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DOCTORAL SCHOOL OF ANIMAL BIOTECHNOLOGY AND ANIMAL SCIENCE

ASSESSMENT AND IMPROVEMENT OF AGRICULTURAL GAME DAMAGE ESTIMATION METHODS

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Thesis of PhD dissertation

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1. Introduction and objectives

1.1. Background

Wildlife is an important natural resource, but there is a wide range of human-wildlife conflicts. Inhibition of the agricultural production is one of the main problem sources. The farmers and the game managers aim to mitigate the damage with different measures, but wild animals reduce the yield of cultivated plants on a global scale.

In Hungary, the agricultural game damage causes significant financial problems to the game managers, and often leads to conflicts between them and the farmers. Many farmers take their legally provided opportunity [(Act LV., 1996; Ministerial order, 79/2004. (V. 4.)] to request financial compensation from the game managers, who are obliged to pay for the damage. It is often impossible to reach an agreement without involving an expert, who has to determine the level of the game damage and define the amount of the compensation.

Different parameters (accuracy, bias, cost-efficiency etc.) of the available estimation methods are less examined, therefore the experts have choosen among them on a subjective basis for a long time. The Ministry of Agriculture aimed to change this by releasing the Unified Agricultural Game Damage Estimation Guide, which is not obligatory to use, but provides opportunity to follow publicly available recommendations. However, studies regarding the game damage estimation are still important, as the stakeholders demand using scientifically tested methods.

1.2. Aims

The goal of my PhD programme was to develop a methodology that is based on GIS (Geographical Information System) simulations, and is suitable for testing certain agricultural game damage estimation methods regarding statistical parameters and factors that affect the results. By using my own maize (*Zea mays*) and winter wheat (*Triticum aestivum*) GIS field models (supported with the necessary fieldwork) I have tested sampling methods that are currently used or potentially suitable in crops with narrow or wide row spacing.

My further goal was to analyse the possibilities of using aerial imagery (in the visible spectrum) taken with a simple unmanned air vehicle (drone) as a tool of the game damage estimation.

The cost-efficiency has also been analysed, as it is important to assess the practical applicability of the samplings based on the required sample size and labour time.

Assuming that the estimations are affected by multiple factors (e.g., field size and expected spatial damage distribution due to the surrounding land cover), my goal was to help the experts to select the sampling that is expected to provide the least biased result in the given circumstances in a scientifically sound manner. The questions of my study were the following:

1. How can be the labour time requirements of the examined agricultural game damage estimation methods characterised?

2. How effectively can a simple, commercially available unmanned air vehicle (UAV) be applied in game damage estimation?

3. Is it appropriate to use the Variable Area Transect (VAT) sampling for game damage estimation in maize?

4. How can be the traits of the examined sampling methods applicable for agricultural game damage estimation (results, statistical parameters) characterised in simulated circumstances?

5. Does the spatial distribution and the true rate of the game damage affect the bias of the examined estimation methods?

6. Considering the time requirement and the cost of the sampling (beside the statistical parameters), how can be the examined game damage estimation methods ranked?

2. Material and methods

2.1. Field studies

2.1.1. Pilot study

In order to test different game damage estimation methods [quadrats with V and double diagonal (X) tracks, grid arrangement method (GAM), VAT] of maize, I simulated damage in three real maize fields with different spatial distributions (**Table 1.**) with the assistance of my colleagues.

Table 1. Data on the maize fields in the pilot study

Field	Damage distri-bution	Area (ha)	Row w. (cm)	Estimated plant density (ind/ha)	Total est. plants (ind)	Damaged plants (ind)			Dam. rate (%)
						Painted	Calc.	Total	
A	dis-persed	1.53	74.6 (±1.0) [1]	70 237 (±10 804) [4]	107 463	9 015	-	9 015	8.39
B	aggr. in patches	1.97	76.0 (±0.8) [2]	68 872 (±8 998) [5]	135 678	8 149	4 502	12 651	9.32
C	aggr. in edge	3.27	75.5 (±1.2) [3]	67 842 (±8 503) [4]	221 843	7 229	5 561	12 790	5.77

[1] n = 8; [2] n = 10; [3] n = 17; [4] n = 38; [5] n = 39

In each field, 20 quadrats with the area of 0.001 ha were distributed evenly along V and X tracks (fitted to the shape of the given field). The quadrat length was calculated based on the area and the row width. During sampling, the total number of plants and the number of damaged plants were recorded.

When applying the GAM, the observer walked along each 5th maize row, and allocated one sample plot at each 5th metre (5 × 5 grid density). The plots were 1 m long segments of a maize row, where the total number of the plants and the damaged plants were recorded.

The damage rate was calculated as the ratio of the damaged plants to the total number of plants, based on the aggregated data of the quadrats.

For the VAT sampling, 30 random points were generated in each field (*n*), then the distance between the starting point and the 6th damaged plant was measured ($r = 6$) in each case. The transect width (*w*) was equal to the width of two maize rows, therefore both rows on the two sides of the observer were taken into account simoultaneously. The measured distances were summarised ($\sum d_i$), then the density of damaged plants was calculated according to the following formula:

$$D = \frac{nr - 1}{(w \sum d_i)}$$

The damage rate was calculated as the ratio of this density to the total plant density that had been previously calculated for each field.

2.1.2. Examination of labour time requirements

I collected data on the labour time requirement of three different sampling units (1 m and 10 m row sections, 1 m^2 quadrats) for crops with narrow row spacing in a winter wheat field damaged by big game (with five repetitions). In each sampling unit, the total number of the plants and the damaged plants were recorded.

In maize, three sampling units [1 m row section, 2 × 1 m row section on the two sides, 0.001 ha quadrats (see **2.1.1.**)] and a double-row transect were involved in the time measurements (with five repetitions). The study area was a maize field damaged by big game. In each sampling unit, the total number of the plants and the damaged plants were recorded. In the case of the parallel transect, 5 × 20 m long sections were examined (both rows on the two sides simoultaneously) by recording the same data.

The walking speed (at a sustainable pace) was measured in the same fields, by covering 5 × 100 m distances. In maize, the parallel and perpendicular directions to the rows were treated separately.

2.1.3. Estimation of rooting damage with UAV

The device used was a DJI Phantom 4 drone.

During the initial flights, I tested the identitification of wild boar (*Sus scrofa*) rooting damage in the aerial photos, then examined the possibilities of area measurement in the photos taken with the drone. I took photos of a pasture and of a sunflower (*Helianthus annuus*) field two weeks after it was sown (with wild boar rooting at both sites). In the latter study area, I placed markers around a rooted patch, then recorded their coordinates. After georeferencing the photos with the aid of the markers, I digitialised the rooting manually.

Later I examined how the strong sunlight affects the identification of rooting damage. In addition, I simulated rooting by using a shovel (near to a natural patch), in order to examine wheather this method is appropriate in possible aerial photography studies when natural rooting is not available.

At the last step, in a field with an area of 9.3 ha, I performed traditional rooting damage survey as it is recommended for winter wheat right after sowing: data were collected at 25 sampling plots, within 1×1 m quadrats (divided into 4 equal parts). The plots were allocated along parallel tracks. The estimated damage rate (ratio of damaged sampling units to total number of units) was calculated with two approaches: based on the aggregated data of the quadrats, moreover considering the quadrat quarters.

In the same field, 255 aerial photos were taken during an autonomous flight controlled by the DroneDeploy application. A georeferenced ortophoto with 5×5 cm resolution was obtained from the cloud service. I marked the rootings manually, then calculated the total area of the poligons. Furthermore, another method was used for marking the rooting: the ortophoto was covered with a hexagon grid (with 1.5 m side length), then each cell that contained rooting was marked.

2.2. GIS simulations in maize

2.2.1. Examination of VAT sampling through GIS simulations

In connection with the pilot field study (see **2.1.1.**), I examined the performance of the VAT sampling through GIS simulations as well. I generated a maize field model with 100 × 100 m side lengths, 76.2 cm row width and 17.57 cm plant spacing. I deleted a randomly selected 10% of the points to simulate the incomplete germination. The spatial damage distributions were the following: random, aggregated in patches (DAinP), aggregated along one and two field edges (DAinE-1, DAinE-2). In combination with the distributions, three different true damage rates were tested (10%, 20%, 30%).

The random pattern was created through random selection of points. The patches were freehand created and randomly allocated (in terms of the number, shape, area and location of the patches). For the DAinE-2 distribution, a 20 m buffer zone was used on two adjacent sides of the field. To simulate the effect of a neighbouring forest, 80% of the total damage was generated by random selection within the buffer zone. In the case of the DAinE-1 distribution, a similar protocol was followed, with a 25 m buffer zone.

The distance measurements were carried out manually ($n = 30$, five repetitions), from the starting points to the 6th damaged plants ($r = 6$). Both rows on the two sides of the observer were taken into account simoultaneously. The damage rate was calculated as described in **chapter 2.1.1**.

Beside the visualisation of the results, the estimations were chacterised by the standard error (SE), the mean squared error (MSE), the bias, and the percentage relative bias (PRB) (see **2.2.4.**).

Two-way ANOVA was conducted to identify the factors (true damage rate, spatial distribution of the damage or the interaction of these two values) that had significant impacts on the PRB of the estimations. Pairwise comparisons were performed with Tukey post-hoc test.

2.2.2. Settings of plants and game damage in the complex simulations

In the complex GIS simulation involving maize, the following field sizes were examined: 3 ha, 10 ha, 30 ha, 60 ha (each with a 1:2 side ratio). The row width was 76.2 cm, the plant spacing was set as 20.15 cm. A randomly selected 10% of the points was deleted to simulate the incomplete germination. The simulated true damage rates were 10%, 30%, 50%, 70% and 85%.

The first simulated damage pattern was a random distribution. In order to simulate the effect of a neighboring forest, aggregated patterns were created according to three different scenarios (**Fig. 1.**).

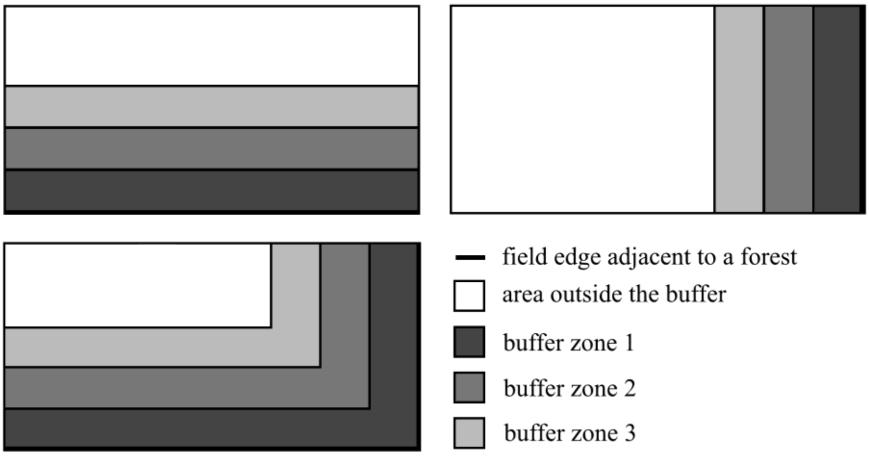

Fig. 1. Sketch of field edges adjacent to a forest and of buffer zones in the case of field models with the area of 30 ha

In the case of the aggregated damage in 1 field edge, the long and short edges were treated as damaged separately (DAinE-1L, DAinE-1S). Fort he third pattern (DAinE-2), two connecting field edges were modeled to be adjacent to a forest. Along the damaged edges, three buffer zones of equal depth were created to simulate the real spatial distribution of game damage, where the damage level gradually decreases with increasing the distance from the forest. The side lengths and buffer zone depths can be found in **Table 2.**

Table 2. Side lengths, buffer zone depths and number of plants in the maize field models

Area (ha)	Side length (m)		Buffer zone depth (m)		Number of plants (ind)
	horizontal	vertical	horizontal	vertical	
3	244.9	122.5	24.5	49.0	176 199
10	447.2	223.6	44.7	89.4	587 412
30	774.6	387.3	77.5	100.0	1 761 395
60	1 095.5	547.7	100.0	100.0	3 518 283

The fundamental requirement was that 70% of the damage shall be randomly located in buffer zone 1 (BZ1). The remaining 30% was allocated also randomly in the rest of the field (treated as one homogenous area). Where the total number of plants in buffer zone 1 was higher than the 70% of the damaged plants, total damage was set in BZ1, and the remaining part from 70% of the damage was distributed randomly in buffer zone 2. When it was necessary, buffer zone 3 was utilised with the same method.

2.2.3. The examined methods and execution of the samplings

Similarly to the pilot field study, 0.001 ha quadrats and the GAM method were tested. As a possible improved version of the latter, I designed a double grid arrangement method, where the observer examines a 1 m long section not only in one, but in two rows (on the two sides). In this new sampling, 2 × 1 m are examined, therefore the extent of the data collection is doubled. Beyond the aforementioned ones, the parallel transect method was involved as well (which was designed and used for research purposes, similarly to the GAM).

The length of the quadrats was 13.12 m. In the case of each field size, 10, 15, 20, 25 and 30 quadrats were used in order to analyse the results provided by different sample sizes. The quadrats were tested with V, W and X sampling tracks (**Fig. 2.**).

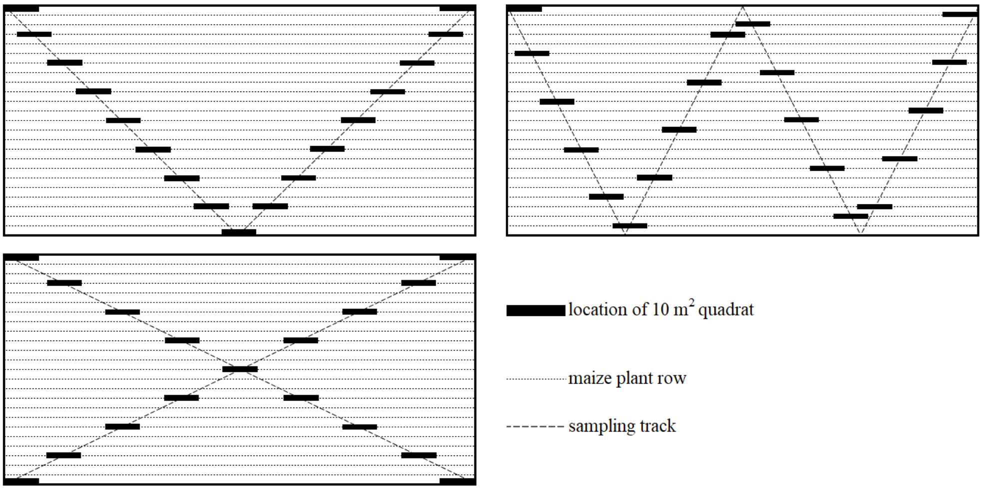

Fig. 2. Sketch of the sampling track and the location of the quadrats

In the case of the GAM and DGAM samplings, I tested different grid densities. The highest sample size was achieved with the 5 × 5 density (see **2.1.1.**), the lower densities were set as 10 × 10, 20 × 20, 40 × 40 and 80 × 80.

For the parallel transects, I created two poligons (both covered two rows) along the two long field edges, then the field size determined the number of two-row transects inside the field (3 and 10 ha: 2, 30 and 60 ha: 6). The transect inside the field were distributed evenly. Considering the original description of the method, the ending points were connected by shorter transects that also covered observed plants (**Fig. 3.**).

Fig. 3. Sketch of the observed transects in the case of field models with the area of 10 ha

The damage rate was calculated as $(\sum DP / \sum TP) \times 100$, where DP was the number of damaged plants recorded and TP was the total number of individual maize plants observed.

In the case of each field model and estimation method, the samplings were carried out with five repetitions. The background of the repetitions is that if multiple game damage experts work on an arable field in a real-life situation (even with the same method), their sampling units are not located at the exact same place, and my aim was to implement these minor individual differences in the simulations. Another reason is that the repetitions facilitate the statistitical analyses and the calculation of parameters that characterise the samplings.

2.2.4. Statistical analyses

The statistical analyses were performed in four steps. At first, I queried the complete dataset (n = 10,400), and the data from the repetition groups in order to obtain the descriptive values (i.e., minimum, maximum, mean, median).

In the next section, I used ANOVA to determine the groups in which it is appropriate to identify the factors that affect the difference between the true and the esimated damage rate. I found it expedient to analyse the different methods separately. Using both the bias and the PRB, the ANOVA (for the entire dataset) showed significant difference among the estimation results. Regarding the quadrats, the same applied to the field sizes, sampling tracks and sample sizes. In the case of the GAM and DGAM samplings, the results were significantly affected by the field sizes and the grid densities. Concerning the parallel transect, only the bias of the samplings was affected by the field sizes. With these facts taken into account, every combination of field areas, sample sizes and tracks (only in the case of quadrats) were treated separately when I conducted two-way ANOVA to analyse how the true rate and spatial distribution of the damage (and their interaction) affected the bias and the PRB. Pairwise comparisons were performed with Tukey post-hoc test.

In the next step, I examined the results of the quadrat sampling grouped by the sampling tracks.

In the final section, I calculated the following parameters for the repetition groups, then I identified the method (and sample size) that provided the best and the poorest values for each field model.

I charavterised the estimations with the Standard Error (SE), the Mean Squared Error (MSE) and the bias. The latter was calculated not only for the repetition groups, but also for the individual samplings. To acquire information on the difference between the estimated and the true damage rate compared to the latter, I calculated the Percentage Relative Bias (PRB).

2.2.5. Analysis of cost-efficiency

In the framework of the first cost-efficiency analysis, I examined how often an increase in the sample size led to a decrease in the bias.

After that, I calculated the labour time requirement of the sampling for each estimation in the case of the different field models. The time requirement (see **3.1.2.**) was defined as 0.5 min/plot for the GAM and DGAM, 2 minutes for a 0.001 ha quadrat and 3 minutes for a 20 m long section of a double-row transect.

The walking distance was calculated taking the special traits of the different methods into account, then the total sampling time was calculated with the aid of the measured walking speed (parallel to rows: 1.29 m/s, perpendicular to rows: 0.56 m/s) and the sample size.

There were no publicly accessible expert fees that could have been used for the cost calculations. Based on interviewing three practicing experts who are familiar with the typical fees, I used a medium level expert fee (17,500 HUF/hrs with a 0.5 hrs scale) to calculate the cost of the different samplings.

In the final step, I ranked the samplings based on 6 parameters (absolute value of the bias and the PRB, SE, MSE, time requirement, cost). The sampling that provided the best value (e.g., lowest bias, shortest time required) was given 1 point. The highest score (determined by the length of the list) was assigned to the sampling that was responsible for the poorest value. The 16 groups were formed by the 4 field sizes and the 4 spatial damage distributions. The aggregated ranking was obtained by summarising the 6 sub-scores, and the lower the total score of a sampling was, the higher it was ranked on the final list. I also created a filtered version of the list, in which only the scores for the bias, SE and time requirement were used. The samplings that require a longer time than 8 hours (the length a general working day) were excluded from these rankings.

2.3. GIS simulations in winter wheat

2.3.1. Settings of plants and game damage

Regarding the GIS simulations in winter wheat, it acts as a remarkable barrier, that it may require to generate a hundred times more points per hectars than it is used in the case of maize. Therefore, in my study I worked with field models only with an area of 3 ha (1:2 side ratio, 245 m and 122.5 m side lengths.

The row width was 12 cm, the plant spacing was set as 1.67 cm. A randomly selected 15% of the points was deleted to simulate the incomplete germination. The final number of points was 12,729,624.

The simulated true damage rates were 10%, 30%, 50% and 70%. The first simulated damage pattern was a random distribution. In order to simulate the effect of a neighboring forest, two different aggregated patterns (DAinE-1, DAinE-2) were created with 30 m buffer zone depths.

The fundamental requirement was that 80% of the damage shall be randomly located in the buffer zone. Where the total number of plants in the buffer zone was higher than the 80% of the damaged plants, total damage was set in the buffer zone, and the remaining damage was distributed randomly in the rest of the field.

2.3.2. The examined methods and execution of the samplings

Three different sampling tracks (V, W, X) and three sampling units (square shaped quadrats with an area of 1 m^2, 1 m and 10 m long row sections) were tested. In the case of each sampling 10, 15, 20, 25 and 30 units were used in order to analyse the results provided by different sample sizes.

The damage rate was calculated as $(\sum DP / \sum TP) \times 100$, where DP was the number of damaged plants recorded and TP was the total number of individual plants observed. In the case of each field model and sampling unit type, the estimations were carried out with five repetitions.

2.3.3. Statistical analyses

Similarly to the complex simulations in maize, the statistical analyses were performed in four steps. At first, I queried the complete dataset (n = 2,700), and the data from the repetition groups in order to obtain the descriptive values.

In the next section, I used ANOVA to determine the groups in which it is appropriate to identify the factors that affect the difference between the true and the esimated damage rate. Using both the bias and the PRB, the ANOVA (for the entire dataset) showed significant difference among the estimation results of the different sampling units. The same applied to the sampling tracks and sample sizes. Every combination of sampling units, sample sizes and tracks were treated separately when I conducted two-way ANOVA to analyse how the true rate and spatial distribution of the damage (and their interaction) affected the bias and the PRB. Pairwise comparisons were performed with Tukey post-hoc test.

In the next step, I examined the results of the samplings grouped by the different sampling tracks.

In the final section, I calculated the bias, PRB, SE and MSE values for the repetition groups, then I identified the sampling unit (and sample size) that provided the best and the poorest values for each field model.

2.3.4. Analysis of cost-efficiency

In the framework of the first cost-efficiency analysis, I examined how often an increase in the sample size led to a decrease in the bias.

After that, I calculated the labour time requirement of the sampling for each estimation in the case of the different field models. The time requirement (see **3.1.2.**) was defined as 2 min/plot for the 1 m row sections, 9.5 min/plot for the 10 m row sections and 6.5 minutes for a 1 m^2 quadrat.

The walking distance was calculated taking the traits of the different sampling tracks into account, then the total sampling time was calculated with the aid of the measured walking speed (1.71 m/s) and the sample size. I used the expert fee (17,500 HUF/hrs with a 0.5 hrs scale) described in **chapter 2.2.5.** to calculate the cost of the different samplings.

In the final step, I scored and ranked the samplings with the same methodology that was used in the case of maize (see **2.2.5.**).

3. Results

3.1. Results of field studies

3.1.1. Results of the pilot study

The samplings (**Fig. 4.**) resulted only in underestimations in the case of field B, while in field A, all samplings but one underestimated the damage. In field C, three samplings led to overestimation. The largest bias was obtained with the VAT sampling in each field. The least biased estimation was provided by the quadrats (V track, n = 10) in field A, while by the GAM in fields B and C (10 × 10 and 5 × 5, 10 × 10, respectively).

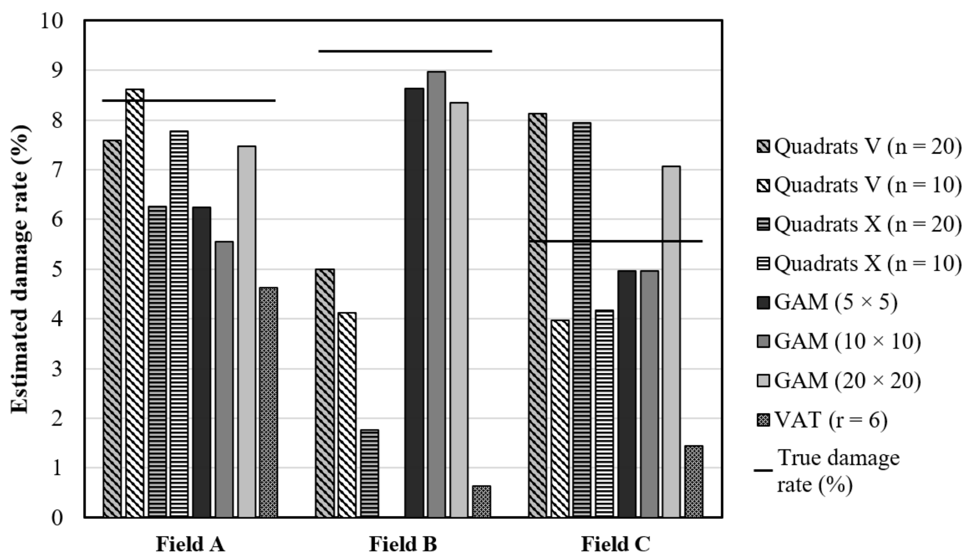

Fig. 4. Estimation results in the pilot study

In field B (with damage aggregated in patches), no damaged plants were found with the quadrats (X track, n = 10), therefore the value of the relative bias was 100%.

3.1.2. Labour time requirements of the sampling

In maize, data collection along the 1 m row sections took 6 to 8 seconds, while the plant counts along 2 × 1 m row sections required 10 to 16 seconds. Working with a 0.001 ha quadrat took between 1.6 and 1.9 minutes. It took 2.2 to 3.1 minutes to survey a 20 m long row section with simultaneous counts in both rows on the two sides. There was no correlation between the number of plants and the time spent in a sampling unit.

In winter wheat, data collection along the 1 m row sections took 1.6 to 2.8 seconds (the latter value is an outlier). The shortest time spent at a 10 m row section was 6.1 minutes, while longest was 17.2 minutes (the latter is also an outlier, $\bar{x}$ = 9.3 min). The labour time requirement of the 1 m^2 quadrats varied between 5.1 and 8 minutes ($\bar{x}$ = 6.2 min). I found no correlation between the number of plants and the time spent in a sampling unit.

Regarding the time required to cover a 100 m distance on foot, the highest walking speed was measured in winter wheat ($\bar{x}$ = 1.71 m/s). In the case of maize, parallel to the plant rows, the mean of the walking speed was 1.29 m/s (median = 1.28 m/s), while walking perpendicular to the rows proved to be more than two times slower ($\bar{x}$ = 0.56 m/s).

3.1.3. Estimation of rooting damage with UAV

During the initial operations, in the photos taken of the pasture, the wild boar rootings, as well as the patches trampled by cattle were clearly visible. The patches caused by the two species appeared to be rather similar. In the aerial photos taken in the same year of the sunflower field, the wild boar tracks and rootings were also well visible from each altitude tested. The width of the largest patch found was measured to be 12 m on the surface, while the length was 87 m. After georeferencing the photo taken from a 90 m altitude, I measured the width again as 12 m, while the length was 92 m in the aerial photo. After digitalising the complete rooted patch manually, the damaged area was measured to be 1,092 m^2.

There were no large, continous patches in the other sunflower field that has been examined, but the rootings could be identified in each photo. In fact, not the rootings, but their inner shadows were visible due to the bright sunshine. In the grassland, the natural and the simulated rootings were equally visible, but the patch that was created manually by a shovel proved to be darker than the natural rooting.

During the last traditional field survey, I found rooting damage in 5 quadrats out of the total 25. Accoring to the simpliest calculation, the estimated damage rate was 20%. Considering the quadrat quarters, two quadrats showed 100% damage, while the damage level was 25% in three quadrats. This calculation resulted in an 11% estimated damage rate for the entire field.

When processing the rootings in the ortophoto (**Fig. 5.**), I marked 30 patches manually during a 1.5 hours work. The total area was 5,061 m^2, therefore the estimated damage rate was calculated to be 5.4%. By using the hexagon grid, the work also took 1.5 hours and the summarised area of the marked cells was 4.972 m^2. After rounding up the end result, the estimated damage rate was also 5.4%.

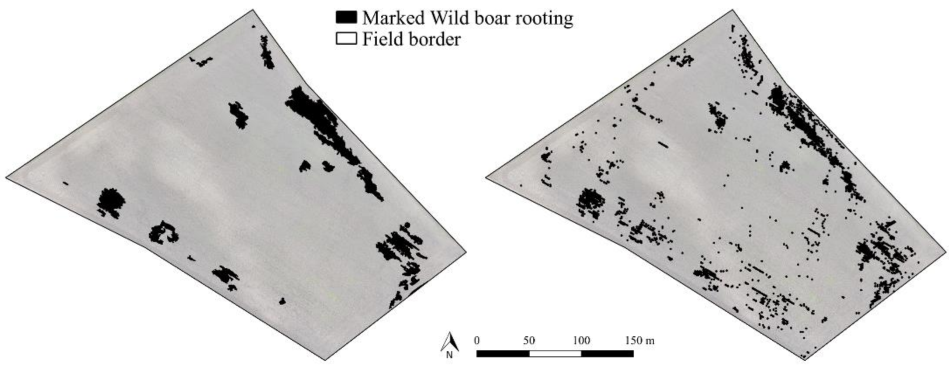

Fig. 5. Marking the rootings in the ortophotos by freehand (left) and with the aid of a hexagon grid (right)

3.2. Results of the GIS simulations

3.2.1. Estimation results of the VAT samplings

The VAT sampling resulted in a remarkable underestimation in the case of each damage rate and spatial pattern, except the random distribution. In the case of a random damage distribution, both under- and overestimations occurred at each true damage rate (**Fig. 6.**).

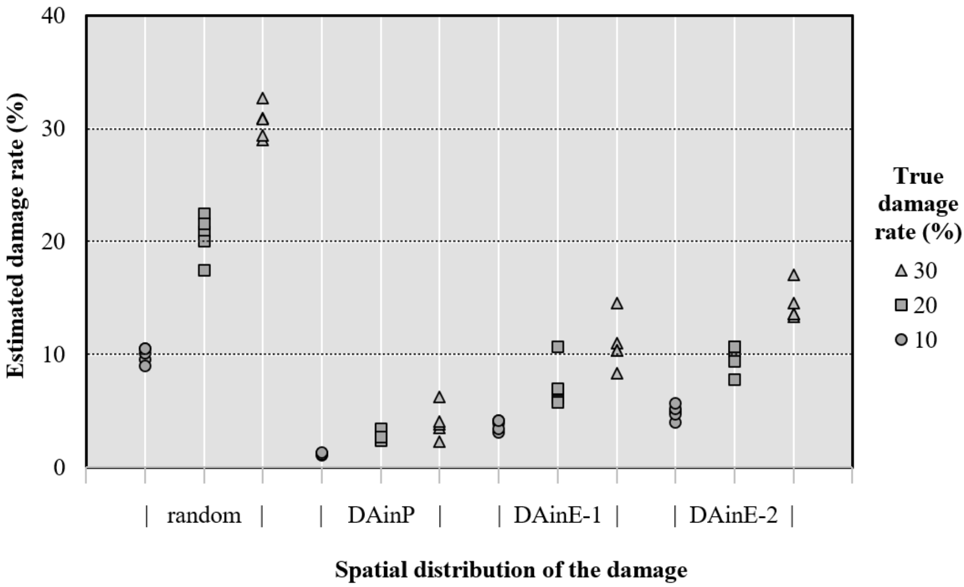

Fig. 6. Results of the VAT samplings in the GIS simulations

Concerning the statistical parameters, the further the spatial pattern of the damage fell from a random distribution, the larger were the bias and the PRB, moreover the MSE was impaired, while the SE did not change remarkably.

The PRB was significantly affected only by the damage distribution ($F = 538.7$; $df = 3$; $p < 0.001$), while the bias was affected by the distribution ($F = 459.7$; $df = 3$; $p < 0.001$), by the true damage rate ($F = 272.0$; $df = 2$; $p < 0.001$), furthermore by the interaction of these factors ($F = 39.64$; $df = 6$; $p < 0.001$) as well.

3.2.2. Results of the complex GIS simulations in maize

In the complete dataset (n = 10,400) the minimum of the bias was -13.1%, the maximum was 18.7%. The minimum of the PRB was -43.2%, the maximum was 141.4%. The medians were 0.09% and 0.18%, respectively.

In the repetition groups (n = 2,080) the minimum of the SE was 0.02%, the maximum was 7.1%. The minimum of the MSE was 0.001%, the maximum was 191.2%. These datasets also differed from a normal distribution, the medians were 0.9% and 1.3%, respectively. The minimum of the mean of the bias was -7.2%, the maximum was 13.5% (median = 0.05%). The minimum of the bias expressed as an error in the compensation payment was -308,543 HUF, the maximum was 173,556 HUF.

The difference between the true value and the damage rate estimated with the quadrats was affected by the distribution and rate of the damage and their interaction in several cases. The poorest estimations of this method occurred in the case of the 60 ha field models. The damage distribution had an effect on the result in almost every sampling. The damage rate and the interaction were significantly effective factors mostly when smaller sample sizes were set. In most cases, the results of GAM and DGAM samplings were less affected by the examined factors when larger sample sizes were used. Both factors and their interaction had an effect on the parallel transect sampling at each field size. There was no pattern in the results of the pairwise comparisons.

The best values of the parameters calculated for the repetition groups (mean of the bias, PRB, SE, MSE) were obtained with mostly GAM and DGAM samplings (mostly with 5 × 5 and 10 × 10 grid densities). Both the quadrats and the parallel transects provided the majority of the best values in one case (quadrats: bias-PRB, 3 ha; parallel transects: SE, 3 ha). The majority of the poorest values was obtained with quadrats at the two larger field sizes, while with the GAM or the DGAM (mostly with 40 × 40 and 80 × 80 grids) at the two smaller field sizes.

In the graph (**Fig. 7.**) that presents the quadrat estimations regarding the mean of the bias grouped by the sampling tracks, it is visible that the interquartile ranges and min-max intervals show nearly the same characteristics (at the 10 ha fields the W track provided the best estimations, but the differences were minor).

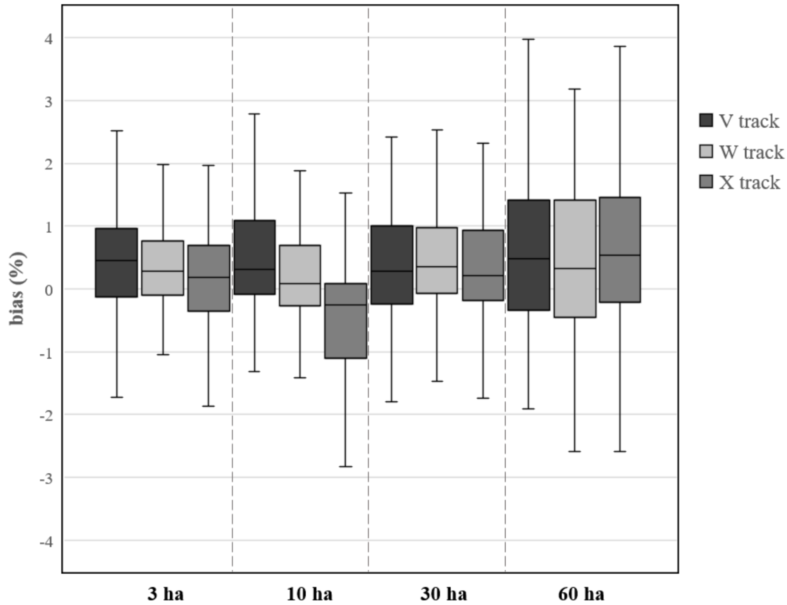

Fig. 7. Mean of the bias by sampling tracks, at different field sizes, in the case of maize (n = 100 in each group)

In the graph (**Fig. 8.**) that presents the quadrat estimations on 3 ha field models regarding the mean of the bias grouped by the sample sizes, it is visible that the interquartile range was the smallest at the largest sample size (however, the smaller sample sizes provided similar results). The same parameter was improving with increasing the grid density of GAM and DGAM samplings, but it required to increase the sampling resolution from 20×20 to 10×10 to achieve the same performance that was available with the quadrats.

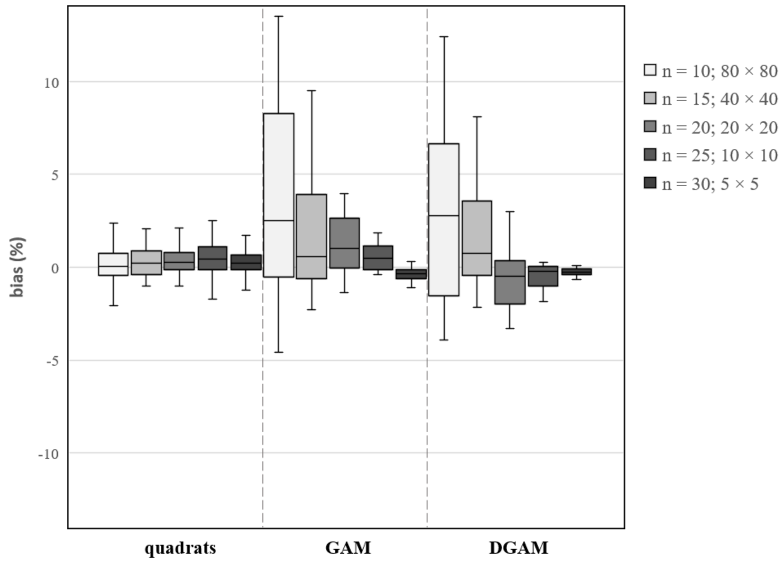

Fig. 8. Mean of the bias in the case of 3 ha maize field models (quadrats: n = 60, GAM and DGAM: n = 20)

At a 10 ha field size (**Fig. 9.**), the interquartile range of the quadrat samplings was the smallest at the largest sample size (the smaller ones provided similar results). The same parameter was improving with increasing the grid density of GAM and DGAM samplings.

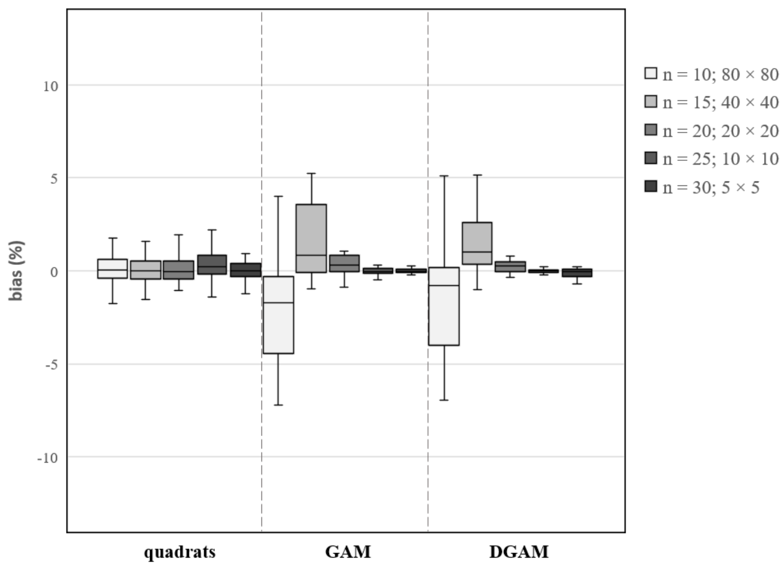

Fig. 9. Mean of the bias in the case of 10 ha maize field models (quadrats: n = 60, GAM and DGAM: n = 20)

At a 30 ha field size (**Fig. 10.**), the interquartile range of the quadrat samplings was the smallest at the largest sample size once again, while the smaller ones provided similar results (except n = 25, which was slightly poorer). The same parameter was improving with increasing the grid density of GAM and DGAM samplings. It required to increase the sampling resolution from 40 × 40 to 20 × 20 to achieve or even surpass the same performance that was available with the quadrats.

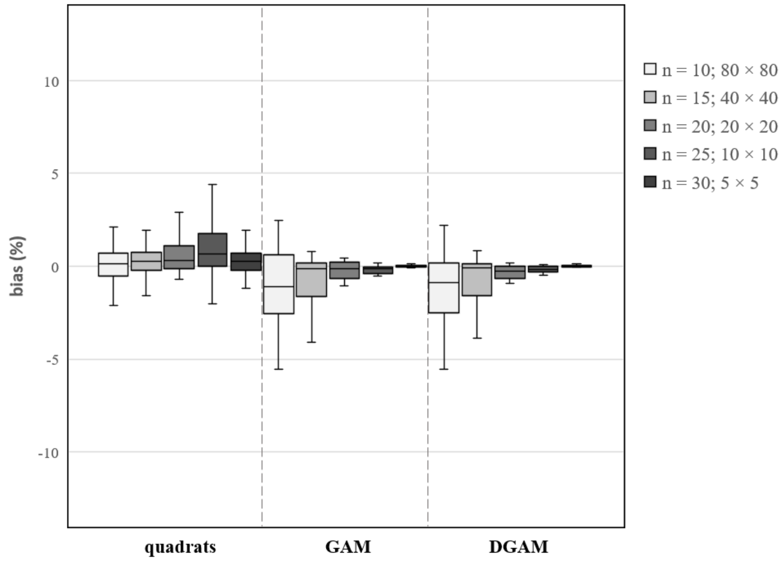

Fig. 10. Mean of the bias in the case of 30 ha maize field models (quadrats: n = 60, GAM and DGAM: n = 20)

At a 60 ha field size (**Fig. 11.**), the interquartile range of the quadrat samplings was the smallest at the largest sample size once again. The smaller ones provided similar or slightly poorer results (but similar to each other). At the largest field size, GAM and DGAM samplings (with each the grid density) provided the same or higher performance than what was available with the quadrats.

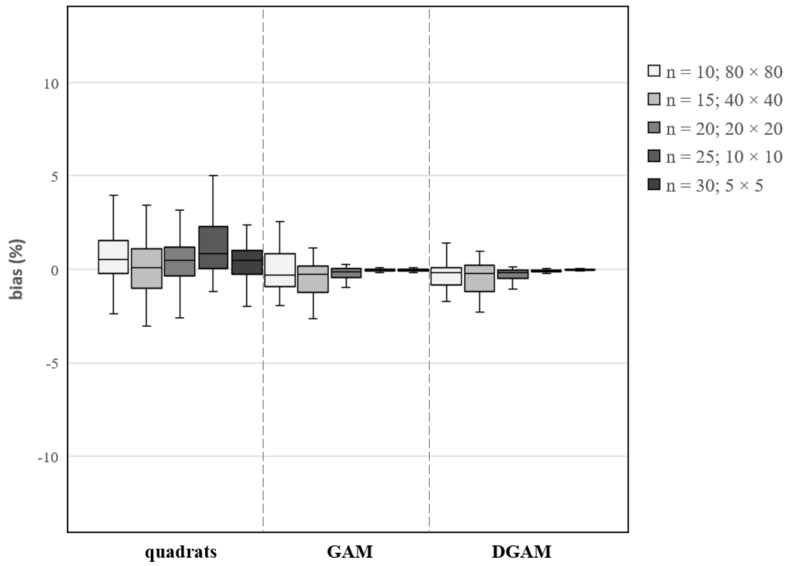

Fig. 11. Mean of the bias in the case of 60 ha maize field models (quadrats: n = 60, GAM and DGAM: n = 20)

Fig. 12. shows the number of quadrat samplings where increasing the sample size led to a decrease in the mean of bias of the repetition groups. Each sampling is included in the n = 10 category, and only the samplings where the estimation became less biased "passed to" the next column.

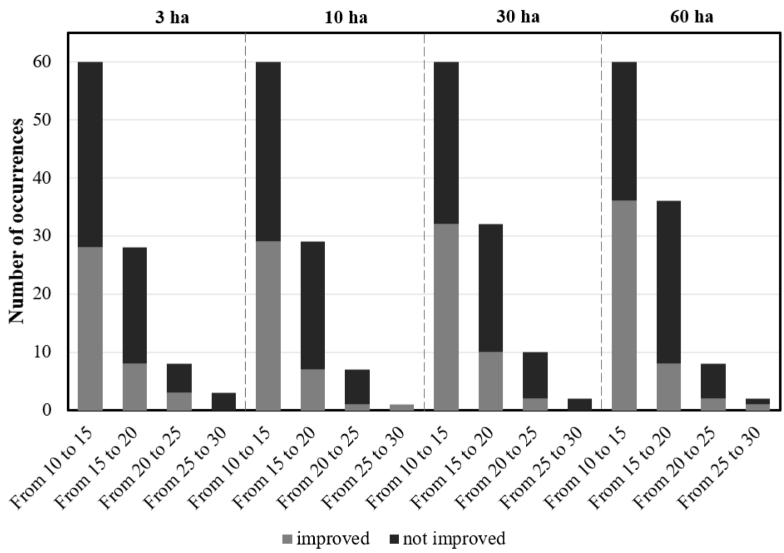

Fig. 12. Decreasing bias in the case of quadrat samplings with larger sample sizes

Similarly to the previous one, **Fig. 13.** shows the number of GAM and DGAM samplings where increasing the sample size led to a decrease in the mean of bias of the repetition groups.

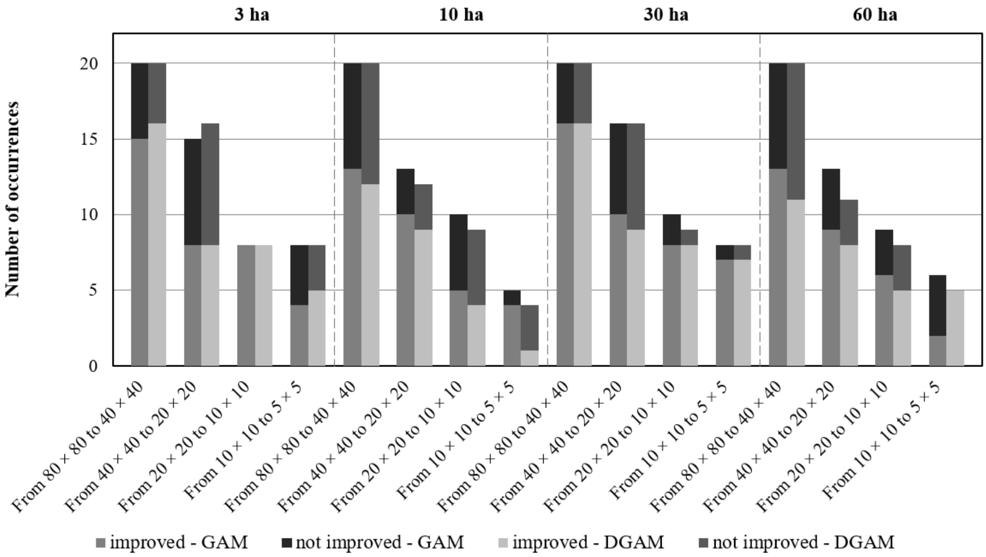

Fig. 13. Decreasing bias in the case of GAM and DGAM samplings with larger sample sizes

In my study, the longest real-life labour time requirement of a quadrat sampling was 2.3 hours (60 ha field size, W track, n = 30 sample size), which would have costed 43,750 HUF. The shortest required time of a simulated sampling was 0.5 hours (3 ha field size, V track, n = 10 sample size), which would have costed 17,500 HUF.

In the case of the other game damage estimation methods (**Table 3.**), the real-life sampling would take a longer time than a general workday (8 hours) in several scenarios. Among the samplings that could be completed in less than 8 hours, it would take the longest time (5.1 hours at a 96,250 HUF cost) to perform a parallel transect estimation on a field with an area of 10 ha.

Table 3. Labour time requrement of the GAM, DGAM and parallel transect samplings (bold values show samplings that cannot be completed in less than 8 hours)

Field area	GAM and DGAM			Parallel transect	
	Grid density (row × m)	**Labour time (hrs)**	**Cost (HUF)**	**Labour time (hrs)**	**Cost (HUF)**
3 ha	80 × 80	0.3	8 750	2.8	52 500
	40 × 40	0.6	17 500		
	20 × 20	1.5	26 250		
	10 × 10	4.5	78 750		
	5 × 5	**14.8**	**262 500**		
10 ha	80 × 80	0.6	17 500	5.1	96 250
	40 × 40	1.6	35 000		
	20 × 20	4.4	78 750		
	10 × 10	**14.2**	**253 750**		
	5 × 5	**50.0**	**875 000**		
30 ha	80 × 80	1.8	35 000	**16.6**	**297 500**
	40 × 40	4.4	78 750		
	20 × 20	**12.9**	**227 500**		
	10 × 10	**41.7**	**735 000**		
	5 × 5	**148.8**	**2 607 500**		
60 ha	80 × 80	3.6	70 000	**23.5**	**411 250**
	40 × 40	**8.6**	**157 500**		
	20 × 20	**25.1**	**446 250**		
	10 × 10	**83.1**	**1 461 250**		
	5 × 5	**296.9**	**5 197 500**		

In the case of the 3 ha field models, mostly the quadrat samplings appeared as top 10 elements of the rankings (with all the three tracks and variable sample sizes). The parallel transects appeared once, while the GAM (40 × 40) was represented in 2 positions and the DGAM (20 × 20, 40 × 40) appeared three times in total.

In the case of the 10 ha fields, once again the quadrat samplings were the most common among the top 10 elements of the rankings. All the three tracks appeared, the sample sizes were variable (mostly under n = 30). The DGAM (20 × 20, 80 × 80) appeared twice in total. The parallel transects and the GAM were not represented.

In the case of the 30 ha field models, the GAM (40 × 40) was represented in 2 positions and the DGAM (20 × 20, 80 × 80) appeared five times in total. The quadrats appeared with each track shape (the sample sizes were highly variable). The parallel transects were not represented.

In the case of the 60 ha field models, only the quadrat samplings appeared as top 10 elements of the rankings (with all the three tracks and highly variable sample sizes).

3.2.3. Results of GIS simulations in winter wheat

In the complete dataset (n = 2,700) the minimum of the bias was -6.1%, the maximum was 7.1%. The minimum of the PRB was -31.9%, the maximum was 32.9%. The medians were 0.04% and 0.12%, respectively.

In the repetition groups (n = 540) the minimum of the SE was 0.1%, the maximum was 4.7%. The minimum of the MSE was 0.01%, the maximum was 34.1%. The medians were 0.6% and 1.6%, respectively. The minimum of the mean of the bias was -4.7% (-42,188 HUF), the maximum was 5.8% (52,212 HUF). The median was 0.02%.

In terms of how often the difference between the true value and the damage rate was affected by the distribution and rate of the damage and their interactions, 10 m row sections proved to be the poorest sampling unit. The other two sampling types were also affected by the spatial distribution in several cases, but they were less sensitive to the true damage rate and the interaction (this was particularly true for the 1 m row sections allocated along a W track). The results of the pairwise comparisons followed no pattern.

The best values of the parameters calculated for the repetition groups (mean of the bias, PRB, SE, MSE) were obtained with mostly 10 m long row sections (with n = 25 or n = 30 sample size and different sampling tracks). The majority of the poorest values was obtained with 1 m row sections (with varied sample sizes and tracks).

Regarding the mean of the bias grouped by the sampling tracks, the median was close to 0 in each group. Based on the interquartile ranges and min-max intervals, no sampling track provided results of remarkably higher or lower quality than the other two.

In the graph (**Fig. 14.**) that presents the estimations regarding the mean of the bias grouped by the sample sizes, it is visible that the interquartile ranges of 1 m and 10 m row section samplings were rather similar to one another. In the case of the 1 m^2 quadrats, these results were less variable over n = 10. The same parameter was improving with increasing the grid density of GAM and DGAM samplings, but it required to increase the sampling resolution from 20 × 20 to 10 × 10 to achieve the same performance that was available with the quadrats. Both the row sections and quadrats provided the best interquartile ranges and min-max intervals at n = 25.

The above-mentioned findings applied to the PRB, as well.

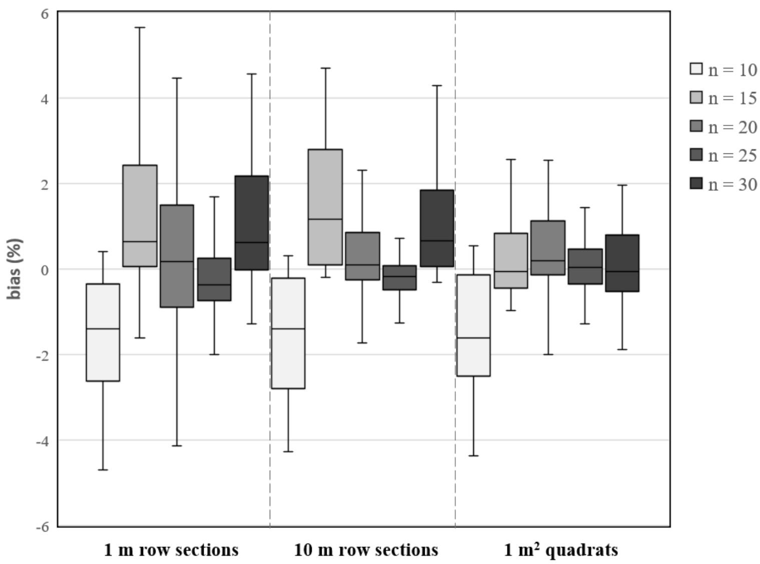

Fig. 14. Mean of the bias in the case of 3 ha winter wheat field models (n = 36 in each group)

Fig. 15. shows the number of samplings where increasing the sample size led to a decrease in the mean of bias of the repetition groups.

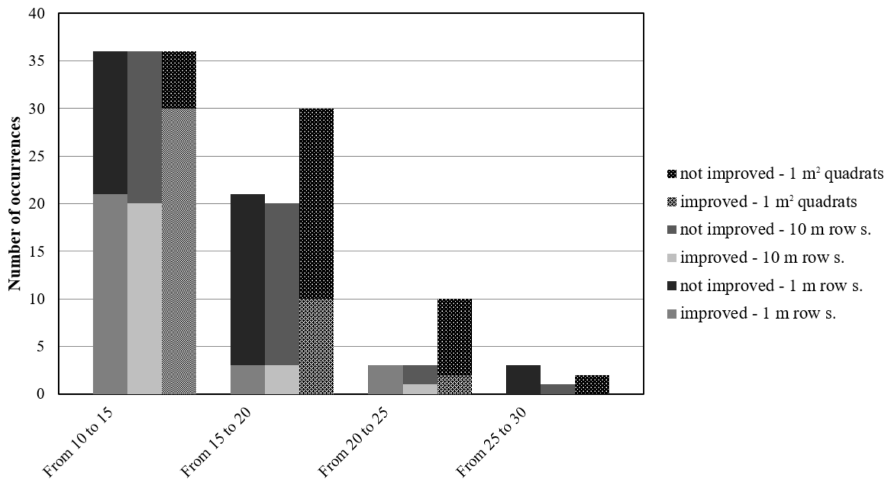

Fig. 15. Decreasing bias in the case of different samplings with larger sample sizes

Regarding the real-life labour time requirement of the sampling, the work with 1 m long row sections with the largest sample size could be completed in 1.1 hours (26,250 HUF), while the 10 m row sections and 1 m^2 quadrats would require the same or longer time even with the smallest sample size. The longest work with these units would take 4.9 hours (87,500 HUF) and 3.4 hours (61,250 HUF), respectively.

Regarding the rankings based on different parameters, the 10 m long row sections appeared only twice as top 10 elements of the rankings. In the case of a random damage distribution, mostly the quadrat sampling was represented. At the DAinE-1 spatial distribution, all but one of top 10 positions were taken by samplings with 1 m row sections. The distribution of the sampling tracks was even in the lists that considered all the 6 parameters, while mostly the V and X tracks appeared at the top 10 positions of the filtered rankings. In the case of the DAinE-2 damage distribution, the 1 m row sections (with variable sample sizes and mostly X track) dominated the top 10 positions of the complete rankings. Regarding the filtered rankings, the sample sizes were also variable, and the 1 m^2 quadrats took several positions in the top 10. The V and X tracks took a nearly equal proportion (the W appeared only once).

4. Discussion and conclusions

4.1. Estimation of rooting damage with UAV

The fact that the patches trampled by cattle appeared to be similar to wild boar rooting in the aerial photos taken of the pasture, confirmed that using drones can help the game damage experts, but does not make the verification of the game damage on the ground unnecessary.

Based on the photos taken of the sunflower field in bright sunshine, I found that they were not the rootings, but their inner shadows that were visible. Considering that, taking drone photos in bright sunshine should be avoided, as it can make the area measurement inaccurate.

I find the simulated wild boar rooting suitable for research activities, where it is necessary to precisely set the true damage rate.

The manual georeferencing of the aerial photos proved to be rather complicated. In comparison, the automated flight and generating the ortophoto with the DroneDeploy service was fluent. Digitalising the rootings in the ortophotos resulted in a remarkably lower estimated damage rate than the traditional field sampling. I assume that the damage rate estimated with the drone methodology was closer to the true damage rate than the result of the traditional field survey.

4.2. The pilot study and the VAT sampling

In the pilot field study, the results of the VAT sampling differed the most from the true damage rate where the spatial pattern of the damage was the least similar to a random distribution. On these fields, the GAM sampling provided the least biased estimations. In several cases, a lower bias could have been achieved with smaller sample size or lower grid density.

Summarising the findings from the pilot study and the GIS simulations, the VAT provides acceptable results on if the intrafield distribution of the damage is random. Thus, the VAT is not recommended for practical application, as the spatial distribution of the game damage shows an aggregated or clustered pattern in most cases. Furthermore, I experienced that the VAT is not capable of reducing the labour time.

4.3. GIS simulations in maize and winter wheat

Considering every individual estimation result, all values of the bias fell between -13.1% and +18.7% in the case of maize, while between -6.1% and +7.1% in the case of winter wheat. In other words, taking any combination of field model settings and samplings into account, there was no estimation with a larger difference between the true and the estimated damage rate. The bias of the poorest estimations can be assessed based on the error of the compensation payment. In my study, it meant -308,543 HUF and 173,556 HUF in the case of maize, while -42,188 HUF and 52,212 HUF in the case of winter wheat. It suggests that even if the bias in percentage appears to be less remarkable, the value expressed as an error in the compensation payment puts a light on that an inappropriate sampling method may cause a significant disadvantage for either the game manager or the land user.

As relevant supplementary information regarding this topic, 96.8% of the estimations in maize (n = 10,400) fell within a ±5% bias compared to the true value, while 78.5% was within ±2% and 55.6% was within ±1%. The proportions in the case of winter wheat (n = 2,700) were 98.2%, (within ±5%), 72.7% (within ±2%) and 50.9% (within ±1%).

Both in maize and in winter wheat, the estimations were affected mostly by the spatial distribution of the damage, but the true damage rate and the interaction of the two factors also had an effect on the results in several cases.

Regarding the parameters calculated for the repetition groups in maize, the results of the quadrat sampling proved to be the most balanced. It is confirmed by the fact that the GAM and DGAM samplings provided not only the best, but also the poorest values in several cases. I found that the modified DGAM version of the GAM sampling does not provide results of higher quality in general. In winter wheat, the majority of the best values were provided by 10 m row section samplings, while 1 m row sections were dominant regarding the poorest values.

While assessing the examined tracks of the quadrat samplings in maize, I found no difference in the practical applicability of the V, W and X patterns. There was also only a marginal variability among the tracks in the case of winter wheat. When selecting the track, it is acceptable if the experts make their decision based on the labour time requirements.

The problem of the sample size is also important. The bias of quadrat samplings performed in maize showed similar characteristics at the two smaller field sizes (n = 30 proved to be the best, but only with minor diefferences). On the field models with an area of 30 ha or 60 ha, also n = 30 provided the best results, and the bias varied in a broader range in the case of n = 25. According to the Unified Agricultural Game Damage Estimation Guide, the minimal recommended sample size for 3 ha fields is n=15, but this sample size did not provide less biased results than n = 10. Similarly to this, at the 10 ha field size the recommended n = 20 did not resulted in better estimations, than the lower sample sizes. At the 30 ha field size, the recommended n = 25 was responsible for the poorest results, therefore increasing the minimal sample size to n = 30 could be considered. In the case of fields with an area of 60 ha, increasing the minimal sample size to n = 30 would also be reasonable (the recommendation between 30 ha and 99.99 ha is n = 25).

The larger the field size was, the less grid density increase steps were required to surpass the performance of the quadrat sampling with the GAM and DGAM methods. However, it is important to note that one step between two quadrat sample sizes and two grid densities mean a significantly different increase in the labour-intensitiy of the sampling. Even if the increase in the quality of the results of GAM and DGAM samplings was much more remarkable after one step in the sample size, the estimation also became much more labour-intensive when it managed to replicate or surpass the performance of the quadrat method.

In winter wheat, the quality of row section estimations performed with different sample sizes was highly variable, which less applied to the quadrat sampling. Each sampling unit type provided the best estimations with the $n = 25$ sample size, which equals to the recommendation that can be found in the Unified Agricultural Game Damage Estimation Guide.

Both in maize and in winter wheat, I found that increasing the sample size does not necessarily lead to a better estimation, which prevented me from finding the optimum where the increase in the labour time (and therefore the cost of the sampling) would exceed the increase in the quality of the results. Because of this phenomenon, I decided to assess the estimation methods based on different parameters and rankings that involved those values. In maize, the top 10 positions of the ranking lists were taken almost exclusively by the quadrat sampling. This confirms that most of the experts have been using the correct method for a long time, and that the Unified Agricultural Game Damage Estimation Guide also recommends appropriate sampling principles. In winter wheat, the rankings suggest that using both 1 m long row sections and 1 m^2 quadrats is acceptable. However, if reducing the cost of the damage estimation is not the main goal, the quadrat sampling is recommended. Considering the ranking, 10 m row sections are not recommended for sampling on small fields.

Using the data presented in my thesis, the experts may calculate the personalised time requirement of the samplings, which would allow them to create detailed price lists. My results can be utilised by the forensic experts as well, who retrospectively assess the appropriateness of the fieldwork. In order to extend my study, it is possible to create GIS field models with further field shapes and sizes, as well as with further damage distributions and rates.

5. New scientific results

1. I developed and successfully applied a GIS-based methodology involving arable field models for testing different game damage estimation methods of crops with narrow or wide row spacing.
2. Using maize as an example, aided by GIS simulations and field studies with known true damage rate, I confirmed that the Variable Area Transect method is not suitable for game damage estimation.
3. I found that in crops with wide row spacing (at 3, 10, 30 and 60 ha), the results of quadrat, grid arrangement (GAM), double grid arrangement (DGAM) and parallel transect samplings are mostly affected by the spatial distribution of the damage, but the true damage rate and the interaction of these factors also has an effect on them in several cases.
4. I found that in crops with wide row spacing, the modified DGAM version of the GAM sampling does not provide results of higher quality in general, thus the improvement of the method with that approach is inexpedient. Among the examined ones, the quadrat method is recommended for practical application. At a 1:2 field side ratio, using V, W and X tracks can be accepted equally. At 3 and 10 ha field sizes, n = 10 sample size can be sufficient, while at 30 and 60 ha, n = 30 is recommended.
5. I found that in crops with narrow row spacing (at 3 ha), 1 m and 10 m row sections, as well as 1 m^2 quadrats are suitable for sampling. The estimations are mostly affected by the spatial distribution of the damage, but the true damage rate and their interaction also has an effect in several cases.
6. I found that in crops with narrow row spacing (at 3 ha), considering the cost-efficiency, primarily 1 m row sections and 1 m^2 quadrats are recommended. At a 1:2 field side ratio, using of V, W and X tracks can be accepted equally, the recommended sample size is n = 25.

6. Publications related to the topic of the dissertation

Article as first author in international journal with Impact Factor

Kovács, I., Tóth, B., Schally, G., Csányi, S. Bleier, N. (2020): The assessment of wildlife damage estimation methods in maize with simulation in GIS environment. **Crop Protection** 127: 104971. ***IF_{2020} = 2,571***

Article in peer-reviewed international journal

Kovács, I., Schally, G., Csányi, S. Bleier, N. (2020): The effect of sample size on wildlife damage estimations in maize (*Zea mays*). **Hungarian Agricultural Research** 29(1): 4-9.

Kovács, I., Szabó, A., Schally, G., Csányi, S., Bleier, N. (2019): Analysis of game damage estimation methods in Winter wheat (*Triticum aestivum*) through GIS simulations. **Review on Agriculture and Rural Development** 8(1-2): 41-46.

Bleier, N., Kovács, I., Schally, G., Szemethy, L., Csányi, S. (2017): Spatial and temporal characteristics of the damage caused by wild ungulates in maize (*Zea mays* L.) crops. **International Journal of Pest Management** 63(1): 92-100. ***IF_{2017} = 1,090***

Article in peer-reviewed Hungarian journal

Kovács, I., Illés, B., S. Bleier, N. (2020): Gímszarvas (*Cervus elaphus*) és vaddisznó (*Sus scrofa*) által okozott kár táblán belüli eloszlásának vizsgálata kukoricában (*Zea mays*). **Vadbiológia** 20: 15-22. [in Hungarian]

Other relevant article

Bleier, N., Kovács, I., Timmel, E., Medve, I., Csányi, S. (2017): Gazdálkodók a vadkárról (IV.). **Magyar Mezőgazdaság** 72(33): 36-38. [in Hungarian]

Bleier, N., Kovács, I., Timmel, E., Medve, I., Csányi, S. (2017): Gazdálkodók a vadkárról (III.). **Magyar Mezőgazdaság** 72(32): 32-34. [in Hungarian]

Bleier, N., Kovács, I., Timmel, E., Medve, I., Csányi, S. (2017): Gazdálkodók a vadkárról (II.). **Magyar Mezőgazdaság** 72(31): 22-23. [in Hungarian]

Bleier, N., Kovács, I., Csányi, S. (2017): Gazdálkodók a vadkárról (I.). **Magyar Mezőgazdaság** 72(30): 24-25. [in Hungarian]

Csányi, S., Bleier, N., Kovács, I., Schally, G. (2016): A mezőgazdasági vadkár a gazdák szemszögéből. **NAKlap** 4(9): 18-19. [in Hungarian]

Presentation on international conference

Kovács, I., Szabó, A., Schally, G., Csányi, S., Norbert, B. (2019): Analysis of game damage estimation methods in Winter wheat (*Triticum aestivum*) through GIS simulations. **17th Wellmann International Scientific Conference**. Hódmezővásárhely, Hungary. 8th May 2019

Kovács, I. (2015): Assessment, improvement and development of agricultural wildlife damage estimation methods. **”Healthy Wildlife, Healthy People” World Forum on Sustainable Hunting**. 62nd CIC General Assembly. Pravets, Bulgaria. 23-25 April 2015

Abstract in international conference abstract book

Kovács, I., Szabó, A., Schally, G., Csányi, S., Norbert, B. (2019): Analysis of game damage estimation methods in Winter wheat (*Triticum aestivum*) through GIS simulations. pp. 44-45. In: Monostori, T. (ed.): **17th Wellmann International Scientific Conference. Book of Abstracts**. Hódmezővásárhely, Hungary. 8th May 2019

Other publication

Csányi, S., Bleier, N., Kovács, I., Schally, G. (2016): A mezőgazdasági vadkár témakörében végzett kérdőíves felmérés értékelése. Jelentés. Megbízó: Nemzeti Agrárgazdasági Kamara (NAK). SZIE Vadvilág Megőrzési Intézet, Gödöllő, 114+193 pp. [in Hungarian]