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Abstract

Ultrasonic sensing technology can contribute significantly to improving smart agricultural practices by recognizing plants and land features. Accurate detection of these field features is essential for the development of unmanned vehicles, which require precision navigation, obstacle avoidance, and successful field operation. Therefore, the objectives of the study were to employ ultrasonic sensors to detect key parameters of pepper plants and land features, specifically plant height, canopy volume, row spacing, and ridge spacing. Row spacing is the space between rows of plants, and ridge features are the raised soil beds that are often made for planting in upland farming systems. A data collection device was developed and tested in both laboratory and open-field environments. Initially, laboratory tests were conducted to evaluate the sensor accuracy of pepper plant height and canopy volume detection. Following successful validation, field trials were carried out in a pepper cultivation area using a remote-controlled vehicle platform to measure plant height, canopy volume, and row and ridge spacing. An open-source application was used to collect data and visualize the outcomes in real-time. The algorithm presented in the study effectively estimated the height, canopy volume, row spacing, and ridge spacing for pepper plants and associated land features. The results showed plant height of 61.34 and 61.49 cm, canopy volume of 0.29 and 0.31 m^3, ridge spacing of 28.88 and 28.94 cm, and row spacing of 44.42 and 43.88 cm, respectively. No significant differences (p>0.05) were found between the measured and estimated plant and land features. Estimation values were strongly correlated with the measured values, with simple linear coefficients of determination (r^2) of 0.95, 0.93, 0.88, and 0.81 for height, canopy volume, row spacing, and ridge spacing, respectively. The RMSE of these measurements ranged from 0.93 to 2.08 cm, highlighting relatively high accuracy of the proposed methods. The developed system shows the potential of ultrasonic sensors to develop automatic crop monitoring systems and support smart crop production and be adaptable to greenhouses, open fields or on-farm vehicles to identify different types of plants and land features.

Key words: Smart agriculture, precision farming, crop monitoring, plant detection, unmanned vehicle.

Introduction

Pepper (*Capsicum annuum* L.) is a well-known vegetable and is the second-most exported crop in the world (Bosland *et al.,* 2000; Maia and de Morais, 2016; Mancinelli *et al.,* 2019). It is widely recognized for its potential application in food, medicine, and industrial products, owing to its high-value bioactive compounds such as capsaicinoids, carotenoids, and flavonoids (Antonio *et al.,* 2018; Barik *et al.,* 2022). Despite its importance, pepper cultivation faces several challenges related to labor-intensive monitoring practices and inefficient crop management, especially under diverse field conditions. Most of the farmers still use manual measurement and monitoring techniques, which are laborious and time-consuming; these practices have proven to be insufficient based on several case studies (Mielcarek *et al.,* 2018).

Smart farming facilitates continuous monitoring and real-time assessment to help farmers to manage crops more effectively and respond to issues across different field environments. This is important because plant physical characteristics like height, leaf area, canopy volume, and biomass strongly affect yield, and their regular monitoring supports key agronomic decisions on irrigation, fertilization, pest control, and harvest timing (Hunt *et al.,* 2010; Poenaru *et al.,* 2015; Chang *et al.,* 2017). To improve such management, smart agriculture practices using advanced technologies have been proposed that enable better management in variety of field conditions (Islam *et al.,* 2020; Gupta *et al.,* 2022; Wei *et al.,* 2023; Wu, 2022). The implementation of such practices is important for properly monitoring crop characteristics and addressing various growth challenges (Ganeva *et al.,* 2022). Observations of the crop characteristics can also be utilized to inform a wide variety of technical fields, such as plant breeding and variety development, agricultural platform design, yield estimation, and site-specific management (Navabi *et al.,* 2006; Abbas *et al.,* 2020; Gupta *et al.,* 2022). Furthermore, with the global population expected to reach 9.7 billion by 2050 (UN, 2019) and labor shortages increasing (Ali *et al.,* 2021), smart crop production technology could contribute to improve productivity and tackle these global challenges.

Sensor-based crop and land recognition systems have become widely used in modern agriculture for autonomous and smart crop monitoring, giving major benefits to farmers. These smart systems require accurate crop sensing and navigation capabilities both at the ground level as well as from remote distances to ensure successful operation. Crop sensing technologies are used to monitor real-time plant characteristics such as height and canopy volume. Also, to automate the movement of vehicle requires up-to-date information on the row and ridge spacing for upland crop cultivation. For accurate path planning and navigation in agricultural fields, sensor-based recognition of crop and land characteristics could be useful to make the correct decisions. Integrating sensor-based crop recognition into navigation systems clearly enhances both data acquisition and operational autonomy. Ultrasonic sensors, for example, can be used as a low-cost, and efficient way to recognize and measure crop and land characteristics (Escolà *et al.,* 2011; Palleja and Landers, 2017). The current study focuses on the crop sensing side—specifically using ultrasonic sensors—to measure plant and land features that support smart monitoring and further contribute to platform navigation and automation.

Field data collection is difficult because of its disruptive nature and implementation complexity. Nevertheless, it is essential for the precise observation of crop growth and maturity in real conditions (Chang *et al.,* 2011; White *et al.,* 2012). In fact, several studies have collected crop information using non-destructive techniques such as spectral data, optical images, and point clouds to measure agronomic traits such as crop size, structure, and color under field conditions (Li *et al.,* 2015; Schirrmann *et al.,* 2016; Moeckel *et al.,* 2018; Nguyen *et al.,* 2018; Das *et al.,* 2019; Islam *et al.,* 2021). LiDAR sensors can be flown over the targeted area to produce a three-dimensional point cloud of the area (Zolkos *et al.,* 2013). Also, there are limited and expensive research on the use of point clouds and spectral data in agriculture (Hosoi and Omasa, 2009; Saeys *et al.,* 2009; Scharr *et al.,* 2016). Consequently, ultrasonic sensors are considered to be a low-cost, and effective method for the rapid monitoring of crop characteristics without extensive data processing (Montazeaud *et al.,* 2021). Guo *et al.* (2002) used an ultrasonic sensor to construct a safety system to detect any individuals approaching a nearby tractor. Other experiments involving ultrasonic sensors have focused on the effects of various ambient conditions and sensor interferences (Jeon *et al.,* 2011). Leidenfrost *et al.* (2013) conducted investigations in which ultrasonic sensors were employed to distinguish items in an outdoor environment; specifically, they utilized an ultrasonic sensor and vision system for the broad detection of obstacles around a self-driving vehicle. Ultrasonic sensors have also been shown to be able to detect important plant characteristics, such as crop height, canopy density, and biomass, allowing farmers to make informed and timely agronomic decisions (Al-agele *et al.,* 2022).

As a result of recent research, automated monitoring systems for pepper plants have been developed in both greenhouse and open-field environments. For instance, Schor *et al.* (2015) developed a robotic system for early disease detection, Tsetkova *et al.* (2024) investigated the possibility of remote sensing for bell pepper management, and Gupta et al. (2022) established a vision-based system for real-time height and width detection. Pepper plants, fruit, and rows were classed in a horticultural environment by Finkelshtain *et al.* (2015). Although research on real-time data collection for agricultural monitoring (e.g., pests, soil moisture, and plant characteristics) in row crops advanced, studies on land characteristics recognition (e.g., row and ridge spacing) remained limited, highlighting the need for unmanned vehicle automation in agricultural fields. The ultrasonic sensor-integrated system proposed in this research is designed to provide a cost-effective and efficient solution for pepper cultivation, with the potential to be applied in a variety of agricultural environments to help mitigate risks and overcome obstacles in smart crop production.

The use of technology in agricultural applications is essential for increasing productivity and sustainability, particularly in upland farming practices where uneven terrain complicates crop management. The demands for efficient crop management in such situations have made it imperative to conduct accurate and timely data collection, which has led to the emergence of automatic field scouting vehicles as a significant development. The present study evaluates the application of low-cost ultrasonic sensors to estimate essential crop and field characteristics such as plant height, canopy volume, row spacing, and ridge spacing under field conditions, with laboratory testing of plant height and canopy volume to evaluate sensor performance prior to field experiment. Finally, this research introduces a simple, cost-effective, vehicle-mounted sensing approach for real-time crop and land characteristics monitoring in pepper fields. Unlike existing solutions that are often expensive and hardware-intensive, the proposed approach is simple, cost-effective, and easy to implement. The scope of this study focuses on integrating plant and land feature recognition into a unified, automated system using low-cost ultrasonic sensors. The proposed system offers practical, affordable, and adaptable solutions that could assist practitioners, researchers, and agricultural technology developers to support automation and smart farming in different types of agriculture.

Materials and Methods

Pepper variety and experimental field layout

Kaltan Nongjawang (Korean: 칼탄농자왕), a widely grown variety of *Capsicum annuum,* was chosen for the experiment. It is a common pepper seedling variety that is produced locally for the fresh market. The pepper plants were grown at the Chungnam National University experimental farm site (latitude 36°22′05″ N, longitude 127°20′46″ E) in Daejeon, Republic of Korea. The experiment was carried out for one growing season from May to October 2022. Two-week-old seedlings collected from the nearby nursery and transplanted during the first week of May. The harvesting occurred in the last week of October. A sprinkler system was used to irrigate the field daily, with additional weekly irrigation depending on crop needs. Fertilizers and pesticides were applied on a regular basis to promote healthy growth and protect against pests and diseases. Mechanical tilling was performed on the experimental field prior to transplanting, and the soil was then leveled and ridged by hand to establish a uniform raised-bed configuration. To limit weed growth and preserve soil water content, each ridge was covered with 30-micron thick black polyethylene mulch film (Kasirajan and Ngouajio, 2012). The field was a total of 270 m^2 (30 m × 9 m) in size, with a furrow width of 170 cm, an inter-row spacing of 2.45 m, and an intra-row spacing of 0.7 m. Despite the cultivation of other crops in the field, only pepper plants were utilized in the experiment. The experimental plot was comprised of two ridges that were 30 m in length and had a total width of 3.2 m, which included the central furrow for the movement of the sensing vehicle platform. For the study, two parallel rows containing a total of 83 pepper plants were selected, which aimed to evaluate the ultrasonic sensor ability to detect pepper plant height, canopy volume, and row and ridge spacing features automatically. Figure 1 shows the schematic diagram of the pepper plant planting arrangement in two parallel rows on a raised bed covered with plastic mulch, with open furrows between the rows. The field was organized as a single block with no plot subdivision or randomized replication, since the focus of this preliminary study was on the functionality and accuracy of the ultrasonic sensor system rather than treatment comparison. A randomized block design will be implemented in future research to facilitate a more comprehensive assessment. The soil preparation process included standard tillage, followed by the leveling and contouring of ridges that were appropriate for the sensing platform. The sensing platform prototype was a remote-controlled, multifunctional electric vehicle prototype. The vehicle was typically designed for off-road agricultural applications (Ali *et al.,* 2024). In order to detect crop and land features for smart crop production, the vehicle was retrofitted to incorporate ultrasonic sensing technology. Its modular design supports use with other ridge-based crops and, based on its performance, future modifications will be developed for future autonomy in field scouting.

Sensor selection and preliminary laboratory testing

Ultrasonic detection could be useful in agricultural fields due to its low cost, convenience of use, and simplicity for field-based sensing activities (Llorens *et al.,* 2011; Zhao *et al.,* 2022). In the study, a low-cost ultrasonic sensor (HC-SR04, OSEPP Electronics, Ontario, CA, USA) was used to recognize pepper plants and land features (plant height, canopy volume, ridge spacing, and row spacing) in an open field. Although ultrasonic sensors showed comparatively lower resolution than other advanced sensing technologies, they are capable of measuring plants and land characteristics in open fields and can be easily connected with microcontrollers in real time (Sui and Baggard, 2018; Colaço *et al.,* 2018). Sensor performance was evaluated in the laboratory under control conditions before the field test. To validate the sensor accuracy, pepper plant height and canopy volume were tested. Even though ridge and row spacing were not tested in the laboratory due to the limitation of the test facility in the laboratory conditions. Figure 2 illustrates the schematic arrangements and calibration steps used to prepare and evaluate the performance of the ultrasonic sensor for the detection and measurement of pepper plants. The data acquisition process was optimized using different algorithms and software for data collection and analysis, including an AT-mega processor-based prototyping platform that was programmed in C++, the ultrasonic sensor, a microprocessor, a 7-inch display screen, a portable battery, and a variety of connectors (Figure 2B).

The Python programming language and several related libraries were used to communicate with the microcontroller to collect and save the data. The results were displayed in real-time on the data monitoring screen. A serial peripheral interface communication protocol was employed to connect the ultrasonic sensors during the operating procedure. The real-time data collected from various positions were displayed, saved as a .csv file, and then retrieved for further data processing. The installation of a data acquisition system allowed for the collection of sensor output, which was subsequently transferred to a computer using the VNC (Virtual network computing) protocol. Detailed technical specifications of the sensors and devices used in the study are shown in Table 1.

The full sensor data collection process was tested and evaluated under laboratory conditions with temperature and humidity readings at 26°C and 37%, respectively. The sensor was positioned 200 cm above the ground using the aluminum bar and was tested on the adjustable plastic plate sheet at different positions, 10 cm apart, in triplicate (Figure 2). For sensor calibration, the height of the reflected surface board was measured using a measuring tape from the sensor location to evaluate the accuracy of the ultrasonic sensor. The module was tested on pepper plants under laboratory conditions to assess the ability of the sensor to measure the height and canopy volume of the upland crops. For the height measurements, the plant (62 cm in real height) was positioned 15 cm above the ground in a total of ten distinct places; data was collected in triplicate. To calculate the canopy volume of the pepper plants, a reflected surface board was positioned on the forehead of the crops (five pepper plants were used for the experiment) as an obstacle and the actual distance from the sensor (D_2) was measured. Later, the original distance between the crop and the sensor (D_1) was subtracted to get the radius of the plant. As the shape of the plant is irregular, the crops were rotated and positioned at 90, 180, 270, and 360-degree angles, respectively, and the average measurement was used as the radius of the plant to calculate the canopy volume of the plants. Finally, the differences between measured and estimated values for each crop position were evaluated. The canopy volume estimation procedure is shown in Figure 3.

Design and production of the upland crop monitoring vehicle platform

The upland crop monitoring platform was developed using a variety of materials (e.g., aluminum profiles, PVC (Polyvinyl chloride) board, and necessary fittings). The structure was 120 cm in length, 100 cm in width, and 65 cm in height, and the platform was mounted on the main chassis of the vehicle prototype used to obtain the crop and land characteristics for automatic crop scouting. An experimental field was prepared (specifically to maintain the furrow between the two ridges and control crop row spacing) according to the vehicle specifications (i.e., length, width, and height). Figure 4 shows a picture of the basic structure of the electric vehicle platform together with the integrated sensor configurations. Two sides of the vehicle were equipped with ultrasonic sensors that were fixed using the adjustable aluminum bar (70 cm in height) such that they could be customized for different field circumstances and crop patterns (height and width). The ultrasonic sensors were placed on the right and top left of the vehicle, and covered with a PVC board sheet during field operation. Another set of ultrasonic sensors was fixed using an adjustable bar 2 m above the ground to obtain a crop top view for pepper height measurements.

The programmable microprocessor device was used to control the ultrasonic sensors to assess their ability to evaluate the following parameters: row and ridge spacing, pepper plant height, and canopy area coverage. Six ultrasonic sensors were linked to the RPI via the microcontroller (Arduino Mega 2560). The serial peripheral interface communication protocol was used to connect the sensors to the RPI operating system. The sensor was utilized to identify the features of pepper plants and ridges. The data collected were saved in the integrated data acquisition system and then processed using data processing software. The processed data was then saved and displayed on the database server. The Arduino microcontroller used to collect the sensor data was controlled by the RPI through serial communication using Python programming language. The workflow of the integrated data acquisition system is shown in Figure 5. The successful operation of the ultrasonic sensor depends on the connection between each system. First, the developed Python programs were initialized by pressing the run button on the Raspberry Pi terminal to collect data from the pepper plant samples—specifically, this caused the ultrasonic sensors to send an echo pulse into the experimental environment. When the echo returned, the sensor counted the pepper plants and recorded the distance of each pepper plant from the sensor.

Experimental field and test procedures

The data acquisition system was incorporated into the electric vehicle prototype (Figure 6). The vehicle was controlled remotely, with the necessary sensors placed in fixed positions. The system allowed for adjustment of the sensor positions based on the distance between the plant and the ground according to field requirements. The foreland ridge height was also estimated using the bottom left-1 and bottom right-1 sensors. Finally, to decrease interference from leaves, the bottom left-4 and bottom right-6 sensors were used to detect plants from both sides of the plants (using their stalks) as well as from underneath their canopies. Figure 6A presents the overall architecture of the ultrasonic sensor placements. The vehicle speeds were fixed at 0.1 m/s for the duration of the field experiment and drove approximately along the central line between each furrow, allowing the data to be collected in triplicate at a constant speed. The vehicle was driven in a straight route without interruption during the experiment. Photographs of the field experiment are presented in Figure 6B. The ultrasonic sensors were inspected and tested in the laboratory before starting the experiment and adjusted prior to data acquisition.

The experiment was performed on pepper plants at the fruiting and ripening stages. The collected data were evaluated and compared with actual measurements to determine the estimated outcomes using statistical analysis. A flexible measuring tape was used to manually measure the morphological features of pepper (e.g., height and canopy area) as well as land features (e.g., plant row and ridge spacing).

Automatic recognition methods

Height and canopy volume

The distance to the external surface of the canopy was measured with the ultrasonic sensor by counting the elapsed time between the emission and reception of the emitted signal. Pepper plants were detected using the ultrasonic sensors that were attached to the aluminum structure on both the right and left sides of the vehicle as shown in Figure 7. In this configuration, the ultrasonic wave could detect the leaves of the nearest peripheral plant branches using the TX (transmitted) and RX (received) signals by calculating the distance between the detection points and the sensor positions. D_d is the horizontal distance of the sensor detection point for each pepper plant (Figure 7). The known row-to-row distance (R_1 to R_2) of the pepper plants (obtained by manual measurement) is indicated by D_r. Assuming that the canopy volume is spheroid, Equations 1 and 2 show that the canopy diameter D is twice the difference between the sensor-based distance (D_d) and the actual distance ($D_r/2$); this means that Equation 2 can be used to estimate the volume of the canopy. The height of the pepper plants was calculated by subtracting the sensor-based distance value (H_E) from the fixed distance value (H_A) of the ultrasonic sensor (Equation 3). Two different canopy parameters, pepper plant height (H_T) and the distance between the ground and the canopy skirt (H_G), were manually measured. Equations 1–3 were used to calculate the canopy volume and height of the pepper plants:

$$D = 2\sum_{i=1}^{n}(0.5\,D_r - D_d) \quad \text{(Eq. 1)}$$

$$C_V = \frac{\pi D^2}{4}\left(\frac{2(H_A - H_C)}{3}\right) + (H_C - H_G) \quad \text{(Eq. 2)}$$

$$H_A = H_E - H_G \quad \text{(Eq. 3)}$$

where: C_V is the canopy volume of the pepper plant; H is the height of the pepper plant in cm.

Row and ridge spacing

The pepper plant row and ridge spacing experiments were conducted by installing the ultrasonic sensor at a fixed height above the ground to ensure consistent measurements. After the estimated time was obtained from a reference, the distance to the obstacle was calculated using Equation 4:

$$D = \frac{\mathrm{T} \times \mathrm{V}}{2} \quad \text{(Eq. 4)}$$

where: D is the distance between the sensor and the detected object, T is the time between the transmitted and received reflected wave, and V is the propagation speed of the ultrasonic wave in the air under ambient conditions (340 m/s).

The sensor was used to detect and calculate the distance between the sensor and each plant. Plant rows were detected based on the accumulation of this distance. The ability to identify row spacing is considered to be a crucial attribute for autonomous travel, as the characteristics of the terrain could be used to detect obstacles along the vehicle's traveling route. Figure 8 highlights the features used for the identification of plant rows and ridges at a distance of 4.5 m.

The overall workflow used for the sensor-based recognition of crop and land characteristics for autonomous traveling and crop scouting using ultrasonic sensors is presented in Figure 9. The measuring system starts with the collection of raw data from the experimental field. Irrelevant sensor values were removed *via* denoising and the value of the moving average was obtained. The sensor sets the position (x, y, and z) of the detected plant and land features by comparison with the manually measured data. Plant height and canopy volume were calculated using the mathematical equations presented previously. Finally, the performance of the sensors concerning land and crop recognition was statistically evaluated by comparing them with actual measurements from the experimental field.

Data analysis procedures

Geometric parameters, such as plant height, canopy area, and row and ridge spacing, were compared with actual measurements using linear regression analysis. The standard deviation (SD), standard deviation error mean (SEM), root mean square error (RMSE), coefficient of determination (r^2), and mean difference bias (b) were used as accuracy metrics for the data processing algorithm. r^2 was computed using Equation 5 as follows:

$$r^2 = 1 - \frac{\sum_{i=1}^{i=N} (y_i - y_a)^2}{\sum_{i=1}^{i=N} (y_i - y_{imean})^2} \quad \text{(Eq. 5)}$$

where: N is the number of pepper plants, y_i and y_a represent the estimated and measured values, respectively, and y_i mean is the average of the measured values. The RMSE was computed using Equation 6 as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{i=N} (y_i - y_a)^2} \quad \text{(Eq. 6)}$$

The standard error (S), standard error mean (SEM), and error (%) were computed using Equations 7–9 as follows:

$$S = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \bar{y}_a)^2}{N-1}} \quad \text{(Eq. 7)}$$

$$\mathrm{SEM} = \frac{\mathrm{S}}{\sqrt{\mathrm{N}}} \quad \text{(Eq. 8)}$$

$$Error\ (\%) = \frac{A_V - M_V}{A_V} \times 100 \quad \text{(Eq. 9)}$$

Higher accuracies are indicated by higher r^2 and lower RMSE values. The r^2 and RMSE were determined for plant height, canopy volume, row spacing, and ridge spacing measurements. The data was analyzed by using statistical software packages (SAS 9.4, SAS Institute Inc., Cary, NC, USA) as well as scripts written using the open-source Python programming language (Python software foundation, version: Python 3.12.0).

Results

Height and canopy volume of pepper plant under laboratory conditions

Figure 10 shows the sensor-based measurements of the paper plants at 10 different heights as well as the corresponding canopy volumes of five plants computed using canopy volume formulae under laboratory conditions. The actual height of the experimental plant was 62 cm. The sensor-based measurements were found to be 61, 62, 65, 63, 62, 60, 64, 62, 63, 61, and 62 cm at sensor heights of 0, 15, 30, 45, 60, 75, 90, 105, 120, 135, and 150 cm, respectively. These pepper plant height measurements had an error of 0.44% compared to the mean values, with a maximum error of 3.15%. The canopy volumes of pepper plants were 0.01, 0.10, 0.12, 0.09, and 0.09 m^3, while the sensor-based measurements returned values of 0.02, 0.10, 0.12, 0.08, and 0.10 m^3, respectively. The maximum error for this measurement was found to be 3.6%. The results obtained in the laboratory provide a reliable reference for evaluating sensor accuracy and performance under real field conditions.

Height and canopy volume of pepper plant under field condition

The characteristics of the individual experimental pepper plants were evaluated via field measurements. The average height and area of the pepper plants were 61.34 ± 7.73 cm and 0.30 ± 0.12 m^2 for the measured data set, respectively. The minimum and maximum height and canopy area coverage of the pepper plants investigated in this study were 38 and 84 cm, and 0.09 and 0.64 m^2, respectively. These parameters were estimated using ultrasonic sensor data obtained from the same plants and compared with the measured data set to evaluate the performance of the sensor.

Figure 11 shows the correlation between those parameters, revealing that the ultrasonic sensor exhibited high r^2 values for the estimation of the height (r^2= 0.95) and canopy volume (r^2 = 0.93) of the pepper plants. The difference in these r^2 values can be explained by the higher accuracy of ultrasonic measurements for height estimation compared to the canopy coverage. Although the accuracy of the sensor varies compared to laboratory results, it still shows a significant correlation with the actual measurements. For any single crop slice, plant height and canopy area are generated by single measurements obtained with the ultrasonic sensors, and there is a higher probability of finding holes (i.e., gaps) in the pepper canopy, which would consequently decrease the calculated canopy area coverage. These differences can be clearly observed when plotting the measured vs. estimated values of canopy volume.

Row and ridge spacing of pepper plant under field conditions

Four ultrasonic sensors were installed on both sides of the vehicle platform to continuously determine the distance to the pepper plants for plant row identification and furrow ridge detection in an experimental field, which had a plant row spacing of 30 m. The results of the pepper plant row and ridge spacing detection experiment are presented in Figure 12, which shows the relationship between the actual and sensor-based measurements of these values. For plant row spacing, the sensor-based identification method was moderately correlated with the manual measurement, with an r^2 value of 0.88, and RMSE of 2.08 cm; these moderately successful results may have been due to the different shapes and sizes of the experimental pepper plants.

The ridge-spacing estimates obtained with the ultrasonic sensors exhibited relatively low correlations (r^2=0.81) and high RMSE values (1.99 cm) compared to the actual measurements. This may be due to the irregular terrain as well as the erroneous detection of weeds due to the sensor position; these would have acted as obstacles, reducing the accuracy of the ultrasonic sensor. Furthermore, positional errors tend to accumulate with increasing travel distance due to changing loads, wheel deformation, and other issues.

The summary statistics—e.g., mean, standard deviation (SD), standard error mean (SEM), and correlation (r^2)—of the actual and estimated measurements of pepper plant height, canopy volume, row, and ridge calculations are summarized in Table 2. The study found no significant differences between the actual and estimated values for plant height, canopy volume, ridge spacing, and row spacing, as indicated by the same letter (A) in the mean values. The standard deviations and standard errors remained consistent across all parameters, confirming the reliability of the estimations. The analysis of variance (ANOVA) conducted at a 5% significance level demonstrated that the estimation approach effectively approximated the actual measurements of the pepper plants and land characteristics.

Estimation biases

The accuracy of the estimated measurements was assessed using raw data on pepper plant height, canopy volume, row-to-row spacing, and ridge-to-ridge spacing (Figure 13). The sensor exhibited a slight negative mean difference bias of -0.10, indicating that the sensor tended to slightly underestimate the true height values. The canopy volume measurements exhibited a mean difference bias of 0.003, suggesting a minimal overestimation in volume measurements. The row spacing measurements exhibited a more significant negative bias of -0.54, suggesting a consistent tendency to underestimate row spacing values. Finally, the ridge spacing measurements exhibited a positive mean difference bias of 0.06, indicating a slight propensity to overestimate ridge spacing.

Discussion

The sensing methodology utilized in this study can be used to determine the plant height, canopy volume, row spacing, and ridge spacing of upland crops such as pepper plants. This spatial and morphological information can be used to improve crop cultivation and support navigation to improve autonomous travel for agricultural vehicles. The sensing performance was validated using actual measurements, showing that the morphological characteristics of the plants could be correctly predicted under field conditions. Furthermore, the sensor performances in the field closely match the outputs obtained in controlled laboratory conditions, which proves the sensing reliability of the system. However, some variations were observed between the sensor data and the manual measurements for individual pepper plants under field conditions. These differences were most likely caused by irregularities in the field surface, the low density of the canopy (including clods or up-lifts towards the crown), and the different crop development stages during the experiment (Scotford and Miller, 2004; Fisher and Huang, 2017; Bronson *et al.,* 2021).

The ultrasonic sensors used in this study were cost-effective, lightweight, and easy to incorporate into pre-existing tools, allowing for their integration into multiple real-time agricultural production applications. Although the experiment was conducted on pepper plants (n=83) that were representative of upland field crops, the modular sensing system is adaptable to other ridge-based or row crops, such as tomatoes, eggplants, or cotton, with minimal modifications. This versatility expands its applicability among varied farming systems, especially those that require both crop monitoring and vehicle navigation. The data collection and data processing methods introduced in this research demonstrated reliable performance for estimating plant morphological characteristics (e.g., plant height and canopy volume). However, the r^2 values for row and ridge spacing estimates were relatively lower, which may have been due to the shape of the ridge as well as the rough terrain in the field. Indeed, Palleja and Landers (2015) showed that volume estimations on irregular surface can deviate by up to 30%. Also, the performance of the ultrasonic sensor may be less accurate due to plant movement caused by wind, and inconsistent canopy structures in field conditions (Forrest *et al.*, 2018; *Escolà et al., 2011)*.

On the other hand, ultrasonic sensors are often considered an alternative to LiDAR (light detection and ranging) and RGB-D (red, green, blue, and depth) cameras in many agricultural applications, especially when low cost, easy setup, and reliable performance in changing lighting conditions are important (Sui and Baggard, 2018; Colaço *et al.,* 2018). Building on these advantages, ultrasonic sensors provided a simple and practical solution for crop and land characteristic recognition, making them particularly well-suited for open-field environments. Accurate sensing under real field conditions provides the scope of this system to support both sensing and navigation for autonomous vehicle guidance in agricultural fields. With further improvement in real-time spatial feedback, the systems could enable path adjustment and obstacle avoidance, making them relevant for automated smart crop production.

Furthermore, a strong correlation was observed in the study between the actual and estimated sensor-based measurements of plant height and canopy volume. These results suggest that the sensing technique could be used to rapidly and precisely measure large numbers of pepper plants to identify their shape and height characteristics. Significant correlations were found in different studies between ultrasonic and manual plant height measurements in various crops, with r^2 values ranging from 0.92 to 0.99 for cotton (Bronson *et al.,* 2020) and 0.93 to 0.97 for poppy crops (Iqbal *et al.,* 2017). Many studies have demonstrated the applicability of the ultrasonic sensors in a wide range of crop types. For example, Schumann et al. (2004) used ultrasonic sensors to get an estimate of the volume of citrus trees with 94% accuracy. Alighaleh *et al.* (2024) found r^2 =0.96 for paddy rice, whereas Montazeaud *et al.* (2021) got a r^2 of 0.99 for sorghum. The findings indicated that the potential of ultrasonic sensors for successful application in row or ridge-based crops as an affordable and cost effective field crop monitoring application.

This study indicated that plant height measurements were more reliable among the evaluated parameters, despite variations in height and canopy volume due to the irregular dimensions of the pepper plants. For example, field measurements of pepper height ranged from 84 to 38 cm, and the canopy area coverage ranged from 0.64 to 0.09 m^2. Consequently, the development of autonomous vehicles for the precise management of agronomic practices could be a solution to the problem of agricultural labor shortage. An integrated system for identifying land characteristics would also contribute to the production of unmanned ground vehicles for smart crop production.

It should be noted that the experiment discussed in this study was assessed under field conditions. Consequently, the accuracy of the ultrasonic estimates was lowered due to a variety of issues, including pepper plant shape and size, unsmooth field conditions, and temperature. The ultrasonic sensor would likely perform better under static conditions; consequently, the device could be employed in research applications that rely on the observation of individual plants. Ultimately, the implementation of non-invasive recognition systems using ultrasonic sensors in pepper cultivation has the potential to revolutionize upland crop production. By providing real-time data on crop and land characteristics, this technology allows for precision agriculture, supports crop health monitoring, and promotes site-specific crop management (Boomsma *et al.,* 2010; Miqueloto *et al.,* 2020). Furthermore, the integration of the information could enhance autonomous navigation and control systems that can contribute to sustainable and resource-efficient farming solutions for smart crop production.

Conclusions

This study proposed an automatic crop monitoring system for smart crop production that would use a vehicle platform and sensor-based technologies to take measurements in real time. The system was tested in an upland experimental field with pepper plants to promote crop growth, support regular monitoring, and collect vehicle automation parameters for future improvements using an ultrasonic distance sensor. This approach can significantly increase yield, allow for the cultivation of more land, and achieve better efficiency with less input to meet the growing agricultural demand. Traditionally, key morphological characteristics are measured manually using a ruler and the cube-fit or cylinder-fit methods, which are labour-intensive, time-consuming, and prone to human error, particularly for large plant populations. In contrast, sensor-based measurement of plant characteristics using automated vehicles allows monitoring various parameters, improving field routes and productivity. These sensors can collect information about the plant height, canopy volume, and row and ridge spacing, which can be used to improve smart farming practices. This study explored the potential of smart techniques, particularly ultrasonic sensors, for field scouting and autonomous applications in upland agriculture, predicting a significant impact on crop productivity in the future. The primary benefit of the proposed system for farmers is the ability to monitor crops more frequently, which reduces labor expenses and allows them to make better judgments about when to irrigate, fertilize, and harvest. Furthermore, the system simplicity and low cost make it accessible to small- and mid-level farmers who may not be able to afford advanced technologies such as LiDAR and RGB-D. With minor modifications, this system could be applied to other ridge-based or row crops such as tomatoes, eggplants, cotton, or maize, as well as greenhouses, controlled research plots, and large open-field farms. The main conclusions and recommendations of this study are as follows:

- The application of ultrasonic sensors provides relevant information regarding pepper plant height and canopy volume and allows for the estimation of row and ridge spacing for autonomous travel in agricultural fields; however, there are limitations associated with sensor activation ranges and increasing signal amplitude based on position.

- Despite the problems outlined above, relevant data such as plant height and canopy volume, or even plant row and ridge spacing, can be predicted with reasonable accuracy.
- To further investigate the robustness of the sensor, it would be useful to measure more complex geometric traits, such as plant height and canopy area for the improved identification of plant and land characteristics.
- This study used a variety of techniques for data segmentation and estimation, which did not always result in higher accuracies. Nevertheless, the data, materials, and concepts presented in this study could be used in future research on different crop types. Future work could focus on making the system more scalable and on integrating it with GPS (Global positioning system) and vision systems to develop algorithms that allow autonomous navigation.

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Table 1. Specifications of the major components used for pepper plant and ridge recognition.

Item	Model	Specifications
Ultrasonic sensor	HC-SR04, OSEPP Electronics, Ontario, CA, USA	Dimensions: 45 × 20 × 15 mm Function: non-contact measurement Measuring distance: 2 cm to 400 cm Effective angle: <15° Resolution: 0.3 cm Measuring angle: 30° Velocity of sound: 340 m/s
Raspberry Pi	Raspberry Pi 4 B+, Raspberry Pi Foundation, Cambridge, UK	Working frequency: 40 kHz IO trigger: 10 us high-level signal Input: Trigger pulse Connector: Standard 40-pin GPIO Storage: Micro-SD card Power: 5 V DC Operating temperature: 0–50°C
Arduino	Arduino Mega 2560, Arduino S.R.L., Ivrea, Italy	Dimensions (length × width): 101.52 × 53.3 mm Microcontroller: ATmega2560 Digital input/output pins: 54 Analog input pins: 16 Flash Memory: 256 kB
Display monitor	Raspberry Pi Foundation, Cambridge, UK	Screen dimensions: 194 × 110 × 20 mm Power requirement: 200 mA @ 5 V LCD display size: 800 × 480 mm

Table 2. Summary statistics for the actual and estimated measurements of pepper plants and ridges under field conditions.

Plant features	Measurement	Sample no.	Mean	SD	SEM
Height	Measured	83	61.34[a] cm	7.73	0.85 cm
	Estimated	83	61.49[a] cm	7.41	0.81 cm
Canopy volume	Measured	83	0.29[a] m^3	0.12	0.015 m^3
	Estimated	83	0.31[a] m^3	0.13	0.14 m^3
Ridge spacing	Measured	83	28.88[a] cm	4.52	0.50 cm
	Estimated	83	28.94[a] cm	4.47	0.49 cm
Row spacing	Measured	83	44.42[a] cm	5.37	0.59 cm
	Estimated	83	43.88[a] cm	5.26	0.57 cm

A one-way ANOVA was conducted at a 5% significance level (p<0.05), followed by Tukey's multiple range test, with same letters on the mean values representing no significant variations.

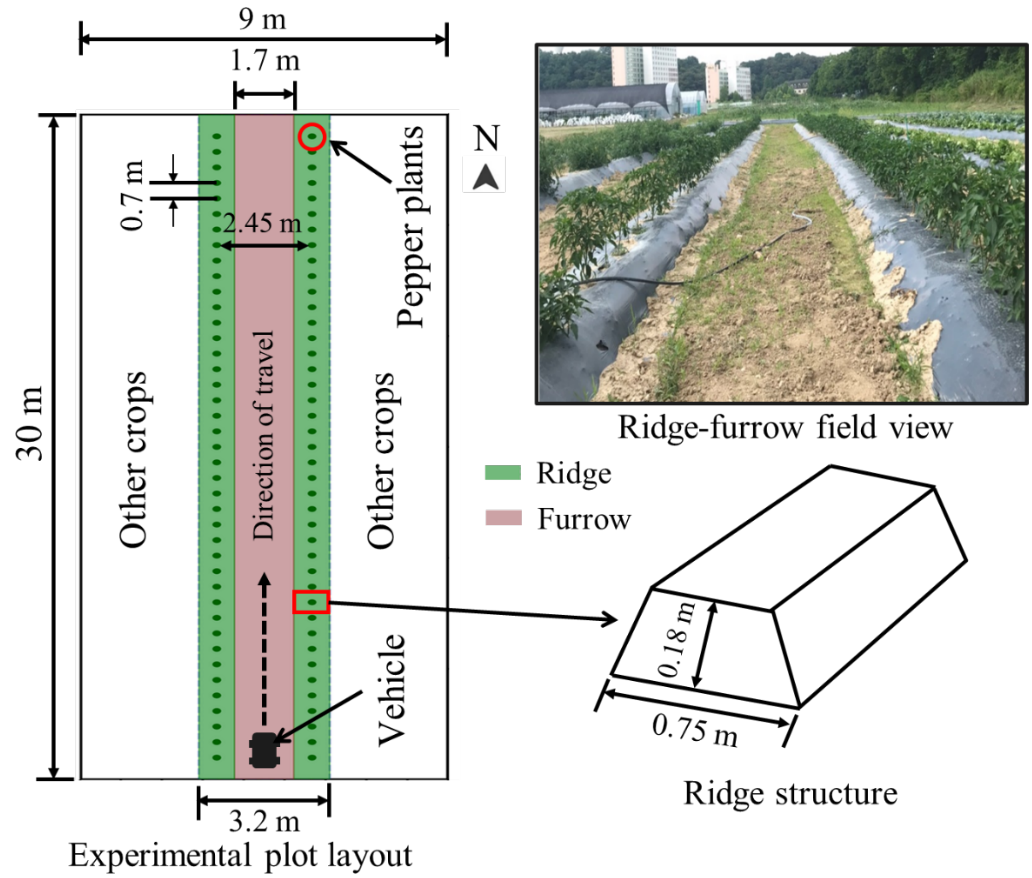

Figure 1. Schematic layout and corresponding field view of the experimental pepper plant plot. The layout illustrates the sensing vehicles travel along the central furrow with pepper plants arranged in single rows on both sides.

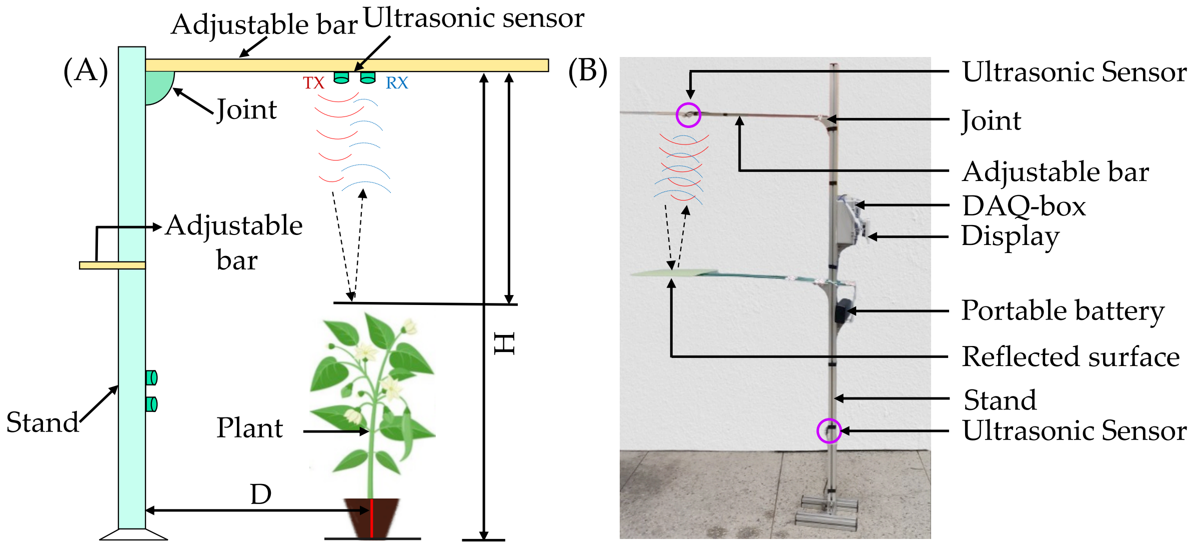

Figure 2. Schematic diagram (A), and photograph (B) of the laboratory setup and calibration steps used to evaluate the performance of the ultrasonic sensor.

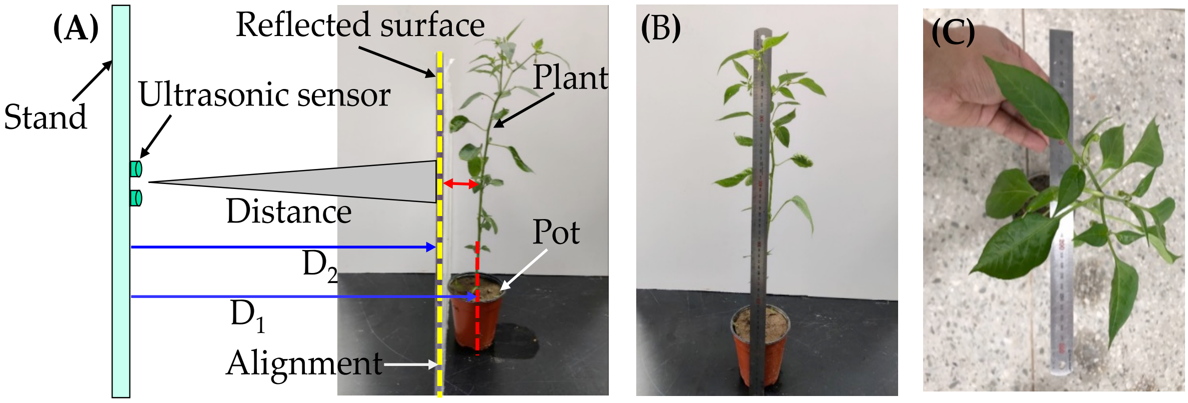

Figure 3. Sensor-based (A) and direct canopy volume measurement of pepper plants (B,C).

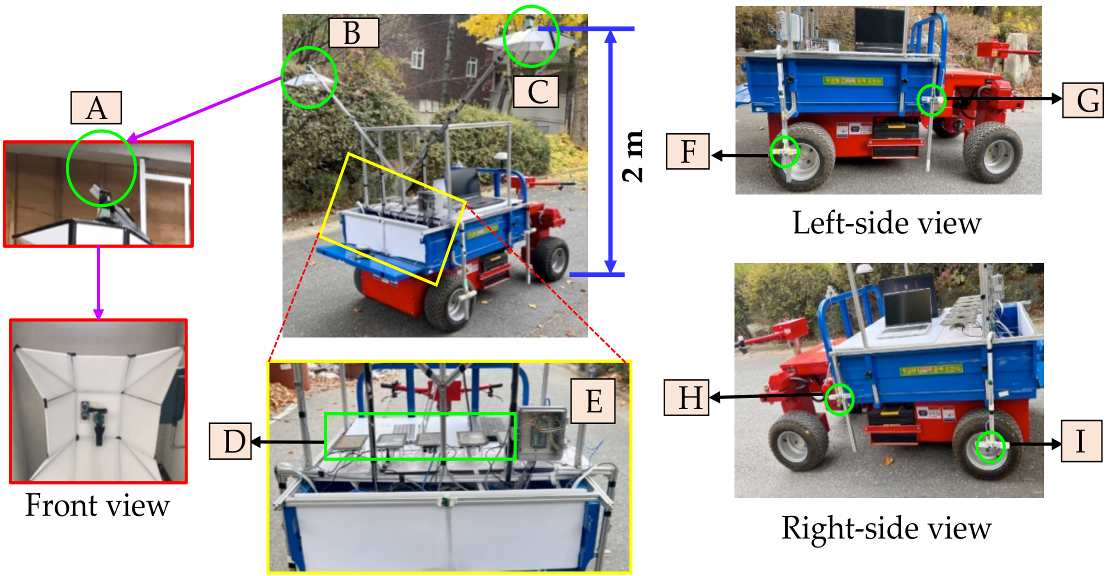

Figure 4. The position of the sensors and data acquisition platform mounted on the main chassis of the 1.6 kW electric vehicle prototype. (A) A photograph of the ultrasonic sensor and its positions on the (B) right and (C) left sides of the vehicle for the height measurement of plants. (D) Raspberry Pi (RPI) module and 7-inch screen, (E) data acquisition box, Sensor position on the right and left side for plant detection (F and G, respectively), and for ridge detection (H and I, respectively).

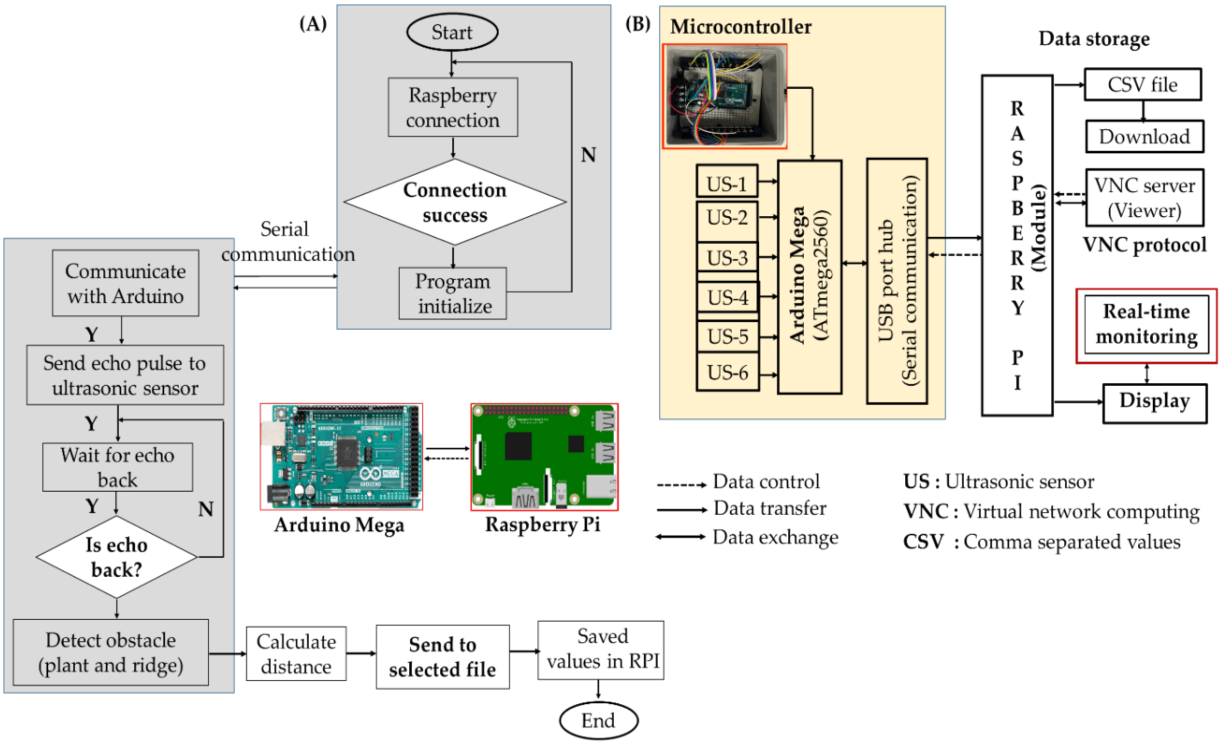

Figure 5. (A) Architecture of the integrated data acquisition system for the automatic recognition of pepper plants and land features. (B) Workflow of the integrated automatic data collection system used for the ultrasonic sensors.

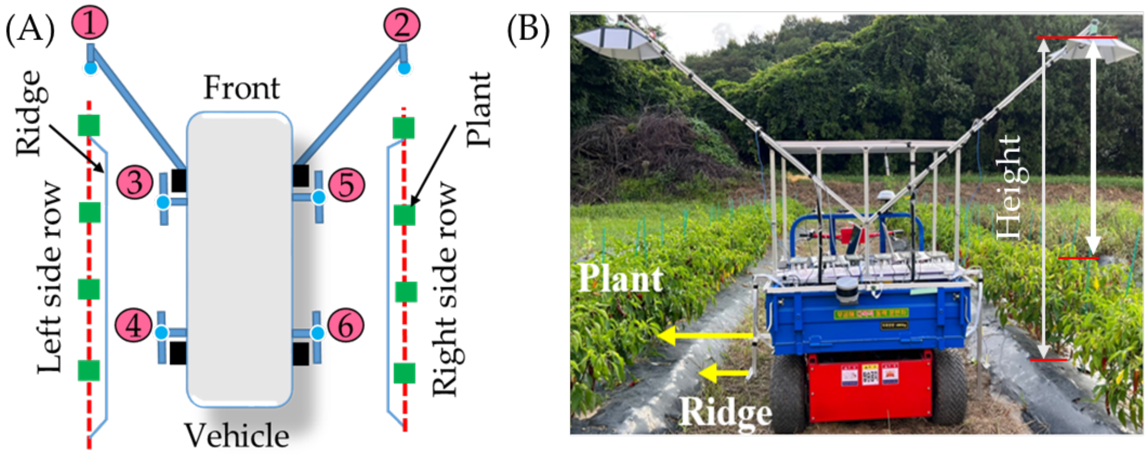

Figure 6. (A) Arrangement and layout of the ultrasonic sensors mounted on the 4WD electric vehicle. (B) A photograph of the experiments conducted under field conditions.

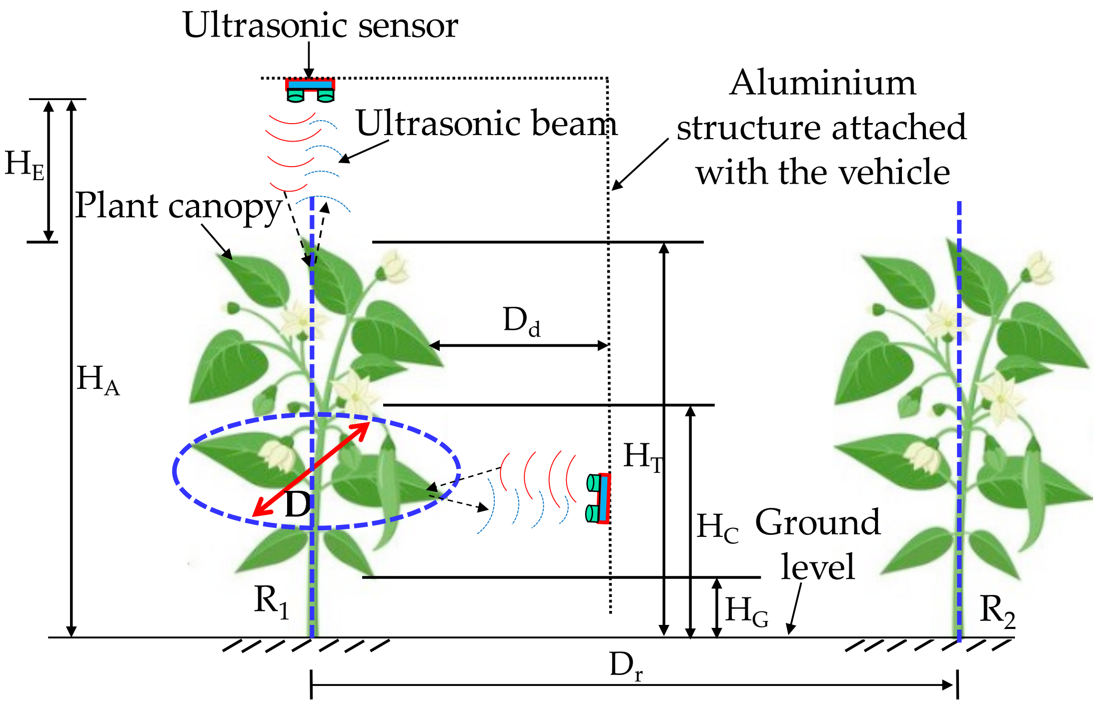

Figure 7. Pepper plant height and canopy volume measurement using ultrasonic sensor.

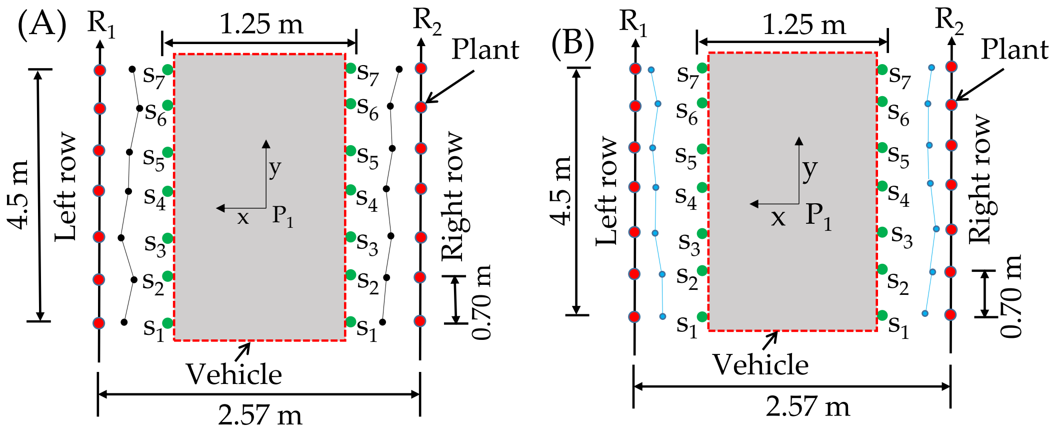

Figure 8. Field condition measurement flow diagram for (A) row and (B) ridge detection using the ultrasonic sensor.

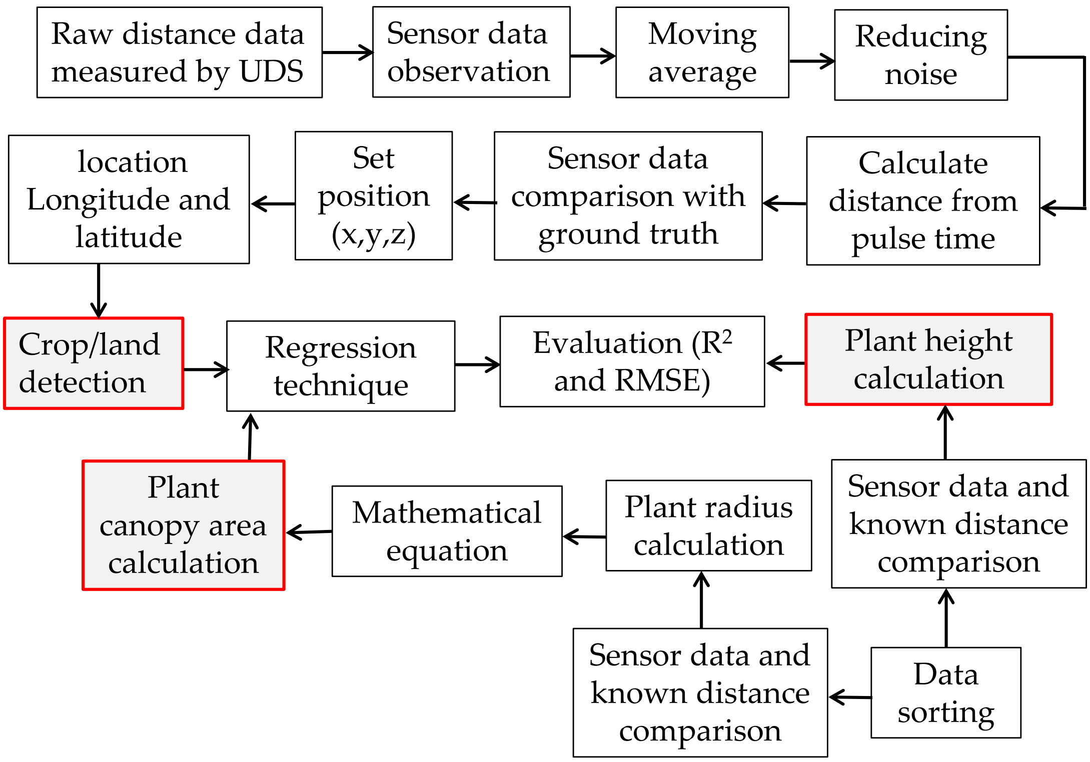

Figure 9. Full workflow for the detection of plant and land characteristics using an ultrasonic sensor.

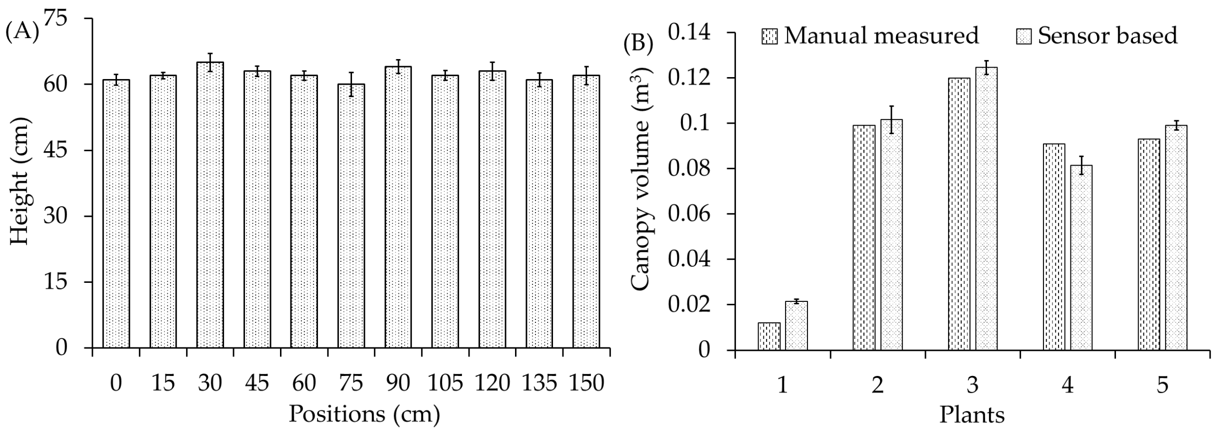

Figure 10. Experimental pepper plant (A) height and (B) canopy volume measurements under laboratory conditions.

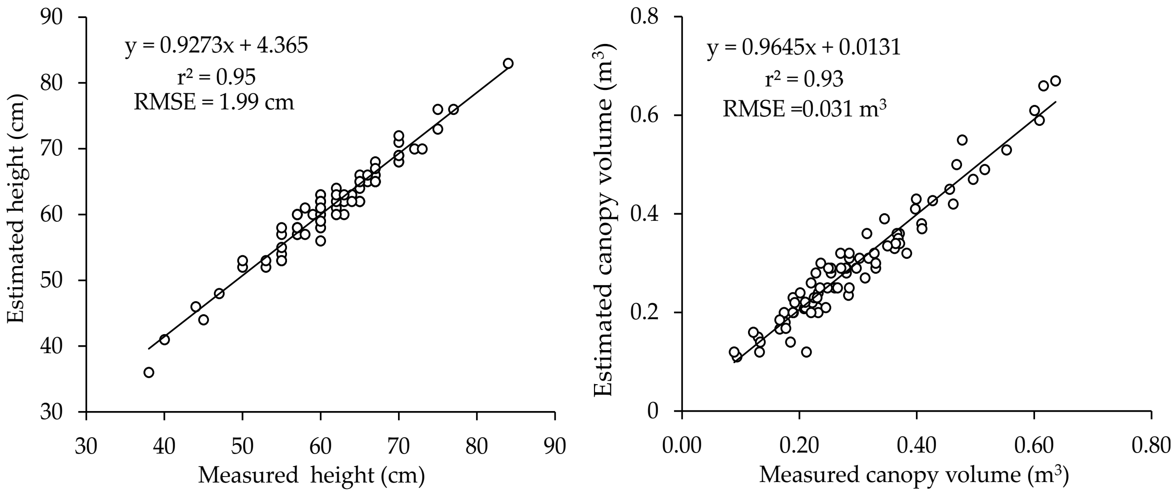

Figure 11. Correlation between measured and estimated pepper plant height and canopy volume.

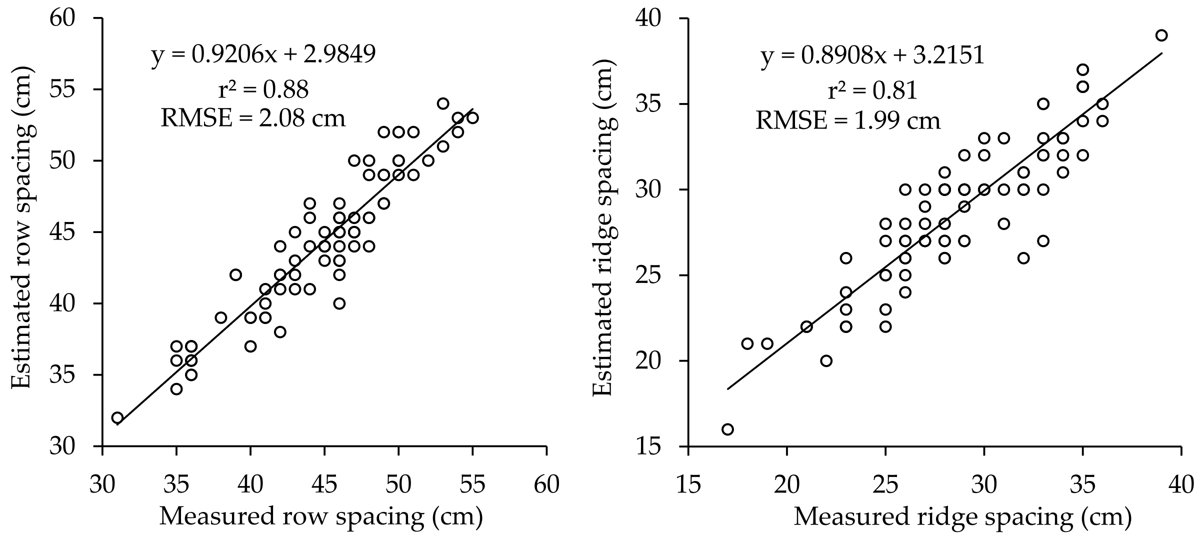

Figure 12. Correlation between measured and estimated pepper plant row and ridge spacing using ultrasonic sensors.

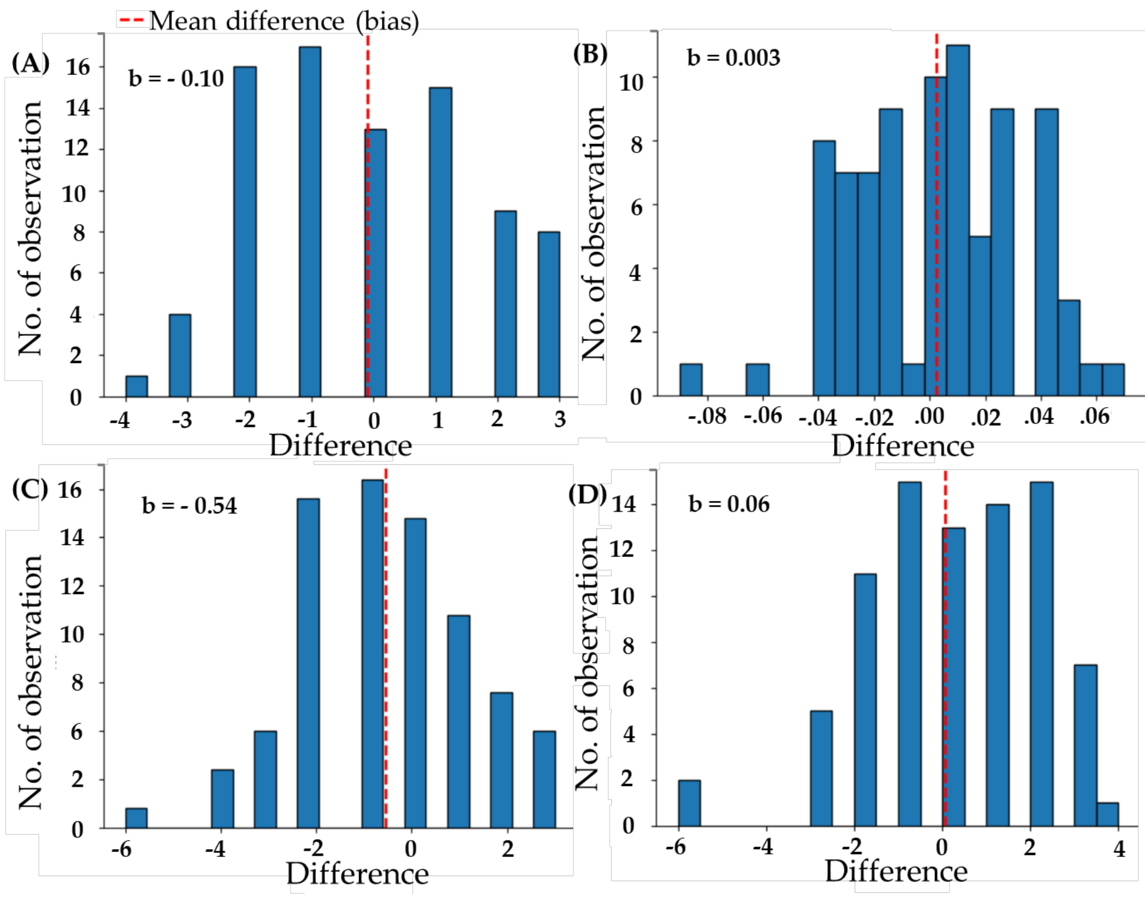

Figure 13. Distribution of differences between estimated and actual measurements using raw data for (A) height, (B) canopy volume, (C) row spacing, and (D) ridge spacing.