monitored and compared to the ones suggested from the Digital Twin, putting in evidence how the system may help to reduce to amount of water, refine the soil hydraulic parameterisation and weather information.

In conclusion, DTs, a technology of growing interest in agricultural applications and services, may help to save water, reduce the risk of yield loss but it also help in increase the spread of satellite data and the knowledge of soils and weather distribution.

Production potential of oilseed rape in Egypt - a modeling study using the CROPGRO model

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Keywords: climate adaptation; canola; rapeseed; model parametrization; agro-ecosystem model

Introduction

Oilseed rape (OSR; *Brassica napus*) is a globally important oil crop with potential to help narrow Egypt's substantial edible oil gap (Kheir et al., 2021). As Egypt's agricultural sector is highly dependet on limited water resources, it is crucial to identify cropping strategies that allow for water use effiecient OSR production. To support OSR's introduction as a novel crop in Egypt, reliable information on expected yields, irrigation requirements, and suitable sowing windows is essential.

Process-based cropping sytems models (CSM) allow to explore the production potential of novel crops in specific target environements. To provide robust simulation results a thorough calibration and evaluation of CSM is essential, building on multi-environment field trial data (Attia et al, 2024; Shawon et al., 2024).

Materials and Methods

For this purpose, we conducted six independent field experiments, one in Germany and five across Egypt's major agro-climatic zones. Building on the detailed trial data on OSR phenology, growth, and yield formation we calibrated and evaluated the CROPGRO model from DSSAT, previously adapted for OSR. We conducted a genotype-specific calibration for the Egyptian OSR cultivar SERW4, which was grown in all six field experiments.

We subsequently applied the parameterized model to simulate OSR production across the five Egyptian sites. Using site-specific soil and weather data, we assessed eight sowing dates between mid-September and beginning of January under two irrigation strategies: (i) fixed schedules reflecting experimental practice, and (ii) automatic irrigation triggered by plant available water thresholds over thirty years (1991–2020). Under automatic irrigation the soil profile was refilled whenever plant available water in the top 30 cm fell below 50% of plant available water capcity. We investigated simulated seed yield, applied irrigation, evapotranspiration, and both irrigation water use efficiency and evaporative water use efficiency (WUE). We finally use mixed linear model analyses to assess differences between sowing dates and irrigation strategies and identify optimal sowing windows for various production regions.

Results and Discussion

Model evaluation showed strong performance, with a d-index of 0.91–0.95 for phenology, biomass, and yield. Long-term simulations indicated that all tested Egyptian sites are generally suitable for OSR production, with average yields ranging from 1.9 to 3.1 Mg ha^{-1} when sown at the location-specific optimum dates. Optimum sowing windows varied geographically, from early October in the hotter southern sites to mid-November in the cooler northern regions. Notably, water use efficiencies differed markedly among sites: southern locations required more irrigation, resulting in lower irrigation WUE, whereas northern sites in the Nile delta showed higher irrigation WUE due to cooler conditions and soils with better water retention. Automatic irrigation consistently improved WUE compared to fixed schedules, though its feasibility under Egyptian conditions remains constrained by technology and infrastructure requirements.

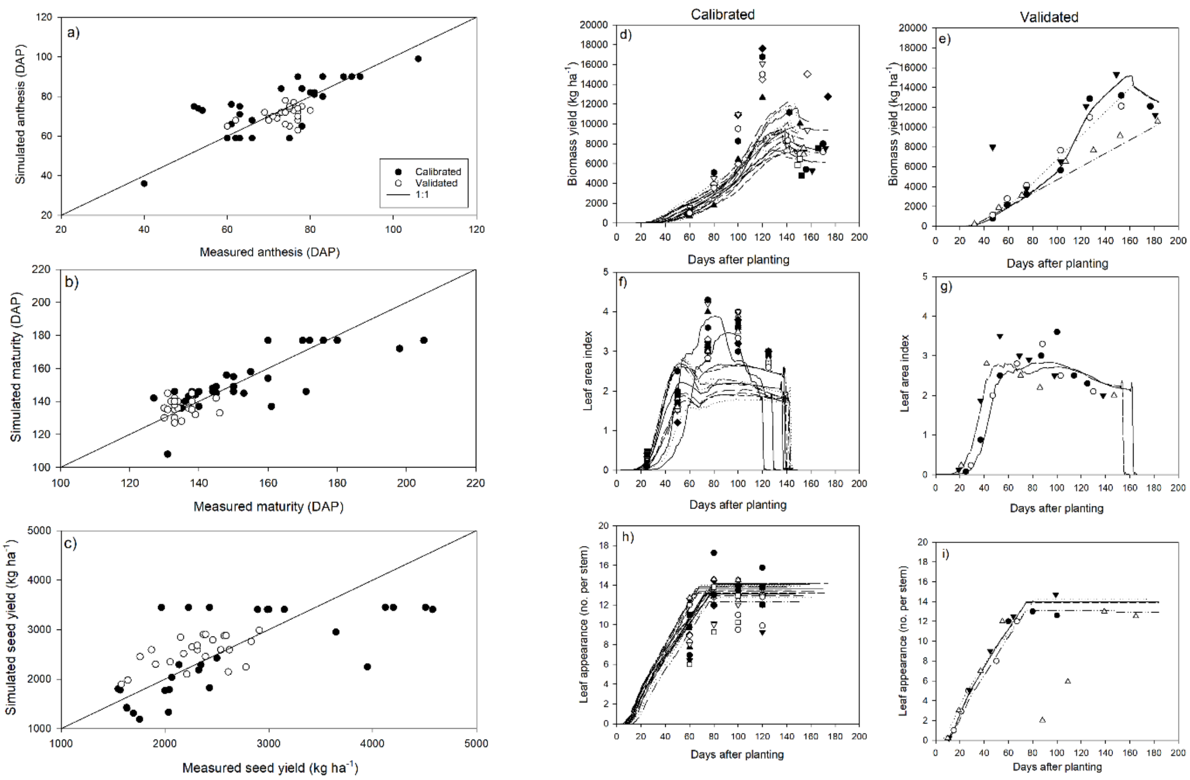

Figure 1 Comparison of simulated and observed phenological development, growth, and yield of oilseed rape using the calibrated CROPGRO model. Data from Edko, Nubariya, and Toshka were used for model calibration, while independent datasets from Shebin and Sadat were used for model validation (see Table 1 for experimental details). Panels show simulated versus measured anthesis (a), maturity (b), and final seed yield (c) for calibration (●) and validation (○) datasets against the 1:1 line, as well as biomass accumulation (d–e), leaf area index (f–g), and leaf appearance (h–i). The results highlight the robustness of the model across diverse agro-climatic conditions in Egypt.

Conclusions

Our findings highlight regionally optimized sowing dates that realize high yields and water use efficiency at the same time as a low-cost, climate-smart strategy supporting water use efficient OSR production in Egypt. The calibrated crop model, integrating yield potentials and water use efficiencies, provides a valuable decision-support tool for policymakers and farmers aiming to expand sustainable OSR cultivation in Egypt and other North African and semi arid regions.

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Integrating crop modeling and remote sensing for precision management of alfalfa under Mediterranean conditions

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Keywords: forage yield prediction; vegetation indices; water stress; yield gap

Introduction

Alfalfa (*Medicago sativa* L.) is among the most important forage crops worldwide, being valued for its high protein content, digestibility, and suitability for ruminant nutrition (Testa et al., 2011). In Mediterranean irrigated systems, alfalfa plays a strategic role as a rotation crop, contributing to soil fertility and providing high-quality feed for dairy chains. However, its productivity is highly dependent on water availability and irrigation efficiency. Increasing climate variability, combined with pressure on water resources, necessitates more sustainable and precise management strategies. The integration of crop simulation models with remote sensing observations is an emerging approach to optimizing management decisions (e.g., Deines et al., 2021). Remote sensing, particularly through freely available satellite platforms such as Sentinel-2, provides timely and spatially explicit information on crop growth and stress. Crop simulation models, on the other hand, provide insights into potential productivity under optimal conditions (e.g., Schils et al., 2018). Combining these tools enables the identification of yield gaps and the factors that explain them, supporting decision-making in precision agriculture. This study, conducted within the Sardinian PSR 16.1 ZOOTRACK project, aimed at testing the integration of crop models and satellite-based vegetation indices for predicting alfalfa yield and quantifying yield gaps in a Mediterranean plain environment.

Materials and Methods

The research was conducted in the Arborea district (Sardinia, Italy; 39.77°N, 8.61°E), an area reclaimed from the Sassu Lagoon and characterized by intensive dairy farming and forage production. Nineteen alfalfa fields, ranging in size from 2 to 12 ha, were monitored over a total area of 140 ha. During the 2023–2024 cropping season, data on yields were collected at each of the three harvest events typically carried out for dehydrated forage production. Yields were measured both as fresh biomass for dehydration and as dry matter (Mg ha^{-1}).

Multispectral data from the Sentinel-2 satellite were processed to obtain time-series of vegetation indices, including NDVI, EVI, NDRE, and NDWI. To reduce noise, daily-smoothed curves were generated, and phenological parameters such as the integral of the index curve and the maximum peak value were derived for each cutting cycle. These features were then used as predictors in Random Forest models to estimate field-level yield. Model performance was assessed through cross-validation, with evaluation metrics including root mean square deviation (RMSD) and Willmott (1982) index of agreement (d).

In parallel, potential yields were simulated using the Decision Support System for Agrotechnology Transfer (DSSAT v4.8; Hoogenboom et al., 2019) crop model under non-limiting water and nutrient conditions. The minimum dataset used for model parametrization and calibration included daily meteorological data (solar radiation [MJ m^{-2} d^{-1}], maximum and minimum temperature [°C], rainfall [mm], wind speed [m s^{-1}], and relative humidity [%]), soil parameters (texture, field capacity, wilting point, bulk density, cation exchange capacity, pH, nitrogen content, and organic matter), and agronomic management information (timing and applied inputs).The comparison between simulated and observed yields allowed for the calculation of yield gaps, which were spatialized across fields. Correlations between yield gaps and stress-related indices, particularly NDWI, were tested to investigate the role of water availability.

Results and Discussion

The Random Forest approach achieved satisfactory predictive performance, with an RMSD of 0.325 Mg ha^{-1} of DM and a high index of agreement ($d = 0.83$). Yield maps revealed high spatial variability both within and across fields. The average annual yield across the 19 monitored fields was 5.55 Mg ha^{-1} of DM. However, coefficients of variation were consistently high (23% on average per cut), highlighting the heterogeneous response of alfalfa under the same management conditions.
Observed (Figure 1A) yields (5.55 Mg ha^{-1} of DM) were on average 27% lower (Figure 1B) than simulated potential yields (7.59 Mg ha^{-1} of DM), with differences being highly significant ($p < 0.0001$). This result indicates a substantial yield gap that cannot be attributed to genetic or climatic limitations, but rather to field-level management inefficiencies. Spatial analysis further showed that yield gaps were significantly correlated ($p < 0.001$) with the NDWI water stress index (Figure 1C). This confirms that, despite being intensive in the Arborea district, irrigation practices are not always effective in preventing water stress.

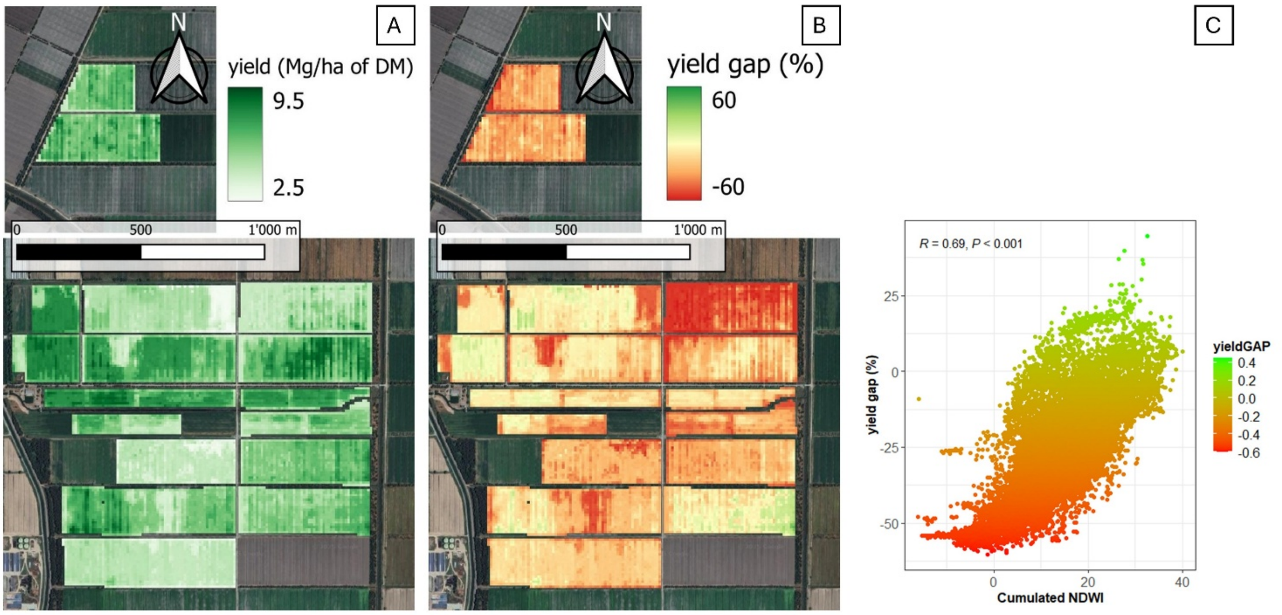

Figure 1. Alfalfa yield (A, Mg/ha of DM), yield gap (B, %), and correlation between the spatialised yield gap (%) and the cumulated Normalised Difference Water Index (NDWI). Data on A and B refer to the sum of the mowing events for dehydrated forage production

Conclusions

This study confirmed that alfalfa yield in Mediterranean irrigated systems can be effectively predicted using remote sensing time-series combined with machine learning approaches. Yield gaps, quantified through the integration of observed data and crop modeling, were primarily attributed to localized water stress resulting from irrigation inefficiencies. The methodological framework tested here offers practical tools for farmers and advisors to improve forage management. By generating spatial yield maps and diagnosing the causes of yield gaps, it is possible to design targeted interventions, reduce resource waste, and enhance sustainability. These results contribute to advancing precision agriculture in forage systems and support the resilience of Mediterranean dairy supply chains facing climate and water challenges.

Acknowledgements

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INTEGRAL NITROGEN FERTILIZATION MANAGEMENT OF BREAD WHEAT IN FRANCE WITH FERTI-ADAPT CHN

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Keywords : Agronomy, Crop model, Sensors, Decision tool, Efficiency.

Introduction

For several decades in France, nitrogen (N) fertilization reasoning has been based on the principle of the "balance sheet" method. This method comes up against strong implementation limitations (Ravier et al., 2016), and a lack of adaptability in the face of climatic hazards. This observation has motivated the emergence of a new concept of "integral management" of N fertilization, which avoids a priori estimates of forecast N rate in favor of reasoning based on instantaneous plant needs. Since 2017, ARVALIS has been developing an integral management tool of N fertilization in wheat, FERTI-ADAPT CHN, which relies on a mechanistic crop model (CHN) to access plant N nutrition levels in real time and forecast canopy N requirements. CHN allows to simulate the development, growth and N nutrition status of a wheat crop on a daily basis in response to its environment using a dynamic approach. The innovative near-real-time coupling of CHN with data from on-board satellite sensors provides an accurate diagnosis of wheat's N nutrition status, improving the accuracy of crop N requirement projections. The fractioning of N inputs does not follow an a priori defined strategy, in favor of a multi-criteria reasoning method that is more integrative of annual variability. The aim of this study is to evaluate the agronomic performance of FERTI-ADAPT CHN under field conditions.

Materials and Methods

This study relies on a French network of 67 field trials of winter bread wheat (Triticum aestivum L.) conducted from 2021 to 2023. Nitrogen management based on the balance sheet method was compared with that based on the FERTI-ADAPT CHN tool. Measurements of grain yield and grain protein concentration were performed at harvest to compare the two practices. The total N rate applied in each treatment was also recorded. These data were used to calculate a nitrogen net profit margin, incorporating several scenarios for N fertilizer prices (from 1.3 to 2.7 € kg N^{-1}) and grain selling prices (from 230 to 350 € t^{-1}). A remuneration scale for grain protein concentration was also used for this evaluation.

Results and Discussion

The tool's performance varies depending on environmental characteristics. When grain yield is constrained by factors other than nitrogen, as observed during the growing season 2022, the tool makes it possible to limit the amount of nitrogen applied to the crop without compromising its technical performance. Conversely, when the environment is more favorable to production, FERTI-ADAPT CHN improves yield and grain protein concentration. For example, in 2023 (Fig. 1), compared with the balance sheet method, integral management of N fertilization significantly improved grain yield by 0.25 t ha^{-1} (p-value = 0.03) without increasing the nitrogen rate applied (-12.1 kg N ha^{-1}, p-value = 0.12) and without penalizing grain protein concentration (+0.2 %, p-value = 0.23). Producing more grain with higher protein concentration using less nitrogen fertilizer mechanically improves the nitrogen net profit margin. Depending on the combination of fertilizer purchase price and grain selling price scenarios, the average gain ranges from 77 to 109 € ha^{-1}.

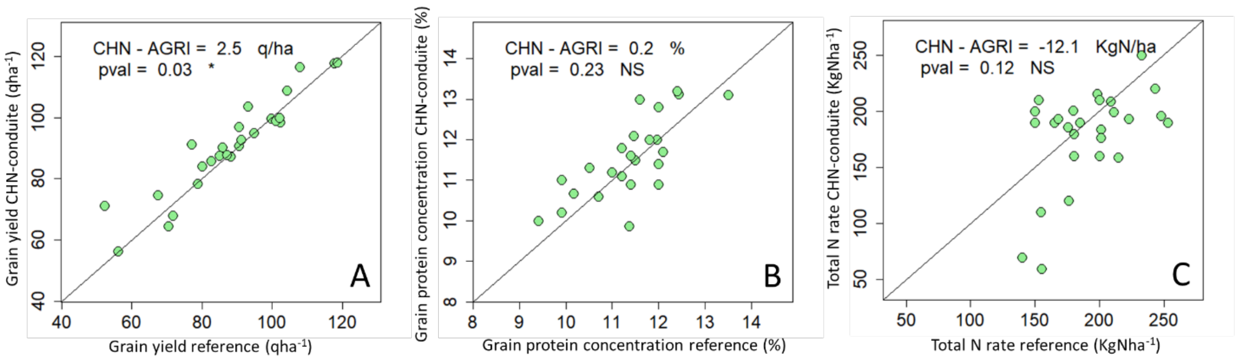

Figure 1. Comparison between agronomic performances obtained by the balance sheet method (reference) and a N management based on CHN-conduite. Comparisons were performed for grain yield at harvest (A), grain protein concentration (B) and total amount on N apllied (C). Data were collected in 27 french trials performed in 2023.

The main factor in the success of a N fertilization strategy is the ability to integrate the effect of the climatic year on the crop's N requirements. Beyond the direct effect of the total N rate, the tactic of splitting is also very important in maximizing nitrogen use efficiency. While an a priori calculation of the total N rate, as proposed by the balance sheet method, allows only very few adjustments during season, the integral management of N fertilization is extremely reactive to growth conditions. Growth projections from the CHN crop model, which determine wheat's nitrogen requirements, are regularly updated during the campaign to incorporate the real year's climate. In addition, by coupling CHN with on-board satellite sensors, the impact of non-climate-related accidents can be taken into account when revising N requirements. The tool's decision rules also enable to optimize intervention dates and adjust the recommended N rates to the dynamics of the wheat's N demand at each application. The combination of these different solutions in the FERTI-ADAPT CHN tool gives it an enhanced ability to propose an optimized fertilization strategy.

Conclusions

The results confirm the potential of this new approach. It also opens up prospects for future developments, which will make it possible to optimize fertilization strategies by integrating new optimization constraints, such as reducing the crop's carbon footprint.

Acknowledgements

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Optimizing sowing dates of chickpea in Southern Germany using the DSSAT CROPGRO-Chickpea model

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Keywords: crop model, chickpea, sowing dates, sensitivity analysis, decision support

Introduction

There is increasing interest in growing chickpea (*Cicer arietinum* L.) in Germany due to rising consumer demand and its positive impacts on crop rotation. Field experiments investigating optimal management strategies are time-consuming, expensive, and often offer only location- and seasonal-specific information. Crop growth models such as the Decision Support System for Agrotechnology Transfer (DSSAT) can be used to optimize management strategies, including sowing dates. Finding the optimal sowing date for a specific location is one of the most important practical foundations for successful cultivation. The DSSAT CROPGRO model is therefore of high value due to its flexibility, which reflects the different sensitivities of the crop to temperature, photoperiod, water deficit, and nitrogen within the various developmental stages of the plant (Boote et al., 1998). In Southern Germany, weather conditions vary significantly throughout the year; therefore, it is necessary to consider the crop's sensitivity to different weather conditions, especially during spring and summer, on plant growth and development. The CROPGRO-Chickpea model was initially developed and calibrated using data from India, collected in 1984 and 1986, and is described in Singh & Virmani (1996). Due to the significant differences of growing conditions in Germany compared to India in terms of growing seasons, climate zones, and cultivars, a calibration and evaluation of the model were necessary to achieve satisfactory simulations with the DSSAT CROPGRO-Chickpea model. The objective of this study was to find the crop model-based optimum sowing date of chickpea in Southern Germany.

Material and Methods

For simulations, the DSSAT CROPGRO-Chickpea model (version 4.8.5, Hoogenboom et al., 2024) was used to generate the results presented in this study. As an experimental site, Ihinger Hof (48 ° 44´ N, 8° 55´ E, 475 m a.s.l), Renningen, a research station of the University of Hohenheim located in Southern Germany, was used. The cultivar and ecotype coefficients were calibrated using a detailed data set collected from a field experiment at this location, sown on 30.04.2024, and evaluated with data from a second sowing date on 15.05.2024. Further evaluation was conducted at an additional location and with two more years of experiments from 2022 to 2023 at Ihinger Hof location (currently submitted). In the field experiment, the Elmo cultivar was used, which is an early-ripening desi-type chickpea, suitable for German growing conditions. For this crop model-based study, a total of four different sowing dates were used, including 30.04.2024 (actual), 15.05.2024 (actual), 15.04.2024 (fictive earlier sowing) and 30.05.2024 (fictive later sowing). Crop model-based sowing date sensitivity analysis was conducted over a long period of weather data (historic weather, 2015-2024) to investigate the impact of in-season weather variability on grain yield for four different sowing dates. Input data for the soil profile and all other X-file inputs were averaged from the experimental data of both sowing dates in 2024.

Results and Discussion

The phenological stages: Emergence date, anthesis date, first pod date, and first seed date of both data sets in 2024 were simulated with a maximum divergence between simulated and observed data of 3 days (Tab. 1). Due to pronounced indeterminate growth of chickpea, physiological maturity was not considered. Yield in 2024 was underestimated with a divergence of 12 kg DM ha^{-1}, respectively 224 kg DM ha^{-1} for the first and second sowing date. Further evaluation also indicated a good agreement between simulated and observed values. A closer examination of the 2024 growing season revealed that sowing on 15.04. led to delayed plant development compared to other sowing dates (Tab. 1). The long-term average of days reaching the corresponding phenological stage indicated that with a later sowing date, phenological stages are reached faster. The underlying reasons for this were that the higher daily temperature sums of later sowing dates led to the faster fulfillment of photothermal days.

Table 1. Comparison of simulated and observed phenological stages in 2024 of cv. Elmo and the days to reach the corresponding phenological stage under four sowing dates. The days shown represent the average number of days from 2015 to 2024 to reach the corresponding phenological stage.

Sowing date	**EDAT**		**ADAT**		**PD1T**		**PDFT**	
	Sim.	**Obs.**	**Sim.**	**Obs.**	**Sim.**	**Obs.**	**Sim.**	**Obs.**
15.04.**2024**	**19**	-	**65**	-	**74**	-	**80**	-
30.04.**2024**	**12**	**15**	**55**	**57**	**63**	**64**	**71**	**72**
15.05.**2024**	**11**	**9**	**50**	**49**	**59**	**56**	**66**	**64**
30.05.**2024**	**12**	-	**55**	-	**63**	-	**71**	-
15.04.**2015-2024** (Avg.)	18.3	-	64.9	-	73.6	-	80.5	-
30.04.**2015-2024** (Avg.)	14.6	-	56.3	-	65.4	-	72.4	-
15.05.**2015-2024** (Avg.)	12.4	-	50.3	-	59.4	-	66.0	-
30.05.**2015-2024** (Avg.)	9.9	-	46.5	-	54.5	-	61.6	-

EDAT= Emergence date; ADAT= Anthesis date; PD1T= First pod date; PDFT= First seed date

Growth-related variables, e.g., grain weight, tops weight, and leaf area index (LAI), were simulated with a high agreement between simulated and observed data (Fig. 1a). Considering the yield average from 2015-2024, the highest average yields were reached on sowing date 15.04. with 3514 kg DM ha^{-1}. Delayed sowing decreases the yield to an average of 3360 kg DM ha^{-1}. Sowing on 15.04. resulted in the most stable yield, whereas later sowing tended to be more susceptible to higher variation (Fig. 1b). The harvest index (HI) is a crucial parameter in chickpea production, particularly in relation to indeterminate growth. The highest HI was achieved on sowing dates: 15.04., 30.04., and 15.05. with an average of 0.44, whereas sowing on 30.05. led to an HI of 0.43 (Fig. 1c).

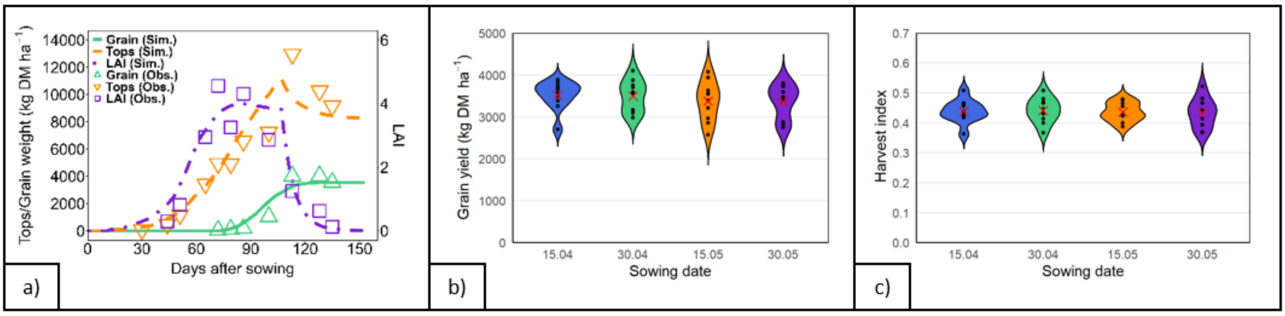

Figure 1. Simulated and measured data for crop model calibration date (30.04.2024) of tops, grain, and LAI (a), boxplots of grain yield (kg DM ha^{-1}) of four sowing dates for 2015-2024 (b), and box plot harvest index of four sowing dates (c) for the period 2015-2024 at Ihinger Hof, Renningen.

Conclusions

The conducted study of varying sowing dates of chickpea under Southern German growing conditions over ten years of historic weather data revealed that for chickpea varieties like Elmo, the optimal sowing window is wide. It should be noted that sowing earlier (up to 15.04.) tends to increase yield, combined with higher yield reliability. Nevertheless, farmers can act flexibly when choosing optimum sowing dates depending on factors like weather or soil conditions.

Acknowledgements

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Assessing the integration of mechanistic modeling and remote sensing data for grass productivity

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Keywords: Pastureland, Biomass production, Machine learning, Random Forest**,** DSSAT.

Introduction

Soil is an essential natural resource that provides goods and services vital for ecosystems and human well-being. Recent advances in geospatial technologies have made it easier to study soil properties and functions, generating data that can be analyzed across space and time. When combined with mechanistic models, this information offers valuable opportunities to deepen our understanding of soil processes (Silvero et al., 2023).

Recognizing the importance of modeling biomass production in pastures and its spatial variability, we propose a robust multidisciplinary approach. In this sense, this research aimed to explore the correlation between DSSAT-derived biomass outputs and environmental covariates, as a basis to support future digital soil mapping in pasturelands of the Brazilian Midwest.

Materials and Methods

The methodology comprises three main stages, as illustrated in Figure 1. First, remote sensing products, climate data, and legacy soil databases will be compiled, harmonized, and prepared as input for modeling pastureland with Urochloa brizantha using the DSSAT model. In the second stage, the harmonized dataset will be used to run DSSAT simulations to model pasture growth under baseline climate conditions (1980–2013). Finally, we will apply the Random Forest (RF) algorithm to explore spatial relationships between environmental covariates and simulated biomass (kg DM ha^{-1}).

Results and Discussion

This research is expected to improve our understanding of the synergy between the DSSAT model and environmental covariates, enhancing model scalability, while also addressing knowledge gaps related to the lack of spatio-temporal information on pasture productivity in Brazil (Bolfe et al., 2024).

Conclusions

By the end of this study, it is expected that the developed methodology, based on the synergy between the DSSAT model and remote sensing data, will provide a robust tool for the scalable digital mapping of *Urochloa brizantha* pasture productivity. This approach directly contributes to filling the spatio-temporal information gap on forage productivity in the Brazilian Midwest, an essential factor for sustainable livestock intensification.

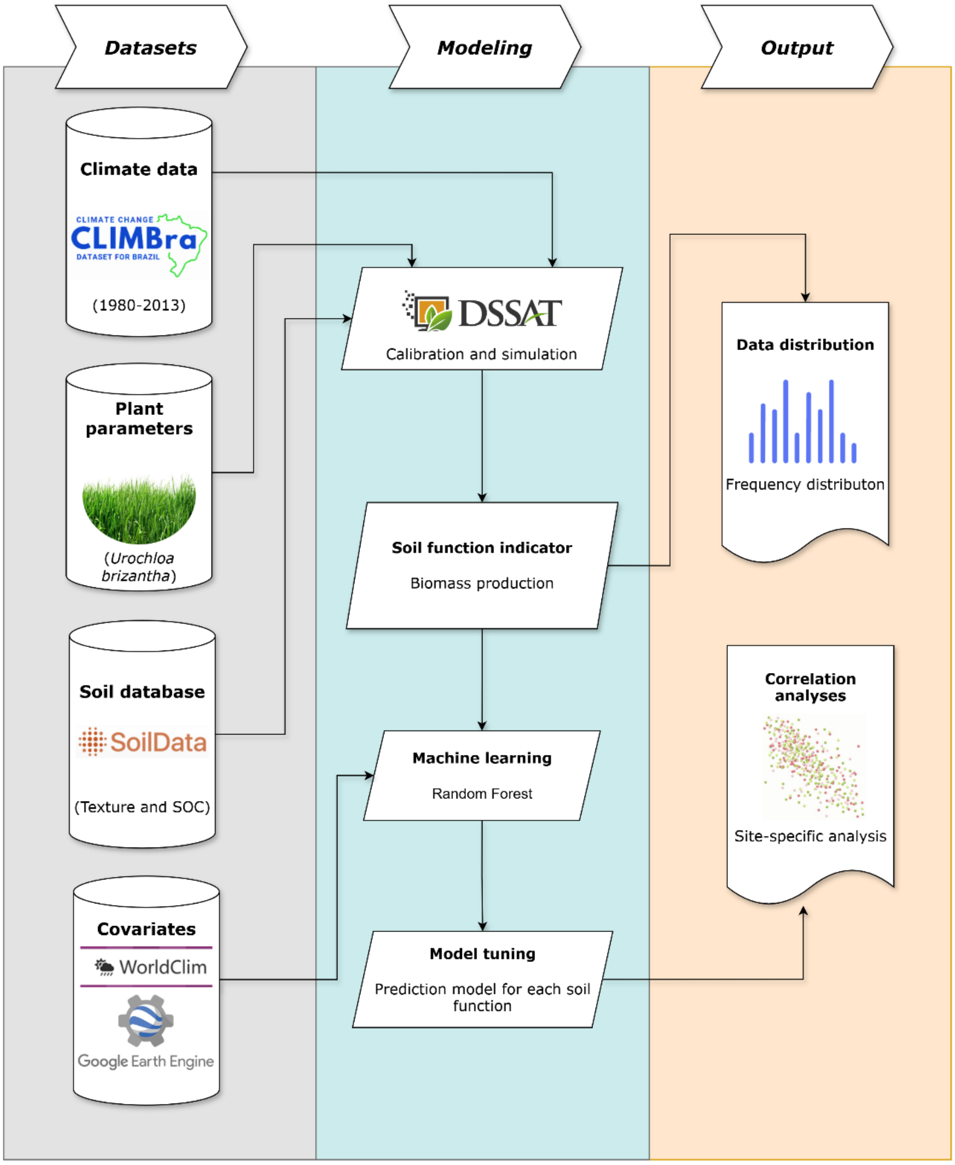

Figure 1. Workflow of the applied methodology. This study used a harmonized, open-access dataset, including climate (Ballarin et al., 2023), plant (Gomes et al., 2025), soil (Samuel-Rosa and Horst, 2024), and environmental covariates derived from remote sensing products processed on the Google Earth Engine platform (Gorelick et al., 2017).

Acknowledgements

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Simulating maize responses to different fertilizers of two crop models in multi-locations in West Africa

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Keywords: APSIM, grain yield, mineral nitrogen, simulation, SIMPLACE, organic manure, uncertainty

Introduction

Maize is an important crop in West Africa (WA). Land degradation and climate change further constraints its productivity and environmental sustainability thus promoting sustainable intensification practices (SIs) is strongly relevant in this context. Comprehensive field trials could provide understanding of the performance of SIs across locations, nevertheless they are often lacking in WA. Moreover, successful upscaling of SIs practices from specific locations to regional scales requires further investigating the suitability of SIs, especially under high spatial and temporal heterogeneity of soil and climatic conditions. Dynamic crop models representing the impact of SIs e.g. manure and/or inorganic fertilizers and their rates theoretically could offer capabilities to investigate the effects of those SI practices on crop yield and soil nutrients.

Materials and Methods

We employ two crop growth models [SIMPLACE<LINTUL5> (S-L5) and APSIM] along with the measured data from maize field in the trial station in Nyankpala and 19 farmer fields (Dimabi and Langa) in Northern Ghana in 2014 with different fertilizer types and rates [no fertilizer-control, inorganic (60N+40P+30K kg ha^{-1}), manure (1.25, 1.5, and 5 ton ha^{-1}), manure and half inorganic, inorganic and half manure] to investigate the suitability of two models to simulate effect of these SIs. The observed data included phenology, aboveground dry biomass (AGB), leaf area index (LAI), and grain yield which were collected from the common growing maize cultivar (Obatanpa) in Ghana. Both models were calibrated based on the given modeling protocol using the data from fertilized plots in the trial station then validated to the remaining treatments and farmer fields. We also examined uncertainties in yield prediction due to use of different combinations of soil (SoilGrid and FAO HWSD2.0) and climate (AgriERA5 and NASAPOWER) input data to the models. This modeling work resulted to 135 modeling combinations (03 soil data inputs x 03 climate data inputs x 3 locations x 5 different fertilizer treatments).

Results and Discussion

Calibration work shows that both models are able to simulate seasonal AGB and LAI. The APSIM model overestimated LAI on 04 August and 27 August. The S-L5 overall simulated higher the AGB than the APSIM and the observed data on 19 September and 15 October. The simulated grain yield of S-L5 and APSIM are 4.33 ± 1.67 and 3.82 ± 0.67 ton ha^{-1}, respectively for the fertilized treatments which are close to the observed yield (3.11 ± 0.75 ton ha^{-1}). Compared to the observed yield in the control treatment (1.47 ton ha^{-1}), two models adequately simulated the low yield due to no fertilizer with 1.62 and 1.26 ton ha^{-1}, respectively. Two models capture well the decline of AGB, LAI, and grain yield caused by the reduced fertilizer rates and types although onset and magnitude of simulated nitrogen stress differ between the models (Figure 1). Earlier and more severe nitrogen stress were observed in the control while later and less severe were found in the manure, the half inorganic and manure and inorganic treatments. Compared the observed data, the grain yield was sastisfactorily simulated by two models under farmer fields with control fertilizer (in Langa) and with manure (1.25 ton ha^{-1}). However, S-L5 overestimated the yield in the farmer field with the inorganic fertilizer while APSIM showed the overestimated yield under the manure application (1.5 tons ha^{-1}) in Dimabi. These illustrate the difference and uncertainty in the modeling performance between two models. Premilinary analysis with regards uncertainty due to the use of different climatic input data reveals that the daily global radiation from AgriERA5 was overall 10% higher than the observed data and NASAPOWER data (in Nyankpala) which could contribute to 10-50% difference in the simulated yield compared to the observed yield. These figures depends on the crop models (i.e. the larger difference was in APSIM compared to S-L5) and on fertilizer treatments (i.e. the difference was more pronounced in the control treatment than in the inorganic treatment). Use the FAOHSWD soil data resulted in the larger simulated yield than the use of measured soil and SoilGrid data under the control treatment.

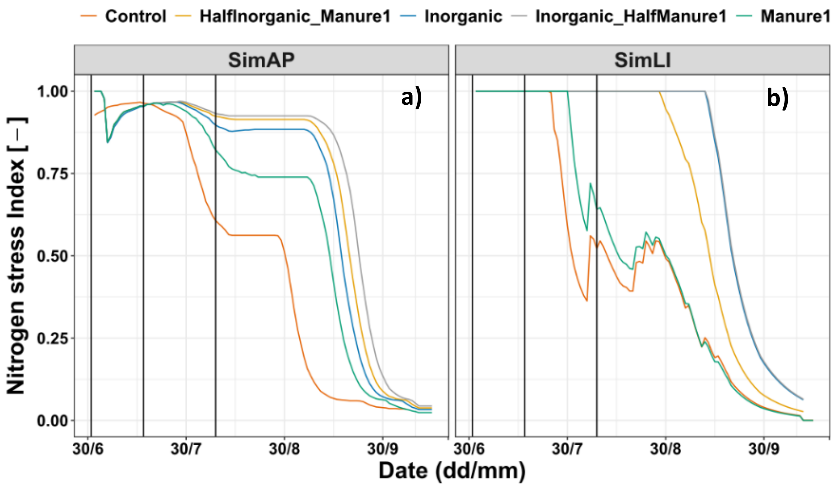

Figure 1. Comparison of nitrogen index over growing season simulated by APSIM (a) and SIMPLACE(LINTUL5) (b) resulted from the different fertilizer treatments in the maize field trial in Nyankpala, Ghana in 2014. The fertilizer treatments were control (no fertilizer), inorganic (60N+40P+30K kg ha^{-1}), manure (5 ton ha^{-1}), manure (5 ton ha^{-1}) and half inorganic (30N+20P+15K kg ha^{-1}), inorganic (60N+40P+30K kg ha^{-1}) and half manure (2.5 ton ha^{-1}). The vertical black lines indicate the fertilizer application events).

Conclusions

Our findings suggest a high potential of two crop models for their regional application for investigating the roles of SIs. However, caution must be paid to uncertain output variables which strongly depend on both model parameterization and on soil and climate input data.

Acknowledgements

Authors thank the Federal Ministry of Research, Technology, and Space (BMRTS) for funding the COINS project in West Africa.

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Optimum maize sowing and variety agro-advisory summary for the Zambezi River Basin

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Keywords: Climate adaptation, crop modelling, decision support, digital agriculture, DSSAT

Introduction

Maize is a crucial food crop in Eastern and Southern Africa, providing at least 40% of the caloric intake for the rural and resource-constrained population. It also serves as an essential input for industrial applications and animal feed (Kornher et al., 2018). While the Zambezi Basin has the potential for high maize yields, actual production is low due to inadequate fertility management and climate risks. This research aimed to develop improved fertilizer recommendations and enhance climate resilience by predicting potential water-limited yields across various season types and maize varieties at scale.

Materials and Methods

The study focused on the Zambezi Basin, which includes Malawi and parts of Mozambique, Zambia, Zimbabwe, and Angola. The CGIAR-Excellence in Agronomy (EiA) Initiative aimed to predict potential maize yields as well as optimal sowing dates and varieties using the AgWise Water Limited Yield crop modeling platform. The AgWise framework incorporates various crop models, including APSIM, DSSAT, WOFOST, and Oryzae. This research utilized the spatialized DSSAT 4.8 crop model, combined with weather and soil data from CHIRPS and AgERA5, along with soil information from ISRIC.

Simulations were conducted using 22 years of historical data (from 2000) for three generic maize varieties (short, medium, and long) across nine weekly sowing dates. The outputs of these simulations were aggregated across different sowing dates, varieties, and ENSO phases, allowing for the determination of optimal sowing dates for various season types. The date with the highest median yield was designated as the optimal sowing date.

Season types were classified based on the three ENSO phases, with phase determination achieved using the Oceanic Niño Index (ONI). An ONI value greater than 0.5°C indicates *El Niño* conditions, while a value less than -0.5°C indicates La Niña. An ONI value between -0.5°C and 0.5°C signifies neutral conditions.

Results

The analysis aggregated maize yields across various sowing dates, varieties, and ENSO phases. Notably, early sowing on November 2 resulted in high yields across all ENSO phases compared to other sowing dates. However, delayed sowing revealed differences in yield performance across the ENSO phases, with a rapid decline in yields under *El Niño* conditions. This pattern was particularly pronounced in long-season varieties during the *El Niño* phase compared to short and medium varieties (Figure 1).

Short and medium-season varieties exhibited greater yield stability, despite lower overall yields, compared to long-season varieties. Yield unpredictability was notably higher under *El Niño* conditions compared to La Niña and neutral conditions, particularly among long-season varieties and, to a lesser extent, medium-season varieties (Figure 1).

El Niño conditions resulted in lower yields in the central and southern parts of the Zambezi Basin compared to the northern, northeastern, and western regions of Zambia. This pattern was consistent across different varieties, with *El Niño* leading to reduced yields for short-season varieties relative to other types.

The northern parts of the basin exhibited a lower standard deviation, indicating higher yield stability compared to the central and southern regions. Consequently, there is a greater likelihood of achieving reliable yields in the northern areas than in the southern parts of the basin (Figure 1).

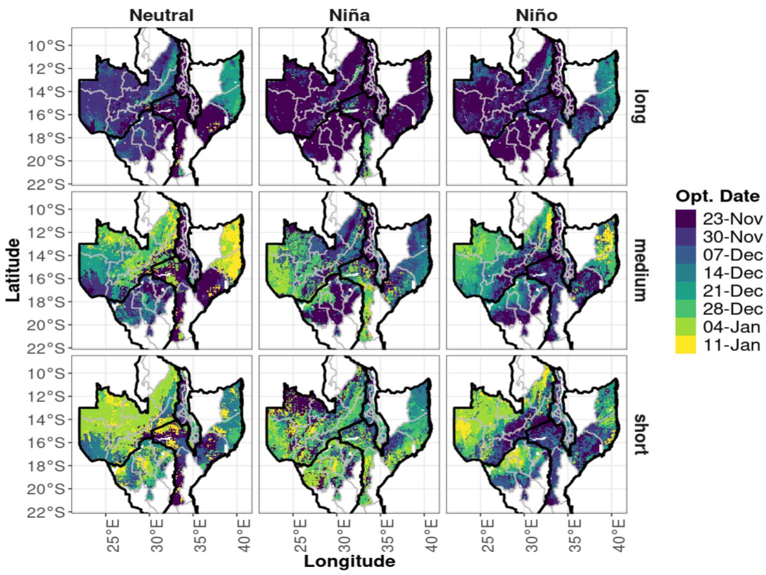

Figure 1: Optimum sowing dates across different varieties and ENSO phases for Maize in the Zambezi River Basin.

The earliest sowing dates, occurring in early November, are predominantly associated with long-season varieties across the three ENSO phases. This trend is particularly pronounced during the *La Niña* and *El Niño* phases. In contrast, medium and short-season varieties generally have slightly delayed optimal sowing dates compared to long-season varieties. Northern Mozambique experiences relatively delayed sowing dates during the neutral and *El Niño* seasons compared to the *La Niña* season (Figure 1).

There is less variation in optimal sowing dates within a specific variety and district. Long-season varieties benefit from early sowing, while medium-season varieties in Msekera experienced relatively delayed sowing dates. For short-season varieties, the neutral phase saw delayed sowing dates, occurring around late December (Figure 1).

Conclusion

Early planting generally results in higher yields; however, this outcome is contingent upon the variety and season type. Specifically, extremely wet and dry seasons may favor delayed sowing in the eastern parts of the Zambezi Basin. Additionally, there are greater chances of achieving higher yields in the northern parts of the basin compared to the southern regions.

Acknowledgements

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A site-specific crop modeling tool system for enhancing management practices in Honduras

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Keywords : Decision-support tools, optimal planting dates, efficient resources use, process-based crop growth model

Introduction

Agriculture plays an important role in Honduras economy, contributing nearly 12% of the national GDP and serving as a primary source of livelihoods, particularly in rural areas (Keller, 2013). Despite its importance, the sector is highly vulnerable to climatic variability and extreme weather events. Smallholders are especially at risk due to limited adaptive capacity, scarce resources, and restricted access to essential information (Jansen et al., 2006). These limitations increase their susceptibility to yield losses. Addressing such challenges requires decision-support tools that provide site-specific information to guide agricultural management planning. Although similar tools have proven their impact in other regions (Sotelo et al., 2020), Honduras currently lacks a crop modeling system capable of delivering locally tailored recommendations.

We propose *"Suelos de Honduras: Site-specific crop modeling",* a tool system designed to generate site-specific recommendations for five crops at the village level. The system integrates process-based crop growth models with historical climate, soil, and agronomic data to guide optimal planting dates and nitrogen fertilization strategies, thereby improving management practices with locally relevant information.

Materials and Methods

Data sources

Three primary inputs were used: climate, soil, and agronomic management data. Climate data were obtained from CHIRPS (precipitation) and AgERA5 (temperature and solar radiation) for 1990–2024. Soil information was derived from SoilGrids, including 12 variables (e.g., pH, sand, clay, organic matter) across five depths. Agronomic data is supplied directly by users when interacting with the platform (Fig. 1A).

Data processing

Environmental data were processed through geospatial transformations in Python V3.12 to generate model-compatible input files. These were combined with user-supplied agronomic data (village location, crop variety, and management practices) to run simulations.

Crop models

The system supports maize, beans, cassava, coffee, and banana. For maize, beans, and cassava, the Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003) was used. Coffee simulations employed a model calibrated for Central American conditions (Van Oijen et al., 2021), and banana simulations were conducted by using a SIMPLE crop model (Zhao et al., 2019) (Fig. 1B).

Results and Discussion Calibri pt 10

Site-specific recommendations

Climate and soil data are extracted at ~1 km resolution for the selected village and aggregated by soil texture classification. This enables simulations that provide both village-level and intra-village recommendations, offering a greater level of detail for decision-making (Fig. 1A).

Optimal planting dates

For coffee, the system simulates annual yield throughout the crop cycle (up to 12 years), showing differences in yield performance when planting occurs in different decades. For the other crops, yield simulations are generated at 7-day intervals across the growing season, allowing farmers to identify favorable planting windows (Fig. 1C, top) and evaluate risks under ENSO conditions such as El Niño and La Niña.

Nitrogen fertilization

A Bayesian optimization framework evaluates combinations of planting dates and nitrogen application rates to maximize yields (Fig. 1C, bottom). The system generates alternative fertilization strategies to improve yield performance for each planting window.

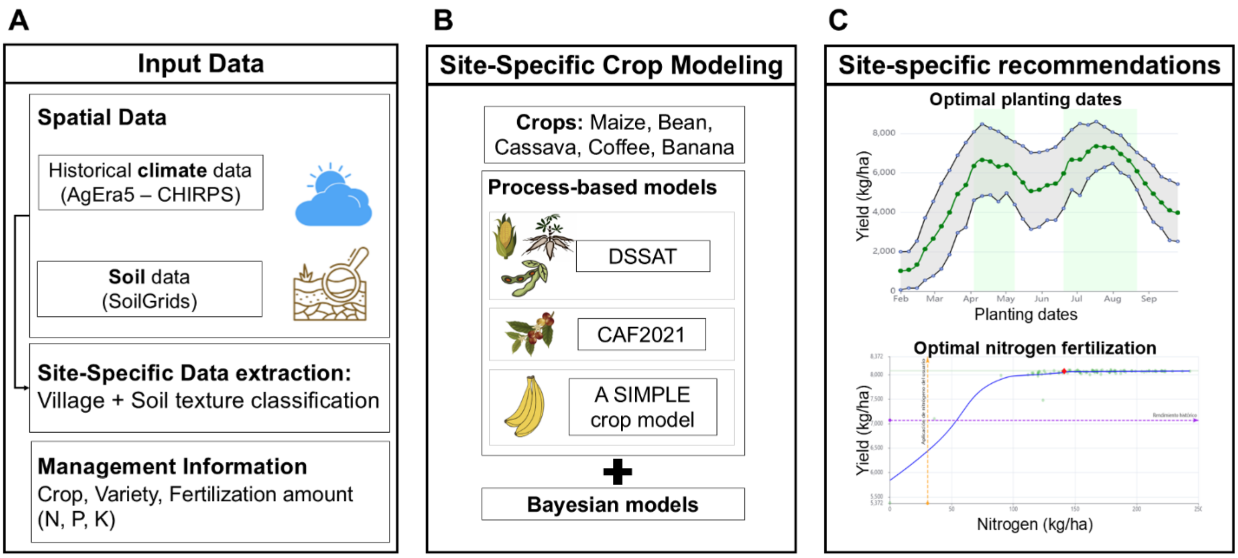

Figure 1. Workflow of the "Suelos de Honduras: Site-specific crop modeling" system for Honduras. A) Input data required for implementing the system. B) Processed-based crop models implemented to simulate plant growth for five different crops. C) Example recommendation results for maize. Top: yield responses across alternative planting dates. Bottom: Nitrogen fertilization recommedations generated using a Bayesian optimization framework

Conclusions

"Suelos de Honduras: Site-specific crop modeling" is the first site-specific, multi-crop modeling system developed for Honduras. By integrating environmental data with smallholder-supplied information, it delivers actionable recommendations that can reduce yield variability, optimize resource use, and enhance resilience in smallholder farming systems.

Acknowledgements

This work was supported by the United States Government in collaboration with the Alliance of Bioversity International and the International Center for Tropical Agriculture (CIAT) and the Government of Honduras through the Secretariat of Agriculture and Livestock (SAG) and its Directorate of Agricultural Science and Technology (DICTA).

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Digital Innovation for Forage Production: the e.INS Platform

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Keywords: Sustainability, Digital platforms, Smart agriculture, Decision support systems, Forage system

Introduction

The climate emergency, closely linked to anthropogenic greenhouse gas (GHG) emissions, requires the adoption of effective mitigation strategies in the agricultural and livestock sectors, which in 2017 contributed 6.1 Gt CO_2 eq per year to global emissions (FAO, 2017). In this scenario, sustainable management of soils and forage production represents a key element for reducing environmental impact, but it also requires an innovative approach to farm management. The FAO (2015), through the "Climate-smart agriculture" model, highlights the importance of increasing productivity while minimizing environmental impact and optimizing the use of resources, also with the support of digital technologies. Within this perspective, Spoke 03 Appàre of the e.INS project – Ecosystem of Innovation for Next Generation Sardinia – aims to support innovation processes, promote their dissemination, facilitate the transfer of technologies to the production system, and engage local communities in the challenges of sustainable innovation. The project focuses on the sheep supply chain in Sardinia and is developing an innovative digital platform capable of integrating existing livestock and health databases, while also acquiring new data through advanced sensor technologies. The ultimate goal is to provide decision-support tools for farmers, processors, and advisors, enhancing the economic and environmental sustainability of the sector and making the sheep production and processing system more competitive and resilient. In this context, the present work focuses on the forage production sector.

Materials and Methods

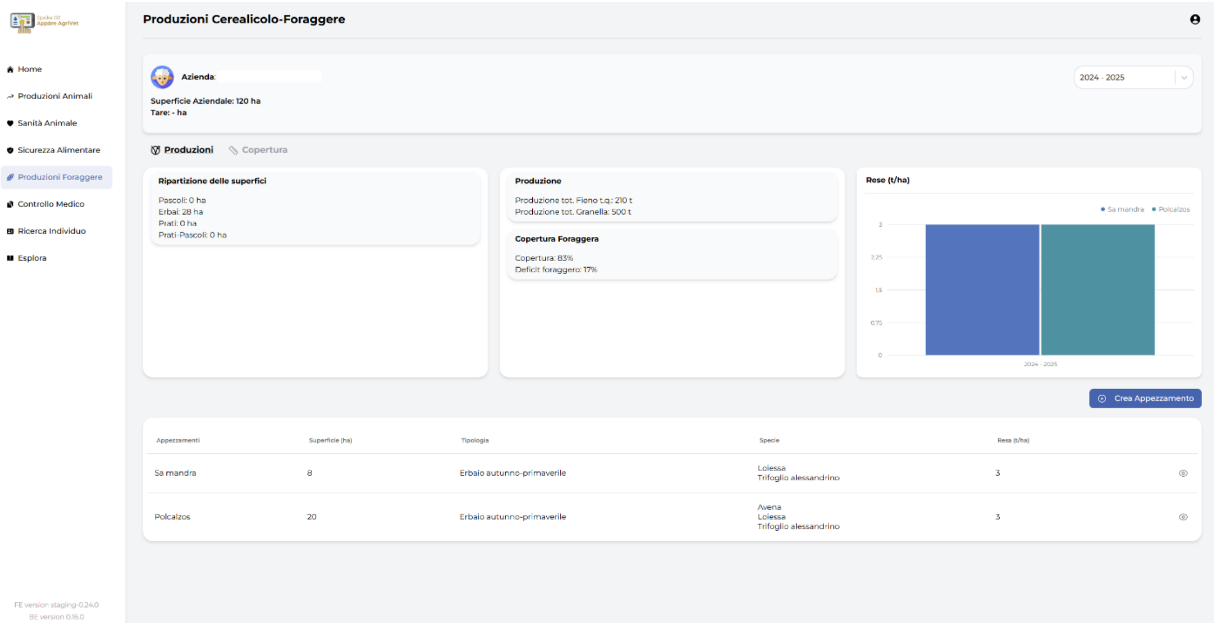
The e.INS platform – *Ecosystem of Innovation for Next Generation Sardinia* (Spoke 03 AGRIVET APPàre), still in the form of a prototype, has been designed as a multi-sector digital tool for the Sardinian sheep supply chain. It is structured into different sections – animal production, animal health, food safety, and a section dedicated to the registration of veterinary inspections – all interconnected with one another. Each section collects specific indicators and contributes to building a decision-support system aimed at fostering innovation in farm management.

The forage production section has been implemented through the development of indicators designed to link both the availability and the quality of biomass to the nutritional requirements of livestock. These indicators were first organized into flowcharts, in collaboration with the IT team at Abinsula, in order to define inputs and outputs. This process allowed the identification of crop productivity through yields per surface unit, considering different production types such as hay, silage, and grain. Forage quality was assessed through chemical-physical parameters such as %NDF, %ADF, protein content, ash, and starch, which also allow the calculation of the Relative Feed Value (RFV). Agronomic practices were also taken into account, including pedoclimatic information (altitude, water availability, sowing time and seed rate) as well as crop management techniques (soil tillage, fertilization, weed control, grazing, and mowing). Another indicator developed was nitrogen use efficiency, estimated through the ratio between nitrogen exported with the harvests (based on protein content) and nitrogen applied through fertilizers, in order to evaluate both resource use and the environmental impact of cropping practices.

These data were then integrated with livestock requirements, considering the number of animals on farm, the length of productive periods, and daily requirements expressed in Forage Unit for Lactation (UFL). This made it possible to estimate forage coverage, namely the farm's ability to meet the herd's nutritional needs.

In its current prototype version, the platform provides synthetic indicators such as UFL production per hectare, analysis of farm forage coverage (required vs available hectares), the effective duration of the coverage period ensured by on-farm production, and the share of unmet nutritional requirements. These outputs will be validated on pilot farms, thus allowing the platform to be tested in real production contexts and its actual usefulness as a decision-support tool to be verified, while also enabling the integration of management and production indicators directly at farm scale.

Results and Discussion



Figures 1. Details of the e.INS – Spoke 03 Appàre platform referring to the forage production section.

The development of the e.INS – Spoke 03 Appàre platform has led to the definition of specific indicators for the forage sector, allowing for the logical structuring of the section dedicated to cereal-forage production. These preliminary results highlight the potential of the platform as a decision-support tool for farmers, thanks to its ability to interconnect information from different sections and provide a clear and comprehensive overview of farm performance, with a focus on improving sustainability. The integration of the various sections represents an added value, as it makes it possible to overcome the fragmentation of farm data and to adopt a systemic view of the sheep supply chain, giving farmers the opportunity to maintain full control over their enterprises.

Future activities will focus on testing the indicators under real farm conditions and refining the platform based on the needs and feedback of farmers, with the aim of making it a truly transferable tool for the production system.

Conclusions

The development of the e.INS – Spoke 03 Appàre platform represents an innovative step forward in the management of the sheep supply chain in Sardinia, as it provides farmers with an updated overview of farm performance. In the forage production section, the integration of selected indicators makes it possible to link yields and product quality, management practices, and resource use efficiency with the other components of the platform, offering a useful tool to ensure farm sustainability. The work carried out in the forage sector represents a concrete example of how the integration of farm data and indicators can be translated into digital tools that support daily management and foster the transition towards more sustainable systems. Since the platform is still available in prototype form, the next activities will focus on its validation, with the aim of making it fully operational for end users.

Acknowledgements

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Advancing Seasonal Maize Yield Prediction in Ethiopia through Climate–Crop Model Integration

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Keywords: Crop Model, Maize Production, Seasonal Climate Forecast

Introduction

Crop production in Ethiopia is dominated by rainfed small hold farming, in which climate variability dictates productivity. Producers and experts have to make decisions, with out a clear knowledge how the season will evolve and the production they are likely to achieve. Despite this challenge, Ethiopia currently lacks an operational crop production forecasting system to support planning and strategic decision-making.

This study investigates the potential of predicting maize yields 1–2 months in advance using an integrated climate–crop modeling framework.

The existing operational crop monitoring systems in East Africa largely focus on water availability without considering the complex reactions between climate variables and crop physiology. If agricultural communities are to benefit from seasonal climate and crop production forecasts in managing climate risks, the information must be presented in terms of production outcomes at a scale relevant to their decisions, with uncertainties expressed in transparent terms (Hansen et al., 2006). One way of achieving seasonal climate and crop yield forecast is using integrated climate-crop modeling framework. In Ethiopia, Tesfaye, et. al. (2023) demonstrate the possibility of seasonal maize yield prediction using CCAFS Regional Agricultural Forecasting Toolbox (CRAFT) (Sheliaet al., 2019).

A functional spatial yield forecasting system could provide risk management options leading to greater economic and social values under highly variable environments. Yet, no such forecasting system exists to support early decision making in developing countries dependent on smallholder agriculture, such as Ethiopia. In this study, we present the methodology, model evaluation, results, and limitations of forecasting maize yield at the national scale using a climate–crop modeling framework.

Materials and Methods

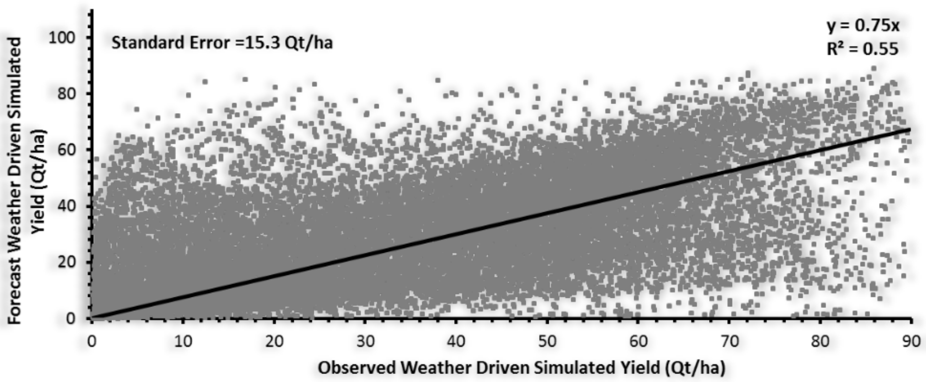
Seasonal forecast from the European Centre for Medium-Range Weather Forecasts (ECMWF) were statistically downscaled using Emprical Quantile Mapping (EQM) and evaluated against reference observation to assess if any improvement archived over raw model outputs. The downscaled seasonal climate forecast was integrated with Decision Support System for Agro technology Transfer (DSSAT) crop simulation model to predict maize production. The crop model run on a national scale simulating maize at 10 km grid points. Simulations were run annually using a rule-based planting strategy within a planting window based on estimates of agronomic onset of the wet-season using AquaBEHER R package (Takele R, and Dell'Acqua M, 2023). First the crop model simulation was evaluated against agregated sub-national level observed yield. Then the seasonal forecast driven simulation (maize prediction) was evaluated against observed weather driven simulation. Model performance was assessed using Root Mean Squared Error (RMSE), Mean systematic error (Bias), Index of agreement (d) and correlation analysis was used in the evaluation.

Results and Discussion

Downscaling improved the spatial representation of mesoscale rainfall patterns, capturing maxima and minima better than the raw forecast. However, the downscaled forecast consistently failed to reproduce the observed seasonal rainfall pattern, particularly in eastern highlands and in dry and wet years.

The maize simulation consistently overestimates the observed yield for all proportions and occurrences. This overestimation by simulation exaggerated, predominantly over highland areas. However, the spatial variation of the inter-annual yield variability was well reproduced by the simulation, which indicates a potential for predictability.

The association between the observed driven simulation and forecast driven simulation is presented in (Figure 1). The forecast showed positive linear relationship with the observed maize simulation. About 55% of the inter-annual variability of the observed yield simulation was explained by the forecast driven simulation. This predictive success of the maize yield suggests, significant predictability of the maize yield across the country can be meet with reasonable skill.



** The Statistics is significant at 5% level*

Figure 1. Comparisons of forecast weather driven simulated yield with observed weather driven simulated yield over the hindicast (1996 – 2010) period.

Conclusions

The study demonstrates the potential and usability of integrated climate-crop models by use case of forecasting maize yield over Ethiopia. We aims to statistically downscale and integrates the output from dynamical seasonal forecast model (ECMWF SEAS5) in to crop simulation model (DSSAT-CERES-Maize) to predict maize production on national scale over Ethiopia.

The assessment of the potential predictability of maize production suggests, the maize forecast does well predict the observed maize yield. However, the forecast not in all cases was accurate. Slightly poor performance by the crop model in lower yield environments and highland climates affected forecast accuracy. Good performance to predict inter-annual and spatial variability of the yields which indicates Maize yield can be forecasted around two months before planting with a reasonable skill. Future work will use this integrated framework to simulate crop production under perturbed climate and management scenarios, identifying agroclimatic stressors and critical genetic traits that can benefit sustainable smallholder farming systems under variable and changing climates.

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FIELD-SCALE DURUM WHEAT YIELD ESTIMATION USING SENTINEL-2 TIME SERIES AND TEMPORAL FUSION TRANSFORMERS IN SOUTHERN ITALY

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Keywords: deep learning, field-scale modelling, yield maps, mediterranean area, grain yield

Introduction

Durum wheat (*Triticum durum* Desf.) plays a pivotal role in food security, nutrition, and agricultural economies across the Mediterranean basin, serving as the primary raw material for pasta and couscous (Taranto and De Vita. 2019; Xynias et al., 2020). Unfortunately, the Mediterranean area is widely recognized as a climate change hotspot (IPCC, 2025). Rising temperatures and altered rainfall patterns are projected to reduce cereal yields and amplify spatial variability, especially in rainfed systems (Lionello and Scarascia, 2018; Sellami et al., 2024). These conditions underscore the need for reliable, high-resolution yield prediction tools to support timely and informed decision-making. Strong spatial gradients in climate, soil, and management practices make yield estimation particularly complex at the field level. To address these challenges and support more precise, data-driven decision-making, we present a deep-learning framework for predicting harvested grain yield at field scale, based on freely available satellite imagery.

Materials and Methods

This study focuses on durum wheat fields located in the Capitanata district (Province of Foggia, Southern Italy), which represents the most important durum wheat-producing area in Italy, accounting for approximately 15% of the national cultivated surface (ISTAT, 2022). The core model is a Temporal Fusion Transformer (TFT) (Lim et al., 2021), which ingests season-long sequences of Sentinel-2-derived vegetation indices (e.g., NDVI, EVI) along with satellite-based weather time series (e.g., temperature and precipitation). Static geospatial covariates, including digital elevation (DEM) and soil texture classes from pan-European sources (e.g., LUCAS), are incorporated as contextual features.

Model hyperparameters were optimized through systematic tuning with early stopping, minimizing validation loss and maximizing R^2. Training follows a leakage-aware strategy that respects field boundaries and temporal coherence; generalization is assessed via spatial cross-validation, leave-one-year-out, and a strict leave-one-farm-out protocol, which withholds entire farms to evaluate transferability across unseen management and site conditions.

In addition to global performance metrics, the model is evaluated through spatially distributed R^2 and RMSE, computed at parcel/tile level, mapped across fields and seasons. Farm-level aggregates are reported under leave-one-farm-out folds to diagnose local bias and uncertainty. Benchmark comparisons include tree-based learners trained on identical inputs (Choudhary et al., 2022; Zhou et al., 2023).

Results and Discussion

Yield observations derived from combine harvesters equipped with calibrated yield monitors, covering approximately 200 fields from multiple farms over five consecutive seasons (2021–2025), and pre-processed to remove lag and outliers (figure 1a). The TFT model achieves R^2 values between 0.60 and 0.75 across seasons, with RMSE ranging from 0.5 to 0.9 t/ha depending on year and location, outperforming baseline model and capturing within-field yield gradients (figure 1b).

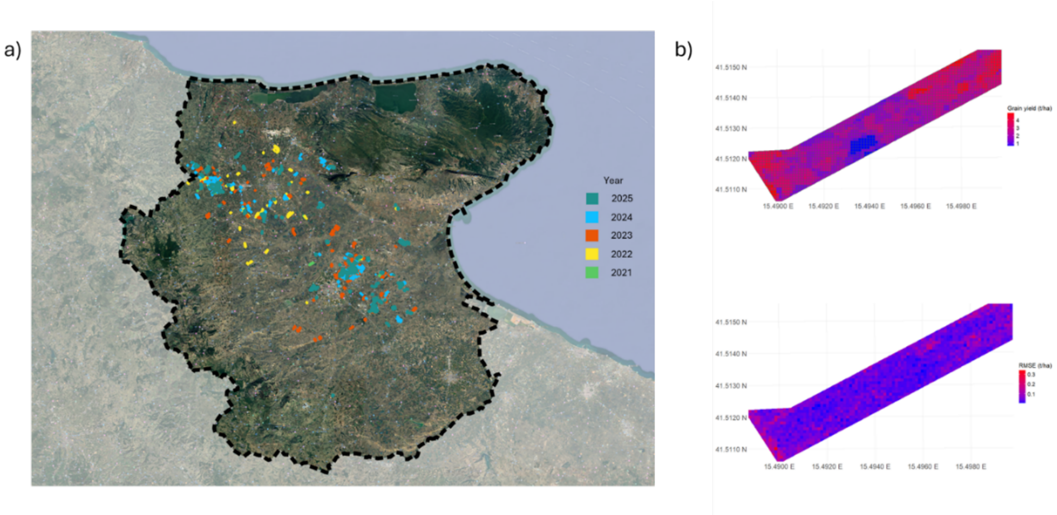

Figure 1. a) Area of the study with yield observations collected for five consecutive season, differentiated by colours; b) Example, derived from one field, of the spatial distribution of grain yield (top) and RMSE of the model (bottom).

Conclusions

This approach builds on recent advances in remote sensing and machine learning, demonstrating the potential of deep neural networks to capture spatio-temporal patterns in multispectral data for accurate and scalable yield estimation.

Acknowledgements

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Adaptation to Disease and Climate Change Impacts on Wheat in Denmark and the North China Plain

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Keywords: Infection temperature thresholds, Host-pathogen interactions, Epidemiological modelling, G × E × M × D interactions, Yield gap analysis

Introduction

Wheat yields are substantially constrained by biotic stress, with pests and diseases (Savary et al., 2019). Disease development is strongly driven by environmental factors, particularly temperature and humidity, through their effects on host–pathogen interactions as conceptualised by the disease triangle (Scholthof 2007, Prasad, Bhardwaj et al. 2021). Among the most prevalent fungal diseases affecting wheat worldwide are yellow (stripe) rust *(Puccinia striiformis*), powdery mildew (*Blumeria graminis*) and Septoria tritici blotch (*Zymoseptoria tritici*) (Wang, Zia-Khan et al. 2019). Climate change is modifying temperature regimes and rainfall patterns, with consequences for disease occurrence and distribution (Eastburn, McElrone et al. 2011, Miedaner and Juroszek 2021). Epidemiological models describe infection processes but are rarely linked to crop growth and yield, whereas crop simulation models represent genotype × environment × management (G × E × M) interactions under climate change (Hammer, Cooper et al. 2006, Asseng, Ewert et al. 2015). Integrating disease processes into crop models remains challenging, but it is necessary for quantifying yield losses under future climatic conditions (Donatelli, Magarey et al. 2017). This research aims to improve an existing wheat disease model and link it with a crop model to analyse the effects of climate change on wheat growth and yield under contrasting disease pressures. The specific objectives are to: (i) enhance the representation of yellow rust, septoria tritici blotch and powdery mildew in a simple epidemiological model; (ii) integrate disease effects into a crop model to represent genotype × environment × management × disease (G × E × M × D) interactions; and (iii) quantify the combined impacts of climate change, disease infection and adaptation strategies on wheat yield in Denmark and the North China Plain.

Materials and Methods

This research examines the effects of foliar wheat diseases on crop growth and yield under current and future climatic conditions using a multi-scale approach that combines literature synthesis, climate-based disease analysis, field experimentation and crop simulation. A meta-analysis synthesises published data on infection temperature thresholds for yellow rust, septoria tritici blotch and powdery mildew, using reported minimum, optimum and maximum temperatures to derive disease-specific temperature response curves and associated uncertainty. These curves provide parameter values for subsequent epidemiological analyses. Temperature and humidity responses will be applied to gridded hourly climate data to estimate climatic suitability for infection under historical conditions from ERA5 and future scenarios from ISIMIP. Field experiments in Denmark will examine the interaction between water availability, nitrogen supply and disease type on wheat growth and yield using controlled inoculation treatments. Disease effects are then incorporated into a crop simulation model to represent genotype × environment × management × disease interactions, with experimental data used for calibration and evaluation in analyses of climate change impacts and adaptation options in Denmark and the North China Plain.

Results and Discussion

The meta-analysis synthesised published information on infection temperature thresholds for yellow rust, septoria tritici blotch and powdery mildew, based on reported minimum, optimum and maximum temperatures. The analysis revealed clear differences among diseases in their thermal preferences, with yellow rust associated with lower temperatures, septoria with intermediate optima, and powdery mildew with higher temperature tolerance. Considerable variability was observed across studies, particularly at minimum and maximum thresholds, reflecting differences in experimental conditions, host cultivars and pathogen populations. Quantitative information on relative humidity and leaf wetness was limited and inconsistently reported, preventing their inclusion in temperature–humidity response relationships.

The derived temperature response curves provide a consistent parameter set for future epidemiological and crop modelling studies. The results indicate that uncertainty in infection thresholds, especially at thermal limits, is likely to influence estimates of climatic infection suitability. Field experiments are designed to examine how disease effects on wheat growth and yield vary under different water and nitrogen conditions, with measurements of leaf area development, canopy function and yield components. Together, these results will provide key inputs for the development of coupled crop–disease models for analysing climate change impacts and adaptation options.

Conclusions

This study synthesises published evidence on infection temperature thresholds for yellow rust, septoria tritici blotch and powdery mildew and derives disease-specific temperature response curves with associated uncertainty ranges. The results show substantial variation among studies, mainly at the minimum and maximum temperature limits, and indicate that quantitative information on relative humidity and leaf wetness requirements is often missing. These gaps contribute to uncertainty in disease parameterisation. The temperature responses, together with experimental evidence that disease effects vary with water and nitrogen supply, provide a basis for later climate-driven disease assessment and crop–disease modelling to examine yield impacts and adaptation options under changing climatic conditions.

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