Determining the Amount of Crop Residue Cover Using Image Analysis

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Abstract

This research investigates the use of UAV-based image analysis to quantify crop residue cover on the soil surface after tillage operations. Crop residue plays a crucial role in sustainable agriculture by reducing nutrient runoff and decreasing the susceptibility of topsoil to erosion. By anchoring the soil and obstructing surface flow, residue helps mitigate the loss of fine particles, especially during seasonal transitions. To assess residue coverage, aerial images were captured using two types of UAVs equipped with different imaging systems: a standard RGB camera and a multispectral camera. The imagery was then analysed to determine the extent of plant debris remaining on the field surface. The research highlights the advantages of using UAV-based imaging, including high efficiency, cost-effectiveness, and superior resolution compared to satellite imagery. This makes the method particularly suitable for field-scale residue mapping. The results demonstrated that images captured with RGB cameras were more compatible with the applied image analysis techniques. Residue was clearly distinguishable, and shadows from soil clods had minimal impact on detection accuracy. Conversely, multispectral imagery posed greater challenges in processing, primarily due to reduced contrast between residue and soil and increased sensitivity to shadow interference. Overall, the findings support the use of RGB UAV imagery as a reliable and practical tool for quantifying crop residue cover. This approach offers a scalable solution for monitoring soil conservation practices and evaluating tillage outcomes across agricultural fields.

1. Introduction

Measuring crop residue cover (CRC) is vital for assessing soil conservation, erosion control, and sustainable agricultural practices. CRC plays a key role in preserving soil moisture, enhancing soil structure, and reducing nutrient loss. Its accurate quantification supports precision agriculture and environmental compliance monitoring.

Traditional ground-based measurements, including line-transect and visual estimation methods, are labour-intensive, time-consuming, and limited in spatial scope. These methods also suffer from subjectivity and inconsistencies due to varying operator experience and environmental conditions. Consequently, there has been a growing reliance on remote sensing techniques to estimate CRC more efficiently and accurately over large areas.

Remote sensing provides non-invasive, repeatable observations and facilitates large-scale monitoring. Spectral indices derived from multispectral and hyperspectral sensors, such as the Cellulose Absorption Index (CAI) and Normalized Difference Tillage Index (NDTI), have proven useful in differentiating crop residue from bare soil and green vegetation (Quemada & Daughtry, 2016). However, their sensitivity to moisture content, soil brightness, and residue orientation poses a challenge to robust estimation under diverse field conditions.

Advances in satellite data integration and modelling techniques, including regression models using multi-sensor platforms, enhance CRC prediction accuracy by combining spectral, spatial, and temporal information (Williams et al., 2024). Additionally, UAV (Unmanned Aerial Vehicle) based imaging and machine learning approaches show promise in improving residue detection in heterogeneous landscapes (Yang et al., 2025).

Despite these advances, challenges remain. Variability in residue type, decomposition stage, and background soil properties complicate remote sensing analyses. Calibration with reliable ground truth data remains essential for model validation and refinement (Sonmez & Slater, 2016).

The structural development of farms, advancements in tillage machinery, and, to some extent, changes in agricultural subsidy policies have collectively driven farms to optimize their cultivation practices over recent decades. Tillage is one of the most time- and resource-intensive operations in crop production. Its efficiency has been improved by shifting from traditional ploughing methods to reduced tillage systems. In reduced tillage, operational efficiency is often achieved by increasing the working width of the tillage implement without significantly raising the power requirements of the machinery.

Previous studies have explored various methods for determining the amount of crop residue cover (CRC) on the soil surface. Most of these studies estimated CRC on untilled fields. Image analysis can be used in determining the amount of crop residue on arable land. It is especially effective in assessing plant cover, as UAVs or satellites can quickly image large areas. However, challenges include image resolution and difficulties in segmenting crop residue from bare soil (Kosmowski et al., 2017). In the study by Kosmowski et al. (2017), a DJI Phantom 2+ UAV with an RGB camera (Sony EXMOR 1/2.3) was used, flying at 7.5 meters altitude, capturing about 80 m^2 with a resolution of 0.27 cm/pixel. Raoufat et al. (2020) used a DJI Phantom 3 UAV with a 12 MP RGB camera, flying at altitudes of 5–35 meters, with image resolution ranging from 0.225 to 0.45 cm/pixel. Image analysis was done using IrfanView-64 and MATLAB software. The studies were conducted on a field where wheat had been previously grown and harvested weeks before imaging. Multispectral imaging is also considered reliable for plant and surface analysis by using satellite images (Gao et al., 2022) and aerial imaging by UAVs (Änäkkälä et al., 2022).

Image analysis can help determine the Crop Residue Cover Index (CRCI), calculated by the proportion of the soil surface covered by residue relative to the total area measured (Asadi et al., 2011). The method is cost-effective and efficient, especially when using UAVs or free satellite data. Kosmowski et al. (2017) used the Excess Green Index for segmentation. The original RGB image

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was transformed into a binary image where crop residue appeared as white pixels and bare soil as black pixels. The CRCI was then calculated as the percentage of white vs. black pixels. Raoufat et al. (2020) used several indices for CRCI detection, with the most effective being Excess Green Index (2G–R–B) and Green Percentage Index (G/(R+G+B)). Both Kosmowski and Raoufat concluded that UAV-based crop residue indexing is a promising and effective method. However, challenges such as camera resolution limitations (especially in Kosmowski's study) exist. Advances in camera technology will likely improve these methods' reliability in the future.

Artificial intelligence and machine learning methods have recently been used increasingly for estimating the amount of CRC on agricultural fields. The methods used vary from simple algorithms such as K-means (Azimi & Jung, 2024) to more advanced machine learning methods (Upadhyay et al., 2024).

The primary objective of the research was to develop and evaluate an efficient method for determining crop residue cover on agricultural fields using UAV-based image analysis. By comparing imagery from RGB and multispectral cameras, the study aimed to identify which imaging approach best supports accurate residue detection. The impact of this research lies in its potential to enhance soil conservation monitoring through precise, cost-effective, and scalable assessments of tillage outcomes. By improving our ability to quantify residue cover, the method supports better decision-making in sustainable land management and also can provide fast feedback about the efficiency of tillage operations for covering crop residue.

2. Materials and Methods

In this research, field measurements were conducted using two different UAVs and a handheld DSLR camera Canon EOS 80D. The larger UAV was equipped with a multispectral camera and the other with a high-quality RGB camera (DJI Mavic 3 Enterprise). The larger UAV, a hexacopter Tarot T960 (Figure 1) carried a multispectral camera MicaSense RedEdge 3 capable of capturing five spectral wavelengths: blue (475 nm), green (560 nm), red (668 nm), red edge (717 nm), and near-infrared (NIR, 840 nm). The measurements were performed on 20 August 2024 between 12:00 and 15:00 o'clock.

Figure 1. Custom-built UAV with a Tarot T960 frame.

The experiment was located in Niinijoki, Loimaa, Finland. Winter wheat (*Triticum aestivum* L.) was grown in the field and harvested before the measurements. Tilling of the test plots were performed with Multiva Wingmaster 360 cultivator with a working width of 3.5 m (Figure 2). Five different blade types were used on the cultivator to create difference in crop residue cover between different plots.
Cultivation with a cultivator represents a form of reduced tillage that combines the benefits of conventional plowing with the advantages of conservation-oriented soil management. One of its key attributes is the ability to loosen the upper soil layer, thereby improving soil aeration and promoting root development, much like traditional plowing. However, unlike deep inversion tillage, cultivation is less disruptive to soil structure and organic matter distribution. As a tillage implement, the cultivator is notably efficient; it offers a favorable balance between operational performance and economic feasibility. The machinery is generally affordable, and its use supports the maintenance of soil structure by minimizing compaction and preserving soil porosity. These characteristics make this type of cultivation a sustainable and cost-effective practice in modern agricultural systems, particularly in regions where maintaining long-term soil health is a priority.

Figure 2. Multiva Wingmaster 360H ja Valtra T174EV.

There were five test plots (from A to E) in which data was collected separately immediately after tilling to avoid soil drying before imaging. Figure 3 shows all the plots and Figures 4-8 present the area chosen for analysis for each plot. Flights were conducted at an altitude of 20 meters with 80% overlap. At this height, image GSD (ground sample distance) for the RGB camera was 0.62 cm/pixel, and 1.29 cm/pixel for the multispectral camera. The multispectral camera was calibrated after each flight. The images from both UAV cameras were stitched into a single large orthomosaic image for each plot using Pix4Dmapper.

Figure 3. The research area and the five tilled test plots. Plot labelling followed a left-to-right order, starting with Plot A on the left and ending with Plot E on the right


Figure 4. Orthomosaic image for field plot A.


Figure 5. Orthomosaic image for field plot B.

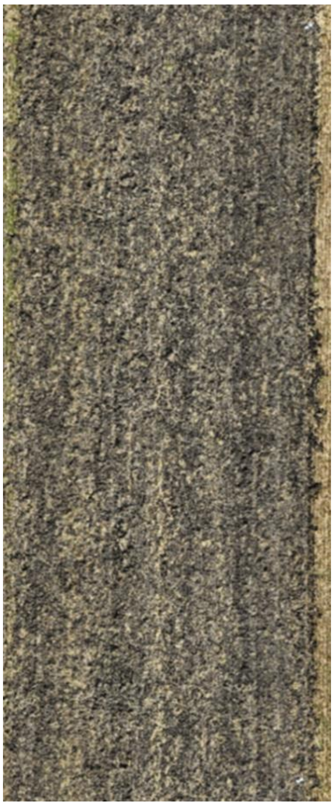
Figure 6. Orthomosaic image for field plot C.


Figure 7. Orthomosaic image for field plot D.

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Figure 8. Orthomosaic image for field plot E.

The DSLR camera images were collected from 1.5 m altitude and with the average GSD value of 0.016 cm/pixel. A 0.5m x 0.5m wooden square was placed in DSLR images to determine the area. Five images were collected from each plot from randomized spots.

The objective was to compare different, rather simple, image analysis methods based on techniques presented in literature. Five methods with the following data were chosen for preliminary analysis:

1. Excess Green index (ExG) from DJI UAV RGB images
2. Excess Green index (ExG) from DSLR camera images
3. Red bandwidth from DJI UAV RGB images
4. Red bandwidth from multispectral images (Tarot UAV)
5. Manually annotated images from DSLR camera images

For each dataset, a specific threshold value was determined and used for generating binary images for calculating the amount of crop residue cover on the tilled field plots. The threshold values used in the analysis were as follows: 3 for Method 1, 16 for Method 2, 130 for Method 3, and 0.108 for Method 4. Thresholding and analysis of the images was performed with Matlab. Methods 1 and 2 used ExG (Excess Green Index) index (Equation 1):

$$ExG = 2 * G - R - B \quad (1)$$

Where G = Pixel value of the Green band
R = Pixel value of the Red band
B = Pixel value of the Blue band

Only the DSLR camera images were manually annotated to present the ground truth for each plot. Figure 9 represents the workflow for analysing these images for ground truth. The DSLR camera images were annotated using a lightweight image editing application (Microsoft Paint). Manual annotations focused on representative regions of crop residue rather than exhaustive pixel-level labelling, to maintain a practical balance between detail and efficiency. After manual annotation the images were processed with Matlab to count the annotated pixels that were classified as crop residue within the wooden frame.

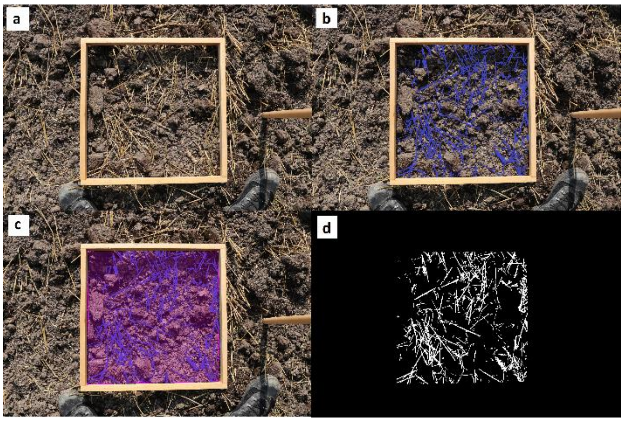

Figure 9. The process of determining ground truth data from the plots. a) the original DSLR camera image. b) the hand annotated image. c) manually drawn polygon over the desired region with Matlab. d) The binary image representing the ground truth

3. Results

Table 1 presents the estimated CRC for each test plot with the five different methods. Across all estimating methods, plots B and C consistently had the most crop residue on the soil surface, while in the plot A, the mixing performance of the tilling machine was considered quite good. Method 1 yielded the highest residue percentages, and Method 2 the lowest, with the most uniform results. Methods 3 and 4 supported the same overall trends, though Method 4 showed the greatest variability between the test plots. The results of test plots D and E were relatively consistent and moderate across methods.

Plot	Crop residue coverage	Method
Plot A	37.47 %	1
	6.73 %	2
	24.93 %	3
	19.79 %	4
	19.53 %	5
Plot B	84.03 %	1
	8.35 %	2
	40.87 %	3
	51.22 %	4
	29.53 %	5
Plot C	72.07 %	1
	7.67 %	2
	36.83 %	3
	34.44 %	4
	19.94 %	5
Plot D	48.92 %	1
	6.10 %	2
	32.37 %	3
	16.91 %	4
	19.84 %	5
Plot E	55.01 %	1
	6.52 %	2
	31.65 %	3
	9.58 %	4
	21.46 %	5

Table 1. CRC values for each plot with the different methods.

Figure 10 shows the original RGB image and binary image calculated from it. Method 1 produced the highest CRC estimations for the plots. Method 1 also resulted in higher clustering of pixels in the UAV images indicating high crop residue. Individual straws and other small crop parts were faintly noticeable with this method. On the contrary, method 2 had the smallest GSD value and therefore it could identify the smallest crop residue as seen in Figure 11. Nevertheless, soil still produced a little bit of noise in the binary image.

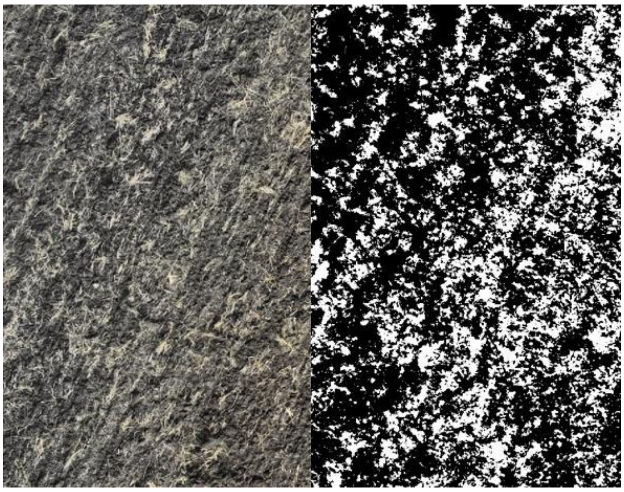
Figure 10. RGB image (left) and binary image with method 1 (right).


Figure 11. DSLR image (left) and binary image with method 2 (right).

Figure 12 shows the original RGB image in the left and the binary image generated with the Method 3. In the binary image produced using Method 3, individual straw fragments and larger crop residue clusters are more clearly distinguishable than in the binary images generated using Methods 1 and 4 (Figures 10 and 13). Generally, Method 3 appears to be more accurate than Method 4. Based on the visual and numerical results, it seemed that the Method 3 was the most reliable method among the used methods. Method 4 had the highest GSD value for the images but could still separate crop residue from the soil. Based on visual inspection method 4 could not detect individual straws.

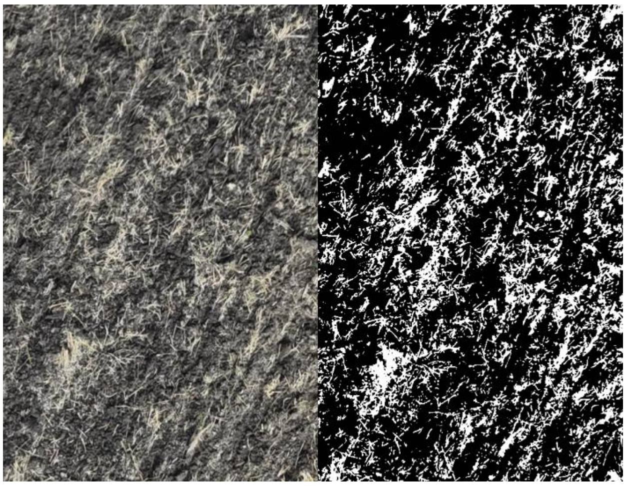
Figure 12. RGB image (left) and binary image with method 3 (right).

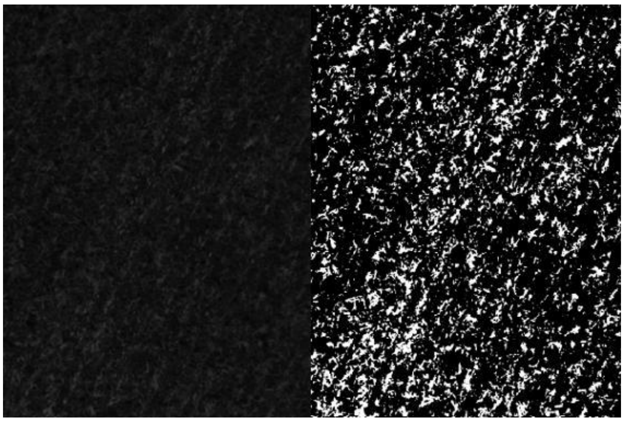
Figure 13. The red spectral band image from the multispectral camera(left) and binary image with method 4 (right).

4. Discussion

The results obtained from Methods 3 and 4 were largely align with the findings of Alakukku et al. (2002), who reported that a cultivator is typically capable of covering 60–80% of crop residue in a single pass. Using Method 4, the covering rates ranged from 49% to 91%, while Method 3 yielded values between 60% and 75%. Among all the measurement methods used, the results from Method 3 corresponded most closely with the range reported by Alakukku et al. (2002).

While the UAV imagery provides broad spatial coverage, the DSLR images represent only small, localized portions of the research plots. This difference in spatial coverage introduces potential variability and may complicate direct comparisons between the methods. For example, in plot B and partially plot C there were high CRC concentrations on the left side of the plots due to higher crop biomass before the soil tillage process.

All CRC estimation methods indicated that Plot B had the highest CRC values. Regarding the second-highest values, methods 1–4 identified Plot C, while Method 5 pointed to Plot E. Upon examining the UAV RGB images, visible crop residues were observed on the left side of Plot C. This may have contributed to elevated CRC values in methods that rely on UAV-based image analysis. Method 5 may have included fewer images capturing the specific area of Plot C where residue accumulation was more prominent.

Method 5 represented the ground truth in this research. Plots B and E exhibited higher CRC values compared to the other plots, while plots A, C, and D showed only minor differences among themselves. When comparing CRC estimates from methods 1–4 against the ground truth, methods 3 and 4 demonstrated the best performance relative to the ground truth, producing values most closely aligned with those of Method 5. To improve the accuracy of CRC estimation in methods 1-4 the threshold values could be further optimized. Applying additional image filtering techniques alongside thresholding may improve the accuracy of CRC estimation and help reduce the influence of soil on CRC values.

5. Conclusions

This research aimed to evaluate the applicability of image analysis for quantifying crop residue on tilled agricultural fields. Four analytical methods were tested, three of which relied on aerial imagery. Aerial imaging is a cost effective, flexible and higher resolution method compared to satellite imaging. The findings suggest that image-based analysis offers a promising, cost-effective, and flexible alternative to satellite-based remote sensing, with higher spatial resolution enabling more accurate residue detection. Results confirmed that crop residue remaining after tillage can be assessed using image analysis techniques. Notable differences were observed among the test plots in terms of residue incorporation and uniformity of tillage. Significant variability was also found between the analytical methods in their ability to detect residue, with methods 3 and 4 performing more reliably. Some methods either under- or overestimated residue presence, particularly with smaller fragments. Nevertheless, all methods consistently indicated that plots B and C retained more surface residue, with plot B showing the least effective residue incorporation. The results underscore the need for further research and data collection to assess method performance under diverse conditions and highlights the potential of emerging camera technologies to enhance future analysis accuracy.

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