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Dicotyledon Weed Quantification Algorithm for Selective Herbicide Application in Maize Crops: Statistical Evaluation of the Potential Herbicide Savings

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***Abstract*—This work contributes a statistical model and simulation framework yielding the best estimate possible for the potential herbicide reduction when using the MoDiCoVi algorithm all the while requiring a efficacy comparable to conventional spraying. In June 2013 a maize field located in Denmark were seeded. The field was divided into parcels which was assigned to one of two main groups: 1) Control, consisting of subgroups of no spray and full dose spraty; 2) MoDiCoVi algorithm subdivided into five different leaf cover thresholds for spray activation. In addition approximately 25% of the parcels were seeded with additional weeds perpendicular to the maize rows. In total 299 parcels were randomly assigned with the 28 different treatment combinations. In the statistical analysis, bootstrapping was used for balancing the number of replicates. The achieved potential herbicide savings was found to be 70% to 95% depending on the initial weed coverage. However additional field trials covering more seasons and locations are needed to verify the generalisation of these results. There is a potential for further herbicide savings as the time interval between the first and second spraying session was not long enough for the weeds to turn yellow, instead they only stagnated in growth.

***Keywords*—Weed crop discrimination, macrosprayer, herbicide reduction, site-specific, sprayer-boom.

I. Introduction

THE key factor enabling significant herbicide savings is increasing the spatial resolution of the weed control [1], [2]. It is possible to increase the resolution of site specific weed control while not reaching single plant weed control but still achieving considerable savings of herbicides. Handling the presence of crop plants means that vegetation will be a mixture of crop and weeds. Several researchers have reported on systems that are able to distinguish crops from weeds under certain limitations [3]–[8].

Gerhards and Oebel [9] report great herbicide savings using weed maps. They used a sprayer boom with three separate spraying circuits enabling them to apply three different herbicide mixtures in response to local weed size, density and species combination. By recording images covering 0.02 m^2 each in a grid structure of 2 x 3 m throughout the field, they construct a full weed map by interpolation between samples. Splitting weed species into different groups related to their reaction against available herbicides results in a total of 4 weed maps. Splitting weeds into groups is vital for the system to be able to realize high herbicide savings because of a general high weed coverage whereas a large spatial variation in the weed species composition means that areas can be left untreated for some weed species. Their research shows that herbicides against broad leaved weeds can be reduced as much as 77%. However, this requires a special sprayer boom, a grouping of weeds that takes the image analysis task beyond weed/crop differentiation and rely on good approximations of weed infestation and composition between sample points. Gerhards and Oebel [9] and Berge et al. [3] achieved herbicide savings between 18% and 97%. This large span of achieved herbicide savings not only shows that a great amount of herbicides can be saved but also that large scale field tests are needed to acquire insight to the general possibility of herbicide savings. These approaches however disregards the presence of monocot weeds, but assessing the amount of dicot weeds has shown to be adequate to estimate a general weed cover or density. Several researchers report remarkable herbicide savings using this approach and implementing such systems in conventional farming would be a huge step towards a greener agricultural industry [2], [5].

A recurring problem in the data processing algorithms is caused by the difficulties in handling overlapping plants [4], [10]. This circumstance introduces noise in the analysis result and ultimately results in less optimal weed control. Jørgensen et al. [11] address this by an algorithm (MoDiCoVi) capable of estimating the ratio between the dicotyledon pixels and the monocot pixels under the assumption that this may represent the ratio between weeds and crop plants in e.g. cereals. This approach was based on the assumption that the relationship between relative area of crop and weeds and the yield loss can give better prediction than a relationship based on weed density [12], [13]. Laursen et al. [14] tried to validate this by training on simulated data and then test on real field images from a maize field with limited success. Ali et al. [15] showed a linear relationship between the yield loss and the weed leaf cover with maize. Hence it may be beneficial altering the MoDiCoVi algorithm to estimate the absolute weed leaf coverage. In 2013, Laursen et al. [16] performed a large field trial evaluating two different image analysing algorithms estimating the weed coverage in maize. The best algorithm of the two evaluated was a modified version of the MoDiCoVi algorithm introduced by Jørgensen et al. [11] which was able

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to estimate the weed coverage instead of the ratio between monocotyledon cereal crops and the dicotyledon weeds. The in-situ trial generating the necessary data for evaluating the latter algorithms and creating the basis for the conclusion by Laursen et al. [16] made use of robots and other specialized machinery which made it possible to manage trials with many small plots. Kristensen [17] pointed that in some cases it is necessary to impose restrictions to the design of such trials due to practical considerations. This was the case for Laursen et al. [16] who used an incomplete split plot parcel design which also ended up being unbalanced due to operational errors resulting in several parcel exclusions. Based on visual data interpretation Laursen et al. [16] concluded that compared to conventional broadcast spraying the potential reduction in the herbicide usage was 75% while maintaining the weed control effect. However, a statistical analysis is needed to confirm this. Bolker et al. [18] pointed out

> Nonnormal data such as counts or proportions often defy classical statistical procedures. Generalized linear mixed models (GLMMs) provide a more flexible approach for analyzing nonnormal data when random effects are present.

However, in reviewing papers in ecology and evolution since 2005 found by Google Scholar, 311 out of 537 GLMM analyses (58%) used these tools inappropriately in some way [18]. On the other hand, Onofri et al. [19] found that despite the mixed model framework is very powerful it is sometimes a disadvantage, because it may encourage to adopt unnecessarily complex models and variance structures. Hence, use of mixed models is one of the cases where expert advice might be justified. Studying the trial layout and the data generated by Laursen et al. [16] and based on expert advice the analysis do not require as complex models as the GLMMs. This is primarily due to the fact that the weeds are not considered as individuals but rather as a whole in form of soil surface covered by the weeds. However, it should be evaluated if the different treatment levels controlling the nozzle activity induces the presence of heteroscedasticity in the resulting weed coverage measured seven days after the second spraying session.

As earlier mentioned, the parcel counts per treatment combination ended up being unbalanced due to multiple parcel exclusions caused by outliers generated through operational errors. Efron [20] suggested handling unbalanced sample counts by employing random sampling. Random sampling allows for the extraction of bootstrap statistics based on Monte Carlo approximation random sampling with replacement is used [20]. The most promising and robust algorithm was the computer intensive MoDiCoVi algorithm based on images acquired with a shortpass filter from Midwest optical systems, (model SP700) between the CMOS imaging sensor and the objective. Hence, the aim of this work is to have a statistical model and a simulation framework enabling the best possible estimate of the potential herbicide reduction possible while maintaining a weed control effect equivalent to spraying 100% of the parcel area. This will not compensate for the lack of additional growth seasons as noticed by Laursen et al. [16].

Fig. 1 The remains of a parcel in which the tool carrier was stuck during spraying

However, the simulation approach will search to get the most out of the trial data currently available by Laursen et al. [16].

II. Materials and Methods

This section is split into four major subsections: A) Evaluating experimental layout is describing the in-situ plot trial enabling an efficient evaluation of the potential herbicide savings of the MoDiCoVi algorithm and is a summary version of the full trial described by Laursen et al. [16]. B) Data pre-processing and visualisation performs an initial filtering of the acquired data with related nozzle activity and weed coverage in order to get an idea of the structures and trends as basis for the statistical analysis and modelling in section C. C) Statistical analysis and modelling contains the core contribution and searches to reach the best possible model of the data linking the MoDiCoVi on/off spraying threshold values to the final weed coverage measured after two spraying sessions. D) Estimation of herbicide usage tries to bring the derived model from the previous subsection into play by linking it to the nozzle activity and thereby creating the basis for estimating the herbicide usage in relation to the MoDiCoVi threshold value.

A. Evaluating Experimental Layout

The trial setup aims at providing the statistical basis for evaluating the weed control effect of the different treatment types and simultaneously measure the herbicide usage. Only the parts relevant for understanding the data basis for analysis of MoDiCoVi will be addressed here. The full experiment is described in details by Laursen et al. [16].

The trial has three experiemental variables, treatment, seeded/non seeded weeds and camera placement. Treatment has 7 levels, defined by no spraying, full dose and five threshold leves set based on weed leaf coverage. Seeded / non seeded weeds has two levels, discriminating whether additional weeds besides the naturally occuring weeds has been seeded (Oil-seed Rape (*Brassica napus* L.), Corn Marigold

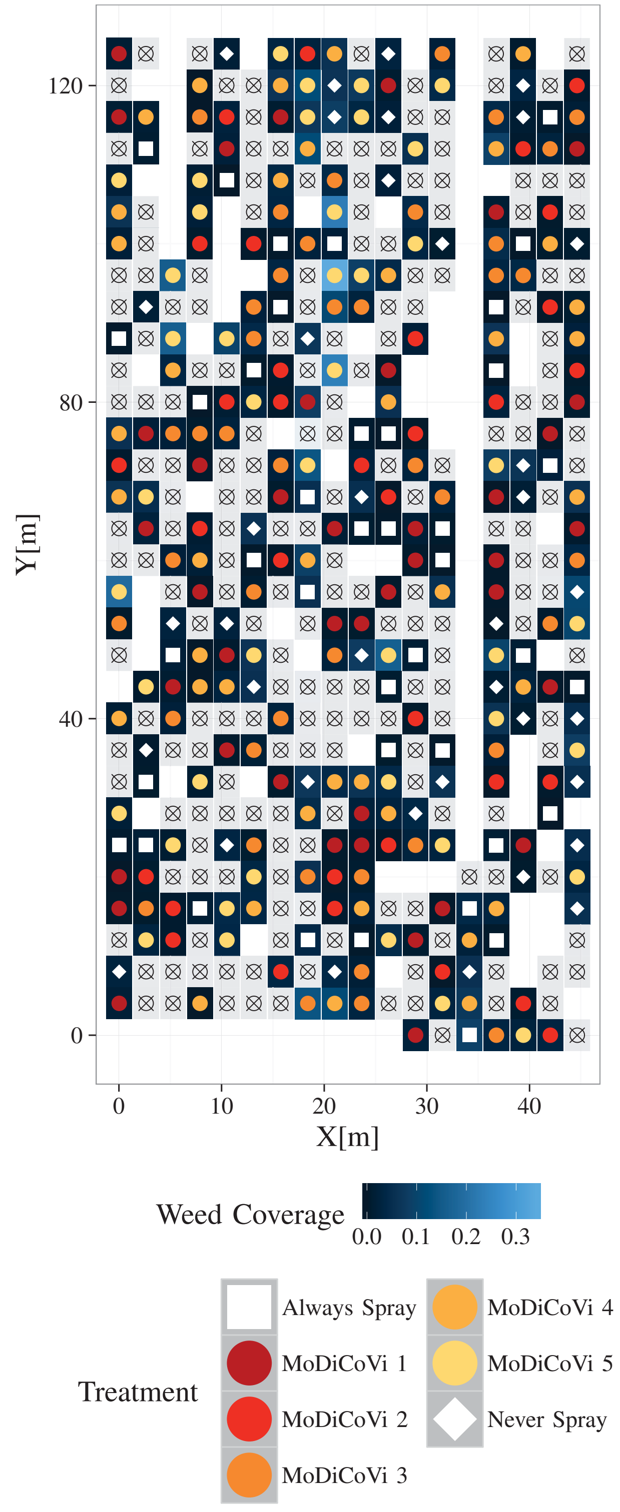

Fig. 2 Overview of trial layout, where squares indicate the ground truth and circles indicate the MoDiCoVi treatments; crossed out circles indicate parcels that are part of a different experiment and blanks indicate parcels that are considered outliers

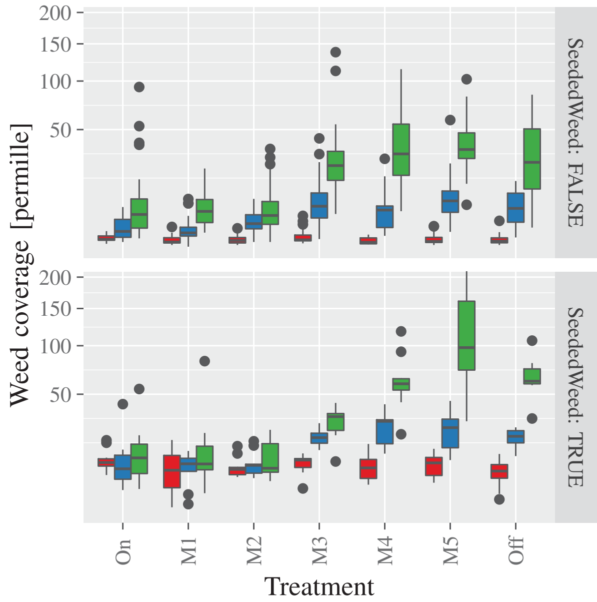

Fig. 3 Weed coverage per area, measured at each session. The scan sessions red, blue, green, corresponding to first to third imaging acquisition. X-axis labels On, M1, ..., M5, Off indicate 100% of the parcel is sprayed, the five MoDiCoVi threshold values for the relative weed coverage, and no spraying of the parcel, respectively

(*Chrysanthemum segetum* L.), and Fat Hen (*Chenopodium album* L.)). Camera placement has two levels which is either centered above the crop row and centered between two crop rows.

The field was divided into parcels measuring 3 m x 4 m (oriented along the driving direction). In total, 299 parcels were randomly assigned with the 28 different treatment combinations. On June 4th 2013, the maize (*Zea mays* cv. Labriora) crop were seeded with a row distance of 750 mm and a seed spacing of 100 mm corresponding to approximately 13 plant m^{-2}. A maize field located at Flakkebjerg, Denmark (GPS coordinates to the field 55.326453N, 11.382436E) was used for the field trial. The herbicide MaisTer (300 g/kg a.i. foramsulfuron + 10 g/kg a.i. iodosulfuron + safener 272 g/kg a.i. isoxadifen, Bayer CropScience DK) was applied with maximum doses of 75 g/ha at the first application date and a max dose of 150 g ha-1 at the second application date. The herbicide application was carried out on June 20th 2013 and on July 2nd 2013 corresponding to 16 and 28 days after seeding. Images were recorded for the whole area of the potentially sprayed part of the parcels. The image recording was performed simultaneously with the two spraying sessions, and was the same images as the spraying algorithms were using. Seven days after the second herbicide application (July 11th 2013, 35 days after seeding) images were acquired in a similar manner as for the first and second spraying session.

B. Data Pre-Processing and Visualisation

The 4 x 3 m parcels used by the automated execution control and spraying system were reduced to the width of the three

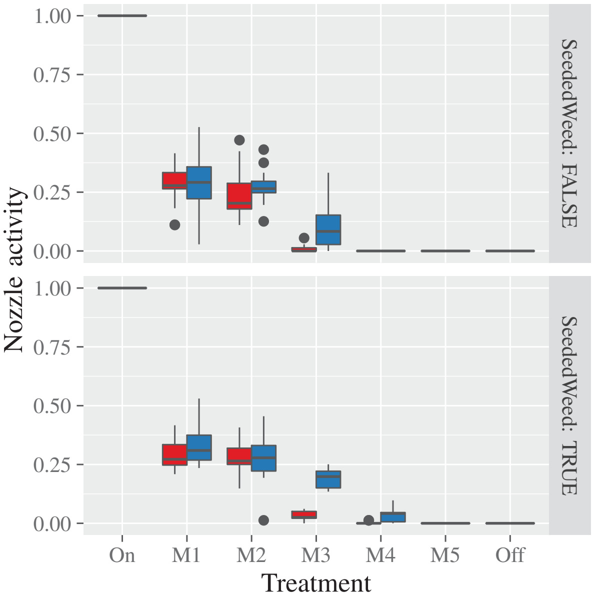

Fig. 4 Nozzle activity for the two spraying sessions, red for the first and blue for the second spraying session. X- axis labels On, M1, ..., M5, off indicate 100% of the parcel is sprayed, the five MoDiCoVi threshold values for the relative weed coverage, and no spraying of the parcel, respectively

spray nozzles and by half a meter entering and leaving the parcels. Hence, the dimension of the net parcels were 3 x 0.75 m. Initial outlier detection of parcels to be excluded due to the spraying implement carrier using too short or too long time passing through the 3 m net parcels was done by removing upper and lower 5 % incidences. For further details see Laursen et al. [16]. In order to know the weed coverage in each parcel, a band of 146 mm to either side of the center of the crop rows mark the area which is to be considered part of the maize row. In order to allow plant leaves to extend beyond the marked area, only the centroid of each plant (defined using blob labeling) must be within the marked area to be considered a maize - otherwise it is considered weed. From this the weed coverage area was estimated by counting the number of segmented pixels not counted as belonging to the maize row. For further details see Laursen et al. [16]. The statistical software environment R [21] was used for pre-processing of data and visualisation of the initial findings. The estimated nozzle activity was estimated based on the recorded spraying log files as the ratio between the on/off nozzle time within the 3 m long net parcels. The estimated weed coverage within a parcel were based on the estimated inter row band counting the segmented vegetation pixels based on Excess Green [22]. The results for nozzle activity and estimated weed coverage were illustrated using standard R boxplot grouped by treatment combinations defined by on/off MoDiCoVi spraying decision algorithm threshold values (inclusive 0% and 100% control spraying) and on/off seeded weed strips.

Laursen et al. [16] pointed out that only 64% of the planned weed strips was seeded, because of a limited amount of

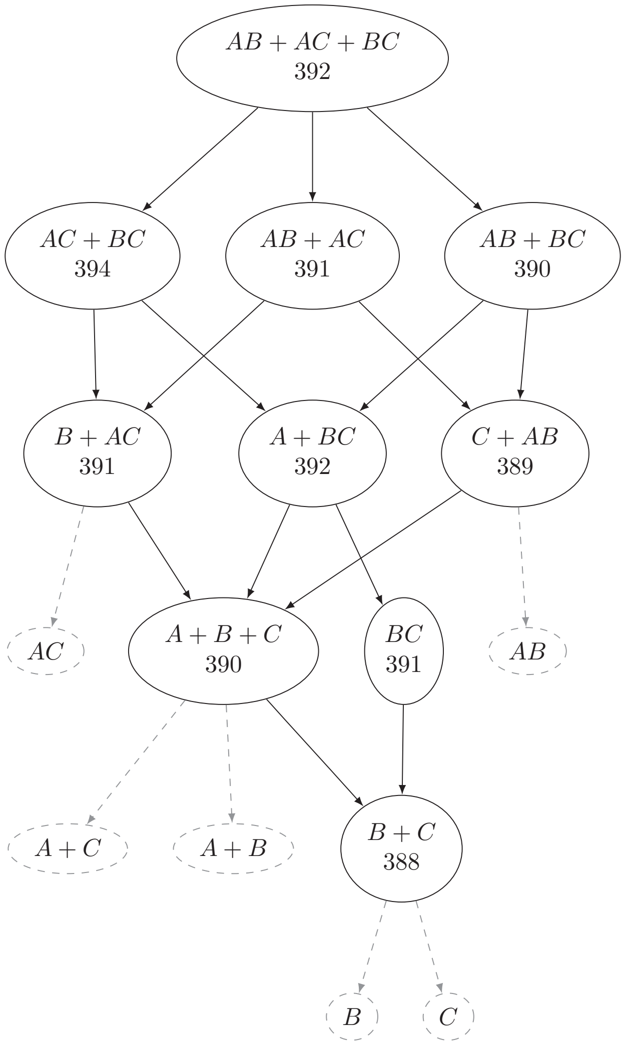

Fig. 5 Model reduction, A: Seeded Weed; B: Threshold; C: Weed Coverage, white nodes and black arrows indicate valid paths, gray indicates invalid paths. The AIC value of each node is denoted within the node with the label. Validity is determined by the 95% confidence intervals, as determined by the bootstrapping

available seeds. In this trial the weed seeding was done to guarantee weed growth in the parcels. Before execution of the actual spray procedure it became clear that the natural weed growth in the parcels where sufficient even without the seeded weeds. Studying the nozzle activity plot and weed coverage plot in Laursen et al. [16], there was no clear difference between the camera locations relatively to the crop row for the MoDiCoVi treatments. Hence, this effect is ignored in this analysis increasing the number of replicates to the range of 11 to 18 and 22 to 34 for parcels with seeded and no seeded weeds, respectively.

C. Statistical Analysis and Modelling

The potential spatial bias will not be modelled within this analysis but minimised by the randomised split plot design and a relative high number of replicates. The temporal dependence

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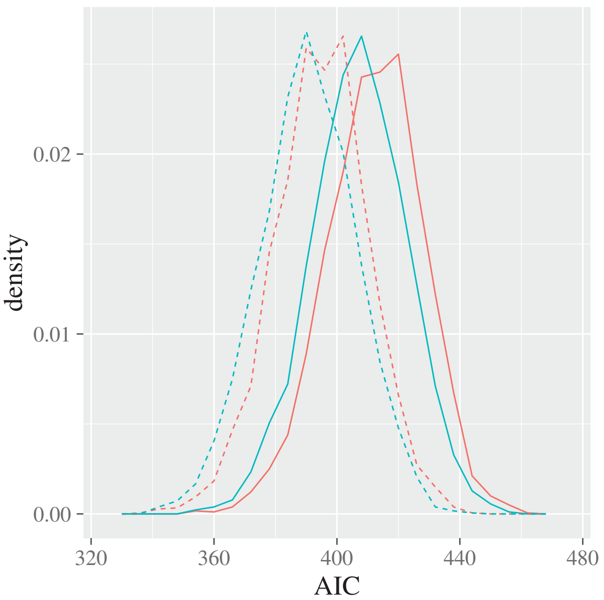

Fig. 6 AIC values determined by 3,000 bootstrap counts. Dashed, solid, red, and blue lines are the heteroscedastic, homoscedastic, full, and reduced models, respectively

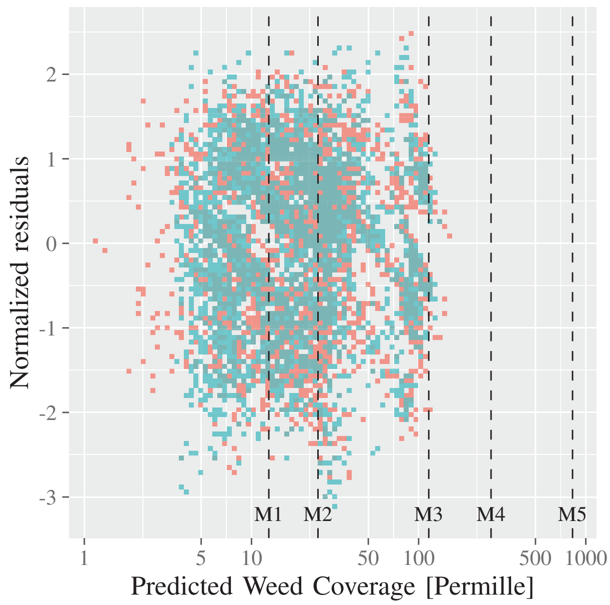

Fig. 7 Residuals of the full model compared to the reduced model; the full model and reduced models are shown in red and blue, respectively. The additional labels M1,..., M5 indicate the five MoDiCoVi threshold values for relative weed coverage

caused by two spraying sessions including image acquisition plus the third session with only image acquisition must be taken into consideration when designing the statistical model. The second spraying session will probably be influenced by the nozzle activity from the first spraying session. The weed coverage on the second and third session probably depend on the initial weed coverage and on the resulting nozzle activity controlled by the MoDiCoVi on/off spraying algorithm and its preset threshold values. This temporal dependence is handled in the statistical model by considering the two successive spraying sessions as a whole resulting in a final weed coverage measured on the last measuring session seven days after the second spraying session. Studying the weed coverage figure within part 1 of this work by Laursen et al. [16] indicates that the variation increases as the weed coverage increase. Hence logarithm transformation of the weed coverage should be considered. The threshold values will be treated as covariates creating the basis for interpolation between the current five MoDiCoVi threshold values. Threshold level 5 results in that the nozzles were never activated during both spraying sessions (see Fig. 4). Therefore, the control parcels never sprayed were merged with the MoDiCoVi threshold M5 parcels and all considered as threshold M5 parcels.

The initial model consists of the response variable in form of the logarithm of weed coverage measured in the third session logWeedCoverageT2 and 3 predictor variables; The on/off factor variable SeededWeed setting whether weed have been seeded within the parcel; the independent covariate Threshold spanned by 6 resulting spraying intensities: (100% sprayed parcels and MoDiCoVi on/off spraying algorithm with the five threshold values (M1,... M5) (Note M5 also includes the never sprayed parcels); and last the logarithm of initial weed coverage logWeedCoverageT0 measured during the first spraying session. In addition all two-way interactions between the predictor variables are included into the model. As the variance seems to vary depending on the treatment a heterogeneous model is used depending on the Threshold and whether there is SeededWeed present.

$$\begin{aligned} log(WeedCoverageT_{i,j}) = \beta_0 & \\ + \beta_1 & \cdot SeededWeed_j \\ + \beta_2 & \cdot Threshold_{i,j} \\ + \beta_3 & \cdot logWeedCoverageT0_{i,j} \\ + \beta_4 & \cdot SeededWeed_j \\ & \cdot Threshold_{i,j} \\ + \beta_5 & \cdot SeededWeed_j \\ & \cdot logWeedCoverageT0_{i,j} \\ + \beta_6 & \cdot Threshold_{i,j} \\ & \cdot logWeedCoverageT0_{i,j} \\ + \epsilon_{i,j} & \end{aligned} \tag{1}$$

Where $log(WeedCoverageT2_{i,j})$ is the weed coverage at time $T2$ of the i^{th} observation in variance class j used to model the heterogeneity and defined at the combination of $SeededWeed$ and $Threshold$ values $\epsilon_{i,j} \sim N(0, \sigma^2_{i,j})$ $j = 1, 2, ..., 11$. Bootstrapping was used balancing the number of replicates within the 7 different treatment combinations by randomly selecting 10 samples for each combination. The number of bootstraps were set to 3000 by studying the resulting bootstrap data graphically while increasing the number of bootstraps in accordance to chapter 6 in Efron and Tibshirani [23]. The bootstrapping were used for estimating the model parameters including the Akaike Information Criterion (AIC) and the confidence of these. Based on AIC from the bootstrapping it is evaluated if the model including the variance heterogeneity can be reduced to a model with homogeneous variation assuming $\epsilon_{i,j} \sim N(0, \sigma^2_{i,j})$. Hereafter, model reduction is performed using stepwise evaluation if the 95% confidence interval of a bootstrapped parameter contains zero. All possible model reductions is automatically evaluated and diagrammed. Based on possible paths in the model reduction diagram, the simplest model is selected which still includes all systematic implied terms like $SeededWeed$ and $Threshold$ even though $SeededWeed$ was proven not to be significant to the model.

D. Estimation of Herbicide Usage

In order to estimate the herbicide usage at the different threshold levels, the recorded images are reevaluated at four initial weed coverage $logWeedCoverageT0$ intervals of interest. The parcels were sorted according to the initial weed coverage and the lower and upper 5% of the parcels were removed. The remaining 90% of the parcels were then split into four groups each containing 25% of the remaining parcels. To estimate how much herbicide was applied within each of the latter four sub groups during the first session the average is taken over treatment combinations. However, the second session is expected to be dependent on the treatment from the first session. Therefore, the second session is calculated as a weighted average of the usage based on the parcels which are treated with the closest threshold just above and just below the current threshold. The fraction of full dose herbicide usage is defined as the usage during the first plus the usage during the second session compared to a usage where the field is only sprayed once using broad spraying. The threshold levels are compared to the estimated increase in weed coverage based on the developed statistical model.

III. Results

At the time of the first spraying date, a significant effort had been put in the integration between the Armadillo tool carrier, the grid spraying implement and its internal sub components, and the calibration and trimming of the dicotyledonous weed quantifying algorithms. The day up till this date had been rainfull and the window to perform the spraying session was restricted to one afternoon due forecasted showers the following day. As a consequence there were not time to collect a calibration dataset from the field. It was decided to use the parameter settings obtained from the previous growth season due to the lack of a calibration dataset and the narrow window to execute the first automated spraying session. The dataset used were based on Laursen et al. [14] which were from another field and growth season but still relatively similar to the conditions experienced. Due to the heavy rain causing saturated soil, prior to the first spraying day, the tracks were filled with clay mud and at one occasion the Armadillo also got stuck resulting in a two hours delay and several disturbed parcels which had to be excluded from the trial. Further details are given by Laursen et al. [23].

A. Data Pre-Processing and Visualisation

The logfile from third session, during which only images were acquired, contained significantly more extremes with regards to the average time used passing a net parcel. Hence the 90% quantile used for session 1 and 2 were narrowed removing additional 5% of the slowest passing times. A crude filtering of parcels with an unusual low or high amount of initial weed coverage at the first spraying session is also be considered outliers and excluded permanently from the analysis. Therefore, parcels below the 2.5% quantile is regarded as outliers. As a result 62 parcels have been rejected in total resulting in the number of treatment replicates were between 8 and 24 replicates and between 9 and 24 after merging M5 and never spraying parcels.

Fig. 3 shows the weed coverage for each of the three sessions despite the two spraying session is considered as a whole for the statistical analysis. This eases the possibility of identifying temporal trends. First of all, the M5 and Off treatments seems similar except for the weed coverage for M5 with seeded weed where the level seems relatively high with the highest variation of all. At spraying session 1 the weed coverage for the parcels with no seeded weed is very similar with regards to level and variation whereas the level is shifted from approximately 0.3 permille with no seeded weed to approximately 7.9 permille and a higher variation when weeds had been seeded. For session 2, there seems be a shift in the weed coverage going from M2 to M3, it seems to be independent of seeded weed. Hereafter the weed coverage for M4, M5, and Off settles at a higher level or plateau. For session 3 the latter shift in weed coverage seems to transcend between M2 and M4 and then settle after M4. Within session 3 the variation in the weed coverage for the no seeded weeds group seems more uneven and heterogen between the different treatment combinations. There is however a tendency to increasing variation with increasing threshold equal to a decreasing spraying activity as seen in Fig. 4 whereas the opposite is the case for seeded weeds (except for the M5).

The nozzle activity in Fig. 4 for session 1 seems similar independent of $SeededWeed$ with a decrease in the activity beginning at approximately 25% for M1 and ending at 0% close to M3. Looking close the nozzle activity tend to have a higher activity in the seeded weed case and most evidence for M3. Session 2 shows similar trends as session 1 in the nozzle activities except for a minor upward shift which becomes more clear with increasing threshold levels. For session 2 there is a clear difference between the seeded and not seeded weed parcels in the nozzle activity with a higher activity in the seeded weed cases for M3 and M4 threshold levels.

B. Statistical Analysis and Modelling

The model reduction based on 3000 bootstraps per possible model reduction is illustrated in Fig. 5. The different paths descending from the full model towards simpler models all agrees meaning no single path terminated prematurely

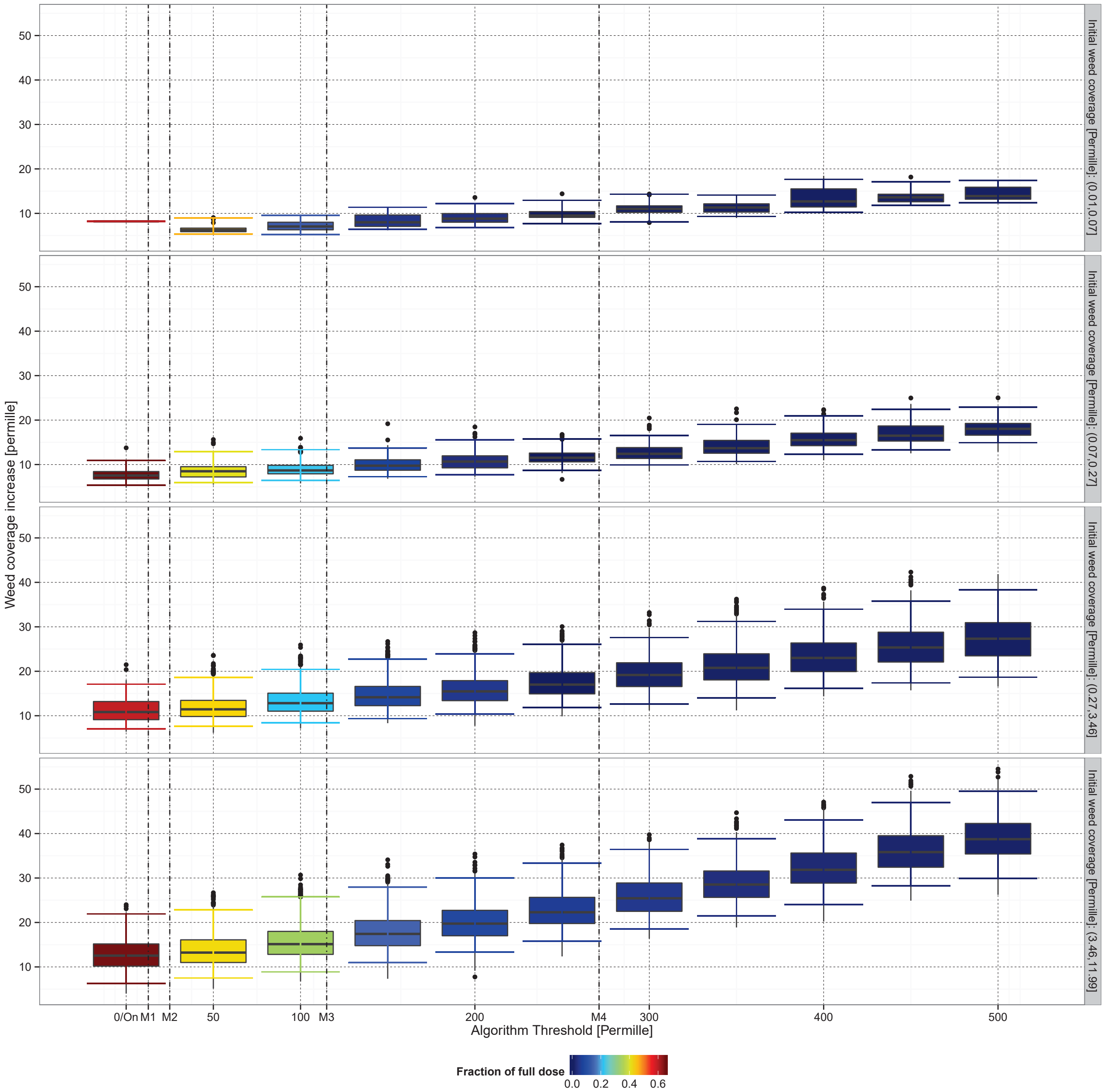

Fig. 8 Predicted increase in weed coverage based on reduced model, showing the herbicide usage that the system would have sprayed with for each threshold level. Additional x-axis labels M1, ..., M4 indicate the first four MoDiCoVi threshold values for the relative weed coverage. Divisions for the subplots have been chosen by the 5%, 25%, 50%, 75% and 95% quantiles of the initial weed coverage, thereby excluding the lower and upper 5% of the data

compared to other paths. The illustrated successive model reduction terminates at a model only containing the threshold term and the logarithm to the initial weed coverage $logWeedCoverageT0$. However, the reduction of $SeededWeed$ is not valid since this term is a systematic and integrated part of the field trial. Therefore, the simplest possible and acceptable model is purely additive consisting of the independent terms $Threshold$, $SeededWeed$, and $logWeedCoverageT0$ corresponding to node A+B+C in Fig. 5.

Based on the AIC values obtained from the bootstraps the effect of simplifying the variance structure from heterogeneous to homogeneous is illustrated in Fig. 6. For both the full model and the reduced models AIC increases assuming homogeneous variance structure and the more complex variance structure is maintained.

Studying the normalised residuals for the full model and the reduced model in Fig. 7 indicates both models are performing well and is not indicating any clear trends. The most obvious difference between the initial mode and the reduced model seems to be the reduced model is not capable of predicting the lowest weed coverages $logWeedCoverageT2$

TABLE I
MODEL PARAMETERS FOR (2)

Coefficient	5%	Mean	95%	P-value
$\beta_1[intercept]$	-4.57	-3.03	-1.03	0.01
$\beta_2[SeededWeed]$	-0.68	0.25	1.01	0.29
$\beta_3[Threshold]$	1.23	1.85	2.47	0.00
$\beta_4[WeedCoverage]$	0.05	0.24	0.48	0.05

TABLE II
MODEL PARAMETERS FOR (3)

Coefficient	5%	Mean	95%	P-value
$\beta_1[intercept]$	0.01	0.05	0.36	0.01
$\beta_2[SeededWeed]$	-0.49	0.28	1.74	0.29
$\beta_3[Threshold]$	1.23	1.85	2.47	0.00
$\beta_4[WeedCoverage]$	0.05	0.24	0.48	0.05

less than approximately 3 permille at the last measuring session. The final model and estimated parameters including 95% confidence levels is given in table I. This model is used estimating the overall herbicide usage in the next sub section.

$$\begin{aligned} logWeedCoverageT2 = \beta_1 \\ + \beta_2 \cdot SeededWeed \\ + \beta_3 \cdot Threshold \\ + \beta_4 \cdot logWeedCoverageT0 \end{aligned} \quad (2)$$

The interpretation of table I in the log space might be hard. Therefore table II is table I rewritten with direct weed coverage in accordance to Carrol and Ruppert [24]. From table II the resulting weed coverage $WeedCoverageT2$ can be seen to depend on the initial weed coverage $WeedCoverageT0$ exponentially by β_4, in the dataset values between 0-12 permille was typically observed resulting in a contribution of 0-0.35. The effect of $SeededWeed$ is either 0 or 300‰ relatively increase in the resulting weed coverage whereas the Threshold value ranging from 0 to 0.5 increase the resulting weed coverage 2500‰. Therefore if weed has been seeded the resulting weed coverage will shift an approximately 280‰ higher weed coverage. However this relatively high shift is far from conclusive taking the confidence interval into consideration.

$$\begin{aligned} WeedCoverageT2 = \beta_1 \\ \cdot WeedCoverageT0^{\beta_4} \\ \cdot (1 + \beta_2 \cdot SeededWeed) \\ \cdot e^{\beta_3 \cdot Threshold} \end{aligned} \quad (3)$$

C. Estimation of Herbicide Usage

Fig. 8 illustrates the modelled overall nozzle activity a.k.a. herbicide usage for the two spraying sessions based on (2). The figure is grouped by the 5%, 25%, 50%, 75% and 95% quantiles of the initial weed coverage. The majority of the parcels have a relatively low weed coverage and including the seeded weeds parcels this creates a relatively left screwed and long tailed distribution. As a consequence the width of the four initial weed coverage grouping is increasing in a close to exponential speed starting with a 0.06 permille range for the first group and ending with a 8.50 permille range for the last grouping. The first two grouping contain no seeded weed parcels whereas the third is a mixture of parcels with and without seeded weed, and the fourth group contains only parcels width seeded weed.

Overall the resulting weed coverage seems not to increase compared to 100% spraying up till threshold level M3. This gives a mean potential herbicide savings of approximately 80% except for the last group only consisting of parcels with seeded weed where the potential savings decline to approximately 70%. If only looking at the first two groups with a relatively low initial weed pressure it looks like there is not a visually significant increase in the resulting weed pressure up till a threshold value of approximately 200 permille. This would have resulted in potential herbicide savings of approximately 95%. These simulated results seems well aligned with the visual interpretation of Figs. 3 and 4.

IV. DISCUSSION

This work together with Laursen et al. [23] indicates significant herbicide savings using MoDiCoVi. The results is based on a dataset of 325 parcels with 7 treatment combinations. Compared to visually obvious herbicide savings the statistical modelling and simulations added additional insight. The model reduction did indicate the MoDiCoVi algorithm was capable of handling the seeding of additional weeds.

The sprayed weeds did not disappear prior to the next spraying and measuring session. The sprayed weeds stopped growing but maintained their green color. At the last measuring session 19 days after the first spraying session some of the parcels with seeded weed did show a negative growth in the weed coverage (not shown). Hence it might have been beneficial for the analysis to have had an additional measuring session. However, the growth of the maize crop closing the interrow area would have complicated this. It is a potential factor, however, the weeds sprayed does not disappear between successive spray sessions. Despite of this the achieved potential savings of 70% to 95% depending on the initial weed coverage is remarkable. This work does not show the impact on the maize yield and quality when potentially saving more than 70% herbicide compared to the conventional spraying of the whole field. Due to the coming rain (as predicted by the weather forecasts) and the crop growth stage at the first spraying session the parameters for the MoDiCoVi algorithm were based on a training from another field the previous growth season Laursen et al. [23]. Despite of this the algorithm performance studying the results were positive with respect to the obtained herbicide savings. So one might say the results are based on two growth seasons where the first season were the training set for the algorithm and the growth season presented and analyzed here were the validation dataset. Furthermore, the savings are in the better part of the savings documented e.g. by Gerhards and Oebel [9] and Berge et al. [3] who achieved herbicide savings between 18% and 97%.

Seefeldt et al. [25] argued the log-logistic model possesses several clear advantages over other analysis methods and suggests it should be widely adopted as a standard herbicide dose-response analysis method. The log-logistic model is not limited to herbicide based studies with plants. Ascard [26] used the model for analyzing the effect of flame weeding on plant size and density. Seefeldt et al. [25] notes that in any case, nonlinear models describing biologically realistic dose-responses are to be preferred over essentially invalid models such as straight lines, polynomials, or inverse polynomials. One of the main advantages of the log-logistic model is that its parameters are biologically meaningful when applied to plant responses to herbicides. Ascard [26] also noticed there were a clear difference in the dose response curves. Even a low, sublethal dose will result in a reduction in fresh weight, whereas a certain dose is needed to reach the sensitive parts and thereby kill a plant completely. This difference will also need to be handled if adapting the MoDiCoVi plot trial design to the log-logistic model. One main difference to classical herbicide dose response trials Seefeldt et al. [25] primary advocate for and also with concern to the flame weeding Ascard [26] is the discrete on/off nature of MoDiCoVi compared to a changing dose applied to the whole field or parcel. Furthermore, the multiple spraying sessions complicate the adoption to log-logistic model setup. According to Seefeldt et al. [25] a minimum of seven logarithmic distributed doses or threshold values to ensure the inclusion of doses near the dose that causes 50% response (I50) and to allow for possible shifts in the curve from one experiment to another. Studying the result in this work also suggest a potential benefit of increasing the number of MoDiCoVi threshold values. However, the most important factor to address is the number of replicated field trials, to span a wider range of weed populations and densities. The primary focus of this work and Laursen et al. [16] were to evaluate the performance of the dicotyledonous weed coverage quantification and the resulting herbicide saving. Therefore, artificial and diffuse illumination and relatively low velocities were used maximising the segmentation quality and the spraying precision. In order for a future commercial MoDiCoVi based real time precision spraying system to work the system needs further maturing. The weakest point is the image acquisition part under natural lighting assuming mounted on a commercial sprayer boom with a forward speed of 2-3 m/s. Weis and Gerhards [27] showed it was possible to acquire images under natural light condition with 2.2 m/s and a resolution of 4 mm pixel^{-1} which is significant for the MoDiCoVi to operate. Laursen et al. [28] shows a camera system capable of capturing images at 50km/h at 4.4mm pixel^{-1}. So the technology is present but the cost implementing 100% visual coverage of for example a 36 m sprayer boom is still far too high. Maize is a row crop with plenty of interrow space. Hence several non imaging systems like WEEDit [29] and WeedSeeker search to utilise this by only quantifying the NDVI response and then extrapolate into the interrow area [30], [31]. Trial results of these non imaging systems indicated this extrapolation is not feasible [32] calling for the necessity of algorithms like MoDiCoVi.

V. Conclusion

Compared to visually obvious herbicide savings the statistical modelling and simulations added additional insight. The model reduction did indicate the MoDiCoVi algorithm is capable of handling the seeding of additional weeds. However the sprayed weeds didnt disappear prior to the next spraying and measuring session. The sprayed weeds stopped growing but maintained their green color.

The achieved potential savings of 70% to 95% depending on the initial weed coverage is remarkable. This work together with Laursen et al. [16] indicates significant herbicide savings but additional field trials are needed to prove this. By studying the results presented here the MoDiCoVi algorithm performance indicates there is a potential of significant herbicide savings. One might say the results are based on two growth seasons where the first season were the training set for the algorithm and the growth season presented and analysed here were the validation dataset.

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