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Food Systems and Food Security

Global Rice Systems in Food Security Under Climate Constraints: Machine Learning for Yield Enhancement

Dadrasi Amir[1], Vačkářová Davina[1 2], Salmani Fatemeh[1], Weinzettel Jan[1]*

[1] Charles University, Environment Centre, 162 00, Prague, Czech Republic, amir.dadrasi@czp.cuni.cz; jan.weinzettel@czp.cuni.cz

[2] Global Change Research Institute of the Czech Academy of Sciences, 603 00, Brno, Czech Republic

Keywords: yield variability, irrigated systems, rainfed systems, shapley analysis, sustainable intensification

Introduction

Rice feeds over 3.5 billion people, yet faces production-demand gaps due to climate change, population growth, and limited resources (FAO, 2023). Irrigated systems dominate global output (85%), relying on managed water and nutrients, while rainfed systems (15%) are vulnerable to environmental stresses like drought and temperature extremes (Cassman & Grassini, 2020). Prior studies address isolated factors (e.g., nutrient management or consumption patterns), but lack an integrated global framework linking yield drivers, supply-demand dynamics, and system-specific strategies under climatic pressures. This study develops a global framework to: (1) identify key biophysical and management factors driving yield variability in irrigated vs. rainfed rice systems across 1,383 climate zones; (2) map spatial production-consumption imbalances in 83 countries (>90% of global rice); and (3) propose tailored interventions for sustainable yield enhancement, aligning with SDG 2 (Zero Hunger).

Materials and Methods

Using 2020 data from FAO, SPAM, USDA, and GYGA-ED, we analyzed yield (Ya), harvested area, and production at 0.5° resolution via ArcGIS Pro. XGBoost models predicted Ya based on inputs: climatic (Tmax, Tmin, Tmean, rainfall, VPD, GDD); soil (OC, CEC, pH, EC, ESP, $CaCO_3$, AWC); and management (sowing/harvest dates, maturity, N/P fertilizers, water use). Shapley Additive exPlanations (SHAP) quantified factor contributions. Models were validated with R^2 (0.85 irrigated, 0.95 rainfed) and RMSE (804 kg ha-1 irrigated, 283 kg ha-1 rainfed) on calibration data; LOOCV yielded R^2 0.50-0.59. Surplus/deficit mapped as production minus demand (population × per capita consumption).

Results and Discussion

Global rice production is concentrated in Asia, with China (188.83 Mt) and India (128.35 Mt) leading, primarily through irrigated systems in fertile deltas like the Yangtze and Mekong. Irrigated rice covers 63 climate zones, with high-yield areas (e.g., CZ 5703: 8.01 t ha-1, 2.08 Mha, 16.67 Mt) suitable for expansion and high-area zones (e.g., CZ 9901: 5.69 t ha-1, 4.42 Mha, 25.16 Mt) dominating production but constrained by management and biophysical factors. SHAP analysis (Figure 1A) reveals N (mean |SHAP|=290.6 kg ha-1) as the top driver, enhancing photosynthesis under controlled conditions (Cassman et al., 2002), followed by maturity period (211.98 kg ha-1) and Tmean (197.38 kg ha-1), where elevated temperatures induce heat stress and reduce yields (Ray et al., 2019). Rainfed rice spans 41 zones, prevalent in sub-Saharan Africa and eastern India, with high-yield zones (e.g., CZ 8102: 2.80 t ha-1, 0.39k ha, 1.1 Mt) offering growth potential and high-area zones (e.g., CZ 9901: 2.19 t ha-1, 8.02k ha, 17.5 Mt) limited by climatic vulnerabilities. SHAP (Figure 1B) identifies Tmax (203.2 kg ha-1) as dominant, increasing evapotranspiration and drought stress (Van Oort & Zwart, 2018), alongside OC (148.2 kg ha-1) for soil resilience (Mishra et al., 2021). Supply-demand mapping shows surpluses in export-oriented nations like India (+17.46 Mt) and Thailand, contrasting deficits in high-consumption areas like Turkey (-5.60 Mt), Nigeria (-2.15 Mt), and Bangladesh, driven by population density and dietary preferences (Maraseni et al., 2018). These disparities underscore irrigated systems' efficiency in surplus regions but highlight rainfed vulnerabilities in deficits, necessitating targeted interventions like site-specific nutrient management in irrigated zones to close 10-15% yield gaps (Pampolino et al., 2007) and water harvesting in rainfed areas to mitigate climate risks (Jaramillo et al., 2020).

a) b)

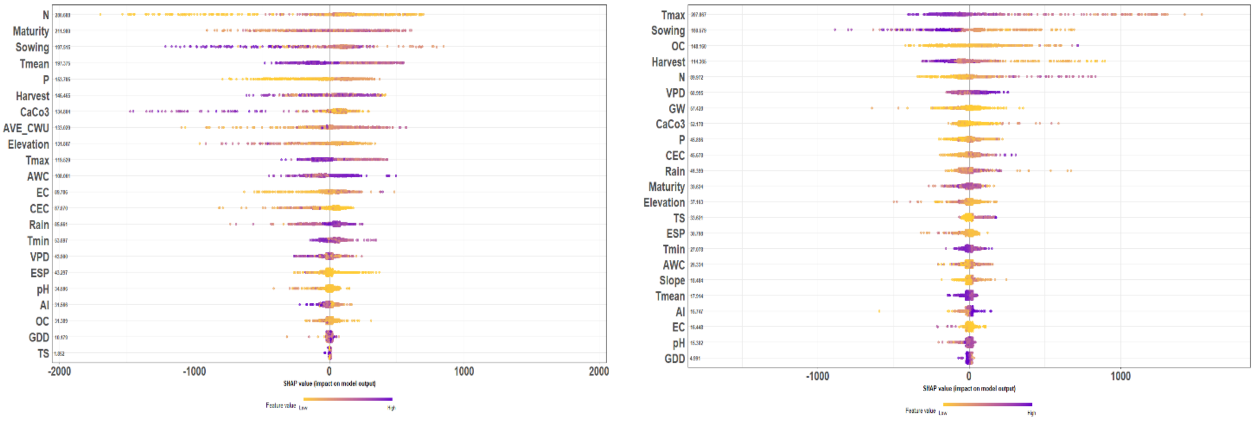

Figure 1. SHAP analysis of yield drivers (660 observations, 83 countries): (A) Irrigated rice, with N (mean |SHAP|=290.6 kg ha-1) and Tmean as key factors; (B) Rainfed rice, with Tmax (mean |SHAP|=203.2 kg ha-1) and OC dominant. High/low values in purple/yellow.

Conclusions

This ML-driven framework identifies system-specific yield drivers and imbalances, recommending precision N management and alternate wetting-drying for irrigated systems; resilient cultivars, soil enhancement, and water harvesting for rainfed. Targeting high-potential zones boosts production, reduces deficits, and enhances food security under climatic pressures.

Acknowledgements

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Dynamic Rice Yield Prediction System

Yao Ming-Hwi[*1], *Li Ting-Yi* [2]

[1] Taiwan Agricultural Research Institute, Agricultural Engineering Division, 413008, Taichung City, Taiwan, mhyao@tari.gov.tw

[2] National Science and Technology Center for Disaster Reduction, 231007, New Taipei City, Taiwan

Keywords : Crop model; Rice; Yield; Grid data

Introduction

Agricultural production is often substantially reduced by meteorological disasters. With the global impact of climate change, ensuring a stable food supply has become a major policy priority for numerous governments. Rice is a staple food crop in Taiwan with self-sufficient production under normal weather conditions. However, rice production can be drastically reduced by typhoons or heavy rainfall. Therefore, acquiring real-time information on total rice production is crucial for food supply management. Crop production is influenced by many factors. These factors are predominantly assessed using crop simulation models, for which mathematical methods are used to describe the actual growth, development, and yield of crops, as well as the interactions between environmental conditions and crop physiology. In this study, a nationwide dynamic assessment system was established for rice yield. Daily gridded weather data were obtained from Central Weather Administration. These data were then input into a crop model, referred to as the Decision Support System for Agrotechnology Transfer (DSSAT), for regional yield prediction. This model enables monitoring of total rice production in real time and provides an early warning for supply shortages, which can serve as a basis for market regulation.

Materials and Methods

Real-Time Weather Data Source

Daily real-time gridded weather data were continually acquired and integrated. This process involved collating and interfacing with daily 1 km × 1 km grid data, with meteorological parameters such as daily maximum temperature, minimum temperature, solar radiation, and precipitation considered. After the dynamic crop yield assessment system was refined, its relationship with actual yields was validated.

Yield Prediction System Development

The proposed system was designed using a client–server architecture and using tools such as Visual Studio 2019, C#, and an MS SQL database. Spatial data were processed using ESRI ArcGIS Engine 10 or a later version to develop an independent operating system.

Results and Discussion

Although this study used daily 1 km × 1 km gridded weather data, actual rice data are available only in statistical form from administrative regions (e.g., townships or villages). Therefore, the gridded data of each administrative region were aggregated and compared with the crop model's predicted data. Although a correlation coefficient of 0.78 was observed between the observed and simulated yields, the simulated yield was predominantly higher than the observed yield, primarily because the DSSAT model was set to have no fertilizer or water stress. In real-life scenarios, collecting detailed information on the cultivation conditions and growth status of rice in every township is not feasible. However, in the present study comparison of cumulative data over 5 years revealed an interannual variation of approximately ±500 kg in rice yield per hectare. In addition, the difference between the simulated and observed yields in most of the townships fell within this range. Therefore, the yield simulation results of the proposed system were considered to be acceptable.

After the proposed system was used to automatically input daily gridded weather data into the DSSAT model for yield estimation, it was used to produce daily nationwide rice yield forecasts. An agriculture-specific gridded weather database was then developed using different spatial and temporal scales. To forecast future yield trends, daily single-grid rice production was directly converted into a township scale or aggregated to obtain the total national rice production. The goal was to establish a practical dynamic crop yield forecasting system. According to the literature, disasters are the main factor affecting crop yield. Because the crop model used in this study has a limited database, it cannot be used to assess typhoons, which represent Taiwan's most substantial disaster type. In the future, we plan to use historical crop loss data to analyze yield reduction when rice production is affected by typhoons at different growth stages. This approach can help establish a reasonable calibration curve, rendering the proposed system's estimates closer to actual yields.

Development of a versatile real-time crop yield prediction platform integrating crop modeling, satellite imagery, and meteorological data

Sharaby Yoav, Haik Oren, Perry Oded, Frank Tal, Perach Omer, and Sadeh Yuval*

SatYield, HaNassi HaRishon 52, Rehovot 7630242, Israel, yoav@satyield.com

Keywords: leaf area index, APSIM, Sentinel-2, cultivar calibration, decision support.

Introduction

Accurate early-season predictions of crop yield, as far in advance of harvest as possible, are essential for ensuring supply chain stability and global food security in the face of accelerating climate change (Becker-Reshef et al., 2020). To date, many yield estimation methods utilize satellite imagery, which is considered a reliable, affordable, large-scale, and timely data source for monitoring seasonal crop growth. However, the conversion from remotely sensed data into yield, often done by vegetation indices, machine learning, or data assimilation, greatly suffers from limited scalability, low interpretability, or the need for ground data (Sadeh et al., 2024). The use of crop models, which can simulate various scenarios representing field-scale agronomic variability in a specific area, has been successfully demonstrated in bridging these gaps (Lobell et al., 2015). Here, we developed a versatile yield prediction platform incorporating satellite imagery (Sentinel-2), crop model simulations (APSIM), and gridded weather data, which does not rely on field-level measurements or significant amounts of data. The platform is currently designed to perform optimally at a spatial scale of a state (level-1 administrative division; ~500K-15M ha), and to be easily applied on various field crops, anywhere in the world, providing accurate estimates starting from three months before harvest. Such intelligence can serve as a reliable decision-support tool for stakeholders in the global food supply chain, therefore assisting in maintaining food security under a changing climate.

Materials and Methods

The versatile yield prediction platform is based on matching remotely sensed and simulated Leaf Area Index (LAI) seasonal profiles, from sowing to harvesting. This crop trait has been previously found to be effective in integrating the two data streams into yield prediction (Pan et al., 2019). The platform was developed and tested on two major field crops, maize and soybean, in the USA, Brazil, Paraguay (both crops), Argentina, and Uruguay (soybean only). State-level reported yields taken from the years 2022-2024 served as the training set, while the 2025 reported yields served as the test set. **First,** the county-level crop area was assessed using per-pixel ML-based crop classification applied to the Sentinel-2 images. The daily LAI values were then estimated based on VI transformative equations (Sadeh et al., 2019) and smoothed into a county-level seasonal profile using harmonic fitting. **Second,** A different APSIM file was prepared for each state, consisting of hundreds of possible combinations representing the state's typical range of agronomic practices, soils, and cultivars. Calibration of state-specific hypothetical cultivars had been based on the 2022-2024 LAI data estimated previously (and yield data if available), using the Markov Chain Monte Carlo (MCMC) Bayesian approach. Calibration of maize/soybean cultivars included modifying 18/13 parameters (both phenological and morpho-physiological), respectively. The state-level APSIM file was then applied to every county (level-2 administrative division; ~1K-500K ha) within the state, using a county-level summarized gridded weather data (GridMet in the USA, ERA-5 in all other countries). **Third,** the county-level simulated LAI trajectories were matched with the remotely sensed LAI, using a feature-based elimination algorithm. The algorithm identified the best-fitted simulations and averaged their coupled yield to provide a county-level predicted yield as a preliminary step. All county-level predicted yields were then summarized, using each county's estimated crop area as weights, to calculate the state-level predicted yield.

Results and Discussion

Calibration of maize cultivars, using the 2022-2024 state-scale yield and LAI data as a training set (n=60), provided an accurate state-level yield estimation featuring an R^2 of 0.98 and RMSE of 0.38 T ha^{-1}. Validation of the calibrated cultivars, which was applied on the 2025 season (n=20), maintained the high accuracy of the platform, as evidenced by an R^2 of 0.97 and an RMSE of 0.54 T ha^{-1}. In addition, the slope of the regression lines between the predicted and the reported yields (0.98 for training, 1.01 for test) indicates no proportional bias when compared to the 1:1 line. In soybean, cultivar calibration using the 2022-2024 seasons (n=81) also provided a high state-level yield estimation accuracy (R^2 = 0.97, RMSE = 0.13 T ha^{-1}) with no proportional bias (regression slope = 0.96). However, the validation on the 2025 season (n=27) resulted in a slightly reduced accuracy (R^2 = 0.88, RMSE = 0.2 T ha^{-1}) with a consistent underestimation (regression slope = 0.86). The reduced yield prediction accuracy in soybean probably resulted from a complex sowing practice in some of the South American states, in which there are several consecutive sowing windows rather than a singular, short-term one (as common in maize, or in soybean in the USA). This phenomenon often leads to an estimation of a multi-peaked county-level LAI profile from the satellite imagery, and to a consequent mismatch with the "correct" APSIM simulations. Since APSIM (and any other crop growth model) simulations are designed to represent a field scale and not a broader scale (county, state), characterized by spatial heterogeneity, one of our main challenges is to bridge this estimated-simulated gap in the yield prediction process.

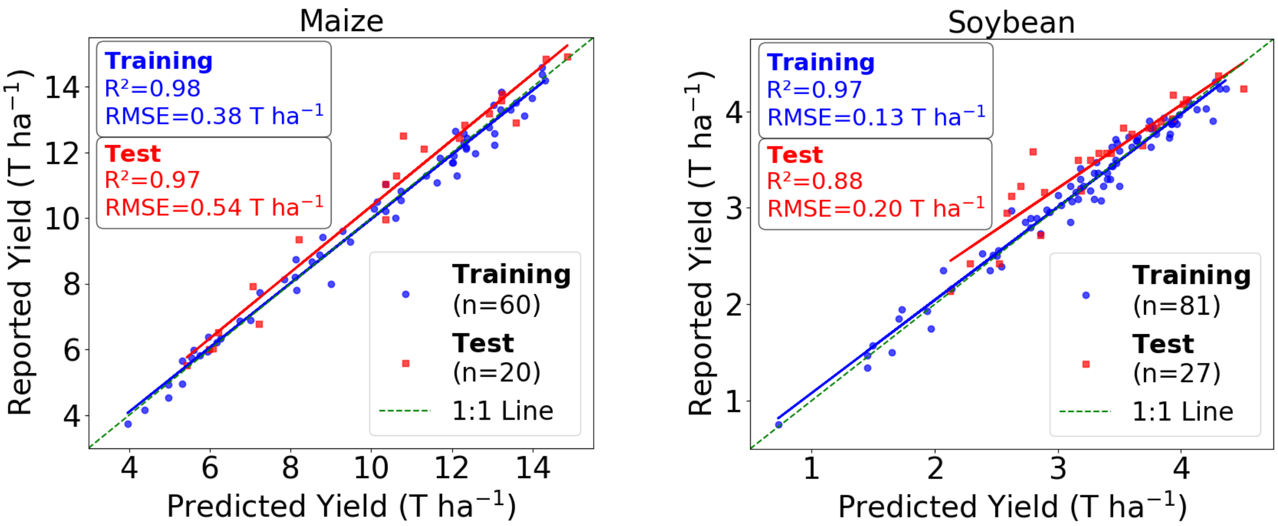

Figure 1. **Predicted vs. reported yields of maize (left) and soybean (right).** Training and test sets, both dots and regression lines, are colored in blue and red, respectively. Performance metrics are presented for each set. The green dashed line indicates the 1:1 line for reference.

Conclusions

This study demonstrates the high potential in coupling satellite sensing and crop model simulations for accurate yield predictions of major crop fields. Our results, obtained from different geographies characterized by different weather, soils, cultivars, and practices, prove the robustness of our platform to be applied everywhere in the world. Cultivar parameterization, which is the major unknown in the crop modeling process, primarily due to a lack of open-source data, was proven to be calibrated using previous years' state-level data. Further research is needed to handle better scenarios where the county-scale seasonal LAI dynamics are substantially different from the simulated ones. Adoption of such a platform will help stakeholders better manage the food supply chain in the face of a changing world.

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Quantifying Climate-Driven Wheat Yield Gaps in Egypt with Multi-Model Ensembles and Multi-Source Evidence

Kheir Ahmed[1,2], Schulthess Urs[3], Feike Til[1], Ruane Alex[4], Asseng Senthold[5]*

[1] Julius Kühn Institute (JKI)—Federal Research Centre for Cultivated Plants, Institute for Strategies and Technology Assessment, 14532 Kleinmachnow, Germany, drahmedkheir2015@gmail.com

[2] Soils, Water and Environment Research Institute, Agricultural Research Center, Giza 12112, Egypt

[3] CIMMYT-Turkey, Izmir, Türkiye

[4]NationalAeronauticsandSpaceAdministration,GoddardInstituteforSpaceStudies,NewYork,UnitedStatesofAmerica

[5]Technical University of Munich, Department of Life Science Engineering, Digital Agriculture, 85354 Freising, Germany

Keywords: Yield stagnation, heat stress, hot-dry-windy events, phenological shifts, DSSAT models.

Introduction

Egypt, the world's largest wheat importer (Asseng et al., 2018), relies heavily on domestic production to safeguard national food security. However, its wheat sector faces intensifying challenges under accelerating climate change (Yi Yang et al., 2024), including rising temperatures, declining radiation, increased frequency of heat extremes, and sporadic compound events such as hot–dry–windy conditions. Despite decades of expansion in cultivated area, improved irrigation, and adoption of high-yielding varieties, national wheat productivity has shown signs of stagnation. A persistent gap remains between potential yields attainable under optimal conditions and actual farm-level performance, reflecting the combined influence of climatic stressors, shortened crop phenology, and regional production constraints. Addressing this gap is critical for enhancing self-sufficiency and reducing vulnerability to global grain market volatility. This study quantifies four decades of climate-induced wheat yield gaps in Egypt's breadbasket, disentangles their primary environmental drivers, and provides robust multi-model and multi-dataset evidence to guide targeted adaptation strategies.

Materials and Methods

We employed a multi-model ensemble of DSSAT-CERES, CROPSIM, and NWheat to simulate wheat yields across 48 representative locations (1980–2019). Diverse datasets were integrated, including FAO statistics, Ministry of Agriculture and Land Reclamation (MALR) farmer survey data (>2000 sites), and CIMMYT multi-environment trials. Climate forcing was derived from AgMERRA and ERA5, with daily-to-hourly disaggregation enabling the assessment of Hot–Dry–Windy (HDW) events. Bias correction aligned trial yields with survey observations. Advanced analyses—including principal component analysis (PCA), linear mixed-effects modeling, and structural equation modeling (SEM)—were applied to disentangle climatic, phenological, and spatial yield determinants.

Results and Discussion

Multi-model simulations and observations show wheat yield stagnation in Egypt since the mid-2000s (Fig. 1I). While potential yields remained stable, FAO and survey data reveal gaps up to 5 t ha^{-1}, linked to rising temperatures (+0.034 °C yr^{-1}) and declining radiation that shortened crop duration and limited biomass. CIMMYT trials (Fig. 1II) consistently outperformed national yields, but bias correction aligned them more closely with farmer outcomes, highlighting the value of integrating diverse datasets. Stress analysis (Fig. 1III) confirmed Tmax as the main driver, reducing yields by ~3.2% per °C during grain filling, whereas HDW events were sporadic and less influential. Overall, sustained warming and reduced radiation explain yield stagnation, and adaptation will depend on heat-tolerant cultivars, optimized sowing, and targeted interventions.

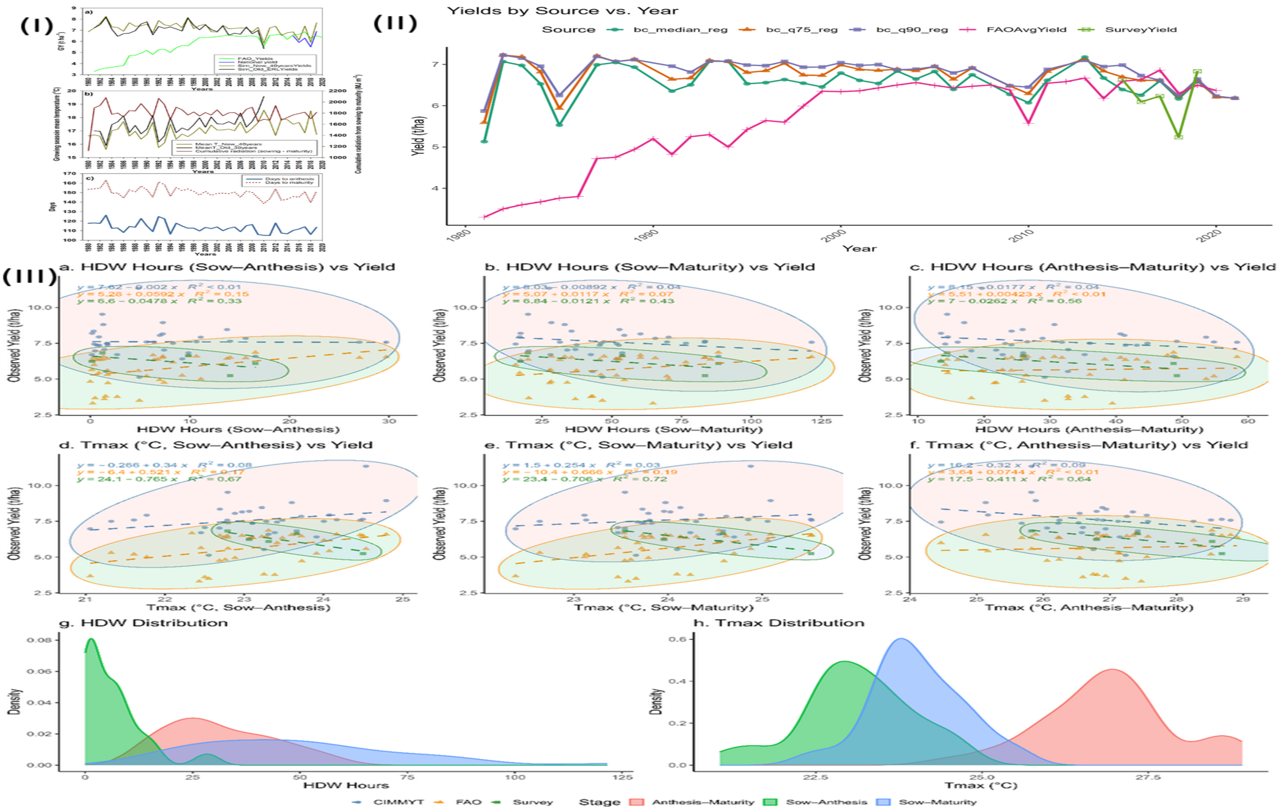

Figure 1. Multi-model and multi-source analysis of wheat yield gaps and climate drivers in Egypt (1980–2020).(I) Simulated yields compared with FAO and MALR survey data, alongside temperature, radiation, and phenology. (II) Bias-corrected CIMMYT trials aligned with national statistics, reducing systematic gaps. (III) Relationships of HDW hours and Tmax with yields from CIMMYT, FAO, and survey datasets. Results show yield stagnation since 2007, shorter crop duration under warming, and Tmax as the dominant driver over HDW.

Conclusions

Sustained warming and reduced radiation, rather than sporadic compound stress events, are the dominant drivers of wheat yield stagnation in Egypt. Targeted adaptation through heat-tolerant cultivars, optimized sowing dates, and region-specific management is essential to close the persistent yield gap and strengthen national food security.

Acknowledgements

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Crop Modelling for Agricolture
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Small-scale farmers critical to curbing deforestation linked to forest-risk commodities. (MSc. Thesis, forthcoming paper)

Celik Aysegul[1], Flach Rafaela[2], van Bodegom Peter[3], zu Ermgassen Erasmus[4], Taherzadeh Oliver A[5]

[1] Institute of Environmental Sciences, Leiden University. Van Steenisgebouw, Einsteinweg 2, 2333 CC Leiden, The Netherlands.

[2] Stockholm Environment Institute, 104 51 Stockholm, Sweden.

[3] Institute of Environmental Sciences, Leiden University. Van Steenisgebouw, Einsteinweg 2, 2333 CC Leiden, The Netherlands.

[4] Earth & Life Institute, UCLouvain, B-1348 Louvain-la-Neuve Belgium

[5] Institute of Environmental Sciences, Leiden University. Van Steenisgebouw, Einsteinweg 2, 2333 CC Leiden, The Netherlands.

Keywords: The European Union Deforestation Regulation (EUDR), crop production, smallholders

Introduction

Despite increasing global attention, deforestation remains a persistent challenge, particularly due to agricultural expansion. Voluntary and market-based initiatives have so far proven insufficient to reverse this trend. In response, the European Union adopted the Deforestation Regulation (EUDR), which requires due diligence and geolocation data for seven key commodities to ensure they are deforestation-free. A major obstacle to addressing deforestation is the lack of understanding of the diversity of farmers within forested landscapes. Most existing agri-food system models evaluate deforestation risk at the national or commodity scale, often overlooking differences between farm types. This hinders the development of effective and targeted policy interventions. To address this gap, the study evaluates how different farm sizes contribute to the production of EUDR-listed crops within forest areas, using spatial datasets on crop distribution, forest cover, and farm size patterns.

Materials and Methods

Three main data sets were used: the Spatial Production Allocation Model (MAPSPAM) SPAM 2020 v1.0 Global data (International Food Policy Research Institute, 2024); the Global Map of Forest Cover 2020, Version 2, developed by the Joint Research Centre (JRC) of the European Commission (Bourgoin et al., 2024); the global farm size distribution raster dataset (Mehrabi and Ricciardi, 2021). Google Earth Engine and ArcGIS were used to quantify total crop production as well as crop production in areas of forest and potential forest and total agriculture overlap, across farm size categories and countries.

Results and Discussion

Figure 1 illustrates the spatial distribution of EUDR-listed crop production within forested areas across 11 farm size categories. The maps highlight three key regions where such production is most concentrated: Central and South America, West Africa, and Southeast Asia. The distribution of farm sizes varies across these regions. In West Africa and Southeast Asia, forest-linked production is predominantly associated with small-scale farms, whereas in Central and South America, it is more commonly linked to medium- and large-scale farms.

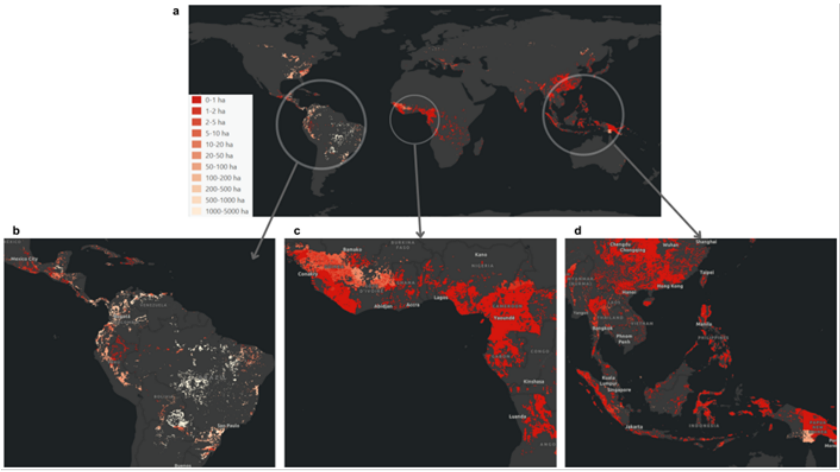

Figure 1.

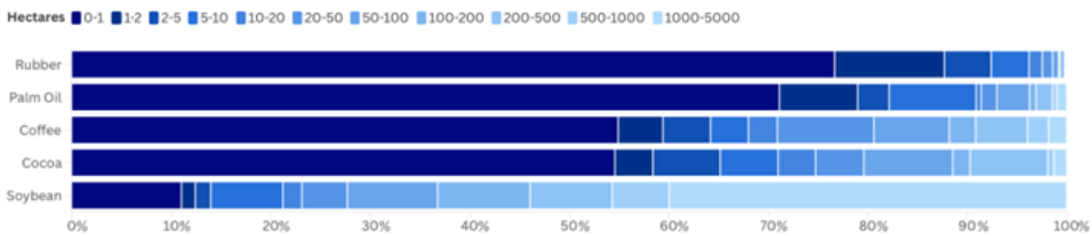

Figure 2.

Figure 2 depicts that small-scale farms' contribution to the production in forest areas is significantly higher than the contribution of any other farm size categories. Small-scale farms annually produce rubber (88%), palm oil (79%), coffee (59%), and cocoa (58%) in forest areas, relative to the total forest-linked production of each crop.

The study also includes a country-level hotspot analysis, identifying countries such as Indonesia, Vietnam, and Côte d'Ivoire where smallholders may face high risks of exclusion from EU supply chains.

Most existing studies have focused on country-level or commodity-level deforestation linkages, without distinguishing between the roles of different producer types (Pendrill et al., 2019a; 2019b; 2022a; 2022b; Singh & Persson, 2024). This study addresses that gap by providing spatially explicit insights into the contributions of small-, medium-, and large-scale farms to the production of EUDR-listed commodities and assessing where and to what extent smallholders may be most vulnerable to exclusion due to their potential production in forest.

Conclusions

This study presents three key findings. First, small-scale farms (<2 ha) are more likely to be located in areas with potential forest competition, whereas large-scale farms (>200 ha) generally exhibit lower levels of forest overlap. Second, the production of EUDR-listed commodities is predominantly associated with small-scale farms, particularly in the Global South. Third, a substantial share of forest-linked production of these crops can be attributed to smallholders. Additionally, the results indicate that the EUDR's country benchmarking does not fully reflect deforestation risks, suggesting a need for more accurate classification.

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Simulating the impact of construction measures and soil heating induced by underground power cables on barley (*Hordeum vulgare* L.) growth and yield within the DSSAT-CSM

Trenz, Jonas[1], Memic, Emir[2], Graeff-Hönninger, Simone[1]*

[1] University of Hohenheim, Institute for Crop Sciences, Department of Agronomy, 70599 Stuttgart, Germany, j.trenz@uni-hohenheim.de

Keywords: HVDC cables; crop growth modeling; soil temperature; soil compaction

Introduction

Germany faces the dual challenge of expanding its electricity grid while transitioning to a carbon-neutral energy system and maintaining a stable energy supply. High-Voltage Direct Current (HVDC) transmission lines are planned to convey electricity from offshore wind farms in the north to the industrial regions in the south. The installation of HVDC cables requires a specific burial depth, involving construction activities such as excavation and backfilling. Beyond soil disturbance, underground HVDC cables generate heat during operation; at full load, a 525 kV HVDC cable releases heat at a rate of 32 W m^{-1}. The overall environmental and agronomic impacts of these underground HVDC installations remain poorly understood. The CHARGE research project addresses this knowledge gap through on-farm experiments. It examines the effects of both construction-related soil disruption and operational soil heating on soil properties and crop performance in Baden-Württemberg and Bavaria. Recent studies by Trenz et al. (2025a, 2025b) have demonstrated the influence of these factors on crop growth and yield. However, crop growth models can provide a valuable tool for analyzing the processes that drive crop growth and yield. For this study, a dataset of spring barley (*Hordeum vulgare* L.) will be used to evaluate how crop growth and yield respond to both construction-related soil disturbances and increasing soil temperatures. The data was integrated into the DSSAT-CSM (Hoogenboom et al., 2019) to quantify the combined effects of excavation, backfilling, and heat emission from underground HVDC cables. This model could serve as a predictive tool for estimating the potential impact of HVDC measures, allowing stakeholders to anticipate the possible effects on crop productivity and optimise mitigation strategies.

Materials and Methods

The effects of trench construction and soil heating on barley growth and yield were investigated using three treatments: 1) heated trench (HT) with 12 plots, 2) unheated trench (UT) with 6 plots, and 3) control with 24 plots. Destructive sampling was carried out five times during the growing season to measure biomass. During each sampling event, canopy assessments, phenological stages, and Leaf Area Index (LAI) measurements were recorded. LAI was determined using an LAI-2200C (LI-COR, Lincoln, USA). Cultivar coefficients were estimated using the Control treatment by targeting LAI, total above-ground biomass, growth stages, and grain yield, using the time-series estimator (Memic et al., 2021). For the UT and HT treatment, a significant increase in soil depth was observed. Therefore, the depth of the soil profiles was increased to 130 cm, whereas the soil profile of the Control was set to 70 cm, as determined by field measurements. Additionally, in the HT treatment, an increase in soil temperature per soil layer was added, calculated from the differences between the measured soil temperatures of the HT and Control treatments at 15 cm (Δ1.6°C) and 50 cm (Δ6.5°C). The difference for the intermediate soil layers was interpolated. The increase in soil temperature was then added to the simulated soil temperature in the source code.

Results and Discussion

The availability of the measured soil temperature for soil layers 2 and 5 revealed that the initial calculated albedo factor in the model was too low, at 0.13, resulting in an underestimation of the soil temperature. Increasing the albedo factor to 0.25 significantly improved the soil temperature model, resulting in a higher goodness of fit (Table 1).

Table 1. Effect of soil albedo factor (SALB) on RMSE and d-stat of simulated vs. observed soil temperature at two soil layer depths.

	Soil **ALB**edo factor (**SALB**)			
Soil layer	**SALB based on initial calculation (0.13)**		**SALB adapted in sensitivity analysis (0.25)**	
	RMSE	**d-Stat**	**RMSE**	**d-Stat**
Soil layer 2	5.47	0.46	1.6	0.94
Soil layer 5	4.13	0.74	2.1	0.925

The model behavior of the DSSAT-CSM showed significant changes in vegetative growth and the generative growth phase for the described treatments of UT and HT. Furthermore, it reflected the increase in LAI accumulation and grain yield with a high goodness of fit. The observed significant differences in the field for the enhanced development in the HT treatment were not reflected.

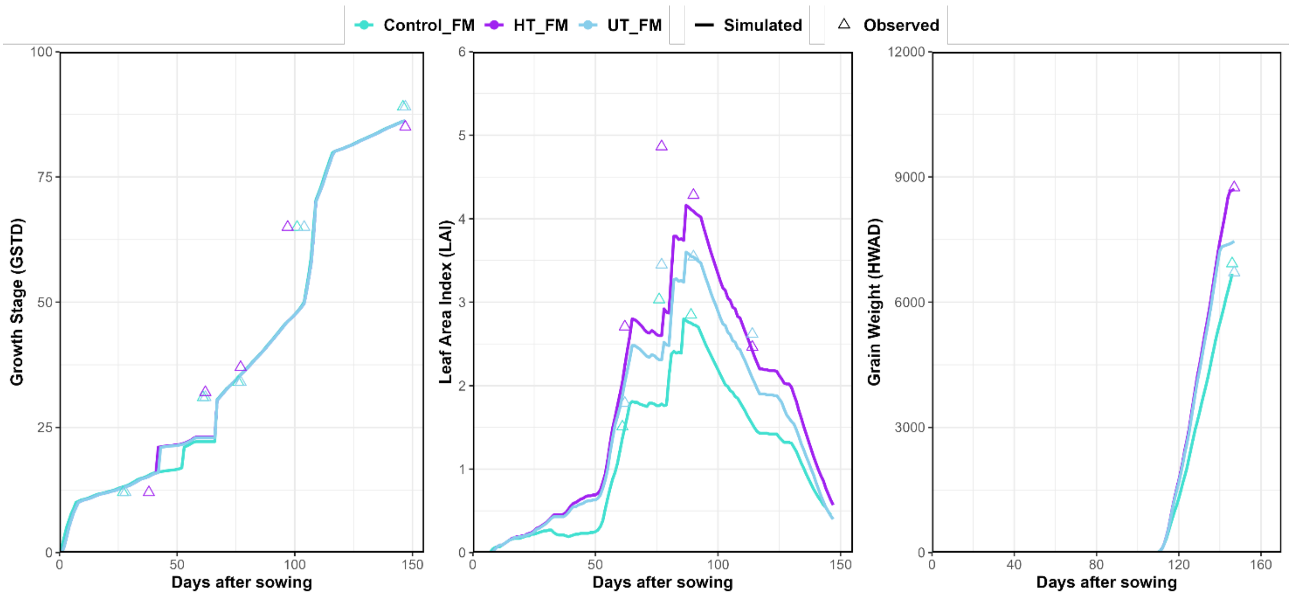

Figure 1. Simulated and observed values for the treatments Control (turquoise), UT (skyblue), and HT (purple) are shown for growth stages, Leaf area index (LAI), and Grain weight.

Conclusions

Adjusting the soil albedo from 0.13 to 0.25 substantially improved the accuracy of soil temperature simulations, providing a more reliable basis for evaluating the impacts of HVDC-related soil disturbances on crop growth and yield. While the model successfully captured treatment effects on biomass and yield, it underestimated the enhanced crop development observed in the heated trench. Overall, these findings underscore the potential of crop growth models to inform decision-making by predicting the agricultural impacts of HVDC installations and guiding mitigation strategies. However, further testing under diverse conditions is needed to strengthen model robustness and applicability.

Acknowledgements

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Determinants of Cropping Patterns and Sorghum Crop Productivity in Maharashtra: A Panel Regression Approach

Shinde Rutuja[1], *Udmale Parmeshwar**[2]

[1] Indian Institute of Technology Bombay, Centre for Technology Alternatives for Rural Areas, 400076, Mumbai, Maharashtra, India
[*2] Indian Institute of Technology Bombay, Centre for Technology Alternatives for Rural Areas, 400076, Mumbai, Maharashtra, India, udmale@iitb.ac.in

Keywords: Crop diversification, Socioeconomic and environmental factors, Panel Regression modeling, Semi-Arid Areas, Sorghum

Introduction

Agriculture plays a crucial role in the Indian economy as it provides livelihood to 70% of the rural population and contributes to national food security. However, social, economic, and environmental (SEE) factors, along with climate change in the region, significantly influence cropping patterns (e.g., degree of crop diversification and crop productivity) (Gupta & Kannan, 2024). Crop diversification is recognized as a crucial factor in enhancing agricultural production, generating employment opportunities, reducing poverty, and ensuring food security (Birthal et al., 2015). Along with cropping patterns, SEE factors, including government policies and domestic demand, have a significant impact on the crop productivity of the region. Maharashtra is one of the agricultural states with varying agro-climatic, socioeconomic and environmental conditions across the districts. A significant variation in crop diversification has been observed across the state. Similarly, the productivity of the sorghum crop has shown variations across the districts. Therefore, it is imperative to identify and analyse the degree of the impact of these SEE factors on crop diversification and crop productivity in Maharashtra.

Materials and Methods

This study uses panel data from 1980 to 2017 to study the determinants of cropping patterns and sorghum crop productivity in Maharashtra (Singh et al., 2022). The Simpson Diversity Index and Gibb's-Martin Index were used for calculating the crop diversification index (Singh, 2015). District level data for Crop diversification Index(CDI), Cropped Area (000'ha), Fertilizer Consumption (Kg/ha), Irrigation Intensity (%), Cropping Intensity (%), Area under High Yielding Varieties (000'ha), Road Length (000'km), Small Marginal Farms_(No.), Banks Per District (No.), No. of Major Markets, No. of Sub Markets, Labour Wages (Rs/Day), % of Electrified Towns Villages, Cultivable Waste Land (000'ha), Current Fallow Land (000'ha), Average Kharif Groundwater Level (m), Average Rabi Groundwater Level (m), Annual Rainfall (mm), Actual Evapotranspiration(mm), Annual Avg Tmax (^{0}C) was collected. Fixed and Random Effect models were employed to analyse diversification and crop yield drivers in Maharashtra.

Results and Discussion

The estimated R-squared value was 0.38, indicating that the SEE determinants collectively explained 38% of the total variation in crop diversification. Every 1% increase in Crop area increases crop diversification by 0.36%. Similarly, Fertilizer Consumption (0.046%), Irrigation Intensity (0.049%), Cropping Intensity (0.17%), Small and Marginal Farmers (0.12%), Current Fallow Land (0.05%), and Average Kharif Groundwater Level (0.032%) had a positive influence on crop diversification. The results showed that Road Length (-0.11%) and Cultivable Waste Land have a statistically negative and significant impact on crop diversification in districts of Maharashtra throughout the study period. The lack of a road network constrains market access and, subsequently, crop diversification.

Fertilizer consumption, cropping intensity, annual water deficit, agricultural worker population, and area of high-yielding varieties all positively impact sorghum yield. With 1% increase in fertilizer consumption, a 0.49% increase in sorghum yield is observed. Similarly, an increase in cropping intensity led to a 0.45% increase in sorghum yield. On the contrary, the Area under small and marginal farms had a significant negative impact of 2.55%.

Conclusions

There's a notable trend in crop diversification, with 11 districts showing an increase and 11 showing a decrease. Key factors influencing this include gross crop area, fertilizer consumption, and irrigation intensity, while cultivable wasteland and road networks have a negative impact. Regarding sorghum, a significant yield increase is noted, averaging 25.58 kg/ha/year across Maharashtra from the agricultural year 2000 to 2022. 13 out of 27 sorghum-producing districts have an increasing trend in Sorghum Yield. This is positively impacted by fertilizer consumption, cropping intensity, and high-yielding varieties, but negatively by road infrastructure and small/marginal farm landholdings.

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Maize yield estimation in Kenya using Earth observation, artificial intelligence, and crop modelling

*Owuor Caroline Akinyi**[1,2], *Leroux Louise*[2,3,4], *Mkuhlani Siyabusa*[2], *Corbeels Marc*[2,3,4], *El-Battay Ali*[1], *Chehbouni Abdelghani* [1]

[1] University Mohammed VI Polytechnic (UM6P), Center for Remote Sensing Applications, 43150, Ben Guerir, Morocco, caroline.owuor@um6p.ma
[2] International Institute of Tropical Agriculture (IITA), c/o ICIPE, P. O. Box 30772-00100, Nairobi, Kenya
[3] Cirad, UPR AÏDA, 00100, Nairobi, Kenya
[4] AIDA, CIRAD, University of Montpellier, Montpellier, France

Keywords: Smallholder farming systems, climate resilience, food security

Introduction

Accurate crop yield estimation remains a major challenge in smallholder farming systems in Sub-Saharan Africa, where fragmented fields, intercropping, and diverse management practices constrain model scalability and precision. Persistent data gaps and limited ground-truth observations further restrict generalization across agroecological zones (Leroux et al., 2019; Sisheber et al., 2024). While simulation-based approaches have been applied to address these gaps, their integration with complementary data sources for operational yield prediction remains underexplored, and many existing methods still fail to capture fine-scale variability (Sisheber et al., 2024).

Traditional yield surveys are costly and limited in coverage, motivating recent efforts to combine Earth Observation (EO), Artificial Intelligence (AI), and process-based Crop Models (CM) for improved prediction. EO platforms supply multi-temporal signals for crop monitoring (Lobell et al., 2020), AI captures non-linear yield relationships (Leroux et al., 2019), and CM simulates crop growth processes that support model calibration, validation, and interpretation (Mkuhlani et al., 2024). In data-scarce settings, uncalibrated approaches increasingly use CM outputs as proxy ground truth (Leroux et al., 2019; Lobell et al., 2020).

This study develops an integrated EO–AI–CM approach for maize yield estimation in Kenya. The preliminary phase applies CM to simulate water-limited yields of short-, medium-, and long-duration maize across ENSO phases, establishing variety–climate interactions and generating pseudo-ground truth yield data to inform and benchmark the integrated framework in the main study.

Materials and Methods

Maize yields were simulated using the DSSAT v4.8 crop model. The model was calibrated and validated using measured grain and biomass yields, soil, and weather data for Kenya. Model spatialization was enabled through coupling the calibrated models with geospatial weather inputs from CHIRPS and AgERA5, and soil data from ISRIC. Simulations covered 22 years (2000–2021) for the three maize varieties and nine weekly sowing dates. Model outputs were aggregated by sowing date, variety, and ENSO phase. ENSO phases were classified using the Oceanic Niño Index (ONI), with values > 0.5°C indicating *El Niño*, < −0.5°C indicating *La Niña*, and −0.5°C to 0.5°C classified as *neutral*.

These simulated yields will be integrated into regression and deep learning models within the uncalibrated approach, and results compared with the calibrated approach.

Results and Discussion

Across Kenya's croplands, yields varied by variety and ENSO phase (Figure 1). Long-duration varieties consistently produced the highest yields, with clear advantages during *El Niño* years. The highest yields were observed in the coastal and western regions, highlighting the combined influence of varietal choice and ENSO conditions on maize productivity in Kenya.

The results underscore the importance of aligning varietal choice with climate variability to enhance resilience and reduce yield gaps.

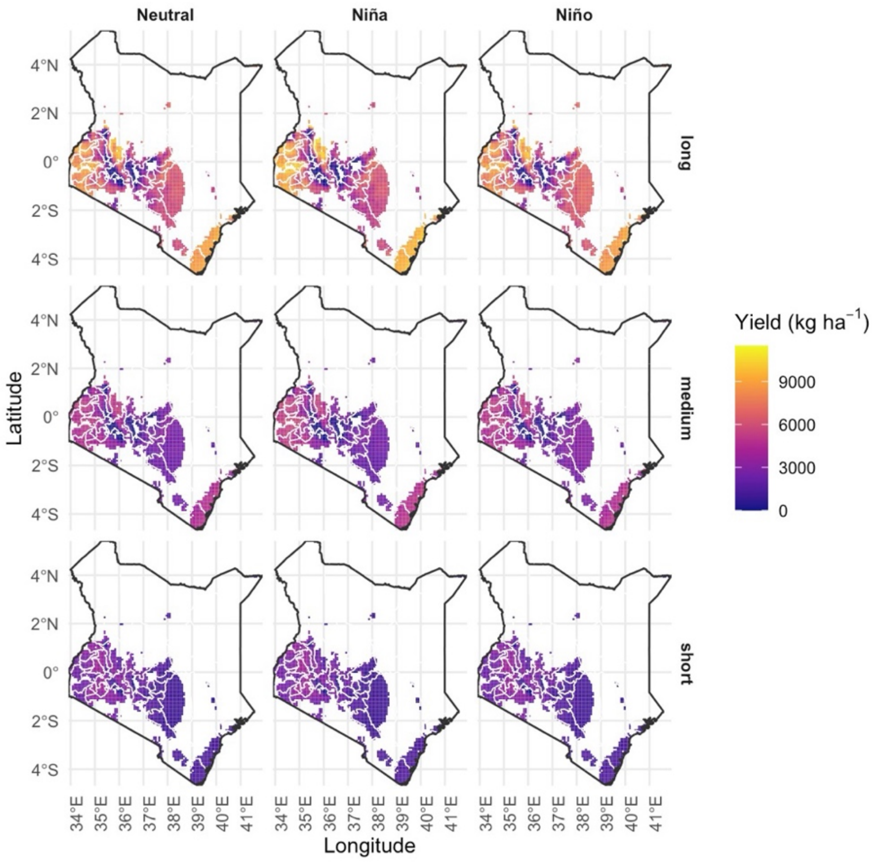

Figure 1: Average maize yields in Kenya across varieties and ENSO phases

Conclusions

This study offers insight into how crop models can be used to estimate yield under different conditions and generates simulated yields to feed into the hybrid framework that integrates EO, AI, and CM for yield estimation. Future work will incorporate multi-temporal satellite imagery and crop model outputs to enhance the spatial and temporal accuracy of predictions. Ultimately, the framework will support digital advisory services, climate adaptation strategies, and food security planning for smallholder farming in Kenya.

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Maize-soybean intercropping in Malawi: Assessing the APSIM capabilities and the feasibility of the cropping systems

Simwaka, P.[1,2*], Huth, N.[3], Maclaren, C.[1], Omondi, J.[2], Nyagumbo, I.[4], , Chiduwa, M.G.[4], Öborn, I.[1], Masikati, P.[5], Lana. M.[1]

[1]Swedish University of Agricultural Sciences, Uppsala, Department of Crop Production Ecology, Box 7043, 75007 Uppsala, Street address: Ulls väg 16

[2]International Institute of Tropical Agriculture (IITA), Chitedze Research Station, Lilongwe, Malawi,

[3]The Commonwealth Scientific and Industrial Research Organization, Forest Hill, Queensland, Australia.

[4]Mount Pleasant Research Station, International Maize and Wheat Improvement Center (CIMMYT), Harare, Zimbabwe

[5]Lusaka Research Station, World Agroforestry (ICRAF), Lusaka, Zambia,

Email:pacsu.simwaka@slu.se

Key words: Maize; Soybean; Intercropping; APSIM; Sensitivity Analysis

Introduction

Maize-soybean intercropping is a key strategy to enhance food security and resource-use efficiency in sub-Saharan Africa, particularly for smallholder farmers. In Malawi, soybean is increasingly being promoted as an entry point for agricultural intensification (Chiduwa et al., 2024). Current modelling efforts are exploring non-traditional planting geometries, such as intercropping and strip cropping, to integrate soybean into existing maize systems (Wu et al., 2021). APSIM has previously been applied to evaluate agronomic interventions, including crop maturity and planting date, to increase soybean productivity (Omondi et al., 2023). However, representing these complex systems in crop models remains challenging, as model configurations often require assumptions that are difficult to validate. Simulation modelling provides a framework to explore system responses and identify the drivers of observed behaviour. Therefore, the objective of the study was to assess the capabilities of the APSIM model in simulating maize-soybean intercropping systems in Malawi and to evaluate the feasibility of these systems for smallholder farming.

Materials and Methods

Field data was collected from maize-soybean intercropping trials at Chitedze, Malawi (13.9815° S, 33.6372° E) from 2022-2025 (three seasons). Six spatial configurations were tested: sole crops (maize, soybean), within-row intercrops, and strip intercropping (1:1, 2:2, 4:4), across three sowing windows (early, medium, late), with standardized fertilizer and crop densities. APSIM simulations (2005-2024) using observed and grided weather data were used to evaluate performance under variable planting dates, spatial arrangements, and seasonal rainfall. A sensitivity analysis using the Morris method (Campolongo et al., 2007) was conducted to identify influential parameters (planting date, number of rows per strip, maize and soybean populations, soil organic matter, maize fertilizer, runoff response, and soil compaction) and improve model representation. Parameter ranges were based on observed treatment variability, and 1800 simulations were run across 20 seasons to capture seasonal variability.

Results and Discussion

Model validation (2022-2025) showed APSIM captured treatment-level variability reasonably well (Figure 1). The validation showed strong performance for both maize and soybean. For maize above-ground biomass, observed values ranged 1740-20000 kg ha^{-1} compared with APSIM predictions of 2000-19000 kg ha^{-1}. Accuracy was high (R^2 = 0.78) with good efficiency (Nash–Sutcliffe Efficiency (NSE) = 0.77). For maize grain yield, observed values were 200-9700 kg ha^{-1} and predictions 700-10000 kg ha^{-1}, also with strong correlation (R^2 = 0.82) and efficiency (NSE = 0.73). For soybean, performance was similarly strong. Biomass prediction achieved a very high correlation (R^2 = 0.91) and moderate efficiency (NSE = 0.56). Observed biomass ranged from 420-2470 kg ha^{-1}, while predicted values were 550-3000 kg ha^{-1}. Soybean grain yield also showed high correlation (R^2 = 0.92) with moderate efficiency (NSE = 0.53). Observed yields were 270-980 kg ha^{-1} compared to predicted yields of 290-1300 kg ha^{-1}. Overall, APSIM reliably captured treatment-level variability across sole crops, strip-cropping, and intercropping systems. The model reproduced maize outcomes with high accuracy and soybean with strong correlations and reasonable efficiency, supporting its capability to simulate maize-soybean intercropping under Malawian conditions. Sensitivity analysis (Figure 1) showed that maize grain weight was most influenced by population density and seasonal rainfall. Enhanced runoff response and rooting depth improved performance under wetter conditions, with maize Mu* exceeding 11000 kg ha^{-1}. Soybean grain weight showed a positive correlation between Mu* and Sigma, indicating higher-yielding treatments had greater variability. Sowing date had a strong, season-dependent effect, while site fertility and fertilizer had minimal direct impact. Strip crop configuration (number of rows) had minor effects, while runoff response was more important than soil compaction. Parameter rankings were consistent across years, though 2021 drought highlighted the system's vulnerability to rainfall deficits, emphasizing caution in extrapolating results.

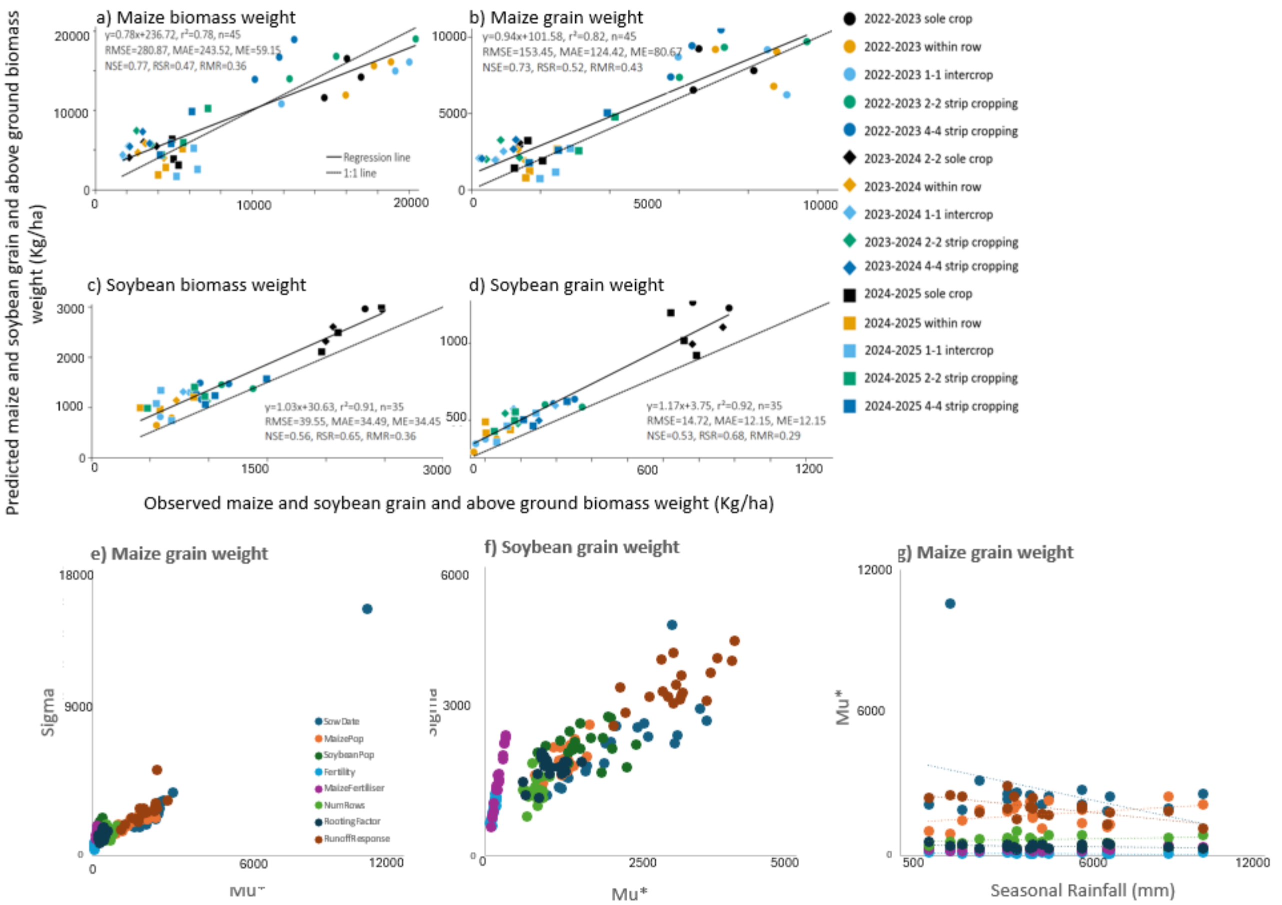

Figure 1: Observed and predicted maize and soybean yields for all three cropping seasons (a-d), Morris sensitivity results for maize (e) and soybean yield for 2005 to 2024 (f) and changes in sensitivity of (g) maize yield to seasonal rainfall are also shown for all chosen parameters at Chitedze Research Station.Hint: Sigma (standard deviation of elementary effects which measures the variability or interaction effect of a parameter) and Mu* (mean of absolute elementary effects it represents the overall influence of a parameter on the output).

Conclusions

- Maize-soybean intercropping is a feasible strategy for improving smallholder food security and resource-use efficiency in Malawi.
- APSIM demonstrated strong capability in simulating maize and soybean yields and treatment effects in sole crops and intercropping.
- Plant population, seasonal rainfall, runoff and sowing date had the highest effect of maize and soybean yields.
- Drought conditions (e.g., 2021) highlighted system vulnerability to rainfall deficits, raising feasibility concerns under climate stress.

Acknowledgements

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