Automatic detection and quantification of wild game crop damage using an unmanned aerial vehicle (UAV) equipped with an optical sensor payload: a case study in wheat

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ABSTRACT
Wildlife-induced damage of agricultural crops is an unfavorable consequence of elevated population densities of wild animals, especially wild boars. For the purposes of financial compensations for crop damage, provided by either governments or hunters responsible for game numbers, it is necessary to precisely assess the range of damage and temporal change. The use of an unmanned aerial vehicle (UAV) with an optical sensor payload represents a potential method of obtaining data of crop conditions without the necessity to enter the field and increase the damage. We propose a novel method for delineation of damaged areas via automatic segmentation of the crop field. Our method is based on photogrammetric reconstruction of the various crop heights within the field through the use of Structure from Motion technique with subsequent automatic classification. In this case study of wheat, the range of damage was estimated with an accuracy of 99.5% and 99.3% using field global navigation satellite system (GNSS) measurements and classification of an orthomosaic generated from UAV-based imagery, respectively.

Introduction
Elevation of wild ungulates’ population densities threatening economic interests of forestry, agriculture and other human activities has been continuously reported for last decades in many European countries and in the United States (Amici et al., 2009). To assess fiscal compensations for crop damage, it is necessary to precisely assess the range of damage and temporal change. Overpopulated game in forests results in excessive browsing, bark stripping and fraying damage (Gill, 1992b) resulting in growth loss, stem deformations, reduced wood quality, increased likelihood of death or secondary infection of individuals (Gill, 1992a) and reduced species diversity in the forest stand (Abildtrup & Jensen, 2014). In agricultural crop fields, game causes damage both by consuming the crops and trampling the plants (Schley & Roper, 2003). Overpopulated game can even significantly change environments by affecting species abundances and richness in both plant and animal communities, altering food webs, and disrupting soil chemistry (Massei & Genov, 2004). As wild game population densities rise, the risk of collisions with vehicular traffic increases (Bruinderink & Hazebroek, 1996); therefore, wild game presents both an economic and human safety issue.

Among large ungulates in Europe, a majority of crop damage is attributed to wild boar (Sus scrofa L.). Due to its body proportions and behavior, wild boar can cause significant damage to a variety of crops (Mackin, 1970; Schley & Roper, 2003), which can only be effectively reduced by limiting the population size (Geisser & Reyer, 2004). Crop damage caused by deer species is usually small or negligible, because field crops frequently recover completely from deer browsing and trampling (Cerkal, Vejražka, Kamlér, & Řád, 2009; Putman & Moore, 1998). Much work has been conducted to study both temporal and spatial distribution of crop damages attributed to wild boar in order to determine spatial patterns of their movements, habitats and predict crop damages in relation to terrain parameters and agricultural structure of the landscape (Amici et al., 2012; Bleier, Lehoczki, Újváry, Szemethy, & Csányi, 2012; Ficetola et al., 2014; Mackin, 1970; Thurmfjell et al., 2009). To assess fiscal compensations for...
crop damage provided either by governments or by hunters responsible for game numbers, it is necessary to determine both operationally and precisely the range of crop damage and its temporal changes, e.g. evolution of the damaged area over time (usually weeks). In situ field measurements using GPS loggers for example do not represent a viable alternative because their use necessitates entering the field, which can lead to increased crop damage. Common remote-sensing alternatives, i.e. manned airplane photogrammetry or high-resolution satellites, do not provide sufficient resolution for crop detection and height reconstruction of small-in-stature plants.

A possible solution for this situation lies in rapid development of unmanned aerial vehicles (UAVs) and their optical payloads during the last decade. Utilization of UAVs has increased efficiency of data acquisition in both agriculture and forestry (Grenzdörffer, Engel, & Teichert, 2008). Improvements in both programmable autonomous navigation and systematic image triggering have enabled UAVs as tools for precision mapping of agricultural lands and numerous other applications including: (1) assessing crop growth; (2) revealing irrigation or fertilization anomalies (Herwitz et al., 2004); (3) determining areas for site-specific interventions; (4) optimize harvests (Grenzdörffer et al., 2008); and advance other precision agriculture applications (López-Granados et al., 2016; Torres-Sánchez, Peña, de Castro, & López-Granados, 2014).

A multi-view stereopsis approach allows reconstruction of three-dimensional (3D) surfaces through the use of sequential images acquired with commercial-off-the-shelf digital cameras (Rosnell & Honkavaara, 2012). Structure from Motion (SfM) techniques utilize identical features identified in subsequent images with algorithms such as Scale-Invariant Feature Transform – SIFT (Lowe, 2004) and Speeded Up Robust Features – SURF (Bay, Tuytelaars, & Van Gool, 2006) to calculate camera positions in a local 3D coordinate system, and subsequently to derive positions of identified features within imagery. The result is a 3D dense point cloud representing points on the surface of reconstructed objects. The SFM technique was successfully utilized in 3D precision vegetation mapping (Dandois & Ellis, 2010; Lucieer, Robinson, & Turner, 2011), as well as in forest biomass prediction (Ota et al., 2015) and forest tree stems reconstruction (Surový, Yoshimoto, & Panagiotidis, 2016) among others.

This study proposes an automatic method for objective assessment and quantification of agricultural crop damage via remote sensed imagery obtained by a UAV together with SFM techniques. This study also examines automatic analysis of 3D point clouds without subjective decisions by humans permitting objective results.

Materials and methods

Data collection and post-processing

Data were collected over a wheat field located 4 km SW from Radonice, Usti Region, Czech Republic, with an altitude of 450 m AMSL. This particular wheat field was selected due to the presence of discernible patchy crop damage caused by wild boar trampling and wallowing, resulting from boars resting on crops and their efforts to find and consume mature grain. These destructive boar behaviors generated easily delimited patches of damaged plants, which were characterized by their texture variation within the imagery, but especially by their contrasting height to adjacent undisturbed plants (Figure 1). The perimeter of the disturbed patches was recorded by manual field measurements to serve as comparative data for assessments of automatic damage detection methods. Data collection was carried out in July 2015, at peak maturity of the wheat crop.

Images were taken using the RGB sensor of a Samsung Galaxy K-Zoom SM-C115 mobile phone due to the low weight of the device, presence of automatic intervalometer and GPS recording capability. The main criterion for the choice of this sensor was maximization of flight endurance of the DJI F550 UAV (Figure 2), so that the selected agricultural field could be completely imaged with the use of available energy resources. The flight was automatically executed using DJI PC Ground Station flight controller software which allowed the setting of critical flight parameters such as height above ground level (50 m), cruise airspeed (4 m s⁻¹) and route, so that imagery were taken with sufficient overlap and with a flight speed low enough to eliminate motion blur. Collected imagery and metadata were post-processed using Agisoft PhotoScan software (Agisoft, 2016). Within the PhotoScan software, we used generic pair selection of images and high quality of alignment options. The result was a 3D point cloud representing the

Figure 1. Patches of damaged wheat as a result of wild boar wallowing showing wheat flattened against the terrain.
surface of the field and an orthomosaic. Local coordinates of the point cloud were transformed into a global coordinate system using ground control points that had been measured with a Leica GPS1200 RX1250 global navigation satellite system (GNSS) device using real-time kinematic method.

Evaluation of damage

The height of the wheat crop was relatively homogeneous throughout the agricultural field. Therefore, the field surface consisted of two classes: the top of the undisturbed wheat crop, and the lower terrain level in the areas possessing damage, where the wheat had been trodden down by game. In order to evaluate damage, the field was segmented into the two classes based on height difference. Processing of the point cloud was carried out using MATLAB R2012b (MathWorks, 2012).

The point cloud composed of 3D points with coordinates \((x, y, z)\) was utilized to generate the digital surface model (DSM). The area of the field was partitioned into a square grid with the cell edge \(c = 0.1\) m. For the cell in the \(i\)th row and \(j\)th column of the grid, the value of surface model DSM\(_{ij}\) was calculated as median height of \(n_{ij}\) points found within the range of the cell having center coordinates \((X_{ij}, Y_{ij})\).

\[
\text{DSM}_{ij} = \{h : \text{count}(z_{ij} \leq h) \geq \frac{c}{2} \text{ AND count}(z_{ij} \leq h) \geq \frac{c}{2}\},
\]

\[
z_{ij} = z(\text{abs}(x - X_{ij}) \leq \frac{c}{2} \text{ AND } \text{abs}(y - Y_{ij}) \leq \frac{c}{2})
\]

The sum of two components determined heights in the DSM: (1) height of terrain and (2) height of the crop. We hypothesized that the crop height varied only gradually within the field with no abrupt changes, and only little in comparison to overall slope and large undulations. In order to eliminate the effects of the overall slope and the undulations of the terrain, a hypothetical undamaged crop surface model (CSM) was created. For each cell, the approximate crop surface height was represented by the height of the highest cell within a short distance. The distance had to be larger than the half size of the largest damage patch so that the CSM covered even the largest patch properly. On the other hand, the distance should be as small as possible in order to account for terrain undulations. A moving circular kernel with radius \(r\) was established and run over the DSM. In each position of the kernel, the central value was replaced by a new value derived from the kernel values. In order to avoid extremes and outliers (high noise), the maximum was replaced by theoretical \(p\) quantile of height distribution below the kernel.

\[
\text{CSM}_{ij}(p) = \{h : P[\text{DSM}(\sqrt{(X - X_{ij})^2 + (Y - Y_{ij})^2} \leq r) \leq h] = p\}
\]

By subtracting the CSM from the DSM, a crop height map (CHM) was generated. This map consisted of two planes: one representing the undamaged crop and the second representing the damaged holes with the height of the terrain. The Gaussian Mixture Models clustering method with two classes was utilized to classify the damaged and undamaged areas.

The result of automatic segmentation of the CHM was a binary grid, which illustrated the damaged gaps in the crop surface. In addition to damaged patches, the CHM also reflected agriculture machinery tracks and other areas of missing crops. Machinery tracks were not considered in the evaluation of the damaged area; they were either manually clipped from the map (Method I), or removed by dilation and following erosion of the undamaged areas (Method II).

To conduct an evaluation of the result, ground truth data was prepared in two ways: (1) the orthomosaic was investigated by a human interpreter who manually determined the extent of damaged crop patches and (2) the perimeters of damaged patches were measured in the field with the use of GNSS RTK method. Visible game tracks were recorded as lines rather than area measurement. The automatically classified map of damaged and undamaged crop areas was compared with both sets of ground truth data.

Filter radius

The optimal radius of the kernel depended on two conditions encountered in the field: (1) the size of the damaged areas and (2) the complexity of the terrain. The following method was used for finding the most appropriate kernel size.

Utilizing a small radius of the filter, kernels established for grid cells in inner parts of damaged patches did not contain any cells of undamaged wheat and the difference between DSM and CSM was close to zero; falsely suggesting that inner parts of damage
patches were undamaged. With an increasing radius of the filter, the proportion of correctly classified cells in patches gradually rose along with the total number of cells classified as damaged. After all the patches are correctly classified, additional enlargement of the filter radius did not affect classification until the filter size reached the size where the terrain undulations took effect, and the lower parts of the field started being misclassified. The gradual rise in the number of cells classified as damaged along with the increasing filter radius illustrated two steep gradients of misclassification bookending a stable range where the classification tendency was constant or a gentle grade, which represented the range of appropriate filter radius values.

To examine the range of the proper filter radius, classification was carried out for a set of kernels with increasing sizes. We tested 20 kernel radii ranging from 0.5 m up to 10 m at an increment of 0.5 m. Using Joinpoint Trend Analysis Software (Kim, Fay, Feuer, & Midthune, 2000), the trend of the associated numbers of cells classified as damaged was evaluated. A partially linear joinpoint model with two join points was fitted to the data, and significance for model parameters was estimated using permutation testing.

Simulation study

For further verification of the method, a set of 27 simulations over a 2500 m² square crop field were carried out using following parameters: (1) three different terrain configurations; (2) three levels of terrain steepness and (3) three levels of damaged patch areas. We simulated convex terrain as a spherical cap (latitude 70° to 90°), and concave terrain as an inverted spherical cap. To simulate complex terrain containing both convex and concave areas, we utilized the MATLAB function Peaks (MathWorks, 2017) – a model surface containing three peaks and two depressions. The three levels of steepness were obtained by linear scaling of the height coordinates so that the height ranges were 2.0 m (max. slope 14%), 4.0 m (max. slope 28%) and 8.0 m (max. slope 56%), respectively. The partially damaged crop was simulated with a flat surface having a height 1.0 m, containing damage patch areas represented by circles with zero height and random radii ranging from 0.5 m to 1.0 m, 0.5 m to 2.0 m and 0.5 m to 3.0 m, respectively, for the three levels of patches size. The damage patches were placed randomly within the simulated field with uniform distribution of X and Y coordinates of the circle centers. The CSM was assessed as the sum of the terrain surface simulation and the crop simulation.

Subsequently, the damage detection algorithm was run over each of the 27 simulation configurations repeatedly using a set of 40 filter radii ranging from 0.2 m up to 8.0 m at 0.2 m increments.

Results

A total of 233 images having ground sample distance of approximately 3 mm covering a portion of the wheat field were processed. The resulting 3D point cloud contained 24.3 million points representing 3200 m² of the total field surface. The area represented by the point cloud was horizontally divided into 721 × 637 cells of size 0.01 m², each containing 76 points on average.

A partial representative row of the heights of individual cells and their classifications from the 0.1 m cell grid are illustrated in Figure 3. Table 1 shows the total error of automatically detected damaged area (m²) compared to the ground-truth data – the RTK GNSS measurement of the damage patches and manual interpretation of the orthomosaic.

Method I

The automatic classification method with manually clipped areas of machinery tracks (Method I) overestimated the total area of damaged wheat in comparison with damage manually interpreted and measured by GNSS by 15.2 m² and 19.3 m², i.e. 3.9% and 5.0%, respectively. A substantial proportion (21.9 m²) of the damaged area surplus was located along game tracks. In fact, this component was not an error of the classification method but reflected the damaged crop that could not be recorded by area measurements (Figure 4). Considering that this component was not an error, the total difference to damage manually interpreted and measured by GNSS decreased to 2.6 m² and 2.1 m² (0.7% and 0.5%), respectively.

As demonstrated in Figure 5, the majority of the differences between the result of classification and the field measurements were distributed along the edges.

![Figure 3. Demonstration of classification result: sample of one row of crop height map grid.](image-url)
Table 1. Damaged area estimated (Method I and Method II) and measured (manual interpretation from orthomosaic and GNSS measurement) and total errors (plus omission and commission in parentheses) of estimation methods in comparison with field measurements.

| Estimation     | Method I | Method II |
|----------------|----------|-----------|
| Field measurement | Damage area (m$^2$) | 385.6 | 419.4 |
| Manual interpretation | 370.4 | 15.2 (−99.6; +114.8) | 49.0 (−83.8; +132.7) |
| GNSS measurement | 366.3 | 19.3 (−78.9; +98.2) | 53.0 (−82.5; +135.5) |

Figure 4. The range of crop damage determined by automatic classification and recorded by GNSS.

Figure 5. Differences between results of Method I (left) and Method II (right) and damage recorded by GNSS.
of damaged crop, and the negative deviations (omissions) were largely compensated by the positive deviations (commissions) within the scope of each individual damaged patch. Negative and positive deviations associated with individual damage patches (i.e. within a 1 m buffer around damaged wheat polygons) were analyzed for all 35 damaged wheat polygons measured with GNSS. The relation between omission and commission of individual polygons (shown in Figure 6) was positive, and had a slope close to one. The root mean square error of damaged area estimates for individual polygons was 1.9 m². These facts confirmed that the omissions and commissions were balanced for each polygon, and that the differences between classification and GNSS measurement are likely caused by inaccurate georeferencing of rasters and generalization of GNSS measurements of damaged wheat patches.

Method II

For larger-scale and rougher analysis, in Method II the machinery tracks were removed from the classified map using dilation and erosion of the areas representing undamaged crop surface. The areas were dilated to half the width of the machinery track and eroded back the same distance (0.4 m). Method II resulted in not only the elimination of the machinery tracks, but also wild game tracks and small damaged wheat crop patches as well. Utilizing this method also overestimated damaged area by including the expanded area of extraordinary wide machinery tracks that were not fully eliminated, as seen in Figure 5. The resulting differences using Method II in comparison with manually interpreted damage areas and those measured by GNSS was 49 m² and 53 m² (11.7% and 12.6%), respectively.

Filter radius and quantile

Radius of the quantile filter strongly affected the result of classification (Figure 7). The trend of increasing number of cells classified as damaged when extending the filter demonstrated three separate segments represented in a joinpoint model with two joinpoints determined as 2.5 m and 7.0 m (Figure 8). The slopes of the first and the third segment were significantly positive; the slope of the middle segment was insignificant (Table 2). With the filter radius up to 2.5 m, crop damage in the inner parts of large patches was not detected. The non-increasing segment between 2.5 m and 7.0 m represents the optimal filter radii where changing the filter radius results in a negligible effect at a global
We considered the center of the interval as the optimal filter radius. When the filter radius exceeded 7.0 m, the effects of terrain undulation caused misclassification of lower parts of the field.

Analysis of the effects of the choice of quantile range for quantile filter processing on the resulting classifications was carried out as well. The results indicated that there was very little or no effect of quantile choice in the range from 0.85 and 0.99. The final classification was therefore completed using a quantile of 0.95.

Simulation study

Because the results of the simulation were very similar for all three terrain types, we present the result of the most complex situation: the model terrain represented by Peaks. Figure 9 shows the dependence of number of cells classified as damaged on filter radius for nine combinations of altitude range and size of simulated damaged patches. For flat terrain, there was a broad tolerance for filter size. With increasing steepness of the terrain and area of the damaged patches, the tolerance was found to tighten. The variable $dh_{\text{max}}$ displayed in each plot of Figure 9 represented the largest height difference of the terrain within the distance of the largest damage patch radius and was found to be an important indicator of the terrain and crop damage combination. If $dh_{\text{max}}$ was higher than the height difference between damaged and undamaged crops – 1 m in our simulation (Figure 9, subplots (f) and (i)), the method was not able to detect correctly all the damaged area without misclassifying the undamaged crop. This happened when terrain was too steep and damage patches were too large. For lower values of $dh_{\text{max}}$ (Figure 9, subplots (a–e), (g) and (h)), there was always a range of optimal filter radii classifying both damaged and undamaged crop patches correctly. The range of optimal filter radius started at half the size (or radius) of the largest damage patch; its end was determined as the distance which was multiplied by the maximum slope equaling the height difference between undamaged and damaged crop patches.

Discussion

This study illustrated that a UAV is a tool that can – in addition to its potential in agriculture described by Grenzdörffer et al. (2008) or other agricultural

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**Table 2. Parameters of the fitted joinpoint model.**

| Parameter | Parameter estimate | Standard error | Test statistic (t) | Prob > | | | |
|-----------|--------------------|----------------|-------------------|--------|
| Intercept 1 | 10.91 | 0.0249 | 438.83 | 0 |
| Intercept 2 | 11.24 | 0.0306 | 366.95 | 0 |
| Intercept 3 | 10.86 | 0.085 | 127.25 | 0 |
| Slope 1 | 0.1331 | 0.0182 | 7.3277 | 0.000009 |
| Slope 2 | 0.0041 | 0.0063 | 0.6512 | 0.53 |
| Slope 3 | 0.0577 | 0.0097 | 5.9438 | 0.000007 |

**Figure 8.** The trend in area classified as damaged crop in relation to filter radius, fitted by joinpoint model.

**Figure 9.** Shows the dependence of number of cells classified as damaged on filter radius for nine combinations of altitude range and size of simulated damaged patches.
applications (López-Granados et al., 2016; Torres-Sánchez, Peña, de Castro, & López-Granados, 2014) – acquire data to aid in one of the current problems in game management: the quantification of agricultural crop damaged by wild game. In addition, it can show spatial and temporal crop damage dynamics. Such knowledge, if put in context analogously to the studies of Ficetola et al. (2014) and Thurfjell et al. (2009), can lead to better management decision for the minimization of its occurrence.

In order to correctly and independently evaluate the area of damage crops, an automatic algorithm capable of distinguishing height between two classes – standing crop and damaged crop – was required. In this study, we presented a morphology-based approach for the delineation of these two classes that can be automated by estimation of a proper kernel filter size. Lastly, the delineated crop patches can be filtered using either morphological filters or color/texture information from the raster products. Similar approach of canopy height classification can be utilized e.g. for detecting forest gaps (Getzin, Nuske, & Wiegand, 2014; Zielewska-Büttner, Adler, Ehmann, & Braunisch, 2016) with the advantage of larger height differences between the two height classes in forest canopies.

We compared our results with field measurement and quantified the levels of omission and commission. Due to the limited number of points that can be recorded with the GNSS device used in field measurements, the polygons resulting from the GNSS measurements represented a generalized model of damaged crop patches, although each of the polygon vertices was measured using RTK method with centimeter-level accuracy. This generalization provides an explanation for the spatial discrepancies between the perimeter of the automatically determined damaged wheat patches and the GNSS-measured polygons. Another explanation of the discrepancy was attributed to inaccuracy in referencing the rasters, which leads to elevated effects of omission and commission along opposite edges of the polygons, and was visible especially in the peripheral parts of the wheat field studied. However, the analyses showed that the omission and commission for each polygon were ultimately in balance, and the accuracy of damage area estimation was high.

Removal of machinery tracks from the CHM using Method I required human intervention but resulted in accurate classification, while Method II was most suitable for rougher analyses of wheat crop damage on larger areas. The inherent consequence of using fully automated removal of machinery tracks is that small patches of damaged crops are misclassified as undamaged, such as wild game tracks, and the perimeters of damaged patches can be generalized, as a result of the smoothing property of dilation-erosion operation (Haralick, Sternberg, & Zhuang, 1987). In using Method II, the extent of dilation and erosion is a compromise between the ability of the method to remove machinery tracks and its propensity to degrade the detected perimeter of damage patches. Successfully balancing dilation and erosion is risky, in that some parts of the machinery tracks are not eliminated completely during the dilation phase and consequently they are excessively restored during the erosion phase. Improper use of Method II risks the periphery areas of a field, where the machinery tracks

Figure 9. Dependence of number of cells classified as damaged by increased filter radius in simulated crops. The red dashed line represents the real extent of damage, i.e. the number of cells defined as damaged crop in the simulation.
lack their regularity and include branching and turning points.

Simulations showed that the success of the patch classification is limited by a combination of large patches of damaged crops and terrain possessing steep slope. However, these limitations can be considered as theoretical or experimental only. For most agricultural fields, the limitations presented would rarely be encountered because from a practical perspective wheat crops are not usually grown successfully on steep lands that are not readily accessible for mechanization (Baker & Capel, 2011). With the average height of wheat being 0.8 m, and area of damaged patches averaging 4.0 m², the theoretical limit to terrain slope is 40%. In our case study, the maximum slope of the wheat field studied was 8.5%, while e.g. in the USA, about 90% of wheat fields are located on land having a slope lower than 4% (Baker & Capel, 2011). Moreover, the overall slope of a homogenously inclined field can be eliminated by least squares fitting and rotating the 3D point cloud before processing; the limit is related to local terrain undulations only.

Regarding the time and cost efficiency of UAV-based approach for data collection compared to field measurements taken on the ground, it should be noted that the field measurement involves difficulty accessing the damaged crop patches, and usually took several hours, not including the fact that in order to detect all damaged patches, the observer had to traverse a really dense walking grid of the whole field, which may render this kind of analysis unfeasible. The time required to map the wheat field in this study, including the necessary pre-flight preparation, did not exceed one hour of work by one person. The automatic analysis consisting of point cloud creation and processing took less than one additional hour. As precision agriculture applications are intended to increase agricultural processes efficiency (Herwitz et al., 2004), based on these facts of time consumption, the automatic method is an ideal tool for objective assessment of crop damage. Future advances in these methods could incorporate automatic detection of artificial features such as machinery tracks or areas where crop did not grow to distinguish such areas from wild game damage. Utilization of spectral information from photographs or object-based image analysis techniques might further develop the methods proposed in this study.

Conclusions

In this study, we presented a novel method for automatically estimating the area of wheat crop damage by wild game based on UAV-acquired imagery, and automatic analysis of a resulting 3D point cloud. Damaged crops were identified from undamaged plants by revealing two distinct height classes; however, obtaining this height data is not possible by means of regular aerial imagery due to insufficient spatial resolution. The alternative ground verification is infeasible as it generally adds damage to the crop by persons walking through the field, and the time invested for processing the recorded data is lengthy.

The proposed data collection can be obtained by using a consumer-off-the-shelf UAV equipped with common optical camera and software for analysis. Our method for automatic analysis of a 3D point cloud shows very high accuracy with ground data (97% and 95%, respectively, depending on the classification type). The method generates reliable data for solving potential conflicts among agriculture producers and game managers, and when used repetitively over the wheat growing season, the knowledge about crop damage dynamics can improve the management of both crops and wild game.

Disclosure statement

No potential conflict of interest was reported by the authors.

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