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(Research Article)

Drone agrotechnology's for cotton (*Gossypium hirsutum* L.) pest and diseases management in Western of Burkina Faso

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Abstract

Drone technologies, also known as "unmanned aerial vehicles" (UAVs) or "unmanned aerial systems" (UAS), have a wide range of applications, including mapping, land-use planning, crop/infrastructure damage assessment, fertilizer spraying and precision crop protection. However, its use is still very limited in the agricultural sector in Africa in general and in Burkina Faso in particular. This study was initiated to explore the potential of UAVs for optimizing cotton yields through monitoring and phytosanitary efficiency. To this end, phytosanitary treatments and monitoring of vegetation status using multispectral drone imagery were carried out on cotton. The experimental sample consisted of four (04) cotton fields in four (04) locations. Phytosanitary treatments and aerial photography were respectively carried out using a DJI AGRAS T16 spray drone and a DJI Phantom 4 Multispectral drone. Phytosanitary treatment with DJI AGRAS T16 drone resulted in savings of 32.41% in treatment duration, 23.58% in water, 1% in pesticides and 10.5% in labor compared with manual spraying, but did not have a positive impact on boll yields due to jassid populations attack. The RGB and NDVI vegetation indices generated by photogrammetric processing of multispectral images acquired by drone enabled us to perceive phytosanitary state of cotton plants during their development cycle. Information provided by these vegetation indices and by this study in general can be used to improve the efficiency of phytosanitary treatments against cotton pests and diseases.

Keywords: Drones; Vegetation indices; Cotton; Phytosanitary treatments; Pest; Diseases

1. Introduction

Agriculture in Burkina Faso is mainly rain-fed and employs over 80% of working population. It accounts for nearly 20% of GDP. Cotton accounts for 60% of export earnings (MAAHM, 2021). It is grown on more than 250,000 farms, representing more than 350,000 producers. Cotton provides a direct livelihood for almost 300,0000 people in Burkina Faso (MAAHM, 2021). Over the years, the cotton industry has proven to be a real tool in fight against poverty and for improving living conditions of rural populations. The spectacular growth in cotton production in recent years has been accompanied by an increase in incomes. Because of its important contribution to development, the cotton sector in Burkina Faso is better organised. Producer groups, cooperatives, research institutes and processing factories are the main actors contributing to the growth of this sector in Burkina Faso (Vognan, 2016).

Despite its importance, cotton production faces many biotic and abiotic constraints that limit its full development. Abiotic constraints are essentially decline in soil fertility, the poor spatio-temporal distribution of rainfall, coupled with socio-economic constraints such as excessive cost of inputs (Vognan, 2016). Biotic constraints include the resurgence

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of diseases and pests and difficulties associated with their management (Cauquil, 1986). Cotton is subject to parasitic attacks at almost every stage of its development, requiring further treatment and monitoring (Miranda et al., 2013). These difficulties persist, all more so as areas sown have increased over years, while methods for phytosanitary treatment and monitoring of cotton have remained rudimentary (Comboigo, 2017).

Faced with these difficulties, a new approach and technology seems necessary to facilitate and make efficient phytosanitary treatments operations against diseases and pests in cotton. Drone technology has developed exponentially, and agriculture is one of the main economic sectors where it is used (Pouya et al., 2020). The data generated by drones has potential to provide farmers with innovative real-time information on the phytosanitary status of crops there, by improving the sustainability and adaptability of their agricultural production system. (Pouya et al, 2020). However, this field is still in its infancy in Africa in general and in Burkina Faso in particular. The present study focuses on contribution of drones to phytosanitary treatment efficiency of cotton in Burkina Faso. The aim objective of this study was to demonstrate the contribution of drones to phytosanitary treatment efficiency of cotton and the assessment of the health status of cotton plants.

2. Materials and methods

2.1. Study areas

The present study took place in the Houndé Cotton Region of Burkina Faso. This cotton- growing region comprises the zones of Houndé Est, Houndé Ouest and Boromo (Plate 1). The Houndé Cotton Region is located in the southwest at 11° 30' 0" North, 3° 31' 0" West and 235 km from the capital Ouagadougou. The study involved the fields of producers who are partners of SOFITEX (Société Burkinabè des Fibres Textiles), one of the three cotton companies in Burkina Faso.

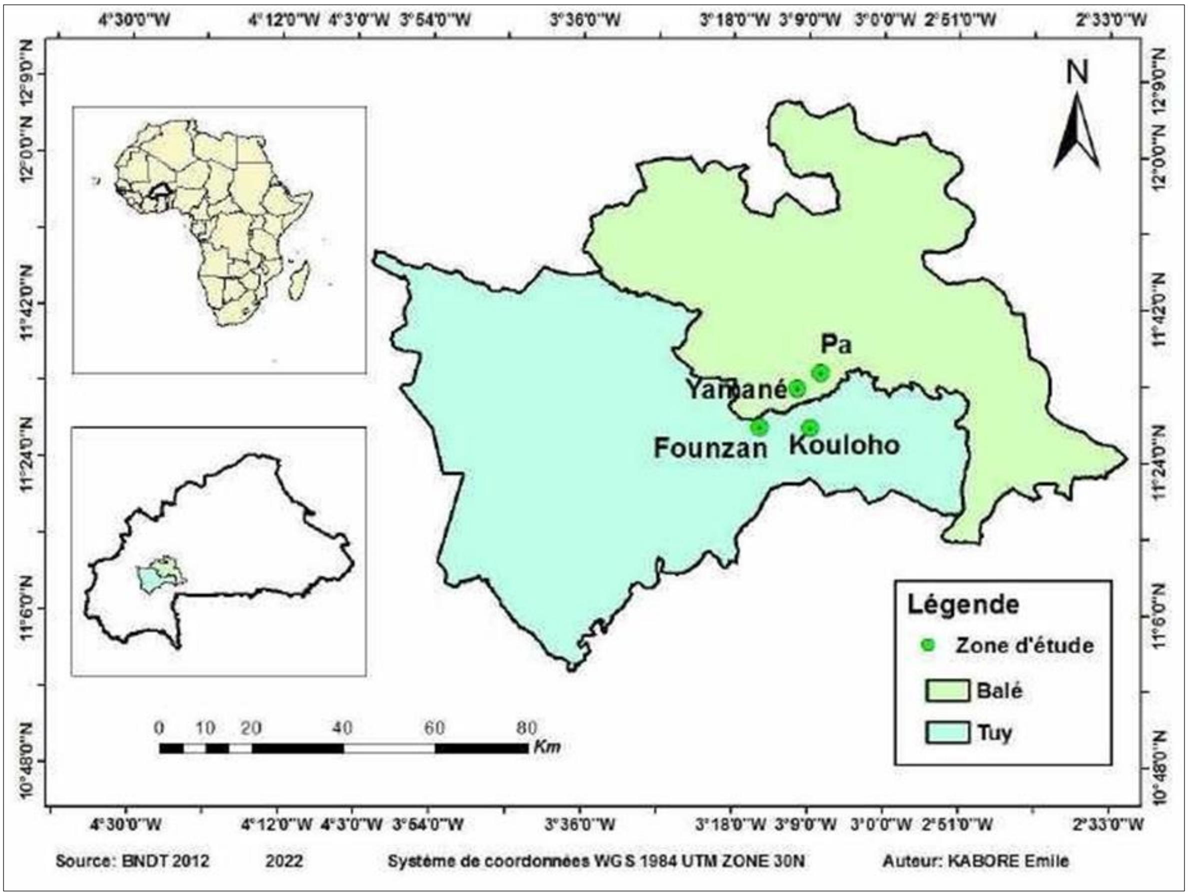


Figure 1 Location of study sites

2.2. Plant material

The plant material consisted of cotton plants of commercial variety FK64 grown in fields of SOFITEX's partner producers in this region. Its potential yield is 1.5 t/ha in the farming environment.

2.3. Technical equipment

The technical equipment consisted of two drones: DJI Phantom 4 Multispectral (P4M) drone for photography, and the DJI AGRAS T16 drone for phytosanitary treatment.

The P4M (Da Jiang Innovations Inc., Shenzhen, China) is an intelligent precision farming drone with a fully integrated multispectral imaging system, designed for agricultural missions and environmental monitoring (Dji, 2020).

The AGRAS T16 drone has a feeder or tank that can hold up to 16 liters of liquid. Its spreading system comprises four pumps and eight XR110015VS nozzles. Spreading width is 6.5 meters for a maximum flow rate of 4.8 l/min and greater spraying precision and stability.

2.4. Pesticides used

The phytosanitary products consisted mainly of pesticides prescribed by SOFITEX (Société Burkinabè des Fibres Textiles) for 2022 season. The pesticides in question were CORAGEN 20 SC, EMIR FORT 104 EC, INDO-PRO 150 EC and LAMDAQUEST 62 EC.

2.5. Methods

2.5.1. Experiment

The experimental set-up consisted of four (04) cotton fields belonging to four SOFITEX partner producers located in the location of Kouloho, Yamané, Pâ and Founzan. During the gridding operations, a survey was carried out in the various localities in order to identify and select the farms for the study. Farms were selected on the basis of ease of access, homogeneity of technical itineraries and producers' willingness to carry out the study. Phytosanitary treatments and photography were carried out on the four cotton fields selected.

Each treatment was carried out according to the prescribed doses. A total of three treatments were carried out. Aerial photography was carried out using a Phantom 4 Multispectral drone and covered four (04) plots of 1 ha each in the four selected fields. They were taken three (03) times and after each phytosanitary treatment.

2.5.2. Phytosanitary treatment using the AGRAS T16 drone

Processing operations are preceded by a grid of cotton fields, performed using the drone's radio control when the accuracy of Global Navigation Satellite System/Remote Controller (GNSS/RC) reaches 2 centimeters. The grid consists of delimiting the boundaries of fields by walking, while taking note of the positions of any obstacles present. This operation provides an automatic flight plan. The flight planning and flight parameter setting operations will enable us to better orientate the flight itineraries according to the direction of the ridges, and to set the flight parameters. For example

The flight height was 1.7 to 2.5 meters depending on cotton growth, the speed was 16km/h, the flow rate 4.8L/mn, a safety distance of 5m and the dose set at 15l/ha. We calibrated the drone's IMU (Inertial Measurement Unit) and Compass (Compass) to adapt them to the physical parameters of the environment for better stability and tracking during spraying. Once the settings have been made, the drone is deployed over a well-cleared area. The product is prepared at a dose of 0.5l/ha, topped up with water to form the spray mixture after homogenization with the 16l MATABI pressure-maintained hand sprayer.

A total of three (03) phytosanitary treatments at 14-day intervals were carried out.

2.5.3. Image capture with the Phantom 4 Multispectral drone

The first step was to deploy the drone and mount accessories in a well-cleared area, in order to pick up as many satellite signals as possible. The radio control system was used to link up the drone, calibrate it, plan the flight plan, set the parameters, carry out the aerial image capture missions and process the aerial photos. Linking involved connecting the drone to the radio control system. Calibration involved adapting the drone's IMU and Compass to the physical parameters of the environment, to ensure greater stability during flight. After calibration, the flight plan was planned.

Flight routes and capture points are automatically generated by the software. For each plot, 80 capture points were generated. The flight height was 50 m and the speed was 12.5 m.s-1 . Overlaps were 60 and 70% horizontally and vertically respectively. During the flight, the P4M mapped and took aerial photos in accordance with the flight plan of the area delimited in automatic mode. For each capture point, six photos are taken. As a result, 580 photos were generated per plot.

Photographs were taken before each treatment in order to perceive the effectiveness of the treatments on the cotton plants. A total of three (03) shots were taken after each spraying at two-week intervals, as follows:

- The first photos were taken at the flowering stage;
- The second shots were taken at the boll development stage;
- The third shots were taken when the bolls were ripe.

Flights for photography take place between 10:00 and 14:00 when the sun's elevation angle is greater than 45 degrees in order to obtain good lighting conditions as recommended by (Bradford, 2018).

2.5.4. Agronomical traits measurement

Three phytosanitary treatments were carried out at 14-day intervals. The phytosanitary products used were those prescribed by SOFITEX for the current season. In order to assess effectiveness of phytosanitary treatments using drones, agronomical and usage-related data were collected. These include:

- Spray time,
- Quantity of water used,
- Quantity of product used,
- number of labors used,

Yield was assessed at maturity using the segment method. This consists of counting the Number of Lines (NL) over 100 meters and the Number of boll (NB) over five segments of 20 meters each. The following formula was used to calculate gross capsule yield:

$$\mathbf{Rdt = NB*NL*PMC}$$

With PMC=Mean capsular weight=3.5g.

These data were compared with those obtained by hand spraying and previously demonstrated by previous studies (Renou, 2007; So, 2021).

2.5.5. Aerial imagery data collection and vegetation index calculation

After shooting, aerial images are extracted from drone's memory and transferred to DJI TERRA software installed on the computer for 2D photogrammetric reconstruction or aerotriangulation or orthomosaicing. This process involves assembling collected images into aerial maps. Following this reconstruction, plot's Near Infra-Red (NIR) and Red (R) spectral bands are generated. The spectral bands generated are imported into QGIS software, which is used to generate RGB (Red-Green-Blue) and NDVI (Normalised Difference Vegetation Index) image maps.

- The RGB maps, produced by combining the red, green and blue spectral bands of RGB sensor, show changes in biomass as clearly as possible. on all three sockets. Indeed, RGB sensors are the most widely used in UAVs, as they provide lightweight, easy-to-use, high-resolution images that can be acquired under a variety of conditions (Issad, 2020). RGB images illustrate the original appearance of the scanned plot, making them easy to interpret. Vegetation assessment is based on the coloring of the RGB images (Red-Green-Blue).
- NDVI is produced from multispectral sensors and is particularly useful for detection of pests, diseases, weeds, creation of a fertilizer prescription and many other crop- related problems (Issad, 2020). It is one of the first analytical remote sensing products used to simplify the complexities of multispectral imagery, is today the most widely used index for vegetation condition assessment and can be calculated with any multispectral sensor equipped with a visible and near-infrared band (Huang et al., 2021). Indeed, at the leaf scale, the spectral bands most commonly used in leaf disease detection are those in the visible (blue, green, red, Red- Edge), near-infrared and short- wave infrared (Albetis, 2019). NDVI is based on absorption in the red due to chlorophyll and

reflectance in the near-infrared and therefore facilitates monitoring of the growth and health of many agricultural crops (Tsouros and Bibi, 2019). NDVI values are calculated according to the formula of Rouse et al (1973);

NDVI = (NIR -R) /(NIR+R)

NDVI values are interpreted according to the scale described by Hamrelaine et al., (2021) (table 1).

Table 1 Scale of NDVI values

Ndvi values	Interpretations
-1 à 0	Non-vegetated surfaces, bare ground
0.1 à 0.3	Low vegetation
0.4 à 0.6	Sparse vegetation
0.7 à 1	Healthy vegetation

Sources: (Rouse et al., 1973),(Hamrelaine et al., 2021)

Crop health (leaf area) is obtained by assessing the variation in mean NDVI values as a function of image collection periods and attack severity, as described by Zhao et al. (2020) (Table 2).

Table 2 Gradings of cotton disease and pest attack severity on normalized vegetation indices

Attack severity Level	Symptom Description	Normalized Vegetation Indices
Level 4 (L4)	Extremely severe	0.8 -1.0
Level 3 (L3)	Severe	0.6 - 0.8
Level 2 (L2)	Medium	0.4 - 0.6
Level 1 (L1)	Slight	0.2 - 0.4
Level 0 (L0)	Latency period	0.0 - 0.2

Zhao *et al.* (20202)

2.6. Data analysis and processing

Agronomical data measured were entered using an Excel 2016 spreadsheet. Excel spreadsheet was used to calculate mean values and standard deviations of phytosanitary treatment indicators by AGRAS T16 drone. These averages were compared with literature data on manual treatment of cotton to see the differences.

Aerial data were entered and arranged using Excel 2016 software. It was also used to draw up treatment indicator tables for the AGRAS T16 drone. The images were analyzed and processed using DJI TERRA software to generate vegetation index maps for assessing chlorophyll activity. The raster calculator in QGIS 3.30.1 software was used to calculate NDVI values.

QGIS 3.30.1 software was used for statistical analysis of NDVI spectral band raster layers, calculation and zonation of NDVI values on vegetation index maps.

3. Results

3.1. Evaluation of crop phytosanitary treatment effectiveness by drone on cotton

The use of AGRAS T16 drone sprayer for phytosanitary treatment helped to reduce treatment time, quantities of water pesticides used, and number of manpower mobilized compared with standard values for manual treatment of a 1 ha area (Table 3). However, treatment did not increase cotton yield due to jassid attack in our study area. The average treatment time (0.35±0.14 hours) was three times shorter than the standard manual treatment time (1.08 hours). The average quantity of product used was 0.5±0.21l, which is relatively lower than standard quantity for manual treatment. In addition, the quantity of water used was 15.00±5.98 l, four times less than that used for manual treatment. The average yield recorded in this study was 0.91±0.21t/ha, which is lower than the average standard yield of 1.5t/ha. This drop in yield is essentially due to the unexpected appearance of jassids in the cotton-growing zone, which caused huge production losses.

Table 3 Impact of drone treatment on duration, average number of resources mobilized and yield

	DT	**QP**	**QE**	**NL**	**Yld**
Average	0,35±0,14	0,5±0,21	15,00±5,98	0,21±0,08	0,91±0,21
Std	1,08	0,6	63,6	2	1,5
Comparison	<Std	<Std	<Std	<Std	<Std

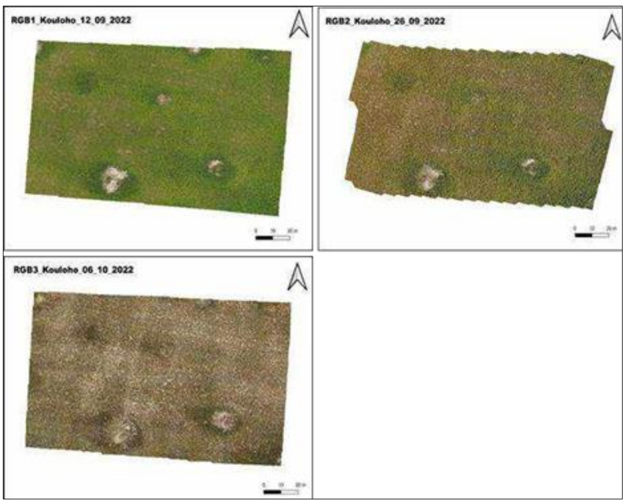
DT=Treatment time in hours, QP=Quantity of pesticides in liters, QE=Quantity of water in liters, NL=Number of laborers, Yid=Capsule yield in tons/ha, Std=standard value for manual treatment.

3.2. RGB vegetation index

The plant health classification maps identified by drone imagery for the four cotton fields during the three periods of visual deprivation are presented in Plate 1. Color is the result of visual cortex's spectral interpretation of incident light, which stimulates retinal photoreceptors known as cones. Biologically, color is encoded in three components, each relating to the spectral sensitivity of one of the three cone families to a specific wavelength range: one component relating to blue, one to green and one to red.

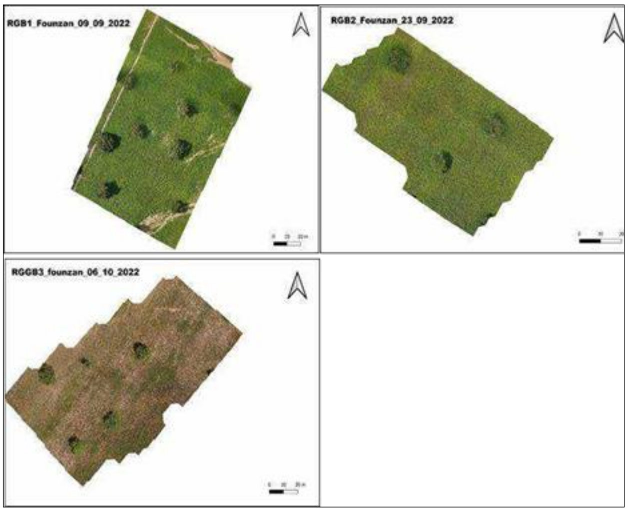
The RGB image is made up of three monochromatic components associated with wave lengths Blue (435.8nm), Green (546.1nm) and Red (700nm). These components form the axes of RGB cube, whose null origin is black. It is used to synthesize and additively display images on screens, and corresponds to physical measurement performed by photosensitive sensors of RGB cameras.

RGB images obtained in the four locations give a clear indication of level of crop vegetation during the different shots. In all locations, the green color of images degraded to light green over the course of the shots. Plots were green at flowering stage, light green and/or russet at boll formation and russet and/or white at boll opening. The vegetation gradually declined over the course of different shots. This deterioration in vegetation coloration perceived through RGB images is due to decrease of photosynthetic activity. This decrease may be natural, depending on plant's evolutionary cycle, but it may also be due to attacks by pests and plant diseases. The RGB2 images taken at boll formation stage of the cotton plant enable us to classify the Founza field as the least attacked (green), Pa field (light green), Yamané field (light green) and Kouloho field (russet), in descending order of pest and disease severity. The russet color observed for all RGB3 images (boll opening stage) is due to the severity of jassid attack in the fields, but also to defoliation marking the end of plant's cycle.

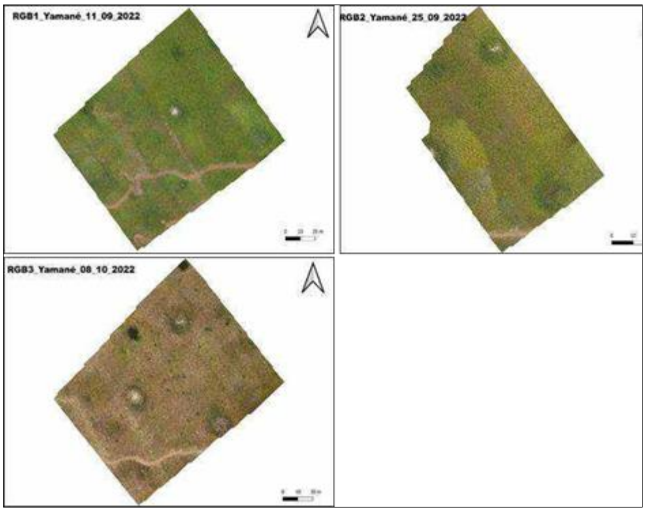


(i)/ RGB imagery map of Kouloho

(ii)/ RGB imagery map of Pa



(iii)/ RGB imagery map of Founzan



(iv)/ RGB imagery map of Yamané

RGB1= Flowering stage, RGB2= Boll formation stage, RGB3= Boll opening stage

Figure 2 Periodic RGB image maps for the four locations

3.3. Normalized Difference Vegetation Index

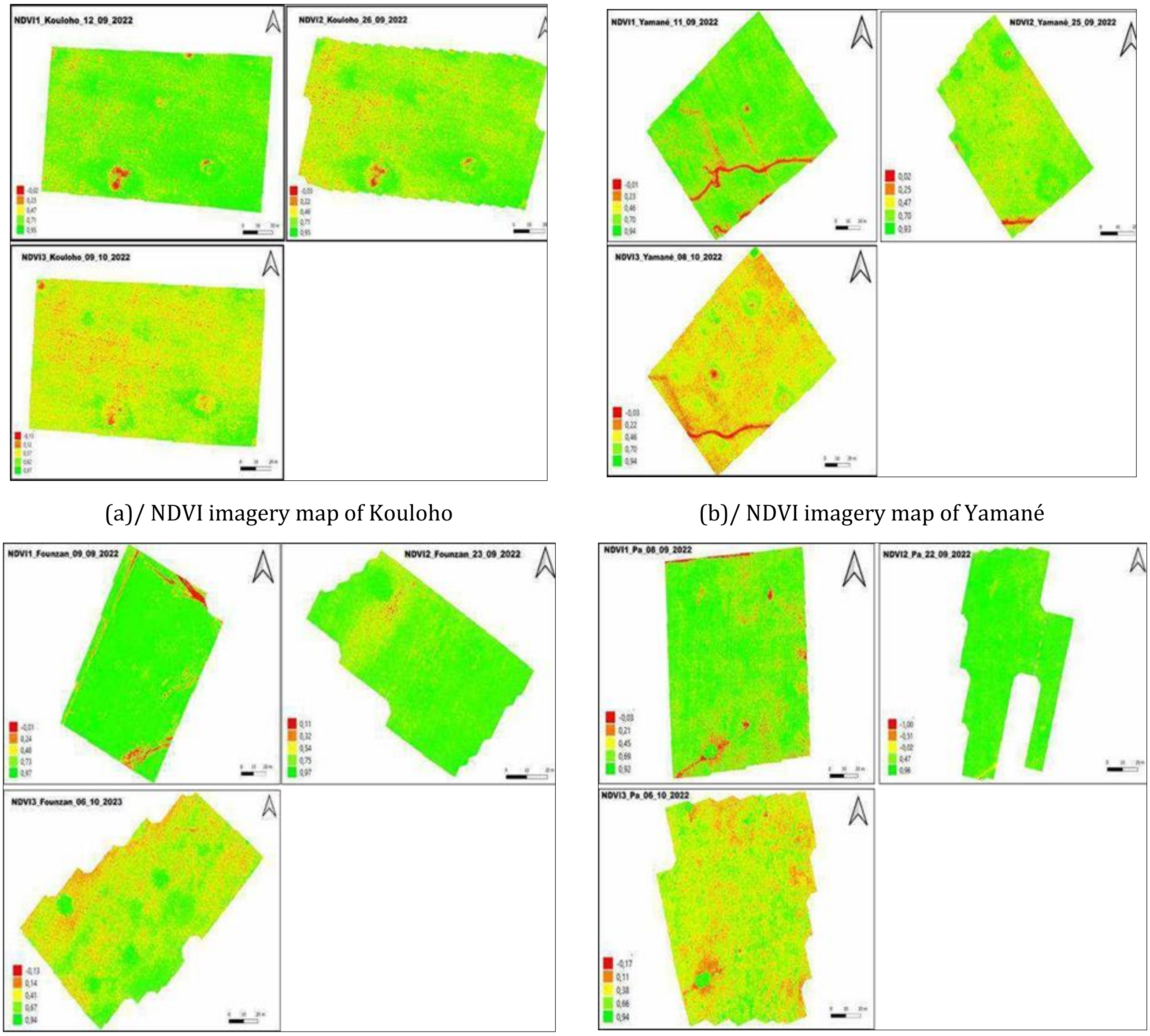
Multispectral sensors exploit reflectance properties of plant cover in the visible (Red) and near-infrared (NIR) parts of the spectrum. Visible spectral signature of leaves reflects chlorophyll activity (Rudnicki, 2010). In near infrared (NIR), reflectance depends on internal structure of leaf cells. NDVI values obtained from ratio of these spectral signatures will inform us about the state of cotton health during the different shots (phenological stages of the cotton). The vegetation index maps (Plate 2) provide a visual overview of the evolution of cotton plant's vegetative state through the definition of coloration classes. Coloration ranges from red through yellow to green. Red corresponds to low NDVI values, yellow to medium values and green to high NDVI values.

Normalised Difference Vegetation Index The variation of Normalised Difference Vegetation Index (NDVI) in cotton crop at different phenophases in all locations is presented in Table 4. NDVI values were maximum in cotton sown at flowering stage and minimum at boll opening stage. Among the localities, the maximum value of NDVI was recorded at Founza followed by Kouloho, Pa and Yamena. According to Zhao et al. (2020), the highest values of NDVI (level 4) were recorded at Founza field at flowering and boll formation stages, indicating an extremely severe attack of pests and diseases on cotton plants. In the remaining localities (Yamane, Pa and Kouloho), NDVI values ranging from 0.6 to 0.8 were recorded.

In general, vegetation condition of cotton decreased over the three shots. Vegetation was healthy at flowering stage (NDVI=0.75). However, it became slightly sparse (NDVI=0.66 with a variation of 0.09) at the boll formation stage. Similarly, vegetation became sparser at boll opening (NDVI=0.46 with a variation of 0.2). The vegetation index maps (Plate 3) provide a visual overview of evolution of cotton plant's vegetative state through the definition of coloration classes. Coloration ranges from red to green to yellow. Red corresponds to low NDVI values, yellow to medium values and green to high NDVI values.

Table 4 Temporal variation of NDVI values of cotton at different phenophases

Locations	**Shooting stages**								
	Flowering stage			**Capsule formationstage**			**Capsule opening stage**		
	Min	**Avg**	**Max**	**Min**	**Average**	**Max**	**Min**	**Average**	**Max**
Kouloho	-0.04	0.75	0.97	-0.13	0.66	0.96	-0.23	0.46	0.89
Pa	-0,07	0,7	0,94	-0,11	0,62	0,97	-0,21	0,49	0,94
Founza	-0,05	0,83	0,98	-0,06	0,8	0,97	-0,22	0,54	0,97
Yamane	-0,21	0,49	0,94	-0,13	0,64	0,95	-0,26	0,45	0,95



(a)/ NDVI imagery map of Kouloho

(b)/ NDVI imagery map of Yamané

(c)/ NDVI imagery map of Founza

(d)/ NDVI imagery map of Pa

NDVI1= Flowering stage, NDVI2= Boll formation stage, NDVI3= Boll opening stage

Figure 3 Periodic maps of NDVI vegetation indices in all localities

4. Discussion

In our study, drone spraying is an extremely important tool for phytosanitary treatment of cotton. Thanks to their speed and automatic system, drone sprayers considerably reduce the time required for treatment operations (0.35±0.14 hours per ha). With a speed 40 times higher than manual method. Drone-assisted phytosanitary treatment saves growers time. These results are in accordance of those of Meng et al, (2020) and So, (2021). Phytosanitary treatment of cotton by drone also reduces water quantities used of (15.00±5.98 l per ha) and pesticides used. Thanks to a sophisticated electromagnetic flowmeter system and modern nozzles, drone sprayers with a wide spreading width (6.5 m) apply pesticides evenly and precisely to cotton. This reduces pesticide overdosing and excess water consumption in manual method. These results are in line with those of Sanon, (2007), who showed that drone spraying saves 90% of water and 30 to 40% of pesticides. In addition, drone spraying operation requires an average of one person for piloting, unlike manual method, which requires at least two people per ha for spraying. Drone spraying solves the problem of manual spraying and the lack of manpower. However, our results showed a drop in cotton yield compared with fields treated manually. Indeed, boll yield was 0.91t/ha, which is lower than standard yield (1.5t/ha). This could be explained by the heavy attack of jassids at flowering and boll formation stages. This attack reduced photosynthetic activity and boll formation process. Indeed, Renou (2007) has shown that jassids disrupt photosynthesis and cause fruiting bodies to fall off. According to same source, overall yield losses due to these pest's average between 20% and 30%. There has also been a drop in cotton yields for 2022 season nationwide. There are several reasons for this, including the poor quality of inputs provide to producers by SOFITEX, inappropriate treatment periods, which has led to increased attacks by jassids and a resurgence of viral diseases transmitted by these jassids.

Over the course of the various recordings, average NDVI values varied considerably. regressions on the three growth phases of cotton plant. This reflects a decline in this, is due to a gradual reduction in photosynthetic activity. Indeed, the drop in photosynthesis reduces the amount of green leaf biomass, hence the drop in NDVI values. In Kouloho, Founzan, Pâ and Yamané locations, vegetation is healthy at cotton flowering stage, with NDVI values respectively equal to 0.75; 0.83; 0.7 and 0.84. However, vegetation is becoming sparse, with declining NDVI values (Kouloho=0.66; Pâ=0.62 and Yamané=0.64), except in Founzan where it has fallen slightly (NDVI=0.8). At the boll opening stage, vegetation levels dropped considerably in all localities (Kouloho=0.46; Founzan=0.54; Pâ=0.49; Yamané=0.45). Decline in vegetation is due to attack of dreaded jassid populations. Feeding by stinging the leaf veins, jassids cause yellowing of leaf blade margins (often accompanied by downward curling), which then spreads to the entire leaf blade, while the margins turn red and the leaf eventually dries out. The plant's photosynthesis is disrupted by these attacks, and fruiting bodies fall off as a result (Renou, 2007). This results in a drop in chlorophyll activity, hence the drop in NDVI. Despite phytosanitary treatments, jassid invasion persisted right up to boll opening, causing yellowing, reddening and massive withering of cotton leaves in all locations. The decline in vegetation condition is also partly linked to senescence of cotton at boll opening stage. Thus, variations in mean NDVI values over the course of different recordings showed the decline in photosynthetic activity of cotton plant, manifested by leaf withering. NDVI vegetation index is a useful indicator for assessing the health and vegetation status of cotton. Indeed, NDVI is an indicator of chlorophyll activity of vegetation, and its decline reflects a decrease in this chlorophyll activity (Razagui, 2014). These results demonstrate the strong potential of vegetation indices derived from processing of multispectral images acquired by UAVs for monitoring vegetation condition and, consequently, detecting cotton pests and diseases. They corroborate the research work of Goulamoussène et al, (2018), Albetis, (2019) and Traore et al, (2021) in the field of remote sensing using drone technology. Indeed, studies by Goulamoussène et al., (2021) have shown that sensor-embedded drones are well suited to monitoring vole-infested agricultural plots in a reduced time interval. Similarly, Albetis, (2019) demonstrated the potential of drone-acquired multispectral images in detecting areas infected by grapevine diseases. Thanks to imaging systems and vegetation index maps generated, drones in cotton production are decision-support tools. By interpreting these indices, producers are able to monitor health of their crops as quickly and accurately as possible. This technology will help cotton producers to effectively monitor crop growth, and guide their decision- making for better production.

5. Conclusion

The aim of this study was to demonstrate the contribution of agriculturaldrones to the efficiency of phytosanitary treatments for cotton in western Burkina Faso. This study generated scientific evidence on the applications and real impact of drones on farmers' productivity. Firstly,thanks to the multispectral imaging systems and vegetation index maps generated, drones are proving capable of monitoring the state of vegetation and detecting cotton pests and diseases in a short space of time. This will enable farmers to effectively guide their crop management interventions. Secondly, UAV sprayingsystems provide a welcome relief for phytosanitary treatment operations on cotton. They ensure even spreading, save water and pesticides, protect producer's health and minimize child labor. In view of their importance, drone technologies should be recommended in production systems for rational resource management, effective cotton pest and diseases control, yield optimization, and protection of producers' health and the environment.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

Author Contributions

Conceptualization, Adama ZONGO; methodology, Adama ZONGO, Emile KABORE and Oumar BADINI; Software, Adama TRAORE; resources, Sylvestre SAWADOGO and Oumar BADINI ;validation, Mahamadou SAWADOGO, and Adama ZONGO; formal analysis, Adama TRAORE and Emile KABORE; writing—original draft preparation, Adama ZONGO; writing review and editing, Adama ZONGO, and Emile KABORE; supervision, Mahamadou SAWADOGO and Sylvestre SAWADOGO.

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