

Article

Developing Site-Specific Prescription Maps for Sugarcane Weed Control Using High-Spatial-Resolution Images and Light Detection and Ranging (LiDAR)

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Abstract: Sugarcane is a perennial grass species mainly for sugar production and one of the significant crops in Costa Rica, where ideal growing conditions support its cultivation. Weed control is a critical aspect of sugarcane farming, traditionally managed through preventive or corrective mechanical and chemical methods. However, these methods can be time-consuming and costly. This study aimed to develop site-specific, variable rate prescription maps for weed control using remote sensing. High-spatial-resolution images (5 cm) and Light Detection And Ranging (LiDAR) were acquired using a Micasense Rededge-P camera and a DJI L1 sensor mounted on a drone. Precise locations of weeds were collected for calibration and validation. Normalized Difference Vegetation Index derived from multispectral images separated vegetation coverage and soil. A deep learning (DL) algorithm further classified vegetation coverage into sugarcane and weeds. The DL model performed well without overfitting. The classification accuracy was 87% compared to validation samples. The density and average heights of weed patches were extracted from the canopy height model (LiDAR). They were used to derive site-specific prescription maps for weed control. This efficient and precise alternative to traditional methods could optimize weed control, reduce herbicide usage and provide more profitable yield.

Keywords: sugarcane; variable rate application; deep learning; LiDAR; canopy height model; Micasense RedEdge-P camera



Citation: Romero, K.F.; Heenkenda, M.K. Developing Site-Specific Prescription Maps for Sugarcane Weed Control Using High-Spatial-Resolution Images and Light Detection and Ranging (LiDAR). *Land* **2024**, *13*, 1751. <https://doi.org/10.3390/land13111751>

Academic Editor: Todd Robinson

Received: 13 August 2024

Revised: 9 October 2024

Accepted: 22 October 2024

Published: 25 October 2024



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1. Introduction

Sugarcane (*Saccharum* spp.) is a tall, perennial grass species mainly used for sugar production and primarily native to warm, temperate, tropical regions of the world. More than 70 countries grow sugarcane, including Costa Rica [1]. With sufficient rainfall, warm temperatures and rich soil fed by volcanos, Costa Rica has ideal sugarcane growing conditions and three large raw material processing and sugar manufacturing companies (Azucarera El Viejo, CATSA, and Taboga) [2]. Also, there are alcohol distillation plants using sugarcane. Costa Rica actively generates bioenergy from residual bagasse and incorporates it into the national grid [2]. Hence, sugarcane provides Costa Rica with commercial value, job opportunities, and infrastructure. Guanacaste province in Costa Rica is the primary sugarcane production area. According to statistics, from 2015 to 2019, Guanacaste province manufactured 56.77% of national sugar, corresponding to 2,410,247 metric tons of sugarcane [2]. However, the province suffers adverse effects of climate change, especially drought [3]. To achieve the optimal yield, sugarcane cultivators should follow agronomic recommendations, cultural management of the plantation, and maintain the crop throughout its growing season.

Angulo et al. [2] identified the guidelines for plantation management in Guanacaste province, and they require immense labor capacity. For example, the guidelines include

cultural work (subsoiling, hilling), fertilization, irrigation, drainage, crop protection (pests and diseases) and weed control (mechanical and chemical control). Among them, weed control is crucial for the proper development of plants, as weeds can reduce sugarcane yield by competing for water, nutrients and light during the growing season. Although mechanical weed control has been a sustainable solution for sugarcane farming, it requires specialized equipment and trained labor instead of chemical control and the use of inputs [4]. Mechanical weed control is challenging and complex. Herbicides are useful and economical within this context, but they must be incorporated into the overall sugarcane management plan to achieve maximum benefits [4]. Hence, weed management is essential to maintaining crop productivity and sustainability and has been identified as one of the main tasks in sugarcane cultivation.

Traditionally, weed management is carried out in a preventive or corrective way depending on the type of weeds, the time of year and the producer's conditions [2]. It is also necessary to decide whether it is mechanical control with cultivation implements or chemical control with terrestrial equipment [5]. Chemical control in agriculture is often based on sampling or visual analysis of representative areas of the field, with the objectives of autecological studies, production studies, and effects of management practices, which ultimately lead to the recommendation of specific products for application throughout the production area [6]. However, this traditional method can be time- and cost-consuming; therefore, a demand exists for exploring alternative approaches such as remote sensing methods and site-specific applications. Remote sensing technologies offer the advantage of automatically evaluating the entire production area, providing more comprehensive and efficient assessments [7]. Different sensors, such as multispectral and hyperspectral cameras and hyperspectral LiDAR sensors [8–10], and various platforms, such as Unmanned Aerial Vehicles (drones), airplanes or satellites, have been used to detect and monitor weeds in multiple crops, including sugarcane [9]. These technologies provide comprehensive and real-time information about weed distribution and abundance, allowing more efficient and targeted weed control strategies [10].

Many remote sensing studies have been carried out to analyze different stages of sugarcane development. For instance, some studies provided solutions using remote sensing (aerial or space) to manage and monitor sugarcane cultivations and thus increase productivity [11]. Cardoso et al. [12] reviewed studies employing Unmanned Aerial Vehicles (UAVs) in sugarcane cultivation in Brazil and found only five studies aimed at weed and pest detection using remote sensing. These studies identified the sustainability and productivity of the combination of remote sensing and the chemical control of weeds. For example, Yano et al. [13] identified invasive species using images acquired from a UAV with an accuracy of 83.1% and a kappa coefficient of 0.775. Huang et al. [14] and Fernández et al. [15] concluded the successful application of remote sensing techniques for weed control in sugarcane cultivation. Further, remote sensing has gained significant attention due to its ability to combine with Variable Rate Applications (VRAs) and optimize management practices.

In precision agriculture, VRA refers to applying input doses such as herbicides or fertilizers based on the precise location or specific condition of the area where input is being applied [16]. Hence, the technique is based on the understanding that different areas within a field may require different amounts of these inputs due to variability in soil conditions, crop needs, and environmental factors [16]. VRA integrates precision tools, remote sensors, and Global Navigation Satellite Systems (GNSS) for real-time field assessment of weed concentrations and prescription maps to adjust herbicide dosages as the equipment moves through the field [17]. By leveraging VRA in site-specific farming, farmers can optimize input usage, improve yields, and make their practices more sustainable. For example, optimizing herbicide application rates through VRA significantly reduces herbicide usage, operational costs, and environmental impact and enhances the yield while maximizing herbicide efficacy [18]. There are two types of VRAs: map-based and sensor-based [19]. The map-based VRA system guides the variable rate application with reference to pre-loaded

prescription maps. These prescription maps are site-specific and vary with the soil type, crop, irrigation, and other environmental factors [19]. Therefore, they can only be used for the area where they were designed. When developing weed-controlling prescription maps, weed types should identify and measure their spatial and volumetric densification for a more accurate weed assessment [19]. The accuracy of the derived information is crucial as it directly influences the herbicide type, quantity, and total volume of the mixture in the prescription. To the authors' knowledge, no sugarcane prescription maps have been developed using a map-based VRA system in Costa Rica. However, there is a demand for developing a regionally customized weed detection method using remote sensing and site-specific variable rate and map-based prescriptions for weed control.

Given that weed control strategies and agricultural conditions vary significantly between regions, it is necessary to tailor these technologies to the local context in Costa Rica. Climatic factors, soil types, and sugarcane cultivation practices in Costa Rica differ from those in other countries, so direct adoption of foreign methods may not yield optimal results. Therefore, this study aimed to develop site-specific, variable rate prescription maps for sugarcane weed control in Costa Rica using remote sensing technology, ensuring that the solution is effective and regionally appropriate. The specific objectives were to (1) capture Light Detection And Ranging (LiDAR) and multispectral images from a UAV over the sugarcane; (2) collect ground truth data for calibration and validation purposes (locations of weeds, species and spread/density); (3) map the emerging patterns of different weeds using machine learning algorithms; (4) analyze different weed control prescriptions and validate the applications using remotely sensed data and field samples; and (5) create site-specific, variable rate weed control prescription maps.

2. Materials and Methods

2.1. Study Area and Data

The study was conducted on one of the commercial sugarcane farms, "Azucarera El Viejo", located in Guanacaste province, Costa Rica (10°23'56" N, 85°31'43" W) (Figure 1). The climate in the study area is tropical sub-humid [20], which includes a season of drought in the summer (from January to April) and rain from May to December. The average annual rainfall is 1825 mm, and the yearly average temperature is 28.7 °C. The predominant soil class is mollisol, with a sandy texture [21]. The cultivated sugarcane variety was CP-722086 and was mechanically planted in 2021, with 1.7 m row spacing. The farm was in its second year of the production cycle. At the time of acquiring remote sensing images, the farm was at the age of 35 days. The farm was treated for weeds at earlier stages by applying pre-emergent herbicide five days after harvest and mechanical control using disc cultivators. This determined that the weeds present during remote sensing data capture were primarily located between crop lines, predominantly grasses and sedges.

The remote sensing data and field samples were captured on 13 May 2023. Multispectral images were captured from a Micasense RedEdge-P camera [22], and Light Detection And Ranging (LiDAR) data were acquired using a DJI Zenmuse L1 laser scanner [23]. These two sensors were mounted on a DJI Matrice 300 UAV [24]. The positional accuracy of the system was increased by incorporating Real-Time Kinematic GNSS techniques using the DJI D-RTK2 differential correction base station [25].

For calibration and validation, two hundred sample points were collected for weed and sugarcane. A random sampling pattern was adapted, and the types of weeds and the center points of the patch (weeds) were recorded using precise GNSS technology. The positional accuracy of these points was about 1–5 cm.

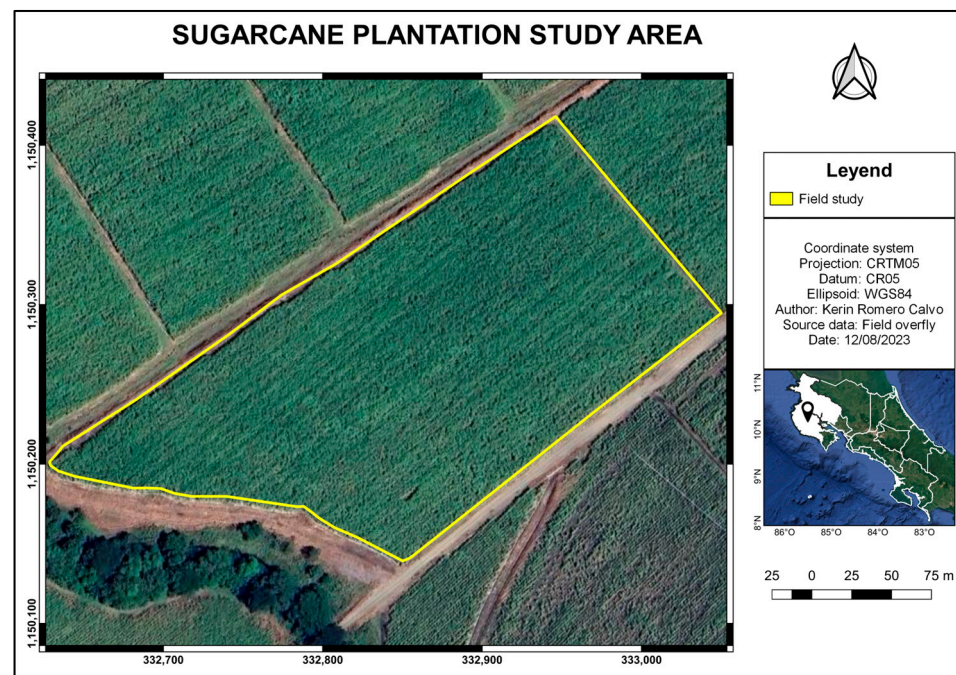


Figure 1. The study area map (the extent of the study area is 5.3 ha).

2.2. Method

The UAV images were processed using Pix4Dmapper software (v.4.5.6) [26] to obtain a radiometrically and atmospherically corrected orthomosaic with a spatial resolution of 5 cm. Then, the Normalized Difference Vegetation Index (NDVI) [27] was calculated using Equation (1). NDVI values generally range from -1 to $+1$, and healthy vegetation shows high positive values due to its sensitivity to leaf chlorophyll content [28]. The histogram of the NDVI showed a distinct pattern at around -0.1 , and the grey level slicing was tested for several values closer to -0.1 . After a few attempts, a threshold value was selected to separate vegetation from soil in the study area.

Raw LiDAR data were processed and classified (classes) using DJI Terra (v 3.5.5) and Terrascan software (v. 023.026) [29,30]. A Digital Elevation Model (DEM), which represents the elevation of the surface of the earth (corresponds to “ground” LiDAR points), and a Digital Surface Model (DSM), which corresponds to the first returned LiDAR points, were created. A Canopy Height Model (CHM) was generated by subtracting DEM from DSM [31]. The CHM corresponds to the height of sugarcane and weed canopies.

$$NDVI = \frac{NIR - R}{NIR + R} \quad (1)$$

2.3. Separating Sugarcane and Weeds

The vegetation coverage included both sugarcane and weeds. Based on the field measured point locations (center of the weed patch), sample polygons for sugarcane and weeds were digitized on screen. The high spatial resolution of the orthomosaic (5 cm) and the precise field locations helped to interpret weed and sugarcane polygons onscreen correctly. The extent of each sample ranged from 0.4 to 2.1 m^2 . Their average spectral information (blue, green, red, near-infrared and red edge) was extracted. These were used to analyze the spectral difference between sugarcane and weeds.

After that, a deep learning (DL) algorithm was used to separate sugarcane and weeds within the vegetation coverage of the study area. To set up the DL classification environment in ArcGIS Pro software (v.3.1.0) [32,33], the region was divided into a series of tiles, each measuring $2 \text{ m} \times 2 \text{ m}$, which was determined based on the spatial structure of the sugarcane plants. The sampling size was adjusted to 2 m, corresponding to the scale of mosaics in

the training dataset, ensuring consistency across different samples. This was based on the average radius of the sugarcane canopy and the typical distances between plants and rows, ensuring appropriate coverage for analysis. The maximum allowable overlap for each tile was set to 25 cm, balancing data coverage and processing efficiency. The Bi-Directional Cascade Network (BDCN) architecture was used to train the model while improving the edge detection for objects at different scales [34,35]. ResNet34, the preconfigured model trained on the Imagenet Dataset, was used for transfer learning [35]. Transfer learning is a machine learning technique that improves the model performance of one dataset by using the knowledge gained from another dataset [36]. That means it reuses a pre-trained model on a new dataset. Transfer learning is a commonly used method in deep learning, as it can train deep neural networks with less data [36].

For the DL model evaluation, the training and validation loss curves were constructed from the training data [33], and a Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) metrics were evaluated [37].

The final pre-trained model was passed to the classifier and applied over the study area to produce the classified raster. This approach allowed for precise differentiation between sugarcane plants and weed species based on their unique spatial and spectral signatures. One-third of field samples were used to evaluate the final classification accuracy based on a confusion matrix. Finally, weed areas were extracted for further analysis.

Bi-Directional Cascade Network and ResNet 34 Model Architectures

The Bi-Directional Cascade Network (BDCN) was introduced to address one of the issues with the Scale Enhancement Module (SEM) in deep learning, which is to avoid repetitive edge detection on image pyramids [34]. Hence, the BDCN employs layer-specific edge learning, and its supervision propagates the output from its adjacent higher and lower layers [34]. The ID Block is the primary component of the BDCN. It produces two edge predictions and contains several convolution layers (Figure 2). The output of these convolution layers will be fused and fed into a final convolution to generate two edge predictions. The final edge prediction will be made by combining those two edge predictions [34].

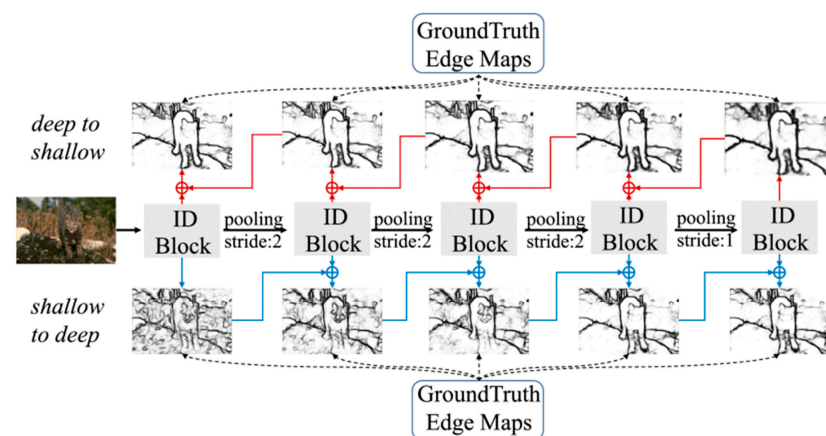


Figure 2. The overall architecture of BDCN. The figure illustrates how each ID Block is trained by layer-specific supervisions inferred by a bi-directional cascade structure. (The figure was adapted from He et al. [34]).

Deep networks integrate low-, medium-, and high-level features and classifiers as multi-layers [38]. The number of stacked layers explains the depth of the network. However, when the network depth increases, the accuracy saturates and degrades rapidly [38]. The Resnet 34 is a pre-trained image classification model (structured as a 34-layer convolution neural network) designed to address the degradation problem by introducing a deep residual learning framework [38]. As described in He et al. [38], the mapping function is

$H(x)$, and stacked non-linear layers fit into the mapping of $F(x) = H(x) - x$, then $H(x)$ can be written as $F(x) + x$. The residual mapping will be optimized to reach zero (Figure 3). He et al. [38] identified plain and residual networks with 34 weighted layers following this concept. Hence, the network is solving the issue of vanishing gradient.

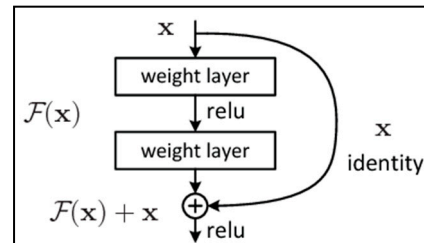


Figure 3. Residual learning: a building block. The figure illustrates how to form $F(x) + x$ by using a forward neural network. (The figure was adapted from He et al. [38]).

2.4. Variable Rate Weed Control Prescriptions

Once the weed areas were extracted, they were intersected with CHM to obtain each weed patch's volume and average height. Weed density was also calculated. Based on this information, weeds were classified into three categories. Subsequently, a VRA recommendation was generated for each class, adjusting the herbicide dose according to the weed density in each area. The dosage adjustment process followed a general management strategy, with taller and denser weeds requiring a higher herbicide concentration. In contrast, zones with lower weed density and shorter height require less product [39].

3. Results

3.1. Separating of Vegetation and Soil

The NDVI values of the study area ranged from -0.99 to 1 . According to the grey-level slicing approach (testing different threshold values), it was found that $NDVI = -0.1$ was the most suitable for distinguishing vegetation and soil. Hence, NDVI values less than or equal to -0.1 were classified as soil, while those above this threshold were identified as vegetation. However, some edges of sugarcane leaves were not detected correctly using this threshold value (Figure 4a). Despite a few areas, most succeeded in the majority (Figure 4b). Therefore, the chosen threshold was adequate for distinguishing sugarcane and weeds.

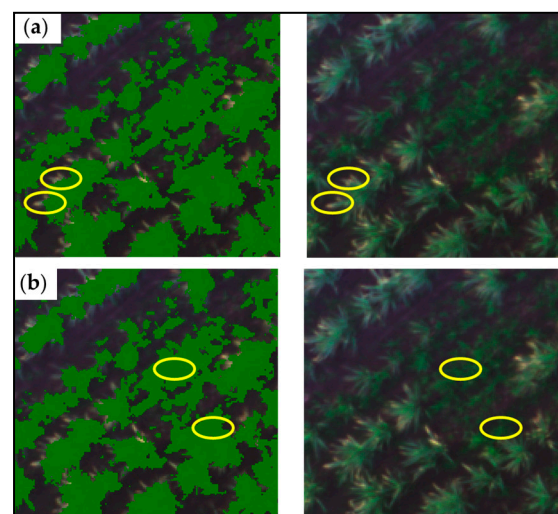


Figure 4. Separating vegetation and soil coverages using the Normalized Difference Vegetation Index. The left column shows the separated vegetation coverage superimposed with the image, and the right column shows the remotely sensed image. (a) An example of undetected sugarcane leaf edges; (b) successful vegetation detection.

3.2. Separating Sugarcane and Weeds

There was a spectral difference between sugarcane and weeds. Table 1 shows the average spectral values of all samples. The most significant differences were found in the blue and green bands, while the red, red edge, and NIR bands showed almost similar values between sugarcane and weeds.

Table 1. Average spectral difference between sugarcane and weeds.

Vegetation	Blue	Green	Red	Red-Edge	NIR
Sugarcane	0.12	0.29	0.16	0.57	0.78
Weed	0.08	0.17	0.14	0.40	0.76

These differences were taken into account when applying the DL algorithm. For instance, Figure 5a shows a sample image and how the algorithm detected sugarcane and weeds at the training stage. The area corresponds to one training tile. Figure 5b shows the optimal values of the DL model's loss function for a training set and its cross-validation. The training and validation loss curves consistently decreased across epochs, indicating that the model was learning effectively without overfitting. The model reached an optimal level of convergence after epoch 13, as both curves seemed stabilized, suggesting that further training yielded minimal improvements only. Figure 5c also shows the accuracy and F1 score, explaining the model's reliability after training. The overall accuracy of 87% demonstrated the model's suitability for classification.

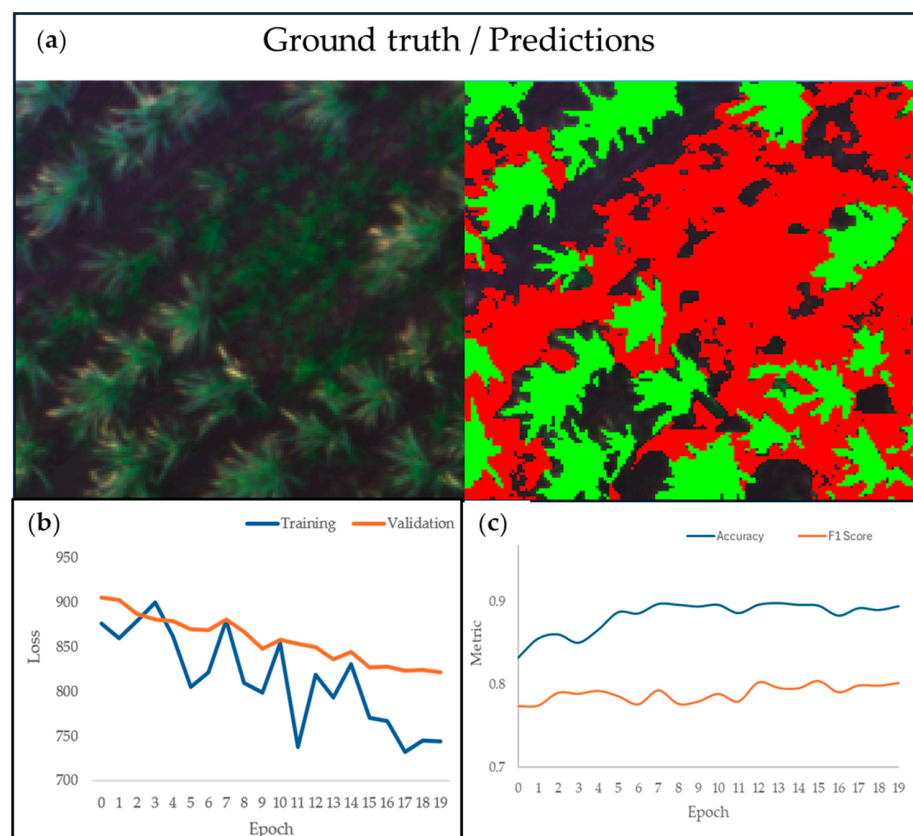


Figure 5. Separation of sugarcane and weeds at the DL model's training stage. (a) A sample image and its prediction, (b) learning curve optimization, and (c) model accuracy metrics.

The true positive rate (TPR) is the proportion of the correctly classified samples, and the false positive rate (FPR) is the proportion of the incorrectly classified samples [40]. The ROC curve is a visual representation of the model performance and is drawn by calculating

TPR and FPR at every possible threshold. Area Under the Curve (AOC) represents the binary classification model's ability to separate classes and ranges from 1 to 0 [40]. Figure 6a shows an AUC of 0.84, highlighting the model's strong performance. Figure 6b displays the confusion matrix, revealing a large number of correct predictions but also showing some misclassifications between “sugarcane” and “weeds”. These results indicate that the model is adequate.

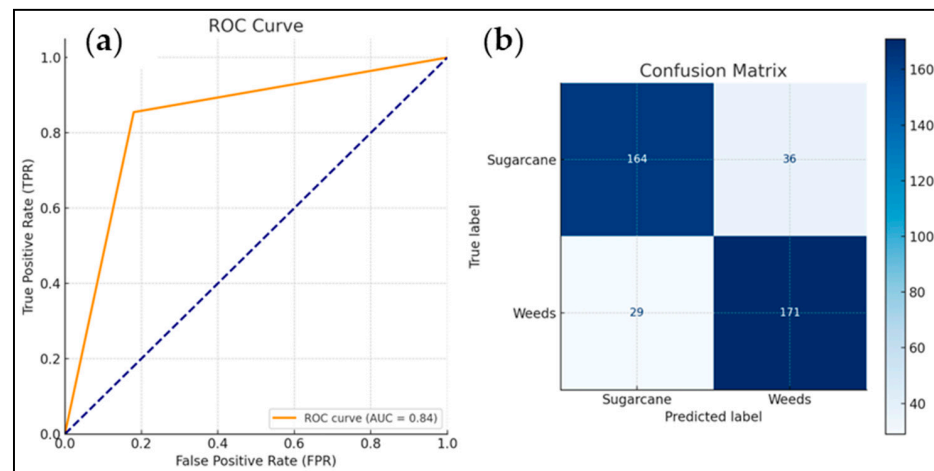


Figure 6. (a) A Receiver Operating characteristics (ROC) curve and Area Under the Curve (AUC); (b) a confusion matrix of sugarcane and weeds.

3.3. Spatial Distribution of Weeds

The classification results showed the spatial distribution of weeds within the study area, highlighting mainly the presence of sedges (*Cyperaceae* spp.) and barnyard grass (*Echinochloa* spp.). The visual analysis shows important patterns, such as the fact that their orientation follows the direction of the sugarcane cultivation lines, and the most significant accumulation of weeds is found at the edges of the field (Figure 7).

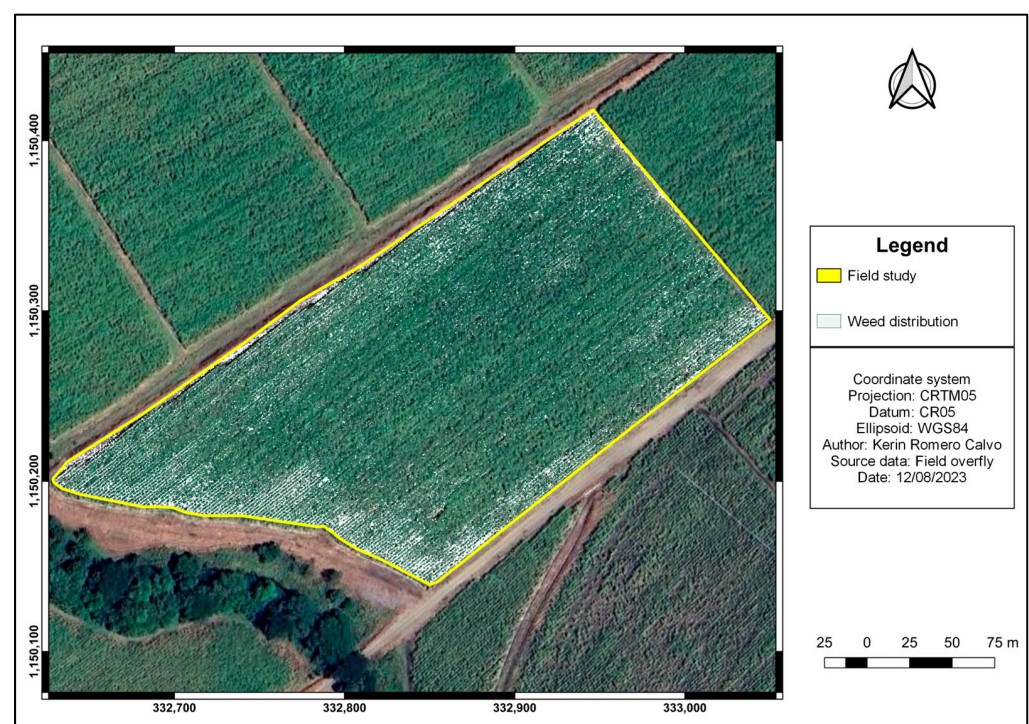


Figure 7. The spatial distribution of weeds within the study area.

3.4. Variable Rate Weed Control Prescriptions

The strategy for developing a VRA was based on the recommended mixture for each type of weed present in the study area. Under normal weed conditions, when they reach 0.25 m height, the mixture should have Atrazine (90%) at 1.5 kg/ha and Hexazinone (75%) at 0.5 kg/ha within a final mixture of 200 L/ha [39]. The weeds were classified into three categories according to their height, which ranged from 0.1 to 0.6 m, allowing the establishment of the rule shown in Table 2 and its final distribution within the field (Figure 8).

Table 2. Weed characteristics and rules for the variable rate applications of herbicides.

Weed Height (m)	Condition	Commercial Dose (%)	Final Dose (L/ha)
≤0	No weeds	0	0
0–0.25	Low weed density	75	150
0.25–0.5	Typical weed density	100	200
>0.5	High weed density	125	250

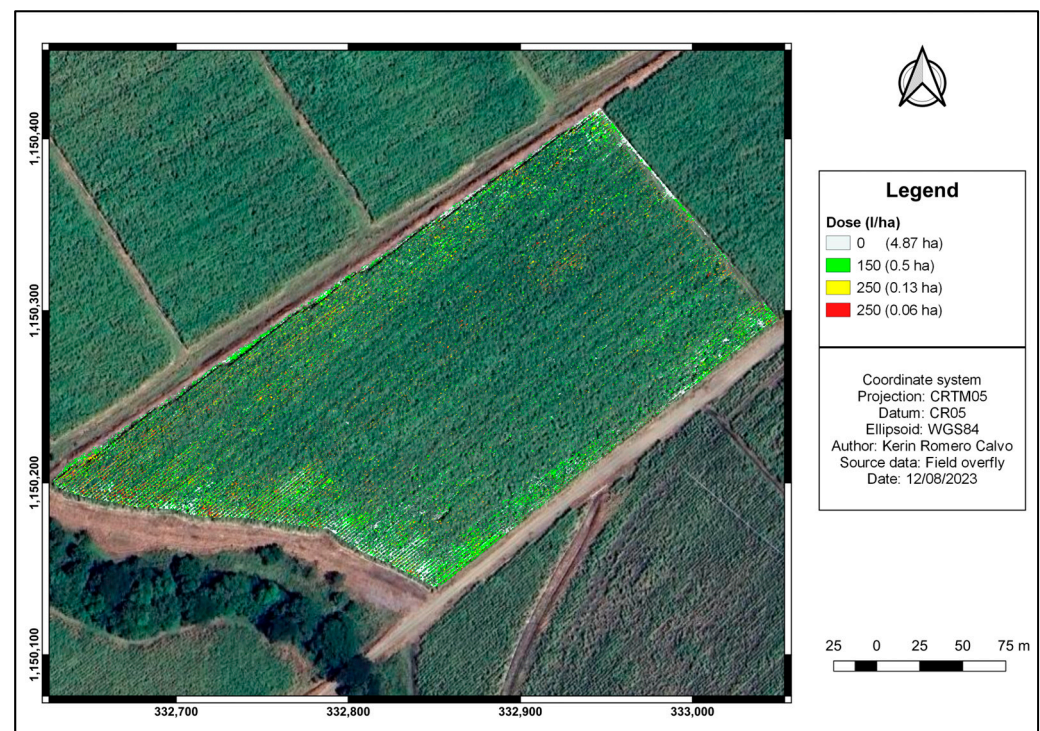


Figure 8. The spatial distribution of variable rate applications.

Table 2 must be converted to a form that a variable rate applicator can use. Therefore, Figure 8 was prepared, showing the spatial distribution of variable rate applications of herbicides (prescription map). The prescription map (application map) contains application rate information for all locations within a field.

Finally, the prescription map will be transferred to a data card (SD card), which can be read by an application system (sprayer). The controller onboard will spray the proper rate at each location in the field. A precise GNSS system should continuously correlate the sprayer's location in the field with locations on the map and the desired application rate for that location.

4. Discussion

Theoretically, NDVI values range from −1 to 1, representing various types of surface coverage and their respective vegetation health and density [41]. This study's selected

threshold value (-0.1) is reasonable for separating soil and vegetation, demonstrating the effectiveness of the threshold between the soil and crops, which often have different spectral characteristics [42]. NDVI for soil is known to be positive but closer to zero. However, values can be changed depending on the soil moisture [42,43]. This was evidenced by the unsuccessful separation of soil and vegetation, especially at the outer edge of the sugarcane rows, closer to drainage lines (Figure 4). According to Mulianga et al. [44], detecting sugarcane leaves at the edge of the plot or rows was impossible due to their representation of mixed ground features, for example, a combination of soil and vegetation as one pixel. However, this was mitigated to a greater extent in this study by using the high spatial resolution of images.

When separating sugarcane and weeds, de Souza et al. [45] and Johnson et al. [46] found significant spectral differences after 1000 nm, which could not be captured by the sensor used in this study. However, this study used the spectral differences between blue, green and red bands to delineate vegetation and weeds (Table 1). However, when training the DL algorithm, sugarcane plants' spatial structure (canopy radius and row spacing) was incorporated to compensate for the spectral resolution of the sensor [47]. The Bidirectional Cascade Network process accurately delineated edge contours, adhering closely to the training samples' patterns (Figure 5a,b). For instance, ID Blocks (tiles) provide two edge predictions, with one propagated from the shallow layer to the deep layer and the other from the deep layer to the shallow layer, thus forming a bi-directional cascade structure. The final prediction is a fusion of the intermediate edge map predictions [34]. This high precision (Figure 5c) in edge detection significantly enhanced the separation and extraction of weeds, confirming the model's efficacy in distinguishing between sugarcane and weeds despite their overlapping and visually similar characteristics. The Resnet34 model is trained on the ImageNet 2012 classification dataset of 1.28 million images and 1000 classes [38]. Hence, if the training samples in our model are insufficient, the pre-existing data pool was used to train the model. This provided many low- and middle-level feature definitions [36,38]. The model performance was assessed in many ways, and the model converged to its optimal level after 13 epochs. Training and validation loss curves showed a consistent decrease, indicating that the model had reached optimal convergence without any signs of overfitting [40]. This is crucial, as prolonged training could have degraded the model's performance. The ROC and AUC showed promising results. For instance, the model's AUC is 0.84, indicating the probability that the model differentiates sugarcane and weed [40].

The confusion matrix revealed misclassifications between the two classes, but the model maintained robust overall performance. The accuracy of 87% aligns well with the AUC, demonstrating a well-balanced model (without overfitting or underfitting). Higher accuracy was achieved mainly when the weed coverage was larger than 0.04 m^2 in extent and higher than 5 cm in height, coinciding with the results achieved by Zisi et al. [48]. However, Zisi et al. [48] incorporated DSM (height information) and multispectral images from UAVs to map weed patches.

The spatial distribution of weeds within the study area revealed stimulating patterns to identify weed-positive environments and their characteristics. Sedges (*Cyperaceae* spp.) and barnyard grass (*Echinochloa* spp.) were identified as the predominant weed species, with a notable concentration along sugarcane cultivation lines (rows) (Figures 7 and 8). This alignment suggests a correlation between agricultural practices, field structure, and weed growth direction [49]. The highest density of weeds was at field edges, attributed to increased moisture levels and access zones, pathways and machinery transit areas, which inherently support the persistence of grass and weeds due to regular disturbance and less stringent weed management practices in these zones [50]. These peripheral areas act as reservoirs for weed seeds and provide favorable conditions for their growth, thereby impacting the central cultivation areas over time [51,52].

The strategy of controlling weeds through variable rate application (VRA) of herbicides offers a specific approach to weed management by adjusting the herbicide doses

according to the density, height and type of weeds present in different areas of a field [53,54]. According to Buzanini et al. [55], this precision application method not only improves the effectiveness of weed control but also generates significant input savings by reducing herbicide use. By applying herbicides only where necessary and in adequate quantities, VRA optimizes crop yield, reduces input costs, and promotes sustainable and responsible agricultural practices [56]. Additionally, VRA plays a crucial role in preventing herbicide resistance in weeds by avoiding uniform and repetitive applications that can encourage the development of resistant strains. Further, site- and pattern-specific weed management practices can be carried out based on the spraying patterns [49].

This technology ensures that herbicides are used efficiently and only in areas where they are needed, reducing environmental impact and improving the ecosystem's overall health. In summary, implementing VRA enhances the efficiency and economy of weed management and contributes to environmental protection and sustainable agricultural practices.

5. Conclusions

This study aimed to develop site-specific, variable rate weed control prescriptions for sugarcane using remote sensing techniques in Costa Rica. Multispectral images obtained from a Micasense RedEdge-P camera and LiDAR data from a DJI Zenmuse L1 sensor were used as remote sensing data. Field data the locations of 200 weed and sugarcane samples and their species were used for calibration and validation. First, the NDVI values of the study area were analyzed to isolate the vegetated areas in the orthomosaic. Then, the DL algorithm was used to separate sugarcane and weeds within the vegetated area. The isolated weed distribution was incorporated with the CHM generated from LiDAR to calculate the heights and density of each weed patch. Based on the density and height of each weed species, herbicide prescriptions were developed. Hence, the study demonstrated the significant potential of applying remote sensing technology combined with VRA for precision weed management in sugarcane cultivation. UAV-mounted multispectral and LiDAR sensors enabled detailed weed distribution and density mapping across the study area, providing crucial data for developing targeted weed control strategies. Despite some challenges in detecting the edges of sugarcane leaves, the combined use of spectral and geometric data allowed for precise classification and enhanced weed maps.

The spatial analysis of weed distribution revealed significant patterns, such as the alignment of weeds along sugarcane cultivation lines and higher weed densities at field edges. These findings underscore the importance of considering field structure and agricultural practices in weed management strategies. Identifying predominant weed species, such as sedges and barnyard grass, provides valuable insights for developing species-specific control measures. Implementing VRA for herbicide application based on weed density and type presents a promising approach to optimizing weed control in sugarcane fields. By adjusting herbicide dosages in real-time and applying them only where necessary, VRA enhances the efficacy of weed management while reducing herbicide usage, operational costs, and environmental impact. This precision application method supports sustainable agricultural practices by minimizing herbicide resistance risk in weeds and promoting responsible input usage. The study's findings contribute to the growing knowledge of precision agriculture and highlight the potential of integrating remote sensing and VRA technologies for improved weed management. However, further research is needed to refine these methodologies and adapt them to local conditions in Costa Rica. Since the topography, weather and soil types are different from region to region, developing region-specific weed management plans using remote sensing data will be crucial for maximizing the benefits of these technologies in different agricultural settings.

In conclusion, integrating remote sensing technology and VRA offers a transformative approach to weed management in sugarcane cultivation. By providing detailed and accurate information on weed distribution and density, these technologies enable the development of targeted and efficient weed control strategies. This not only improves the productivity and sustainability of sugarcane farming but also contributes to environmental

protection by reducing the reliance on chemical herbicides. The continued advancement and adoption of these precision agriculture tools hold great promise for the future of sustainable weed management.

Author Contributions: Conceptualization, K.F.R.; methodology, K.F.R. and M.K.H.; software, K.F.R.; formal analysis, K.F.R.; writing—original draft preparation, K.F.R.; writing—review and editing, M.K.H.; supervision, M.K.H.; project administration, K.F.R.; funding acquisition, K.F.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially funded by the Mitacs-CALAREO Globalink Research Award, grant number IT36449.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: We would like to express our sincere gratitude to Gabriel Hernández and the “Azucarera El Viejo” farm team for their invaluable collaboration in collecting data for this study.

Conflicts of Interest: The authors declare no conflict of interest.

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