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Evaluating Mechanically-caused Crop Damage Using Two Simple UAV-based Assessment Techniques

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Abstract

The increasing frequency of hydrometeorological extremes, such as torrential rainfall, strong winds, and hailstorms, often causes widespread mechanical damage to crops. This study evaluates the potential of cost-effective unmanned aerial vehicle (UAV) photogrammetry with a standard RGB camera for quantifying crop damage. A maize field with mechanical damage caused by wild boar activity was used as an analogue for storm-induced damage. Two approaches were applied: (i) a 3D structural method based on Canopy Surface Models (CSMs) derived from Structure-from-Motion (SfM) photogrammetry, and (ii) automated image classification using a Support Vector Machine (SVM) combined with Object-Based Image Analysis (OBIA). The accuracy of the damage assessment was compared using two terrain inputs: a UAV-derived DEM (UAV DEM) and the official Czech national LiDAR-based DEM (DEM 5G). The results showed high consistency between both methods and datasets. The relative crop damage rate was 29.25% with the UAV DEM and 26.76% with the DEM 5G, with a spatial agreement exceeding 95%. Jaccard similarity coefficients confirmed strong concordance (0.8953 and 0.9207). The findings highlight the applicability of UAV-based 3D structural analysis for late-stage crop monitoring, when spectral indices lose reliability. They also emphasise that the official DEM 5G can serve as a suitable substitute for a UAV-derived DEM in damage assessment. The methodology thus represents a rapid, cost-effective, and operationally feasible solution for agricultural monitoring, insurance claims, and environmental management.

1. Introduction

Ongoing climate change is increasing the occurrence of hydrometeorological extremes (Trnka et al., 2009), such as torrential rainfall, drought, or rising average annual temperatures (ČHMÚ, 2025). These changes, combined with shifts in crop rotation and the intensification of agriculture, increase the vulnerability of crops and soil to both mechanical and ecological damage (Dobosz et al., 2023). Agricultural land is an irreplaceable natural resource, and its protection is crucial for food production and the sustainable functioning of landscape ecosystems. Accurate and up-to-date information about the condition of the soil and crops is essential for farmers to optimize protective measures, reduce yield losses, and, if necessary, apply for damage compensation from insurance companies or other institutions (Dobosz et al., 2023; Drimaj et al., 2023).

Modern technologies – especially unmanned aerial vehicles (UAVs) and digital photogrammetry – offer a fast, objective, and highly accurate alternative to classical methods of damage mapping. Their usage allows for recording the current state of an area at a very high resolution, creating detailed 3D surface models, and subsequently delineating damaged areas of the crop. This is a versatile tool with a wide range of applications in agriculture and environmental monitoring, including the assessment of vegetation status, biomass, and crop phenotyping, as seen in studies such as (Aszkowski et al., 2024; Belton et al., 2019; Bendig et al., 2013; Montzka et al., 2023; Yue et al., 2019). Mechanical crop damage can be quantified from UAV data by analysing changes in crop and surface structure. In current literature, the analysis of these changes has been performed in three main directions: (i) 3D structural methods, (ii) machine and deep learning, and (iii) texture analysis with object-based image analysis (OBIA). For instance, Rutten et al. (2018) uses OBIA analysis in their work to assess damaged maize.

The most widely used method for 3D structural reconstruction is the photogrammetric technique Structure from Motion (SfM). This technique is used to create a Digital Surface Model (DSM) or a Canopy Surface Model/Canopy Height Model (CSM/CHM) by subtracting the terrain model (DTM/DEM). This method, with its notable high reliability, has been successfully applied in numerous studies to quantify crop damage (Bendig et al., 2013, 2014; Kuželka & Surový, 2018; Ziliani et al., 2018). A key advantage of this method is its emphasis on structural information rather than spectral data, which often provides significant benefits over, for example, machine learning (Dobosz et al., 2023; Han et al., 2019). Although computationally demanding (Ziliani et al., 2018; Glendell et al., 2017), structural methods based on 3D data (such as SfM or LiDAR) are also highly versatile and suitable for assessing vegetation status in later growth stages (Dobosz et al., 2025; Drimaj et al., 2023).

In this study, a simple and sufficiently accurate 3D structural method based on SfM image processing was used to evaluate mechanical damage to an agricultural crop (maize lodging caused by wild boars). The analysis was conducted using a conventional cost-effective UAV equipped with a RGB camera. The mechanical damage to the crop caused by wild boar activity exhibits signs analogous to the effects of torrential rainfall accompanied by hail. The specific objective is to determine the extent of mechanical damage to the degraded crop in the late growth stage using both a 3D structural method and a machine learning-supported image analysis method utilising OBIA. This is done by using both an official state-provided DEM and a self-generated photogrammetrically constructed DEM, with a comparison of the accuracy of the results.

2. Study site

The application of 3D structural methods and OBIA-supported image analysis for non-contact quantification of damaged crops was carried out in an intensively farmed area in the cadastral territory of Lovčice u Kyjova (hereinafter referred to as Lovčice) in the Chřiby Hills (South Moravian Region) (Figure 1). The affected area spans 24.8 ha with a predominant soil type of pararendzina. It is situated on a gentle slope ranging from 3% to 7%, at an altitude between 318 and 372 m above sea level. According to the Land-Parcel Identification System (LPIS) register, maize was cultivated on the plot in both 2023 and 2025.

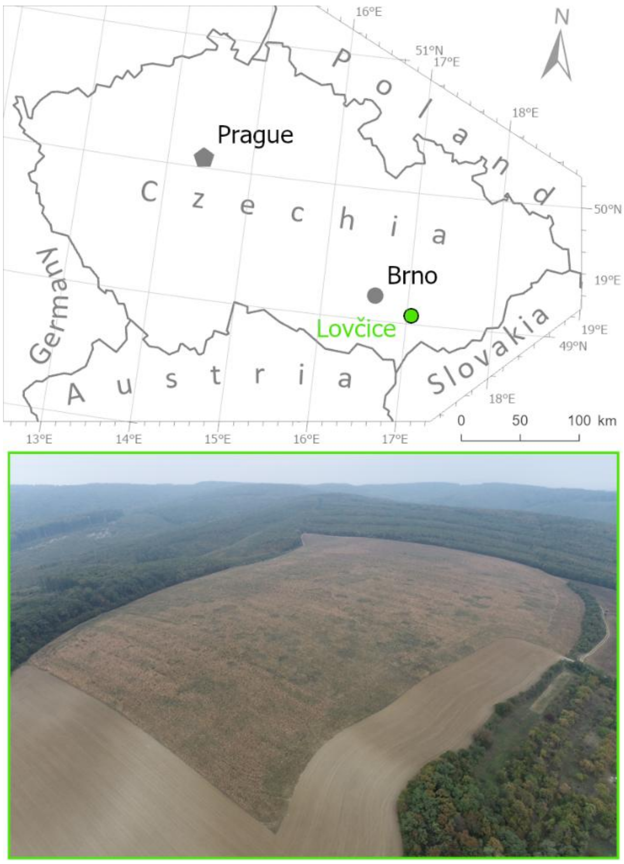

Figure 1. Location of the studied area where the extent of mechanical damage to crops was determined.

The site is situated in an area traditionally known for sugar beet production, but due to climate change, it is now better suited for maize cultivation. According to the Czech Hydrometeorological Institute (ČHMÚ, 2025), environmental changes have led to a 2 °C increase in the average annual temperature and shifts in rainfall distribution and intensity between 1961 and 2021. Monitoring by the Research Institute for Soil and Water Conservation (RISWC) (VÚMOP, 2025) indicates that approximately one-third of the plot is designated as an erosion-prone or highly erosion-prone slope. Several erosional events have been recorded in the vicinity of the plot, and at the time of the measurements, no anti-erosion measures were applied to the affected slope.

3. Methodology

3.1 Field campaigns and UAV settings

A multirotor UAV platform was utilized for data collection, followed by the creation of an orthophoto map and a Digital Surface Model (DSM). The cost-effective DJI Phantom 4 Pro+ was employed, featuring a 1-inch CMOS sensor, which also serves as a built-in 20 MP RGB camera. It is capable of UltraHD (4K) quality at a frame rate of 60 frames per second, has a focal length of 24 mm, and a tilt range from -90° to +30°. The camera is mounted on a three-axis gimbal that eliminates unwanted movements and rolling shutter effects during flight. (DJI, 2025)

The collection of primary geodata, in the form of vertical aerial images, was carried out in two separate field campaigns. The first took place on 19 October 2023, just before the crop was harvested, and recorded the damaged surface of the maize crop. The second campaign was conducted on 15 December 2023 with the aim of capturing the current state of the terrain surface after the crop had been harvested. Both monitoring campaigns were performed under overcast conditions with a light, variable wind.

Geolocation of the UAV during flight is determined by GPS and GLONASS satellite systems. However, their maximum achievable accuracy, at the level of tens of centimetres, is insufficient. For the purpose of georeferencing the orthophoto map and correcting possible structural errors – and thus for more effective joining of the captured photographs – Ground Control Points (GCPs) were placed and surveyed on the monitored plot. The correct placement, sufficient number, and precise surveying of GCPs significantly affect the final accuracy of the digital models (Nesbit and Hugenholtz, 2019). The accuracy of the measurement can be influenced by factors such as terrain ruggedness, the number of visible satellites, or signal shielding by obstacles in the terrain. The corrected horizontal and vertical accuracy of RTK using VRS (Virtual Reference Station) reaches 0.01 m and 0.02 m, respectively (Trimble Inc., 2024).

The GCPs used at the Lovčice site were circular with a diameter of 0.3 m, and a small depression was located at the geometric centre of each one. The pole of a professional dual-frequency GNSS receiver, a Trimble R2, was placed in this depression. In RTK (Real-Time Kinematic) mode, this enabled the surveying of planimetric and altimetric data with high precision. For both campaigns, seven GCPs were surveyed on the agricultural plot, which was situated in a moderately undulating terrain with minimal shading from surrounding vegetation. The number of visible satellites was 15 or more at every moment of the measurement. These conditions allowed for the GCPs to be surveyed with a high degree of accuracy.

The site was imaged using an autonomous flight, with parameters (flight altitude, photo overlap, image frequency, target DSM resolution, etc.) set by the UAV operator based on the size, shape, and ruggedness of the area of interest, as well as the prevailing weather conditions. Data collection then took place automatically along a pre-defined flight path. For the Lovčice site, the average flight altitude was set at 70 metres above the area, with a photo overlap of 60% for side overlap and 80% for forward overlap. This high overlap ensures that each point is captured in multiple images, which is crucial for reconstruction using the SfM method (Westoby et al., 2012). A total of 1052 aerial images were captured for the first campaign and 987 for the second. The autonomous UAV flight time for both campaigns, given the settings and meteorological conditions, was approximately 51 minutes.

3.2 Image processing by SfM method

The datasets acquired in the field were processed using digital photogrammetry methods in Agisoft PhotoScan Professional software, which utilises the SfM method (Agisoft, 2018). This approach allows for the generation of a 3D surface model from overlapping images without the need for prior knowledge of their spatial position.

In the first stage of processing, Image Alignment occurs, where distinctive image features, known as key points, are automatically detected and identified on the individual aerial photographs. The software utilises algorithms such as SIFT (Scale-Invariant Feature Transform) to find recurring points between images captured from different distances and angles. Subsequently, the geometric relationships between the photographs are determined, their relative orientation is established, and the spatial arrangement of the images, along with their internal parameters (focal length, lens distortion) are calculated. The output is a sparse point cloud, which represents a preliminary 3D model of the scene. In the next step, the GCPs are manually identified on the photographs, and the altimetric and planimetric information obtained from the field survey is assigned to them. The software then uses this data to georeference the model, thus obtaining absolute orientation for the final outputs. Concurrently, the position and scale are refined within the real-world coordinate system.

Based on the known geometry and image overlap, stereophotogrammetric triangulation is performed. For each pixel, a corresponding point is found in different images, and its spatial position is calculated. The result is a dense point cloud, often containing hundreds of millions of points, which represents the detailed geometry of the surface. This point cloud can then be filtered by quality (e.g., to remove noise or erroneous points). From the dense point cloud, a polygonal mesh can be generated, where individual points are connected by triangular facets (TIN) to form a DSM that includes all above-ground objects, including vegetation, or a DEM, which represents only the terrain itself. This step can be performed manually or semi-automatically through point classification. Another output is the orthophoto map. In this case, the software combines information about the camera's position and the 3D model to create a seamless mosaic image with an accurate scale (Agisoft, 2018). The basic data from the processing of both campaigns in Agisoft PhotoScan Professional software is shown in Table 1.

Output parameter		Field campaign	
Study site	Lovčice	before harvest	after harvest
Taken photos	N	1052	987
Ground resolution	(cm/pix)	1,96	1,56
Point density	(pts/m^2)	684,464	1031,11
GSD	(m)	0,05	0,05
RMS	(pix)	0,045	0,047
RMSE-xy	(m)	0,0019	0,0049
RMSE-z	(m)	0,0003	0,0013

Table 1. Quality and accuracy parameters of the photogrammetric models for both campaigns at the Lovčice site.

3.3 Datasets and crop damage GIS processing

This chapter describes the methodological framework for spatial and image analysis within a GIS environment, focused on assessing the extent of mechanically-induced crop damage. For this purpose, a 3D structural method, which works with changes in crop height, was applied alongside a machine learning-based image analysis method supported by object-based image analysis (OBIA). The latter analyses the spectral reflectance of the images in combination with the average crop heights obtained through the 3D structural method. Both methods were applied to two different terrain models – an official state model and a self-generated photogrammetrically constructed model – with the aim of comparing their accuracy. The resulting damage extent values were then compared using a raster analysis tool to quantify the differences.

For these purposes, three datasets were used:

(1) orthophoto map and DSM before crop harvest, with a resolution of 0.05 m and a vertical and horizontal accuracy of 0.014 m and 0.019 m,

(2) orthophoto map and DSM after crop harvest, which served as a more accurate RGB-based UAV DEM (UAV DEM), with a vertical and horizontal accuracy of 0.008 m and 0.016 m,

(3) the 5th generation LiDAR-based digital relief model of the Czech Republic (DEM 5G), managed by the State Administration of Land Surveying and Cadastre, is based on a point cloud with X, Y, Z coordinates and has a vertical accuracy of up to 0.18 m in open terrain and up to 0.3 m in forested terrain (ČÚZK, 2025).

The raw DEM 5G was first transformed from its original point-based form into a spatial representation as a Triangulated Irregular Network (TIN). This vector model was then rasterised into a regular grid with a cell size of 0.05 m, which ensured compatibility with all subsequent calculations and datasets.

3.3.1 Assessment by 3D structural method: Crop height is determined by Canopy Surface Models (CSMs), which were constructed using a map algebra operation. Specifically, this was done by calculating the difference between the crop surface model (DSM before harvest) and a selected terrain model (UAV DEM and DEM 5G).

The raw CSM contained extreme and erroneous values that could be incorrectly interpreted as crop height. Positive outliers, such as a hunting stand, reached a height of up to 7.23 m. Negative values reached a minimum of -5.48 m. Erroneous values, which also constitute outliers, are a result of the photogrammetric image processing method, and include, for instance, image alignment errors caused by insufficient overlap or low/high contrast (James & Robson, 2012), or a reduction in the quality of paired points and the model in areas with low texture due to reflections (Nesbit & Hugenholtz, 2019). Consequently, before the analysis, these extremes and errors were removed based on a defined interval, resulting in a clean CSM (hereinafter referred to as CSM). The total area of data outside the defined interval covers 3.5% of the total area, of which values below -0.15 m constitute 1.76% and values above 2.0 m constitute 1.74%. The lower boundary of the interval, -0.15 m, expresses the deviation that resulted from the difference between the DSM and the terrain models (UAV DEM or DEM 5G). Values in the range of 0 to -0.15 m account for the difference between the DSM and the terrain models used, while also preserving depressions created by agricultural activities, wild animals, or erosion, which are not processing artefacts. The upper boundary of the interval, 2 m, sets the maximum observed maize height and, in addition to positive extreme values, also eliminates isolated taller individual plants. The CSM height threshold for detecting the presence or absence of damage was set at 0.2 m. According to field observations, this value accounts for the height of the crop's base, above which ears are formed and where most of the biomass is located. CSM height values above this threshold indicated an undamaged crop, while values below it indicated crop damage. Crop damage was expressed relatively as the proportion of the damaged area to the CSM area in one of 60 equal area polygons (each with an area of 4119 m²), which were distributed throughout the entire area of interest.

The final normalised relative damage takes into account the effect of inter-row spaces, which could have been incorrectly interpreted as damaged crop. This distortion was eliminated by subjectively establishing the location of four reference squares, each with an area of 10 m². These squares were chosen because they contained no damaged crop but had varying crop densities. Consequently, the average relative area of inter-row spaces within the healthy crop was calculated to be 13% of the CSM area within the polygon, and this value was then subtracted from the damage determined relatively in each polygon.

3.3.2 Assessment by image classification using OBIA-assisted machine learning: The aim of the automated image classification, using machine learning supported by Object-Based Image Analysis (OBIA) in ArcGIS Pro software (ESRI, California, Redlands), was to create the simplest and most accurate classification model possible. This model was designed to distinguish between damaged and undamaged parts of the crop based on plant height and image characteristics captured in the images. The analysis was performed twice: the first analysis used an orthophoto map from before the crop harvest with a CSM constructed from the UAV DEM, while the second was based on the DEM 5G.

Subsequently, the image was segmented – divided into smaller, visually coherent units called objects (or segments) – through automatic segmentation. In this context, an object represents a group of neighbouring pixels with similar properties (colour, texture, height) that together form a compact unit with greater analytical significance than individual pixels. This OBIA approach was used, for instance, by Hunt et al. (2017) to detect crop damage caused by the Colorado potato beetle.

The segments were then further analysed using a machine learning technique, specifically the Support Vector Machine (SVM) classification algorithm. This algorithm is one of the most widely used methods for analysing image and spatial data, as it can find the boundary between two or more classes of objects. In this case, the objective was to distinguish between two classes: damaged vs. undamaged parts of the crop. SVM learns based on pre-labelled training samples, which were manually selected to cover the widest possible spectrum of appearances for both classes. To prevent one class from dominating (for example, if significantly more training objects were selected for the undamaged crop), the training samples were selected systematically and evenly across the entire site.

Furthermore, the maximum number of training objects was set to 1000 for each class. This number was determined by testing several variants (250, 500, 1000, and 5000 objects), with 1000 yielding the most accurate classification results in terms of agreement with the known damage extent derived from the CSM. Setting this limit also reduced the computational complexity of the classification, ensuring the process remained computationally manageable and did not exceed the capacity of a standard desktop computer.

For each object, the average values of its properties were calculated, such as the Mean Digital Number, which represents the average value of reflectance intensity or height within the object. These values served as inputs for the classifier. The result of the entire process is a classification output that displays the spatial distribution of damaged and undamaged parts of the crop in the analysed area. (ESRI, 2025b)

3.3.3 Comparison of assessed damages by using different DEMs: To assess the extent of the differing results obtained from the two CSMs constructed based on two terrain models, a relational raster tool was used to compare the values of individual cells between the two raster layers. The output of this tool is a binary layer where a value of 1 indicates a match in values and a value of 0 indicates a difference (ESRI, 2025a). The interval of deviations between the CSM values derived from the DSM using the UAV DEM and the DEM 5G, which ranged from -0.02 m to 0.02 m, was considered tolerable. This interval was determined based on the manufacturer-guaranteed vertical accuracy of the Trimble R2 GNSS receiver, which reaches a maximum of 0.02 m (Trimble Inc., 2024). The same relational tool was also used to assess the spatial agreement in determining damaged and undamaged crop areas, with the comparison based on the CSMs calculated from both input DEMs. The result was a quantitative evaluation of the relative extent of similarity between the outputs obtained from different data sources.

The Jaccard similarity coefficient was used to evaluate the degree of similarity between two sets. This coefficient is used to compare the extent to which two sets overlap, specifically, the number of elements they have in common in proportion to their combined total number of elements. The coefficient was originally, according to Jaccard (1901), defined to measure the similarity between the species composition of different localities as follows:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}, \tag{1}$$

where $|A \cap B|$ = number of common elements
$|A \cup B|$ = number of unique elements from both sets

The value is always between 0 (no similarity) and 1 (identity). Today, it is widely used in fields such as machine learning and image classification to compare datasets. The coefficient, therefore, quantifies the proportion of common pixels labelled as damaged relative to the total number of pixels labelled as damaged in at least one of the rasters being compared.

The similarity rate was performed twice. In the first instance, the raster layers of the constructed CSM models, based on the different terrain models, were compared. In the second, the results of the image classification were compared. This classification was also performed twice, once for each CSM derived from the different terrain models.

4. Results

To begin, the crop damage rate was primarily assessed using a 3D structural method based on a selected height threshold. The results were derived from two CSM models: the first was created by calculating the height difference between the DSM (recording crop height before harvest) and the UAV DEM (as shown in Figure 2), and the second was based on the height difference between the DSM and the DEM 5G. As a secondary approach, an automated image classification method was used for verification. This method was based on the Support Vector Machine (SVM) algorithm and Object-Based Image Analysis (OBIA). The inputs for this classification were the CSM models created using the 3D structural method, as well as the orthophoto map of the study area before harvest.

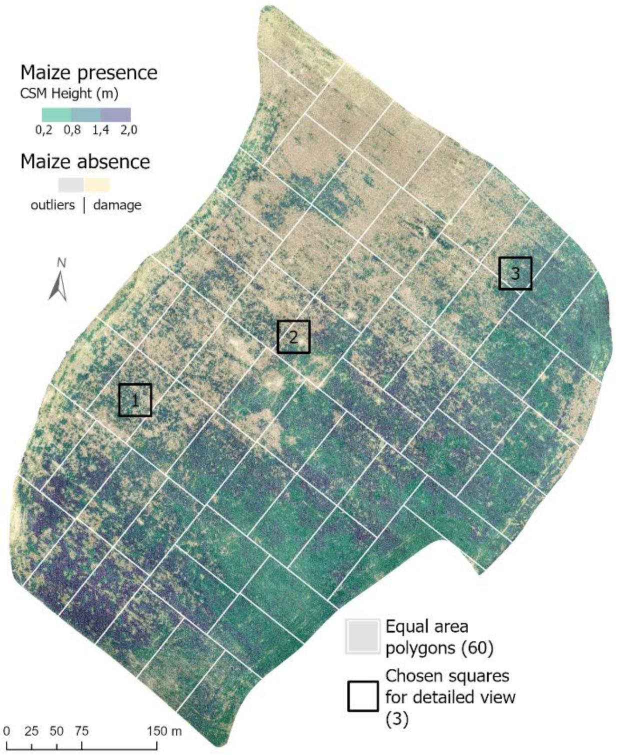

Figure 2. Example of maize crop damage extent in the form of its presence and absence, with a classification of CSM height constructed by the 3D structural method based on the official state DEM 5G.

A comparison of the terrain models themselves, using the difference between the UAV DEM and the DEM 5G, showed that the UAV DEM is higher across 38.19% of the area. The tolerated vertical deviation, determined by the guaranteed accuracy of the GNSS receiver and representing a height difference of ±0.02 m, covers 23.73% of the identified height difference in the area. The remaining 15.46% of the area exceeds this threshold, which may lead to an overestimation or underestimation of the damage extent depending on the direction of the deviation. Despite these differences, the results of the damage extent calculation spatially agree across 95.75% of the area, regardless of which terrain model was used as the basis.

4.1 Damage assessed by 3D structural method

The relative crop damage rate, expressed as the percentage of the damaged area in individual polygons, was quantified based on two different terrain models. The results are visualised in Figure 3 as a cartogram with percentage damage intervals: 1%, 15%, 35%, and 60%. The normalised relative damage across the entire area was 29.25% for the UAV DEM and 26.76% for the DEM 5G. The absolute difference in damaged crop area is 0.62 ha.

However, the differences between the models were not so significant or spatially distinct as to cause a fundamental change in the relative damage assessment across the chosen intervals. In both cases, the most damaged polygons, with over 60% damage, were located in the northern part of the area. The height deviations outside the tolerated boundary were most apparent in the eastern part of the area. When using the DEM 5G, the polygons there were assessed as undamaged (up to 1%), whereas with the UAV DEM, the damage rate reached up to 15%.

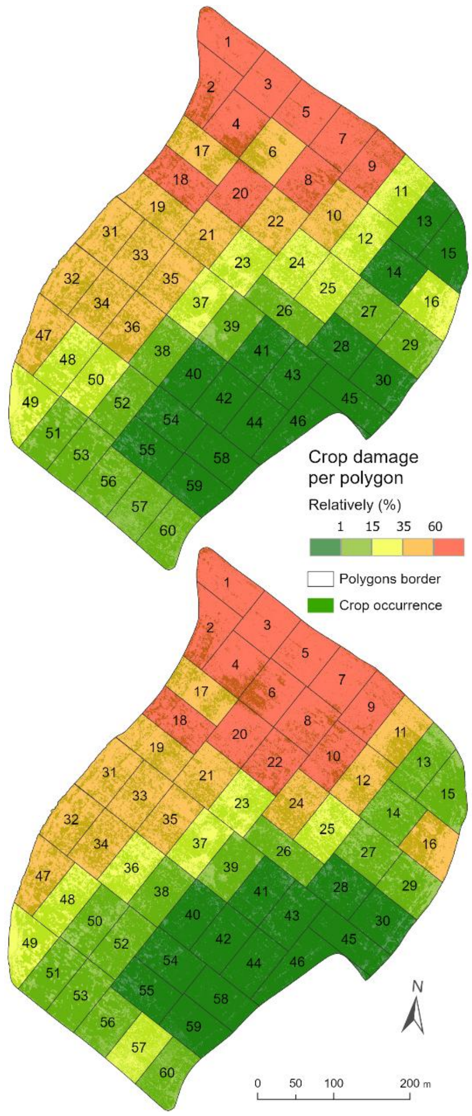

Figure 3. Extent of maize crop damage, expressed as a relative value in equally sized polygons, determined from CSMs constructed from two terrain models: the top shows the official LiDAR-based Digital Relief Model DEM 5G, and the bottom shows the UAV DEM derived from proprietary data.

4.2 Damage assessed by image classification

All the outputs shown were processed using the DEM 5G terrain model. Figure 4 illustrates the detailed spatial agreement between the two methodological approaches for assessing maize crop damage: the 3D structural method and the machine learning-supported OBIA method. Three selected representative areas, each with an area of 1,000 m², were chosen as examples to visualise the qualitative agreement between the results of the assessment approaches. The visualised data corresponds with the overall assessment for the entire study area, where the results of the OBIA-supported image classification based on CSMs constructed from the UAV DEM and DEM 5G showed a very similar spatial distribution, with a spatial agreement of 94.01% and 91.08% of the area, respectively. This indicates a high degree of mutual consistency in damage determination, regardless of whether the UAV DEM or the DEM 5G is used as a basis.

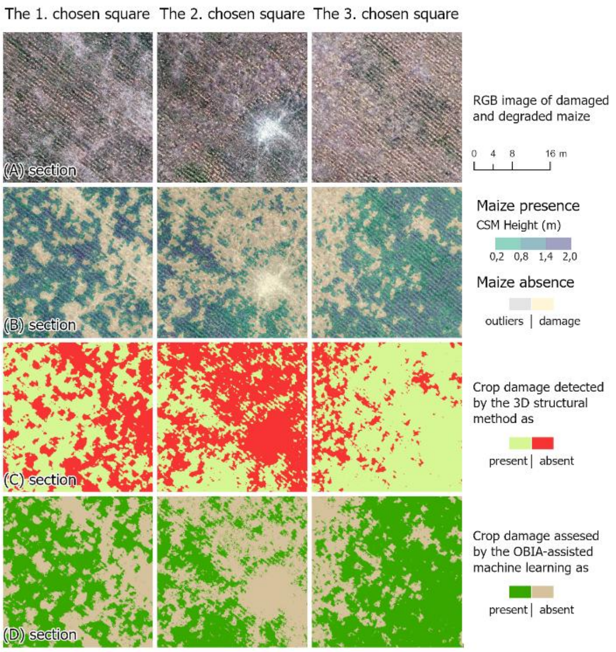

Figure 4. Three selected squares in the study area are illustrated in detail: (A) the condition of the maize crop, (B) the CSM crop height and the extent of its damage, (C) the extent of damage determined by the 3D structural method, and (D) the extent of damage determined by OBIA-supported image analysis. (Note: all displayed analyses were performed using the DEM 5G).

4.3 Differences in damage results when comparing DEMs

The results of the similarity assessment using the Jaccard coefficient confirmed a high consistency of the outputs from both the two terrain models and the two assessment approaches. A comparison of the crop damage rasters created by the 3D structural method based on the UAV DEM and DEM 5G yielded a coefficient of 0.8953, which indicates significant spatial consistency between these height models. An even higher level of agreement, 0.9207, was achieved in the image classification using machine learning supported by OBIA, again when comparing outputs generated from the UAV DEM and DEM 5G. These values suggest that the differences between the height data have only a minimal impact on the overall evaluation of crop damage extent.

5. Discussion

The results confirm the high application potential of UAV photogrammetry for assessing mechanical crop damage caused by hydrometeorological extremes. Damage to the crop by wild boars shows visual and structural signs similar to damage caused by torrential rainfall, strong winds, or hail, which allows for their joint assessment within a single methodology. In this study, a cost-effective UAV equipped with a consumer-grade RGB camera and the SfM method achieved high spatial resolution and accuracy that do not differ significantly from the results published in similarly focused research (Bendig et al., 2014). The applied methodology also proved to be robust, as confirmed by other studies (Aszkowski et al., 2024; Rutten et al., 2018).

An advantage of 3D structural methods is their ability to detect the extent of agricultural crop damage even in the late growth stage, when spectral indices fail (Aszkowski et al., 2024). In this study, a high spatial resolution was achieved for the input DSMs, which allows for the identification of damaged areas even in the absence of a spectral response. In the late growth stage (October–November), this is a fundamental advantage over indices such as NDVI, which suffer from a saturation effect in areas of high vegetation density and also lose their descriptive capability with low chlorophyll content, when the spectral response of the vegetation decreases significantly (Dobosz et al., 2023).

This study also expands the professional discussion on the importance of 3D structural and spectral data in the context of crop assessment. Studies such as (Yue et al., 2019) and (Han et al., 2019) demonstrate that a combination of textural properties, the 3D structural method, and spectral reflectance provides the most accurate results, while approaches based exclusively on spectral data show significant limitations. This study confirmed that 3D structural data can be sufficient on its own for determining crop damage in the late growth stage. This supports the conclusions of (Dobosz et al., 2023), who consider the structural approach to be more universal and less dependent on the data acquisition period and the use of expensive sensors.

The availability of cost-effective UAV systems increases the accessibility of this methodology to a wider range of users. The results demonstrate that even without the use of expensive hyperspectral or NIR sensors, it is possible to obtain accurate and quantifiable data (Belton et al., 2019). A significant advantage of this technology is also its temporal and operational flexibility, which allows for simple, rapid, and non-invasive deployment of UAVs during the period before and after crop harvest.

Despite its significant benefits, the SfM method also has certain limitations. One is its high time and computational complexity, which can be exacerbated when monitoring large areas due to the requirement for a high image overlap, although it remains lower compared to LiDAR data (Ziliani et al., 2018). The accuracy of the outputs depends on the quality of the input photographs; thus, poor lighting conditions or dense vegetation cover can lead to a reduction in accuracy. While SfM models achieve very accurate results in open terrain, in forested or shaded areas, the use of active sensors like LiDAR remains a more suitable solution (Montzka et al., 2023). Further limitations include the UAV's dependence on weather conditions, as well as the need for a qualified operator and adequate software (Glendell et al., 2017).

When comparing the results with alternative processing methods, such as deep learning, machine learning, and texture analysis methods, it is apparent that algorithms like CNN (Teshome et al., 2023) offer high accuracy and automation potential. Conversely, they require an extensive training dataset, higher computational power, and well-lit, high-resolution input photographs. Texture analysis (e.g., SFTA) is useful in situations where chlorophyll is absent, but its spatial distinguishability may be lower than that of CSMs and DSMs (Tan et al., 2021). OBIA approaches offer an advantage in object classification, but they are sensitive to segmentation parameterisation and do not always handle the natural heterogeneity of damage well (Rutten et al., 2018). From the perspective of practical applicability (speed, cost, accuracy, and robustness in different phenological stages), the 3D structural method appears to be the most effective compromise, a conclusion also supported by other studies (Glendell et al., 2017).

In the context of crop damage assessment, the results of the 3D structural method using the UAV DEM and DEM 5G showed a high degree of spatial similarity when the same height threshold was used. However, damage expressed as a relative value in equally sized polygons differed between the DEMs in individual parts of the area. The high similarity of the results between the two DEMs indicates that significant differences in accuracy were not apparent. Therefore, for determining the extent of crop damage using the 3D structural method, the use of the DEM 5G along with a suitably chosen height threshold and tolerated deviations appears to be sufficient and recommended.

The deployment of a cost-effective UAV system allows for the acquisition of a comprehensive picture of a crop's current condition in a very short time and, in combination with SfM methods, provides detailed spatial information of the captured surface. The technology is economically accessible and easily reproducible. The methodology applied in this article confirms that UAV photogrammetry significantly supplements, or even partially replaces, traditional methods of crop damage assessment. Despite the limitations of data acquisition, cost-effective UAVs equipped with a standard RGB camera represent a competitive solution that achieves the required level of accuracy. The method has wide application potential not only in research but also in practice, where it can serve as a valuable tool for damage assessment, planning crop rotation, or designing anti-erosion measures.

6. Conclusion

This study confirmed that UAV photogrammetry, based on the Structure from Motion (SfM) image processing technique and simple 3D structural approaches, is an effective and affordable tool for assessing mechanical agricultural crop damage, even in the late growth stages when traditional spectral indices lose their descriptive value. The results showed that by using a crop height threshold of 0.2 m, it was possible to accurately identify the extent of maize crop damage, with the damage rate determined by the 3D structural method reaching 29.25% (UAV DEM) and 26.76% (DEM 5G). Subsequent image classification with machine learning supported by OBIA confirmed the high consistency between both approaches and between the terrain models used, as documented by Jaccard coefficients above 0.89.

The findings highlight the practical utility of the officially available DEM 5G terrain model in the Czech Republic for creating Canopy Surface Models without the need for proprietary data acquisition and the creation of a terrain model after crop harvest. This simplifies the entire process, saves time and costs, and also offers opportunities for the broader use of this assessment approach in agricultural practice. The high spatial agreement of the outputs suggests that UAV data combined with the state elevation model provides a sufficiently accurate and robust basis for the rapid mapping of damage caused by wild animals or hydrometeorological extremes.

Despite its proven benefits, the used methodology also has limitations, particularly the time and computational demands of data processing with the SfM method and its sensitivity to the quality of input images. Therefore, it is advisable to further test the methodology on other crop types and different kinds of mechanical damage, as well as to expand it by combining it with spectral or textural approaches. The integration of multiple data sources can contribute to increased accuracy and universality of the assessment.

This study expands the general knowledge of the possibilities of UAV photogrammetry in agricultural damage assessment and confirms its significant application potential in the areas of agronomic decision-making, environmental monitoring, and crisis management.

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