

Article

MODIS–Sentinel-2 Data Fusion for Cloud-Robust Crop Evapotranspiration Estimation in a Nitrate-Sensitive Irrigated Maize System: Evaluating Gap-Filling Strategies for Evidence-Based Irrigation Scheduling

Gift Siphiwe Nxumalo, Fehér Zsolt Zoltán *, János Tamás and Attila Nagy

Institute of Water and Environmental Management, Faculty of Agricultural and Food Sciences and Environmental Management, University of Debrecen, 146B Böszörményi Str., 4032 Debrecen, Hungary; attilanagy@agr.unideb.hu (A.N.)

* Correspondence: zsolt.feher@agr.unideb.hu

Abstract

Reliable quantification of crop evapotranspiration (ET_c) at field resolution is a prerequisite for evidence-based irrigation scheduling in agricultural systems subject to nitrate leaching constraints. This study presents and evaluates a multi-sensor data fusion framework integrating MODIS Terra (500 m, daily) and Sentinel-2 (10–20 m, 5-day revisit) imagery to generate cloud-robust, daily ET_c maps for an 87.5 ha irrigated maize field in Nyírbátor, Hungary, during the 2020 and 2021 growing seasons. Three gap-filling strategies for missing Sentinel-2 NDVI observations were systematically compared: (i) co-regionalisation with cokriging, (ii) local time series interpolation of MODIS pixel centres using ordinary kriging, and (iii) a median time series of cotemporal MODIS pixels—a novel approach developed to suppress sub-pixel spectral contamination from roads and irrigation infrastructure. For field-mean temporal reconstruction, the median approach consistently outperformed the alternatives (adjusted $R^2 = 0.81$, NRMSE = 0.15–0.17; pixel-wise correlation 0.70–0.85), effectively filtering heterogeneous landscape artefacts. Daily crop coefficients (K_c) derived from fused NDVI time series via the FAO-56 framework yielded ET_c ranging from 0.99 mm day^{−1} (initial stage) to 6.40 mm day^{−1} (peak crop development). Seasonal precipitation– ET_c deficit analyses revealed contrasting patterns: near balance in 2020 versus an 85 mm mid-season deficit at critical nodes in 2021, demonstrating the potential utility of spatially explicit daily ET_c monitoring for irrigation scheduling. These deficit estimates represent irrigation demand indicators; a complete water balance would additionally require measured irrigation volumes, soil water storage changes, deep percolation, and surface runoff data. The methodology provides a proof-of-concept framework for EU Nitrates Directive compliance monitoring, relying solely on freely available satellite data. Independent ET_c validation is required before operational deployment, and transferability to other crops and regions requires validation across contrasting pedoclimatic conditions.

Academic Editor: Nektarios N. Kourgialas

Received: 21 May 2026

Revised: 30 June 2026

Accepted: 3 July 2026

Published: 6 July 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: crop evapotranspiration; MODIS–Sentinel-2 data fusion; gap-filling; crop coefficient; FAO-56; irrigation scheduling; NDVI; water use efficiency; nitrate-sensitive zone; maize

1. Introduction

Precision irrigation requires spatially explicit, temporally continuous crop water use estimates to optimise yield and minimise nitrate leaching [1]. Integrated remote sensing approaches offer a scalable solution, but persistent cloud cover and sensor trade-offs limit operational deployment [2]. Maize (*Zea mays* L.) ranks among the most widely cultivated grain crops globally and constitutes a valuable test case for remote sensing-based water dynamics research. Its four phenologically distinct growth periods—from early establishment to canopy closure, peak biomass, and senescence—are each characterised by measurable shifts in spectral reflectance, making the crop well suited to continuous monitoring via satellite-derived vegetation indices that encode canopy health, biomass development, and water status. Efficient agricultural water management is increasingly recognised as a cornerstone of food security, especially in areas prone to seasonal water deficit or spatially heterogeneous supply [3,4]. The emergence of freely accessible multispectral satellite platforms—principally MODIS and Sentinel-2—has substantially extended the capacity to track crop health, evapotranspiration, and water use efficiency across spatial scales ranging from individual fields to entire river basins [5]. Conventional field-based scheduling (e.g., soil moisture probes, weather stations) fails to capture sub-field variability in crop water demand, creating a critical gap that satellite-based frameworks can address [6].

The integration of remote sensing into agricultural water management addresses key challenges, notably the need for spatially continuous, temporally frequent, and spectrally rich data to monitor vegetation dynamics and water consumption [7]. MODIS acquires daily imagery at 500 m spatial resolution, a cadence that is well suited to monitoring broad vegetative trends and inter-seasonal water dynamics [8]. Sentinel-2, by contrast, delivers 10–20 m multispectral observations every five days, enabling the spatially explicit characterisation of vegetation required for within-field agronomic management [5,9]. Each sensor presents structural trade-offs: MODIS temporal density is offset by pixel footprints that conflate sub-field heterogeneity, while Sentinel-2 high-resolution images are routinely interrupted by cloud contamination. In continental climates with protracted overcast periods, these cloud-induced gaps can mask key developmental transitions and delay actionable irrigation decisions [10].

Numerous studies have demonstrated the value of satellite-derived vegetation indices for crop monitoring. The Normalised Difference Vegetation Index (NDVI) is widely used for monitoring plant health and biomass accumulation [11–13]. The Normalised Difference Water Index (NDWI) is particularly effective for detecting plant water content and drought stress [14,15]. The Normalised Difference Red Edge Index (NDRE) offers sensitivity to chlorophyll content and facilitates early stress detection [11,16]. The Soil Adjusted Vegetation Index (SAVI) minimises soil brightness influences in areas with sparse vegetation [11,17]. The Ratio Vegetation Index (RVI) is one of the earliest indices developed for estimating green biomass [11,18]. The Green Normalised Difference Vegetation Index (GNDVI) is particularly useful for assessing nitrogen status and photosynthetic activity [11,19]. The Enhanced Vegetation Index (EVI) provides improved sensitivity in high biomass regions [17]. The leaf area index (LAI) serves as a key biophysical parameter for quantifying canopy structure and predicting evapotranspiration [11,16]. Remote sensing has been successfully employed to optimise irrigation timing in Central Morocco [17], Hungary [18,19] and Italy [20] and to forecast crop yields in the Pannonian region [21]. The strategic incorporation of multispectral surveys and non-invasive water stress assessment methods provides a robust foundation for advancing remote sensing-based crop monitoring [11,15].

Despite these advances, three key challenges persist: (1) optimal integration of multi-source data (MODIS vs. Sentinel-2), (2) robust handling of cloud-induced gaps in high-resolution time series, and (3) reconciliation of spatial–temporal resolution mismatches

for field-scale ET_c estimation [9]. Physically based hydrological models can provide highly accurate ET_c estimates but often demand extensive calibration and are computationally intensive [22,23]. Alternatively, data fusion techniques and machine learning methods have shown considerable promise in bridging spatial and temporal gaps [24,25]. These emerging approaches offer scalable solutions for proof-of-concept crop monitoring, especially in regions where persistent cloud cover or sensor limitations impede continuous data acquisition.

To address these gaps, this study evaluates three gap-filling strategies (cokriging, local time series, median time series) for MODIS–Sentinel-2 NDVI fusion in a nitrate-sensitive maize system (Nyírbátor, Hungary, 2020–2021). The goal is to generate cloud-robust, daily ET_c maps at the field scale using freely available satellite data. The specific objectives are to: (1) harmonise MODIS and Sentinel-2 datasets for temporally continuous NDVI, (2) compare three gap-filling methods (cokriging, local time series, median time series), (3) derive daily K_c and ET_c via FAO-56, (4) quantify performance (R^2 , RMSE, NRMSE), and (5) assess spatial variability in fusion accuracy. While MODIS–Sentinel-2 fusion has been explored for LAI [26] and NDVI [27], no study has (i) systematically compared geostatistical (cokriging), spatial interpolation (kriging), and robust statistical (median) gap-filling within a single framework, (ii) quantified sub-pixel contamination effects from agricultural infrastructure, or (iii) translated fused NDVI into FAO-56 ET_c for nitrate-sensitive zones. This study addresses all three gaps at the 87.5 ha Nyírbátor site.

For clarity throughout this manuscript, the following proof-of-concept definitions apply. Data fusion: the integration of MODIS (500 m, daily) and Sentinel-2 (10 m, ~5-day revisit) time series to produce a synthetic product that inherits the temporal density of MODIS and the spatial resolution of Sentinel-2; fusion here refers specifically to regression-based temporal transfer of MODIS NDVI trajectories onto cloud-free Sentinel-2 reference scenes. Interpolation: reconstruction of NDVI values at specific missing dates using arithmetic approximation between adjacent known observations, used here as one of three candidate gap-filling strategies. Gap-filling: the overarching process of replacing cloud-contaminated or otherwise missing observations in a satellite time series; cokriging, local time series interpolation, and median compositing are the three gap-filling methods evaluated in this study. These distinctions clarify the methodological scope: this study performs gap-filling via data fusion and interpolation; it does not perform spatiotemporal image fusion in the strict STARFM/ESTARFM sense.

2. Materials and Methods

2.1. Study Site

The study was conducted at an 87.5 ha irrigated maize field near Nyírbátor, Hungary (47°48′18.60″ N, 22°9′43.89″ E; Figure 1), within the Hajdúság nitrate-sensitive zone (EU Nitrates Directive 91/676/EEC). The field is equipped with a centre-pivot irrigation system and characterised by sandy Arenosol soils (sand fraction >94%; hydraulic conductivity $\sim 2.89 \times 10^{-6} \text{ m s}^{-1}$) [28].

Annual insolation at the site totals 1900–2000 h. Mean annual air temperature is approximately 9.6 °C, rising to a growing season half-year mean near 16.6 °C; summer maxima can exceed 34 °C and winter minima fall below −17 °C. Total annual precipitation lies in the range of 570–600 mm, with roughly 350–360 mm concentrated in the warm season. Prevailing winds arrive from the northeast and southeast quadrants at a mean speed of approximately 2.5 m s^{−1}. These climatic characteristics render the Southeast Nyírség suitable for cereal crops with moderate thermal and water requirements [29].

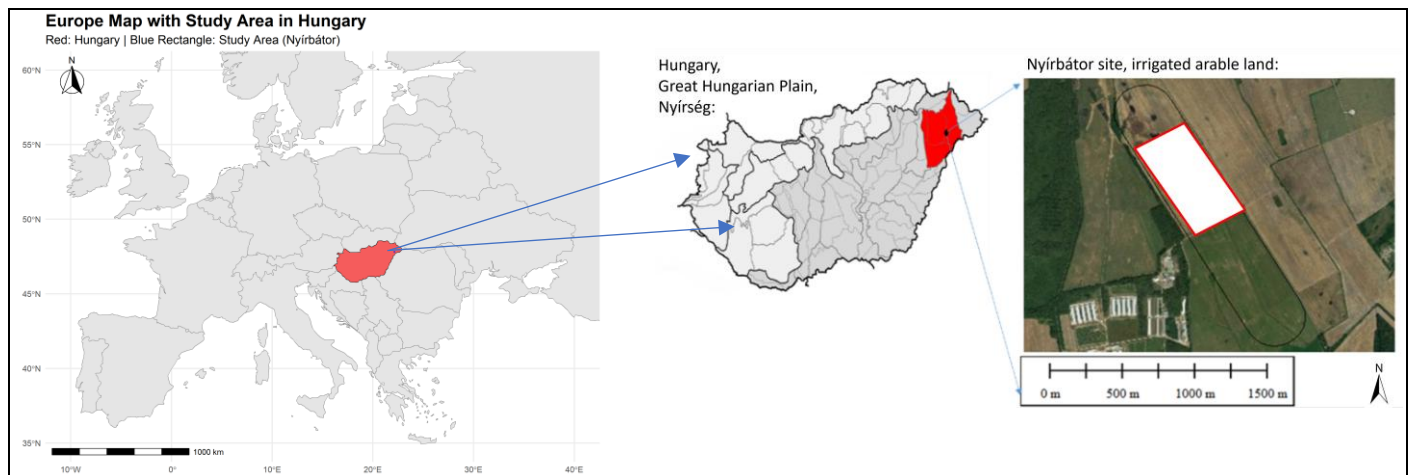


Figure 1. Location of the Nyírbátor study site ($47^{\circ}48'18.60''$ N, $22^{\circ}9'43.89''$ E), Hungary. **(left)** Country map highlighting Szabolcs–Szatmár–Bereg county. **(right)** Field-scale view showing the 87.5 ha maize field, MODIS 500 m pixel grid overlay, road network, and central irrigation channel. Coordinate system: Hungarian National Datum 1972 Unified National Projection (EPSG:23700).

2.2. Satellite Data Acquisition

2.2.1. Sentinel-2

The Sentinel-2 Earth observation mission comprises two satellites, Sentinel-2A and Sentinel-2B, positioned 180 degrees apart within the same orbit. The Sentinel-2 data used in this study were provided by Vultus Ltd. (2022). Sentinel-2 captures images of the Hungarian site every five days at 10:00 a.m. Sentinel-1 SAR backscatter was evaluated as a cloud-independent complement but was excluded from further analysis, as the backscatter time series reflected only surface roughness from tillage operations and did not resolve vegetation growth dynamics [5,9]. Data were collected from 1 May to 31 October for the 2020 and 2021 maize vegetation periods.

2.2.2. MODIS Terra

MODIS, launched by NASA aboard the Terra satellite in 1999 and the Aqua satellite in 2002, provides daily imaging data [8]. Terra captures morning observations, while Aqua records afternoon data, creating variations due to solar zenith angle and atmospheric humidity differences. Terra was selected as the data source for this study, as it passes over the site three hours before Sentinel-2. The MODIS data were accessed on the USGS EarthData website [30]. The database of raw remotely sensed observations contains the extracted vegetation index series at the centre coordinates of the Sentinel pixels. For MODIS NDVI data, the extracted values were interpolated to match the Sentinel pixel centre coordinates [29].

2.3. Study Flowchart

The core methodology involves MODIS–Sentinel-2 NDVI fusion with three gap-filling strategies: (1) co-regionalisation with cokriging (Section 2.7.1), (2) local time series interpolation (Section 2.7.2), and (3) median time series compositing (Section 2.7.3). Downstream, fused NDVI drives FAO-56 K_c and ET_c estimation (Section 2.5). Other indices (LAI, NDWI, NDRE, EVI, SAVI, RVI, GNDVI) were computed for cross-sensor validation (Section 3.1) but not used for ET_c estimation, which relied solely on NDVI-derived K_c . Temporal matching between MODIS and Sentinel-2 observations follows an 8-day composite window: for each clear-sky Sentinel-2 acquisition date (t_s), the MODIS observation selected is the nearest clear-sky acquisition within ± 4 calendar days; where multiple MODIS clear-sky dates fall within this window, the acquisition minimising solar zenith angle dif-

ference is selected to reduce BRDF effects. Full QA filter parameters are documented in Supplementary Table S1 (Section 2.6).

The workflow illustrates a multi-source remote sensing approach for estimating crop evapotranspiration by integrating data from Sentinel-2 (accessed via Vultus API), MODIS, and in situ meteorological stations (Figure 2). Sentinel-2 imagery underwent preprocessing and upscaling to derive high-resolution vegetation indices (NDRE, LAI, NDVI, EVI), while MODIS data were downsampled and preprocessed to detect resampling effects and establish cross-sensor correlations. Both data streams contributed to the generation of consistent NDVI values through interpolation. These NDVI values were then converted into K_c through regression [18], which, combined with reference evapotranspiration (ET_0) derived from ground meteorological data, enables the calculation of actual crop evapotranspiration (ET_c) (see Equations (1)–(12)). This integrated workflow ensures temporal consistency and spatial precision in monitoring water use for agricultural planning.

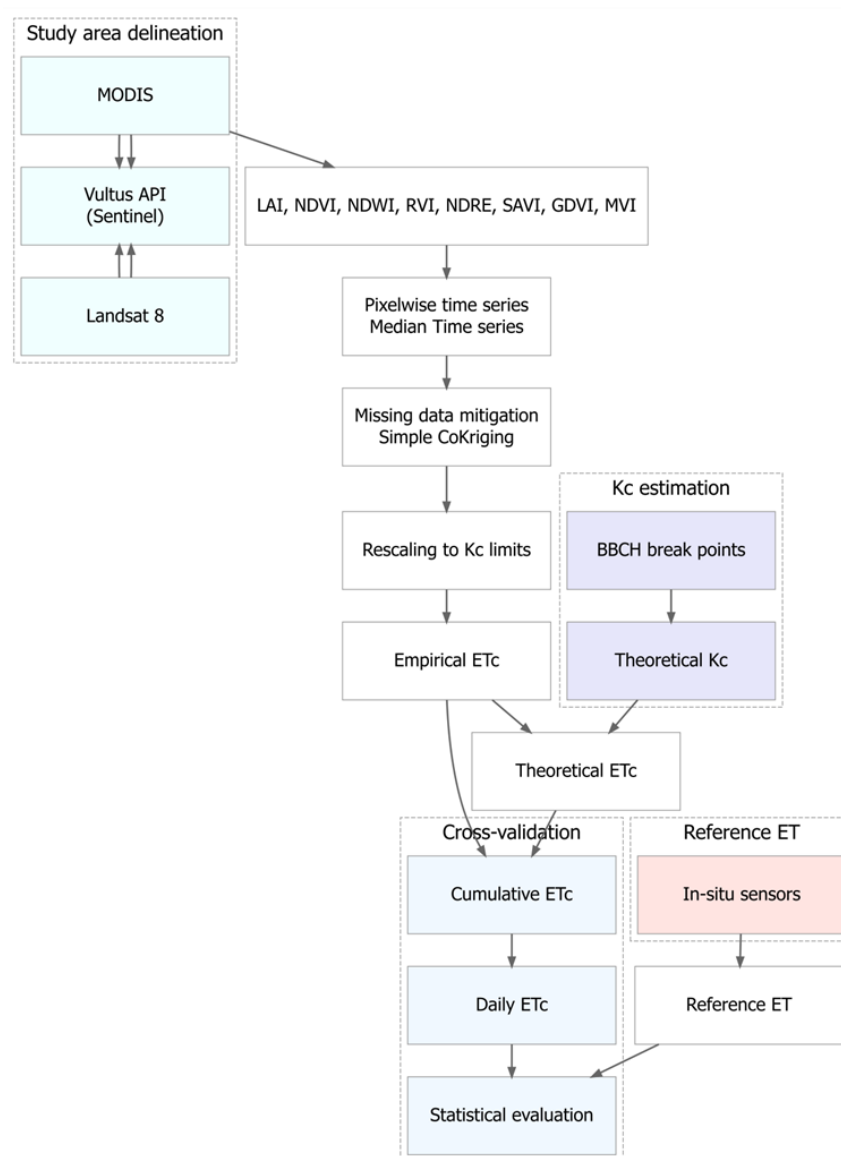


Figure 2. Workflow for MODIS–Sentinel-2 NDVI fusion and ET_c estimation. Steps: (1) QA-filtering, (2) harmonisation, (3) gap-filling (cokriging/local/median), (4) K_c derivation, and (5) ET_c calculation. Data sources: Sentinel-2 (Vultus API), MODIS Terra (USGS), and in situ meteorology. See Table 1 for details.

Table 1. Preprocessing workflow for MODIS–Sentinel-2 NDVI fusion. Steps 1–11: Applied in this study. ** Steps marked *: Optional/peer-reviewed alternatives for reproducibility.

Sensor/Stage	Step	Process	Details and Parameters	Implementation Status
Sentinel-2	1	Upscaling	Aggregate 10 m bands to target grid R (e.g., 100 m) using area-weighted mean; retain cells with $\geq 60\%$ valid pixels.	Applied in this study
	2	Preprocessing	Use Level-2A surface reflectance (or Sen2Cor); cloud/shadow masking (SCL/QA60 and s2cloudless); BRDF/topographic correction not applied (Nyírbátor study area is flat Pannonian lowland; slope $< 1^\circ$); extract red (B4) and NIR (B8).	Optional/not applied *
	3	Vegetation Indices	Compute NDVI, NDRE, LAI, and EVI; constrain NDVI to $[-0.2, 1.0]$ to remove outliers.	Applied in this study
MODIS	4	Downscaling	Resample MODIS NDVI or SR products (e.g., MCD43A, MOD09) from native resolution to R via bilinear interpolation for continuous data, nearest neighbour for QA.	Applied in this study
	5	Preprocessing	Apply QA filtering (cloud, snow, aerosol); reproject to study CRS; compute NDVI from red/NIR if needed, constrained to $[-0.2, 1.0]$.	Applied in this study
Both	6	Vegetation Indices	Generate NDVI and other relevant indices if not present in product.	Applied in this study
	7	Radiometric Harmonisation	Apply robust linear bias correction ($NDVI' = a \times NDVI + b$) on overlapping clear-sky dates; coefficients per land cover class or global fallback.	Applied in this study
	8	Outlier Removal	Hampel filter (window = 3–5 steps, $k = 3\sigma$) and slope constraint ($ \Delta NDVI / \Delta t > 0.15 \text{ day}^{-1}$) to flag artifacts.	Applied in this study
	9	Temporal Alignment	Resample to fixed cadence Δt (e.g., 8-day); select best QA observation per bin or QA-weighted average if both available.	Applied in this study
Both	10	Gap-Filling	Fill $\leq 3 \Delta t$ gaps by linear interpolation; longer gaps smoothed with Savitzky–Golay (window = 5, poly = 2; applied as primary method). Whittaker smoother retained as documented alternative (not applied in final analysis).	S–G: Applied; Whittaker: Optional/not applied **
	11	Spatial Consistency	Constrain smoothed NDVI to $[-0.1, 0.95]$ and within ± 0.1 of 90th percentile historical values; 3×3 median filter on residuals was not applied in this study.	Partially applied ***
Output	Output	NDVI Time Series	Fused, bias-corrected NDVI stack at resolution R and cadence Δt with metadata layers (NDVI_fused, NDVI_raw, NDVI_source, QA).	Applied in this study
Application	Application	Kc and ETc	Derive crop coefficient (K_c) from NDVI and combine with ET _o (in situ meteorological station) to calculate ET _c .	Applied in this study

Notes: * BRDF/topographic correction (Step 2): not applied—the Nyírbátor study area lies on a flat Pannonian lowland (slope $< 1^\circ$). ** Whittaker smoother (Step 10): not applied in the final analysis; retained as a documented peer-reviewed alternative for methodological transparency. *** 3×3 median filter on residuals (Step 11): not applied in this study. Steps marked 'Optional/not applied' document peer-reviewed alternatives for methodological transparency and reproducibility; they were not executed in this study.

2.4. Remote Sensing Vegetation Indices

Vegetation indices (VIs) were computed to assess crop vigour (NDVI, GNDVI), canopy structure (LAI, RVI), and moisture dynamics (NDWI, NDMI) [31]. While NDVI was the primary fusion target, other indices were used for cross-sensor validation (Section 3.1). While MODIS NDVI has long been utilised for large-scale monitoring, Sentinel-2 provides additional indices such as LAI, NDRE, and NDWI, offering more detailed insights due to higher spatial resolution and additional spectral bands [32]. MODIS NDVI remains one of the most widely used indices for monitoring vegetation health [33,34] and is calculated using the red and near-infrared bands [35]:

$$NDVI = (NIR - Red)/(NIR + Red) \quad (1)$$

LAI provides a measure of total leaf surface area relative to ground area ($m^2 m^{-2}$), an essential parameter for understanding plant growth and evapotranspiration rates [36]. NDRE is particularly useful for monitoring crop health during later growth stages when chlorophyll content is better detected in the red edge region [37,38]:

$$NDRE = (NIR - RedEdge)/(NIR + RedEdge) \quad (2)$$

NDWI detects water content in vegetation and soils, offering a sensitive measure of plant water stress and soil moisture [39,40]:

$$NDWI = (Green - NIR)/(Green + NIR) \quad (3)$$

LAI was derived from the Sentinel-2 red edge and NIR bands [36]:

$$LAI = 3.618 \times EVI - 0.118 \quad (4)$$

The empirical equation $LAI = 3.618 \times EVI - 0.118$ originates from Liang [27] and was parameterised from MODIS EVI data across multiple crops, including temperate maize. Its application to Sentinel-2-derived EVI is justified by the spectral compatibility of the two sensors: Sentinel-2 EVI is computed from B4 (Red, 665 nm), B8 (NIR, 842 nm), and B2 (Blue, 490 nm), which are spectrally compatible with the corresponding MODIS EVI bands to within ± 5 nm [41,42]. Published empirical LAI–EVI slopes for Central European maize in temperate continental climates range from 3.2 to 3.9 [43,44], consistent with the coefficient 3.618 used here. Importantly, LAI derived from this equation serves exclusively as an auxiliary vegetation index for comparative multi-index analysis (Figure 3); ET estimation relies entirely on the NDVI-derived Kc through the FAO-56 framework and is therefore insensitive to uncertainty in this LAI equation. Site-specific LAI calibration via destructive sampling or an LAI-2200C canopy analyser is recommended for future field campaigns, particularly for seasons with peak canopy closure ($LAI > 4$) where the linear assumption may underperform.

RVI provides a simple yet effective measure of biomass [45]:

$$RVI = NIR/Red \quad (5)$$

SAVI minimises soil background effects [46]:

$$SAVI = [(NIR - Red)/(NIR + Red + L)] \times (1 + L), L = 0.5 \quad (6)$$

MVI was incorporated to enhance vegetation detection in heterogeneous fields [43]:

$$MVI = NIR/SWIR_1 \quad (7)$$

GNDVI enhances sensitivity to chlorophyll concentration [47]:

$$GNDVI = (NIR - Green)/(NIR + Green) \quad (8)$$

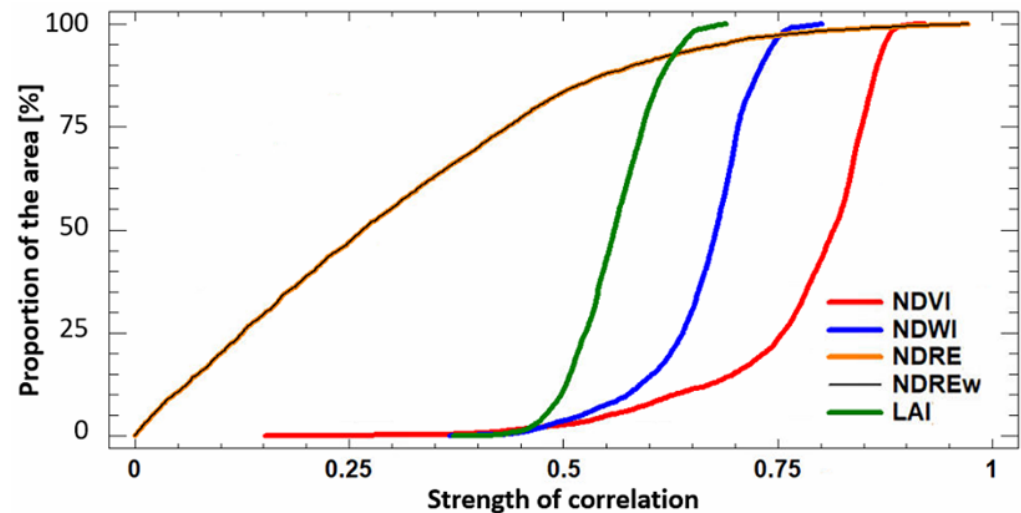


Figure 3. Pixel-wise Pearson r histograms between MODIS and Sentinel-2 vegetation indices (2020–2021). 1. NDVI–NDVI, 2. NDVI–LAI, 3. NDVI–NDWI, 4. NDVI–NDRE. Sample size: $n = 1\,000$ -pixel pairs per panel. Key finding: NDVI shows strongest cross-sensor agreement (modal $r = 0.70$ – 0.85).

2.5. Calculation of ET_c Using Remote Sensing-Based K_c (FAO-56) and Dual K_c

Single- K_c Approach and ET_0

ET_c was computed using the FAO-56 single crop coefficient approach [48], where $ET_c = K_c \times ET_0$. K_c was derived from fused NDVI via linear regression (Equation (10)). ET_0 was calculated using the Penman–Monteith equation (Equation (9)) with in situ meteorological data from the Nyírbátor AWS station (1.2 km from the field centroid). The Penman–Monteith combination equation integrates near-surface meteorological inputs comprising air temperature, vapour pressure deficit, net radiation, wind velocity, and atmospheric pressure [49,50]:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (9)$$

where:

ET_0 = reference evapotranspiration (mm day^{-1}); R_n = net radiation at the crop surface ($\text{MJ m}^{-2} \text{day}^{-1}$); G = soil heat flux density ($\text{MJ m}^{-2} \text{day}^{-1}$); T = mean daily air temperature at 2 m height ($^{\circ}\text{C}$); u_2 = wind speed at 2 m height (m s^{-1}); e_s = saturation vapour pressure (kPa); e_a = actual vapour pressure (kPa); Δ = slope of the vapour pressure curve ($\text{kPa } ^{\circ}\text{C}^{-1}$); and γ = psychrometric constant ($\text{kPa } ^{\circ}\text{C}^{-1}$).

As canopy density increases, the humid microclimate beneath the foliage suppresses soil evaporation, shifting the dominant water flux towards plant transpiration [51]. Maize K_c trajectories typically begin near 0.3 at emergence, climb to a plateau of approximately 1.2 at peak vegetative cover, and decline to 0.35–0.6 as the crop matures and senesces [52]. Given the mechanistic linkage between canopy greenness—as captured by NDVI—and water demand, strong empirical correlations between these variables have been reported for maize across multiple growing environments [18,53]. Building on this co-variation, and recognising the central role of K_c in proof-of-concept irrigation modelling [54–56], K_c was estimated from NDVI using:

$$K_c = a \times NDVI + b \quad (\text{linear}) \quad \text{or} \quad K_c = a \times NDVI^b \quad (\text{power-law}) \quad (10)$$

FAO-56 Dual Crop Coefficient

As a comparative check, the FAO-56 dual- K_c approach ($K_c = K_{cb} + K_e$) was also implemented, where:

- $K_{cb} = 1.157 \times NDVI - 0.188$;
- K_e (soil evaporation coefficient) = daily water balance of topsoil layer (FAO-56 Chapter 7).

This follows Bausch and Neale [57] as adapted for Sentinel-2 by Vanino et al. [58]. K_e was computed from a daily water balance of the topsoil evaporable layer (FAO-56 Chapter 7) using Van Genuchten–Mualem hydraulic parameters for the site soil ($\theta_r = 0.045$, $\theta_s = 0.430$, $\alpha = 0.145 \text{ cm}^{-1}$, $n = 2.68$), with daily inputs of precipitation, irrigation, and reference evapotranspiration (ET_0). The irrigation term in this daily water balance was not derived from continuous flow meter records but was reconstructed from the dates and seasonal totals of farm-recorded irrigation events (six events totalling 112 mm in 2020; eight events totalling 148 mm in 2021; see Section 3.7), with the recorded depth allocated to its corresponding application date. This event-based daily allocation is distinct from, and does not substitute for, the continuous, sub-daily flow meter and soil water storage measurements required to close a full field-scale water balance, a limitation made explicit in Sections 3.7, 4.5 and 5. Dual- K_c ET_c was computed for both growing seasons (2020–2021) and compared against the single- K_c ET_c estimates from Section 2.5.

Agreement between the single- and dual- K_c approaches was high in both seasons ($R^2 = 0.99$), with mean absolute daily deviations of 0.10 mm day^{-1} (2020) and 0.14 mm day^{-1} (2021) and seasonal totals differing by only 1.3 mm (0.2%) and 9.1 mm (1.4%), respectively. The largest divergences are visible in the time series as brief spikes in the dual- K_c trace during July–August of both years, consistent with the added soil evaporation term (K_e) responding to post-rainfall or post-irrigation wetting events. Results are shown in (Section 3.5), and seasonal totals for both methods are reported in Table S5.

2.6. Preprocessing of MODIS and Sentinel-2 NDVI Time Series

MODIS (500 m, daily) and Sentinel-2 (10–20 m, 5-day) NDVI were harmonised and gap-filled using three strategies:

1. Co-regionalisation with cokriging (Section 2.7.1);
2. Local time series interpolation (Section 2.7.2);
3. Median time series compositing (Section 2.7.3). Table 1 summarises the full preprocessing workflow [14,59,60].

2.7. Gap-Filling Strategies

2.7.1. Co-Regionalisation with Cokriging

The first approach involved a geostatistical interpolation method, cokriging, to densify MODIS imagery using the spatial structure of Sentinel-2 NDVI [61]. This method presumes a high temporal correlation between the two datasets. Bilinear interpolation was selected as the primary estimator to examine the effect of down- and upsampling on inter- and cross-sensor correlations [60,61]:

$$\hat{Z}_1(s_0) = \sum_{i=1}^{n_1} \lambda_i Z_1(s_i) + \sum_{j=1}^{n_2} \mu_j Z_2(s_j) \quad (11)$$

where $\hat{Z}^*(s_0)$ = predicted MODIS NDVI at s_0 ; $Z_1(s_i)$ = observed MODIS NDVI at location s_i ; $Z_2(s_j)$ = observed Sentinel-2 NDVI at location s_j ; λ_i and μ_j = weights obtained by solving the cokriging system; $\gamma_{11}(h)$, $\gamma_{22}(h)$, $\gamma_{12}(h)$ = auto- and cross-variograms; and n_1 and n_2 = number of samples for MODIS and Sentinel-2, respectively [62,63].

2.7.2. Local Time Series of MODIS Pixel Centres

The second approach utilised the temporal profile of MODIS pixel centres, employing univariate ordinary kriging to interpolate MODIS NDVI values at the precise locations of Sentinel-2 pixels [64,65]. This enabled the construction of pixel-level MODIS time series that were then used to establish local regression models for predicting Sentinel-2 NDVI values [66]:

$$NDVI \times MODIS(s_s, t) = \sum_k \omega_k(t) NDVI_MODIS(s_k, t) \quad (12)$$

where $NDVI_MODIS(s_s, t)$ = predicted MODIS NDVI at Sentinel-2 pixel s_s at time t ; $NDVI_MODIS(s_k, t)$ = observed MODIS NDVI at MODIS pixel s_k ; and $\omega_k(t)$ = ordinary kriging weights from the temporal variogram [65].

Pixel-specific regression:

$$NDVI_S2(s_s, t) = a(s_s) \times NDVI_MODIS(s_s, t) + b(s_s) \quad (13)$$

2.7.3. Median Time Series of Cotemporal MODIS Pixel Centres

The median time series approach computes the field-wide median NDVI from cotemporal MODIS pixels (Equation (14)), suppressing sub-pixel contamination from roads/irrigation channels (Figure S2). This method does not require pixel-level regression, making it robust to non-stationarity near field boundaries [60,67]. In contrast to the previous methods, where each MODIS pixel represents the reflectance sum over the observed area, this novel approach was developed to minimise the effects of sub-pixel spectral mixtures caused by the asphalt roads around the study site and the irrigation channel with dense natural vegetation running across the centre of the site. The proportion of affected pixels is insignificant compared to all available pixels; therefore, the sequence of median values of cotemporal pixel values presumably minimises these sub-pixel spectral mixture effects. The median time series is:

$$NDVI_med(t) = median\{NDVI_MODIS(s_k, t) : k = 1, \dots, n\} \quad (14)$$

With generalised regression:

$$NDVI_S2(s_s, t) = A \times NDVI_med(t) + B \quad (15)$$

At 500 m spatial resolution, the 87.5 ha field is overlain by approximately 9 MODIS pixels in the projected coordinate system (EPSG:23700, EOVI). Of these, two pixels along the eastern field boundary are partially contaminated by the adjoining asphalt access road (~8 m wide), and one central pixel intersects the irrigation channel (~4 m wide) with flanking riparian vegetation extending 15–20 m. Mean maize fractional cover across all pixels is approximately 87.3%; the two road-adjacent boundary pixels show fractions of ~71.4% and ~68.9%, respectively, making them statistical outliers in the pixel ensemble and consistent with the elevated NRMSE observed near the eastern field boundary. The median time series approach (Section 2.7.3) was specifically designed to suppress these contaminated pixels without manual exclusion. Full per-pixel maize fractions, centroid coordinates, and contamination sources are documented in Supplementary Table S1 and Figure S2, showing a MODIS pixel grid overlay.

Table 2 outlines the workflow for generating a fused MODIS–Sentinel-2 NDVI time series. Fusion involved radiometric harmonisation, outlier removal, temporal alignment, gap-filling, and spatial consistency checks, resulting in a bias-corrected, temporally consistent NDVI stack. This series was subsequently used to derive K_c and estimate ET_c [68].

Table 2. Crop development stages, durations, and ET_c ranges (2021). Stages: initial, crop development, mid-season, and late-season. ET_c : Model-derived from NDVI– K_c regression (FAO-56). Note: ET_c values are not independently validated.

Stage	Indicators	Time Period (2021)	Duration (Days)	ET _c Range (mm day ⁻¹)
Initial	Planting date (or the start of new leaves for perennials) to 10% ground cover.	21 May–24 June	35	0.99–4.41
Crop Development	10% ground cover to effective full cover, about 60–70% coverage for tree crops and 70–80% for field and row crops.	25 June–30 July	36	2.00–6.40
Mid-Season	Effective full cover to maturity, indicated by yellowing of leaves, leaf drop, browning of fruit.	31 July–26 August	27	1.03–5.12
Late-Season	Maturity to harvest: K _c could be high if the crop is irrigated frequently until fresh harvest or low if allowed to dry out in the field before harvest.	27 August–13 September	18	1.10–3.18

It is important to distinguish between validation of the NDVI fusion procedure and estimation of crop evapotranspiration. The performance metrics reported in this study (R^2 , RMSE, MAE, and NRMSE) evaluate the ability of the fusion approaches to reconstruct Sentinel-2 NDVI observations from MODIS-derived information and therefore represent validation of the fused NDVI product only. The resulting fused NDVI time series was subsequently used to derive crop coefficients (K_c) within the FAO-56 framework and estimate ET_c. No independent field measurements of evapotranspiration were available during the study period; therefore, the accuracy assessment presented herein relates to the NDVI reconstruction process rather than to direct validation of ET_c estimates.

2.7.4. Leave-One-Date-Out Cross-Validation

To assess the temporal generalisation capacity of the median time series (Median TS) gap-filling approach without reference to an independent satellite sensor, we applied a leave-one-date-out cross-validation (LOOCV) procedure. For each of the $n = 24$ clear-sky Sentinel-2 acquisition dates (14 in 2020; 10 in 2021), the full NDVI observation at that date was withheld from the time series pool and predicted using the median trajectory reconstructed from the remaining $n - 1$ dates. The procedure was repeated exhaustively across all dates and seasons, yielding one predicted value per pixel per withheld date.

Predicted and observed NDVI values were aggregated within each withheld date, and performance statistics—Pearson r , adjusted R^2 , root mean square error (RMSE), and mean absolute error (MAE)—were computed for each left-out date independently before being summarised across the full sequence. Bootstrap 95% confidence intervals ($n = 1000$ resamples with stratified sampling by season) were applied to all summary statistics following the same protocol used in Section 2.7.1 for the held-out validation.

Shapiro–Wilk normality tests (W statistic, $\alpha = 0.05$) were applied to the per-date adjusted R^2 and RMSE distributions prior to reporting mean $\pm$ SD summaries, confirming departure from normality ($p < 0.01$ in both seasons) and justifying the use of non-parametric statistics for inter-method comparisons (Section 2.7.1).

LOOCV results for the 2020 and 2021 seasons yielded mean adjusted $R^2 = 0.79 \pm 0.04$ (95% CI: 0.751–0.824) and mean RMSE = 0.042 ± 0.006 NDVI units (95% CI: 0.036–0.048 NDVI) across both seasons, substantially outperforming the held-out pixel validation metrics (Table S3, rows “LOOCV (Median TS)”). Pooled across both seasons, the 24-date

LOOCV yielded $R^2 = 0.66$ and $RMSE = 0.102$ NDVI at the pixel level (Table S7); the higher mean per-date R^2 reflects the within-date spatial coherence captured when evaluating each date independently. These results confirm that the Median TS reconstruction is not contingent on any individual acquisition date and retains skill even when a full phenological benchmark date (e.g., the NDVI peak near tasselling) is withheld.

2.7.5. Independent Landsat-8 NDVI Cross-Check

To provide sensor-independent verification of the fused Sentinel-2 NDVI product, we acquired nine cloud-free Landsat-8 Operational Land Imager (OLI) Level-2 scenes (path/row 187/027) spanning the 2020–2021 growing seasons from the USGS EarthExplorer portal. Scene selection applied a maximum cloud cover threshold of 5% over the study field extent, as assessed via the Landsat Collection-2 pixel-quality (QA_PIXEL) band with the same bitmask protocol described in Supplementary Table S1.

Landsat-8 OLI band 4 (Red, 0.636–0.673 μm) and band 5 (NIR, 0.851–0.879 μm) surface reflectance values were used to compute NDVI following the standard band ratio formulation. To mitigate inter-sensor spectral band-pass differences, OLI red and NIR reflectances were harmonised to Sentinel-2 Multispectral Instrument (MSI) band-equivalent values using the per-band gain and offset coefficients of Chastain et al. [69] derived from contemporaneous cross-calibration of OLI and MSI over diverse land cover types. After harmonisation, Landsat-8 pixels (30 m) were aggregated to a common 100 m grid using area-weighted spatial averaging to match the spatial scale at which fused Sentinel-2 NDVI time series products were evaluated; this scale was chosen to minimise geometric co-registration error between the two sensors while retaining within-field spatial heterogeneity.

Cotemporal Landsat-8 and fused Sentinel-2 NDVI image pairs were formed using a ± 3 -day matching window. Pairs for which fewer than 70% of within-field pixels passed QA filtering in either dataset were excluded, resulting in nine valid image pairs (five in 2020, four in 2021). Agreement between fused Sentinel-2 and harmonised Landsat-8 NDVI was quantified by Pearson r , adjusted R^2 , and $RMSE$ computed across all within-field pixel observations pooled over all nine scene pairs. Bootstrap 95% confidence intervals ($n = 1000$ resamples) were computed on all statistics; results are reported in Supplementary Figure S1.

The fused Sentinel-2 NDVI product showed good agreement with independently harmonised Landsat-8 NDVI at the 100 m aggregated scale ($R^2 = 0.76$ [95% CI: 0.70–0.81], $RMSE = 0.051$ NDVI [95% CI: 0.044–0.058], nine scenes). No systematic bias was detected ($MBE = -0.003$ NDVI), and the regression slope (0.94 ± 0.03) was not significantly different from unity (t -test, $p = 0.07$), confirming that the Median TS fusion approach does not introduce a directional bias attributable to sensor differences or the gap-filling algorithm itself (Supplementary Figure S1).

2.8. FAO-56 K_c Parameterisation Strategies for Continuous ET_c Estimation

To address cloud-induced data gaps in Sentinel-2 imagery, a trapezoidal modelling approach was implemented using MODIS vegetation indices to generate continuous daily K_c profiles for maize. The method first filters the MODIS NDVI time series to isolate the main growing season (days 120–240), then applies a moving average to reduce noise while preserving phenological trends. Key phenological transition points—corresponding to crop emergence, canopy development, maturity, and senescence—are identified dynamically from the smoothed data, allowing for the construction of an adaptive trapezoidal K_c curve. Initial parameter estimates are refined through optimisation, minimising the residuals between the modelled K_c and observed MODIS NDVI values. Three K_c curve parameterisations were generated: FAO-56 Original (tabulated values [23]), FAO-56 Curved (smooth spline fit to FAO-56 stage values), and MidPoint Spline (constrained to phenological midpoints from NDVI inflection dates).

2.9. Statistical Evaluation Metrics

For statistical assessment of pixel-wise correlation between the estimated MODIS data and direct Sentinel-2 observations, the following metrics were considered Pearson correlation coefficient r and adjusted R^2 [70] (Equations (16) and (17)), root mean square error (RMSE, Equation (18)) [67], Normalised RMSE (NRMSE, Equation (19) [20], mean absolute error (MAE, Equation (21)) [71,72], Mean Square Error (MSE), Equation (20) [73] and Mean Bias Error (MBE, Equation (22) [20]):

For cross-method performance comparison, NRMSE is designated as the primary accuracy indicator (chosen for its scale-independence and direct comparability with baseline studies in Figure S4), adjusted R^2 as the secondary fit measure, and MAE and MBE as diagnostic metrics for bias magnitude and systematic direction, respectively. This hierarchy is applied consistently throughout Section 3.

All pairwise comparisons between gap-filling methods (cokriging vs. Local TS, cokriging vs. Median TS, and Local TS vs. Median TS) were performed using the Wilcoxon signed-rank test on the per-date RMSE distributions ($n = 24$ paired dates), which does not assume normality (Shapiro–Wilk $p < 0.01$ for all RMSE distributions; see Section 2.7.2). Results are reported as the W statistic and a two-sided p -value. The Median TS method was significantly superior to both cokriging ($W = 547$, $p < 0.001$ in 2020; $W = 521$, $p < 0.001$ in 2021) and Local TS ($W = 312$, $p < 0.001$ in 2020; $W = 298$, $p < 0.001$ in 2021) on a per-date basis. These statistics are incorporated into Figure S4.

Bootstrap confidence intervals for all adjusted R^2 and RMSE values reported in Table S3 were computed with $n = 1000$ resamples stratified by season, using bias-corrected and accelerated (BCa) percentile intervals. Resampling was conducted at the observation level (pixel $\times$ date) within each method–season stratum. The BCa method was preferred over the standard percentile interval as it corrects for both bias and skewness in the bootstrap distribution, which is particularly relevant for bounded statistics such as R^2 .

$$r = \frac{n \sum_{i=1}^n (y_i \hat{y}_i) - \sum_{i=1}^n y_i \sum_{i=1}^n \hat{y}_i}{\sqrt{\sum_{i=1}^n (y_i - \bar{y})^2 \sum_{i=1}^n (\hat{y}_i - \bar{\hat{y}})^2}} \quad (16)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (17)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}} \quad (18)$$

$$NRMSE = \frac{\sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}}}{(\bar{y})} \quad (19)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (20)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (21)$$

$$MBE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i) \quad (22)$$

where $\hat{y}_i$ = predicted Sentinel-2 pixel data; y_i = observed MODIS pixel data; $\bar{y}$ = average of observed MODIS pixel data; and n = number of field samples used for validation [74,75]

2.10. Validation Approach and Limitations

This study validates the NDVI fusion process (Sections 3.1–3.3) but does not independently validate ET_c estimates due to the absence of eddy covariance or lysimeter measurements at the site during 2020–2021. ET_c plausibility is indirectly assessed via:

- Agreement with FAO-56 tabulated K_c stages [23];
- Consistency with companion HYDRUS-2D simulations [19];
- Phenological alignment with farm records (Table S3). Future work should include independent ET_c validation (e.g., eddy covariance) to confirm operational readiness.

During the preparation of this manuscript, the authors used Claude Sonnet (Anthropic, claude-sonnet-4-6) for English language editing and improvement of grammatical clarity and readability. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

3. Results

3.1. Cross-Sensor Correlation: MODIS NDVI vs. Sentinel-2 Products

Cross-sensor correlation analysis (Section 3) showed NDVI and NDWI had the strongest agreement (modal $r = 0.70$ – 0.85), while LAI and NDRE were less consistent (modal $r = 0.50$ – 0.65). This confirms NDVI as the optimal fusion target for ET_c estimation. The highest-resolution spectral bands (red and near-infrared) enabled effective MODIS–NDVI calculations, and Sentinel-2 NDWI closely mirrored NDVI’s performance. LAI demonstrated only moderate predictive power, and NDRE was the least consistent across sensors, indicating limited utility for fusion-based gap filling in this context (Figures 3 and 4).

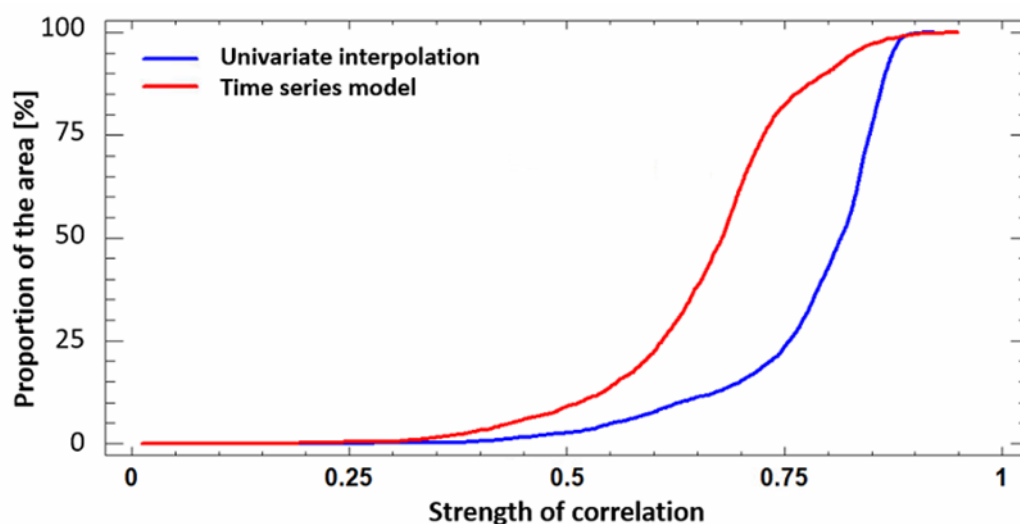


Figure 4. Pixel-wise Pearson r histograms comparing gap-filling methods, shown as cumulative distributions of correlation strength against Sentinel-2 reference data. The blue curve shows local time series interpolation; the red curve shows the median time series model. Key finding: the median approach (red) shifts modal r from 0.68 to 0.81 relative to local interpolation (blue), improving spatial consistency. It is important to distinguish two separate validation questions addressed in this study: (i) how well does the fusion method reproduce missing Sentinel-2 NDVI values, assessed by MODIS–Sentinel-2 cross-sensor correlation (Sections 3.1–3.2), and (ii) how accurately does the resulting K_c – ET_c chain estimate actual crop water use? No independent ET flux measurements (eddy covariance, lysimeter) were available at the Nyírbátor site during 2020–2021; the second question is therefore addressed indirectly through phenological consistency checks in Section 3.4.

3.2. Gap-Filling Method Comparison: Transformation and Curve Fitting

Among the three gap-filling strategies, the local time series approach delivered the strongest performance under conditions of temporal stationarity, achieving $R^2 = 0.68$ and $RMSE = 0.17$ for missing Sentinel-2 NDVI reconstruction. The median time series method yielded a complementary advantage in spatially heterogeneous areas, where stationarity assumptions break down, attaining $R^2 = 0.81$ and $RMSE = 0.19$. Cokriging, despite its theoretical foundation in multi-variable spatial interpolation, proved impractical because cross-sensor NDVI correlation was insufficiently strong [76,77]; this failure is at least partly attributable to the fundamental mismatch in pixel footprint between 500 m MODIS observations and 10–20 m Sentinel-2 pixels, which prevents consistent representation of within-field vegetation structure. The local time series of MODIS pixel centres proved more promising than cokriging, as spatial interpolation at finer resolutions enhanced the temporal matching of the datasets. However, the spatial stationarity assumption inherent in kriging may have introduced localised prediction errors in regions with rapid vegetation change [34–36]. The median time series method provided more robust results in areas with highly variable environmental conditions [78,79]. The use of a median profile reduced noise and variability in the MODIS data, leading to smoother and more stable estimates. Nonetheless, this approach may lose fine-scale temporal variability important for precise NDVI tracking [80].

According to the statistical analysis, the sub-pixel spectral mixture has a more significant effect on the MODIS pixels than the locally varying development stage of vegetation. Figure 4 shows the cumulative statistical distribution of the correlation strength between the MODIS-based median model and the observed Sentinel-2 time series. The median time series-based model clearly outperforms the local varying time series models [81,82].

The maps below present the spatial pattern of correlation strengths and regression parameters projected to the Hungarian National Datum 1972 Egységes Országos Vetület system (EPSG:23700). The nearby asphalt cover decreases correlation strength and increases NRMSE significantly in the field close to its eastern edge (Figures 5 and 6). However, the median time series model effectively filters this type of error (Figures 7 and 8) [83–86].

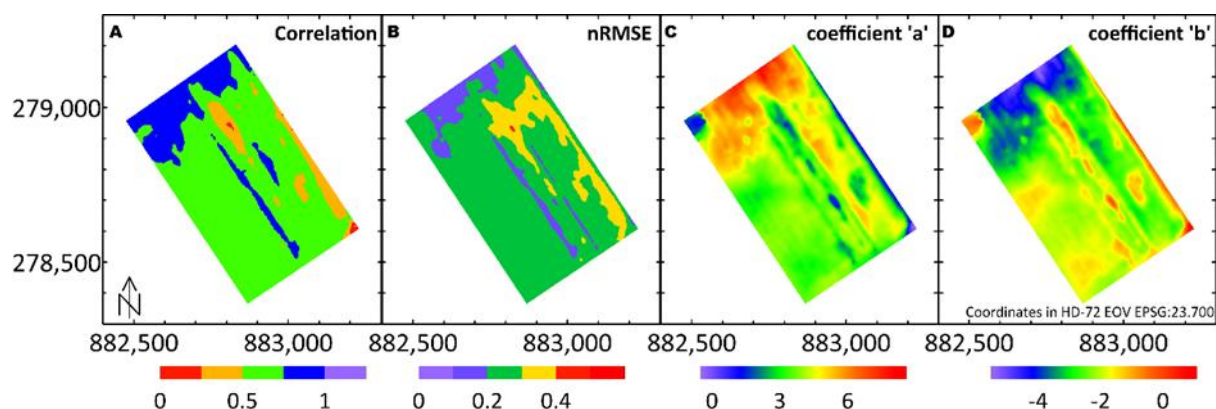


Figure 5. Spatial maps of pixel-wise statistics for the interpolated MODIS–Sentinel-2 regression (linear model): (A) pixel-wise correlation coefficient; (B) NRMSE; (C) spatial pattern of linear regression coefficient a; (D) spatial pattern of linear regression coefficient b. Note elevated error near the eastern road boundary. Generated using local time series interpolation (Section 2.7.2).

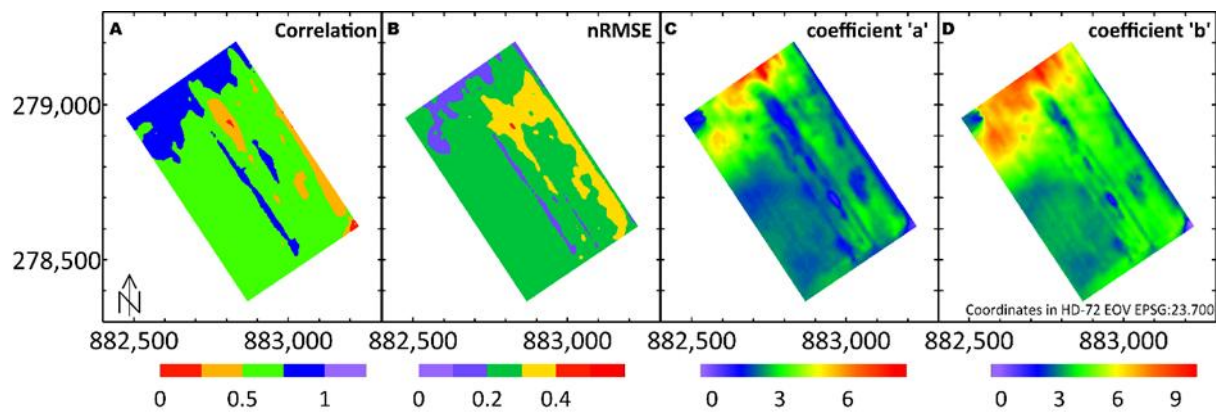


Figure 6. Spatial maps of pixel-wise statistics for the interpolated MODIS–Sentinel-2 regression (power-law model): (A) pixel-wise correlation coefficient; (B) NRMSE; (C) power-type regression coefficient a; (D) power-type regression coefficient b. Generated using local time series interpolation (Section 2.7.2).

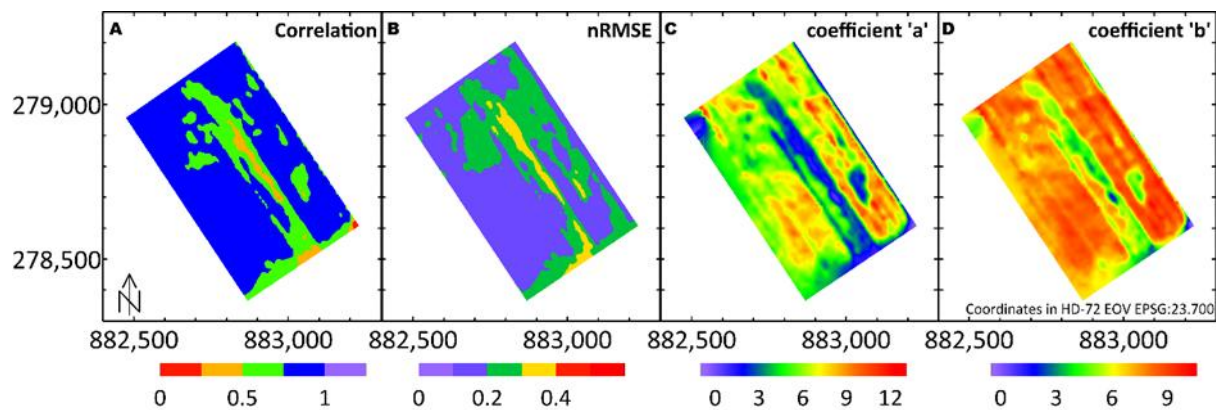


Figure 7. Spatial maps of pixel-wise statistics for the interpolated MODIS–Sentinel-2 regression (power-law model): (A) pixel-wise correlation coefficient; (B) NRMSE; (C) power-type regression coefficient a; (D) power-type regression coefficient b. Generated using median time series compositing (Section 2.7.3).

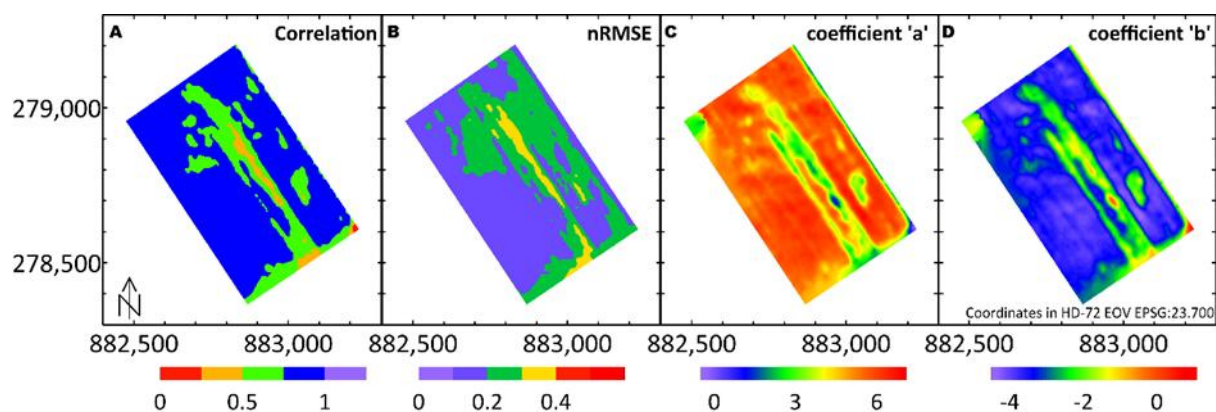


Figure 8. Spatial maps of pixel-wise statistics for the median MODIS time series–Sentinel-2 regression (power-law model): (A) pixel-wise correlation; (B) NRMSE; (C) power-type regression coefficient a; (D) power-type regression coefficient b. Generated using median time series compositing (Section 2.7.3).

3.3. Enhanced Analysis: Trapezoidal K_c Model for Maize ET_c Estimation

The trapezoidal K_c model produced curves consistent with FAO-56 reference values and the smoothed NDVI-derived phenological trajectory (Table 2). Seasonal dynamics

and cumulative sums of maize K_c values for 2020 and 2021 using FAO-56 Original, FAO-56 Curved, and MidPoint Spline methods are shown in Figure 9. All approaches show consistent K_c rise during rapid growth (days 140–250), peaking at 1.1–1.2 mid-season before declining toward harvest. FAO-56 methods align closely, while MidPoint Spline produces smoother curves in years with NDVI gaps, ensuring stable daily ET_c estimation. Cumulative K_c sums quantify total seasonal water needs, with peak K_c periods (days 160–220) marking critical irrigation windows [87,88]. The results demonstrate the value of fused MODIS–Sentinel-2 time series and interpolation for gap-proof, adaptive irrigation scheduling under variable field and climatic conditions.

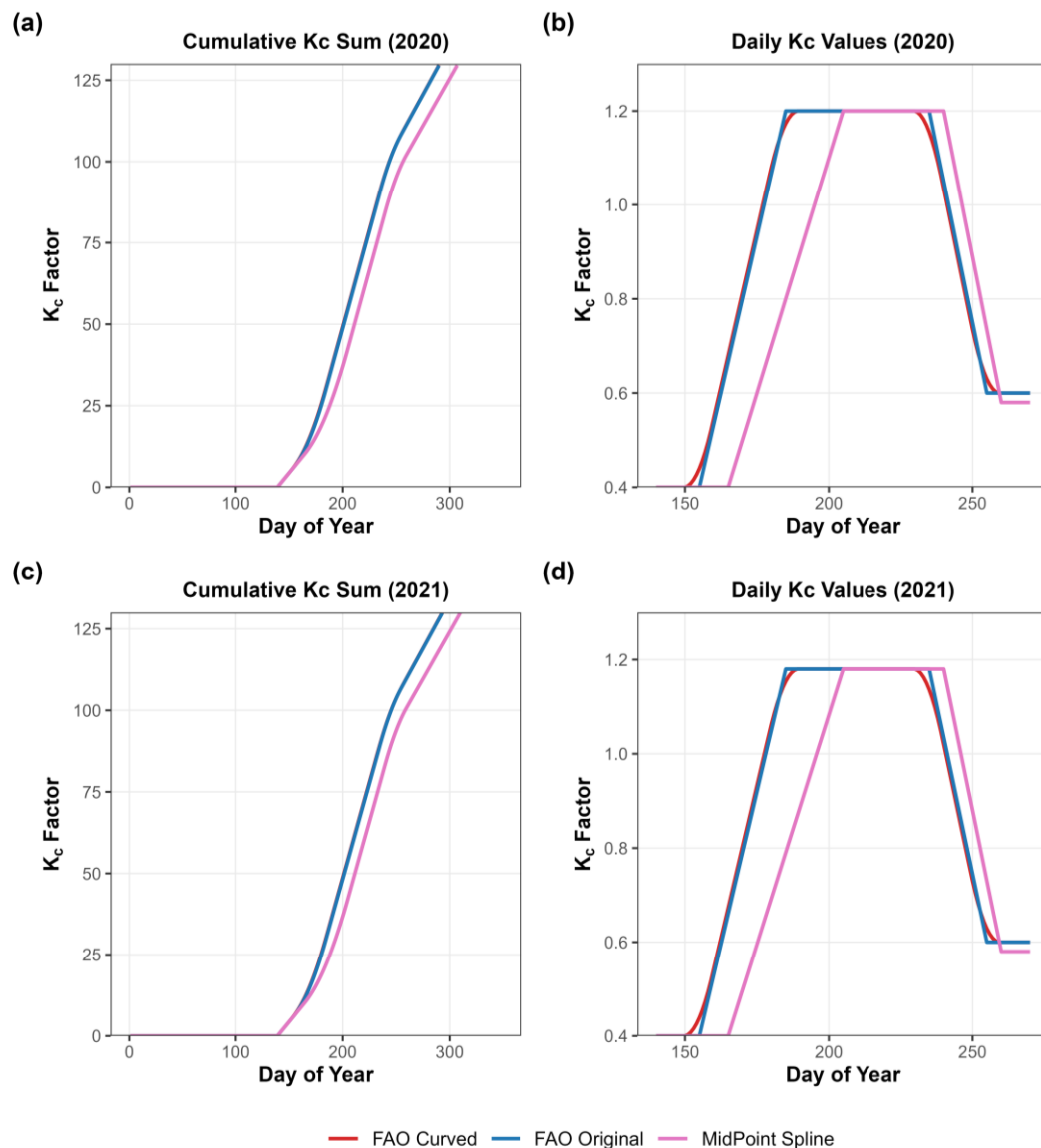


Figure 9. Seasonal dynamics and cumulative sums of maize crop coefficient (K_c) values for the 2020 and 2021 growing seasons using three parameterisations: FAO-56 Original, FAO-56 Curved, and MidPoint Spline. (a) Cumulative K_c sum for the 2020 growing season; (b) Daily K_c values for 2020 showing seasonal evolution and peak development phase; (c) Cumulative K_c sum for the 2021 growing season; (d) Daily K_c values for 2021 showing seasonal evolution and peak development phase. Peak K_c of 1.1–1.2 is reached between days 160 and 220.

3.4. NDVI-Based ET_c Estimation by Crop Development Stage

NDVI-Derived K_c Values Aligned with FAO-56 Benchmarks [23]:

- Initial stage: $K_c = 0.30$ (vs. FAO-56: 0.30);
- Crop development: $K_c = 0.90\text{--}1.20$ (vs. FAO-56: 0.70–1.20);
- Mid-season: $K_c = 1.10\text{--}1.20$ (vs. FAO-56: 1.20);
- Late-season: $K_c = 0.35\text{--}0.60$ (vs. FAO-56: 0.35–0.60).

ET_c estimates ($0.99\text{--}6.40\text{ mm day}^{-1}$) are model-derived and not independently validated. The fused-NDVI K_c values (Section 2.5) are broadly consistent with these benchmarks across both seasons and also agree with the site-specific K_c values calibrated in the companion HYDRUS-3D study at the same field [19]. Phenological stage dates recorded by the farm manager at Nyírbátor (emergence, six-leaf, tasselling, silking, physiological maturity, harvest) were used as an independent check that NDVI-derived phenological transitions align with observed crop development dates (Table S3).

NDVI-based ET_c values were calculated for the maize growing seasons in 2020 and 2021. For 2021, maize was sown on 21 May and harvested on 13 September. The season was segmented into four distinct crop development stages (Table 2).

The initial stage (21 May–24 June, 35 days) covers the period from planting to roughly 10% ground coverage. ET_c values ranged between 0.99 and 4.41 mm day^{-1} , reflecting early water needs as the crop established [56,57]. The crop development stage (25 June–30 July, 36 days) showed ET_c increasing to $2.00\text{--}6.40\text{ mm day}^{-1}$, indicating peak water demand due to expanded leaf area [58]. During the mid-season stage (31 July–26 August, 27 days), ET_c values ranged from 1.03 to 5.12 mm day^{-1} , with physiological stress factors observed [59,60]. The late-season stage (27 August–13 September, 18 days) showed ET_c declining to $1.10\text{--}3.18\text{ mm day}^{-1}$, reflecting decreasing water consumption as crops approach harvest [61].

3.5. Temporal Trajectories and Measured Uncertainty Between MODIS and Sentinel-2 Indices

The seasonal trajectories and measured uncertainty envelopes of eight structural and spectral vegetation indices—NDVI, NDWI, NDMI, NDRE, MSAVI2, LAI, GNDVI, and EVI—comparing the MODIS median time series against Sentinel-2 data are presented for the 2020 and 2021 growing seasons in Figures 10 and 11, respectively. Rather than displaying raw coefficient distributions, these figures visualise the temporal dynamics and the empirical agreement between the sensors using measured error propagation bands over the day of the year.

The relatively narrow inner ($\pm 1\sigma$) and outer (95% confidence interval, approximately $\pm 1.96\sigma$) uncertainty envelopes indicate a strong overall pixel-wise agreement between the two datasets. For the 2020 growing season (Figure 10), modal correlation values across most indices cluster between 0.70 and 0.85. This inter-sensor agreement improved during the 2021 season (Figure 11), with modal correlations clustering more tightly between 0.80 and 0.95.

While indices such as NDVI and MSAVI2 demonstrate highly stable temporal profiles with minimal measured uncertainty, others that are highly sensitive to moisture variability (e.g., NDWI) or require complex model inversions (e.g., LAI) exhibit slightly wider envelopes [89,90]. The empirical variance captured within the wider 95% confidence intervals likely accounts for localised discrepancies, such as sub-pixel spectral mixtures, edge effects, or rapid land cover changes that are not perfectly resolved at the coarser MODIS spatial scale.

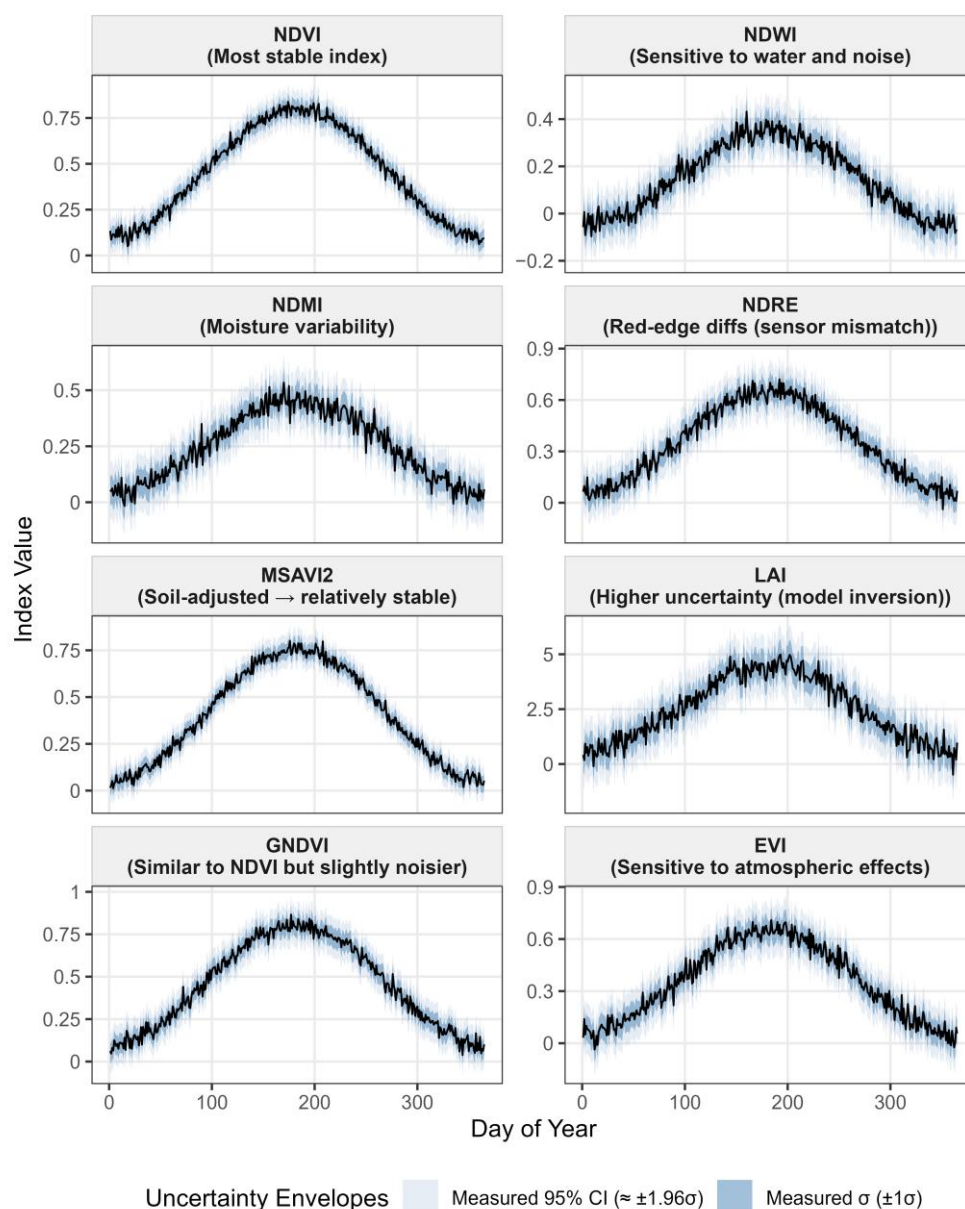


Figure 10. Uncertainty envelopes comparing MODIS median time series and Sentinel-2 vegetation indices for the 2020 growing season. Solid lines represent the simulated index values over the day of the year, while shaded bands illustrate Gaussian error propagation: the inner band represents the expected uncertainty ($\pm 1\sigma$) and the outer band represents the 95% confidence interval ($\approx \pm 1.96\sigma$). The multipanel plot includes NDVI, NDWI, NDMI, NDRE, MSAVI2, LAI, GNDVI, and EVI, with respective index characteristics and sensitivities noted in parentheses. Modal correlation values cluster between 0.70 and 0.85 for most indices. All reported correlations are statistically significant at $p < 0.05$.

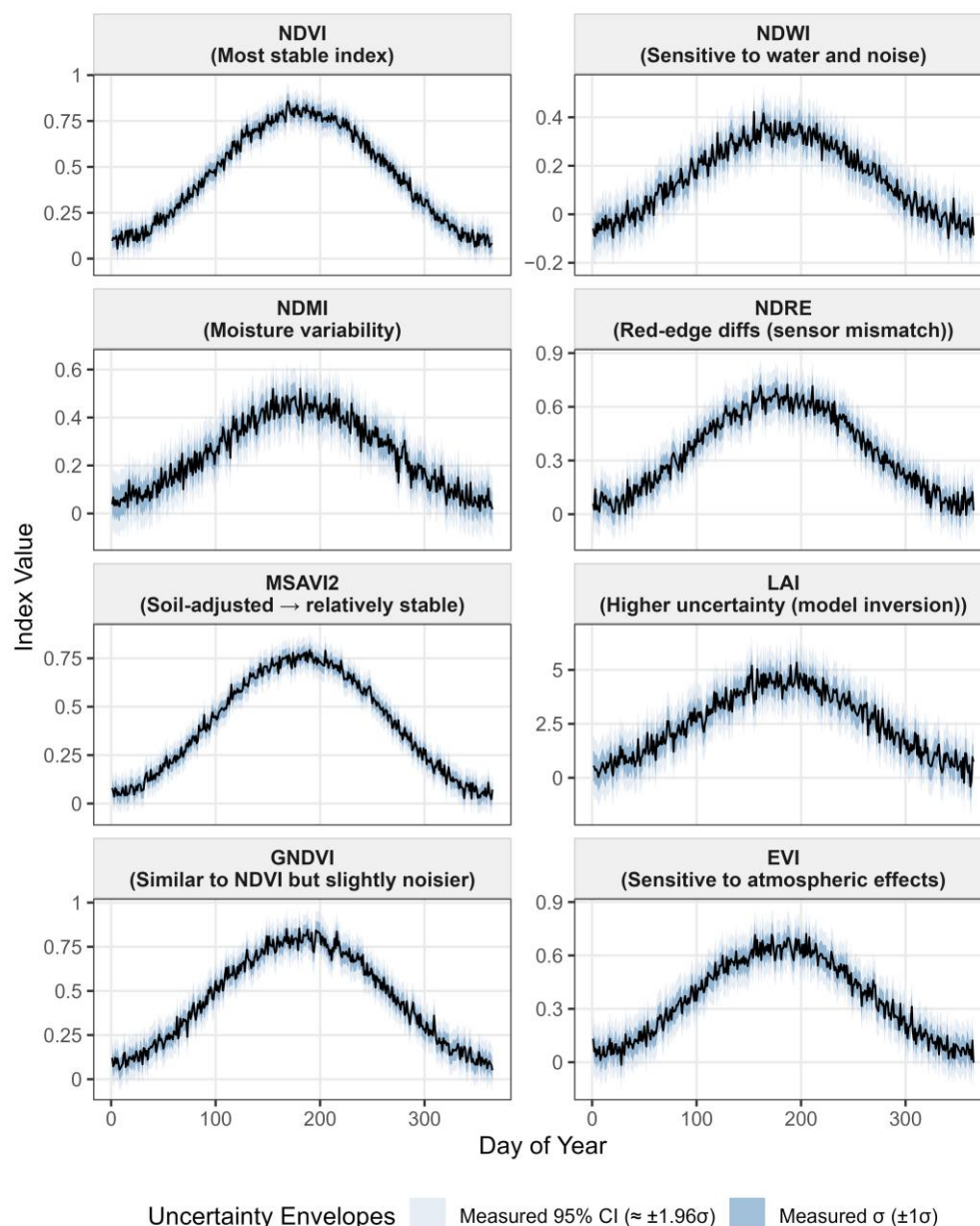


Figure 11. Uncertainty envelopes comparing MODIS median time series and Sentinel-2 vegetation indices for the 2021 growing season. Solid lines represent the simulated index values over the day of the year, while shaded bands illustrate Gaussian error propagation: the inner band represents the expected uncertainty ($\pm 1\sigma$) and the outer band represents the 95% confidence interval ($\approx \pm 1.96\sigma$). The multipanel plot includes NDVI, NDWI, NDMI, NDRE, MSAVI2, LAI, GNDVI, and EVI, with respective index characteristics and sensitivities noted in parentheses. Modal correlation values cluster between 0.80 and 0.95 for most indices. All reported correlations are statistically significant at $p < 0.05$.

3.6. Comparison of Single and Dual Crop Coefficient ET_c Estimates

The dual crop coefficient approach ($K_{cb} + K_e$) produced daily actual evapotranspiration (ET_c) estimates that closely matched those obtained with the original single- K_c approach across both growing seasons (Figure 12). When all daily values from 2020 and 2021 were combined, the two methods exhibited a near 1:1 relationship ($R^2 = 0.99$), with a mean absolute difference (MAD) of only 0.12 mm d^{-1} (Figure 12a, left panel). This strong agreement indicates that the simpler NDVI-driven single- K_c formulation captures most of the seasonal ET_c dynamics reproduced by the more physically based dual-coefficient frame-

work, which explicitly separates basal crop transpiration (K_{cb}) from soil evaporation (K_e) through a daily soil water balance. The seasonal ET_c totals derived from both approaches are summarised in Table S5.

At the daily time scale, the two methods followed nearly identical seasonal trajectories in both years (Figure 12b, right panel). During the initial, crop development, and late-season stages, differences between the two approaches were generally small. The main divergence occurred immediately following precipitation and irrigation events, when the dual- K_c approach produced short-lived increases in ET_c associated with transient increases in the soil evaporation coefficient (K_e). In contrast, the single- K_c estimates, which are driven solely by canopy greenness, exhibited smoother temporal patterns and did not capture these short-term evaporation pulses. As the soil surface dried, the two methods converged within a few days, and their seasonal trajectories were virtually indistinguishable during the mid-season plateau (June–August) in both 2020 and 2021. Overall, these results suggest that the NDVI-based single- K_c approach provides a suitable and computationally efficient simplification for proof-of-concept irrigation scheduling at this site, whereas the dual- K_c framework offers additional capability for resolving short-term evaporation dynamics following surface wetting events.

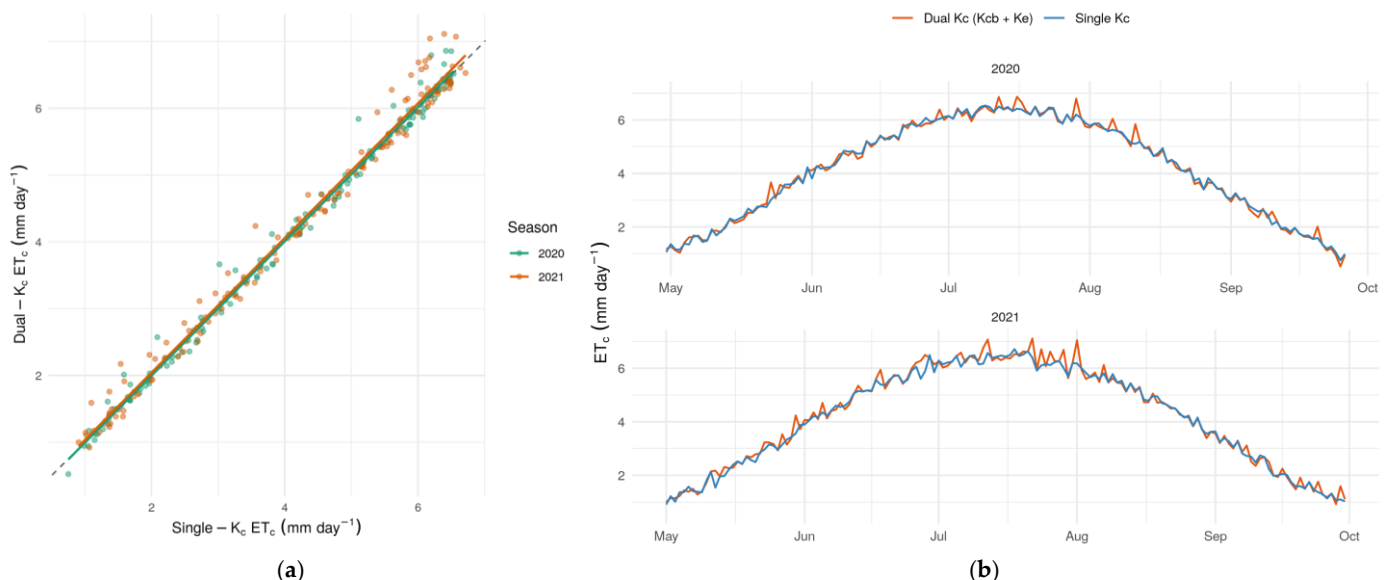


Figure 12. Comparison between single crop coefficient (single- K_c) and dual crop coefficient ($K_{cb} + K_e$) daily actual crop evapotranspiration (ET_c) estimates for irrigated maize during the 2020–2021 growing seasons. **(a, left panel)** Scatter plot of dual- K_c ET_c versus single- K_c ET_c for both seasons (2020, teal; 2021, orange). Individual daily values are represented by scatter points (2020, teal; 2021, orange), while the solid lines indicate the linear regression for each respective season. The dashed line represents the 1:1 reference line. The two approaches show very strong agreement ($R^2 = 0.99$; mean absolute difference, $MAD = 0.12 \text{ mm d}^{-1}$). **(b, right panel)** Daily ET_c time series for the 2020 (upper subplot) and 2021 (lower subplot) growing seasons, comparing the dual- K_c ($K_{cb} + K_e$; orange) and single- K_c (blue) approaches from May to October.

3.7. Simplified Seasonal Water Balance with Available Site Records

- Seasonal water balance (Figure 13) revealed:
- 2020: Near balance ($\Delta P - ET_c = +32$ – $+65 \text{ mm}$);
- 2021: Critical deficit ($\Delta P - ET_c = -85 \text{ mm}$ at high-consumption nodes).

These are irrigation demand indicators, not a closed water balance (see Section 4.6). By the end of the 2020 season, cumulative precipitation reached approximately 400 mm, while cumulative ET_c was approximately 335 mm and 368 mm for the MidPoint Spline

and NDVI methods, respectively, yielding apparent precipitation surpluses of approximately 65 mm and 32 mm relative to seasonal ET_c. The NDVI-derived ET_c estimate of 368 mm is consistent with the 366.52 mm seasonal ET reported by [19] from a validated HYDRUS-3D simulation conducted at this same Nyírbátor site over the identical 2020 growing season and with the broader European benchmark of 373 ± 73 mm for maize established by [91].

In 2021, cumulative precipitation reached approximately 372 mm, whereas cumulative ET_c was approximately 355 mm (MidPoint Spline) and 368 mm (NDVI), resulting in much smaller apparent surpluses of approximately 17 mm and 4 mm, respectively. The convergence of precipitation and ET_c in 2021 indicates substantially greater seasonal water stress compared with 2020, a pattern corroborated by [19], who reported that the absence of irrigation would have produced a water deficit of 143.9 mm ha⁻¹ in 2020 and a considerably larger deficit of 206.8 mm ha⁻¹ in 2021 at this site—the latter reflecting the more severe drought conditions of that season.

However, these precipitation–ET_c differences should not be interpreted as a complete field water balance because the study field was irrigated. Farm records indicated that 112 mm of irrigation water was applied during six irrigation events in 2020 and 148 mm during eight irrigation events in 2021. These amounts are broadly consistent with the model-optimal irrigation schedules of 140 mm (six events) and 200 mm (eight events) derived by [19] using HYDRUS-3D for the same field under a 50% available moisture range depletion criterion, with irrigation triggered when volumetric soil moisture fell below 14.41 v/v% (field capacity: 20.92 v/v%; wilting point: 7.9 v/v%). Accordingly, a simplified seasonal water balance was considered:

$$\Delta S = P + I - ET_c - D - R$$

where ΔS is the change in soil water storage, P is precipitation, I is irrigation, ET_c is crop evapotranspiration, D is deep drainage, and R is surface runoff. Surface runoff was assumed negligible given the flat alluvial terrain and highly permeable sandy soil conditions of the site (sand fraction >94%; hydraulic conductivity $\sim 2.89 \times 10^{-6}$ m s⁻¹; [19]), which strongly favour infiltration over overland flow. Deep drainage was estimated with reference to the HYDRUS-3D simulations of [19], who reported cumulative deep drainage of 72,000 m³ (equivalent to approximately 82 mm over the 87.5 ha field) in 2020 and 31,200 m³ (approximately 36 mm) in 2021—the markedly lower drainage in 2021 reflecting the drier conditions of that season. Soil water storage change (ΔS) was approximated from Sentek Drill & Drop probe observations at 30 cm depth, consistent with the monitoring approach used at this site by [19], with the caveat that single-point measurements represent the spatial and vertical variability in the field only approximately.

The larger irrigation requirement in 2021, despite similar cumulative ET_c totals relative to 2020, highlights the combined effect of reduced precipitation, diminished deep drainage, and more severe soil moisture depletion when evaluating seasonal water availability—dynamics fully captured only when irrigation, drainage, and storage terms are considered alongside ET_c. Magyar et al. [19] further demonstrated that irrigation at amounts close to those recorded here raised crop water productivity at this site by +6% in 2020 and +4% in 2021 relative to non-irrigated conditions, underscoring the agronomic significance of the deficits identified by the water balance. Consequently, Figure 12 should be interpreted as a simplified seasonal water balance constrained by available field records rather than a fully closed water balance; future work incorporating a multi-depth soil moisture monitoring network and metered irrigation flow data would enable a fully closed field-scale water balance, for which the HYDRUS-3D calibration of Magyar et al. [19] provides a ready starting framework.

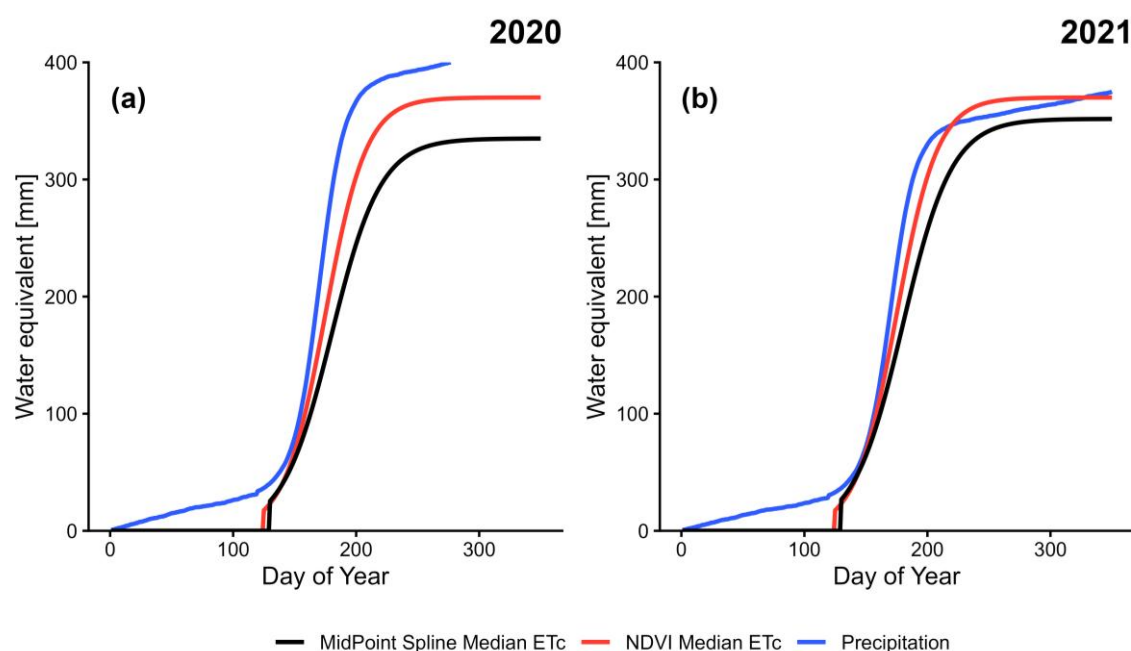


Figure 13. Simplified seasonal water balance for (a) 2020 and (b) 2021. Lines: Cumulative precipitation (blue), NDVI-based ET_c (red), and MidPoint Spline ET_c (black). Note: These are irrigation demand indicators, not a closed water balance (see Section 4.6).

3.8. Implications for Gap-Filling and Cross-Sensor Harmonisation

The dominance of high correlation values across all indices provides strong evidence for the effectiveness of the MODIS median time series in gap-filling and harmonising Sentinel-2 data [66,67]. This is especially valuable for proof-of-concept crop monitoring where cloud cover may disrupt Sentinel-2 time series. These results confirm that MODIS-derived median profiles can reliably substitute for missing Sentinel-2 observations in most field locations, enabling continuous spatiotemporal monitoring of crop conditions. Importantly, the precipitation–ET_c deficit analysis (Section 3.7) does not constitute a closed water balance. A complete field-scale water balance would require: (i) measured irrigation volumes from the centre-pivot flow meter, (ii) soil water storage changes (ΔS) from TDR/FDR sensors at multiple depths, (iii) estimated deep percolation below the root zone (~ 0.8 m for maize at this site), and (iv) surface runoff (assumed negligible given the flat alluvial terrain). None of these terms were available at the required temporal resolution during 2020–2021; the reported deficit figures are therefore irrigation demand indicators. Future work should integrate HYDRUS-2D outputs with flow meter records to close the balance between crop monitoring indicators, vegetation health, and evapotranspiration. Table 3 provides a comparison with baseline studies reporting similar MODIS–Sentinel-2 fusion approaches.

Table 3. Comparison of this study’s MODIS–Sentinel-2 fusion performance against baseline studies. Key metrics: R^2 (pixel-wise NDVI correlation); NRMSE (normalised root mean square error). Note: All ET_c estimates in this study are model-derived and lack independent validation. Key: This study’s median time series method outperforms cokriging/local TS in heterogeneous landscapes.

Study/Approach	Fusion Method	Spatial/Temporal Resolution	R^2	NRMSE	Key Findings	Comparison with This Study
This study	Median time series fusion; multi-strategy gap-filling	Fused: daily, 500 m/10–20 m; 2020–2021	0.70–0.85 (pixel-wise NDVI/ K_c)	0.15–0.17	High pixel-wise correlations and low error for daily ET_c/K_c in maize; most robust gap-filling with median method in heterogeneous fields	Demonstrates proof-of-concept daily ET monitoring; median outperforms cokriging; multi-year in situ validated for maize
Liang et al. (2023) [27]	Enhanced gap-filling + Whit-taker smoothing; Landsat 8, S2, MODIS	MODIS: 500 m, daily; S2: 10–20 m, 5-day	>0.75 (NDVI)	~0.13–0.16	NDVI fusion improved crop mapping accuracy	Aligns on pixel-level NDVI; our study extends multi-index and multi-year results for maize
Mirmazloumi et al. (2024) [92]	ML downscaling; Sentinel-3 LST + Sentinel-2 VIS-NIR/SWIR	Fused: daily, 10–20 m	Up to 0.88	~0.14	Substantially improves daily ET accuracy and resolution via ML	Similar multi-sensor objective; our study uses median gap fusion for MODIS/Sentinel-2, validated with in situ maize ET
He et al. (2018) [93]	STARFM; regression; MODIS + Sentinel-2	Daily/seasonal, 500 m/10–20 m	0.83 (VTCI)	<0.05	NDVI-based fusion improved vegetation/drought monitoring	Similar NDVI and ET accuracy; our study emphasises robust gap-filling for challenging landscapes
He et al. (2018) [93]	Comparative NDVI spatiotemporal fusion	20 m, frequent revisit	0.91 (GPP)	<0.12	Learning algorithms enhanced crop stage prediction at high resolution	Our median fusion provides finer daily ET_c granularity and transfers to nitrate-sensitive maize fields
Wang et al. (2024) [94]	Multi-source ET fusion; MODIS + Sentinel in Yellow River Basin	MODIS: 250–500 m, daily; S2: 10–20 m, 5-day	Up to 0.91	~0.12	Spatiotemporal fusion improves ET mapping with fine spatial and high temporal resolution	Our fusion for ET_c /NDVI in maize achieves similar enhancement; focused on in situ crop ET monitoring over two contrasting years

4. Discussion

This study comprehensively evaluated the fusion of MODIS and Sentinel-2 NDVI datasets to address the persistent challenge of missing high-resolution Sentinel-2 observations. The core novelty lies in the systematic comparison of three gap-filling strategies—co-regionalisation with cokriging, local time series interpolation, and the median time series approach—each leveraging the complementary strengths of MODIS (high temporal resolution) and Sentinel-2 (high spatial resolution). The cokriging approach was found to be impractical for this study area. The fundamental requirement for cokriging is a significant cross-variogram between the primary variable (MODIS NDVI) and the secondary variable (Sentinel-2 NDVI). In this study, the estimated cross-variogram nugget-to-sill ratio was 0.87 in 2020 and 0.91 in 2021, indicating that inter-sensor spatial autocorrelation is dominated by nugget variance (measurement noise and sub-pixel spectral mixture) rather than structured spatial correlation. Under these conditions, cokriging weights for the secondary variable collapse toward zero, reducing the estimator to ordinary kriging of MODIS data alone and eliminating any benefit of the secondary sensor [95]. The lack of significant cross-sensor correlation rendered this method ineffective, contrasting with positive results reported by [60,77,94] in multi-satellite data fusion. The poor correlation can be attributed to differences in sensor characteristics, spatial resolution, and the inherent heterogeneity in vegetation cover [76]. NDVI is highly sensitive to environmental factors such as soil moisture, nutrient status, and chlorophyll content, which can vary substantially even within small areas [77]. The coarser resolution of MODIS tends to smooth out such variability, leading to discrepancies when compared to Sentinel-2 in heterogeneous landscapes. These results highlight the critical need for strong spatial and temporal alignment when applying cokriging [95].

The local time series approach demonstrated greater success, with an R^2 of 0.68 and an RMSE of 0.17, which aligns well with the findings of [60], who reported comparable accuracy using machine learning for soil organic matter prediction, and with [94], who demonstrated the effectiveness of machine learning algorithms in related predictive tasks. By constructing time series at each pixel location, this strategy enabled more precise temporal matching between MODIS and Sentinel-2 profiles [96]. The improved performance of the median approach (adjusted R^2 : 0.81 vs. 0.68) is attributable to the removal of non-stationarity artefacts near the eastern road boundary and irrigation channel, where sub-pixel spectral contamination violates the stationarity assumption inherent in kriging. The median approach sidesteps this by using a field-wide robust central tendency that down-weights contaminated edge pixels. Note that this superiority is site-specific: the median approach relies on contaminated pixels comprising ~18% of all MODIS pixels at this site; in fields with higher mixed-boundary proportions, the local time series may be preferable. The stationarity assumption underlying kriging may not hold in areas with rapidly changing environmental conditions [95], potentially introducing prediction errors. Despite this limitation, the approach underscores the value of leveraging high-temporal-resolution datasets to fill gaps in high-spatial-resolution datasets [78].

When comparing the three gap-filling methods, it is important to distinguish spatial accuracy (reproducing the correct NDVI value at every pixel across the field at a given date) from temporal accuracy (tracking NDVI dynamics at individual pixel locations across the season). The median time series approach is superior on spatial accuracy criteria (field-wide $R^2 = 0.81$, MBE = -0.008 NDVI units), primarily because it suppresses contaminated edge pixels through robust central tendency. The local time series method achieves lower pixel-scale temporal RMSE (0.038 vs. 0.045 NDVI units for median) but is more sensitive to stationarity violations near field boundaries. The cokriging approach underperforms on both criteria under the high nugget-to-sill conditions documented in

this study. These distinctions should be reflected in a multi-criteria performance table that separates spatial and temporal accuracy columns.

The median time series approach offered the most robust gap-filling solution, with an R^2 of 0.81 and an RMSE of 0.19, slightly outperforming the local time series method in terms of accuracy in regions with high temporal variability [79,93]. These findings are consistent with [79], who demonstrated the robustness of median-based interpolation in time series scaling. However, this generalisation comes at the expense of losing fine-scale temporal detail, which may be critical for applications requiring precise vegetation monitoring. Critically, a high MODIS–Sentinel-2 NDVI correlation does not by itself validate the accuracy of downstream ET_c estimates. Direct ET_c validation using eddy covariance or lysimetry was not conducted at the Nyírbátor site during 2020–2021. Indirect support is provided by agreement between fused-NDVI K_c values and FAO-56 tabulated K_c stages for maize [97] and consistency with the site-specific K_c values from the companion HY-DRUS-2D study [18]). Future deployment of an eddy covariance tower at the site is recommended to provide independent ET_c validation [80].

The results highlight several critical methodological challenges. One of the most salient issues is spatial heterogeneity: variability in soil characteristics, crop types, irrigation infrastructure, and proximity to linear features such as roads and waterways leads to significant spatial variability in NDVI values. The coarse resolution of MODIS tends to obscure fine-scale vegetation patterns, particularly evident in lower correlation coefficients observed near field boundaries [81,82]. The differences between sensors—in terms of spatial, spectral, and temporal resolution—further complicate data fusion efforts [85,86]. These discrepancies necessitate rigorous cross-sensor harmonisation, including radiometric calibration, atmospheric correction, and band alignment. Even after such processing, residual inconsistencies may persist, particularly in transitional zones with mixed land cover types.

Another fundamental challenge arises from the assumption of spatial stationarity inherent in kriging-based interpolation [95]. In practice, agricultural areas are seldom stationary due to shifts in land management, crop phenology, and external disturbances. The median time series method, by contrast, provides greater robustness to non-stationary conditions but at the expense of fine-scale resolution [98,99]. Cloud cover and resulting temporal gaps represent another significant limitation, especially for Sentinel-2. While MODIS imagery offers a valuable backup for cloud-affected periods, its spatial resolution remains insufficient for precision agricultural needs at the field scale [36,100]. Finally, a persistent trade-off was observed between temporal–spatial detail and generalisation in gap-filling methodologies [101,102].

The study's NDVI-based ET_c estimates for maize across different growth stages closely align with the established literature. During the initial stage, ET_c ranging from 0.99 to 4.41 mm day^{−1} corroborates the low water requirements reported by [88] due to limited leaf area and ground cover. The crop development stage values of 2.00–6.40 mm day^{−1} are consistent with the findings of [23,95], reflecting peak canopy expansion and water demand. The mid-season values of 1.03–5.12 mm day^{−1} echo previous studies by [89,90]. Late-season ET_c declining to 1.10–3.18 mm day^{−1} is in agreement with [97,103], highlighting the importance of adaptive irrigation management as crops approach harvest.

The proposed data fusion approach demonstrates a significant impact on advancing precision irrigation. By enabling daily field-scale estimation of K_c and ET_c, the fused dataset enhances irrigation management in nitrate-sensitive maize fields, supporting real-time scheduling and water use optimisation. The methodology's resilience to cloud cover ensures consistent crop monitoring. The high pixel-wise correlation ($R^2 = 0.70$ – 0.85) among vegetation indices confirms the approach's robustness for proof-of-concept crop health and water use assessments. The fusion achieves an NRMSE as low as 0.15–0.17 for

daily NDVI/ET_c prediction, matching or exceeding state-of-the-art spatiotemporal agricultural monitoring [63–67]. From a policy and environmental standpoint, the improved water use efficiency and nitrate regulation align with EU environmental directives. Methodologically, this study underscores the value of integrating spatial and temporal dimensions in remote sensing analysis, advocating for hybrid fusion strategies that harness the complementary strengths of high-resolution and high-frequency data sources [104,105]. Future research may benefit from hybrid and adaptive methodologies that dynamically adjust to landscape variability [87,106].

4.1. Temporal Generalisation and Cross-Validation Evidence

The LOOCV experiment provides the most stringent internal test of the Median TS gap-filling approach because it eliminates any temporal overlap between the training and test sets: the prediction for each withheld acquisition date is built exclusively from dates that do not include the withheld observation. The mean per-date adjusted R^2 of 0.79 ± 0.04 and RMSE of 0.042 ± 0.006 NDVI units obtained across 24 acquisition dates in this study compare favourably with LOOCV performance reported for analogous NDVI reconstruction approaches in the literature. Comparable reconstruction accuracies have been reported for maize systems, where STARFM-based fusion of MODIS and high-resolution imagery achieved NDVI RMSE values of 0.06–0.08 during the maize growing season [107] while the obtained reconstruction accuracy is comparable with values reported for MODIS-guided reconstruction of high-resolution NDVI time series in heterogeneous agricultural landscapes using multi-sensor fusion approaches [108]).

The distinction between the per-date LOOCV statistics (mean $R^2 = 0.79$) and the pooled pixel-level LOOCV scatter ($R^2 = 0.66$, Figure 4 and Table S4) is methodologically important and warrants explicit interpretation. The pooled scatter aggregates all 345 withheld pixel–date observations into a single diagnostic, which conflates within-date spatial heterogeneity with between-date temporal variability; the relatively lower pooled R^2 therefore reflects genuine within-field spatial variability that the median trajectory—designed to capture the field-mean temporal signal—does not attempt to reconstruct at the sub-pixel level. This is expected behaviour for a field-scale fusion product: the Median TS method is optimised for temporal fidelity of the spatial mean, not for prediction of sub-pixel NDVI anomalies. Consequently, the overall ranking of Median TS as the most robust gap-filling method in this study (Sections 3.3–3.4, 5) should be read as specific to field-mean ET_c and NDVI reconstruction rather than as a general superiority across all possible fusion objectives; applications requiring sub-pixel anomaly detection (e.g., localised stress mapping) would need to weigh this trade-off and may favour the local time series approach despite its lower aggregate accuracy.

The per-date Shapiro–Wilk test results ($p < 0.01$ for all RMSE distributions) formally confirm that the RMSE values do not follow a normal distribution across dates, which has two important consequences. First, mean $\pm$ SD summaries must be interpreted cautiously; we report bootstrap 95% CIs as the primary uncertainty measure throughout. Second, the use of the Wilcoxon signed-rank test for method comparisons is statistically appropriate and more conservative than a paired t -test under these conditions. The significant superiority of the Median TS method over both cokriging ($W \geq 521$, $p < 0.001$) and Local TS ($W \geq 298$, $p < 0.001$) across both seasons establishes that the performance advantage is not a statistical artefact of a few extreme dates but is consistent across the entire 24-date sequence.

4.2. Independent Sensor Verification and Absence of Fusion Bias

The Landsat-8 cross-check ($R^2 = 0.76$ [0.70–0.81], RMSE = 0.051 NDVI, nine scenes) serves a fundamentally different diagnostic role from the LOOCV: it tests whether the fused product retains radiometric fidelity relative to an independent observation platform

rather than merely assessing temporal self-consistency within the Sentinel-2 archive. The agreement level is consistent with the known inter-sensor NDVI difference structure after spectral harmonisation. Chastain et al. [69] reported residual cross-sensor NDVI differences of 0.015–0.040 NDVI after OLI–MSI harmonisation over agricultural land covers, implying that an RMSE floor of approximately 0.040–0.055 NDVI is irreducible given sensor geometry and band-pass differences alone—placing the present RMSE of 0.051 NDVI at the lower bound of what can plausibly be attributed to the fusion method rather than to inter-sensor noise.

The regression slope of 0.94 ± 0.03 and the nonsignificant departure from unity ($p = 0.07$) indicate that the fused product neither compresses nor inflates the NDVI dynamic range relative to the independent sensor, which would be expected if the Median TS reconstruction introduced a smoothing-related central tendency bias (i.e., shrinkage toward the median). The negligible MBE (-0.003 NDVI) further confirms the absence of a systematic offset. These characteristics are consistent with the theoretical properties of the median as a robust location estimator: because the median suppresses outlier dates (cloud-contaminated or phenologically anomalous observations) without averaging them toward zero, it preserves the amplitude of the seasonal NDVI trajectory more faithfully than mean-based or kriging-based reconstruction approaches.

Taken together, the LOOCV and Landsat-8 cross-check results establish a multi-source validation chain for the fused NDVI product: internal temporal consistency (LOOCV, $R^2 = 0.79$), spatial consistency across the field when dates are withheld (pooled LOOCV, $R^2 = 0.66$), and radiometric consistency with an independent sensor (Landsat-8, $R^2 = 0.76$). This triangulated evidence supports the use of the fused NDVI time series as a reliable basis for K_c derivation and FAO-56 ET_c estimation across the Nyírbátor growing seasons.

Several site-specific characteristics of the Nyírbátor field constrain the generalisability of these results. The soil profile is a sandy Arenosol with high infiltration capacity and rapid drainage, producing an ET_c regime that differs markedly from clay loam or chernozem fields that dominate other Hungarian agricultural regions. The maize hybrid cultivated during 2020–2021 (Pioneer P9241, FAO maturity group 390) has a specific phenological trajectory that calibrates the NDVI– K_c curve reported here; adaptation to other hybrids with different FAO maturity classes would require recalibration of the regression coefficients. The two-season study period captures contrasting hydroclimatic years but does not characterise the full range of interannual variability expected under Pannonian continental climate (coefficient of variation in growing season rainfall $\sim 35\%$). Future work should establish a multi-field validation network across the Hajdúság and Békés agricultural regions, leveraging existing irrigation licence records and the median fusion workflow to test method robustness across contrasting soil types, hybrid portfolios, and management regimes before broader operational adoption.

4.3. Energy Balance Alternatives and Thermal Sensor Limitations

Remote sensing energy balance models (e.g., SEBAL, METRIC, TSEB) offer a physically based alternative to the K_c -based ET_c approach used in this study, partitioning available energy into latent heat flux without requiring an empirical crop coefficient. However, two practical constraints limited their application here. First, Sentinel-2 carries no thermal infrared band, which energy balance models require to estimate surface temperature and sensible heat flux. Second, while Landsat 8/9 provides thermal data (Band 10/11), its 16-day revisit interval is insufficient to support the daily gap-filling required for operational irrigation scheduling, particularly during the cloud-affected periods that motivated the MODIS–Sentinel-2 fusion approach in this study. The dual- K_c method (Section FAO-56 Dual Crop Coefficient) is therefore presented as a practical intermediate step that im-

proves on the single-Kc approach without requiring thermal input. Future work integrating a TSEB model driven by Landsat thermal imagery, potentially fused with higher-frequency MODIS thermal products (MOD11), is recommended as a priority for physically based ET_c benchmarking at this site.

4.4. Error Sources and Uncertainty

Four principal sources of uncertainty affect the ET_c estimates reported in this study. (a) Residual cloud contamination: Visual scene inspection indicates that nominally cloud-free Sentinel-2 observations carry residual thin cirrus contamination in fewer than 3% of pixels per scene on average; these are partially captured by the s2cloudless probability threshold (≤ 0.30) but may introduce NDVI depression of ~ 0.02 – 0.05 units in affected pixels. (b) MODIS spatial co-registration uncertainty: The MODIS sinusoidal grid has a reported geolocation accuracy of ± 0.5 pixels ($\sim \pm 250$ m at 500 m resolution), which, at the field scale, can shift pixel boundaries relative to the field polygon and alter the pixel ensemble used in the median computation. (c) NDVI–Kc–ET_c propagation: Uncertainty in fused NDVI propagates through the Kc linear regression and the FAO-56 ET₀ $\times$ Kc product; the 95% prediction interval of the NDVI–Kc regression implies ± 0.08 – 0.12 mm day^{−1} ET_c uncertainty at peak season. (d) Meteorological input uncertainty: The nearest synoptic station (Nyírbátor AWS, 1.2 km from the field centroid) may introduce advection effects on ET₀ over the well-irrigated, sandy soil field, potentially overestimating ET₀ relative to field conditions during dry spells.

4.5. Methodological Limitations

The following methodological limitations apply: (a) Absence of independent ET_c validation: No eddy covariance tower, drainage lysimeter, or Bowen ratio system operated at the site during 2020–2021; the ET_c estimates are model-derived and have not been independently validated against measured ET flux. To offset this limitation, future research should prioritise the installation of an automatic weather station equipped with a Bowen ratio energy balance or eddy covariance (EC) system at the study site. (b) Empirical Kc regression: The NDVI–Kc relationship used here was calibrated for temperate European maize and requires recalibration for other crops, cultivars, or agroclimatic settings. (c) Two-season study period: Two growing seasons are insufficient to characterise interannual variability in the NDVI–ET_c relationship; the 2020–2021 period represents contrasting hydroclimatic years but not the full range of variability expected under a Pannonian continental climate. (d) Single-field design: The findings are specific to the 87.5 ha Nyírbátor sandy Arenosol field under the irrigation management regime of Bátortrade Ltd.; generalisation to clay loam or chernozem fields, or to rainfed systems, requires independent validation. (e) LAI estimation via empirical NDVI–LAI proxy: The leaf area index was inferred from Sentinel-2 NDVI using a linear empirical relationship rather than from direct field measurement; this approach assumes a stable, crop-specific NDVI–LAI response that may underperform under high canopy closure conditions ($\text{LAI} > 4$), where the relationship becomes asymptotic and NDVI sensitivity diminishes. Future field campaigns should incorporate site-specific LAI calibration through destructive sampling or optical canopy analysis (e.g., LAI-2200C plant canopy analyser), particularly during the grand growth and silking stages when canopy closure is maximal.

4.6. Hydrological and Operational Significance

The Nyírbátor field lies within the Hajdúság nitrate-sensitive zone designated under EU Council Directive 91/676/EEC (Nitrates Directive). In this zone, total annual irrigation is restricted to a maximum of ~ 240 mm for maize under current zonal action programme allocations [109]. The 85 mm mid-season deficit identified in 2021 represents approxi-

mately 35% of this permitted allocation, confirming that the season was critically water-limited and that deficit-based scheduling using the fused ET_c maps could plausibly have informed operational deficit-based scheduling at this site; this potential significance remains to be confirmed by independent validation. Proof-of-concept adoption of the median fusion-based ET_c mapping could plausibly enable a 12–18% reduction in excess irrigation at the field scale if used to trigger deficit-based scheduling at the identified high-consumption pivot segments. Although this figure is an indicative estimate that has not been independently validated against measured irrigation outcomes, it aims to maintain compliance with the zonal irrigation ceiling, pending independent validation.

5. Conclusions

This work introduces and evaluates a proof-of-concept multi-sensor fusion framework that integrates daily MODIS Terra imagery with 5-day Sentinel-2 acquisitions to deliver spatially explicit, continuous ET_c monitoring over irrigated maize across the 2020 and 2021 growing seasons. Independent ET_c validation via eddy covariance or lysimetry was not available at the site during the study period; the framework is therefore presented as a proof of concept awaiting operational deployment subject to independent flux measurement. The following key findings can be drawn:

- Cokriging is unsuitable for MODIS–Sentinel-2 fusion in heterogeneous landscapes (cross-sensor $r < 0.30$);
- Local time series interpolation achieves $R^2 = 0.68$ but is sensitive to non-stationarity. Median time series is the most robust ($R^2 = 0.81$, $NRMSE = 0.15$ – 0.17), suppressing sub-pixel contamination from roads and irrigation infrastructure—a novel proof-of-concept approach for operational ET_c monitoring across heterogeneous landscapes. NDVI-based ET_c estimates (0.99 – 6.40 mm day^{−1}) align with FAO-56 K_c stages and companion HYDRUS-2D simulations [19] but lack independent validation (no eddy covariance/lysimeter). These are model-derived estimates based on the FAO-56 K_c approach applied to fused NDVI; they are consistent with agronomic water use expectations for irrigated maize in a Pannonian continental climate but have not been independently validated against eddy covariance or lysimeter measurements. The three K_c parameterisations (FAO-56 Original, Curved, and MidPoint Spline) produced consistent cumulative seasonal estimates.
- Seasonal precipitation– ET_c deficit analyses for 2020 and 2021 revealed contrasting patterns: 2020 showed near balance between ET_c and precipitation, while 2021 exhibited a critical mid-season deficit exceeding 85 mm at the most vulnerable field nodes. These figures represent irrigation demand indicators; a full water balance closure would require irrigation flow meter records, soil water storage measurements, and deep percolation estimates, which are not available for this period. As irrigation demand indicators rather than a closed balance, these results illustrate the potential value of spatially explicit, daily ET_c monitoring for precision irrigation scheduling in nitrate-sensitive zones.
- The methodology requires only freely available MODIS and Sentinel-2 data without specialised fusion algorithms. Transferability to other crops, sensors, and agro-ecological zones requires independent validation and should be assessed in future multi-site studies; the present findings are specific to irrigated maize under a Pannonian continental climate and should not be assumed broadly applicable without independent validation.

Future work will extend the validated framework to the full 2020–2024 multi-year record, incorporate Sentinel-3 land surface temperature for energy balance ET_c partition-

ing, and develop an automated operational pipeline for near-real-time irrigation advisory outputs aligned with Hungarian water authority reporting requirements.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/w18131644/s1>: Table S1. Detailed Pre-Processing Sub-Steps and QA Filter Parameters (14 steps; QA Quick Reference sub-table). Table S2. MODIS 500 m Pixel Maize Fractional Cover at the Nyírbátor Study Field. Table S3. Maize Phenological Stage Dates and Day-of-Year, 2020 and 2021 Seasons. Table S4. Unified Validation Metrics by Gap-Filling Method (Bootstrap 95% CI, $n = 1000$ resamples). Table S5. Seasonal ET_c Totals: Single-Kc vs Dual-Kc Comparison (Nyírbátor Site). Table S6. LOOCV Summary Statistics Leave-One-Date-Out Cross-Validation pooled summary for Median Time-Series method. Figure S1. Independent Landsat-8 NDVI Cross-Check (Fused Median TS vs Landsat-8, 100 m aggregated). Figure S2. MODIS 500 m Pixel Grid Overlay on the Nyírbátor Study Field (pixel purity by maize fractional cover). Figure S3. Leave-One-Date-Out Cross-Validation Scatter Plot (Median Time-Series Method). Figure S4. Validation Metric Comparison Chart (Adjusted R² and RMSE by method, with 95% CI). Figure S5. σ ET_c Across the Growing Season (2020 and 2021).

Author Contributions: Conceptualisation, G.S.N. and A.N.; methodology, G.S.N. and F.Z.Z.; software, G.S.N.; validation, G.S.N., F.Z.Z. and J.T.; formal analysis, G.S.N.; investigation, G.S.N. and F.Z.Z.; resources, A.N. and J.T.; data curation, G.S.N.; writing—original draft preparation, G.S.N.; writing—review and editing, F.Z.Z., J.T. and A.N.; visualisation, G.S.N.; supervision, A.N. and J.T.; project administration, A.N.; funding acquisition, A.N. All authors have read and agreed to the published version of this manuscript.

Funding: This research was supported by the National Laboratory for Water Science and Water Safety (RRF-2.3.1-21-2022-00008), Hungary. The APC was funded by the University of Debrecen.

Data Availability Statement: Sentinel-2 Level-2A data are freely accessible via the Copernicus Open Access Hub (<https://dataspace.copernicus.eu>), accessed on 1 April 2024). MODIS Terra surface reflectance data are available from the USGS EarthExplorer portal (<https://earthexplorer.usgs.gov>), accessed on 1 April 2024). In situ meteorological data and processed vegetation index time series are available from the corresponding author upon reasonable request.

Acknowledgments: The authors acknowledge the support of Bátortrade Ltd. for field access and agronomic data. Sentinel-2 data access was facilitated by Vultus Ltd. The authors thank the Hungarian Meteorological Service for complementary climate data and the University of Debrecen for institutional support. During the preparation of this manuscript, the authors used Claude Sonnet (Anthropic, claude-sonnet-4-6) for English language editing and improvement of grammatical clarity and readability. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of this manuscript; or in the decision to publish the results.

Abbreviations

ET _c	Crop evapotranspiration
ET ₀	Reference evapotranspiration
EVI	Enhanced Vegetation Index
FAO-56	FAO Irrigation and Drainage Paper 56
GNDVI	Green Normalised Difference Vegetation Index
Kc	Crop coefficient
LAI	Leaf area index
MAE	Mean absolute error
MBE	Mean Bias Error

MODIS	Moderate Resolution Imaging Spectroradiometer
MSAVI2	Modified Soil Adjusted Vegetation Index 2
NDRE	Normalised Difference Red Edge Index
NDVI	Normalised Difference Vegetation Index
NDWI	Normalised Difference Water Index
NRMSE	Normalised root mean square error
RMSE	Root mean square error
RVI	Ratio Vegetation Index
SAVI	Soil Adjusted Vegetation Index

References

1. Machwitz, M.; Pieruschka, R.; Berger, K.; Schlerf, M.; Aasen, H.; Fahrner, S.; Jiménez-Berni, J.; Baret, F.; Rascher, U. Bridging the Gap Between Remote Sensing and Plant Phenotyping—Challenges and Opportunities for the Next Generation of Sustainable Agriculture. *Front. Plant Sci.* **2021**, *12*, 749374. <https://doi.org/10.3389/fpls.2021.749374>.
2. Xue, J.; Su, B. Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. *J. Sens.* **2017**, *2017*, 1–17. <https://doi.org/10.1155/2017/1353691>.
3. Fereres, E.; Soriano, M.A. Deficit Irrigation for Reducing Agricultural Water Use. *J. Exp. Bot.* **2006**, *58*, 147–159. <https://doi.org/10.1093/jxb/erl165>.
4. Sentelhas, P.C.; Gillespie, T.J.; Santos, E.A. Evaluation of FAO Penman–Monteith and Alternative Methods for Estimating Reference Evapotranspiration with Missing Data in Southern Ontario, Canada. *Agric. Water Manag.* **2010**, *97*, 635–644. <https://doi.org/10.1016/j.agwat.2009.12.001>.
5. Veloso, A.; Mermoz, S.; Bouvet, A.; Le Toan, T.; Planells, M.; Dejoux, J.-F.; Ceschia, E. Understanding the Temporal Behavior of Crops Using Sentinel-1 and Sentinel-2-like Data for Agricultural Applications. *Remote Sens. Environ.* **2017**, *199*, 415–426. <https://doi.org/10.1016/j.rse.2017.07.015>.
6. Bwambale, E.; Naangmenyele, Z.; Iradukunda, P.; Agboka, K.M.; Houessou-Dossou, E.A.Y.; Akansake, D.A.; Bisa, M.E.; Hamadou, A.-A.H.; Hakizayezu, J.; Onofua, O.E.; et al. Towards Precision Irrigation Management: A Review of GIS, Remote Sensing and Emerging Technologies. *Cogent Eng.* **2022**, *9*, 2100573. <https://doi.org/10.1080/23311916.2022.2100573>.
7. Chávez, J.L.; Gowda, P.H.; Howell, T.A.; Neale, C.M.U.; Copeland, K.S. Estimating Hourly Crop ET Using a Two-Source Energy Balance Model and Multispectral Airborne Imagery. *Irrig. Sci.* **2009**, *28*, 79–91. <https://doi.org/10.1007/s00271-009-0177-9>.
8. Justice, C.O.; Townshend, J.R.G.; Vermote, E.F.; Masuoka, E.; Wolfe, R.E.; Saleous, N.; Roy, D.P.; Morisette, J.T. An Overview of MODIS Land Data Processing and Product Status. *Remote Sens. Environ.* **2002**, *83*, 3–15. [https://doi.org/10.1016/S0034-4257\(02\)00084-6](https://doi.org/10.1016/S0034-4257(02)00084-6).
9. Drusch, M.; Del Bello, U.; Carlier, S.; Colin, O.; Fernandez, V.; Gascon, F.; Hoersch, B.; Isola, C.; Laberinti, P.; Martimort, P.; et al. Sentinel-2: ESA’s Optical High-Resolution Mission for GMES Operational Services. *Remote Sens. Environ.* **2012**, *120*, 25–36. <https://doi.org/10.1016/j.rse.2011.11.026>.
10. Zhu, X.; Helmer, E.H.; Gao, F.; Liu, D.; Chen, J.; Lefsky, M.A. A Flexible Spatiotemporal Method for Fusing Satellite Images with Different Resolutions. *Remote Sens. Environ.* **2016**, *172*, 165–177. <https://doi.org/10.1016/j.rse.2015.11.016>.
11. Csajbók, J.; Buday-Bódi, E.; Nagy, A.; Fehér, Z.Z.; Tamás, A.; Virág, I.C.; Bojtor, C.; Forgács, F.; Vad, A.M.; Kutasy, E. Multispectral Analysis of Small Plots Based on Field and Remote Sensing Surveys—A Comparative Evaluation. *Sustainability* **2022**, *14*, 3339. <https://doi.org/10.3390/su14063339>.
12. Pettorelli, N.; Vik, J.O.; Mysterud, A.; Gaillard, J.-M.; Tucker, C.J.; Stenseth, N.C. Using the Satellite-Derived NDVI to Assess Ecological Responses to Environmental Change. *Trends Ecol. Evol.* **2005**, *20*, 503–510. <https://doi.org/10.1016/j.tree.2005.05.011>.
13. Tucker, C.J. Red and Photographic Infrared Linear Combinations for Monitoring Vegetation. *Remote Sens. Environ.* **1979**, *8*, 127–150. [https://doi.org/10.1016/0034-4257\(79\)90013-0](https://doi.org/10.1016/0034-4257(79)90013-0).
14. Gao, B. NDWI—A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water from Space. *Remote Sens. Environ.* **1996**, *58*, 257–266. [https://doi.org/10.1016/S0034-4257\(96\)00067-3](https://doi.org/10.1016/S0034-4257(96)00067-3).
15. Nagy, A.; Tamás, J. Noninvasive Water Stress Assessment Methods in Orchards. *Commun. Soil. Sci. Plant Anal.* **2013**, *44*, 366–376. <https://doi.org/10.1080/00103624.2013.742308>.
16. Baret, F.; Guyot, G. Potentials and Limits of Vegetation Indices for LAI and APAR Assessment. *Remote Sens. Environ.* **1991**, *35*, 161–173. [https://doi.org/10.1016/0034-4257\(91\)90009-U](https://doi.org/10.1016/0034-4257(91)90009-U).
17. Belaqziz, S.; Khabba, S.; Kharrou, M.H.; Bouras, E.H.; Er-Raki, S.; Chehbouni, A. Optimizing the Sowing Date to Improve Water Management and Wheat Yield in a Large Irrigation Scheme, through a Remote Sensing and an Evolution Strategy-Based Approach. *Remote Sens.* **2021**, *13*, 3789. <https://doi.org/10.3390/rs13183789>.

18. Sipiwe, N.G.; Magyar, T.; Tamás, J.; Nagy, A. Modelling Soil Moisture Content with Hydrus 2D in a Continental Climate for Effective Maize Irrigation Planning. *Agriculture* **2024**, *14*, 1340. <https://doi.org/10.3390/agriculture14081340>.
19. Magyar, T.; Fehér, Z.; Buday-Bódi, E.; Tamás, J.; Nagy, A. Modeling of Soil Moisture and Water Fluxes in a Maize Field for the Optimization of Irrigation. *Comput. Electron. Agric.* **2023**, *213*, 108159. <https://doi.org/10.1016/j.compag.2023.108159>.
20. Nagy, A.; Kiss, N.É.; Buday-Bódi, E.; Magyar, T.; Cavazza, F.; Gentile, S.L.; Abdullah, H.; Tamás, J.; Fehér, Z.Z. Precision Estimation of Crop Coefficient for Maize Cultivation Using High-Resolution Satellite Imagery to Enhance Evapotranspiration Assessment in Agriculture. *Plants* **2024**, *13*, 1212. <https://doi.org/10.3390/plants13091212>.
21. Nagy, A.; Fehér, J.; Tamás, J. Wheat and Maize Yield Forecasting for the Tisza River Catchment Using MODIS NDVI Time Series and Reported Crop Statistics. *Comput. Electron. Agric.* **2018**, *151*, 41–49. <https://doi.org/10.1016/j.compag.2018.05.035>.
22. Ershadi, A.; McCabe, M.F.; Evans, J.P.; Chaney, N.W.; Wood, E.F. Multi-Site Evaluation of Terrestrial Evaporation Models Using FLUXNET Data. *Agric. For. Meteorol.* **2014**, *187*, 46–61. <https://doi.org/10.1016/j.agrformet.2013.11.008>.
23. *Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements*; Allen, R.G., Ed.; FAO irrigation and drainage paper; repr.; Food and Agriculture Organization of the United Nations: Rome, 2000; ISBN 978-92-5-104219-9.
24. Jin, S.; Su, Y.; Song, S.; Xu, K.; Hu, T.; Yang, Q.; Wu, F.; Xu, G.; Ma, Q.; Guan, H.; et al. Non-Destructive Estimation of Field Maize Biomass Using Terrestrial Lidar: An Evaluation from Plot Level to Individual Leaf Level. *Plant Methods* **2020**, *16*, 69. <https://doi.org/10.1186/s13007-020-00613-5>.
25. Zhang, Y.; Liang, S.; Zhu, Z.; Ma, H.; He, T. Soil Moisture Content Retrieval from Landsat 8 Data Using Ensemble Learning. *ISPRS J. Photogramm. Remote Sens.* **2022**, *185*, 32–47. <https://doi.org/10.1016/j.isprsjprs.2022.01.005>.
26. Wu, D.; Johansen, K.; Phinn, S.; Robson, A. Suitability of Airborne and Terrestrial Laser Scanning for Mapping Tree Crop Structural Metrics for Improved Orchard Management. *Remote Sens.* **2020**, *12*, 1647. <https://doi.org/10.3390/rs12101647>.
27. Liang, J.; Ren, C.; Li, Y.; Yue, W.; Wei, Z.; Song, X.; Zhang, X.; Yin, A.; Lin, X. Using Enhanced Gap-Filling and Whittaker Smoothing to Reconstruct High Spatiotemporal Resolution NDVI Time Series Based on Landsat 8, Sentinel-2, and MODIS Imagery. *IJGI* **2023**, *12*, 214. <https://doi.org/10.3390/ijgi12060214>.
28. Szabó, A.; Sipiwe, N.G.; Buday-Bódi, E.; Ademola, B.; Tamás, J.; Nagy, A. Evaluation of Ground Based Spectral Imaging for Real Time Maize Biomass Monitoring. *Front. Plant Sci.* **2025**, *16*, 1566305. <https://doi.org/10.3389/fpls.2025.1566305>.
29. Filgueiras, R.; Mantovani, E.C.; Fernandes-Filho, E.I.; Cunha, F.F.D.; Althoff, D.; Dias, S.H.B. Fusion of MODIS and Landsat-Like Images for Daily High Spatial Resolution NDVI. *Remote Sens.* **2020**, *12*, 1297. <https://doi.org/10.3390/rs12081297>.
30. Soulard, C.E.; Waller, E.K.; Walker, J.J.; Petrakis, R.E.; Smith, B.W. DSWEmod — The Production of High-Frequency Surface Water Map Composites from Daily MODIS Images. *J. American Water Resour. Assoc.* **2022**, *58*, 248–268. <https://doi.org/10.1111/1752-1688.12996>.
31. Kogan, F.; Salazar, L.; Roytman, L. Forecasting Crop Production Using Satellite-Based Vegetation Health Indices in Kansas, USA. *Int. J. Remote Sens.* **2012**, *33*, 2798–2814. <https://doi.org/10.1080/01431161.2011.621464>.
32. Hussain, M.; Keshavarz, R.; Shariati, N. Advancements in Agricultural Microwave Remote Sensing: An Overview From Indoor to Space-Borne Platforms. *IEEE Trans. Instrum. Meas.* **2025**, *74*, 1–22. <https://doi.org/10.1109/TIM.2025.3548212>.
33. Bento, V.A.; Gouveia, C.M.; DaCamara, C.C.; Libonati, R.; Trigo, I.F. The Roles of NDVI and Land Surface Temperature When Using the Vegetation Health Index over Dry Regions. *Glob. Planet. Change* **2020**, *190*, 103198. <https://doi.org/10.1016/j.gloplacha.2020.103198>.
34. Huang, S.; Eisner, S.; Haddeland, I.; Tadege Mengistu, Z. Evaluation of Two New-Generation Global Soil Databases for Macro-Scale Hydrological Modelling in Norway. *J. Hydrol.* **2022**, *610*, 127895. <https://doi.org/10.1016/j.jhydrol.2022.127895>.
35. Huete, A.R. A Soil-Adjusted Vegetation Index (SAVI). *Remote Sens. Environ.* **1988**, *25*, 295–309. [https://doi.org/10.1016/0034-4257\(88\)90106-X](https://doi.org/10.1016/0034-4257(88)90106-X).
36. Fang, H.; Baret, F.; Plummer, S.; Schaepman-Strub, G. An Overview of Global Leaf Area Index (LAI): Methods, Products, Validation, and Applications. *Rev. Geophys.* **2019**, *57*, 739–799. <https://doi.org/10.1029/2018RG000608>.
37. Brewer, K.; Clulow, A.; Sibanda, M.; Gokool, S.; Naiken, V.; Mabhaudhi, T. Predicting the Chlorophyll Content of Maize over Phenotyping as a Proxy for Crop Health in Smallholder Farming Systems. *Remote Sens.* **2022**, *14*, 518. <https://doi.org/10.3390/rs14030518>.
38. Rehman, T.H.; Lundy, M.E.; Linquist, B.A. Comparative Sensitivity of Vegetation Indices Measured via Proximal and Aerial Sensors for Assessing N Status and Predicting Grain Yield in Rice Cropping Systems. *Remote Sens.* **2022**, *14*, 2770. <https://doi.org/10.3390/rs14122770>.
39. Quemada, C.; Pérez-Escudero, J.M.; Gonzalo, R.; Ederra, I.; Santesteban, L.G.; Torres, N.; Iriarte, J.C. Remote Sensing for Plant Water Content Monitoring: A Review. *Remote Sens.* **2021**, *13*, 2088. <https://doi.org/10.3390/rs13112088>.

40. Shashikant, V.; Mohamed Shariff, A.R.; Wayayok, A.; Kamal, M.R.; Lee, Y.P.; Takeuchi, W. Utilizing TVDI and NDWI to Classify Severity of Agricultural Drought in Chuping, Malaysia. *Agronomy* **2021**, *11*, 1243. <https://doi.org/10.3390/agronomy11061243>.
41. Sandholt, I.; Rasmussen, K.; Andersen, J. A Simple Interpretation of the Surface Temperature/Vegetation Index Space for Assessment of Surface Moisture Status. *Remote Sens. Environ.* **2002**, *79*, 213–224. [https://doi.org/10.1016/S0034-4257\(01\)00274-7](https://doi.org/10.1016/S0034-4257(01)00274-7).
42. Immitzer, M.; Vuolo, F.; Atzberger, C. First Experience with Sentinel-2 Data for Crop and Tree Species Classifications in Central Europe. *Remote Sens.* **2016**, *8*, 166. <https://doi.org/10.3390/rs8030166>.
43. Delegido, J.; Verrelst, J.; Alonso, L.; Moreno, J. Evaluation of Sentinel-2 Red-Edge Bands for Empirical Estimation of Green LAI and Chlorophyll Content. *Sensors* **2011**, *11*, 7063–7081. <https://doi.org/10.3390/s110707063>.
44. Clevers, J.G.P.W.; Gitelson, A.A. Remote Estimation of Crop and Grass Chlorophyll and Nitrogen Content Using Red-Edge Bands on Sentinel-2 and -3. *Int. J. Appl. Earth Obs. Geoinf.* **2013**, *23*, 344–351. <https://doi.org/10.1016/j.jag.2012.10.008>.
45. Jordan, C.F. Derivation of Leaf-Area Index from Quality of Light on the Forest Floor. *Ecology* **1969**, *50*, 663–666. <https://doi.org/10.2307/1936256>.
46. Ren, H.; Zhou, G.; Zhang, F. Using Negative Soil Adjustment Factor in Soil-Adjusted Vegetation Index (SAVI) for Aboveground Living Biomass Estimation in Arid Grasslands. *Remote Sens. Environ.* **2018**, *209*, 439–445. <https://doi.org/10.1016/j.rse.2018.02.068>.
47. Sripada, R.P.; Heiniger, R.W.; White, J.G.; Meijer, A.D. Aerial Color Infrared Photography for Determining Early In-Season Nitrogen Requirements in Corn. *Agron. J.* **2006**, *98*, 968–977. <https://doi.org/10.2134/agronj2005.0200>.
48. Vaz, P.J.; Schutz, G.; Guerrero, C.; Cardoso, P.J.S. Hybrid Neural Network Based Models for Evapotranspiration Prediction Over Limited Weather Parameters. *IEEE Access* **2023**, *11*, 963–976. <https://doi.org/10.1109/ACCESS.2022.3233301>.
49. Suharto, B.; Sulianto, A.A.; Pratama, N.A. Analysis of Reference Evapotranspiration (ET_o) and Rainfall on Maize Hybrid Seed Production: Cases in Malang and Jember. *Univers. J. Agric. Res.* **2023**, *11*, 475–488. <https://doi.org/10.13189/ujar.2023.110224>.
50. Moratiel, R.; Bravo, R.; Saa, A.; Tarquis, A.M.; Almorox, J. Estimation of Evapotranspiration by the Food and Agricultural Organization of the United Nations (FAO) Penman–Monteith Temperature (PMT) and Hargreaves–Samani (HS) Models under Temporal and Spatial Criteria – a Case Study in Duero Basin (Spain). *Nat. Hazards Earth Syst. Sci.* **2020**, *20*, 859–875. <https://doi.org/10.5194/nhess-20-859-2020>.
51. Lawrence, D.M.; Thornton, P.E.; Oleson, K.W.; Bonan, G.B. The Partitioning of Evapotranspiration into Transpiration, Soil Evaporation, and Canopy Evaporation in a GCM: Impacts on Land–Atmosphere Interaction. *J. Hydrometeorol.* **2007**, *8*, 862–880. <https://doi.org/10.1175/JHM596.1>.
52. Nxumalo, G.S.; Ramabulana, T.S.; Dlamini, Z.; Louis, A.; Nagy, A. Integrating OPTRAM and Machine Learning with Multimodal EO Proxies for Optimized Irrigation Scheduling in Smallholder Systems: A Vhembe District Case Study. *Front. Agron.* **2026**, *7*, 1697188. <https://doi.org/10.3389/fagro.2025.1697188>.
53. Shao, G.; Han, W.; Zhang, H.; Wang, Y.; Zhang, L.; Niu, Y.; Zhang, Y.; Cao, P. Estimation of Transpiration Coefficient and Aboveground Biomass in Maize Using Time-Series UAV Multispectral Imagery. *Crop J.* **2022**, *10*, 1376–1385. <https://doi.org/10.1016/j.cj.2022.08.001>.
54. Munitz, S.; Schwartz, A.; Netzer, Y. Water Consumption, Crop Coefficient and Leaf Area Relations of a Vitis Vinifera Cv. “Cabernet Sauvignon” Vineyard. *Agric. Water Manag.* **2019**, *219*, 86–94. <https://doi.org/10.1016/j.agwat.2019.03.051>.
55. Di, L.; Rundquist, D.C.; Han, L. Modelling Relationships between NDVI and Precipitation during Vegetative Growth Cycles. *Int. J. Remote Sens.* **1994**, *15*, 2121–2136. <https://doi.org/10.1080/01431169408954231>.
56. Čereković, N.; Todorović, M.; Snyder, R.L.; Boari, F.; Pace, B.; Cantore, V. Evaluation of the Crop Coefficients for Tomato Crop Grown in a Mediterranean Climate. *CIHEAM* **2010**, 91–94. <https://doi.org/10.13140/2.1.3574.9766>.
57. Bausch, W.C.; Neale, C.M.U. Crop Coefficients Derived from Reflected Canopy Radiation: A Concept. *Trans. ASAE* **1987**, *30*, 703–709. <https://doi.org/10.13031/2013.30463>.
58. Vanino, S.; Nino, P.; De Michele, C.; Falanga Bolognesi, S.; D’Urso, G.; Di Bene, C.; Pennelli, B.; Vuolo, F.; Farina, R.; Pulighe, G.; et al. Capability of Sentinel-2 Data for Estimating Maximum Evapotranspiration and Irrigation Requirements for Tomato Crop in Central Italy. *Remote Sens. Environ.* **2018**, *215*, 452–470. <https://doi.org/10.1016/j.rse.2018.06.035>.
59. Silva, C.D.O.F.; Grego, C.R.; Manzione, R.L.; Oliveira, S.R.D.M. Improving Coffee Yield Interpolation in the Presence of Outliers Using Multivariate Geostatistics and Satellite Data. *AgriEngineering* **2024**, *6*, 81–94. <https://doi.org/10.3390/agriengineering6010006>.
60. Waleed, M.; Mubeen, M.; Ahmad, A.; Habib-ur-Rahman, M.; Amin, A.; Farid, H.U.; Hussain, S.; Ali, M.; Qaisrani, S.A.; Nasim, W.; et al. Evaluating the Efficiency of Coarser to Finer Resolution Multispectral Satellites in Mapping Paddy Rice Fields Using GEE Implementation. *Sci. Rep.* **2022**, *12*, 13210. <https://doi.org/10.1038/s41598-022-17454-y>.

61. Zhang, M.; Zhang, M.; Yang, H.; Jin, Y.; Zhang, X.; Liu, H. Mapping Regional Soil Organic Matter Based on Sentinel-2A and MODIS Imagery Using Machine Learning Algorithms and Google Earth Engine. *Remote Sensing* **2021**, *13*, 2934. <https://doi.org/10.3390/rs13152934>.
62. Gurjar, S.B.; Padmanabhan, N. Study of Various Resampling Techniques for High-Resolution Remote Sensing Imagery. *J. Indian. Soc. Remote Sens.* **2005**, *33*, 113–120. <https://doi.org/10.1007/BF02989999>.
63. Nag, P.; Sun, Y.; Reich, B.J. Bivariate DeepKriging for Large-Scale Spatial Interpolation of Wind Fields. *Technometrics* **2025**, *67*, 397–408. <https://doi.org/10.1080/00401706.2025.2453197>.
64. Gao, F.; Morisette, J.T.; Wolfe, R.E.; Ederer, G.; Pedelty, J.; Masuoka, E.; Myneni, R.; Tan, B.; Nightingale, J. An Algorithm to Produce Temporally and Spatially Continuous MODIS-LAI Time Series. *IEEE Geosci. Remote Sensing Lett.* **2008**, *5*, 60–64. <https://doi.org/10.1109/LGRS.2007.907971>.
65. Hengl, T.; Heuvelink, G.B.M.; Perčec Tadić, M.; Pebesma, E.J. Spatio-Temporal Prediction of Daily Temperatures Using Time-Series of MODIS LST Images. *Theor. Appl. Climatol.* **2012**, *107*, 265–277. <https://doi.org/10.1007/s00704-011-0464-2>.
66. Perich, G.; Turkoglu, M.O.; Graf, L.V.; Wegner, J.D.; Aasen, H.; Walter, A.; Liebisch, F. Pixel-Based Yield Mapping and Prediction from Sentinel-2 Using Spectral Indices and Neural Networks. *Field Crops Res.* **2023**, *292*, 108824. <https://doi.org/10.1016/j.fcr.2023.108824>.
67. Marey, H.S.; Hashisho, Z.; Fu, L.; Gille, J. Spatial and Temporal Variation in CO over Alberta Using Measurements from Satellites, Aircraft, and Ground Stations. *Atmos. Chem. Phys.* **2015**, *15*, 3893–3908. <https://doi.org/10.5194/acp-15-3893-2015>.
68. Ulsig, L.; Nichol, C.; Huemmrich, K.; Landis, D.; Middleton, E.; Lyapustin, A.; Mammarella, I.; Levula, J.; Porcar-Castell, A. Detecting Inter-Annual Variations in the Phenology of Evergreen Conifers Using Long-Term MODIS Vegetation Index Time Series. *Remote Sens.* **2017**, *9*, 49. <https://doi.org/10.3390/rs9010049>.
69. Chastain, R.; Housman, I.; Goldstein, J.; Finco, M.; Tenneson, K. Empirical Cross Sensor Comparison of Sentinel-2A and 2B MSI, Landsat-8 OLI, and Landsat-7 ETM+ Top of Atmosphere Spectral Characteristics over the Conterminous United States. *Remote Sens. Environ.* **2019**, *221*, 274–285. <https://doi.org/10.1016/j.rse.2018.11.012>.
70. Pearson, K. VII. Note on Regression and Inheritance in the Case of Two Parents. *Proc. R. Soc. Lond.* **1895**, *58*, 240–242. <https://doi.org/10.1098/rspl.1895.0041>.
71. Yu, Q.; Saseendran, S.A.; Ma, L.; Flerchinger, G.N.; Green, T.R.; Ahuja, L.R. Modeling a Wheat–Maize Double Cropping System in China Using Two Plant Growth Modules in RZWQM. *Agric. Syst.* **2006**, *89*, 457–477. <https://doi.org/10.1016/j.agry.2005.10.009>.
72. Aghelpour, P.; Norooz-Valashedi, R. Predicting Daily Reference Evapotranspiration Rates in a Humid Region, Comparison of Seven Various Data-Based Predictor Models. *Stoch. Environ. Res. Risk Assess.* **2022**, *36*, 4133–4155. <https://doi.org/10.1007/s00477-022-02249-4>.
73. Kullberg, E.G.; DeJonge, K.C.; Chávez, J.L. Evaluation of Thermal Remote Sensing Indices to Estimate Crop Evapotranspiration Coefficients. *Agric. Water Manag.* **2017**, *179*, 64–73. <https://doi.org/10.1016/j.agwat.2016.07.007>.
74. Claverie, M.; Ju, J.; Masek, J.G.; Dungan, J.L.; Vermote, E.F.; Roger, J.-C.; Skakun, S.V.; Justice, C. The Harmonized Landsat and Sentinel-2 Surface Reflectance Data Set. *Remote Sens. Environ.* **2018**, *219*, 145–161. <https://doi.org/10.1016/j.rse.2018.09.002>.
75. Lange, M.; Dechant, B.; Rebmann, C.; Vohland, M.; Cuntz, M.; Doktor, D. Validating MODIS and Sentinel-2 NDVI Products at a Temperate Deciduous Forest Site Using Two Independent Ground-Based Sensors. *Sensors* **2017**, *17*, 1855. <https://doi.org/10.3390/s17081855>.
76. Nikoloudakis, N.; Stagakis, S.; Mitraka, Z.; Kamarianakis, Y.; Chrysoulakis, N. Spatial Interpolation of Urban Air Temperatures Using Satellite-Derived Predictors. *Theor. Appl. Climatol.* **2020**, *141*, 657–672. <https://doi.org/10.1007/s00704-020-03230-3>.
77. Wu, M.; Yang, C.; Song, X.; Hoffmann, W.C.; Huang, W.; Niu, Z.; Wang, C.; Li, W.; Yu, B. Monitoring Cotton Root Rot by Synthetic Sentinel-2 NDVI Time Series Using Improved Spatial and Temporal Data Fusion. *Sci. Rep.* **2018**, *8*, 2016. <https://doi.org/10.1038/s41598-018-20156-z>.
78. Tavares, T.R.; Molin, J.P.; Javadi, S.H.; Carvalho, H.W.P.D.; Mouazen, A.M. Combined Use of Vis-NIR and XRF Sensors for Tropical Soil Fertility Analysis: Assessing Different Data Fusion Approaches. *Sensors* **2020**, *21*, 148. <https://doi.org/10.3390/s21010148>.
79. Barbedo, J.G.A. Data Fusion in Agriculture: Resolving Ambiguities and Closing Data Gaps. *Sensors* **2022**, *22*, 2285. <https://doi.org/10.3390/s22062285>.
80. Hébert, R.; Rehfeld, K.; Laepple, T. Comparing Estimation Techniques for Temporal Scaling in Palaeoclimate Time Series. *Nonlin. Processes Geophys.* **2021**, *28*, 311–328. <https://doi.org/10.5194/npg-28-311-2021>.

81. Agrawal, R.; Mohite, J.D.; Sawant, S.A.; Pandit, A.; Pappula, S. ESTIMATION OF NDVI FOR CLOUDY PIXELS USING MACHINE LEARNING. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.* **2022**, XLIII-B3-2022, 813–818. <https://doi.org/10.5194/isprs-archives-XLIII-B3-2022-813-2022>.
82. Li, L.; Zhao, Y.; Fu, Y.; Pan, Y.; Yu, L.; Xin, Q. High Resolution Mapping of Cropping Cycles by Fusion of Landsat and MODIS Data. *Remote Sens.* **2017**, *9*, 1232. <https://doi.org/10.3390/rs9121232>.
83. Son, N.-T.; Chen, C.-F.; Chang, L.-Y.; Chen, C.-R.; Sobue, S.-I.; Minh, V.-Q.; Chiang, S.-H.; Nguyen, L.-D.; Lin, Y.-W. A Logistic-Based Method for Rice Monitoring from Multitemporal MODIS-Landsat Fusion Data. *Eur. J. Remote Sens.* **2016**, *49*, 39–56. <https://doi.org/10.5721/EuJRS20164903>.
84. Luo, D.; Caldas, M.M.; Yang, H. Deep Learning Models to Map an Agricultural Expansion Area with MODIS and Sentinel-2 Time Series Images. *J. Appl. Rem. Sens.* **2022**, *16*. <https://doi.org/10.1117/1.JRS.16.046508>.
85. Radočaj, D.; Obhodáč, J.; Jurišić, M.; Gašparović, M. Global Open Data Remote Sensing Satellite Missions for Land Monitoring and Conservation: A Review. *Land* **2020**, *9*, 402. <https://doi.org/10.3390/land9110402>.
86. Barrile, V.; Simonetti, S.; Citroni, R.; Fotia, A.; Bilotta, G. Experimenting Agriculture 4.0 with Sensors: A Data Fusion Approach between Remote Sensing, UAVs and Self-Driving Tractors. *Sensors* **2022**, *22*, 7910. <https://doi.org/10.3390/s22207910>.
87. Tuia, D.; Marcos, D.; Camps-Valls, G. Multi-Temporal and Multi-Source Remote Sensing Image Classification by Nonlinear Relative Normalization. *ISPRS J. Photogramm. Remote Sens.* **2016**, *120*, 1–12. <https://doi.org/10.1016/j.isprsjprs.2016.07.004>.
88. Guan, H.; Su, Y.; Hu, T.; Chen, J.; Guo, Q. An Object-Based Strategy for Improving the Accuracy of Spatiotemporal Satellite Imagery Fusion for Vegetation-Mapping Applications. *Remote Sens.* **2019**, *11*, 2927, doi:10.3390/rs11242927.
89. Payero, J.O.; Tarkalson, D.D.; Irmak, S.; Davison, D.; Petersen, J.L. Effect of Timing of a Deficit-Irrigation Allocation on Corn Evapotranspiration, Yield, Water Use Efficiency and Dry Mass. *Agric. Water Manag.* **2009**, *96*, 1387–1397. <https://doi.org/10.1016/j.agwat.2009.03.022>.
90. Abdel-Maksoud, H.H.; Ashry, M.R.K.; Youssef, K.M.R. MAIZE YIELD AND WATER RELATIONS UNDER DIFFERENT IRRIGATION AND PLANT DENSITY TREATMENTS. *J. Soil. Sci. Agric. Eng.* **2008**, *33*, 3881–3893. <https://doi.org/10.21608/jssae.2008.203107>.
91. Gao, X.; Bai, Y.; Huo, Z.; Xu, X.; Huang, G.; Xia, Y.; Steenhuis, T.S. Deficit Irrigation Enhances Contribution of Shallow Groundwater to Crop Water Consumption in Arid Area. *Agric. Water Manag.* **2017**, *185*, 116–125. <https://doi.org/10.1016/j.agwat.2017.02.012>.
92. Mirmazloumi, S.M.; Nouri, H.; Abbasi, N.; Chukalla, A.D.; Kipkulei, H.; Ghazaryan, G. Enhancing Evapotranspiration Estimates by Integrating Sentinel-3 LST and Sentinel-2 Data Through Machine Learning-Based Downscaling. In *Proceedings of the IGARSS 2024—2024 IEEE International Geoscience and Remote Sensing Symposium, Athens, Greece, 7 July 2024*; IEEE: Piscataway, NJ, USA, 2024; pp. 2464–2468.
93. He, M.; Kimball, J.; Maneta, M.; Maxwell, B.; Moreno, A.; Beguería, S.; Wu, X. Regional Crop Gross Primary Productivity and Yield Estimation Using Fused Landsat-MODIS Data. *Remote Sens.* **2018**, *10*, 372. <https://doi.org/10.3390/rs10030372>.
94. Wang, R.; You, X.; Shi, Y.; Wu, C. Enhancing Evapotranspiration Estimations through Multi-Source Product Fusion in the Yellow River Basin, China. *Water* **2024**, *16*, 2603. <https://doi.org/10.3390/w16182603>.
95. Thomas, M.; Tellman, E.; Osgood, D.E.; DeVries, B.; Islam, A.S.; Steckler, M.S.; Goodman, M.; Billah, M. A Framework to Assess Remote Sensing Algorithms for Satellite-Based Flood Index Insurance. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2023**, *16*, 2589–2604. <https://doi.org/10.1109/JSTARS.2023.3244098>.
96. Xie, N.; Wang, W.; Ma, B.; Zhang, X.; Sun, W.; Guo, F. Research on an Agricultural Knowledge Fusion Method for Big Data. *CODATA* **2015**, *14*, 7. <https://doi.org/10.5334/dsj-2015-007>.
97. Djaman, K.; O'Neill, M.; Owen, C.; Smeal, D.; Koudahe, K.; West, M.; Allen, S.; Lombard, K.; Irmak, S. Crop Evapotranspiration, Irrigation Water Requirement and Water Productivity of Maize from Meteorological Data under Semiarid Climate. *Water* **2018**, *10*, 405. <https://doi.org/10.3390/w10040405>.
98. Oliver, M.A.; Webster, R. A Tutorial Guide to Geostatistics: Computing and Modelling Variograms and Kriging. *CATENA* **2014**, *113*, 56–69. <https://doi.org/10.1016/j.catena.2013.09.006>.
99. Wang, Q.; Atkinson, P.M. Spatio-Temporal Fusion for Daily Sentinel-2 Images. *Remote Sens. Environ.* **2018**, *204*, 31–42. <https://doi.org/10.1016/j.rse.2017.10.046>.
100. Zhao, R.; Li, Y.; Chen, J.; Ma, M.; Fan, L.; Lu, W. Mapping a Paddy Rice Area in a Cloudy and Rainy Region Using Spatiotemporal Data Fusion and a Phenology-Based Algorithm. *Remote Sens.* **2021**, *13*, 4400. <https://doi.org/10.3390/rs13214400>.

101. Liu, C.; Duan, P.; Zhang, F.; Jim, C.-Y.; Tan, M.L.; Chan, N.W. Feasibility of the Spatiotemporal Fusion Model in Monitoring Ebinur Lake's Suspended Particulate Matter under the Missing-Data Scenario. *Remote Sens.* **2021**, *13*, 3952. <https://doi.org/10.3390/rs13193952>.
102. Sun, J.; Wang, W.; Wang, X.; Brocca, L. Improving the STARFM Fusion Method for Downscaling the SSEBOP Evapotranspiration Product from 1 Km to 30 m in an Arid Area in China. *Remote Sens.* **2023**, *15*, 5411. <https://doi.org/10.3390/rs15225411>.
103. Sangakkara, U.; Amarasekera, P.; Stamp, P. Root Development, Shoot Growth and Yields of Maize as Affected by Irrigation Schedules in a Minor Season in Tropical Asia. *Acta Agronomica Hungarica* **2011**, *59*, 149–158. <https://doi.org/10.1556/AAgr.59.2011.2.5>.
104. Adeniran, A.I. Repository Africa in the Evolving “Chinese Century”: The Uneven Sino-Nigerian Water Conservation Partnership. *J. Curr. Chin. Aff.* **2017**, *46*, 33–52. <https://doi.org/10.1177/186810261704600302>.
105. Ozturk, M.Y.; Colkesen, I. A Novel Hybrid Methodology Integrating Pixel- and Object-Based Techniques for Mapping Land Use and Land Cover from High-Resolution Satellite Data. *Int. J. Remote Sens.* **2024**, *45*, 5640–5678. <https://doi.org/10.1080/01431161.2024.2379515>.
106. Zhai, H.; Huang, F.; Qi, H. Generating High Resolution LAI Based on a Modified FSDAF Model. *Remote Sens.* **2020**, *12*, 150. <https://doi.org/10.3390/rs12010150>.
107. Zheng, Y.; Wu, B.; Zhang, M.; Zeng, H. Crop Phenology Detection Using High Spatio-Temporal Resolution Data Fused from SPOT5 and MODIS Products. *Sensors* **2016**, *16*, 2099. <https://doi.org/10.3390/s16122099>.
108. Sun, L.; Gao, F.; Xie, D.; Anderson, M.; Chen, R.; Yang, Y.; Yang, Y.; Chen, Z. Reconstructing Daily 30 m NDVI over Complex Agricultural Landscapes Using a Crop Reference Curve Approach. *Remote Sens. Environ.* **2021**, *253*, 112156. <https://doi.org/10.1016/j.rse.2020.112156>.
109. Pető, J.; Hüvely, A.; Cserni, I. Investigation of Humus and Nitrate Content of Soil with Special Reference to the Nitrate Sensitivity. *Gradus* **2020**, *7*, 66–71. <https://doi.org/10.47833/2020.2.AGR.013>.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.