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Precision Crop Farming Framework for Small-Scale Rainfed Agriculture Using UAV RGB High-Resolution Imagery

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Abstract

This paper presents a precision crop farming framework developed for small-scale rainfed agriculture using unmanned aerial vehicle (UAV) red, green, and blue (RGB) high-resolution imagery. The aim is to enhance farm management by providing precise spatial and temporal information in heterogeneous farming systems in Botswana's semi-arid regions. The precision crop farming framework integrates UAVs and Global Navigation Satellite System (GNSS) data, introducing new vegetation indices and employing machine learning algorithms for high-accuracy crop and land use analysis. The framework comprises four components: data collection, applications, data processing, and users. Methods included UAV data acquisition, global navigation satellite system geo-referencing, and machine learning classification. Results demonstrated high spatial resolution and classification accuracy, providing actionable insights into crop conditions, planting patterns, and farm variability. The precision crop farming framework is a tool for improving agricultural productivity and sustainability, providing a foundation for efficient, data-driven farm management practices.

Keywords

Unmanned aerial vehicle imagery, small-scale rainfed architecture, geospatial information system, machine learning, remote sensing.

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Introduction

Sub-Saharan Africa faces severe food insecurity and malnutrition, with nearly 282 million undernourished people in 2022 (FAO, 2023). The region's agriculture, crucial for the economy and employing most of the population, is dominated by small-scale, irregular subsistence farms (Tscharntke et al., 2012). Challenges include food security issues exacerbated by population growth (Blizkovsky and Emelin, 2020), unsustainable land use, and socio-cultural factors contributing to poverty (Apata et al., 2021). Precision farming, utilizing technologies like UAVs, offers data-driven decision support for effective farm management, essential for managing both small and large-scale farms (Finger et al., 2019; Wolfert et al., 2017). Sustainable intensification and climate-smart agriculture enhance productivity and resilience, addressing food production challenges under unreliable climate conditions (Campbell et al., 2014). Exploring precision farming technologies could significantly improve agricultural productivity in Africa (Bolo et al., 2019; McCarthy et al., 2023).

UAV use in precision agriculture

UAVs have emerged as vital tools in precision agriculture, offering several advantages over satellites, particularly in their ability to navigate complex landscapes, operate at high speeds, and provide precise localization data (Gao et al., 2023a). UAVs bridge the spatial resolution gap between ground observations and satellite sensors, making them effective for crop monitoring in small-scale farming environments (Nduku et al., 2023).

One of the most significant advantages of UAVs is their ability to capture high-resolution images, which allows for detailed observation of small-scale features within fields, such as individual plants (Lee et al., 2023; Lin et al., 2023), weeds (Mohidem et al., 2021; Furaste Danilevicz et al., 2023), and signs of disease (Soares da Silva et al., 2022; Yağ and Altan, 2022). This high level of detail is crucial for tasks like crop health monitoring, where immediate data collection is often required to address time-sensitive issues such as pest infestations or damage from weather events (Bouguettaya et al., 2022; Ma et al., 2022a; Bai et al., 2024; García-López et al., 2022).

UAVs also enable real-time data collection and analysis, which is critical for making prompt management decisions. Unlike satellites, which have limited revisit times and lower spatial resolution, UAVs can be deployed on demand, offering the flexibility needed for frequent monitoring. This capability is particularly beneficial for assessing crop growth and predicting yields, as demonstrated in studies focusing on crops like maize, rice, and soybeans (Li et al., 2022; Guo et al., 2022; Zheng et al., 2022; Hassani et al., 2023; Killeen et al., 2024).

For instance, Ma et al. (2023a) utilized UAVs to monitor summer maize growth while Ma et al. (2023b) predicted field-scale winter wheat. Both studies used multimodal imagery. Similarly, Lee et al. (2023) combined UAV data with deep learning algorithms to monitor broccoli plants, while Lin et al. (2023) applied UAV data for automated tobacco plant counting, achieving higher accuracy than traditional methods.

Specific crop traits, such as biomass, nitrogen uptake, and chlorophyll content, can also be effectively monitored using UAVs. Hütt et al. (2022) demonstrated the use of LiDAR-equipped UAVs to monitor biomass and nitrogen uptake in winter wheat. UAV hyperspectral imaging has been used to predict wheat leaf nitrogen content (Ma et al., 2022b) and chlorophyll content in potato crops (Yin et al., 2022), offering non-destructive methods for plant nutrition monitoring.

Weed detection and management are other areas where UAVs have shown considerable promise. UAVs can provide high-resolution imagery that allows for precise weed mapping and identification, as seen in studies by Wang et al. (2022) and Castellano et al. (2023). These capabilities are essential for precision agriculture, where targeted weed management can lead to more efficient use of herbicides and better crop yields.

UAVs have also been employed in early disease detection, a critical aspect of maintaining crop health. Bouguettaya et al. (2022) explored the use of UAVs combined with deep learning to identify plant diseases, offering a cost-effective and efficient solution. UAVs equipped with multispectral cameras have been used to detect coffee leaf rust at an early stage (Soares da Silva et al., 2022) and to classify plant diseases in real-time using advanced sensors like the NVIDIA Jetson Nano (Yağ and Altan, 2022). Additionally, UAVs have been utilized to detect Fusarium head blight in wheat using RGB sensors and advanced algorithms (Bao et al., 2024).

In the area of topographic mapping and irrigation management, UAVs offer high precision and adaptability. Du et al. (2022) developed a topographic mapping system for precision farmland leveling using UAVs equipped with LiDAR and PPK-GNSS, achieving centimeter-level accuracy. UAVs have also been employed to detect irrigation gaps in vineyards, helping to prevent water wastage (Sulemane et al., 2022), and to monitor crop moisture levels (Gao et al., 2023b; Peng et al., 2023).

The ability of UAVs to navigate complex terrains and provide data from areas difficult or impossible to reach with ground equipment further enhances their utility in precision agriculture (Akstinas et al., 2022; Xin et al., 2022; Sandino et al., 2023). This capability, combined with their cost-effectiveness and flexibility, makes UAVs invaluable tools for modern farming. Although satellites provide extensive coverage and frequent revisits, their limitations in spatial resolution and ground-level detail capture often make UAVs the preferred choice for detailed agricultural monitoring.

UAVs offer high-resolution, flexible, and timely data collection capabilities that significantly enhance precision agriculture practices. Their ability to integrate multiple data sources and operate in various terrains, coupled with real-time data analysis, positions them as essential tools for modern agricultural management. The integration of UAV and satellite data can provide a comprehensive approach, leveraging the strengths of both platforms to improve overall data quality and application in precision agriculture.

Existing frameworks using UAV data

Recent advancements in UAV technology have led to the development of various frameworks and models for precision agriculture and environmental monitoring. These frameworks leverage UAVs' capabilities to capture high-resolution data, offering innovative solutions for diverse applications.

Du et al. (2022) developed a topographic mapping system specifically designed for precision farmland leveling. This system integrates low-altitude

UAVs with LiDAR and PPK-GNSS, achieving centimeter-level accuracy. This technology enables efficient topographic surveys, providing crucial data for precision leveling in agriculture.

Haumont et al. (2022) introduced a model to predict leek dry biomass and nitrogen uptake using UAV-based multispectral imaging. The researchers tested various modeling approaches using 12 spectral vegetation indices (VIs) and their interquartile ranges as predictors. The best-performing models were a lasso regression model for dry biomass and a simple linear regression model based on the red wide dynamic range vegetation index (RWDRVI) for nitrogen uptake. However, the model's accuracy diminished with data from different growing seasons, suggesting a need for recalibration for consistent performance.

Kumar et al. (2022) presented a transformer-based encoder-decoder architecture for precise semantic segmentation of UAV images. This architecture incorporates a self-attention-based transformer in the encoder to capture global contextual information and a token spatial information fusion (TSIF) module to integrate local details. The resulting pixel-level semantic predictions demonstrated high accuracy in segmenting complex aerial scenes, validated on the UAVid and Urban Drone datasets.

Ma et al. (2022a) developed a model using a combination of a one-dimensional convolutional neural network (1D-CNN), random forest (RF), and support vector machine (SVM) to identify forest tree damage levels caused by Erannis jacobsoni Djak. These models were built using sensitive features extracted from UAV multispectral vegetation indices and texture features. Among the models, the 1D-CNN based on vegetation index-sensitive feature sets showed the highest accuracy. The study's results offer a practical reference for accurately identifying forest tree damage levels and managing forest pests.

In the domain of wildfire management, Muksimova et al. (2022) introduced a deep encoder-decoder network with a two-pathway architecture for real-time wildfire segmentation using UAV images. The advantages of UAVs in this context include their ability to capture images from different angles, cover large areas quickly, and provide high-resolution data, which is critical for accurate fire detection and segmentation.

Yağ and Altan (2022) developed a robust hybrid classification model using AI algorithms for real-time plant disease detection in agricultural environments. The model combines swarm optimization-supported feature selection with machine learning and deep learning algorithms to classify diseases in apple, grape, and tomato plants. This model is embedded in the NVIDIA Jetson Nano developer kit on a UAV, allowing real-time classification tests with high accuracy.

Zheng et al. (2022) utilized simple linear regression models and random forest regression algorithms to predict rice grain yield from UAV multispectral imagery. The random forest regression algorithm was particularly effective in handling nonlinear and hierarchical relationships among multiple variables, making it suitable for diverse datasets involving different years, cultivars, and climatic zones.

Agrillo et al. (2023) developed a model for detecting coastal dune habitats by combining very high-resolution UAV imagery with field survey data. This approach involved object-based image analysis (OBIA) and supervised machine learning classification using a random forest model. Conducted in a protected coastal ecosystem in Italy, the model achieved an overall accuracy of 78.6%, demonstrating the potential of UAV imagery for accurate and efficient habitat mapping in coastal areas.

Ma et al. (2023a) introduced a comprehensive growth monitoring indicator (CGMI) for summer maize based on UAV-collected multispectral remote sensing imagery. The CGMI integrates key growth indicators such as leaf area index (LAI), relative chlorophyll content (SPAD), and plant height (VH). The model utilizes partial least-squares regression (PLSR) and sparrow search optimization kernel extremum learning machine (SSA-KELM) algorithms to preict the CGMI, offering an efficient and non-destructive tool for monitoring maize growth.

Ma et al. (2023b) created the MultimodalNet model, which uses dynamic fusion of multimodal UAV imagery, including RGB, hyperspectral near-infrared (HNIR), and thermal imagery, for accurate field-scale yield prediction of winter wheat. The model's adaptive modality attention mechanism significantly improved yield prediction accuracy, particularly during the flowering stage, highlighting the importance of integrating HNIR and thermal imagery in yield prediction under different irrigation regimes.

Peng et al. (2023) created a framework for energy flux modeling using high-resolution thermal and multispectral UAV data to estimate canopy transpiration and soil evaporation accurately. This framework employs a two-source energy balance model, which provides detailed insights into the diurnal and seasonal dynamics of evapotranspiration, aiding in precise irrigation management and improving water use efficiency, particularly under drought conditions.

Ramachandran et al. (2023) developed a decision framework for selecting the most suitable survey strategy for characterizing microtopography in urban areas. This framework assesses the accuracy and elevation differences between UAV-based RGB data and aircraft LiDAR across various land use classes and flood features, ensuring the most effective characterization for flood management and risk assessment.

Lastly, Xie et al. (2024) introduced ResMANet, a deep-learning network designed for high-resolution remote sensing imagery. This network features a multiscale convolutional structure for extracting features at different scales, an attention mechanism for refining feature maps, and a joint loss function to address imbalanced data. The model was trained on a dataset created from UAV images and used to predict the invasion of Cassytha filiformis in the Xisha Islands, China.

While these frameworks and models advance UAV technology for precision agriculture and environmental monitoring, there are certain challenges and gaps identified. Integrating multiple sensor data types, such as RGB, HNIR, and thermal imagery, can increase complexity and cost. Moreover, models like the transformer-based encoder-decoder (Kumar et al., 2022) and ResMANet (Xie et al., 2024) require significant computational resources, limiting their practicality in field settings. There is a need to develop more efficient algorithms that maintain high accuracy while reducing computational demands. Additionally, some models are tailored to specific conditions or crops, limiting their scalability to other applications. Developing versatile and adaptable models for various agricultural and environmental contexts, especially for small-scale, irregular farms, remains a priority.

Justification of the use of RGB sensors over multispectral alternatives for small-scale rainfed agriculture

RGB sensors were chosen for this study due to their high spatial resolution, cost-effectiveness, and accessibility, making them suitable for small-scale farmers in resource-limited environments. While multispectral sensors require expensive near-infrared (NIR) bands to compute indices like the normalized difference vegetation index (NDVI), RGB sensors can still facilitate effective crop classification through alternative vegetation indices such as the visible atmospherically resistant index (VARI) and the triangular greenness index (TGI) (Gerardo & de Lima, 2023) or indices proposed by this study. Unlike multispectral sensors, which often have lower spatial resolution, RGB sensors provide high spatial resolution imaging (Digital Agriculture Laboratory, 2023). High-resolution UAV RGB imagery has been widely utilized for land cover classification (Gkillas et al., 2022; Li et al., 2022; Azizi et al., 2024) and advanced machine learning applications for crop monitoring, including disease detection (Bao et al., 2024; Liu et al., 2024; Wieme et al., 2024), yield prediction (Killeen et al., 2024; Qu et al., 2024; Zhang et al., 2024), and crop condition assessment (Feng et al., 2024; Tian et al., 2024). These studies demonstrated the effectiveness of using UAV RGB imagery alone without relying on multi-spectral, hyperspectral, or other complementary data sources. High spatial resolution imaging is particularly useful for assessing heterogeneous smallholder farms. The affordability and ease of deployment of RGB sensors make them a scalable solution for precision agriculture in semi-arid regions, where financial and technical constraints limit access to advanced remote sensing technologies (Cucho-Padin et al., 2019).

Proposed framework

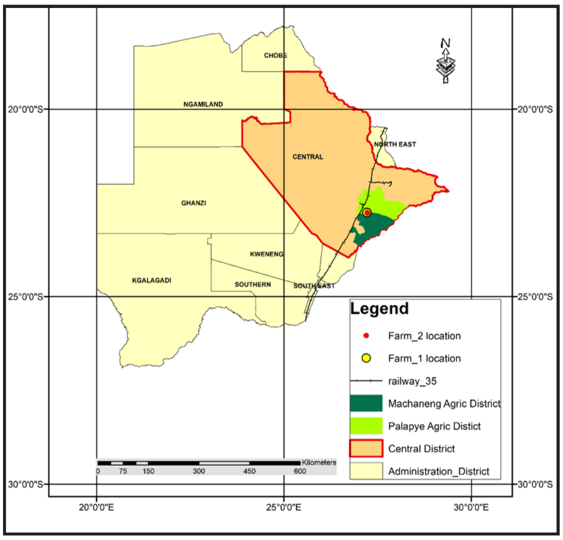
This research developed a precision crop farming framework (PCFF) for small-scale rainfed agriculture using UAV RGB high-resolution imagery to address several gaps identified in existing frameworks and models. Precision crop farming in this research is defined as the management of heterogeneous farm activities based on UAV imaging remote sensing systems integrated with global positioning and information systems. The research was carried out on small-scale subsistence farms under rainfed agriculture in semi-arid regions. The aim is to enhance farm management by providing precise spatial and temporal information in heterogeneous farming systems in Botswana's semi-arid regions. The framework was specifically designed for small-scale farming systems, where farmers practice heterogeneous planting and crop mixing on small plots of land. It provides agricultural land use planners with essential information about the location of farms, plowed areas, crops planted, and their growth patterns for informed decision-making. Additionally, it helps farmers understand the variabilities across their entire farms.

The study's aim to enhance farm management by providing precise spatial and temporal information in heterogeneous farming systems in Botswana's semi-arid regions aligns with the broader goal of reducing Botswana's reliance on food imports, thereby contributing to greater food security and self-sufficiency in the country (FAO, 2023).

Materials and methods

Description of the study area

The research was conducted in the agricultural districts of Palapye and Machaneng in Botswana, specifically focusing on the areas of Lecheng and Pilikwe (Figure 1). These locations were selected due to their traditional small-scale crop production practices under rainfed farming conditions. The geographical coordinates of the study area range from 27.091° to 27.097° East and from -22.640° to -22.855° South.



Source: Own elaboration based on publicly available information from Ministry of Agriculture of Botswana, 2018

Figure 1: Map showing the study area within the agricultural districts of Palapye and Machaneng.

The soil types in this area include arenosols, leptosols, and luvisols, each with distinct characteristics that influence agricultural productivity (IUSS Working Group, 2015; Sileshi et al., 2022). Arenosols, characterized by sandy texture, have low resilience to erosion and poor water and nutrient retention, limiting crop performance in arid and semi-arid regions. Despite these challenges, arenosols are easy to cultivate and suitable for root and tuber crops. Leptosols, which are shallow and coarse-textured, are prone to erosion and require careful management to support sustainable crop growth. In contrast, luvisols are fertile soils with high-activity clays and high base saturation, making them suitable for a wide range of agricultural uses. These soils contribute to the varied agricultural potential of the study area, necessitating tailored management practices to optimize crop production.

The vegetation covering the area predominantly consists of mopane (Colophospermum mopane) and acacia species. Sorghum is the most popular grain crop, followed by maize and millet. Other crops grown in the area include melons, pulses, and beans. The agricultural practices are primarily focused on subsistence farming, with an emphasis on rainfed crops.

Research design

The research design adopted a mixed-methods approach, combining both quantitative and qualitative methods to achieve the study's objective. This approach allowed for a comprehensive analysis of the data collected, ensuring that the research questions were thoroughly addressed (Cresswell and Cresswell, 2022; Yin, 2018).

The study employed a combination of observational and experimental designs. The data collection process using UAV imagery followed an observational design, wherein agricultural conditions were observed and recorded without manipulation of variables. In the subsequent stages, particularly when developing and applying machine learning algorithms to the UAV imagery, the study transitioned to an experimental design. This dual approach facilitated a robust analysis of the data, allowing for both descriptive and inferential insights.

UAVs equipped with RGB cameras and GNSS were used to capture high-resolution images of farmland at various heights, ensuring accurate geo-referencing with ground control points (GCPs). The data underwent preprocessing steps like orthorectification and mosaicking to create seamless images.

Critical thinking was a core component of the research design, guiding the linkage and analysis of the PCFF components (Paul and Elder, 2006; Heard et al., 2020). This process involved incorporating both the collected data and external data sources to ensure a comprehensive and well-rounded analysis. Four systematic steps were followed: (1) selecting spatial data collection platforms, (2) defining UAV-based data acquisition methods, (3) processing data using spatial analysis tools and new vegetation indices, and (4) presenting the framework to diverse user groups through publications and conferences. Machine learning algorithms, ISODATA and SVM, were developed and applied for data classification, achieving high accuracies. The framework was validated through statistical methods, as follows: (1) confusion matrices, (2) cross-validation using inverse distance weighting (IDW), mean absolute error (MAE) and root mean squared error (RMSE), and (3) t-tests (Bolo et al., 2024).

Methods for spatial data collection

The spatial data for this study was collected using a combination of UAV and GNSS systems, providing a comprehensive dataset for subsequent analysis. Ground control points were gathered using a GNSS receiver handheld instrument and stored as point vector data. UAVs were used to collect spatial data on plowed areas and crops (raster data). This data was subsequently stored in a computer system for processing and analysis, transforming it into geospatial information accessible for decision-making purposes. GNSS position data (latitudes and longitudes) was employed to geo-reference the UAV data, ensuring accurate alignment and integration of spatial information.

The UAV data was captured with a passive sensor using manual flying control. The UAV used in this study was a DJI Phantom 4 quadcopter, equipped with a gimbal-stabilized imaging system allowing pitch adjustments from -90° to +30°. This UAV was chosen for its high-resolution imaging capabilities and inbuilt GPS and GNSS systems, which provided near-real-time data with high positioning accuracy.

The UAV had a normal airspeed of 20 m/s, a maximum flight duration of 28 minutes, and a payload capacity of 1380 g. It featured an RGB camera with a spectral sensor range of 0.45 to 0.69 micrometers (μm). An RGB sensor was preferred over multispectral sensors because it provided clear views of agricultural fields, allowing for easy counting of plants. The camera had a focal length of 4 mm, which was used to calculate the spatial resolution of the captured data. The captured data had a pixel resolution width and height of 4000 and 3000 pixels, respectively, resulting in a maximum image size of 4000 x 3000 pixels. The swath width was 2.4 m at a height of 120 m, 1 m at a height of 50 m, and 0.2 m at a height of 5 m. The UAV collected data on farm activities, including plowed areas and crops. The spatial resolution of the collected data was 0.19 cm per pixel at 5 m, 1.93 cm per pixel at 50 m, and 4.63 cm per pixel at 120 m.

The UAV was operated under controlled conditions to capture high-resolution images of the farmland at various heights, ensuring accurate geo-referencing with ground control points (GCPs). The data underwent several preprocessing steps, including orthorectification and mosaicking, to create seamless images that accurately represented the study area. An 80% forward and backward overlap was adopted during data collection to minimize edge distortions. Different flight heights were utilized − 120 meters to view the entire farm, 50 meters to identify crop types, and 5 meters to assess crop conditions. These heights were selected based on experimental observations, to capture detailed and accurate data on farm boundaries, crop types, and planting patterns. The spatial resolution was calculated based on the flight height (H), sensor height (H_s), focal length (f), sensor width (W_s), and image width (W_i) using the following formulas:

$$GSD_h = \frac{H \cdot H_s}{f \cdot H_i}, \tag{1}$$

$$GSD_w = \frac{H \cdot W_s}{f \cdot W_i}, \tag{2}$$

where GSD_h and GSD_w are the round spatial distance height and width, respectively.

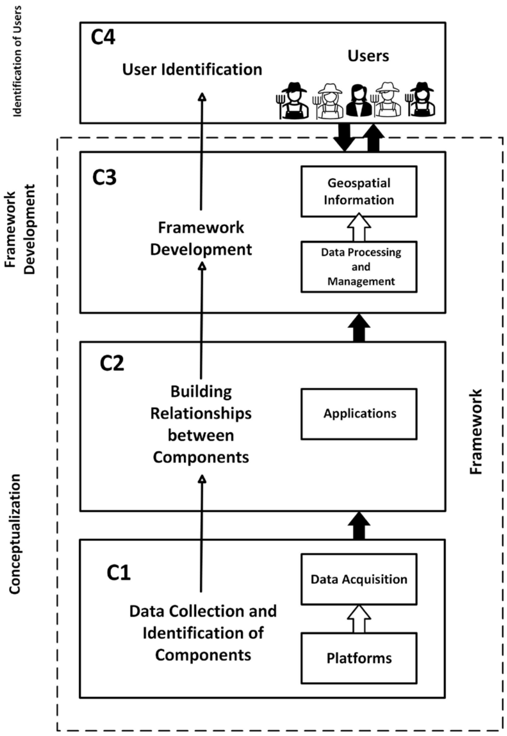
The UAV data provided a comprehensive view of the farm activities, including plowed areas and crop conditions, essential for building the PCFF.

Methods for building a precision crop farming framework (PCFF) for small-scale rainfed agriculture using UAV RGB high-resolution imagery

The development of the PCFF was guided by a critical thinking analysis approach, which involved evaluating the linkages between the various components of the framework (Paul and Elder, 2006; Heard et al., 2020). This approach was essential in ensuring that the framework was not only theoretically sound but also practically applicable in the context of small-scale rainfed agriculture. During this process, external information was also considered rather than relying solely on the collected data. Information on data collection methods, including airborne (aircraft) and satellite imaging systems, was considered for comparison. Before reaching conclusions, alternative possibilities, such as changing the sensor height to collect images with better spatial resolution, were also evaluated to ensure well-reasoned outcomes.

In this study, data and component analysis, as well as their linkages, were conducted continuously, both during and after data collection. The analysis aimed to evaluate the data and link it with the framework components. An inductive and descriptive analysis method was used to trace these relationships, which were essential to the framework. The relationships between components were described and explained as part of the framework.

Four steps were taken to develop a precision crop farming framework (PCFF) for small-scale rainfed agriculture using UAV RGB high-resolution imagery as illustrated in Figure 2.



Source: Own elaboration, 2024

Figure 2: The PCFF development structure.

The first step, linked to Component C1, involved selecting the platforms to be used for spatial data collection. An extensive literature review was conducted to identify platforms capable of providing high-resolution spatial and temporal data. UAVs were identified as the primary platform for this purpose, offering the flexibility to collect data anytime and anywhere. The Global Navigation Satellite System (GNSS) was chosen as a crucial platform for providing accurate location and navigation data.

The second step, related to Component C2, focused on the data acquisition approach, specifically how the UAV platform captured spatial data. The UAV was applied to manage various crop farm activities, including crop cover assessment, planting methods, area coverage, and crop variability across the entire field. The components identified in the first step were linked together to establish relationships between variables, using a critical thinking analysis approach. This step also involved optimizing the data acquisition process by considering alternative methods, such as adjusting sensor heights and employing different UAV flight patterns, to enhance the quality and accuracy of the collected data.

The third step, associated with Component C3, involved processing and managing the collected spatial data using various tools and techniques. This included the development of new vegetation indices − visible green vegetation index (VGVI) and only visible green vegetation index (OVGVI). VGVI and OVGVI were introduced in this study to address limitations in vegetation monitoring using RGB imagery, particularly for small-scale rainfed agriculture. These indices were designed to utilize only the visible spectrum, making them suitable for UAV-based precision agriculture applications (Bolo et al., 2024). These indices were calculated using the following formulas:

$$VGVI = \frac{G - R}{2G + R}, \tag{3}$$

$$OVGVI = \frac{(G - R)}{(G + R)} \div (G + R), \tag{4}$$

where G is green band reflectance, and R is red band reflectance.

Additionally, machine learning algorithms such as ISODATA and SVM were applied for data classification. These tools and techniques were integral to producing agricultural spatial information, such as crop cover and health status. The data processing also involved the use of advanced spatial analysis software, which allowed for the integration of multiple data sources and the generation of detailed maps and models representing the agricultural landscape.

The final step was to identify the framework users (Component C4). This was accomplished by presenting the framework to stakeholders in various sectors through journal publications, international conferences, and national agricultural shows. By engaging with a broad audience, the framework was positioned for widespread adoption and application. The identification of user groups also involved gathering feedback from potential users, which was used to refine and improve the framework, ensuring its relevance and usability in real-world agricultural settings.

By employing critical thinking throughout these steps, the research produced a precision crop farming framework for small-scale rainfed agriculture using UAV RGB high-resolution imagery.

Validation of data processing models using statistical methods

The validation of the PCFF was a critical aspect of the research, ensuring that the framework was both accurate and reliable. The validation process involved several steps, each designed to assess different aspects of the framework's performance.

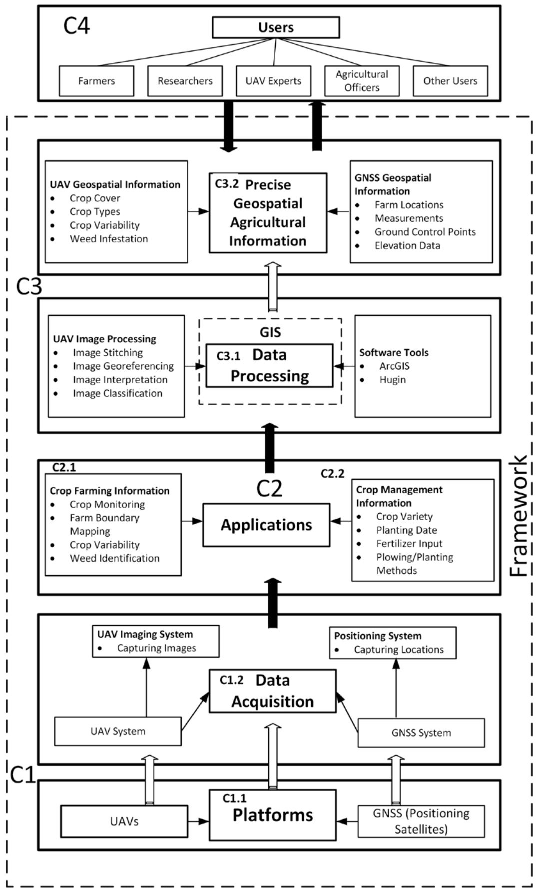
Data collected during the study was processed and transformed into geospatial information, providing insights into farm layout, land use, and cover. The performance of the ISODATA and SVM data processing models was evaluated using statistical methods, including correlation matrices, confusion matrices, and t-tests. These methods provided a comprehensive assessment of the models' accuracy, including omission and commission errors, producer's and user's accuracy, and overall accuracy.

Confusion matrices were employed to evaluate the classification performance of the ISODATA and SVM models, comparing the predicted classes against the ground truth data. The results were expressed in terms of accuracy, precision, recall, and F1-score, providing a detailed understanding of the strengths and weaknesses of each model. Additionally, cross-validation techniques were used to assess the robustness of the models, ensuring that they performed consistently across different subsets of the data (Bolo et al., 2024).

The results of these evaluations indicated no statistically significant difference between the performance of the ISODATA and SVM models, suggesting that both could be used effectively, depending on the specific requirements of the application and available computational resources. This finding was further supported by the t-test results, which confirmed the models' equivalence in terms of classification accuracy.

Results and discussion

This study developed a precision crop farming framework (PCFF) tailored for small-scale rainfed agriculture in Botswana, leveraging UAV RGB high-resolution imagery as the primary data source. The framework, as illustrated in Figure 3, serves as a user-friendly system designed for efficient crop management by integrating UAV RGB imagery with GNSS data. The PCFF comprises four main components: the data collection component (C1), the applications component (C2), the analysis and results component (C3), and the users component (C4).



Source: Own elaboration, 2024

Figure 3: Precision crop farming framework (PCFF) for small-scale rainfed agriculture using UAV RGB high-resolution imagery.

Each of these components plays a critical role in transforming raw spatial data into actionable geospatial information, ultimately supporting decision-making processes in precision crop farming.

The data collection component (C1)

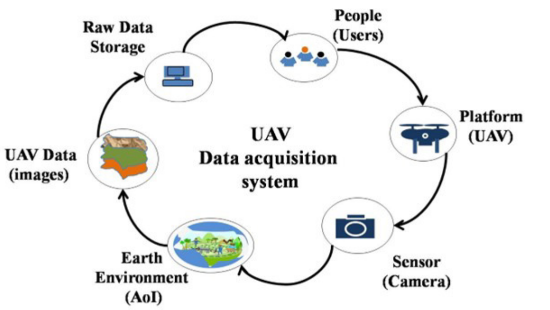
The first component, C1, initiates the data pipeline by collecting high-quality spatial data essential for precision farming. This component is subdivided into two key subcomponents: *platforms* (C1.1) and *data acquisition* (C1.2).

Platforms subcomponent (C1.1)

Platforms within the PCFF refer to the devices and instruments responsible for capturing spatial data and ensuring its precision. In this study, two primary platforms were utilized, namely UAVs and GNSS receivers. The UAVs used were equipped with high-resolution RGB cameras capable of capturing detailed imagery of farm activities. These UAVs also featured integrated signal receivers compatible with both GPS and GNSS systems, enabling accurate spatial referencing of the captured images. The GNSS receiver played a crucial role in collecting location data by providing accurate geospatial coordinates that were essential for mapping farm boundaries, crop zones, and GCPs.

Data acquisition subcomponent (C1.2)

The data acquisition subcomponent, C1.2, is responsible for capturing, processing, and storing the spatial data. The UAV data acquisition system within this framework is composed of six elements, as demonstrated in Figure 4: users, UAV platforms, sensors (cameras), agricultural environment (area of interest), UAV imagery data, and data storage.



Source: Own elaboration, 2024

Figure 4: The UAV data acquisition system where AoI is an area of interest.

The users in this context include farmers, decision-makers, and researchers who operate the UAVs to collect imagery data. The UAV platform, carrying sensors, flies over the agricultural environment (the area of interest) to capture detailed images of ground features such as plowed areas, crop types, and crop health. These images are then stored and processed to generate geospatial information that is critical for planning and decision-making. This subcomponent ensures that the data captured is precise, timely, and relevant to the needs of the end users.

The applications component (C2)

The second component of the PCFF, C2, focuses on the application of UAV imagery in managing crop farming activities through the generation of geospatial agricultural information. C2 is divided into two subcomponents: crop farming information (C2.1) and crop management information (C2.2).

Crop farming information (C2.1)

Crop farming information refers to the data and insights derived from UAV imagery that are directly related to the cultivation and management of crops. This study achieved a remarkably high spatial resolution of 0.19 cm/pixel, which enabled the precise identification of individual crops from the captured images. Such high resolution is essential for monitoring crop health, identifying areas with pest infestations or nutrient deficiencies, and assessing the effectiveness of farming practices.

The UAV systems employed in this study provided farmers with the ability to monitor their fields in real time, identifying areas that required specific attention. For instance, through the analysis of UAV imagery, farmers could determine which areas needed irrigation, fertilizer application, or pest control, thereby optimizing resource use and improving crop yields.

Crop management information (C2.2)

Crop management information encompasses the broader aspects of farm management that benefit from the geospatial data captured by UAVs. This includes the planning of planting schedules, selection of crop varieties, and implementation of precision farming techniques. The UAV imagery was used to generate detailed maps showing crop cover, field boundaries, and variability within the fields. These maps were instrumental in guiding farmers on where to plant specific crops, how to optimize field layouts, and how to manage different areas of the farm based on soil and crop conditions.

Moreover, the study introduced new vegetation indices derived from UAV RGB imagery, such as the visible green vegetation index (VGVI) and the only visible green vegetation index (OVGVI) (Bolo et al., 2024). These indices were calculated using Equations (3) and (4). NDVI, first introduced by Rouse et al. (1974) as a measure of plant health, is still widely utilized for various applications (Ma et al., 2022a, 2022b, Soares da Silva et al. 2022; Ma et al., 2023a, 2023b; Mndela et al., 2023; Sandino et al., 2023; Ferro et al., 2024; Kodl et al., 2024). However, NDVI relies on HNIR, and, therefore, requires expensive multispectral sensors, making it less accessible for small-scale farmers. In contrast, VGVI and OVGVI utilize only RGB bands from UAV imagery, providing a cost-effective alternative for assessing vegetation in resource-limited settings. While NDVI offers a broader measure of vegetation health, VGVI and OVGVI effectively distinguish green vegetation from non-vegetation areas, particularly in rainfed agricultural environments. The study validated these indices using high-resolution UAV images, demonstrating their ability to provide detailed spatial differentiation of crops and land cover, making them highly suitable for precision agriculture.

These indices were crucial in distinguishing vegetated areas from non-vegetated ones, particularly in the semi-arid regions of Botswana where drought conditions and soil fertility issues are prevalent. This would help identify areas that required intervention, such as replanting or soil amendment, to ensure optimal crop growth.

The analysis and results component (C3)

The third component of the PCFF, C3, is where the data collected from components C1 and C2 is managed, analyzed, and transformed into useful geospatial information. This component consists of two subcomponents: data processing and geographical information systems (GIS) (C3.1), and geospatial information (C3.2).

Data processing and GIS (C3.1)

The data processing subcomponent involves the transformation of raw UAV imagery and GNSS data into actionable geospatial information. The study employed various image processing techniques such as image stitching, enhancement, geo-referencing, and classification to convert the raw data into geospatial formats. The UAV RGB images were stitched together to form continuous, high-resolution images of the entire farm, which were then geo-referenced using ground control points collected by the GNSS receiver. This process ensured that the imagery was accurately aligned with real-world coordinates, allowing for precise mapping and analysis.

The study also utilized classification algorithms like ISODATA and SVM to analyze the UAV RGB images. These algorithms were employed to classify different crop types and assess crop cover across the fields. The ISODATA algorithm, in particular, showed superior performance with an accuracy of 82.5% and a kappa coefficient of 0.825, indicating a high level of agreement between the classified images and the ground truth data. The SVM algorithm, while slightly less accurate with an 81.1% accuracy and a kappa coefficient of 0.688, was still effective in distinguishing between different crop types, particularly in areas with mixed vegetation (Bolo et al., 2024).

Geospatial information (C3.2)

Geospatial information refers to the final output of the data processing activities, presented in the form of digital maps, charts, and databases. These outputs are crucial for decision-making in precision crop farming. The study produced various types of geospatial information, including vector maps showing farm boundaries, crop zones, and areas of interest, as well as raster images displaying crop cover and variability across the fields.

The digital maps generated from the processed data were used to visualize the spatial distribution of different crops and to assess the variability in crop health and soil conditions across the farms. For example, the study created detailed maps of two farms, showing the exact locations of different crop types, the extent of plowed areas, and the variability in crop cover. These maps provided farmers with a clear understanding of their fields, enabling them to make informed decisions about planting, irrigation, and fertilization.

Additionally, the study introduced new geospatial information products, such as the rasterized UAV RGB images and the vectorized farm activity maps. These products would allow farmers to monitor their fields more effectively and to plan their farming activities with greater precision.

The users component (C4)

The fourth component of the PCFF, C4, represents the users of the framework. This component is divided into internal and external users, each playing a distinct role in the operation and utilization of the framework.

Internal users

Internal users are those directly involved in the operation of the UAVs and the processing of the data. This group includes UAV experts, GNSS operators, and data analysts who are responsible for capturing, processing, and analyzing the spatial data. These users ensure that the data collected is accurate and that the geospatial information produced is reliable and useful for decision-making.

External users

External users are the end-users of the geospatial information generated by the PCFF. This group includes farmers, agricultural extension workers, researchers, and other stakeholders such as students and young farmers. The external users rely on the information provided by the framework to make informed decisions about their farming activities. For instance, farmers might use geospatial information to determine where to plant specific crops, how to manage their fields, and when to apply fertilizers or pesticides.

Results of the framework validation

The study validated the framework by applying it to two farms and assessing the accuracy of the geospatial information produced. The results of the validation showed the effectiveness of PCFF in capturing and processing spatial data, producing accurate and detailed geospatial information that could be used for precision crop farming.

Validation of the UAV data collection process and image processing techniques

The UAV data collection process was validated by comparing the captured images with ground truth data. The UAV used in the study, a DJI Phantom 4, captured high-resolution RGB imagery at various flight heights, ranging from 5 meters to 120 meters. The images were then processed to produce detailed maps of the farms, showing crop cover, field boundaries, and variability in crop health.

The image processing techniques used in the study, including image stitching, geo-referencing, and classification, were validated by comparing the processed images with the ground truth data. The results showed that the image processing techniques were highly effective, producing accurate geospatial information with minimal errors.

Validation of geospatial information products

The geospatial information products generated by the framework, including digital maps and classified images, were validated by comparing them with existing geospatial data and related work in the field. The results showed that the PCFF produced geospatial information with high accuracy, with extraction precision and kappa coefficients comparable to or better than those reported in related studies.

For instance, the study's use of UAV RGB imagery for generating geospatial information on land use and crop cover achieved accuracies of 83% to 94%, with kappa coefficients indicating strong agreement with the ground truth data. These results validate the effectiveness of the PCFF in producing reliable geospatial information that can be used for precision crop farming.

Conclusion

This study presents a precision crop farming framework (PCFF) tailored for small-scale rainfed agriculture, utilizing UAV RGB high-resolution imagery to enhance farm management and productivity. The mmain contributions of this research include the development of a user-friendly framework that integrates UAV and GNSS data for precise spatial and temporal farm monitoring. By focusing on small-scale, heterogeneous farming systems, the PCFF addresses the specific needs of farmers in semi-arid regions, providing actionable insights into crop conditions, planting patterns, and farm variabilities.

However, our research has several limitations. The reliance on RGB sensors, while cost-effective and suitable for resource-limited settings, limits the ability to capture detailed spectral data available from multispectral or hyperspectral sensors. In addition to that, the framework's applicability to other contexts may be constrained by its design, which is tailored specifically for semi-arid, small-scale farming systems.

To address these limitations and expand the PCFF's applicability, the following areas are suggested for future research. The incorporation of multispectral and/or hyperspectral sensors would allow researchers to capture a broader range of data for more detailed crop and land use analysis. Machine learning algorithms other than ISODATA and SVM should be implemented and tested to establish whether they could reduce computational load while maintaining high accuracy. Further studies should also be conducted to adapt and test the framework in different agricultural contexts and regions (i.e., other Southern African countries) to enhance its versatility and applicability.

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She was responsible for the primary research, data collection, analysis, and initial drafting of the manuscript. Prof. Irina Zlotnikova is a co-supervisor of Ms. Bolo. She participated in the writing and revision of the manuscript, prepared the review of the most recent relevant publications, and produced visual materials (Figures 2 and 3). Dr. Dimane Mpoeleng, as the principal supervisor of Ms. Bolo, provided the initial idea for this research, helped conceptualize the study, and participated in the revision and correction of the manuscript.

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