



OPEN Water status and plant traits of dry bean assessment using integrated spectral reflectance and RGB image indices with artificial intelligence

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This study investigated the potential of using remote sensing indices with artificial neural networks (ANNs) to quantify the responses of dry bean plants to water stress. Two field experiments were conducted with three irrigation regimes: 100% (B100), 75% (B75), and 50% (B50) of the full irrigation requirements. Various measured parameters including, wet biomass (WB), dry biomass (DB), canopy moisture content (CMC), soil plant analysis development (SPAD), and soil water content (SWC) as well as seed yield (SY) were evaluated. The results showed that the highest values for WB, DB, CMC, SWC, and SY were achieved under B100, while the highest SPAD values were achieved under B75. The study also found that most of the RGB image indices (RGBIs) and spectral reflectance indices (SRIs) exhibited a linear relationship with the measured parameters and SY, with R^2 values ranging from 0.34 to 0.95. In contrast, SPAD showed a significant quadratic relationship, with R^2 values ranging from 0.34 to 0.79. Additionally, the newly developed SRIs demonstrated 5–40% higher correlations compared to the best-performing published SRIs across all measured parameters and SY. ANNs using RGBIs and SRIs separately demonstrated high prediction accuracy with R^2 values ranging from 0.79 to 0.97 and 0.86 to 0.97, respectively. Combining the RGBIs and SRIs, the ANNs achieved higher prediction accuracy, with R^2 values ranging from 0.88 to 0.99 across different parameters. In conclusion, this study demonstrates the effectiveness of using SRIs and RGBIs with ANNs as practical tools for managing the growth and production of dry bean crops under deficit irrigation.

Keywords Deficit irrigation, Precision agriculture, RGB color indices, Hyperspectral reflectance, Machine learning

The challenge of water scarcity poses a significant barrier to sustainable agriculture in arid regions, particularly in the face of rapid climate changes¹. Projections indicate a potential 20% increase in global water scarcity because of profound climate shifts. Notably, around 80% of farmlands in dry regions such as Egypt heavily rely on irrigation, drawing from 85% of the area's freshwater resources². Projections indicate that Egypt is on course to surpass the critical threshold of absolute water scarcity (500 m³/capita per year) by the year 2025³. With escalating competition for water, up to 40% of available water may need to be redistributed across sectors, with agriculture facing a disproportionate impact due to its substantial water demands. The threat of limited irrigation water jeopardizes future food security on a global scale, highlighting the pressing need for water-efficient strategies that optimize crop yields per unit of irrigation water, as opposed to per unit of land⁴.

In 2022, dry bean cultivation areas in Egypt spanned approximately 43,816 hectares, yielding 159.42 thousand tons⁵. The growth and development of dry bean plants are significantly influenced by minor errors in irrigation management. These errors typically include inaccuracies in the amount of water applied or failure to align irrigation schedules with critical growth stages. Such mistakes can disrupt crops by inducing water stress⁶. Many studies highlight the dangers of exposing crops to water stress, especially during critical growth

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stages such as flower development. The flower development is highly sensitive to water stress, which impairs nutrient transport and weakens growth. This stress can trigger flower drop, disrupt pollination, and hinder pod formation ultimately reducing yield potential^{7–11}. These negative effects also affect yield quantity, ranging from 10 to 50%, depending on the crop type, severity of water stress, and the growth stage affected. Hence, precise irrigation water management is crucial to optimize yield of dry bean crops when facing water stress scenarios¹².

Deficit irrigation is a strategic approach that involves applying less water than the crop's full requirement. This method aims to conserve water resources while minimizing potential yield losses¹³. Plant parameters such as wet and dry matter, plant moisture content, and SPAD as well as crop yield play a crucial role in effectively implementing deficit irrigation strategies. These parameters are commonly employed to assess crop conditions during water scarcity¹⁴. Nevertheless, the effective application of these parameters relies on consistent monitoring and precise evaluation of its reactions to water shortages at frequent intervals. By doing so, farmers can identify sustainable threshold levels of water stress that crops can tolerate without significant yield loss and adjust irrigation schedules to maintain optimal plant health and productivity¹⁵. Typically, conventional methods for evaluating these plant parameters are time-consuming, costly, labor-intensive, and data collected often lack spatial representativeness, failing to capture the overall status of crop populations comprehensively^{16–21}. However, SRIs often yield inconsistent results when estimating crop parameters under diverse environmental and spatial conditions. Developing optimal SRIs is crucial to ensure the efficacy of this rapid and straightforward method in accurately estimating plant parameters. Generally, previous research has primarily focused on using published SRIs to evaluate various plant characteristics. This study's advantage lies in selecting the best two-band SRIs through the creation of 2D contour maps, providing a robust method for choosing the best effective SRIs in evaluating the plant parameters.

Digital cameras are valuable instruments for proximal sensors, enabling the assessment of diverse plant parameters during water scarcity²². These cameras utilize sensors to photograph images of the plant within the visible wavelength range, focusing on wavelengths roughly between 400 and 499 nm for blue, 500–549 nm for green, and 550–750 nm for red regions. By analyzing data from these regions, numerous indices can be generated. These indices provide ample information for estimating various plant parameters affected by different stresses, encompassing both biotic and abiotic factors²³. Interestingly, plant parameters that are difficult to accurately assess visually can be easily distinguished by examining the variations in reflectance within RGB images²⁴. For instance, Elsayed et al.²⁵ demonstrated that RGB images of the plant canopy can effectively track WB, DB, CMC, and yield of potato plants to gauge its response to water deficit stress. This tool offers a cost-effective means to capture images of numerous plants and extract various plant traits with minimal effort. However, the widespread adoption of RGB images for estimating plant parameters has been limited. Only a few studies have utilized RGB image analysis to assess how different morpho-physiological parameters and dry bean plant yields respond to varying levels of irrigation, especially in dry environments.

Data obtained from proximal sensors often lacks specificity and can result in significant overlap, necessitating careful handling. In recent years, a range of ANNs has emerged as reliable and precise solutions to tackle this challenge. ANNs are intricate mapping structures inspired by the complex workings of the human brain²⁶, adept at learning and formulating mathematical models. These networks have demonstrated their efficacy in various real-world scenarios²⁷, notably in agriculture, where they develop models rooted in intrinsic variable relationships, thereby circumventing the necessity for prior expertise²⁸. Neural network models have been extensively employed in predicting a range of crop parameters, encompassing growth, yield, and other biophysical phenomena in various vegetable crops^{29–33}. For example, Dutta Gupta and Pattanayak³⁴ utilized digital images of potato leaves to estimate chlorophyll content. Their study demonstrated that the ANN model showed superior performance with an R^2 compared to the linear model's R^2 of 0.41. Sarkar et al.³⁵ employed ANNs to estimate peanut plant growth and pod yield based on RGBs combinations. Their models achieved high predictive accuracy, with R^2 values exceeding 0.95.

To the best of our knowledge, little research has utilized ANNs with spectral reflectance indices (SRIs) or RGB imaging indices (RGBIs) to construct innovative and robust models for accurately estimating and monitoring the measured parameters, including wet biomass (WB), dry biomass (DB), canopy moisture content (CMC), relative chlorophyll content (SPAD), and soil water content (SWC), as well as seed yield (SY) of dry bean crops under varying irrigation regimes. In the context, the study aims to achieve the following objectives: (i) Quantify the measured parameters and SY of dry bean crop under deficit irrigation; (ii) extract the optimized newly developed two-band SRIs for estimating measured parameters and SY of dry bean crop using the 2D contour maps; (iii) Evaluate the effectiveness of both RGBIs and SRIs as non-destructive techniques for estimating the measured parameters and SY of dry bean crop; and (iv) Assess the performance of ANN models, which are based on published and newly developed SRIs as well as RGBIs, in predicting the measured parameters and SY of dry bean crop.

Materials and methods

Experimental site, conditions, and design

Field experiments were conducted at a private farm in Talkha, Dakahlia Governorate, Egypt, during the consecutive spring growing seasons of 2022 and 2023 (located at 31.09° N, 31.38° E, and an elevation of 17 m). The NASA POWER Data Access Viewer website, available at <https://power.larc.nasa.gov/data-access-viewer/>, supplied daily data on maximum and minimum temperatures, average air humidity, average wind speed, and rainfall to gather precise meteorological information for the experimental site³⁶. In the first and second seasons, the average daily minimum temperatures were recorded at 9.3 °C and 7.2 °C, respectively, while the average daily maximum temperatures stood at 46.1 °C and 42.3 °C. Relative humidity ranged from 35 to 79.3% in the first season and from 25.9 to 68.5% in the second season. Notably, Fig. 1 illustrates the daily rainfall during the growth period for both seasons. The cumulative rainfall was 20 mm and 24.2 mm for the first and second

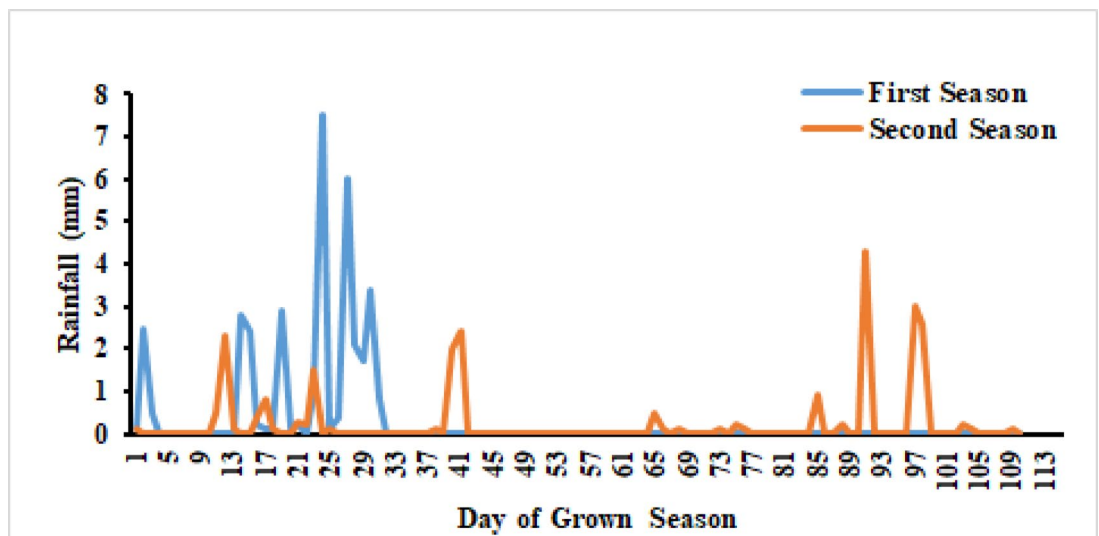


Fig. 1. Daily rainfall during the growth period for both seasons.

seasons, respectively. The soil in the experimental area was classified as sandy clay, with the irrigation water exhibiting a pH of 7.21 and an electrical conductivity of 0.83 dS/m.

The tested dry bean (Giza-6 cultivar) seeds were obtained from Field Crops Research Institute, Agricultural Research Center, Giza, Egypt. On February 23 of the first season and March 3 of the second season, six seeds were manually placed inside two hills on either side of each dripper. After two weeks, the number of plants on each hill was reduced to two plants. In the first season, harvesting was done on June 12; in the second season, it was done on June 20. The fertilizer requirements were satisfied by adhering to the guidelines provided by the Egyptian Ministry of Agriculture. A venturi-type injector was used to apply fertilizers through the drip irrigation networks, guaranteeing accurate and effective nutrient delivery to the plants. Phosphorus (P) was supplied to the dry bean crops in the form of phosphoric acid (85% P_2O_5), 205 kg/ha of nitrogen (N) in the form of urea (46.5% N), and 96 kg/ha of potassium (K) in the form of potassium sulphate (50% K_2O).

The dry bean plants were irrigated using a drip irrigation network, as shown in Fig. 2. The irrigation network consists of several components in the control head including an 80 mm-diameter centrifugal water pump that can deliver water at a rate of 1050 L/min and with 4.8 hp. In order to remove impurities, a disk filter was included. Pressure gauge allowed for monitoring the irrigation network's pressure. Venturi-type injectors were used to inject water-soluble nutrients into the irrigation network. Control valves were used to manage the irrigation processes. Bypass valve was served to control pressure in a system by diverting a portion of the flow. Polyethylene (P.E.) pipes with a 75 mm diameter make up the main line, and P.E. pipes with a 63 mm diameter make up the sub-main. Lateral lines have built-in emitters and are made of P.E. with a 16 mm diameter. At an operating pressure of 1 bar, these emitters typically discharge 6 L/hr. T-shaped plastic valves with a 16 mm diameter were positioned at the start of each lateral line to independently regulate the irrigation depth for each line. These valves made it possible to precisely modify the irrigation depth in accordance with the intended irrigation schedules. Each lateral was closed with an end cap at the end. A drip irrigation network was built and tested before being used at the experimental site. The system's estimated distribution uniformity (DU) is 92%. Equation 1, as explained by Ella et al.³⁷, was used to calculate the DU.

$$DU = \frac{\text{average of the lowest quartile}}{\text{the average of all readings}} * 100\% \quad (1)$$

Irrigation water requirements and regimes

Following Gabr et al.³⁸ recommendations, the CROWAT model used the “FAO Penman-Monteith” to calculate the daily reference evapotranspiration (ET_o). The crop coefficient (K_c) unique to each growth stage was multiplied by the ET_o to determine the crop evapotranspiration (ET_c). The growth stages of the dry bean crop are classified as initial (20 days), developmental (30 days), mid (40 days), and harvest (20 days), according to³⁹. The corresponding K_c for each growth stage were 0.35, 0.75, 1.1, and 0.5, respectively, according to⁴⁰.

Dry bean crops were subjected to three different irrigation regimes: 100% (B100), 75% (B75), and 50% (B50) of the full irrigation requirements. The CROWAT program was employed to determine the irrigation scheduling in both seasons, as shown in Figs. 3 and 4. Prior to implementing the different irrigation regimes, uniform water depths of 46.2 mm in the first season and 66.9 mm in the second season were applied during the initial 20-day period to ensure seedling survival. In the first season of 2022, the total gross depths throughout the growing season were 331.15 mm, 473.63 mm, and 616.1 mm, corresponding to B50, B75, and B100, respectively, with a total of 18 irrigation events. In the second season of 2023, the total gross depths added during the growing season were 366 mm, 515.55 mm, and 665.1 mm for B50, B75, and B100, respectively, with 19 irrigation events. Irrigation was halted 15 days before harvesting to allow for proper crop maturation in both seasons. To reduce

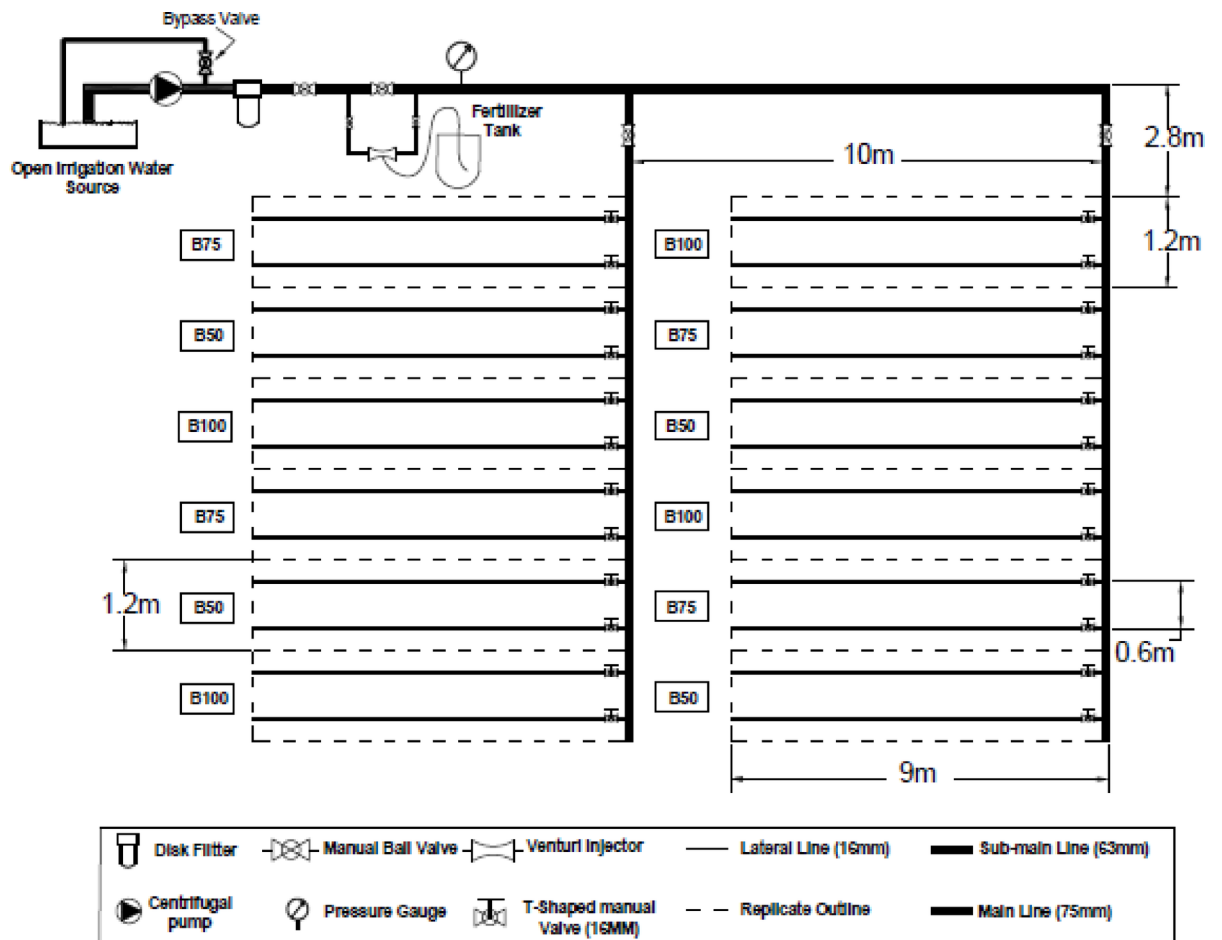


Fig. 2. The layout of experimental design for the different irrigation regimes.

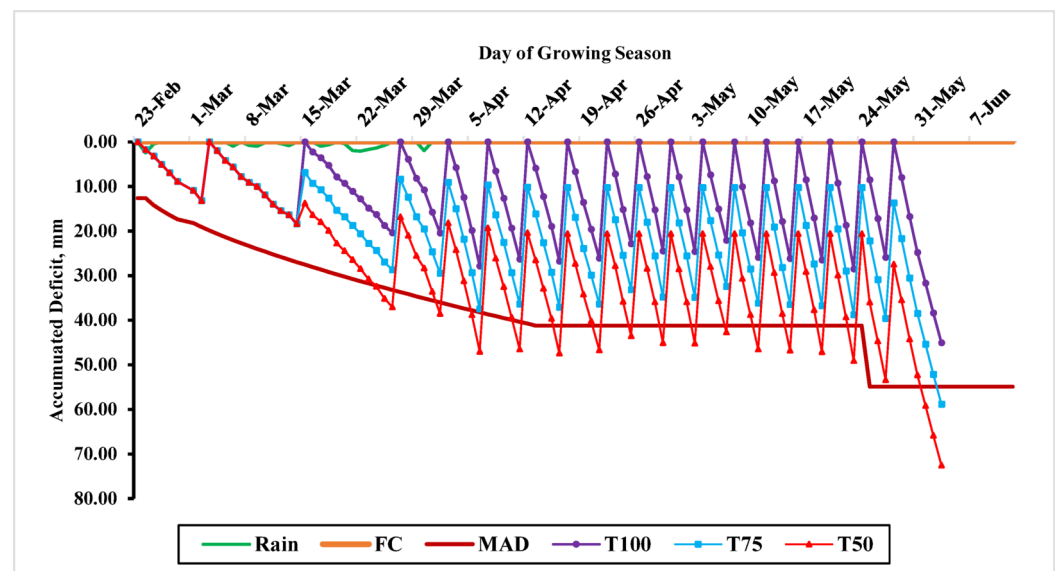


Fig. 3. Irrigation scheduling during season 2022 at different irrigation regimes.

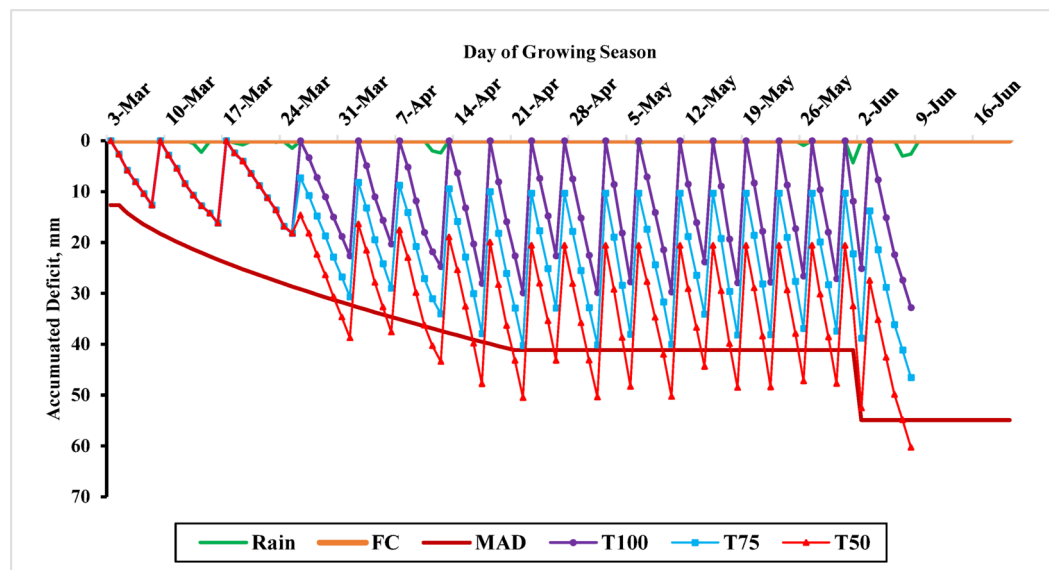


Fig. 4. Irrigation scheduling for during season 2023 at different irrigation regimes.

spatial variations, a randomized, complete block experimental design with four-replicate was used. Two P.E. lateral lines made up each replicate. With emitters spaced 0.30 m apart, each lateral line was 9.0 m long. The lateral lines were separated by 0.60 m. The area of each replicate was 10.8 m².

Ground based-remote sensing techniques

The canopy spectral reflectance and the RGB digital image were captured from the same selected plant. To guarantee that the measured parameters and SY of dry bean can be linked to the vegetation indices that were computed from the canopy spectral reflectance and RGB digital image. The measurements were taken at 67 DAS for the first season and 68 DAS for the second season, which corresponds to the flowering growth stage.

Spectral reflectance measurements

The spectral reflectance of dry bean canopies was measured using a passive reflectance sensor called HandySpec Field[®] (tec5, Oberursel, Germany). The sensor's bandwidth was 2 nm, and its spectral range was 302 to 1148 nm. There were two units in the sensor. The first unit was used as a reference signal to measure the incident light radiation and was attached to a diffuser. The second unit measured the plant canopy's reflectance using a fiber optic. A calibration factor based on a grey reference standard was used to adjust the canopy reflectance. Data such as rows, reflectance spectra, integration time, and file name assignments were automatically saved by the instrument.

The detector was held vertically at a height of about 80 cm above the plants, creating a sensing area of about 20 cm², in order to reduce the impact of the soil background. This configuration was put into place in accordance with⁴¹ methodology. The majority of the spectral measurements were made between 11:00 and 13:00 when there were no clouds. As used in a related study by Zhao et al.⁴², this guaranteed that the plants would receive the maximum amount of solar intensity from direct sunlight. Furthermore, as recommended by Dobos et al.⁴³, this time period was selected to reduce the impact of air humidity. Following the methodology of⁴⁴, three scans were measured and averaged for each plant to represent its spectral characteristics.

The lattice package (R Foundation for Statistical Computing, 2013) in R statistics v.3.0.2 was used to create various 2D contour maps. The most efficient spectral reflectance indices (SRIs) were found by contour map analysis for all dual wave-length combinations between 302 nm and 1148 nm. These SRIs are mathematical formulas that provide information about particular plant characteristics by combining wavelengths as a ratio spectral index. The contour map analysis in this study yielded the mean R² of the SRIs with comparable wavelengths, which includes data pertinent to the dry bean crops' WB, DB, CMC, SPAD, SY, and SWC. Table 1 listed the formulas and relevant references for newly developed SRIs. Also, Table 2 listed the formulas and relevant references for some widely published SRIs.

Digital RGB imaging

The study captured images of bean plant canopies in different treatments using a 14-megapixel digital camera (SM-A035 F/DS, Galaxy A03) between 11:00 and 13:00. The camera, equipped to take 8-bit RGB pictures ranging from 0.4 to 0.7 micrometers with a resolution of 3120 × 4160 pixels, was manually operated in a vertical downward position at an 80 cm distance from the plants, ensuring measurement consistency without flash usage. The resulting images, saved in JPG format, underwent analysis through the OpenCV library and Python software (Version 3.11).

During the feature extraction process, depicted in Fig. 5, image segmentation and extraction techniques were employed to eliminate disturbances from non-canopy elements like soil, weeds, and straw that occasionally

SRI	Formula	References
SRI _{574, 1134}	$\frac{R_{574}}{R_{1134}}$	Current work
SRI _{580, 1130}	$\frac{R_{580}}{R_{1130}}$	Current work
SRI _{586, 1130}	$\frac{R_{586}}{R_{1130}}$	Current work
SRI _{636, 630}	$\frac{R_{636}}{R_{630}}$	Current work
SRI _{642, 632}	$\frac{R_{642}}{R_{632}}$	Current work
SRI _{648, 622}	$\frac{R_{648}}{R_{622}}$	Current work
SRI _{662, 610}	$\frac{R_{662}}{R_{610}}$	Current work
SRI _{970, 946}	$\frac{R_{970}}{R_{946}}$	Current work
SRI _{1104, 710}	$\frac{R_{1104}}{R_{710}}$	Current work
SRI _{1120, 1142}	$\frac{R_{1120}}{R_{1142}}$	Current work

Table 1. Newly developed SRIs with its formulas and relevant references used in this study. Where R indicates the reflectance at corresponding wavelength, nm.

SRI	Formula	References
Normalized water index 1 (NWI-1)	$\frac{(R_{970} - R_{900})}{(R_{970} + R_{900})}$	45
Normalized water index 3 (NWI-3)	$\frac{(R_{970} - R_{880})}{(R_{970} + R_{880})}$	46
Normalized water index 4 (NWI-4)	$\frac{(R_{970} - R_{920})}{(R_{970} + R_{920})}$	47
Normalized water index 5 (NWI-5)	$\frac{(R_{970} - R_{910})}{(R_{970} + R_{910})}$	48
Normalized water index 6 (NWI-6)	$\frac{(R_{780} - R_{670})}{(R_{780} + R_{670})}$	49
Normalized difference index NDI _{570, 540}	$\frac{(R_{570} - R_{540})}{(R_{570} + R_{540})}$	50
Normalized difference index NDI _{686, 620}	$\frac{(R_{686} - R_{620})}{(R_{686} + R_{620})}$	50
Anthocyanin index (NAI)	$\frac{(R_{760} - R_{720})}{(R_{760} + R_{720})}$	51
NDI _{780, 550}	$\frac{(R_{780} - R_{550})}{(R_{780} + R_{550})}$	47
NDI _{800, 670}	$\frac{(R_{800} - R_{670})}{(R_{800} + R_{670})}$	52
Pigment-Sensitive Ripening Monitoring Index (PRMI)	$\frac{(R_{750} - R_{678})}{R_{550}}$	53
Water Index (WI)	$\frac{R_{900}}{R_{970}}$	54

Table 2. Widely published SRIs with its formulas and relevant references used in this study. Where R indicates the reflectance at corresponding wavelength, nm.

appeared in the images. The vegetation extraction image processing pipeline involved creating red (R), green (G), and blue (B) channels from the original image. According to⁵⁵, Color Index of Vegetation Extraction (CIVE), a vegetation index derived from variations in the G, B, and R channels, facilitated vegetation area identification within the image. Subsequently, the CIVE image underwent Otsu thresholding, separating it into background and foreground (vegetation) areas based on pixel intensity distributions⁵⁶. Through this process, the vegetation areas were successfully isolated, and the original image was masked using the binary image from the Otsu thresholding, retaining only the vegetation-associated regions. This segmented image provided crucial information for analyzing the distribution and characteristics of vegetation in the scene. Finally, various RGB image indices (RGBIs) of the segmented image were calculated, with each pixel in an RGB digital image represented by values corresponding to the R, G, and B channels, as outlined by Kumaseh et al.⁵⁷.

The mean values of RGB channels are extracted as sample features using the following equations:

$$R = \frac{1}{S_{\text{num}}} \sum_{i=1}^{S_{\text{num}}} R_i \quad (2)$$

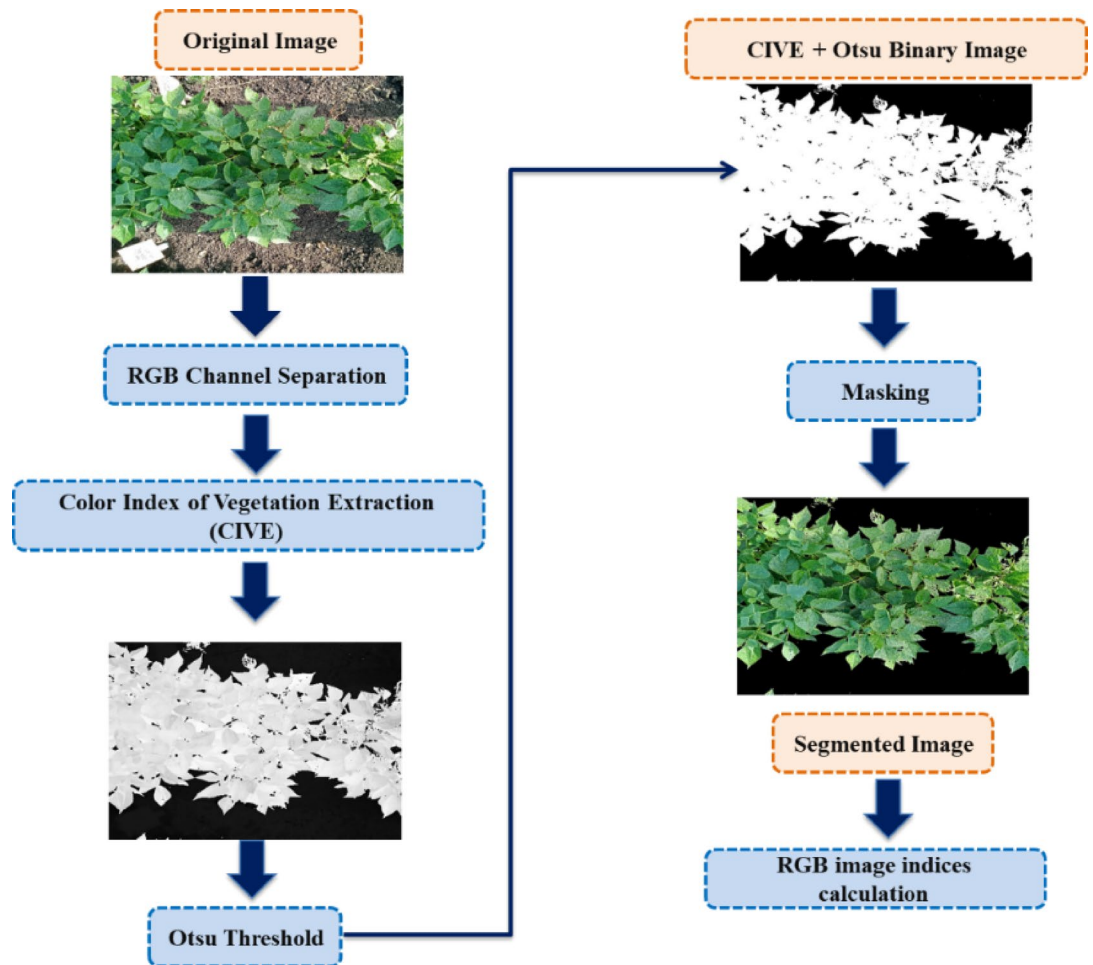


Fig. 5. Image processing pipeline for vegetation extraction.

$$G = \frac{1}{S_{\text{num}}} \sum_{i=1}^{S_{\text{num}}} G_i \quad (3)$$

$$B = \frac{1}{S_{\text{num}}} \sum_{i=1}^{S_{\text{num}}} B_i \quad (4)$$

where R_i , G_i , and B_i are the pixel values for the red, green, and blue channels in the segmented image respectively; i represents the first pixel and S_{num} indicates the maximum number of pixels; Additionally, R , G , and B represent the mean values of the red, green, and blue channels, respectively. The formulas and references of the twenty RGBIs were calculated in this study are detailed in Table 3.

Measured parameters

Following the capture of RGB digital images and spectral reflectance of the dry bean canopies, measurements of all parameters were made simultaneously on the same selected plants. The methods outlined by Semananda et al.⁷⁰ were used to estimate wet biomass (WB) weight, dry biomass (DB) weight, and canopy moisture content (CMC). In each treatment, twenty-four bean plants were chosen at random from the ground-level monitored area. These selected plants were immediately weighed to determine their WB weight (g). These plants were fragmented and subjected to a 24-hour drying process at 105 °C in a forced-air oven. The DB weight (g) of the dried plant material was then weighed. The following equation is used in the CMC calculation:

$$\text{CMC, (\%)} = \left(\frac{\text{WB} - \text{DB}}{\text{WB}} \right) * 100\% \quad (5)$$

The relative chlorophyll content was assessed using the SPAD-502 chlorophyll meter. Following the methodology of^{71,72}, SPAD readings were taken on the most recently fully expanded leaf of each selected plant, positioning the meter approximately midway between the leaf's edge and its midpoint. The average of the values from four

RGBIs	Formula	References
Red pixel percentage (R %)	$\frac{R}{R+G+B}$	57
Green pixel percentage (G %)	$\frac{G}{R+G+B}$	57
Blue pixel percentage (B %)	$\frac{B}{R+G+B}$	57
Green red simple ratio (GR)	$\frac{G}{R}$	58
Red blue simple ratio (RB)	$\frac{R}{B}$	58
Green blue simple ratio (GB)	$\frac{G}{B}$	58
Modified Green Red Vegetation Index (MGVRI)	$\frac{(G)^2 - (R)^2}{(G)^2 + (R)^2}$	58
Red Green Blue Vegetation Index (RGVBI)	$\frac{G - (B \cdot R)}{(G)^2 + (B \cdot R)}$	58
Excess red vegetation index (ExR)	$(1.4 \cdot R) - G$	59
Excess green vegetation index (ExG)	$(2 \cdot G) - R - B$	59
Excess green minus Excess red index (ExGR)	$ExG - ExR$	59
Vegetative index (VEG)	$\frac{G}{R^a \cdot B(1-a)}, a = 0.667$	60
Color Index of Vegetation Extraction (CIVE)	$(0.441 \cdot R) - (0.811 \cdot G) + (0.385 \cdot B) + 18.78745$	61
Combination (COM)	$(0.25 \cdot ExG) + (0.3 \cdot ExGR) + (0.33 \cdot CIVE) + (0.12 \cdot VEG)$	62
Visible atmospherically resistant index (VARI)	$\frac{(G-R)}{(G+R+B)}$	63
Green-red vegetation index (GRVI)	$\frac{(G-R)}{(G+R)}$	64
Normalized difference index (NDI)	$128 \cdot \left[\left(\frac{G-R}{G+R} \right) + 1 \right]$	65
Triangular Greenness Index (TGI)	$G - (0.39 \cdot R) - (0.61 \cdot B)$	66
Principal component analysis index (IPCA)	$0.994 \cdot (R - G) + 0.961 \cdot (G - B) + 0.914 \cdot (G - R)$	67
Green Leaf Index (GLI)	$\frac{(2 \cdot G) - R - B}{(2 \cdot G) + R + B}$	68
Modified Excess Green Index (MExG)	$(1.262 \cdot G) - (0.884 \cdot R) - (0.311 \cdot B)$	69

Table 3. Various RGBIs with its formulas and relevant references are used in this research.

leaves per plant was used to calculate the SPAD values. According to⁷³, soil samples were taken 30 cm from the base of the plants in order to estimate the soil water content (SWC). Following the recommendations made by Paltineanu and Starr⁷⁴ and Evett et al.⁷⁵, the SWC were evaluated using the gravimetric method (see Eq. (6)).

$$SWC (\%) = \left(\frac{M_{wet} - M_{dry}}{M_{wet}} \right) * 100\% \quad (6)$$

where: M_{wet} : Weight of moist soil, g; M_{dry} : Weight of dry soil, g.

During harvesting (110 DAS) in both seasons, a random sample of six plants was selected from each replicate in each treatment. The average weight of four replicates was used to determine the SY for each treatment, which was then expressed in tons per hectare.

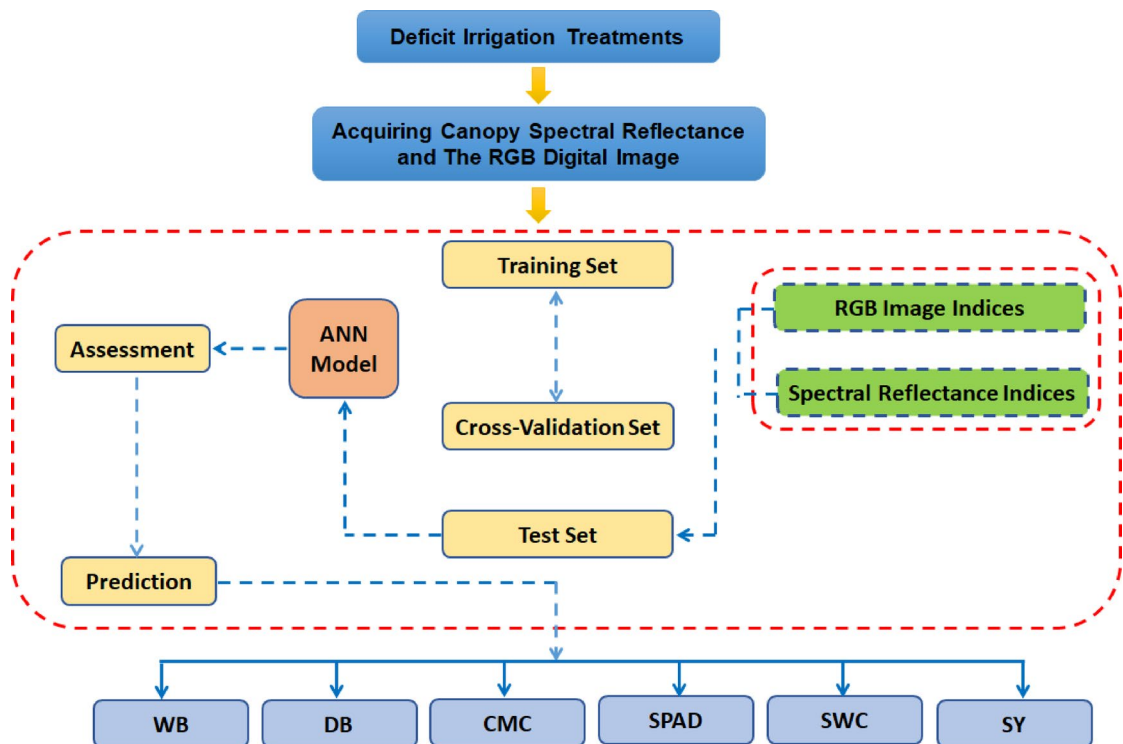
Artificial neural network model

Recent research has emphasized the potential of ANNs as a regression tool, especially in tasks related to pattern recognition and function determination. Unlike traditional methods, ANNs exhibit the remarkable ability to draw meaningful insights, effectively manage incomplete information, and demonstrate resilience against outliers, as evidenced by Elsayed et al.²⁵ and Huang et al.⁷⁶. In order to predict the measured parameters, such as WB, DB, CMC, SPAD, and SWC, as well as SY for dry bean crops under deficit irrigation, an ANNs were developed. The Quasi-Newton method (QN), illustrated in Eq. (7), was chosen as the optimization technique to reduce the variance between predicted and actual values, iteratively adjusting connection weights⁷⁷.

$$\omega_{j+1} := \omega_j - \alpha \cdot \mathcal{L} \cdot \left(\frac{\partial \mathcal{L}}{\partial \omega_j} \right)^{-1} \quad (7)$$

ω_{j+1} : Weights of next iteration, ω_j : Weights of current iteration, α : Learning rate. $\frac{\partial \mathcal{L}}{\partial \omega_j}$: The first partial derivative of the loss function ($\mathcal{L}$). Before the model training process, hyperparameters were predetermined instead of being acquired from the data, playing a crucial role in shaping the model's performance⁷⁸. These predetermined hyperparameters were essential for optimizing the models' performance and enhancing its ability to generalize effectively. On the training dataset, different combinations of hyperparameters were tested using the grid-search method included in the scikit-learn library and cross-validation with a fold-size of 5. The

Name	Equations
Hyperbolic Tangent (Tanh)	$f(x) = \frac{(e^x - e^{-x})}{(e^x + e^{-x})}$
Logistic (Sigmoid)	$f(x) = \frac{1}{1 + e^{-x}}$
Rectified Linear Unit (ReLU)	$f(x) = \max(0, x)$
Linear (Identify)	$f(x) = x$

Table 4. Types of activation function in ANN models.**Fig. 6.** Flowchart depicting a broad outline of the ANN models designed to indirectly measure WB, DB, CMC, SPAD, and SWC, as well as SY for dry bean crops under deficit irrigation.

hyperparameters that need tuning include the number of hidden layers (ranging from 1 to 5), the number of neurons per hidden layer (ranging from 2 to 10), the learning rate (0.001), the maximum iteration (500, 600, 700, 800, 900, 1000), and the activation functions (see Table 4) for specific functions used, as described in⁷⁹. According to⁸⁰, experience and testing were usually used to determine the structure of an ANN. Based on the highest R^2 value and the lowest RMSE (see Eqs. (9) and (10)), the model with the best performance and the best set of hyper-parameters was chosen. A comprehensive flowchart depicted in Fig. 6 outlines the proposed ANNs for indirectly estimating measured parameters and SY in dry bean crops.

Data analysis software and datasets

To facilitate the model training process, the dataset underwent normalization using Eq. (8), following the methodology outlined by Thara et al.⁸¹ This normalization technique was employed to standardize the vegetation indices, ensuring its mean values were centered around zero and its standard deviation was set to one. Here, z denotes the transformed dataset value; x represents the actual value; μ denotes the mean value; and σ signifies the standard deviation.

$$z = \frac{x - \mu}{\sigma} \quad (8)$$

The dataset was randomly divided, with 70% (50 samples) allocated for training and validation of the ANNs, while the remaining 30% (22 samples) was set aside for testing to compare predicted results against actual values, thus evaluating the model's performance. The ANNs employed SRIs and RGBIs as input features, selected based on their correlation surpassing a predefined threshold. Subsequently, the ANNs underwent training and validation using 5-fold cross-validation, a method aimed at enhancing generalization, preventing overfitting, and offering

a more precise assessment of the model's predictive capacity⁸². Our data analysis, model creation, and setup were conducted using Python version 3.12.1 and the Spyder software. The ANN modules were obtained from the Scikit-learn library, customized for regression tasks.

Model evaluation

In order to determine the difference between the actual value and the predicted value by the model, the evaluation of ANN models was estimated using metrics like the determination coefficient (R^2 score, the root mean squared error (RMSE) value, and normalized root mean squared error (NRMSE) (see Eqs. (9–11)). In this context, Y_a refers to the actual value determined in the laboratory; Y_p refers to the predicted value; $\bar{Y}$ represents the mean value; and N represents all the data points. The NRMSE values are categorized based on its range to assess the accuracy and reliability of the predictions. The categories are defined as follows: Excellent: NRMSE values between 0% and 10%, Good: NRMSE values between 10% and 20%, Fair: NRMSE values between 20% and 30%, Poor: NRMSE values exceeding 30%. The best-performing model with the optimal combination of hyperparameters and optimum indices was selected based on the lowest RMSE and the highest R^2 value, indicating better predictive accuracy and a better fit to the data.

$$R^2 = \frac{\sum (Y_a - Y_p)^2}{\sum (Y_a - \bar{Y})^2} \quad (9)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Y_a - Y_p)^2} \quad (10)$$

$$NRMSE = RMSE * \frac{100}{\bar{Y}} \quad (11)$$

Statistical analysis

The experiment was arranged using a Randomized Complete Block Design (RCBD) with four replicates per treatment. Following a homogeneity test, the data underwent ANOVA to identify distinctions among the different irrigation regimes. Duncan's multiple range test was then applied to detect significant variations in the mean values of the measured parameters, SY, and various tested indices across the different irrigation regimes in the two seasons. Statistical analysis was performed using the SPSS software package (Version 28.0). Simple regression analysis was utilized to determine the relationship between the different tested indices, measured parameters, and SY. The significance of the R^2 values for these relationships was evaluated at p-values of ≤ 0.001 , 0.01, and 0.05.

Results and discussion

The impact of irrigation regimes on measured parameters

A one-way ANOVA revealed that there was a statistically significant effect on all measured parameters and SY of dry bean plants ($p < 0.01$) due to the deficit irrigation regimes, as shown in Fig. 7. The WB, DB, CWC, and SWC have similarly showed a parallel trend ($B100 > B75 > B50$), as shown in Fig. 7. The B100 consistently displayed the highest WB and DB weights during the flowering stage in both seasons, as shown in Fig. 7a and b. This result can be ascribed to the drip irrigation's constant supply of water, which made sure the plants got its optimal water requirements. The current study's findings concur with previous studies on dry bean plants, including^{72,83–85}. They also showed that inadequate water availability causes smaller plants, thinner stems, and less leaf area, which in turn causes a decrease in WB and DB weights.

A comparison of various irrigation regimes with the CMC and SWC showed a consistent pattern of reduced CMC and SWC as irrigation water application decreased, as shown in Fig. 7c and d. So, scientists have utilized CMC and SWC to schedule irrigation and identify plant water stress⁸⁶. These results are consistent with^{87–89}. Additionally, there were highly significant differences in the SPAD values, which represent the relative chlorophyll content in leaf samples, between irrigation regimes, as shown in Fig. 7e. The B75 had the highest SPAD values, followed by the B50 and B100. Our findings indicates that a slight reduction in CMC does not result in chlorophyll degradation. Therefore, when CMC decreases while chlorophyll levels remain stable, the chlorophyll concentration increases, leading to higher SPAD values, as seen in B75. However, under severe water stress conditions, a significant lack of CMC causes chlorophyll breakdown in the leaves, resulting in a decline in SPAD values, as seen in B50. This pattern aligns with findings from previous studies⁹⁰, which are consistent with the results of our research.

A one-way ANOVA revealed that there was a statistically significant difference in mean seed dry bean yield between at least two treatments ($F(2) = 388.485$, $p < 0.01$) due to irrigation regimes, as shown in Fig. 7f. The effect size, eta squared (η^2), was 0.990, indicating a large effect. Duncan's multiple range test showed that the B100 scored significantly higher than both B75 and B50. In comparison to B75 and B50, B100 produced a higher seed bean yield in the first season by 18.49% and 39.75%, respectively. Likewise, the increases in second season were 20.18% and 40.00%, respectively. Sufficient water availability in the root zone promotes better absorption of nutrients and water, which in turn improves plant metabolic processes. Water stress during the flowering can result in fewer flowers and pod abortion⁷². These findings align with^{8,91,92}.

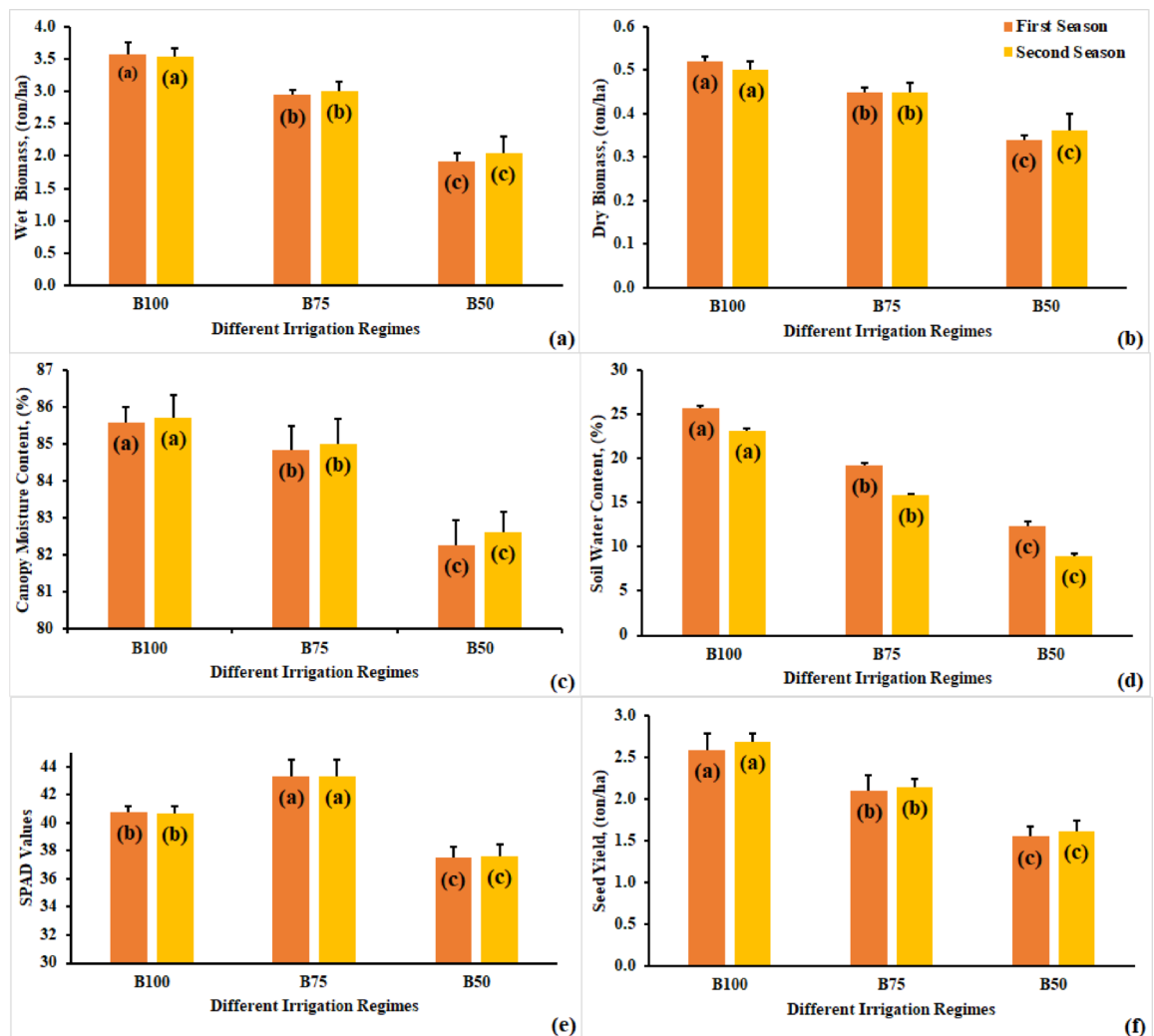


Fig. 7. The Impact of Different Irrigation Regimes on (a) WB, (b) DB, (c) CMC, (d) SWC, (e) SPAD, and (f) SY of dry bean crops. Means having the different alphabetical letter (s) are significantly differ between regimes at 0.01 level according to Duncan's multiple range test.

Advantage of remote sensing method to estimate measured parameters and SY

Irrigation water management can be significantly enhanced by accurately identifying various plant-related parameters that are closely related to soil moisture availability. Implementing deficit irrigation strategies can significantly reduce crop yields, as demonstrated with^{93–95}. This yield reduction can be predicted by indirectly evaluating plant parameters, such as DB, during the initial growth phase. Therefore, it is essential to regularly and concurrently evaluate these plant parameters using quick, practical, and non-destructive techniques to maximize irrigation water use and achieve desired yields. Modern approaches leveraging advanced technologies such as spectral reflectance indices and RGB image analysis offer scalable, cost-effective, and timely solutions, empowering farmers to make data-driven decisions that maximize yield potential while minimizing resource waste and environmental impact^{96,97}.

Response of RGB image indices to different irrigation regimes

In Table 5, the average RGB image indices (RGBIs) display statistically significant differences ($p < 0.01$) across various irrigation regimes in both seasons. This disparity in the RGBIs' mean values suggests that the proportions of the R%, G%, and B% values were impacted by deficit irrigation. In particular, compared to the fully irrigated plants, the water-stressed plants displayed lower G% values and higher R% and B% values. Vinod et al.⁹⁸ state that the water-stressed plants showed the lowest G% value, suggesting that photosynthetic pigment affected by water stress. While, fully irrigated plants appear to absorb more R and B channels for photosynthesis. The response of R, G, and B channels across various irrigation regimes highlights potential practicality and cost-effectiveness of employing RGB techniques as a monitoring method for managing deficit irrigation. Wenting et al.⁹⁹ and Christenson et al.¹⁰⁰ emphasized the potential of the visible region for effectively monitoring various plant parameters such as CMC and chlorophyll content with $R^2 = 0.70$. Additionally, Mercado-Luna et al.¹⁰¹ and

Season	Regimes	R %	G %	B %	GR	RB	GB	MGVRI
First	B100	0.23 ± 0.04c	0.56 ± 0.03a	0.21 ± 0.03c	2.59 ± 0.75a	1.12 ± 0.33a	2.75 ± 0.53a	0.71 ± 0.09a
	B75	0.30 ± 0.03b	0.44 ± 0.02b	0.26 ± 0.03b	1.52 ± 0.22b	1.15 ± 0.23a	1.72 ± 0.28b	0.38 ± 0.10b
	B50	0.34 ± 0.04a	0.33 ± 0.03c	0.33 ± 0.03a	1.00 ± 0.23c	1.03 ± 0.20a	0.99 ± 0.13c	−0.03 ± 0.20c
Second	B100	0.25 ± 0.02c	0.56 ± 0.02a	0.20 ± 0.02c	2.30 ± 0.24a	1.27 ± 0.31a	2.88 ± 0.52a	0.68 ± 0.05a
	B75	0.30 ± 0.03b	0.44 ± 0.02b	0.26 ± 0.03b	1.51 ± 0.18b	1.12 ± 0.22bc	1.67 ± 0.22b	0.38 ± 0.10b
	B50	0.34 ± 0.04a	0.32 ± 0.03c	0.33 ± 0.02a	0.95 ± 0.19c	1.05 ± 0.16c	0.97 ± 0.12c	−0.07 ± 0.18c
Season	Regimes	RGVBI	ExR	ExG	ExGR	VEG	CIVE	COM
First	B100	−0.12 ± 0.03a	−60.21 ± 16.59c	170.96 ± 16.25a	231.17 ± 31.38a	2.62 ± 0.49a	−49.58 ± 6.82c	96.04 ± 11.19a
	B75	−0.28 ± 0.04b	−7.81 ± 13.66b	90.59 ± 16.06b	98.40 ± 27.47b	1.58 ± 0.17b	−16.52 ± 6.58b	46.90 ± 9.97b
	B50	−0.51 ± 0.06c	36.16 ± 20.27a	−4.83 ± 19.42c	−40.99 ± 38.39c	0.99 ± 0.16c	22.02 ± 8.19a	−6.12 ± 13.60c
Second	B100	−0.13 ± 0.02a	−55.46 ± 10.31c	172.92 ± 11.57a	228.38 ± 20.62a	2.47 ± 0.18a	−50.15 ± 4.78c	95.49 ± 7.44a
	B75	−0.28 ± 0.03b	−7.37 ± 13.27b	87.98 ± 12.00b	95.35 ± 22.22b	1.56 ± 0.13b	−15.50 ± 4.93b	45.67 ± 7.85b
	B50	−0.52 ± 0.06c	39.69 ± 18.86a	−8.98 ± 20.31c	−48.67 ± 38.25c	0.96 ± 0.15c	23.76 ± 8.51a	−8.89 ± 13.70c
Season	Regimes	VARI	GRVI	NDI	TGI	IPCA	GLI	MExG
First	B100	0.34 ± 0.07a	0.43 ± 0.09a	182.46 ± 11.59a	86.01 ± 7.75a	77.84 ± 8.24a	0.44 ± 0.05a	110.14 ± 11.78a
	B75	0.15 ± 0.04b	0.20 ± 0.06b	153.69 ± 7.82b	46.31 ± 8.25b	44.71 ± 10.23b	0.23 ± 0.04b	59.71 ± 10.25b
	B50	−0.01 ± 0.06c	−0.01 ± 0.10c	126.29 ± 12.88c	−2.23 ± 9.06c	−1.25 ± 8.59c	−0.01 ± 0.06c	1.92 ± 14.28c
Second	B100	0.31 ± 0.03a	0.39 ± 0.04a	178.06 ± 5.51a	87.75 ± 5.64a	82.27 ± 6.54a	0.43 ± 0.03a	109.58 ± 8.42a
	B75	0.15 ± 0.04b	0.20 ± 0.06b	153.59 ± 7.29b	44.86 ± 6.29b	42.88 ± 9.46b	0.22 ± 0.03b	58.44 ± 8.12b
	B50	−0.02 ± 0.06c	−0.03 ± 0.09c	123.71 ± 11.89c	−4.13 ± 9.58c	−2.23 ± 8.15c	−0.03 ± 0.07c	−1.11 ± 14.40c

Table 5. Comparing the average RGBIs values across three irrigation regimes for the dry bean crop during the flowering stage.

Qian et al.¹⁰² identified a positive correlation between the G region and the nitrogen status of tomato plants, whereas the B and R regions have an adverse correlation with the nitrogen status of tomato plants.

Potential of RGBIs to estimate the measured parameters

The majority of the RGBIs showed a strong and significant linear relationship with all measured parameters and SY, with the exception of SPAD, which demonstrated a significant quadratic relationship with all RGBIs. On the other hand, all measured parameters and SY showed a significant negative correlation with the R (%), B (%), ExR, and CIVE indices. However, it is crucial to note that there was no correlation found between the RB index and the measured parameters or SY.

The R^2 values between the RGBIs, measured parameters, and SY were examined. WB, DB, CMC, SPAD, SWC, and SY had R^2 values ranging from 0.59 to 0.93, 0.60 to 0.95, 0.47 to 0.81, 0.34 to 0.79, 0.60 to 0.95, and 0.56 to 0.84, respectively, for the first season (Fig. 8a). R^2 values for WB, DB, CMC, SPAD, SWC, and SY in the second season ranged from 0.56 to 0.87, 0.52 to 0.77, 0.48 to 0.82, 0.43 to 0.74, 0.68 to 0.96, and 0.68 to 0.91, respectively, as shown in Fig. 8b. The R^2 values for combining the data from both seasons were 0.57 to 0.89 for WB, 0.56 to 0.86 for DB, 0.50 to 0.80 for CMC, 0.35 to 0.76 for SPAD, 0.61 to 0.89 for SWC, and 0.60 to 0.87 for SY, as illustrated in Fig. 8c.

Our image analysis results indicate that the B and R channels alone is inadequate for accurately predicting measured parameters and yield estimation. The RB ratio neglects the crucial G component of vegetation, which plays a significant role in evaluating vegetation health and biomass. Since greenness is strongly correlated with chlorophyll content and overall plant health¹⁰³, these indices hold significant potential as cost-effective tools for monitoring plant yield and growth. Previous research, including the work of¹⁰⁴, has demonstrated the effectiveness of RGBIs in predicting wet biomass and SY across a wide range of growing conditions. Recent studies on beans and cassava crops by Parker et al.¹⁰⁵ and Wasonga et al.¹⁰⁶ have further corroborated these findings, underscoring the significance of RGBIs in capturing key biometric variables with R^2 up to 0.90.

Response of crop spectral reflectance signature to different irrigation regimes

The spectral signature of dry bean canopies under various irrigation regimes were displayed in Fig. 9a and b. Although there were differences between the treatments, the canopy reflectance signatures for the three irrigation regimes displayed comparable trends within the 302–1148 nm range. A detailed analysis of the spectral reflectance signatures revealed distinct dips at approximately 350 nm and 670 nm, attributed to the significant

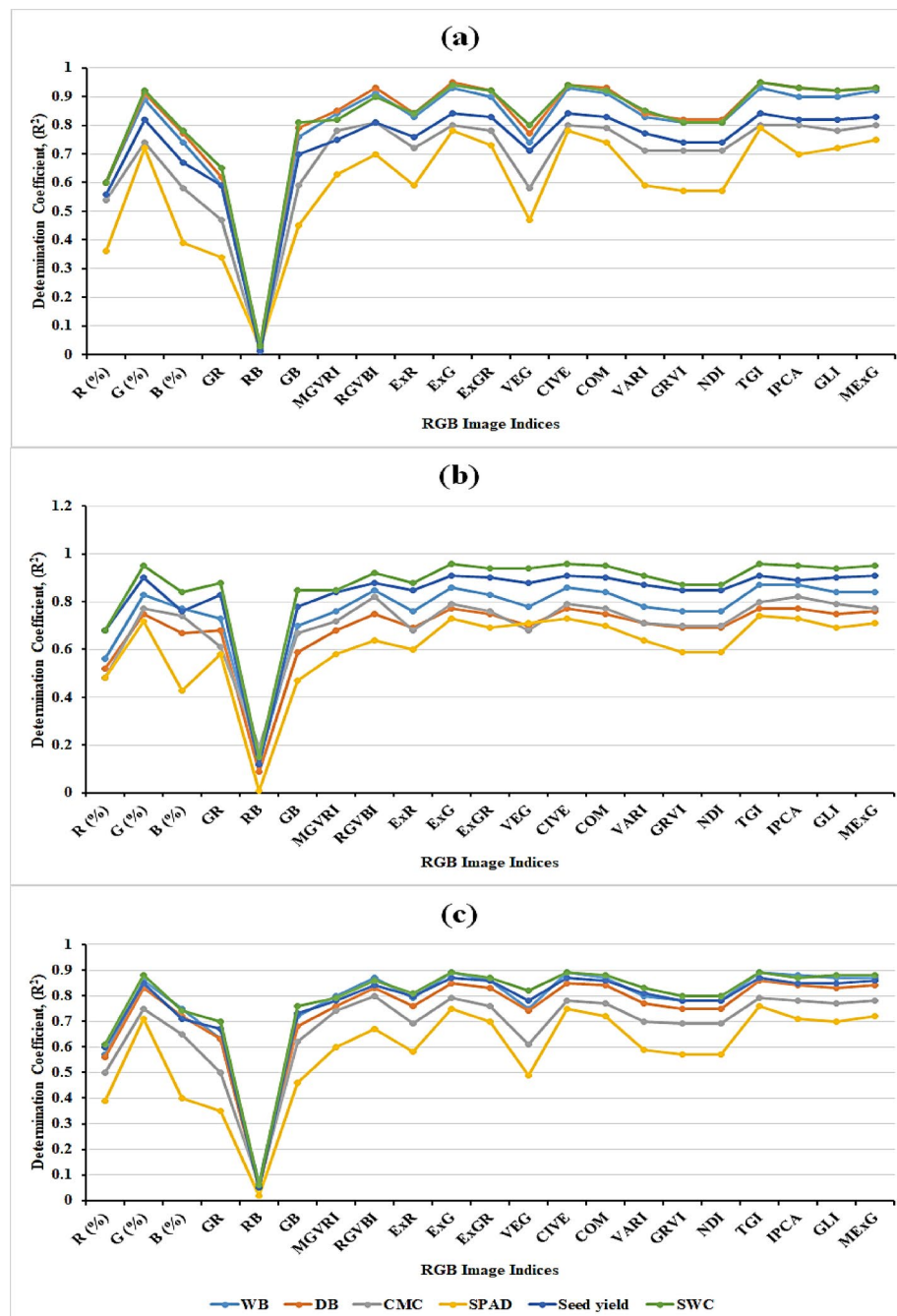


Fig. 8. The determination coefficients of relationships between the RGBIs with measured parameters and SY of dry bean under different irrigation regimes at (a) first season, (b) second season, and (c) combining the data from both seasons. The full names of the abbreviations of RGBIs are listed in Table 3.

absorption of chlorophyll. Additionally, the absorption characteristics of the canopy moisture content led to the observation of troughs near 970 nm. These findings concur with¹⁰⁷.

When the various irrigation treatments were compared, it was discovered that fully irrigated plants (B100) had the highest reflectance values in the red edge (700–760 nm) and near-infrared (NIR) regions (> 760 nm), and the lowest reflectance values in the visible region (< 700 nm). In contrast, water-stressed plants (B50) showed the lowest reflectance values in the NIR and red edge regions and the highest reflectance values in the visible. These results are consistent with¹⁰⁸. These findings suggest that fully irrigated plants have reduced reflectance in the visible spectrum as a result of absorbing visible light for photosynthetic processes. Furthermore, the red edge region showed higher reflectance in well-irrigated plants, which are recognized for having a higher chlorophyll content and healthier photosynthetic activity. The internal structure and moisture content of the plants affect how much NIR energy is reflected. Adequately irrigated plants contain ample water, filling the inter-cell spaces, increasing the number of cell layers and cell size, ultimately leading to amplified NIR light reflection^{14,109}. Padilla

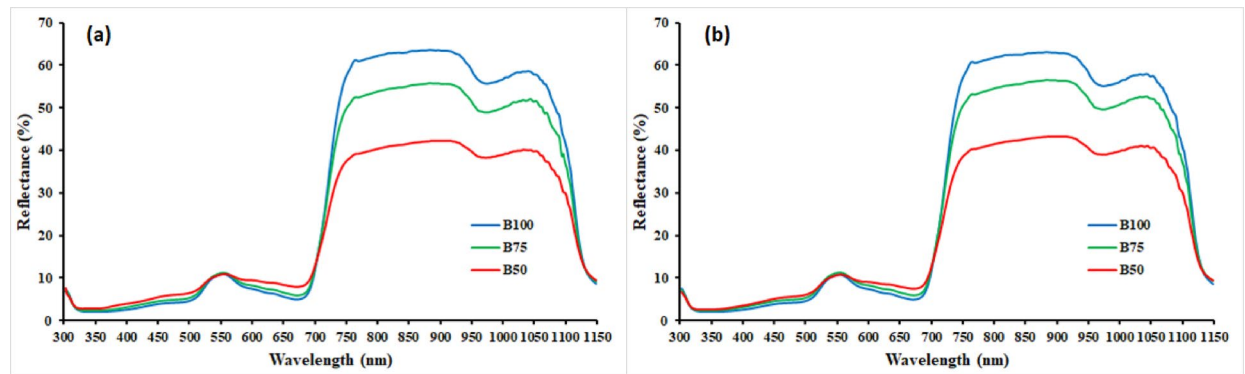


Fig. 9. Spectral signature of dry bean plants under different irrigation regimes in the range from 302 to 1148 nm during flowering stage in (a) first season and (b) second season.

et al.¹¹⁰ used SRIs to determine tomato chlorophyll content and achieved an R^2 in the range of 0.88–0.93 ($P < 0.001$). Additionally, Elvanidi et al.¹¹¹ discovered that canopy spectral reflectance can determine a tomato plant's chlorophyll content and nitrogen levels under water stress, with R^2 values of up to 0.81.

Contour map analysis of the spectral reflectance data

To derive various spectral reflectance indices (SRIs), the study utilized processed spectra obtained from the dry bean canopy plants, spanning wavelengths between 302 nm and 1148 nm. Through using 2D contour maps, depicted in Fig. 10, the study successfully found the most robust and consistent correlations among newly developed SRIs, measured parameters, and SY. This analysis was conducted by pooled data from various irrigation treatments, replications, and seasons. As indicated in Table 2, the study identified the newly developed SRIs with the highest R^2 values as the most appropriate matches for the study.

The contours revealed robust relationships between measured parameters, SY, and newly developed SRIs combine wavelengths from VIS, red-edge, and NIR regions of the spectrum. This phenomenon is likely attributed to the close relationship between wavelengths in the VIS region and plant characteristics such as photosynthetic capacity, vigor, and pigment status, which are essential for crop growth and productivity. Observations from tomato and bean plants subjected to varying irrigation regimes also suggest that alterations in these wavelengths serve as indicators of the plants' water status^{112,113}. The red-edge wavelengths serve as indirect stress indicators for plants thriving in challenging conditions, as it provides vital insights into plant biomass, health, and vigor^{114,115}. Internal factors like cell arrangement in the mesophyll layer, the ratio of palisade to spongy mesophyll cells, and the presence of intercellular air and water spaces significantly influence NIR wavelengths^{116–118}. Notably, spectral reflectance in the NIR spectrum is highly sensitive to plant water status due to water absorption properties in this region, enabling deeper leaf penetration^{119,18}. Analyzing reflectance patterns at specific wavelengths within the VIS, red-edge, and NIR spectra offers valuable insights into plant parameters, water status, and stress levels. With this information, it can enhance overall crop productivity, optimize water use efficiency, and facilitate effective monitoring and management of crop irrigation practices.

Previous researchers have utilized all possible combinations of the two bands (contour maps) to identify newly developed SRIs for determining CMC, biomass, chlorophyll content, and crop production under various environmental conditions^{18,120–122}. For instance, Elsayed et al.²⁰ investigated the relationships between newly developed SRIs and parameters such as WB, DB, and CMC in potato crops grown under various irrigation schedules. They discovered that the measured parameters and yield showed significant and strong relationships with newly developed SRIs that were dependent on effective wavelengths. These studies have emphasized the significance of contour maps, which entail looking at every possible combination of two bands. In contrast, Barmerier and Schmidhalter¹²³ reported that they did not observe any improvement in the selection of SRIs based on contour map analyses in their study. These disparities in findings may be due to differences in crop varieties, environmental factors, and experimental designs between studies.

Response of published and newly SRIs to different irrigation regimes

Table 6 presented the means and standard deviations of various SRIs under varying irrigation regimes. Statistical analysis revealed significant relationships between specific SRIs and different irrigation regimes. $SRI_{574, 1134}$, $SRI_{580, 1130}$, $SRI_{586, 1130}$, $SRI_{642, 632}$, $SRI_{648, 622}$, $SRI_{1104, 710}$, and $SRI_{1120, 1142}$ were significantly related to different irrigation regimes. However, there were no significant differences between B100 and B75 for the remaining SRIs. These variations highlight the differing responses of dry bean canopies' spectral reflectance to varying irrigation regimes. Changes were found in the average values of published SRIs. These values ranged from 2.75 to 4.81 for PRMI, 0.22 to 0.31 for NAI, and 1.10 to 1.14 for WI (as seen in Table 6). Additionally, newly developed SRIs such as $SRI_{574, 1134}$, $SRI_{580, 1130}$, and $SRI_{586, 1130}$ showed significant changes in its mean values, ranging from 0.82 to 0.89, 0.68 to 0.79, and 0.64 to 0.77, respectively.

Remarkably, these changes in SRIs corresponded to variations in measured parameters and SY. The magnitude of these changes depended on the irrigation regimes. The findings highlight that different irrigation regimes significantly impact various biophysical and biochemical parameters of dry bean canopies. As a result,

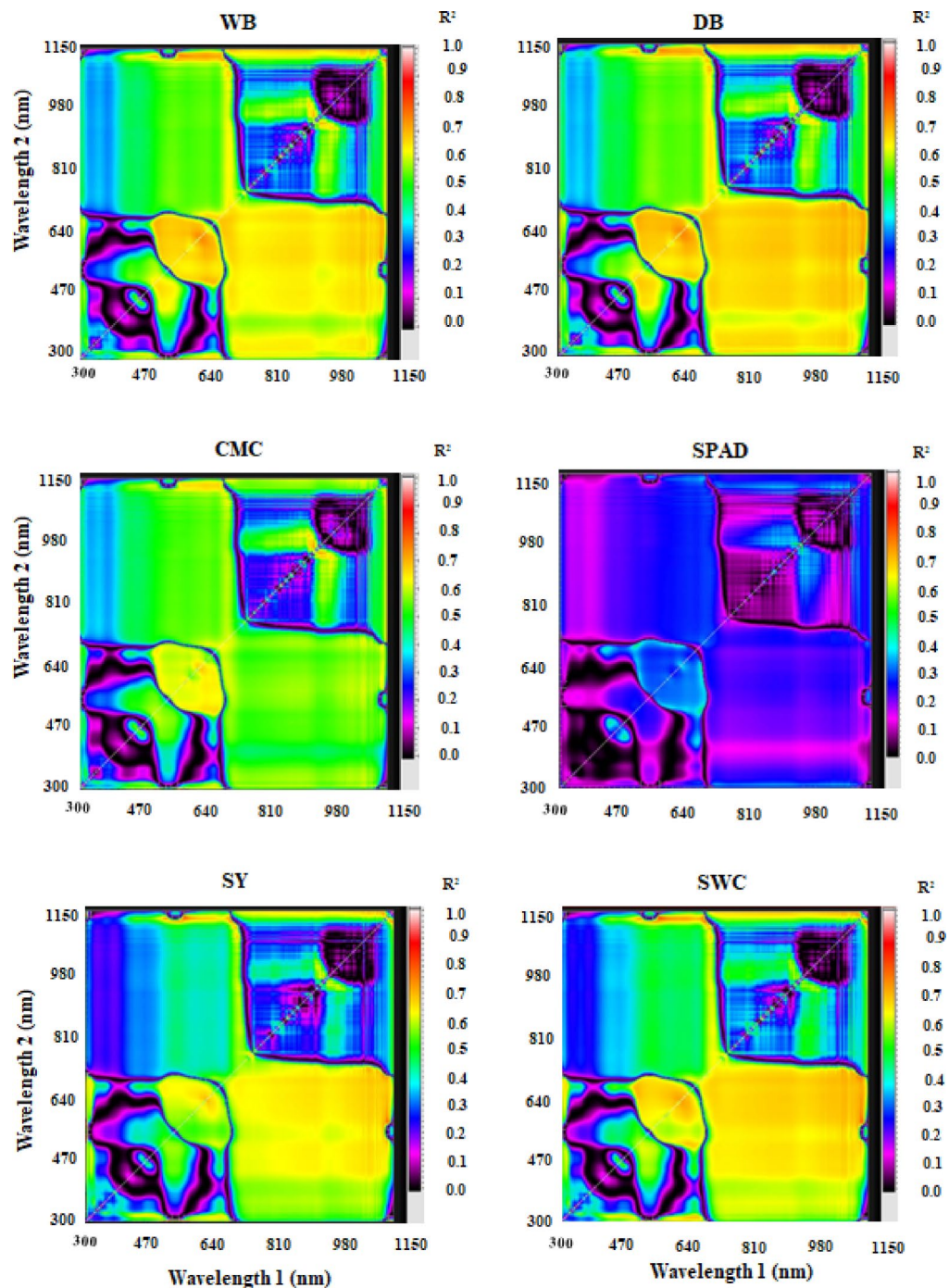


Fig. 10. displays correlation matrices indicating the R^2 values for all dual wavelength combination of the hyperspectral reflectance with WB, DB, CMC, SPAD, SY, and SWC for dry bean crop using combined data during flowering stage in both seasons.

the spectral signatures of the canopy experience notable changes in the VIS, red edge, and NIR spectrums. These findings are supported by^{124,9,125–127}. Therefore, creating SRIs with practical wavelengths from these spectral regions can be a reliable way to estimate crop yield and measured parameters in dry bean plants that are grown under varying water regimes. Crucially, this method provides a quick and non-invasive way to evaluate.

Potential of both published and newly developed SRIs in estimating the measured parameters

The study investigated the relationships between different SRIs, measured parameters, and SY under varying irrigation regimes during the flowering stage across two seasons, as illustrated in Fig. 11. In the first season, R^2 values for WB, DB, CMC, SPAD, SWC, and SY ranged from 0.45 to 0.74, 0.48 to 0.68, 0.28 to 0.53, 0.18 to 0.59,

Season	Regimes	SRI _{574, 1134}	SRI _{580, 1130}	SRI _{586, 1130}	SRI _{636, 630}	SRI _{642, 632}	SRI _{648, 622}	SRI _{662, 610}	
First	B100	0.89 ± 0.01a	0.79 ± 0.03a	0.77 ± 0.04a	0.99 ± 0.00a	0.97 ± 0.01a	0.94 ± 0.02a	0.86 ± 0.04a	
	B75	0.86 ± 0.01b	0.73 ± 0.01b	0.70 ± 0.01b	0.98 ± 0.00b	0.95 ± 0.00b	0.89 ± 0.01b	0.78 ± 0.02b	
	B50	0.82 ± 0.02c	0.68 ± 0.03c	0.65 ± 0.03c	0.98 ± 0.01b	0.94 ± 0.01c	0.87 ± 0.02c	0.73 ± 0.04b	
Second	B100	0.88 ± 0.02a	0.79 ± 0.04a	0.77 ± 0.05a	0.99 ± 0.00a	0.97 ± 0.01a	0.93 ± 0.02a	0.85 ± 0.05a	
	B75	0.85 ± 0.01b	0.73 ± 0.01b	0.70 ± 0.01b	0.98 ± 0.00b	0.95 ± 0.00b	0.89 ± 0.01b	0.78 ± 0.02b	
	B50	0.82 ± 0.02c	0.68 ± 0.03c	0.64 ± 0.04c	0.98 ± 0.00b	0.94 ± 0.01c	0.87 ± 0.02c	0.73 ± 0.05b	
Season	Regimes	SRI _{970, 946}	SRI _{1104, 710}	SRI _{1120, 1142}	NWI-1	NWI-3	NWI-4	NWI-5	
First	B100	0.96 ± 0.01a	1.47 ± 0.11c	1.65 ± 0.09c	−0.05 ± 0.02a	−0.05 ± 0.02a	−0.05 ± 0.01a	−0.05 ± 0.02a	
	B75	0.94 ± 0.01b	1.65 ± 0.06b	1.85 ± 0.07b	−0.06 ± 0.01b	−0.07 ± 0.01b	−0.06 ± 0.00b	−0.06 ± 0.01b	
	B50	0.93 ± 0.01b	1.83 ± 0.12a	2.05 ± 0.17a	−0.07 ± 0.01b	−0.07 ± 0.01b	−0.06 ± 0.00b	−0.07 ± 0.01b	
Second	B100	0.95 ± 0.01a	1.48 ± 0.11c	1.65 ± 0.12c	−0.05 ± 0.01a	−0.05 ± 0.01a	−0.05 ± 0.01a	−0.05 ± 0.01a	
	B75	0.94 ± 0.01b	1.65 ± 0.07b	1.84 ± 0.06b	−0.06 ± 0.01b	−0.07 ± 0.01b	−0.06 ± 0.01b	−0.06 ± 0.01b	
	B50	0.93 ± 0.01b	1.85 ± 0.14a	2.07 ± 0.15a	−0.07 ± 0.01b	−0.07 ± 0.01b	−0.06 ± 0.01b	−0.07 ± 0.01b	
Season	Regimes	NWI-6	PRMI	NDI _{570, 540}	NDI _{686, 620}	NAI	NDI _{780, 550}	NDI _{800, 670}	WI
First	B100	0.65 ± 0.15b	2.75 ± 0.94b	−0.01 ± 0.02a	−0.02 ± 0.01a	0.22 ± 0.05b	0.56 ± 0.11b	0.66 ± 0.15b	1.10 ± 0.03b
	B75	0.80 ± 0.02a	3.94 ± 0.22a	−0.03 ± 0.01b	−0.05 ± 0.01b	0.27 ± 0.01a	0.65 ± 0.01a	0.80 ± 0.02a	1.14 ± 0.01a
	B50	0.84 ± 0.04a	4.76 ± 0.76a	−0.04 ± 0.01b	−0.06 ± 0.02b	0.31 ± 0.04a	0.69 ± 0.03a	0.85 ± 0.04a	1.14 ± 0.01a
Second	B100	0.68 ± 0.10b	2.92 ± 0.72c	−0.01 ± 0.02a	−0.03 ± 0.02a	0.22 ± 0.03b	0.58 ± 0.06b	0.69 ± 0.09b	1.11 ± 0.02b
	B75	0.80 ± 0.02a	3.96 ± 0.27b	−0.03 ± 0.01b	−0.06 ± 0.01b	0.27 ± 0.02a	0.65 ± 0.01a	0.80 ± 0.02a	1.13 ± 0.01a
	B50	0.84 ± 0.04a	4.81 ± 0.78a	−0.04 ± 0.01b	−0.06 ± 0.01b	0.31 ± 0.04a	0.70 ± 0.04a	0.85 ± 0.04a	1.14 ± 0.01a

Table 6. Comparing the average SRIs values across three irrigation regimes for dry bean crop during flowering stage.

0.34 to 0.79, and 0.33 to 0.80, respectively, as depicted in Fig. 11a. For second season, R^2 values spanning from 0.51 to 0.75 for WB, 0.46 to 0.68 for DB, 0.47 to 0.67 for CMC, 0.24 to 0.45 for SPAD, 0.43 to 0.76 for SWC, and 0.38 to 0.72 for SY, as showcased in Fig. 11b. Pooling data from both seasons enabled, revealing R^2 values ranging from 0.50 to 0.73 for WB, 0.48 to 0.71 for DB, 0.52 to 0.66 for CMC, 0.23 to 0.48 for SPAD, 0.32 to 0.72 for SWC, and 0.26 to 0.83 for SY, as demonstrated in Fig. 11c.

The study's results underscored the efficacy of a majority of SRIs in accurately estimating measured parameters and SY. For instance, SRI_{574, 1134}, SRI_{580, 1130}, and SRI_{586, 1130} exhibited robust correlations with WB, DB, CMC, SY, SWC, and moderate associations with SPAD, as depicted in Fig. 11. The SRI_{574, 1134} exhibited high R^2 values: 0.68, 0.69, and 0.68 for WB, 0.69, 0.66, and 0.67 for DB, 0.57, 0.53, and 0.54 for CMC, 0.37, 0.34, and 0.35 for SPAD, 0.73, 0.75, and 0.74 for SY, and 0.79, 0.75, and 0.72 for SWC at flowering stage in first season, second season, and combined data for both seasons, respectively, as depicted in Fig. 11a. The SRI_{580, 1130} exhibited high R^2 values: 0.73, 0.71, and 0.72 for WB, 0.73, 0.68, and 0.70 for DB, 0.63, 0.56, and 0.59 for CMC, 0.37, 0.35, and 0.36 for SPAD, 0.68, 0.76, and 0.71 for SY, and 0.79, 0.76, and 0.71 for SWC, respectively, as depicted in Fig. 11b. The SRI_{586, 1130} exhibited high R^2 values: 0.74, 0.71, and 0.72 for WB, 0.74, 0.67, and 0.70 for DB, 0.65, 0.57, and 0.61 for CMC, 0.39, 0.33, and 0.36 for SPAD, 0.66, 0.74, and 0.70 for SY, and 0.77, 0.75, and 0.70 for SWC in that order, as presented in Fig. 11c.

Additionally, the newly developed SRIs outperform the best-performing published SRIs across all measured parameters and SY. For WB, they demonstrate 10–23% higher correlations compared to PRMI ($R^2 = 0.62$). Similarly, for DB, the correlations are 9–23% higher than PRMI ($R^2 = 0.62$). In predicting CMC, the newly developed SRIs show 5–14% higher correlations relative to NDI_{570,540} ($R^2 = 0.59$). For SPAD, the improvement ranges from 3 to 25% compared to NDI_{686,620} ($R^2 = 0.45$). Regarding SWC, the newly developed SRIs achieve 15–40% higher correlations than PRMI ($R^2 = 0.57$). Finally, for SY, the correlations are 15–39% higher compared to PRMI ($R^2 = 0.59$).

Leveraging artificial neural networks with vegetation indices to predict measured parameters of dry bean crop

Performance of ANN model based on published and newly developed SRIs for predicting the measured parameters and SY of dry bean crop

Simple SRIs are commonly employed for indirectly estimating crop parameters and yields. The spectral signatures of canopies can be distorted by a blend of soil background reflectance and vegetation saturation. To counteract these adverse impacts on canopy spectral properties, the amalgamation of diverse SRIs into a unified index proves beneficial^{128–131}. Similarly, research by El-Hendawy et al.¹¹⁹, Winterhalter et al.¹³², and Elazab et al.¹²⁹ have echoed these observations. For instance, in scenarios of full irrigation, excessive biomass can lead to SRI saturation, whereas conditions of severe stress that diminish biomass accumulation can markedly alter canopy spectral reflectance due to heightened exposure of bare soil.

Our study utilized ANN models to precisely forecast measured parameters and SY of dry beans by integrating SRIs as independent variables. By pooled data from both seasons, ANN models were trained to predict the

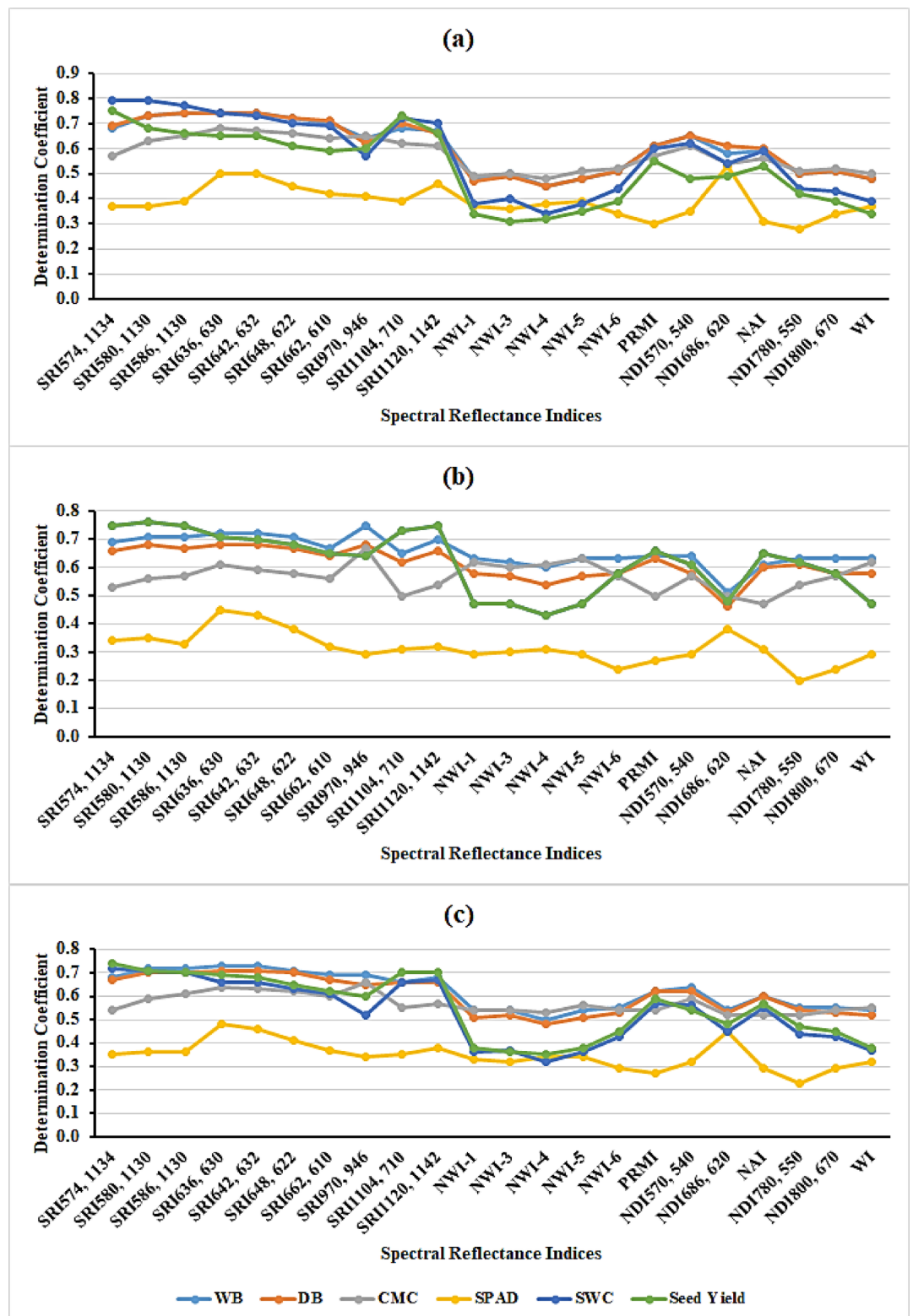


Fig. 11. The determination coefficients of relationships between the SRIs, the measured parameters, and the SY of dry beans under various irrigation regimes. The complete names of the SRIs can be found in Tables 1 and 2.

measured parameters and SY of dry beans, detailed in Table 7. Among the models, ANNB-WB1 emerged as the standout performer, demonstrating a robust correlation between its SRIs and WB. Notably, this model achieved an R^2 value of 0.94 with an RMSE of 3.09 g/plant in training, and an R^2 of 0.93 with an RMSE of 2.48 g/plant in testing. Similarly, the ANNB-DB1 model excelled in predicting dry bean parameters, demonstrating remarkable accuracy with R^2 of 0.96 in training and 0.88 in testing, along with low RMSE values of 0.26 g/plant and 0.33 g/plant for training and testing, respectively. Additionally, the ANNB-CMC1 model distinguished itself as the top performer in assessing CMC, achieving an R^2 of 0.88 and an RMSE of 0.53% in training, and an R^2 of 0.86 with an RMSE of 0.45% in testing. The ANNB-SPAD1 model displayed outstanding predictive prowess for SPAD values, boasting high R^2 values of 0.97 for both training and testing, with corresponding RMSE values of 0.43 and 0.46. For SWC prediction, the ANNB-SWC1 model emerged as the most accurate, attaining R^2 values of 0.97 and 0.95, alongside RMSE values of 0.96 and 1.26 for training and testing, respectively. Furthermore, the ANNB-SY1 model yielded outstanding results in SY predictions, achieving R^2 values of 0.98 (RMSE = 1.14 g/plant) for training and 0.98 (RMSE = 0.99 g/plant) for testing. According to the NRMSE during training phase, the ANNB-WB1, ANNB-DB1, ANNB-CMC1, ANNB-SPAD1, ANNB-SY1, and ANNB-SWC1 models demonstrated exceptional prediction accuracy (0–10%). Considering the NRMSE during testing phase, the ANNB-WB1, ANNB-DB1, ANNB-CMC1, ANNB-SPAD1, ANNB-SY1, and ANNB-SWC1 models demonstrated outstanding prediction accuracy (0–10%).

In this study, employing a combination of SRIs integrated into ANN models has enhanced the indirect prediction of parameters and SY for dry bean, as detailed in Table 7. This research was compared to other studies on plant growth and yield prediction using ANN. Osco et al.¹³³ evaluated water-stress-induced lettuce using hyperspectral response and ANN, achieving R^2 values up to 93%. Elvanidi and Katsoulas¹³⁴ developed an ANN model leveraging hyperspectral data to predict different types of water stress in tomato crops. The ANN model performed exceptionally well, achieving a remarkable accuracy rate of 96%. These results highlight the potential and accuracy of ANN models in agriculture, particularly in tasks related to plant water status and stress detection.

Performance of ANN model based on RGBIs for predicting the measured parameters and SY of dry bean crop
The RGBI data were analyzed using ANN models, as outlined in Table 8. Among these, the ANNB-WB2 model proved to be the most effective predictor, demonstrating exceptional performance and establishing a strong correlation between the RGBIs and WB. It achieved R^2 values of 0.96 for training and 0.94 for testing, alongside RMSE values of 2.37 g/plant in training and 3.29 g/plant in testing. Similarly, the ANNB-DB2 model excelled in evaluating DB, recording R^2 values of 0.79 for training and 0.78 for testing, with RMSE values of 0.51 g/plant and 0.63 g/plant, respectively. The ANNB-CMC2 model distinguished itself as the most precise for CMC, achieving R^2 values of 0.95 and 0.89 for training and testing, respectively, alongside RMSE values of 0.39% and 0.57%. Designed for predicting SPAD values, the ANNB-SPAD2 model surpassed expectations with R^2 values of 0.96 for training and 0.94 for testing, and RMSE scores of 0.46 and 0.62 for the respective phases. In terms of SWC, the ANNB-SWC2 model demonstrated high accuracy, attaining R^2 scores of 0.92 for training and 0.86 for testing, with low RMSE values of 1.65% and 2.12%. Finally, the ANNB-SY2 model emerged as the leading model for assessing SY, achieving an R^2 of 0.94 and an RMSE of 0.52 g/plant in the training dataset, along with an R^2 of 0.87 and an RMSE of 0.75 g/plant in the testing dataset. Based on the NRMSE during the training phase, the ANNB-WB2, ANNB-CMC2, ANNB-SPAD2, ANNB-SY2, and ANNB-SWC2 models exhibited excellent prediction accuracy (0–10%), while the ANNB-DB2 model fell within the good prediction range (10–20%). Additionally, based on the NRMSE, the ANNB-WB2, ANNB-CMC2, and ANNB-SPAD2 models exhibited excellent prediction accuracy (0–10%), while the ANNB-DB2, ANNB-SWC2, and ANNB-SY2 models fell within the good prediction range (10–20%).

Model	Optimal SRIs	Hyper-parameter (Z, L, N, I)	Training			Testing		
			R^2	RMSE	NRMSE (%)	R^2	RMSE	NRMSE (%)
ANNB-WB1	SRI _{580,1130} , SRI _{586,1130} , SRI _{636,630} , SRI _{642,632} , SRI _{648,622}	(Tanh, 1, 6, 700)	0.94***	3.09	6.15	0.93***	2.48	4.63
ANNB-DB1	SRI _{574,1134} , SRI _{580,1130} , SRI _{586,1130} , SRI _{636,630} , SRI _{642,632} , SRI _{648,622} , SRI _{662,610} , SRI _{970,946} , SRI _{1104,710} , SRI _{1120,1142} , PRMI, NDI _{570,540} , NAI	(Logistic, 2, 4, 600)	0.96***	0.26	3.36	0.88***	0.33	4.08
ANNB-CMC1	SRI _{586,1130} , SRI _{636,630} , SRI _{642,632} , SRI _{648,622} , SRI _{662,610} , SRI _{970,946}	(Relu, 1, 8, 500)	0.88***	0.53	0.63	0.86***	0.45	0.53
ANNB-SPAD1	SRI _{574,1134} , SRI _{580,1130} , SRI _{586,1130} , SRI _{636,630} , SRI _{642,632} , SRI _{648,622} , SRI _{662,610} , SRI _{970,946} , SRI _{1104,710} , SRI _{1120,1142} , NWI-1, NWI-3, NWI-4, NWI-5, NDI _{570,540} , NDI _{686,620} , WI	(Tanh, 1, 5, 500)	0.97***	0.43	1.07	0.97***	0.46	1.12
ANNB-SWC1	SRI _{574,1134} , SRI _{580,1130} , SRI _{586,1130} , SRI _{636,630} , SRI _{642,632} , SRI _{648,622} , SRI _{662,610} , SRI _{1104,710} , SRI _{1120,1142}	(Logistic, 1, 8, 600)	0.97***	0.96	5.53	0.95***	1.26	6.99
ANNB-SY1	SRI _{574,1134} , SRI _{580,1130} , SRI _{586,1130} , SRI _{636,630} , SRI _{642,632} , SRI _{648,622} , SRI _{662,610} , SRI _{970,946} , SRI _{1104,710} , SRI _{1120,1142} , PRMI, NDI _{570,540} , NAI	(Logistic, 1, 5, 700)	0.98***	1.14	3.02	0.98***	0.99	2.49

Table 7. Performance of various ANN models in forecasting measured parameters and SY of dry bean crop using different SRIs. Z, L, N, and I represent activation function, layers number, neurons number in each layer, and iterations number, respectively.

Model	Optimal RGBIs	Hyper-parameter (Z, L, N, I, O)	Training			Testing		
			R ²	RMSE	NRMSE (%)	R ²	RMSE	NRMSE (%)
ANNB-WB2	RGVB, G %, ExGR, ExG, COM, CIVE, IPCA, TGI, MExG, GLI	(Logistic, 1, 7, 600)	0.96***	2.37	6.33	0.94***	3.29	8.95
ANNB-DB2	MGVRI, G %, ExR, ExG, RGVBI, CIVE, ExGR, VARI, COM, NDI, GRVI, IPCA, TGI, MExG, GLI	(Logistic, 1, 6, 500)	0.79***	0.51	13.20	0.79***	0.63	16.55
ANNB-CMC2	RGVBI, MGVRI, ExGR, ExG, COM, CIVE, IPCA, TGI, MExG, GLI	(Tanh, 1, 8, 500)	0.95***	0.39	6.66	0.89***	0.57	9.62
ANNB-SPAD2	RGVBI, MGVRI, ExGR, ExG, COM, CIVE, IPCA, TGI, MExG, GLI	(Relu, 1, 5, 500)	0.96***	0.46	5.30	0.94***	0.62	7.66
ANNB-SWC2	RGVBI, G %, ExGR, ExG, CIVE, VEG, TGI, COM, GLI, IPCA, MExG	(Identity, 1, 4, 500)	0.92***	1.65	9.57	0.86***	2.12	12.66
ANNB-SY2	ExGR, ExG, COM, CIVE, MExG, TGI	(Tanh, 1, 4, 500)	0.94***	0.52	6.89	0.87***	0.75	12.70

Table 8. Performance of various ANN models in forecasting measured parameters of dry bean crops using different RGBIs. Z, L, N, and I represent activation function, layers number, neurons number in each layer, and iterations number, respectively.

Model	Optimal SRI and RGBIs	Hyper-parameter (Z, L, N, I)	Training		Testing	
			R ²	MSE	R ²	MSE
ANNB-WB3	ExG, CIVE, TGI, IPCA, SRI _{580,1130} , SRI _{586,1130} , SRI _{636,630} , SRI _{642,632} , SRI _{648,622}	(Logistic, 2, 5, 700)	0.97***	2.09	0.96***	2.35
ANNB-DB3	ExG, CIVE, COM, TGI, IPCA, MExG, SRI _{580,1130} , SRI _{586,1130} , SRI _{636,630} , SRI _{642,632} , SRI _{648,622}	(ReLU, 1, 9, 700)	0.99***	0.10	0.987***	0.20
ANNB-CMC3	RGVBI, ExG, CIVE, TGI, IPCA, MExG, SRI _{586,1130} , SRI _{636,630} , SRI _{642,632} , SRI _{648,622} , SRI _{662, 610}	(Logistic, 1, 8, 500)	0.93***	0.41	0.88***	0.53
ANNB-SPAD3	ExG, CIVE, COM, TGI, MExG, SRI _{636,630} , SRI _{642,632} , SRI _{648,622} , NDI _{686,620}	(ReLU, 2, 5, 500)	0.935***	0.61	0.933***	0.71
ANNB-SWC3	ExG, CIVE, COM, TGI, GLI, MExG, SRI _{574,1134} , SRI _{580,1130} , SRI _{586,1130} , SRI _{636,630} , SRI _{642,632} , SRI _{1104,710} , SRI _{1120,1142}	(Tanh, 1, 8, 800)	0.98***	0.77	0.977***	0.81
ANNB-SY3	ExG, ExGR, CIVE, COM, TGI, MExG, SRI _{574,1134} , SRI _{580,1130} , SRI _{586,1130} , SRI _{636,630} , SRI _{642,632} , SRI _{1104,710} , SRI _{1120,1142}	(Tanh, 1, 6, 500)	0.99***	0.39	0.988***	0.57

Table 9. Performance of different ANN models for prediction of measured parameters and SY of dry bean using RGBIs and SRIs together. Z, L, N, and I represent activation function, layers number, neurons number in each layer, and iterations number, respectively.

This study highlights the effectiveness of combining RGBIs with ANN in predicting measured parameters and SY for dry bean crops under deficit irrigation. Deficit irrigation induces dehydration and wilting, leading to changes in plant pigmentation, CMC, and stomatal closure. These changes are effectively captured by RGBIs²⁵. By utilizing the variations in these indices, measured parameters and SY for dry bean were successfully quantified using ANN models, resulting in good values for R², RMSE. The incorporation of highly correlated RGBIs, indicative of plant health, likely played a pivotal role in achieving these favorable results. Accurate predictions during the flowering stage hold particular significance for informed decision-making. Our research was compared to other studies on plant growth and yield prediction using ANN. Hamdane et al.¹³⁵ used ANN in combination with RGBIs to estimate the canopy vigor and biomass of tomato, eggplant, and pepper plants, achieving an R² of 0.82. Similarly, Hassanijalilian et al.¹³⁶ utilized RGBIs of soybeans captured with smartphones to develop an estimation machine learning model for chlorophyll content. The study demonstrated the efficiency and cost-effectiveness of this image processing approach with machine learning modeling, offering a scalable and adaptable solution for estimating chlorophyll content in soybeans and potentially other large-scale agricultural settings.

Performance of ANN model based on RGBIs and published and newly developed SRIs for predicting the measured parameters of dry bean crop

This study examined multiple ANN models based on selected combinations of RGBIs and SRIs to enhance the predictive capability for measured parameters and SY. Displayed in Table 9; Fig. 12, the ANN models were trained using RGBIs and SRIs as independent variables to forecast the measured parameters and SY of dry beans. Standing out among the models, ANNB-WB3 emerged as a robust predictor for WB, yielding R² values of 0.97 (RMSE = 2.09 g/plant) in training and 0.96 (RMSE = 2.35 g/plant) in testing. The ANNB-DB3 model excelled in measuring DB, achieving R² of 0.99 (RMSE = 0.10 g/plant) in training and 0.98 (RMSE = 0.20 g/plant) in testing. In terms of CMC, the ANNB-CMC3 model showcased superior precision, with R² values of 0.93 and 0.88, and RMSE values of 0.41% and 0.53% for training and testing, respectively. Leading the pack in predicting SPAD values, the ANNB-SPAD3 model achieved R² values of 0.94 (RMSE = 0.61) in training and 0.93 (RMSE = 0.71) in testing. The ANNB-SWC3 model, tailored for estimating SWC, reached R² values of 0.98 (RMSE = 0.77%) in training and 0.98 (RMSE = 0.81%) in testing. Lastly, for SY assessment, the ANNB-SY3 model demonstrated exceptional accuracy with R² outputs of 0.99 (RMSE = 0.39 g/plant) in training and 0.98 (RMSE = 0.57 g/plant) in testing. Elsherbiny et al.¹³⁷ emphasized the importance of employing multiple training

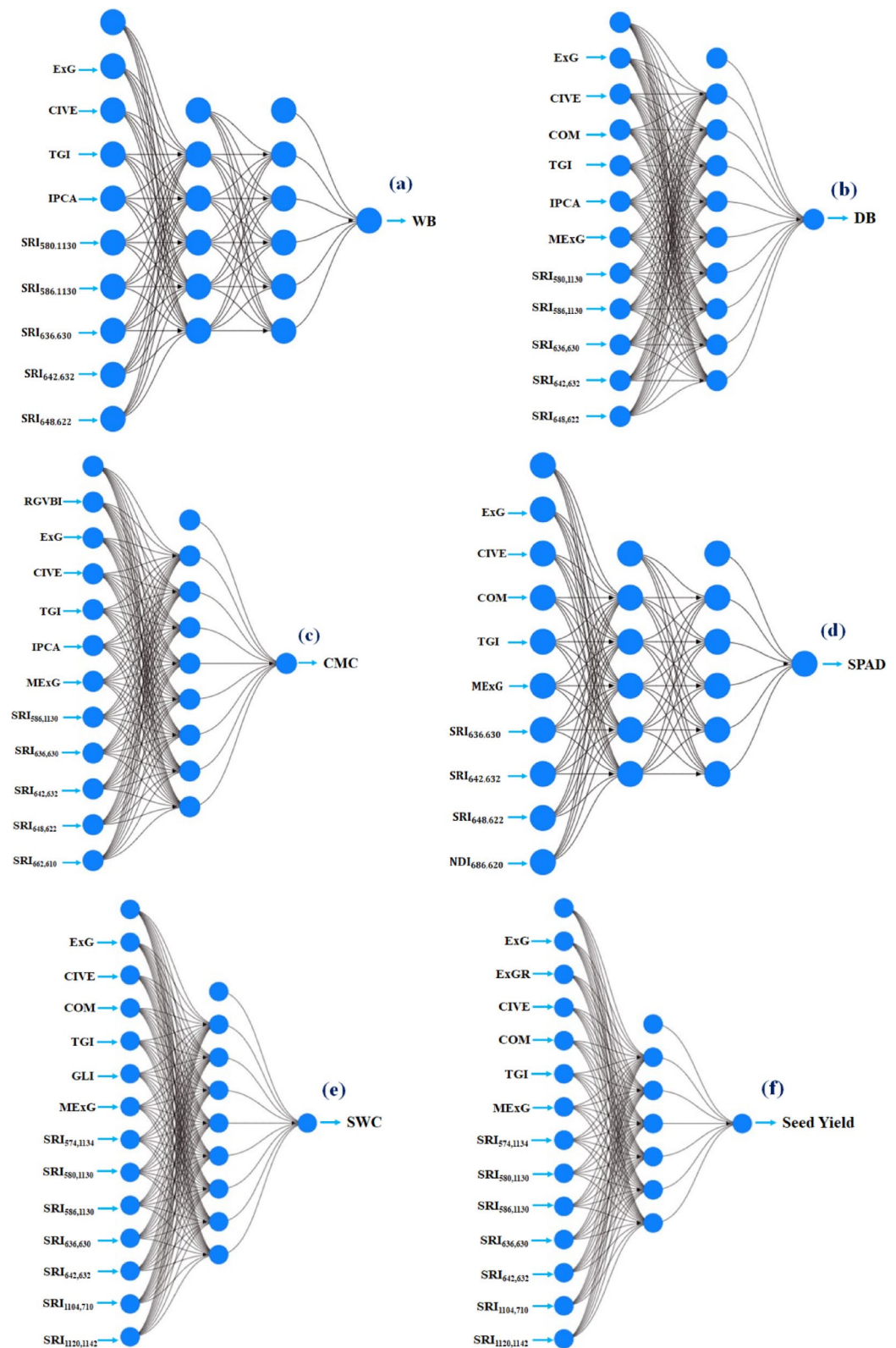


Fig. 12. Illustrates the ANN architecture that integrates SRIs and Rgps to identify the measured parameters and SY of dry bean crops grown under deficit irrigation regimes.

steps to enhance performance, including feature filtering and hyperparameter optimization. This study aims to elevate the precision and robustness of the predictive model for measured parameters and SY of dry bean, emphasizing the critical role of incorporating diverse features in this endeavor.

Limitations and future outlook

The spectroradiometer measurement technique was complex for obtaining data over large fields, primarily because collecting spectral data was time-consuming. However, its 2 nm bandwidth positively contributed to the study's accuracy. Additionally, the combination of SRIs and RGBIs with ANN models enhanced the overall accuracy values. For future studies, integrating the spectroradiometer or specialized RGB cameras into a UAV platform could streamline data collection, save time, and improve prediction accuracy. Expanding the dataset to include dry bean measurements from different years and locations would help verify the applicability and stability of the variables. Moreover, we plan to apply deep learning models to analyze images at the pixel level for improved dry bean yield prediction.

Conclusion

Water stress significantly affects crop production by impeding nutrient uptake, photosynthesis, and respiration. Remote sensing technology facilitates the early detection of water stress, enabling timely management interventions that optimize yields in precision farming. Through field experiments conducted in 2022 and 2023, three drip irrigation regimes: 100% (B100), 75% (B75), and 50% (B50) of full irrigation requirements were evaluated for dry bean crops. Spectral reflectance indices (SRIs) and RGB image indices (RGBIs) were employed to assess key parameters such as wet biomass (WB), dry biomass (DB), canopy moisture content (CMC), SPAD, soil water content (SWC), and seed yield (SY). Results indicated that the B100 regime yielded the highest values for WB, DB, CMC, SWC, and SY, while the B75 regime showed the highest SPAD values. The study also revealed that newly developed SRIs outperformed previously published indices in estimating crop parameters and yield, demonstrating their potential for precision agriculture. Additionally, most RGBIs incorporating the green component showed strong correlations with crop parameters, while the RB index (excluding green) was ineffective. ANN models utilizing both published and newly developed SRIs achieved high prediction accuracy, with R^2 values ranging from 0.86 to 0.97. Similarly, ANN models using RGBIs demonstrated high prediction accuracy, with R^2 values ranging from 0.81 to 0.97 for WB, DB, CMC, SPAD, SWC, and SY. Combining SRIs and RGBIs further enhanced model performance, with R^2 values ranging from 0.88 to 0.99, making them robust tools for crop management under deficit irrigation. This research highlights the practical application of remote sensing and ANN models for optimizing irrigation strategies and improving crop productivity under water-limited conditions. The integration of SRIs and RGBIs provides a cost-effective and scalable approach for real-time monitoring and management of dry bean crops, offering valuable insights for precision agriculture and sustainable farming practices.

Data availability

The dataset can be shared upon request from the corresponding author.

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Declarations

Competing interests

The authors declare no competing interests.

Experiment location ownership

The land on which the experiment was conducted belongs to one of the authors (Salah Elsayed).

Additional information

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