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Abstract:

Assessing crop condition and biomass throughout the growth period provides valuable insights into plant performance relative to optimal (stress free) growth conditions and supports precise agricultural management. In this study, biomass estimation was conducted using vegetation indices (LAI and CC) derived from both UAV (Unmanned Aerial Vehicle) and satellite based remote sensing in combination with the AquaCrop model. For this purpose, crop images were acquired with a digital camera under four different imaging setups during the growing season to determine field-scale canopy cover (CC). UAV imagery was also collected on the same dates at two flight altitudes (214 and 430 m). In addition, destructive plant sampling was carried out at 11 stages during the maize growing season to measure LAI and aboveground biomass. Evaluation of different canopy cover (CC) determination models showed that CC derived from GreenCrop Tracker (GCT) from bottom-up digital camera imagery without a fisheye lens (BU-NF) provided the most accurate farm yield estimation, with an error of 3.29%. GCT also demonstrated the best performance in determining CC at both UAV flight altitudes of 214 m and 430 m above ground level. Moreover, Sentinel-2, owing to its favourable spatial and temporal resolution, performed well in estimating LAI and daily maize biomass. In cases where Sentinel-2 imagery is unavailable, applying CC derived from GCT at 214 m UAV altitude or CC estimated by ENVI using top down imaging without a fisheye lens within AquaCrop is recommended for reliable biomass monitoring.

Keywords: LAI; Canopy Cover; Sentinel-2; Landsat; MODIS; Qazvin

1. Introduction

Maize is one of the world's most important crops, playing a key role in food production, livestock feed, bioenergy systems, and the pharmaceutical industry (Kazerooni et al., 2019). Based on reported statistics for 2023 to 2024, global maize cultivation exceeded 208.01 million hectares, with total production reaching 1,231.140 million tonnes (USDA Foreign Agricultural Service, 2026). Climatic parameters such as temperature and precipitation have a substantial impact on maize yield (Herrera et al., 2023; López Hernández et al., 2025). Given the importance of maize and its extensive cultivation worldwide, improving crop productivity under changing climatic conditions is a high priority. One approach to assessing crop status throughout the growing season, which enables timely fertilization, efficient irrigation, plant disease management to improve crop condition, and yield forecasting, is biomass estimation (Geng et al., 2021a). Estimating this index throughout the crop growth period enables the adoption of appropriate management practices to increase yield and improve crop condition (Y. Li et al., 2024).

Traditional approaches to crop biomass estimation have primarily relied on field measurements, typically involving destructive sampling, laboratory oven drying, and subsequent weighing. Given the workflow and steps involved in biomass estimation, monitoring it on a daily basis in the field is associated with substantial practical challenges. While this approach typically yields accurate estimates, its broader use is constrained by the need for skilled labour and the time-consuming nature of the procedures. Moreover, in large fields, limited sampling cannot adequately capture spatial variability and within-field heterogeneity across the entire farm (Geng et al.,

2021b; T. Wang et al., 2021). Therefore, there is a growing need to develop and improve indirect, farm scale methods for biomass estimation, which can support the wider adoption of smart and precision agriculture (T. Wang et al., 2021).

Various indirect approaches, including remote sensing techniques and crop growth models, have been developed for biomass estimation, each with distinct strengths and limitations. In particular, satellite observations have been regarded as a suitable tool for biomass monitoring, as they have provided valuable information on vegetation properties, have offered broad spatial coverage, and have enabled long-term time series analyses (Fang et al., 2019; Geng et al., 2021a). Several studies have demonstrated that crop growth and biomass can be estimated by establishing empirical relationships between satellite-derived vegetation indices and biomass (Dong et al., 2020a; L. Wang et al., 2018). Among the vegetation indices that have served as good proxies for crop condition in biomass estimation, leaf area index (LAI) and the normalized difference vegetation index (NDVI) can be highlighted (Petcu et al., 2003; Tian et al., 2020). It should be noted that the uncertainty level and accuracy of LAI estimation in these approaches have been of critical importance. Estimating LAI from satellite imagery has been subject to several limitations, including LAI underestimation due to the assumption of a random leaf distribution, errors in atmospheric correction, and residual cloud and aerosol contamination (Fang et al., 2019; Yan et al., 2019). Optical, LiDAR¹, and SAR² data, as well as hybrid approaches, have been considered promising tools for biomass estimation. However, their practical use has been constrained by cloud contamination in

¹ . Light Detection and Ranging

² . Synthetic Aperture Radar

optical sensors, limited spatial coverage for LiDAR acquisitions, signal saturation in SAR at high biomass levels, scale mismatches that introduce additional uncertainty, and the limited availability of field plots for data integration and validation (Ullah et al., 2025). Also, the application of Sentinel-2, particularly in heterogeneous environments, has faced serious limitations in biomass estimation and in capturing field-level details when multi-source data fusion has not been used (Feng, Yang, et al., 2025; Vajsová et al., 2020). In contrast, UAV³-based observations have been highly suitable for assessing field conditions and estimating biomass and vegetation indices, because they have provided much higher spatial resolution and have not been affected by cloud cover in the acquired imagery (Olson & Anderson, 2021). However, the solar illumination angle and the image acquisition time have needed to be carefully considered when using UAVs. Despite the advantages noted above, UAV applications have also been associated with several limitations, including high initial investment costs, short battery life, particularly for long duration flights, flight restrictions in certain areas, constraints on flight altitude, and the need for skilled operators (Agrawal & Arafat, 2024; Olson & Anderson, 2021). Crop growth models have also been recognized as effective tools for biomass estimation. Previous studies have indicated that the AquaCrop model has been able to simulate biomass with relatively good accuracy (Boudhina et al., 2019; X. L. Jin et al., 2014; Stričević et al., 2023). However, the large number of required input parameters, the uncertainty associated with estimating each parameter, and the need for calibration have increased the uncertainty of the biomass estimates produced by these models (Coudron et al., 2023).

³ .Unmanned Aerial Vehicle

Given the advantages and limitations of each approach, it has become clear that the strengths of different methods can be complementary. Therefore, multi-source data integration can be regarded as a promising strategy to improve biomass estimation accuracy. Several studies have been conducted on different data-integration (fusion) approaches. Dong et al. (2020b) showed that observation frequency substantially affects parameter-optimization uncertainty and, consequently, biomass estimation accuracy, and that this uncertainty can be reduced by jointly assimilating LAI and other variables from multi-source satellite data. Bahmanabadi et al. (2023) found that incorporating canopy cover (CC), derived from a relationship based on downscaled satellite LAI, into AquaCrop has improved the accuracy of biomass estimation. Panek-Chwastyk et al. (2024) showed that integrating field measurements with satellite data has enhanced the efficiency and accuracy of the AquaCrop model. One of the key parameters in AquaCrop, for which accurate estimation has a substantial influence on biomass and yield predictions, is canopy cover (CC)(Feng, Miao, et al., 2025; Luiz et al., 2022). Despite the importance of this parameter, some studies have either assumed CC to be equal to LAI or treated the CC reported by the model as the true value for implementation (Bahmanabadi et al., 2023; X. Jin et al., 2020). which has increased uncertainty in the resulting estimates. Contreras et al. (2025) have estimated canopy cover (CC) from satellite imagery through a processing chain and have examined whether CC can be used as a proxy for aboveground biomass. They have found that CC depends on canopy architecture, management practices, and the spatial distribution of biomass, and that, due to its high uncertainty, CC has not provided a reliable indicator of aboveground biomass. Pasetto et al. (2018) examined the use of remote sensing in combination with

crop models. Their results highlighted scale mismatches between remote sensing products and model requirements, gaps in remote sensing observations on specific days, and the need for daily inputs in models, which in turn have increased uncertainty in data integration and, in some cases, have led to misleading results. Shuai et al. (2024) have shown that NDVI and EVI saturation under dense canopies has reduced the reliability of LAI estimates, especially for maize, leading to larger errors in LAI–biomass relationships at high canopy density. Wu et al. (2023) also found that model–remote sensing (RS) integration has inherently faced challenges related to scale and field structure, because RS outputs represent pixel-averaged values over heterogeneous surfaces, whereas crop models typically assume spatial homogeneity. From the reviewed literature, it has become evident that, despite recent advances in integrating remote sensing with crop growth models, several factors have continued to increase error and uncertainty in field-scale biomass estimation. These include limited access to sufficient ground measurements such as LAI and or CC, the lack of calibration of model and satellite information against field data, and the use of satellite products whose spatial scale is not well matched to farm-level applications(Contreras et al., 2025; Panek-Chwastyk et al., 2024; Tewes et al., 2020). Despite these advances, farm-focused frameworks that systematically integrate multi-scale calibration of ground, UAV, and satellite data, and validate model outputs against an independent empirical reference, have remained limited. This gap has been particularly critical in heterogeneous fields and under limited availability of daily observations, where it has further amplified uncertainty in biomass estimation.

Therefore, the aim of this study is to develop and evaluate a farm-focused, multi-source integrated framework for daily estimation of maize biomass at the field scale. The innovation of this study lies in the systematic linkage of ground, UAV, and satellite data within a process-based model and the structured evaluation of its outputs. In this framework, calibrated canopy cover derived from UAV imagery is used as an input to the AquaCrop model, and model performance is evaluated using an independent biomass estimate based on calibrated satellite-derived LAI. This approach enabled the analysis of daily biomass dynamics and allowed the assessment of its sensitivity to different factors throughout the growing season.

2. Material and Methods

2.1 Study Area

Qazvin was one of the central provinces of Iran, located between the longitudes of 48°53' and 36°50' and the latitudes of 50°35' and 35°18'. The area of this province was 15,821 km². The annual air temperature in Qazvin has ranged between 42°C and -24°C. The average annual precipitation was 210 mm in the eastern parts and exceeded 510 mm in the northern highlands(Ahmadi et al., 2024). The present study was conducted on a 29 hectare farm located at 36°09'06.20" N latitude and 50°01'13.93" E longitude in Qazvin province in central of Iran (Figure 1). An analysis of meteorological data for the year 2024 indicated a dry climate based on the De Martonne Climate Classification Method for the study area.

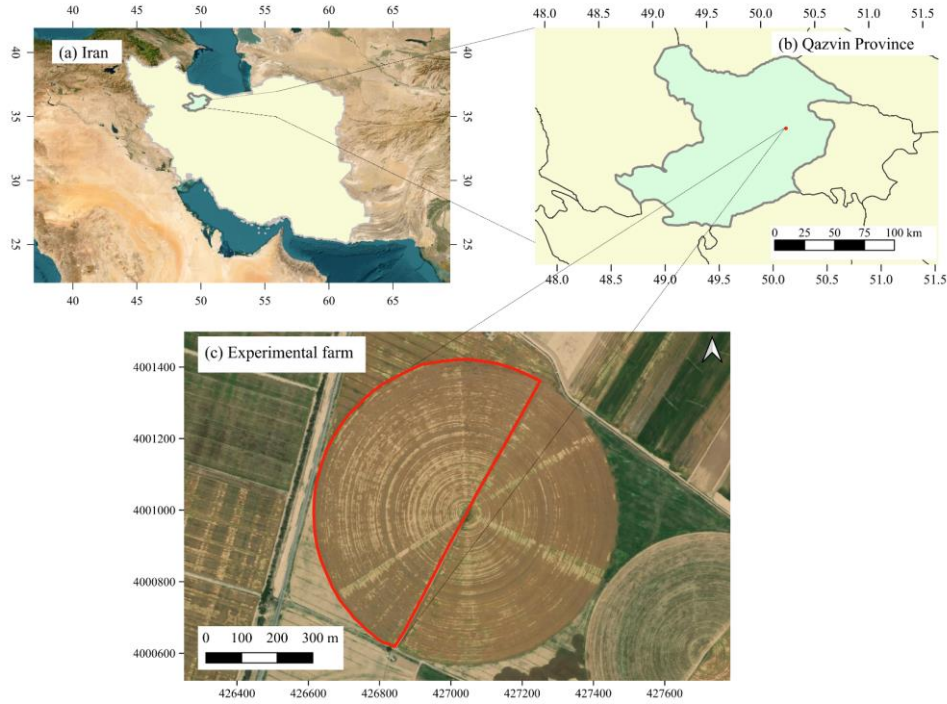


Figure 1. Location of the experimental farm within Qazvin Province, Iran

2.2 Field Data Collection

2.2.1 Imaging Methods

To increase the field of view in tall-stature crops such as maize, the use of fisheye lenses in vegetation imaging has become a common practice. Therefore, in this study, a fisheye lens was used for image acquisition with the camera (Figure 2). This lens, which was mounted on the phone's camera using a clip mechanism, allowed for imaging with a wide field of view (up to 180 degrees). In fact, this type of lens was used during the field monitoring period to increase the coverage of each image and due to its easy installation and high portability. The imaging modes used by the camera included: 1) Top-down without fisheye lens (TD-NF), 2) Top-down with fisheye lens (TD-F), 3) Bottom-up without fisheye lens (BU-NF), and 4) Bottom-up with fisheye lens (BU-F).

In top-down imaging, all photographs were consistently captured at a fixed distance of 50 cm above the plant canopy using the camera. Additionally, the bottom-up images were captured at a height of 5 cm above the ground surface. A 64-megapixel camera of the Xiaomi Redmi Note Pro phone was used for image acquisition. To cover the entire field, approximately 3 to 5 points were randomly selected each time for imaging, representing the whole field. As a result, 182 images of growing maize were obtained (Table1).

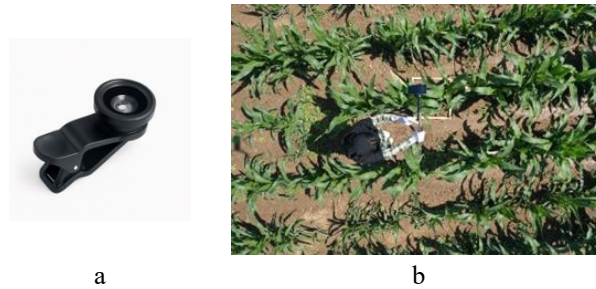


Figure 2.a) fisheye lens, b) Farm photography

Table 1. Dates of Field Imaging

Date	Day after growing	Top-down		Bottom-up	
		without fisheye lens	with fisheye lens	without fisheye lens	with fisheye lens
2023-06-22	17	☒	☒	☐	☐
2023-06-27	22	☒	☒	☐	☐
2023-07-06	31	☒	☒	☒	☒
2023-07-13	38	☒	☒	☒	☒
2023-07-18	44	☒	☒	☒	☒
2023-07-25	51	☒	☒	☒	☒
2023-08-01	58	☒	☒	☒	☒
2023-08-09	66	☒	☒	☒	☒
2023-08-20	77	☒	☒	☒	☒
2023-08-31	88	☒	☒	☒	☒
2023-09-05	93	☒	☒	☒	☒

2.2.2 UAV-based imaging

On the days of visiting the farm, the Mavic 2 Pro UAV also conducted photography at two altitudes of 214 and 430 meters above ground level. The Mavic 2 Pro UAV was designed and manufactured by the Chinese company DJI. It is equipped with a Complementary Metal-Oxide Semiconductor (CMOS) sensor, which offers high sensitivity and better performance under low-light conditions. The ISO range of the sensor is adjustable from 3200 to 12800. Additionally, the UAV's camera aperture is variable from f/2.8 to f/11, allowing for more precise exposure control. The pixel size of the imagery was 5 cm and 10 cm, respectively. Aerial imaging was conducted by the UAV on all farm visit dates (Table1). A total of 22 images were captured during the maize growth period at the two mentioned heights. To increase accuracy, an overlap of 75% was considered during the imaging of the field. Agisoft Metashape software was used to create a unified image and mosaic the photos (Figure 3).

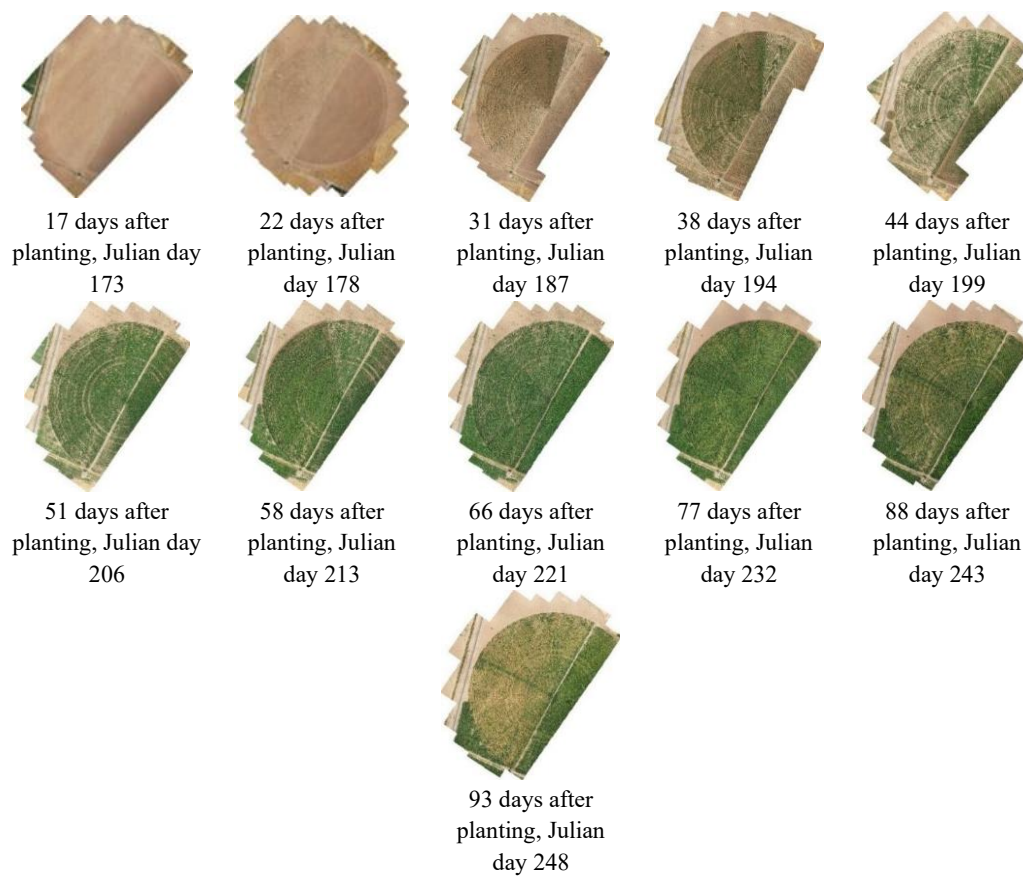


Figure 3.Changes in maize plant growth during the growth period (images captured at an altitude of 214 meters)

2.2.3 Field Measurement of Biomass and LAI

To determine the LAI of maize in the field, sampling began at the two-leaf stage and continued until harvest. On each sampling date, four points were randomly selected in the field. At each point, plants were sampled from an 80×80 cm area, and all leaves within this area were cut and collected. The leaf samples were then taken to the laboratory, where leaf area was measured using a Delta-T leaf area analysis system (Figure 4). LAI was finally calculated by dividing the total leaf area by the corresponding sampled ground area. Finally, the calculated LAI values were used as field-observed LAI and ground reference data for validation.



Figure 4. Leaf area was measured using the Delta-T leaf area meter

2.3 Determining CC

2.3.1 ENVI

The classification of the pixels that make up the images involves assigning each pixel to a specific class. In the ENVI software, image classification can be performed in two ways: unsupervised and supervised. In this study, supervised classification was used to determine CC. The selection of a specific classifier or decision rule depends on the nature of the input data and the desired output. The Maximum Likelihood classification approach was employed in this study (Partovi et al., 2025). After classification, the value of CC was estimated using the following equation:

$$CC = \frac{\text{The number of pixels related to the plant section}}{\text{The total pixels of the image}} \quad (1)$$

2.3.2 Canopeo

Canopeo is a digital, image-based software for measuring canopy cover, developed by

Oklahoma State University (Govindasamy et al., 2022). Canopeo analyzes and classifies all the pixels in an image. The analysis is based on selecting pixels according to the R/G and B/G ratios, as well as the Excess Green Index. The result of this analysis is a binary image, in which white pixels correspond to those that meet the selection criteria (green canopy cover), and black pixels represent those that do not meet the criteria (non-canopy areas). The fraction of green canopy cover ranges from 0 (no green canopy cover) to 1 (100% green canopy cover). The classification of canopy cover is based on the following criteria:

$$\frac{R}{G} < P_1 \text{ \textit{and} } \frac{B}{G} < P_2 \text{ \textit{and} } 2G - R - B > P_3 \quad (2)$$

P_1 and P_2 are typically assigned values close to 1 to classify pixels that primarily fall within the green band (500–570 nanometers). P_3 is a parameter that sets the minimum Excess Green Index and is usually given a value around 20 to identify green vegetation cover. The default parameter values for Canopeo are: $P_1 = 0.95$, $P_2 = 0.95$, and $P_3 = 20$ (Patrignani & Ochsner, 2015).

2.3.3 *GreenCrop Tracker*

The GreenCrop Tracker(GCT) software was developed by the Agriculture and Agri-Food Canada organization. It is an open-source licensed tool designed to assist researchers in processing color digital images to extract structural descriptors of agricultural crops, such as leaf area index (LAI) and green cover fraction in farmland. This tool was developed using the IDL Virtual Machine, which is freely available. GCT

can process both Nadir images (taken vertically above the ground) and images taken at a 57.5-degree angle, either upward- or downward-facing. The GCT model converts images into vegetative textures and empty spaces, and uses a histogram thresholding algorithm to distinguish between empty spaces and plant textures (Sandhu et al., 2019).

2.3.4 AquaCrop

The AquaCrop software is part of the Cropwat program, which was explained in FAO publication No. 33. AquaCrop simulates crop growth, development, and senescence using the CC. One of the key features of the AquaCrop model is that it uses green cover on the soil surface instead of the leaf area index. In this model, the growing degree day's index plays a crucial role, and rather than focusing on the relative yield reduction coefficient, the model emphasizes productivity indices. The value of CC in the AquaCrop model is simulated using three equations (FAO, 2012).

$$CC \leq CC_x/2 \rightarrow CC = CC_x \cdot e^{-tCGC} \quad (3)$$

$$CC > CC_x/2 \rightarrow CC = CC_x - 0.25 \frac{CC_x^2}{CC_0} e^{-tCGC} \quad (4)$$

$$CC = CC_x \left[1 - 0.05 \left(e^{\frac{CDC}{CC_x}} - 1 \right) \right] \quad (5)$$

CC: canopy cover at time t , CC_0 : initial canopy cover at time $t = 0$, CC_x : maximum canopy cover, CGC: canopy growth coefficient, CDC: coverage reduction factor and t : time (in growing degree days).

In the present study, the CC values obtained from the AquaCrop model were used to determine the standard CC in the field for comparing the results of different treatments. The findings indicate the model's capability in accurately estimating CC (Shan et al., 2022; Sodari et al., 2021; N. Wang et al., 2022).

2.4 LAI and Biomass Derivation from Satellite Data Using GEE⁴

To estimate LAI and biomass using satellite imagery, data from four satellites were used: MODIS, Landsat 8, Landsat 9, and Sentinel-2. The MODIS was designed as an instrument that could be used for comprehensive studies of the atmosphere and Earth's surface. This satellite had 36 spectral bands ranging from 0.4 μm to 14.4 μm . MODIS had low spatial resolution but offered good spectral and temporal resolution (MODIS, 2024). In this study, images captured by this satellite with a spatial resolution of 500 meters and daily temporal resolution were used.

Landsat 8 ensured continuous data acquisition and the availability of Landsat data through its two sensors: the Operational Land Imager (OLI) and the Thermal InfraRed Sensor (TIRS). These two sensors collected image data for nine shortwave bands and two thermal wavelength bands. Landsat 9 was fully similar in features to Landsat 8 and replaced Landsat 7. The temporal resolution of both Landsat 8 and Landsat 9 was 16 days, and when their images were used together, the temporal

⁴ Google Earth Engine

resolution improved to 8 days (NASA, 2024a, 2024b). Therefore, combined images from Landsat 8 and Landsat 9 with a spatial resolution of 30 meters and a temporal resolution of 8 days were used in this study.

The Sentinel-2 satellite captured 13 bands in the visible, near-infrared, and shortwave infrared regions of the electromagnetic spectrum at three spatial resolutions of 10, 20, and 60 meters with 12-bit radiometric resolution. It provided global and systematic coverage of the Earth's surface from 56 degrees south to 48 degrees north latitude, including coastal waters and all parts of the Mediterranean Sea. The images provided by the Sentinel-2 mission included data captured by the Sentinel-2A and Sentinel-2B satellites, each with a temporal resolution of 10 days. The combined use of these images improved the temporal resolution to 5 days (ESA, 2024). In this study, Sentinel-2 satellite images with a spatial resolution of 10 meters and a temporal resolution of 5 days were used.

2.4.1 GEE

Google Earth Engine (GEE) was a cloud-based geospatial analysis platform that provided access to satellite imagery and geospatial datasets along with powerful computational resources for large scale monitoring and analysis. GEE was used for a wide range of applications, including land cover classification, deforestation monitoring, hydrological modeling, and climate change studies. Therefore, LAI was estimated during the maize growing period using satellite imagery in the GEE environment based on the following equations.

$$LAI = -\ln \frac{\frac{3,8 - SAVI}{3,66}}{0,018} \quad (6)$$

$$LAI = 3,618 \times EVI - 0,118 \quad (7)$$

where SAVI was the Soil Adjusted Vegetation Index accounting for soil effects, and EVI was the Enhanced Vegetation Index.

Additionally, after determining the relationship between biomass and the LAI obtained in the field, biomass was also estimated in the GEE environment.

2.5 Statistical evaluation

To evaluate and select the best method for determining CC and other research steps, the following statistical indices were also used: root mean square error (RMSE), correlation coefficient (R), normalized root mean square error (NRMSE), mean absolute error (MAE), and Relative Bias (RBIAS).

Table 2. The statistical indicators employed for the evaluation of the results

Indicator	Estimation Method	Description
RMSE	$\sqrt{\frac{1}{N} \sum_{i=1}^N (G_i - R_i)^2}$	(Hyndman & Koehler, 2006)
NRMSE	$\frac{RMSE}{\bar{G}}$	

R^2	$1 - \frac{\sum_{i=1}^n (G_i - R_i)^2}{\sum_{i=1}^n (G_i - \bar{G})^2}$	(Zhang et al., 2025)
MAE	$\frac{1}{N} \sum_{i=1}^N (G_i - R_i)$	(Willmott & Matsuura, 2005)
RBIAS	$\frac{\sum_{i=1}^N (\bar{G} - G_i)}{\sum_{i=1}^N G_i} \times 100$	(D. N. Moriasi et al., 2007)
CC^{*5}	$\frac{\sum_{i=1}^n (G_i - \bar{G}) \sum_{i=1}^n (G_i - R_i)}{\sqrt{\sum_{i=1}^n (G_i - \bar{G})^2} \sqrt{\sum_{i=1}^n (G_i - R_i)^2}}$	(Zhang et al., 2025)
NSE	$1 - \frac{\sum_{i=1}^n (G_i - R_i)^2}{\sum_{i=1}^n (G_i - \bar{G})^2}$	(Melsen et al., 2025)

G_i : the observed (ground truth) value of the parameter of interest; R_i : the simulated value of the parameter; $\bar{G}$: the mean of the observed values; $\bar{R}$: the mean of the simulated values; and N : the number of data points.

3. Result and Discussion

3.1 CC Determination and Maize Yield Estimation (Camera)

The results obtained from classification using the three models, ENVI, Canopeo, and GreenCrop Tracker, based on the image captured by the camera 66 days after planting, are presented in Figure 5. Based on Figure 5 and visual evaluation, it can be observed that all three models were capable of effectively identifying the plant section. The ENVI model did not directly report the CC value. But, the CC value was obtained directly from the other two models.

⁵ . Correlation Coefficient

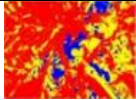
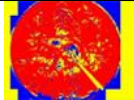
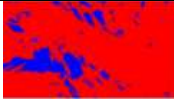
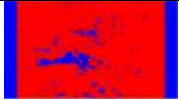
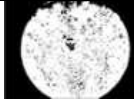
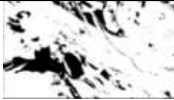
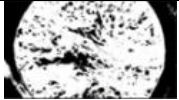
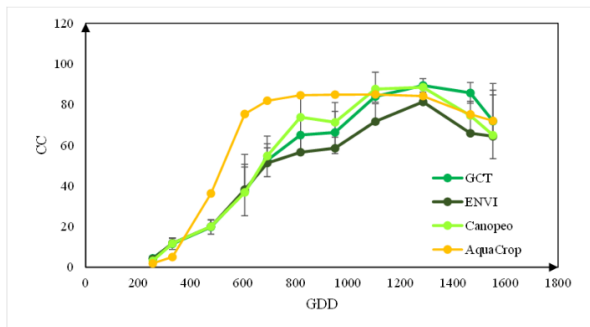
Imaging mode	TD-NF	TD-F	BU-NF	BU-F
Before classification				
ENVI				
	<ul style="list-style-type: none"> 0: Unclassified 1: Other 2: Soil 3: Plant 		<ul style="list-style-type: none"> 0: Unclassified 1: Sky 2: Plant 	
Canopeo				
GCT				

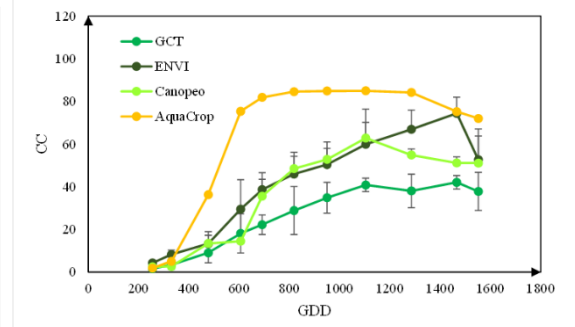
Figure 5. Visual evaluation of image classification with different models (66 days after planting).

After determining CC using different models from the images obtained by the camera, the trend of CC variations was plotted in comparison with the CC changes derived from AquaCrop against the growing degree days (GDD) (Figure 6). Since 3 to 5 images were obtained during each field visit, the SD (Standard deviation) value for each data point was also presented in the SD variation charts for each model. An increase in SD at each point indicated non-uniform crop growth in the studied field. One of the possible reasons for this could be the non-uniform irrigation in the field. A decrease in the uniformity of water distribution has led to reduced crop growth and yield (Nascimento et al., 2019).

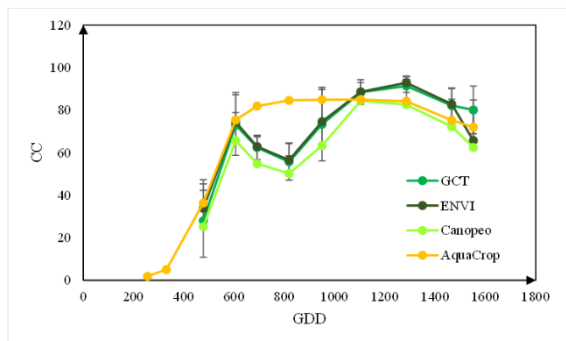
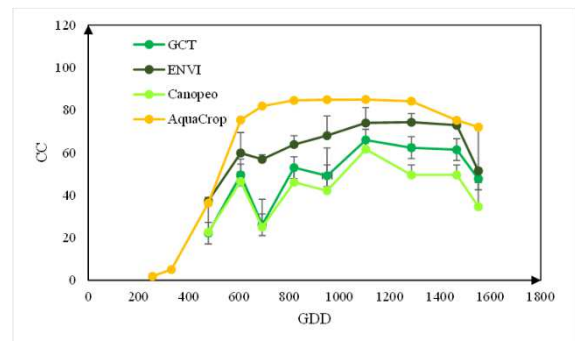
Based on the chart obtained from AquaCrop, it was observed that the changes in CC corresponded to the growth stages of maize. The CC value was at a minimum at the beginning of the growth, then increased with a slope, reaching its maximum during the plant's maturity phase. Overall, in all cases, the trend of CC changes was similar to the CC changes obtained from AquaCrop. However, the alignment of CC obtained from the top-down images, both with and without a fisheye lens, was the highest compared to other imaging methods (Figure 6.a,b). Based on Fig 6.b, it can be observed that the top-down imaging with a lens resulted in a higher overestimation compared to other methods. One of the reasons for this could have been the increased field of view, which in turn led to an increase in the number of pixels unrelated to the plant (such as soil, operator, etc.). In the bottom-up images, the fluctuations in CC were significant (Figure 6.c,d). Due to the presence of the sun in the sky, some of the pixels in the bottom-up images were lost. This issue led to a decrease in the plant pixels relative to the total pixels in the image. As a result, the CC value experienced fluctuations and a decrease.



a



b



c

d

Figure 6. Analysis of CC variations during the maize growth period based on imaging methods: a) TD-NF, b) TD-F, c) BU-NF, and d) BU-F

After determining the CC value from the images obtained by the camera, the AquaCrop model was applied to estimate the yield at the field level using the CC values and farm information. The maize yield in the farm under study at the time of the present research was 63 ton.ha⁻¹. Based on the yield obtained from the plant model, the error percentage was estimated for different CC determination conditions (Figure 7). In GCT, the BU-NF imaging method resulted in the lowest error percentage (3.29%). The application of CC obtained from the BU-NF in the ENVI model resulted in the minimum error percentage when using this model (Error =2.10%). Canopeo performed well in TD-NF. The error percentage in yield estimation in this case, compared to the farm, was 6.31%. Although the results of the study conducted by Shepherd et al. (2018) on soybeans highlighted the capability and speed of the Canopeo model in determining canopy cover, our findings demonstrated the superior performance of ENVI and GCT. The maximum error percentages were obtained by applying the CC derived from the GCT and Canopeo models using the TD-F and BU-F imaging methods, respectively, and were 41.07% and 22.98%. Overall, the TD-NF and BU-NF imaging methods were found to provide the best performance in determining CC.

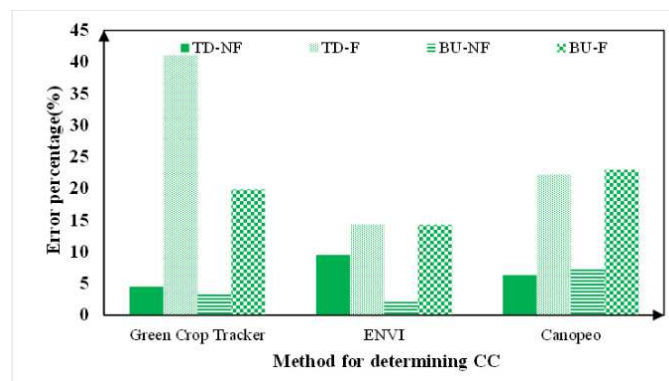
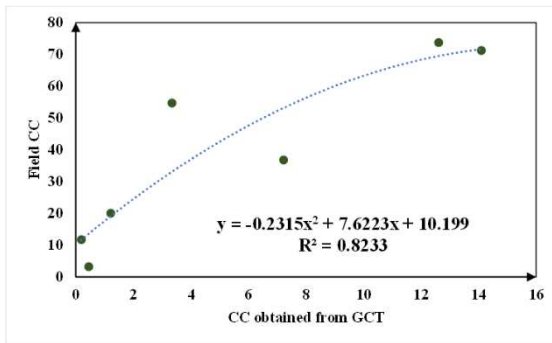


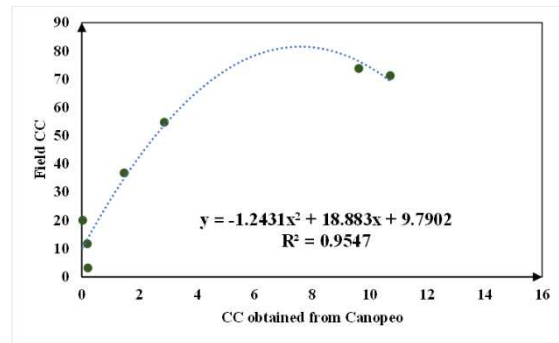
Figure 7. The error percentage in yield estimation by the AquaCrop model under the application of CC obtained from the camera images

3.2 CC Determination and Maize Yield Estimation (UAV)

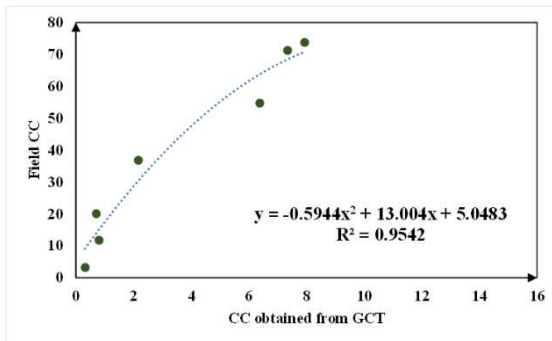
Considering the imaging orientation of the UAV and the low error percentage in farm yield estimation by AquaCrop when using TD-NF images in GCT, the CC obtained from this method was used to calibrate the UAV derived CC. As shown in Figure 8, the relationship between ground CC and the CC obtained from UAV images at two altitudes, 214 and 430 m above ground level, followed a second-order polynomial function. At the altitude of 214 m, the correlation coefficient between the UAV-derived CC from Canopeo and the ground CC was at its highest value ($R^2=0.95$). However, at the altitude of 430 m, the coefficient of determination (R^2) obtained from GCT was 0.95, which was the highest among all methods.



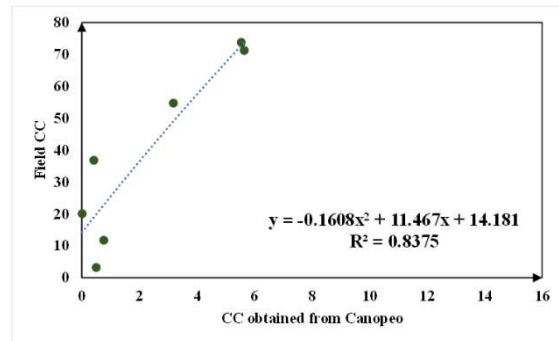
a



b



c



d

Figure 8. Calibration of UAV-derived CC using field camera-derived CC: a,b) 214 m and c,d) 430 m above ground level

A 1:1 line was plotted to validate the accuracy of the developed relationships (Figure 9). As shown in Figure 9.a, the data points estimated by the GCT are well aligned with the 1:1 line, suggesting that the method provides highly accurate estimations. The values obtained from the GCT and Canopeo, after calibration, tended to underestimate compared to field measured values. This is because most of the data points were positioned above the 1:1 line. Given the close proximity of the data points, it can be concluded that the calibration was performed effectively and the results are acceptable.

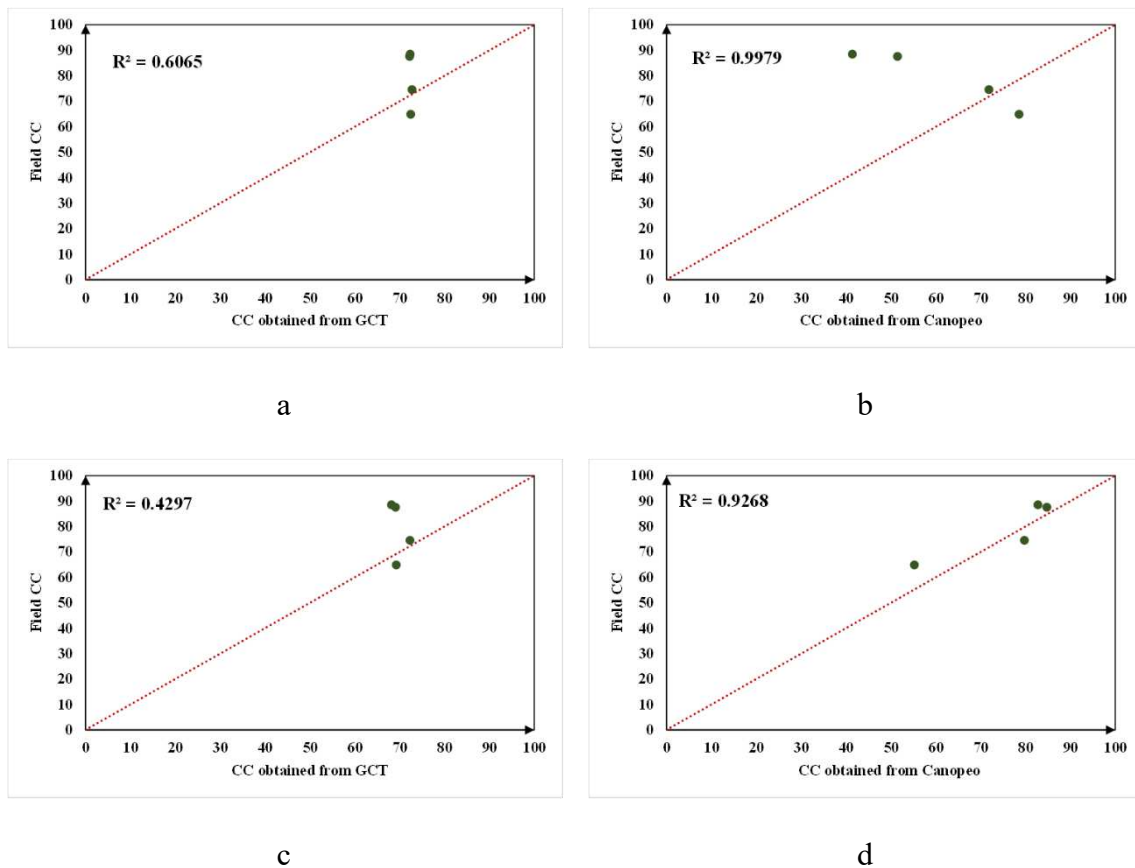


Figure 9. Validation of the calibration of UAV-derived CC: a,b) 214 m and c,d) 430 m above ground level

After calibrating the UAV derived CC, the trend of CC variation throughout the maize growth period was plotted. At both flight altitudes, the trend of CC variation observed

from UAV imagery was consistent with the CC pattern simulated by the AquaCrop model. The results obtained from the study conducted by Shu et al. (2023) also indicated the satisfactory performance of UAV derived images in determining canopy coverage. Initially, CC was low, then increased steadily with plant growth, reached its peak at maximum development, and subsequently declined at a defined rate (Figure 10). In the CC estimated from UAV acquired images, discontinuities were observed in the CC estimation curve. One of the reasons for the overestimation or underestimation of the CC obtained from the UAV compared to AquaCrop can be attributed to the inconsistency in the imaging range at each stage of the imaging process. This issue has led to a reduction in the number of pixels related to the farm under study compared to the total pixels of the image, resulting in the underestimation of the CC. On the other hand, the presence of green pixels related to other lands in UAV image has also led to the overestimation of the CC at certain times.

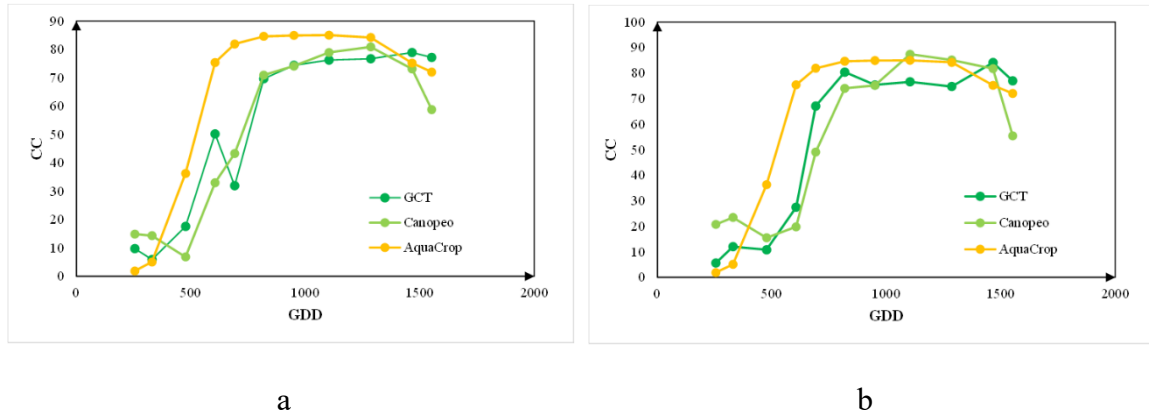


Figure 10. Analysis of CC variations during the maize growth period of UAV: a) 214m and b)430 m above ground level

By incorporating the CC obtained from the UAV images into the AquaCrop model, the farm's yield was estimated (Figure 11). The AquaCrop model achieved minimum yield estimation errors of 9.50% and 5.73% using CC from Canopeo processed images at altitudes of 214 m and 430 m, respectively. Overall, considering the low error

percentage, it can be inferred that the application of CC obtained from the UAV has improved the yield estimation of maize. The study conducted by García-Martínez et al. (2020) demonstrated a strong correlation between the canopy cover estimated from UAV images and maize yield ($R^2 = 0.77$). Similarly, the study conducted by (Guo et al., 2024) showed that the use of UAV (especially those equipped with various sensors) was effective for determining vegetation indices to predict maize yield.

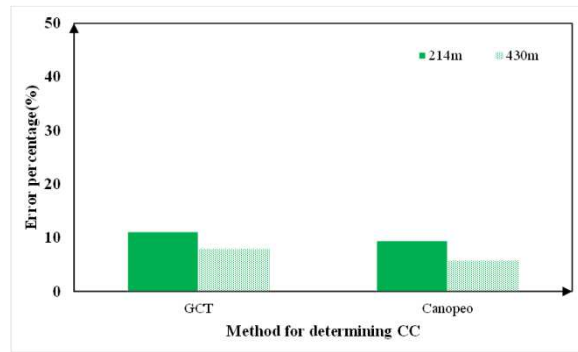


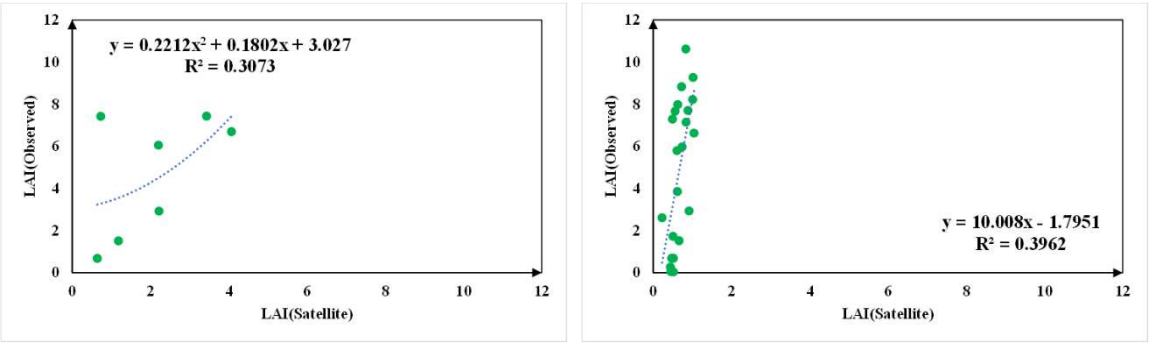
Figure 11. The error percentage in yield estimation by the AquaCrop model under the application of CC obtained from the UAV

3.3 LAI Estimation Using GEE

After determining LAI using Equ.6 and 7, satellite LAI calibration was performed with 70 percent of the field estimated LAI data. Validation was carried out using the remaining 30 percent of the data. The correlation coefficient of the fitted relationship between LAI from Equation 6 (derived from MODIS satellite images) and field measured LAI was low (Figure 12.a) ($R^2 = 0.30$). The correlation coefficient between LAI obtained by applying Equ.7 to MODIS satellite images and field measured LAI was also low. Therefore, the relationship between MODIS derived LAI and field measured LAI was not significant. The LAI obtained by applying Equ.6 to Landsat satellite images showed higher correlation with field measured LAI compared to MODIS derived LAI ($R^2 = 0.58$) (Figure 12.c). While the LAI derived from Equ.7 also showed low correlation at this stage ($R^2 = 0.47$) (Figure 12.d). However, the LAI

estimated from Sentinel-2 satellite imagery demonstrated strong correlation with field-measured LAI (Figure 12.e,f). The stronger performance of Sentinel-2 is likely related to its higher spatial resolution and the presence of red-edge bands. These bands are not available in the same way in Landsat and MODIS, and they are particularly useful for capturing changes in canopy structure and vegetation condition. This can improve the estimation of LAI. Another possible reason is the difference in spatial scale between field measurements and satellite pixels. This effect is more pronounced for Landsat and especially MODIS, because their coarser pixels may include not only crop canopy but also bare soil, field edges, or other surrounding features. Such mixed-pixel effects can weaken the relationship between satellite-derived LAI and field-measured LAI.

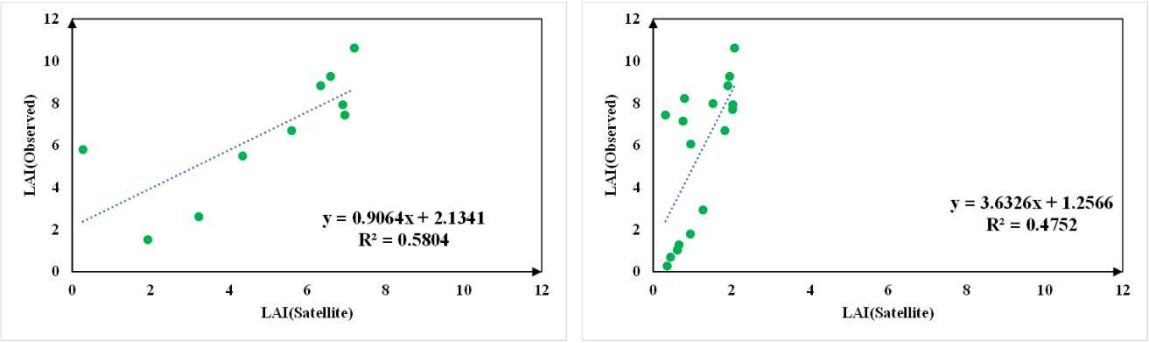
MODIS



a

b

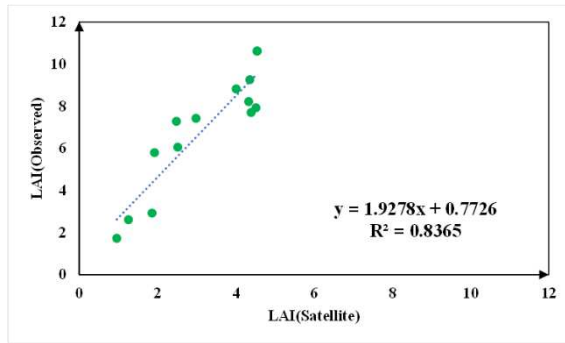
Landsat



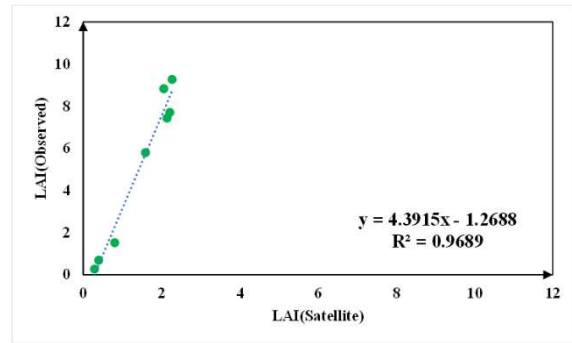
c

d

Sentinel-2



e

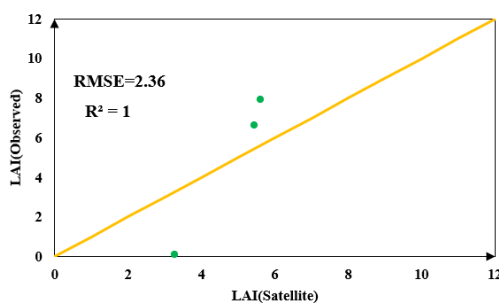


f

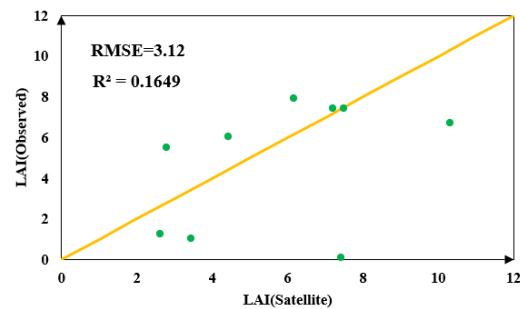
Figure 12. Calibration of LAI Derived from Satellites Images: a,c,e) LAI from Equ.6,
b,d,f) LAI from Equ.7

The validation of the relationships presented in Figure 12 indicated higher accuracy and better performance of the Sentinel satellite in estimating LAI (Figure 13). The minimum RMSE value related to the comparison of LAI obtained by applying Equ.7 to Sentinel satellite images was 0.77 (Figure 13.f). The maximum RMSE (RMSE=3.12) value was obtained by applying Equation 7 to MODIS satellite images (Figure 13.b). The scatter of points relative to the bisector line indicated the accuracy of the calibration relationships. Points below the bisector line indicated overestimation of satellite derived LAI, while points above the bisector line indicated underestimation of satellite derived LAI. The distance of the points from the bisector line in LAI estimation using Sentinel satellite images was smaller compared to the other two satellites.

MODIS

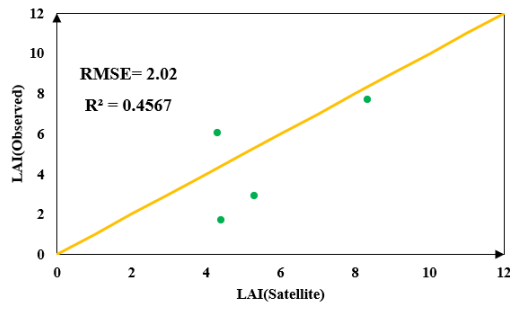


a

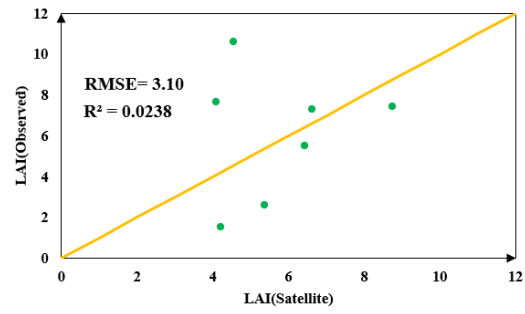


b

Landsat

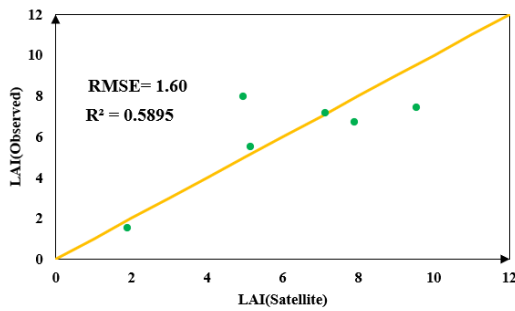


c

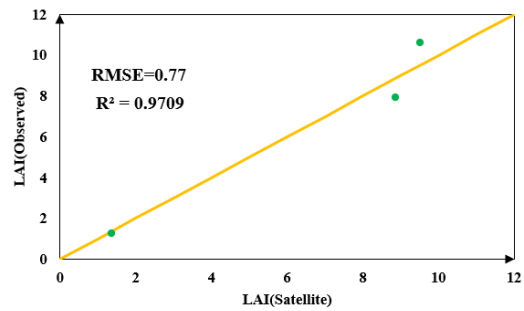


d

Sentinel-2



e



f

Figure 13. Validation of LAI derived from Satellites Images: a,c,e) LAI from Equation 6, b,d,f) LAI from Equation7

3.4 Daily Biomass Estimation Using GEE

Using 70 percent of the field derived LAI and biomass data (170 observations), a relationship was established between LAI and daily maize biomass (Figure 14.a). The correlation between biomass and LAI was high ($R^2=0.80$). Based on the relationship and the R^2 value, higher LAI values were generally associated with higher biomass. In the validation, biomass was estimated from the relationship between LAI and biomass using 30% of the field measured LAI data (73 observations) (Figure 14.b). Then, the estimated biomass was compared with the field measured biomass. The maximum observed biomass suggests that the error magnitude is relatively low in relation to the total biomass range (RMSE=13.4 ton/ha). Moreover, the data points were well

distributed along the bisector line, indicating a high level of accuracy in the established relationship.

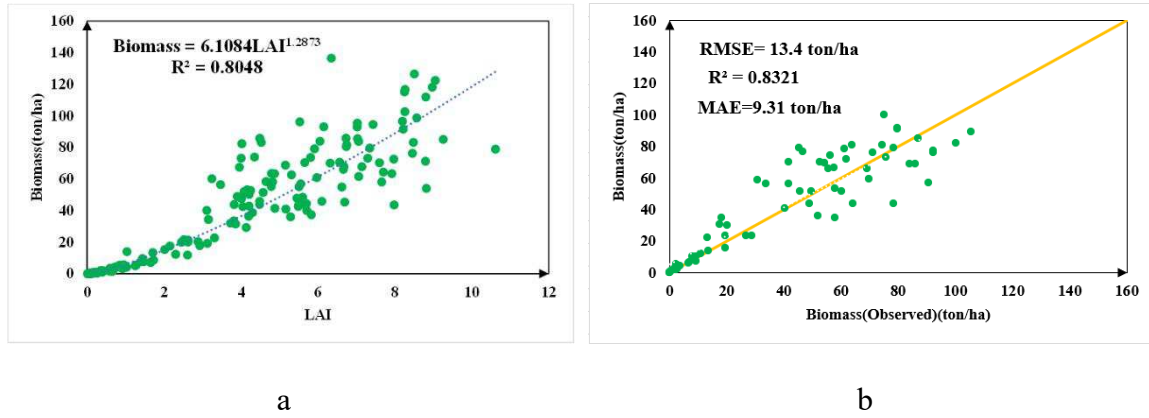


Figure 14. Calibration and Validation of the Relationship Between Field Biomass and LAI

After applying the relationship between biomass and LAI in the GEE, the biomass values were estimated using MODIS, Landsat, and Sentinel-2 satellite images. Subsequently, the biomass obtained by applying different CC (Canopy Cover) in the AquaCrop model was statistically compared with the satellite derived biomass on a daily time scale. Comparison of AquaCrop derived biomass using different CCs with MODIS derived biomass (Table3). A strong correlation was found between the biomass estimated by AquaCrop under various conditions and the MODIS derived biomass ($CC^*=0.78$). RMSE was used as an indicator to evaluate the accuracy of the model in estimation and simulation. The comparison between AquaCrop derived biomass and MODIS data revealed that the application of CC obtained from the GCT model using TD-F imagery resulted in the lowest RMSE (8.47 ton/ha), whereas applying the CC estimated by the ENVI model (BU-NF) led to the highest RMSE (18 ton/ha). The application of CC derived from TD-NF and BU-NF resulted in NRMSE values greater than 1, indicating substantial deviations between AquaCrop estimated biomass and MODIS data, and suggesting that the biomass estimated by AquaCrop under these

conditions was unreliable. The comparison between MAE and RMSE revealed a considerable difference between the two indices in some cases, which indicates the presence of outliers and substantial errors under those conditions. Except when the CC derived from GCT (TD-F) was applied for biomass simulation in AquaCrop (RBIAS= -7.74%), the model generally overestimated biomass compared to MODIS in all other cases (RBIAS>0). In all cases, the NSE values were below zero, which indicates that the AquaCrop model performed poorly relative to MODIS. Overall, when all statistical indices were taken into account, the CC derived from Canopeo (TD-F) was found to provide the best performance relative to the other scenarios. It should be noted that, despite the daily temporal resolution of MODIS imagery, its performance in estimating LAI was suboptimal (Fig. 12), and thus it cannot serve as a suitable benchmark for evaluating AquaCrop performance. However, various studies have indicated good performance of MODIS in biomass estimation when combining NDVI and LSWI data (Zheng et al., 2016). Additionally, when using the extreme gradient boosting (XGBoost) algorithm for seasonal maize biomass estimation, data from MODIS demonstrated satisfactory performance (Geng et al., 2021c).

The analysis of Table 4 revealed a moderate correlation between AquaCrop derived biomass and Landsat derived biomass ($CC^*=0.50$). In all cases, the RMSE values were found to be higher compared to those of MODIS. The lowest RMSE value (23.29 ton/ha) was achieved through the application of CC derived from ENVI (BU-F). The NRMSE values ranged from 70% to 80%, suggesting that, across all scenarios, the model error was equivalent to about 70–80% of the mean data value, indicating that this magnitude of error is substantial. In some cases, such as when the CC derived from Canopeo (BU-NF) was applied, the difference between MAE and RMSE was large, indicating the presence of outliers and substantial errors. In all scenarios, AquaCrop

consistently underestimated biomass relative to the Landsat derived estimates (RBIAS<0). The NSE index was also less than 0 in all cases, indicating the poor performance of AquaCrop in estimating biomass compared to Landsat. When all statistical indices were taken into account, the biomass derived from ENVI (BU-NF) provided the best performance in comparison with Landsat.

Table 3. Statistical comparison of AquaCrop-estimated biomass (using CC from various methods) with MODIS-derived biomass

Statistical index							
Imaging method	Model	CC*	RMSE(ton/ha)	NRMSE(%)	MAE(ton/ha)	RBIAS(%)	NSE
TD-NF	GCT	0.78	17.28	111	11.44	46.99	-2.58
	ENVI	0.78	15.82	102	5.78	39.44	-2.00
	Canopeo	0.78	16.75	108	4.08	44.23	-2.37
TD-F	GCT	0.78	8.47	54	7.54	-7.74	0.14
	ENVI	0.78	14.48	93	4.17	32.32	-1.51
	Canopeo	0.78	12.34	79	4.17	20.25	-0.83
BU-NF	GCT	0.78	17.64	113	4.28	48.81	-2.73
	ENVI	0.78	18.00	116	4.02	50.62	-2.89
	Canopeo	0.78	16.41	105	3.04	42.41	-2.23
BU-F	GCT	0.78	12.94	83	3.52	23.72	-1.01
	ENVI	0.78	14.49	93	2.82	32.35	-1.52
	Canopeo	0.78	12.14	78	3.47	19.08	-0.77

Table 4. Statistical comparison of AquaCrop-estimated biomass (using CC from various methods) with Landsat- derived biomass

Statistical index							
Imaging method	Model	CC*	RMSE(ton/ha)	NRMSE(%)	MAE(ton/ha)	RBIAS(%)	NSE
TD-NF	GCT	0.50	23.35	74	19.57	-20.99	-0.04
	ENVI	0.50	23.26	74	10.46	-25.06	-0.03
	Canopeo	0.50	23.31	74	6.96	-22.48	-0.04
TD-F	GCT	0.50	25.50	81	11.54	-50.50	-0.24
	ENVI	0.50	23.29	74	6.45	-28.90	-0.04
	Canopeo	0.50	23.63	75	6.42	-35.41	-0.07
BU-NF	GCT	0.50	23.39	74	5.65	-20.01	-0.04
	ENVI	0.50	23.43	74	5.21	-19.04	-0.05
	Canopeo	0.50	23.30	74	4.20	-23.46	-0.04
BU-F	GCT	0.50	23.51	74	4.94	-33.45	-0.06

ENVI	0.50	23.29	74	3.95	-28.89	-0.04
Canopeo	0.50	23.68	75	4.73	-36.04	-0.07

The statistical indices comparing the biomass estimated by AquaCrop under different conditions with the biomass derived from Sentinel-2 are presented in Table 5. The correlation coefficient between the biomass estimated by AquaCrop and that derived from Sentinel-2 increased compared to the other two satellites ($CC^*=0.85$). Consequently, a strong correlation was found between AquaCrop estimated biomass and Sentinel-2 derived biomass. Given the maximum biomass of 105 ton/ha, the RMSE was considered acceptable. Based on the fluctuation of NRMSE, errors equivalent to 40–50% of the mean value of the data were observed. Applying CC obtained from images captured in TD- F, BU-NF, and BU-F led to MAE values exceeding RMSE, suggesting a low dispersion of errors. The range of RBIAS values was reduced. With the exception of the case where CC from ENVI (BU-NF) was applied in the AquaCrop model, biomass was underestimated in all other scenarios. The NSE index was greater than 0 in all cases, indicating the good performance of AquaCrop in biomass estimation. In other words, given the pronounced fluctuations in biomass throughout the growth period, the AquaCrop model was able to accurately reproduce these variations in comparison with Sentinel-2. When all statistical indices were taken into account, the AquaCrop model achieved its best biomass estimation performance with the application of CC derived from ENVI (TD-NF).

In addition to the biomass obtained by applying CC derived from camera based imaging, the biomass obtained by applying CC from the UAV in AquaCrop was also statistically evaluated (Table 6). Similar to the previous section, the highest correlation (0.85) was observed between AquaCrop estimated biomass and Sentinel-2-derived biomass, whereas the lowest correlation (0.50) was obtained with Landsat. The

comparison of biomass estimated by AquaCrop using UAV derived CC revealed that both RMSE and NRMSE reached their lowest values with Sentinel-2, compared to the other satellites. A considerable difference between MAE and RMSE was observed for UAV derived biomass when compared with MODIS and Landsat, suggesting the presence of outliers and significant errors in these datasets. Biomass estimated using CC derived from UAV imagery exhibited substantial overestimation relative to MODIS, considerable underestimation relative to Landsat, and closer agreement with Sentinel-2. These deviations were identified through the examination of RBIAS values. The NSE value exceeded zero only in the comparison between UAV derived biomass and Sentinel-2, which, given its range, reflected the good performance of AquaCrop in biomass estimation when using CC derived from UAV imagery relative to Sentinel-2. When all statistical indices were considered, biomass estimated with CC derived from the GCT model at both UAV flight altitudes demonstrated the highest level of agreement with Sentinel-2 derived biomass.

Table 5. Statistical comparison of AquaCrop-estimated biomass (using CC from various methods) with Sentinel-2-derived biomass

		Statistical index					
Imaging method	Model	CC*	RMSE(ton/ha)	NRMSE(%)	MAE(ton/ha)	RBIAS(%)	NSE
TD-NF	GCT	0.85	11.48	45	8.09	-1.34	0.56
	ENVI	0.85	10.95	43	9.44	-6.41	0.60
	Canopeo	0.85	11.26	44	9.41	-3.20	0.58
TD-F	GCT	0.85	13.46	53	37.17	-38.10	0.40
	ENVI	0.85	10.67	42	20.82	-11.20	0.62
	Canopeo	0.85	10.81	42	27.24	-19.30	0.61
BU-NF	GCT	0.85	11.64	46	28.17	-0.12	0.55
	ENVI	0.85	11.81	46	30.32	1.09	0.54
	Canopeo	0.85	11.15	44	26.35	-4.42	0.59
BU-F	GCT	0.85	10.71	42	38.01	-16.98	0.62
	ENVI	0.85	10.68	42	32.04	-11.18	0.62
	Canopeo	0.85	10.86	43	45.69	-20.09	0.61

Table 6. Statistical comparison of AquaCrop-estimated biomass using UAV -derived CC with satellite-derived biomass

			Statistical index					
	Imaging height	Model	CC*	RMSE(ton/ha)	NRMSE(%)	MAE(ton/ha)	RBIAS(%)	NSE
MODIS	214m	GCT	0.78	15.41	99	2.60	37.37	- 1.85
		Canopeo	0.78	15.82	102	2.32	39.44	- 2.00
	430m	GCT	0.78	16.33	105	2.58	42.21	- 2.20
		Canopeo	0.78	16.93	109	2.53	45.20	- 2.44
Landsat	214m	GCT	0.50	23.23	73	3.51	-26.18	- 0.03
		Canopeo	0.50	23.26	74	3.10	-25.06	- 0.03
	430m	GCT	0.50	23.25	74	3.38	-23.57	- 0.03
		Canopeo	0.50	23.31	74	3.23	-21.96	- 0.04
Sentinel-2	214m	GCT	0.85	10.80	42	34.26	-7.81	0.61
		Canopeo	0.85	11.07	43	35.99	-4.56	0.59
	430m	GCT	0.85	10.95	43	35.09	-6.41	0.60
		Canopeo	0.85	11.32	44	40.31	-2.55	0.57

To facilitate the comparison between the selected methods for biomass estimation by AquaCrop and the satellites, a heatmap was plotted (Figure 15). For the statistical indices RMSE, NRMSE, and MAE, lower values indicate better performance, while for RBIAS and NSE, the optimal values are 0 and 1, respectively. Among the methods where CC was derived from camera based imagery, AquaCrop estimated biomass achieved the best agreement with Sentinel-2 biomass when CC from ENVI (TD-NF) was used. AquaCrop estimated biomass achieved the highest agreement with Sentinel 2 biomass when CC derived from the UAV image captured at 214 m altitude using the GCT method was applied. The LAI estimated by the Sentinel-2 satellite showed higher accuracy compared to that of the Landsat and MODIS satellites (Figure 12). Since biomass was estimated based on LAI values, the accuracy of biomass estimation using Sentinel-2 was higher compared to the other two satellites. This is due to the better

spatial and temporal resolution of Sentinel-2 compared to the other two satellites. Other studies conducted on the assessment of maize performance and biomass using Sentinel-2 satellite images also demonstrated the high potential of this satellite (C. Li et al., 2022; Soccolini & Vizzari, 2023)

Comparing biomass estimated by applying UAV derived CC with biomass estimated by satellite indicates that applying UAV based CC reduces error. Therefore, UAV imagery resulted in an accurate estimation of biomass using the crop model. The study conducted by Han et al. (2019) demonstrated the capability of UAV remote sensing in estimating maize biomass using the random forest algorithm. Similarly, the results of the study on wheat biomass estimation from UAV RGB images using the random forest algorithm demonstrated high estimation accuracy(Zhai et al., 2023).

	Methods	RMSE(ton/ha)	NRMSE(%)	MAE(ton/ha)	RBIAS(%)	NSE	
Camera	TD-F, Canopeo (MODIS)	12.34	61.96	3.79	20.25	-0.83	Max
	BU-NF, ENVI (Landsat)	23.43	35.68	5.21	-19.04	-0.05	
	TD-NF, ENVI (Sentinel_2)	10.95	22.04	9.44	-6.41	0.6	
Drone	214m, GCT(MODIS)	15.41	57.01	2.6	37.37	-1.58	Min
	214m, Canopeo(Landsat)	23.26	35.4	3.1	-25.06	-0.03	
	214m, GCT(Sentinel_2)	10.8	21.75	34.26	-7.81	0.61	

Figure 15. Heatmap of statistical indices used to identify the best-performing method

4. Conclusions

Nowadays, determining the vegetation indices of agricultural crops at different growth stages is recognized as a vital resource for large scale monitoring of agricultural fields, compared to field observations. Using these indices, assessing the status of a farm becomes significantly easier. Additionally, this data can also be used for predicting crop yield. Indeed, accurate biomass estimation is essential for assessing plant growth. These insights provide farmers and decisionmakers with accurate and timely spatial data. One of these indices is the plant canopy cover. Accurate determination of this index makes it

possible to estimate maize yield with high precision using a crop modelling approach. Therefore, one of the objectives of this study was to determine CC using three software tools, GCT, ENVI, and Canopeo, based on images captured by camera and UAV (at two altitudes of 214 and 430 m) in the field, and to estimate performance using the AquaCrop model. Additionally, the limited spatial and temporal resolution of satellite images restricts their capability for accurate biomass estimation. Whereas the use of UAV remote sensing can overcome these limitations. Therefore, another objective of this study was to evaluate the feasibility of estimating biomass and LAI using remote sensing.

The results indicated the satisfactory capability of all three software tools in determining CC from the images captured at the farm level. However, the error percentage between the yields indicated the high accuracy of CC determination by GCT from images captured from a BU-NF by the camera (Error = 3.29%). In the images captured by the UAV, the application of CC obtained from GCT at 214 m and 430 m altitudes provided the most accurate estimation of farm yield. However, overall, it can be inferred that, given the possibility of comprehensive and integrated monitoring of the entire land in the images captured by the UAV, its use in the maximum growth stages for CC and, consequently, farm performance is recommended for large fields. Despite the daily temporal resolution of MODIS satellite images, its spatial resolution of 500 meters resulted in low accuracy in LAI estimation (RMSE for SAVI = 2.36; for EVI = 3.12). With improved spatial resolution, Landsat showed better performance in LAI estimation (RMSE for SAVI = 2.02; for EVI = 3.10). However, the best LAI estimation was achieved by Sentinel-2 (RMSE for SAVI = 1.60; for EVI = 0.77). Therefore, Sentinel-2 showed high potential in estimating daily biomass based on LAI. The error in biomass estimated by AquaCrop compared to Sentinel-2 was at its

minimum, and the best biomass estimation by the AquaCrop model was achieved when CC derived from UAV images captured at an altitude of 214 m (GCT) was applied (CC*=0.85, RMSE=10.8 ton/ha, NRMSE=42%, MAE= 34.26 ton/ha, RBIAS= -7.81%, and NSE= 0.61).

Building on the strong performance of Sentinel-2, future research should investigate the downscaling of Sentinel-2 imagery using UAV data to further enhance precision agriculture and improve the accuracy of vegetation index and biomass estimations at finer spatial scales.

Declaration

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Conflicts of interest/Competing interests

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Authors' contributions

Zahra Partovi: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing - Original Draft, Visualization; **Abbas Kaviani:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing - Review & Editing, Visualization, Supervision; **Hadi Ramezani:** Conceptualization, Methodology, Validation, Formal analysis, Supervision; **Masoud Soltani:** Methodology, Investigation, Resources, Data Curation; **Leila Khosravi:** Methodology, Investigation, Resources, Data Curation.

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