



RESEARCH ARTICLE

Unmanned Aerial Vehicle (UAV) based image capturing of iron chlorosis in sugarcane crop and digital image processing

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Abstract

Agricultural productivity must increase to meet global food demand while conserving natural resources. Unmanned aerial vehicles (UAVs) offer a rapid and non-destructive approach for crop monitoring. In this study, UAV-based imaging was used to capture sugarcane (variety Co 86032) under healthy and iron-deficient conditions. Images were pre-processed and analysed using RGB, HSV, YCbCr, and L*a*b* colour spaces. Quantitative colour parameters were extracted and compared between healthy and iron-deficient leaves. Iron-deficient leaves showed higher brightness and yellow tonal components (e.g., R values increased from $\sim 145 \pm 12$ to 198 ± 15 , and L* values from 50-70 to 70-90). The results demonstrate that UAV-acquired imagery combined with digital colour analysis can effectively differentiate iron chlorosis in sugarcane under field conditions.

Keywords: Colour spaces; digital image processing; iron deficiency; image analysis; machine vision; precision agriculture; sugarcane; UAV

Introduction

Global food requirements are rising steadily, placing increasing pressure on agricultural systems to enhance productivity while ensuring sustainable resource use (FAO, 2020). Sugarcane (*Saccharum* spp.) is a major industrial crop cultivated widely in India, with productivity influenced by climatic, soil and stress-related factors (1, 2). Both biotic and abiotic stresses are major constraints that adversely affect crop yield and farm profitability.

In crops such as paddy and cotton, field inspection is relatively easy due to shorter canopy height. However, sugarcane develops a dense canopy exceeding two metres, making visual diagnosis of nutrient deficiencies and diseases difficult after early growth stages. This limitation delays timely management interventions, resulting in yield losses (3).

Unmanned aerial platforms enable efficient and rapid acquisition of crop information, offering a practical approach for large-scale field monitoring. When combined with digital image processing, UAV imagery allows quantification of leaf colour, which is an important indicator of crop health (4-7). Colour analysis using standardized colour spaces enables objective assessment of crop stress.

Image processing holds equal importance to image capturing using drones, and it is essential to differentiate and quantify the different colour images scientifically. Colorimetry is the scientific area that measures, quantifies and represents colour (8). It is beneficial in different areas because it provides the ability to turn

colour into an objective factor rather than a subjective one. By complementing this scientific area with computer vision technology, it is possible to view colour characteristics in a digital and standardized manner, in addition to performing colour evaluation using a non-invasive and non-contact procedure (9). This makes it a suitable technology for application in agriculture and the food industry for quality assessment (10, 11). Therefore, this study aimed to capture UAV-based images of sugarcane leaves and analyze colour parameters to differentiate healthy and iron-deficient leaves.

Materials and Methods

Study area and UAV system

A quadcopter UAV (DJI Inspire 1) equipped with an RGB camera (12 MP, 4000 × 3000 pixels, 20 mm focal length) was used. The sensor operates in the visible spectrum (400-700 nm). Flights were conducted at ICAR-Sugarcane Breeding Institute, Coimbatore. Although flights were performed at heights ranging from 2-100 m, image acquisition for analysis was standardized at 2 m above canopy to ensure high spatial resolution suitable for leaf-level analysis.

Image acquisition conditions

Images were captured under uniform lighting conditions between 10:00 AM and 12:00 PM under clear skies. Camera settings (exposure, ISO, white balance) were kept constant. Environmental disturbances such as wind and shadows were minimized. Radiometric calibration was not performed, but acquisition conditions were standardized.

Sample selection

A total of 100 leaf samples (50 healthy and 50 iron-deficient) were collected from sugarcane plants. Iron deficiency was identified based on interveinal chlorosis symptoms with expert validation. Healthy leaves were selected from symptom-free plants.

(i) RGB (Red Green Blue): RGB stands for "Red Green Blue." It refers to the three hues of light (red, green, and blue) that can mix to form any colour. When the highest intensity of each colour is mixed, white light is created. When each hue is set to zero intensity, the result is black (12).

(ii) HSV (Hue Saturation Value): HSV stands for hue, saturation, and value. Hue is a key parameter of color appearance and is defined as the extent to which a stimulus can be perceived as similar to red, green, blue, or yellow. In cylindrical color space models, hue is represented along the central vertical axis, whereas saturation and lightness are expressed by radial distance from the axis and axial position, respectively (13).

(iii) YCbCr: In YCbCr, Y is luminance, meaning that light intensity or brightness of the image, which is nonlinearly encoded based on gamma-corrected RGB primaries, and Cb and Cr are the blue-differential and red-differential chroma components (14).

(iv) $L^*a^*b^*$: The Commission Internationale de l'Éclairage (CIE) establishes standards and recommendations for color measurement. The CIELAB colour space is an international standard developed by the CIE in 1976. Within CIELAB, a psychometric index of lightness (L^*) and two-colour coordinates (a^* and b^*) are defined. L^* is a qualitative attribute of relative luminosity, which is the property according to which each colour can be considered as equivalent to a number on the gray scale, ranging between black ($L^* = 0$) and white ($L^* = 100$). Negative values from a^* correspond to greenish colours, and the positives to reddish ones, whereas the yellowish colours take negative values from b^* and the positives for bluish ones (15).

Image processing

Images were pre-processed by extracting regions of interest. Colour parameters were extracted using MATLAB (version 2015) in four colour spaces: RGB, HSV, YCbCr and $L^*a^*b^*$.

Statistical analysis

Descriptive statistical measures including mean, standard deviation, and coefficient of variation were calculated to summarize the extracted data. Differences between healthy and deficient samples were analyzed using independent sample t-test ($p < 0.05$).

Analytical framework

The workflow included: (i) UAV image acquisition (ii) Image pre-processing (iii) Colour feature extraction (iv) Statistical analysis and interpretation (Fig. 1).

Results and Discussion

The pre-processed sugarcane leaf images, captured by a drone, were processed using MATLAB software version R2024b (Fig. 2). Colours threshold application was selected among the different applications present in the image processing and computer vision of MATLAB software. The images were processed for the colour threshold using the colour space window in the software (Fig. 3). The results of the image processing of various sugarcane leaves using the MATLAB software for defining the colour value through RGB value, Hue Saturation Value (HSV), YCbCr value and $L^*a^*b^*$ values are

presented here in the form of different graphs generated in the software.

The Fig. 4 shows the RGB colour threshold values of the healthy sugarcane leaf imagery. It is observed from Fig. 4 that the Red (R) value varied from 90 to 200, the Green (G) value ranged from 110 to 210, and the Blue (B) value stretched from 75 to 200. The software also offers the advantage of selecting the specific region of interest in the leaf for further studying and quantifying the change in colour in the same leaf (Fig. 5). The Fig. 6 shows the Hue Saturation Value of the normal sugarcane leaf imagery. It is learnt from Fig. 6 that the Hue Saturation (S) ranged from 0.2 to 0.3 and Value (V) ranged from 0.4 to 0.7. The colour threshold of the healthy sugarcane leaf imagery in terms of YCbCr values (Fig. 7). It is observed from the Fig. 7 that the Y (Luma-brightness) value stretched from 100 to 200, Cb (Blue chroma component) value ranged from 110 to 130 and Cr (Red chroma component) value recorded from 110 to 130 for normal/healthy sugarcane leaf images. L^* , a^* , b^* values of the healthy sugarcane leaf are illustrated (Fig. 8). It shows that L^* value ranged from 50 to 70, a^* value extended from -25 to 0, and b^* value varied from 0 to 25, for the healthy sugarcane leaves. The colour threshold values obtained for different colour scales through image processing indicated that the imagery is in green colour.

RGB colour threshold values of the sugarcane leaf imagery with iron deficiency (Fig. 8). It is visualized from Fig. 9 that the Red (R) value varied from 150 to 230, the Green (G) value ranged from 175 to 240, and the Blue (B) value stretched from 100 to 160. Hue Saturation Value of the iron-deficient sugarcane leaf imagery (Fig. 10). It is clear from Fig. 10 that the Hue Saturation (S) ranged from 0.3 to 0.45 and Value (V) ranged from 0.7 to 0.9. The colour threshold of the iron-deficient sugarcane leaf imagery in terms of YCbCr values (Fig. 11). From Fig. 11 the Y value stretched from 150 to 210, the Cb value ranged from 90 to 120, and the Cr value recorded from 120 to 130 for sugarcane leaf images with iron deficiency symptoms. L^* , a^* , b^* colour threshold values of the sugarcane leaf with iron deficiency are illustrated in Fig. 12. It is learnt from Fig. 12 that L^* value ranged from 70 to 90, a^* value extended from -25 to +1 and the b^* value varied from 0 to 48, for the iron deficient sugarcane leaves. The colour threshold values obtained for four different colour scales through image processing indicated that the imagery is closer to the yellow colour.

A total of 100 images were analyzed. The analyzed colour features exhibited distinct variations between healthy and iron-deficient leaf samples across all colour spaces. Healthy leaves exhibited dominant green characteristics, while iron-deficient leaves showed increased brightness and yellow tonal components. For example, RGB values indicated higher red and reduced green dominance in chlorotic leaves. Similarly, L^* and b^* values increased significantly, indicating higher brightness and yellow chromaticity. Statistical analysis confirmed significant differences between healthy and deficient leaves ($p < 0.05$). For instance, R values increased from 145 ± 12 to 198 ± 15 , demonstrating clear separation (Table 1). A simple threshold-based classification using L^* and b^* values showed effective differentiation between classes, indicating potential for automated detection.

Among colour spaces, $L^*a^*b^*$ and HSV were more effective than RGB due to better separation of brightness and chromaticity. RGB values were more sensitive to illumination variations. Some overlap in values was observed due to variability in leaf age, lighting conditions, and symptom severity. However, combining multiple colour parameters improved discrimination.

Iron deficiency is characterized by interveinal chlorosis in young leaves, whereas nitrogen deficiency affects older leaves uniformly, and sulphur deficiency shows uniform chlorosis without vein retention. These differences justify the observed variation in colour parameters. Earlier investigations have also demonstrated the effectiveness of digital image analysis techniques for crop monitoring and stress detection. (16-23). The present study extends these findings to UAV-based sugarcane monitoring under field conditions.

The colour assessment of fruits and vegetables in the food industry and colour assessment based on leaves in agriculture using machine vision and image processing has become a trend in recent years (24). A machine vision system for agricultural and horticultural products requires the ability to capture, process, and analyze colour images, where algorithms are suitable to detect, extract and quantify the attributes of Colour (25).

In a report, it was able to classify fruits using high-resolution images of various fruits, including apple, orange, banana, mango, and pomegranate, with an accuracy level of 90 % based on colour (26). The different extracted colour images of the fruits were processed through an artificial neural network to extract all specified

features, and these extracted features were compared with stored features in the neural network. Based on this comparison, the fruits were classified. This methodology demonstrated the improvement in the classification accuracy using MATLAB software. Similar results were observed by (27) for banana and (28) for olive fruits using image processing. The distinguishable colour difference of various images obtained from image processing would help develop an artificial vision system for carrying out the analysis of the key attributes in extracting colour parameters in an efficient and non-destructive manner. These quantitative values of colour contribute to visual observation and quantification of various crop stresses in agriculture, enabling better and earlier management of the sugarcane crop.

Limitations and practical implications

Colour-based analysis may lead to misclassification under overlapping stress conditions or variable lighting. Integration with texture, spectral data, and machine learning models is required for improved accuracy. The study was conducted at low altitude (2 m), representing a high-resolution experimental scenario. Future work should evaluate performance at operational UAV heights.

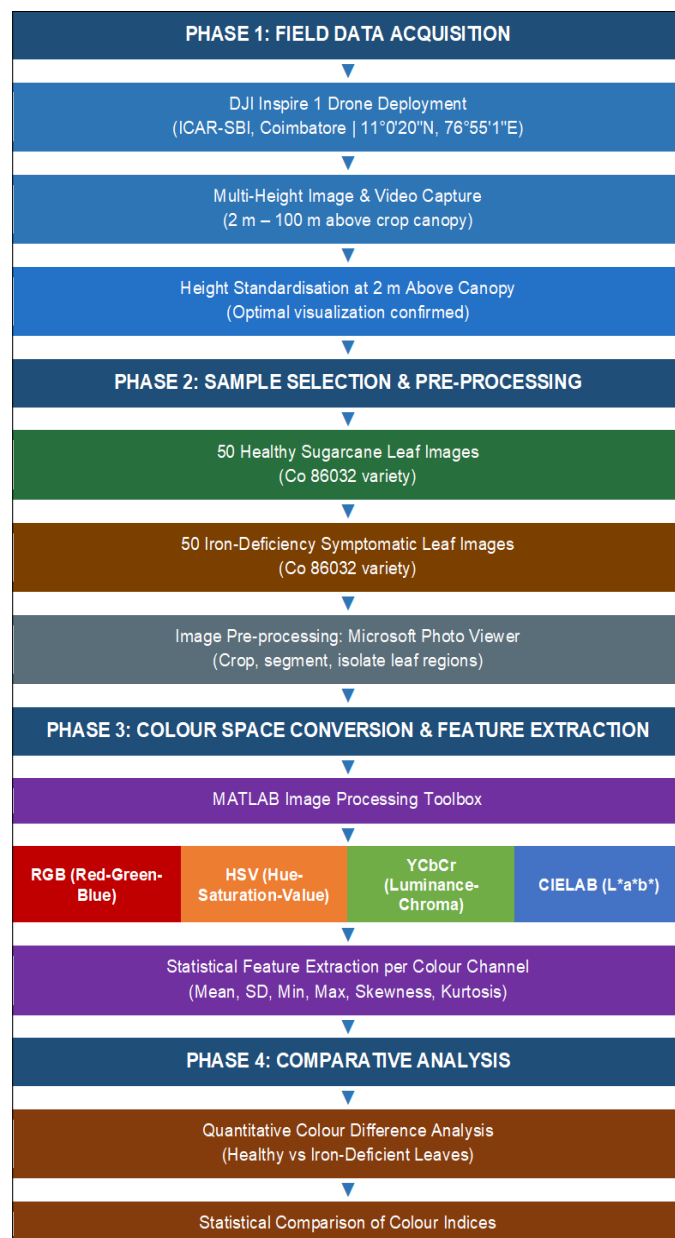
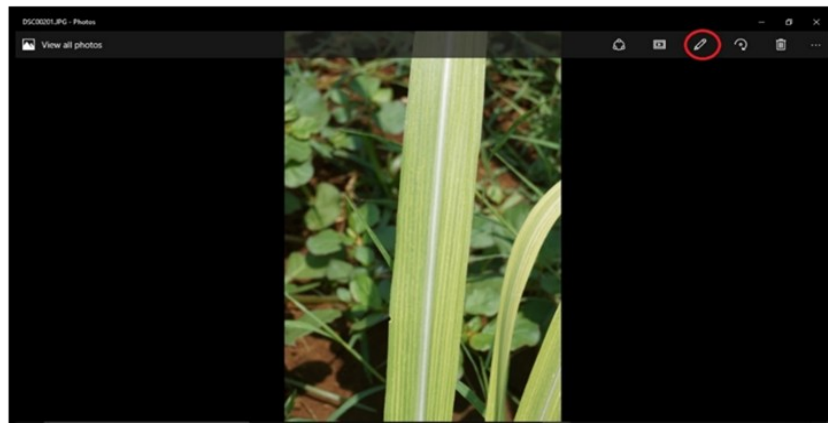
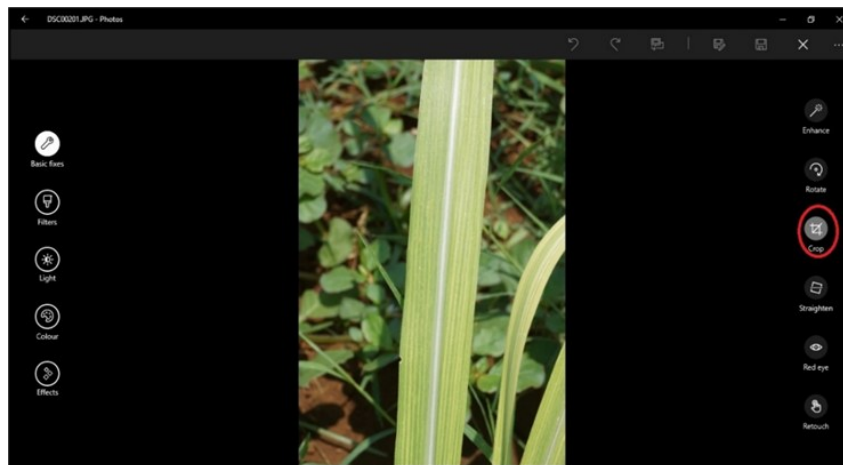


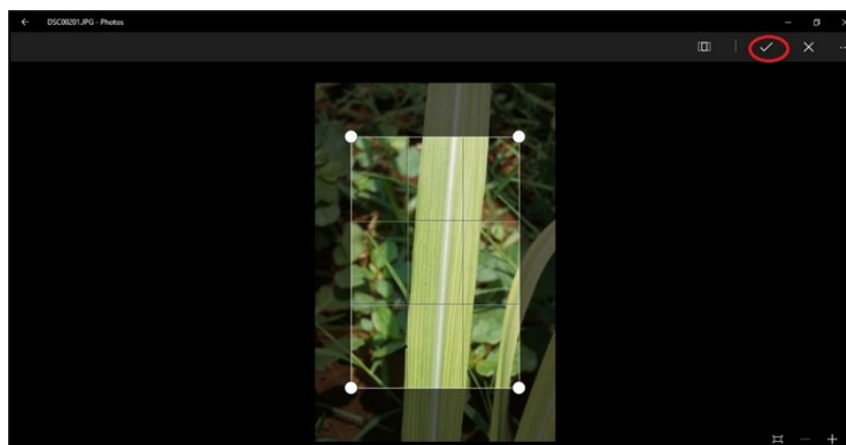
Fig. 1. Analytical framework for drone-based multi-colour space analysis of sugarcane leaf iron deficiency.



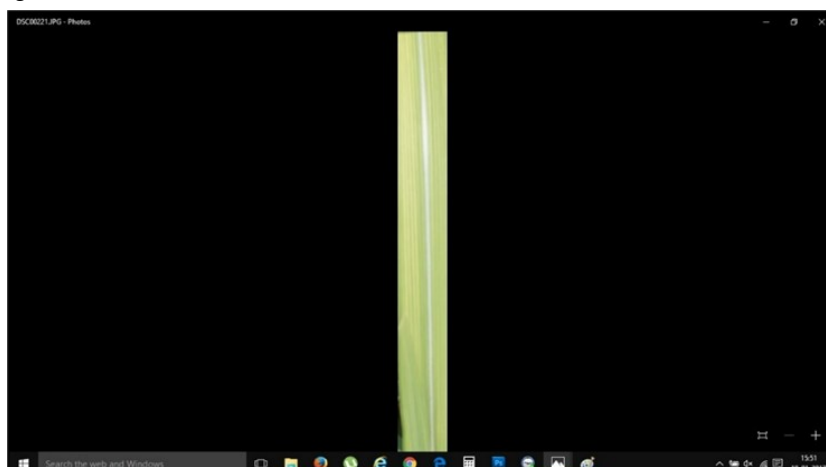
STEP 1. Open the image in the photo viewer and click the edit command



STEP 2. Click the crop command to select the required region



STEP 3. Select the required region and save



STEP 4. Pre-processed/extracted leaf image

Fig. 2. Pre-processing/extracting the leaf images for image processing.

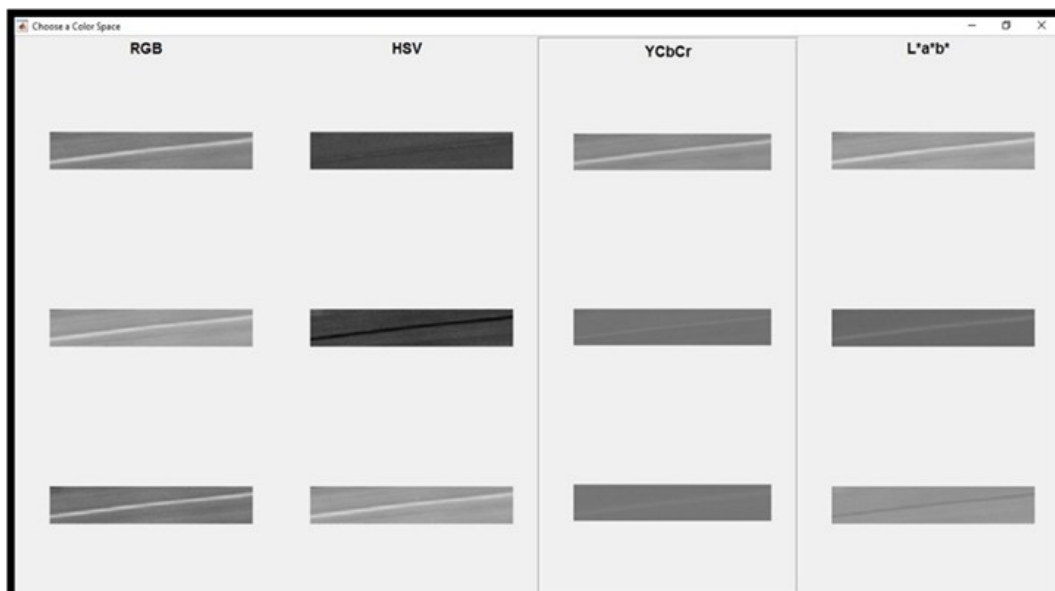


Fig. 3. Colour space window in the colour thresh holder application in the software.

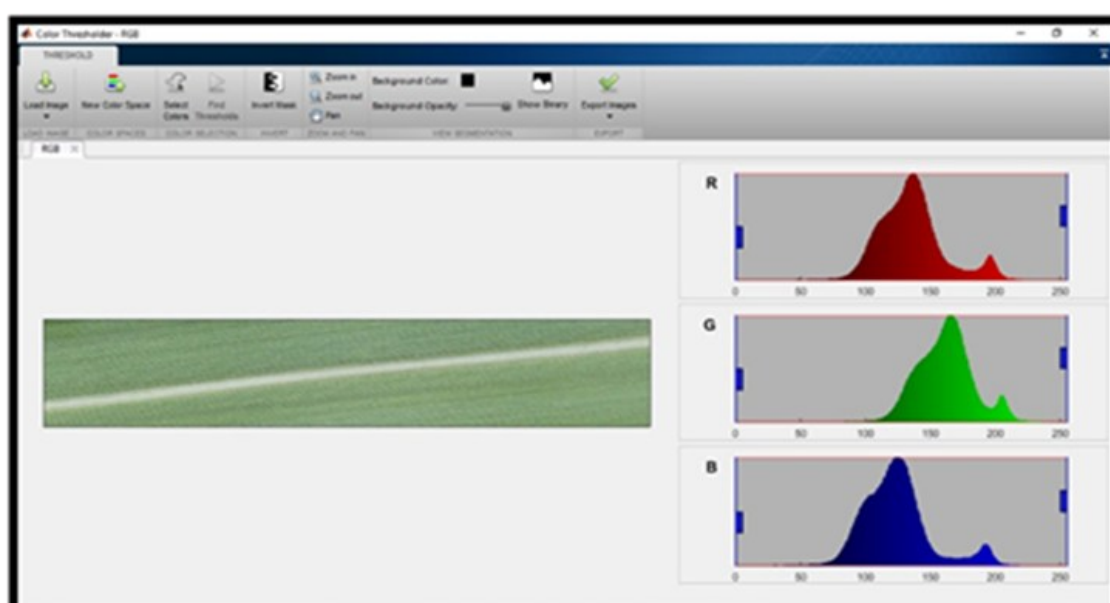


Fig. 4. Distribution of RGB colour parameters for healthy sugarcane leaf images showing dominance of green intensity, characteristic of normal chlorophyll content.

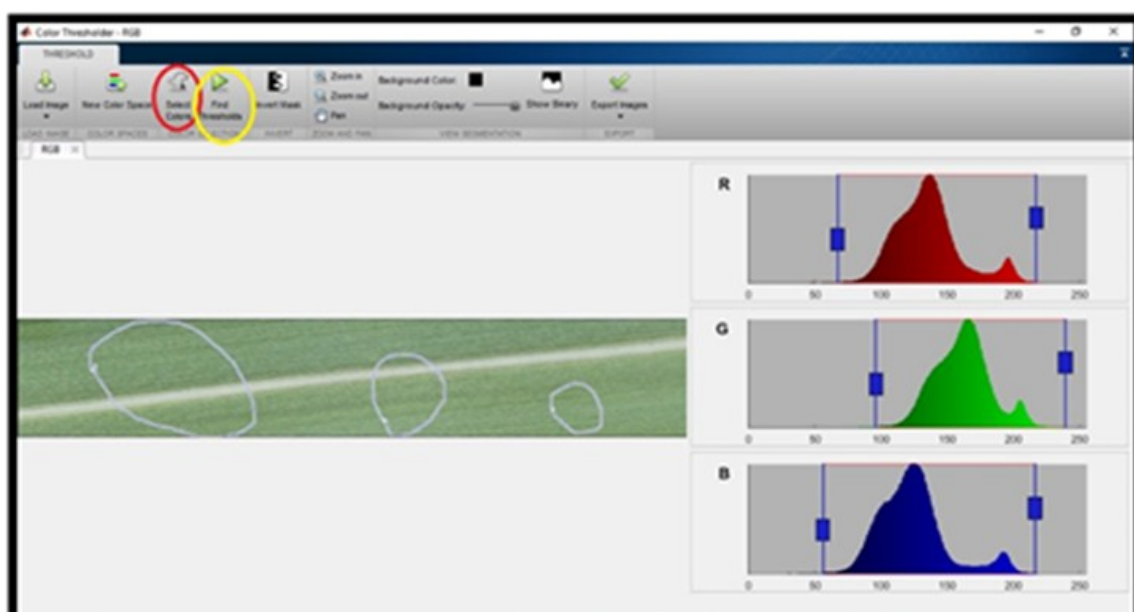


Fig. 5. Healthy sugarcane leaf Colour parameter distribution for RGB for specific region.

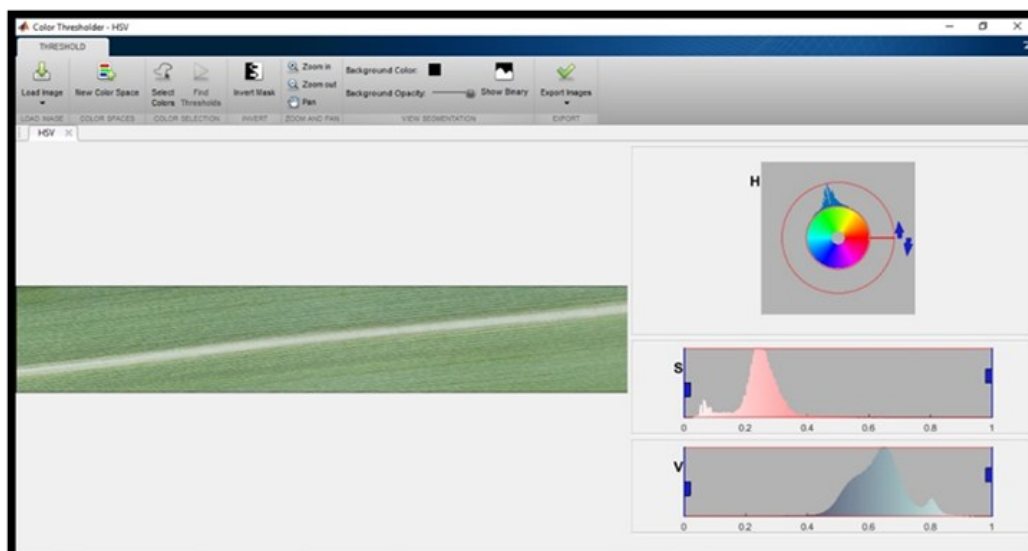


Fig. 6. Distribution of HSV colour parameters for healthy sugarcane leaf images, indicating moderate saturation and value corresponding to healthy green foliage.

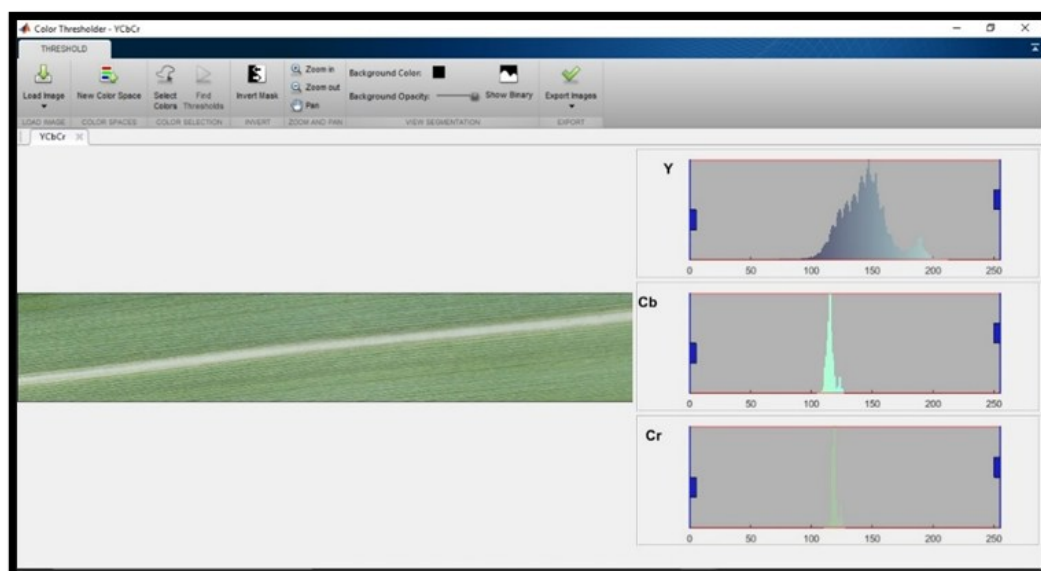


Fig. 7. YCbCr colour parameter distribution for healthy sugarcane leaf images, reflecting balanced luminance and chroma components associated with normal leaf colour.

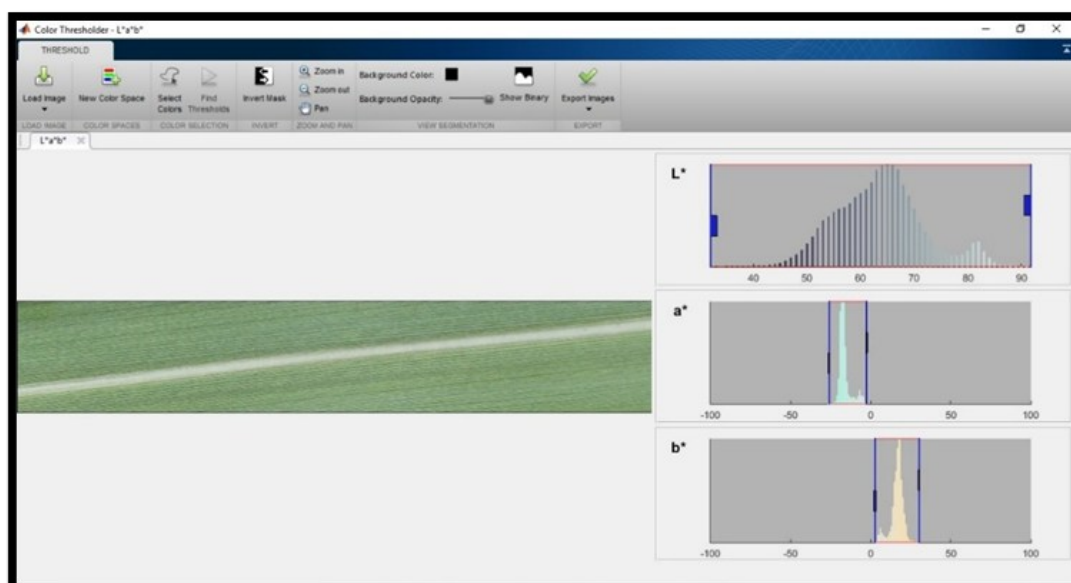


Fig. 8. L*a*b* colour parameter distribution for healthy sugarcane leaves, showing moderate lightness (L^*) and negative a^* values corresponding to green tonal characteristics.

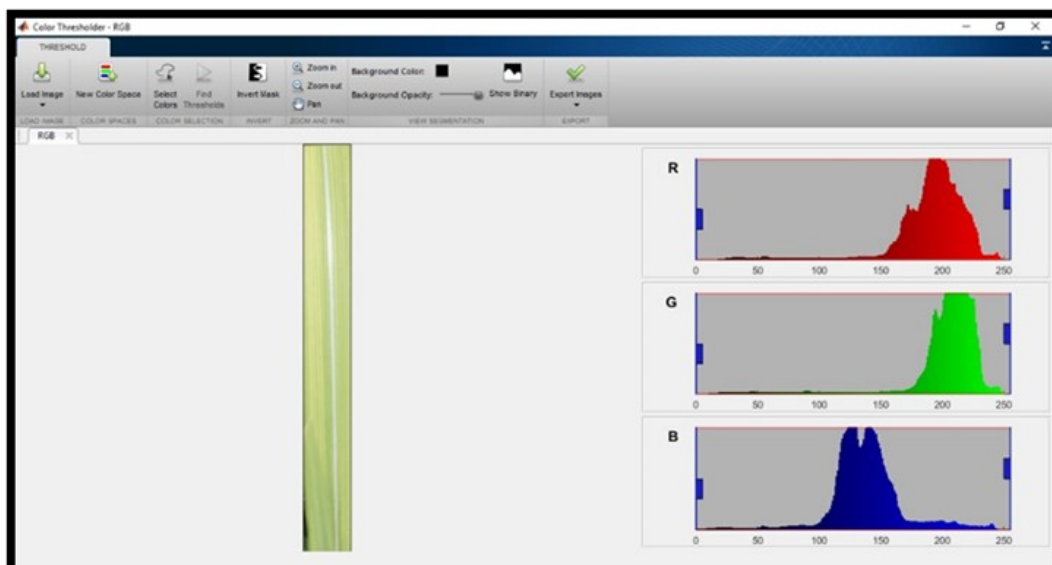


Fig. 9. Distribution of RGB colour parameters for iron-deficient sugarcane leaves, indicating increased red and reduced green intensity associated with chlorosis.

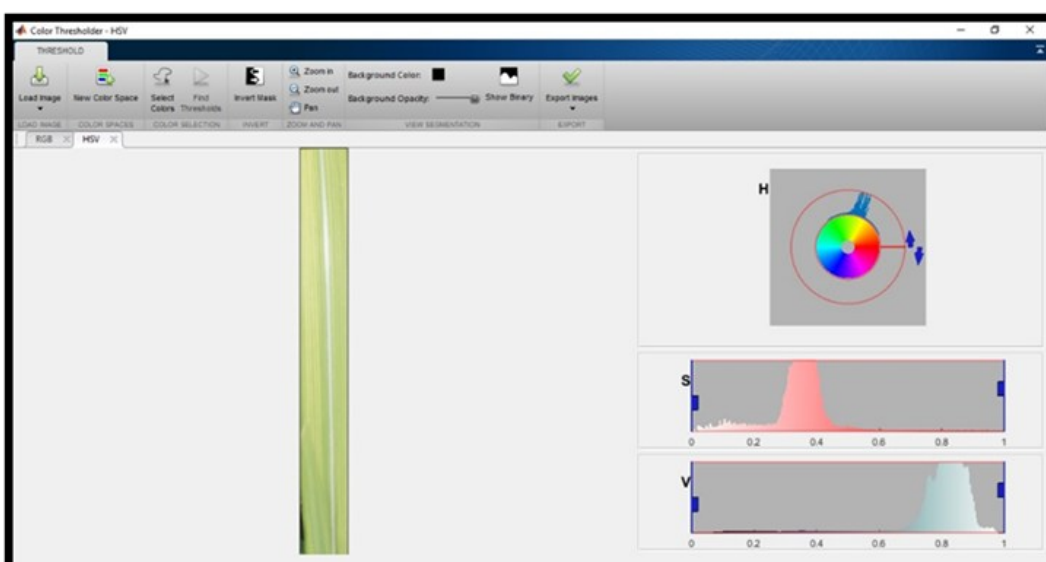


Fig. 10. HSV colour parameter distribution for iron-deficient leaves, showing higher value (brightness) and altered saturation corresponding to yellowing symptoms.

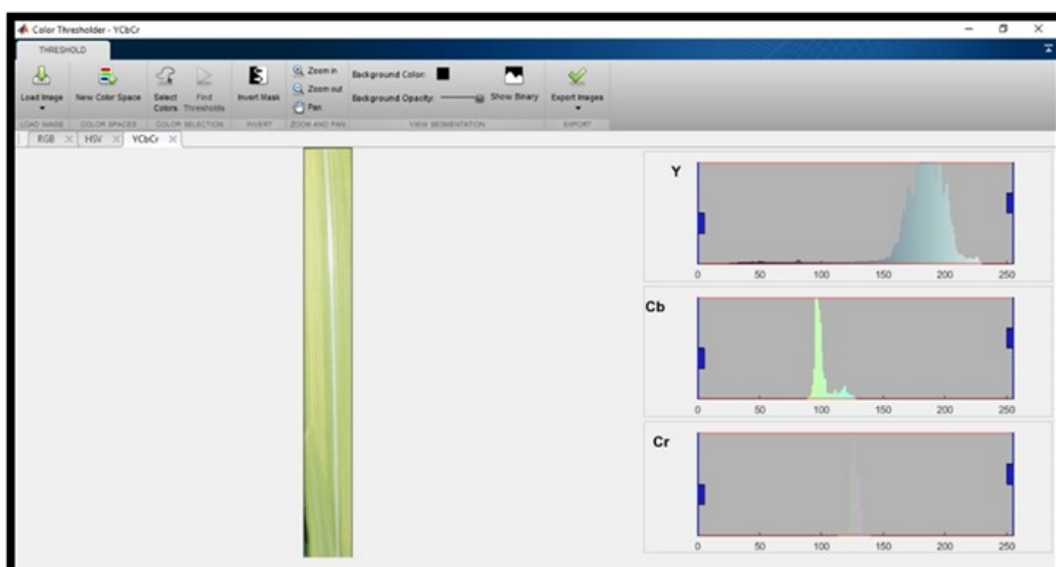


Fig. 11. YCbCr parameter distribution for iron-deficient leaves, indicating increased luminance and shifts in chroma components due to chlorotic changes.

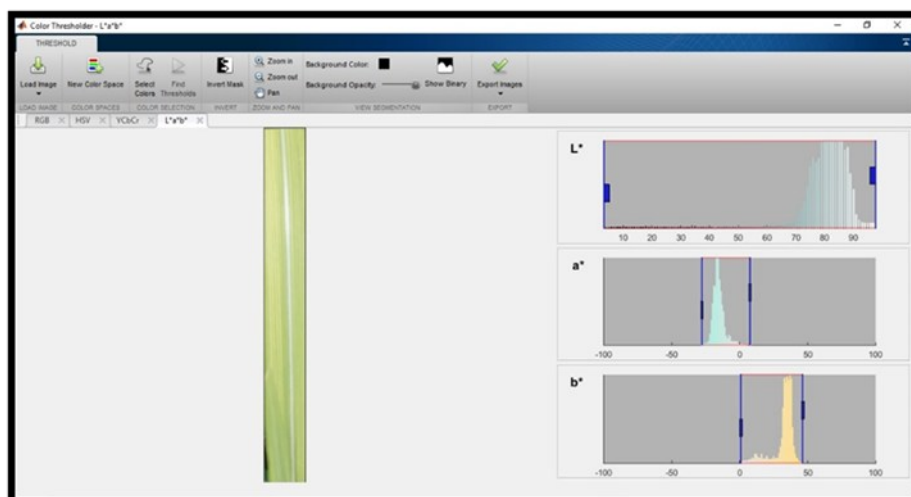


Fig. 12. L*a*b* colour parameter distribution for iron-deficient sugarcane leaves, showing higher lightness (L*) and increased b* values indicating yellow coloration.

Table 1. Statistical comparison of colour parameters between healthy and iron-deficient sugarcane leaves

Parameter	Healthy (Mean $\pm$ SD)	Deficient (Mean $\pm$ SD)	p-value
R	145 $\pm$ 12	198 $\pm$ 15	< 0.05
G	160 $\pm$ 15*	207 $\pm$ 18*	< 0.05
B	137 $\pm$ 20*	130 $\pm$ 15*	< 0.05
S	0.25 $\pm$ 0.03*	0.37 $\pm$ 0.04*	< 0.05
V	0.55 $\pm$ 0.08*	0.80 $\pm$ 0.06*	< 0.05
Y	150 $\pm$ 25*	180 $\pm$ 18*	< 0.05
L*	60 $\pm$ 05*	80 $\pm$ 05*	< 0.05
b*	12 $\pm$ 06*	24 $\pm$ 10*	< 0.05

Conclusion

Drone-based imaging presents a transformative opportunity for the early diagnosis of micronutrient deficiencies in sugarcane crops. By capturing high-resolution field images through UAVs and processing them in MATLAB using colour space parameters such as RGB, HSV, YCbCr and L*a*b* values, it becomes possible to clearly distinguish between healthy leaves and those exhibiting deficiency symptoms. Among these parameters, L* and b* values prove particularly reliable as indicators of chlorosis, establishing a measurable, data-driven basis for identifying iron deficiency in sugarcane leaves. Beyond diagnostic accuracy, UAV technology offers significant practical advantages for modern agriculture. Its ability to cover large areas within a short time, combined with the capacity for deployment across multiple stages of the cropping cycle, addresses longstanding challenges associated with delayed diagnosis and inefficient input use. These capabilities translate directly into improved input use efficiency and stronger economic returns for farmers. The value of drone-acquired data is further amplified when UAVs are equipped with additional sensors, enabling a broader range of precision agriculture applications. However, realising the full potential of this technology in rural farming communities will require targeted training programs and sustained awareness initiatives to ensure wider adoption. This study lays a foundational framework for the development of automated crop stress detection systems. Going forward, research efforts should be directed toward large-scale field validation, the integration of machine learning models for predictive analysis, and the incorporation of multispectral sensors to enhance diagnostic precision and scalability.

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Authors' contributions

TA contributed to the conceptualization of the study, UAV-based image acquisition and primary digital image processing for detecting iron chlorosis in sugarcane. AB supported remote sensing data analysis, feature extraction and interpretation of image-based results. PM provided domain expertise in sugarcane crop physiology and iron deficiency symptoms and assisted in validating the agricultural relevance of the findings. CP contributed to experimental design, field-level observations and agronomic validation of iron chlorosis identification. AK was involved in algorithm development, visualization of results and preparation of figures and maps. SAP contributed to supervision, critical review and editing of the manuscript and helped in framing conclusions and implications for precision agriculture applications.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT to a very limited extent in order to check the text flow and grammar. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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