

PRECISION IRRIGATION USING DATA-DRIVEN METHODS IN MAIZE

IRRIGATION DE PRÉCISION DU MAÏS AU MOYEN DE MÉTHODES FONDÉES SUR LES DONNÉES

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ABSTRACT

This study summarizes and integrates the recent results of a Hungarian research group in the field of precision water management. The main focus is on irrigation scheduling design, as well as the development of maize biomass and soil moisture monitoring methods, emphasizing the role of spectral data, remote sensing, machine learning, and physical modeling. Precision agricultural approaches are playing an increasingly important role in monitoring maize (*Zea mays*) productivity, stress responses, and water use. Instead of traditional sampling- and laboratory-based methodologies, non-invasive spectral and remote sensing systems enable real-time determination of pigment content (e.g., carotenoids, chlorophyll), estimation of biomass, and mapping of the spatio-temporal dynamics of plant stress and water use. The combination of machine learning and Earth Observation (EO) data further enhances the accuracy and practical utility of predictive models. Overall, the integration of spectral data processing, machine learning, and physical modeling provide a promising toolkit for real-time monitoring of maize canopy conditions, estimating and detecting water stress symptoms, tracking evapotranspiration and soil moisture dynamics, and ultimately optimizing precision irrigation scheduling. Such interdisciplinary approaches enhance water and yield security under changing climate and water-scarce conditions while offering scalable technological solutions for both precision and conventional agricultural systems.

Keywords: Precision irrigation; Data-driven methods; Irrigation scheduling design; Machine learning; Water-scarce conditions.

RÉSUMÉ

Cette étude synthétise et intègre les résultats récents d'un groupe de recherche hongrois dans le domaine de la gestion de précision de l'eau. Elle porte principalement sur la conception de la programmation de l'irrigation, ainsi que sur le développement de méthodes de suivi de la biomasse du maïs et de l'humidité du sol, en soulignant le rôle des données spectrales, de la télédétection, de l'apprentissage automatique et de la modélisation physique. Les approches d'agriculture de précision jouent un rôle croissant dans le suivi de la productivité du maïs (*Zea mays*), de ses réponses au stress et de son utilisation de l'eau. À la place des méthodes traditionnelles fondées sur l'échantillonnage et les analyses en laboratoire, les systèmes spectraux et de télédétection non invasifs permettent de déterminer en temps réel la teneur en pigments (p. ex., caroténoïdes, chlorophylle), d'estimer la biomasse et de cartographier la dynamique spatio-temporelle du stress végétal et de l'utilisation de l'eau. L'association de l'apprentissage automatique et des données d'observation de la Terre (OT) améliore encore la précision et l'utilité pratique des modèles prédictifs. Dans l'ensemble, l'intégration du traitement des données spectrales, de l'apprentissage automatique et de la modélisation physique offre un ensemble d'outils prometteur pour surveiller en temps réel l'état du couvert de maïs, estimer et détecter les symptômes de stress hydrique, suivre l'évapotranspiration et la dynamique de l'humidité du sol, et, à terme, optimiser la programmation de l'irrigation de précision. De telles approches interdisciplinaires renforcent la sécurité hydrique et celle des rendements dans un contexte de changement climatique et de pénurie d'eau, tout en proposant

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des solutions technologiques évolutives pour les systèmes agricoles de précision comme conventionnels.

Mots clés : Data-driven methods; Méthodes fondées sur les données; Conception de la programmation de l'irrigation; Contexte de pénurie d'eau.

NON-INVASIVE ESTIMATION OF MAIZE PIGMENT CONTENT USING SPECTRAL DATA AND MACHINE LEARNING

The study demonstrated that reflectance-based measurements and machine learning approaches can be effectively applied for the rapid and non-destructive estimation of carotenoid content in maize leaves, providing an alternative to conventional laboratory-based sampling methods. The research was conducted in Hungary between 2021 and 2023 under contrasting climatic conditions, including both drought-affected and wetter growing seasons, using 540 maize leaf samples collected from irrigated and non-irrigated fields. The main objective was to develop maize-specific spectral indices capable of improving carotenoid estimation accuracy compared with traditional vegetation indices, while also evaluating the performance of different machine learning algorithms.

A strong positive relationship was identified between carotenoid and chlorophyll content in maize leaves, with a coefficient of determination of $R^2 = 0.925$, indicating that carotenoid concentration explained more than 92% of the variability in chlorophyll levels. This close relationship highlights the important role of carotenoids in photosynthetic processes and plant physiological status, confirming earlier findings reported by Hashimoto et al. (2016) and Sies et al.

(2022). In addition to their contribution to light harvesting, carotenoids play a key role in photoprotection and stress tolerance by protecting plant tissues from oxidative damage caused by excessive radiation and reactive oxygen species. Spectral analyses revealed that carotenoid concentration significantly influenced leaf reflectance within the visible spectral range, particularly between 500 and 650 nm. Increased carotenoid concentration resulted in lower reflectance values due to the strong absorption of blue and green wavelengths by pigments such as lutein and β -carotene (Mikhailenko, 2022). In contrast, reflectance in the near-infrared region above 700 nm was affected mainly by leaf structural characteristics rather than pigment concentration. These findings confirmed that hyperspectral sensing provides a reliable and non-invasive approach for monitoring pigment composition and physiological condition in maize, supporting previous studies emphasizing the applicability of VIS–NIR spectroscopy in plant monitoring (Davey et al., 2009). Traditional carotenoid vegetation indices, including CRI, SIPI, PRI, PSSR, and mCRI, showed relatively weak predictive performance under the examined environmental conditions.

Their coefficients of determination ranged only between $R^2 = 0.039$ and 0.123, while several indices produced negative Nash–Sutcliffe efficiency values, indicating poor predictive reliability. These limitations were attributed to the fact that such indices were originally developed for broader multispectral or canopy-level applications, where atmospheric effects and canopy structure strongly influence spectral responses (Gitelson et al., 2002; Gitelson et al., 2006). As a consequence, these indices were unable to accurately capture the specific spectral characteristics associated with maize carotenoids.

To improve prediction accuracy, principal component analysis (PCA) was applied to identify the most sensitive wavelengths related to carotenoid content. Two principal components explained more than 92% of the total spectral variance, enabling the selection of four key wavelengths (550 nm, 678 nm, 700 nm, and 800 nm) for the development of nine new maize-specific spectral indices (CAR1–CAR9). Among these, CAR7, CAR8, and CAR9 consistently produced the highest prediction accuracy across both calibration and validation datasets. In several testing periods, these indices achieved R^2 values exceeding 0.80, representing a substantial improvement over conventional vegetation indices. CAR8 produced the lowest prediction errors, while CAR7 showed the most stable overall predictive performance.

Several machine learning algorithms, including Random Forest, REPTree, M5P, Random SubSpace, and Bagging, were also evaluated for carotenoid prediction. Although Random Forest achieved excellent calibration performance ($R^2 = 0.94$), the REPTree model provided the most balanced and reliable results during independent testing. The REPTree algorithm achieved $R^2 = 0.798$, $NSE = 0.820$, and $NRMSE = 13.845\%$, outperforming the other models in terms of robustness and practical applicability. These findings are consistent with previous research demonstrating that machine learning approaches can substantially improve spectral prediction accuracy in agricultural applications (Aghighi et al., 2018; Gao et al., 2018; Zhang et al., 2021) (Figure 1).

Overall, the results demonstrated that maize-specific hyperspectral indices combined with machine learning techniques provide an accurate, rapid, and non-destructive solution for carotenoid estimation in maize. These approaches show strong potential for precision agriculture applications, including crop stress monitoring, physiological assessment, and irrigation management. The integration of hyperspectral sensing and predictive modeling may also support future UAV- and satellite-based monitoring systems aimed at improving large-scale agricultural sustainability and maize production efficiency.

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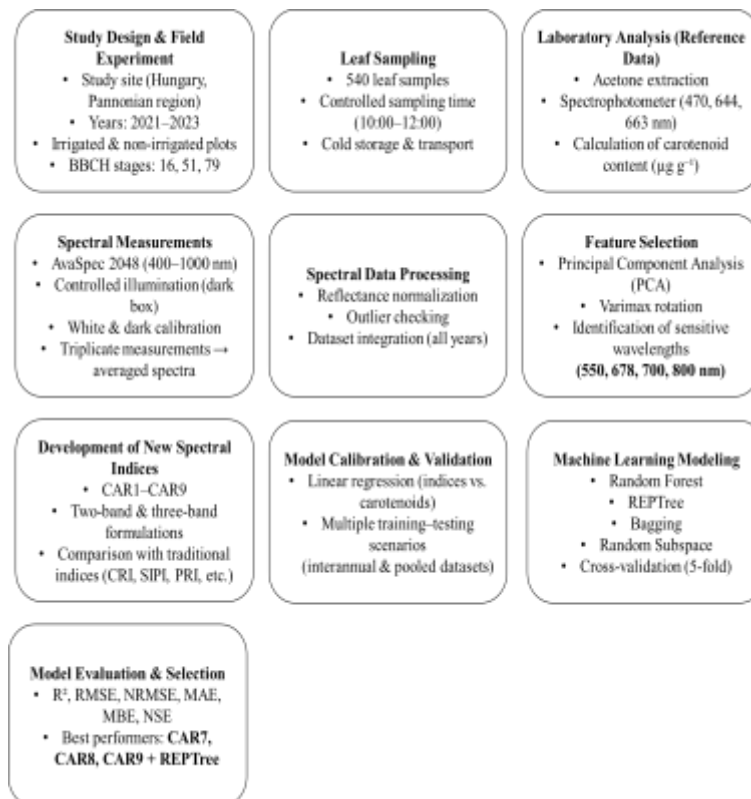


Figure 1. Flowchart of the investigation

BIOMASS ESTIMATION BASED ON NEAR-SURFACE REMOTE SENSING AND SPECTRAL INDICATORS

Accurate, non-destructive quantification of maize (*Zea mays*) above-ground biomass (AGB) is essential for yield forecasting, nitrogen management, and irrigation scheduling. Within the Hungarian precision agriculture research programme, a suite of spectral vegetation indices was evaluated against destructively sampled dry AGB across multiple cultivars and irrigation treatments. Measurements were collected at key BBCH growth stages (30, 51, 65, 75) using a hand-held hyperspectral sensor (350–2500 nm) on a near-surface pole rig at 1.5 m canopy height, cross-validated with a multispectral UAV system (RGB + Red-Edge + NIR). Indices examined included NDVI, SAVI, EVI, GNDVI, and the Red-Edge Chlorophyll Index (Clre). Biomass samples were oven-dried at 70°C for 48 h to determine dry matter content.

Results demonstrated that spectral indicators explain a substantial proportion of AGB variability ($R^2 = 0.54\text{--}0.64$ across indices and growth stages). NDVI and Clre delivered the most consistent relationships, with accuracy peaking during the vegetative-to-reproductive transition (BBCH 51–65), when canopy closure suppresses soil background noise but before senescence reduces spectral sensitivity. A gradient-boosted ensemble combining NDVI, GNDVI, and Clre improved prediction accuracy (RMSE = 112 g DM m⁻²; nRMSE = 8.3%) relative to any single-index regression (Table 1). Importantly, acceptable skill was retained using only non-imaging spectroradiometer data, confirming practical applicability for producers without UAV equipment.

Table 1. Performance of spectral-indicator models for above-ground dry biomass estimation in maize (2021–2023 field seasons; n = 124 validation plots).

Model / Index	R ²	RMSE (g DM m ⁻²)	nRMSE (%)	Best BBCH stage
NDVI (linear)	0.54	158	11.9	65
Clre (linear)	0.61	138	10.4	51–65
GNDVI (linear)	0.57	149	11.2	65
NDVI + Clre + GNDVI (ensemble)	0.79	112	8.3	51–75

The strong response of red-edge indices to canopy nitrogen status positions this approach as a dual-purpose diagnostic tool for both biomass and nutrient stress, supporting integrated precision crop management. When embedded in decision-support workflows alongside weather and irrigation data, spectral biomass proxies can dynamically guide fertiliser and water inputs throughout the growing season.

EARTH OBSERVATION AND ARTIFICIAL INTELLIGENCE FOR EVAPO-TRANSPIRATION PREDICTION

The application of high-resolution Sentinel-2 satellite imagery and vegetation indices significantly improves the estimation of maize crop evapotranspiration (ET_c) and irrigation water demand, providing a more precise alternative to generalized crop coefficient approaches. Accurate evapotranspiration assessment is essential for efficient irrigation management and sustainable agricultural production, particularly under increasing climate variability and water scarcity (Allen et al., 1998). Conventional ET_c estimation methods, such as lysimeters and soil water balance measurements, are often expensive, labor-intensive, and spatially limited. In contrast, remotely sensed vegetation indices derived from satellite imagery enable continuous, field-scale monitoring of crop water use with high spatial and temporal resolution. The methodology was developed using Sentinel-2 imagery collected between 2018 and 2020 at the Acqua Campus experimental farm in the Emilia-Romagna region of northern Italy, an area frequently affected by drought stress and competition for water resources. The analysis relied on Sentinel-2 data with 10 m spatial resolution and a five-day revisit frequency. Four vegetation indicators were evaluated: the Normalized Difference Vegetation Index (NDVI), the

Normalized Difference Water Index (NDWI), the Normalized Difference Red Edge Index (NDRE), and the Leaf Area Index (LAI) (Figure 2).

These indices were integrated with meteorological observations from an in situ weather station to calculate reference evapotranspiration (ET_0) using the FAO Penman–Monteith equation (Allen et al., 1998). Nearly 1000 field observations were analyzed under contrasting climatic conditions, including the severe drought year of 2018.

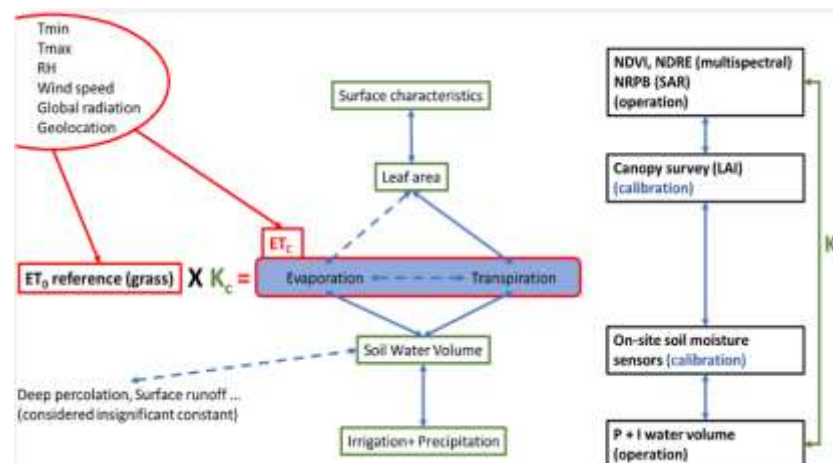


Figure 2. Flow chart of developing VI based ET_c

The temporal dynamics of the vegetation indices closely followed maize phenological development throughout the growing season. During the initial growth stages, NDVI, NDWI, NDRE, and LAI values remained low because canopy cover and leaf area were still limited. As crop development progressed, all indices increased substantially due to biomass accumulation, canopy closure, and increasing transpiration rates. Maximum index values generally occurred around day 174 of the growing season, corresponding to peak crop development and maximum water demand. During the late-season period, vegetation indices gradually declined as senescence and moisture depletion intensified. These seasonal patterns confirmed the strong relationship between canopy development and remotely sensed spectral responses. A particularly important finding was the strong correlation between vegetation indices and FAO-based crop coefficient (K_c) values. Among the evaluated indices, NDVI and NDWI produced the highest correlations with crop coefficients. Using the “MidPoint” smoothing approach, correlation coefficients reached 0.952 for both NDVI and NDWI, while NDRE also achieved a very strong correlation of 0.939. LAI showed comparatively weaker performance than the spectral indices. These results support earlier studies demonstrating the effectiveness of NDVI for estimating crop coefficients and evapotranspiration dynamics in maize cultivation (Reyes-González et al., 2018; Singh and Irmak, 2009). Both linear and power regression models were tested for estimating crop coefficients from vegetation indices. Although both regression approaches provided satisfactory results, power regression models slightly outperformed linear models in several cases.

The highest predictive accuracy was achieved by NDVI- and NDWI-based evapotranspiration models, which produced RMSE values of approximately 0.43–0.44 mm day⁻¹ and NRMSE values close to 11%. In contrast, LAI-based models generated larger prediction errors and lower adjusted R^2 values, indicating lower reliability for operational ET_c estimation. Consequently, NDVI and NDWI proved to be the most suitable vegetation indicators for practical maize evapotranspiration monitoring and irrigation management. The study also demonstrated that the conventional trapezoidal FAO-56 crop coefficient curve does not fully capture the continuous nature of maize growth and water consumption dynamics. By applying “MidPoint” and “curved” smoothing methods, the crop coefficient curve was refined to provide a more realistic representation of crop development and evapotranspiration changes throughout the growing season. This improved representation enhances the precision of irrigation scheduling and water demand estimation (Figure 3, Figure 4).

Overall, the integration of Sentinel-2 imagery, vegetation-index-based crop coefficients, and evapotranspiration modeling provides an effective and cost-efficient framework for precision irrigation management in maize cultivation. The developed methodology supports more accurate irrigation scheduling, optimized water use, and improved agricultural sustainability under increasingly variable climatic conditions. Furthermore, the integration of these approaches into irrigation advisory systems, such as IRRIFRAME, could substantially improve large-scale water management efficiency and decision support in precision agriculture.

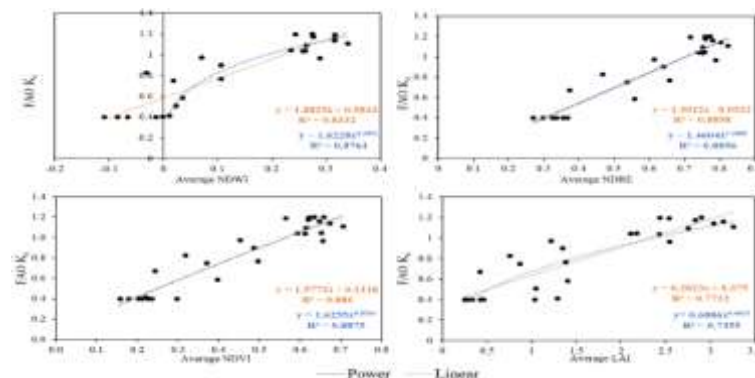


Figure 3. The linear and power regression models between the "MidPoint" K_c and the NDWI ($n = 132$), NDRE ($n = 132$), NDVI ($n = 132$), and LAI ($n = 132$) values of maize.

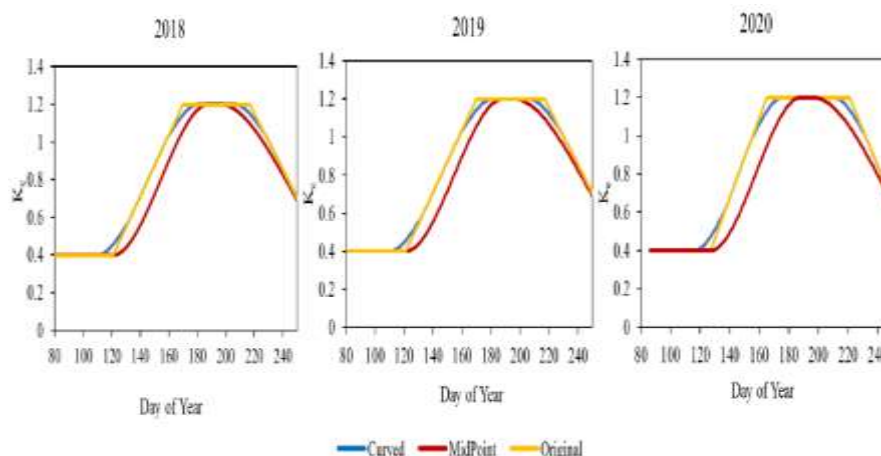


Figure 4. FAO-56-based ("original", "MidPoint", "curved") K_c values for the years (2018–2020).

HYDRUS-BASED SOIL MOISTURE MODELLING SUPPORTED BY REMOTE SENSING DATA

Physically-based modelling of soil water dynamics provides mechanistic insight into crop water availability that empirical spectral methods alone cannot replicate. The Hydrus-2D finite-element model (Šimůnek et al., 2016) solves the Richards equation for variably-saturated flow and has been widely applied to irrigation and drainage simulation. Coupling this model with EO-derived evapotranspiration inputs enables dynamic, spatially consistent soil moisture prediction without exclusive reliance on point-based weather-station data.

Two-dimensional soil moisture distributions were simulated over three growing seasons (2020/21–2022/23) for side-by-side irrigated and non-irrigated maize plots at the University of Debrecen experimental station. The simulation domain extended to 150 cm depth and 200 cm lateral width, discretised into a triangular finite-element mesh (~800 nodes). Soil hydraulic parameters (K_s , van

Genuchten α , n , θ_r , θ_s) were determined from undisturbed soil cores at four depth intervals (0–30, 30–60, 60–90, 90–120 cm).

Upper boundary conditions comprised daily E_{Tc} fluxes combining EO-derived estimates (NDVI-to- K_c regression applied to FAO-56 E_{T0}) and measured rainfall from an on-site tipping-bucket gauge. For the irrigated treatment, drip volumes and scheduling records were incorporated as time-variable flux boundaries. Root water uptake was parameterised using the Feddes reduction function with maize-specific pressure-head thresholds.

Model calibration against the 2020/21 season yielded strong agreement between simulated and observed volumetric soil moisture θ (RMSE = 0.018–0.026 $\text{m}^3 \text{m}^{-3}$; $R^2 = 0.87$ –0.93 across depths). Validation over the subsequent two seasons confirmed temporal transferability: mean RMSE across all sensors and seasons remained below 0.030 $\text{m}^3 \text{m}^{-3}$, within the $\pm 0.05 \text{m}^3 \text{m}^{-3}$ accuracy band required for reliable irrigation trigger decisions.

As illustrated in Figure 2, the irrigated treatment maintained θ consistently above 55% of plant-available water capacity throughout the critical flowering and grain-filling stages (BBCH 60–79), while non-irrigated plots dropped to 30–35% PAW during mid-season dry spells — conditions associated with yield reductions of 15–20% in semi-arid environments (Figure 5, Figure 6).

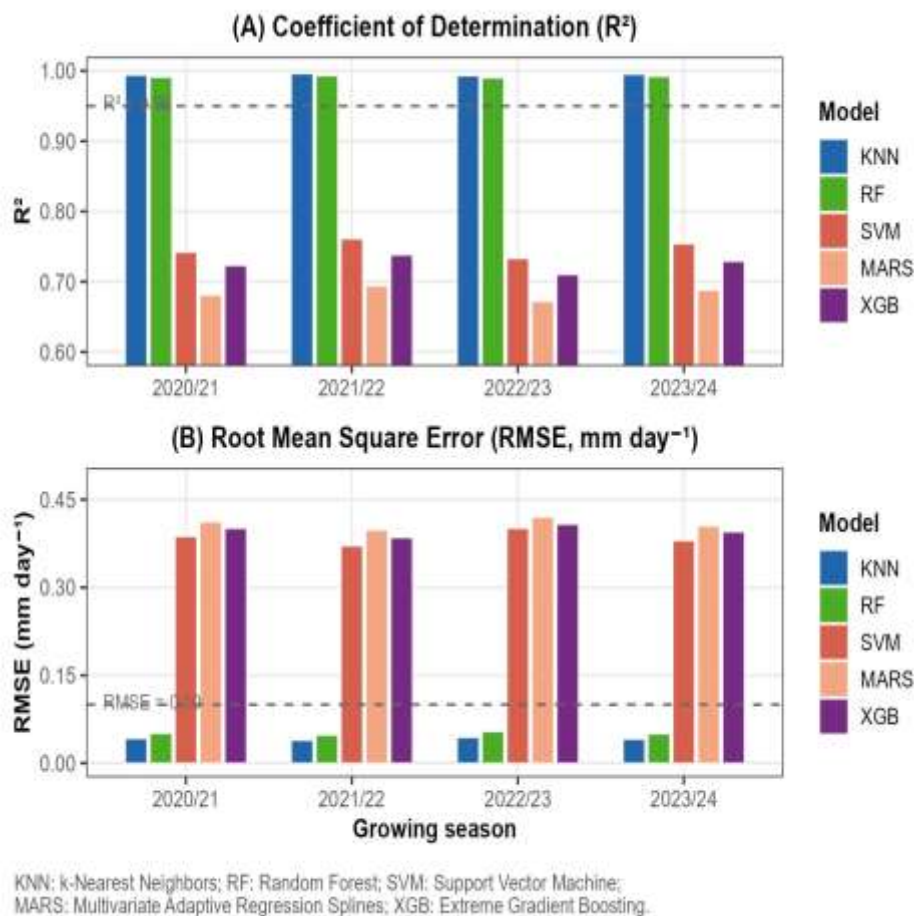


Figure 5. Performance of five machine learning models for daily maize E_{Tc} prediction across four growing seasons in Vhembe District, South Africa (2020–2024). (A) Coefficient of determination (R^2); (B) Root mean square error (RMSE, mm day^{-1}). KNN: k-Nearest Neighbors; RF: Random Forest; SVM: Support Vector Machine; MARS: Multivariate Adaptive Regression Splines; XGB: Extreme Gradient Boosting.

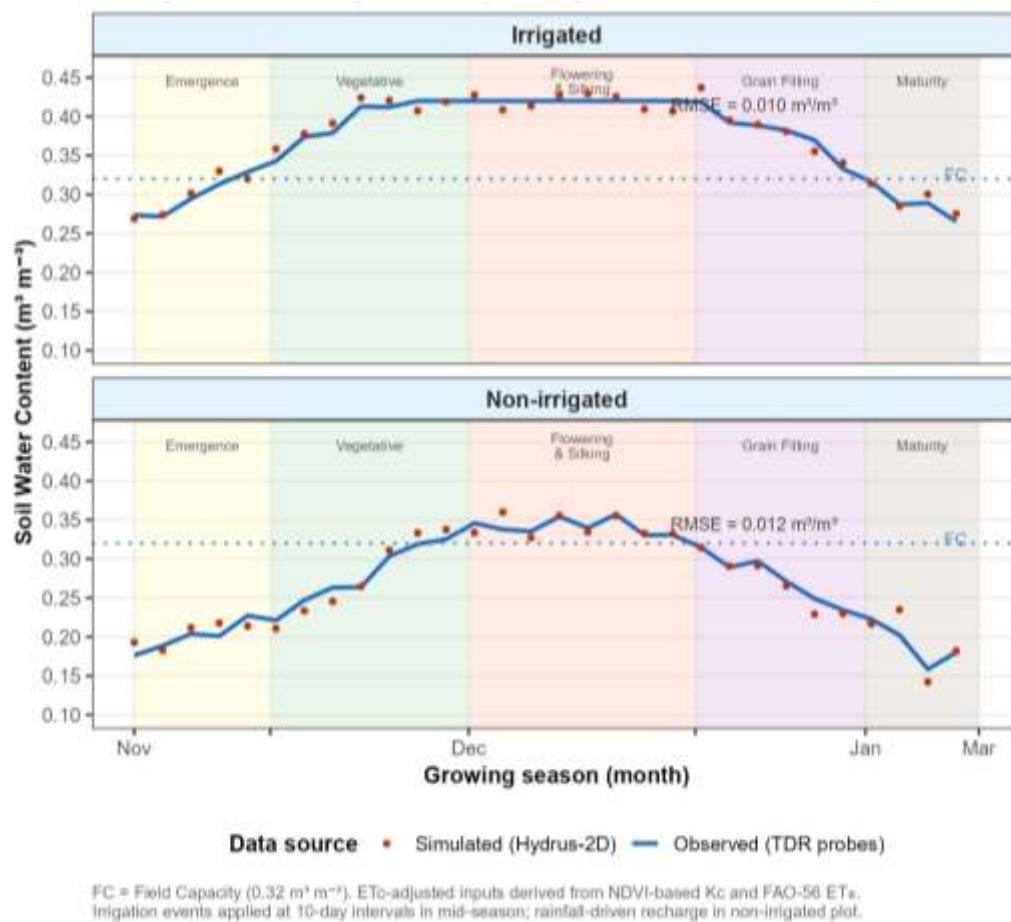


Figure 6. Hydrus-2D simulated (blue line) versus TDR-observed (red points) volumetric soil moisture content ($\text{m}^3 \text{m}^{-3}$, 0–100 cm) for irrigated (top) and non-irrigated (bottom) maize plots (3-year mean, 2020/21–2022/23). Phenological stages indicated by coloured bands. Dotted line = field capacity ($0.32 \text{ m}^3 \text{m}^{-3}$).

SUMMARY

This study presents advanced data-driven methods for precision irrigation and maize monitoring using hyperspectral sensing, remote sensing, machine learning, and physical modeling. The results demonstrated that hyperspectral indices and machine learning models can accurately estimate maize pigment content, biomass, and water stress in a rapid and non-destructive way. Sentinel-2 satellite data significantly improved evapotranspiration and irrigation water demand estimation, supporting more precise irrigation scheduling. HYDRUS-based soil moisture modeling successfully simulated water dynamics under irrigated and non-irrigated conditions. Overall, the integration of Earth Observation data, artificial intelligence, and physical models provides an effective framework for sustainable and water-efficient precision agriculture under changing climatic conditions.

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