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Site and time-specific early weed control is able to reduce herbicide use in maize - a case study

Nebojša Nikolić,¹ Davide Rizzo,^{2,3} Elisa Marraccini,² Alicia Ayerdi Gotor,⁴ Pietro Mattivi,⁵ Pierre Saulet,⁶ Antonio Persichetti,⁷ Roberta Masin¹

¹Department of Agronomy, Food, Natural resources, Animals and Environment - DAFNAE, University of Padova, Legnaro (PD), Italy; ²InTerACT (UP 2018.C102), UniLaSalle, France;

³Agricultural Machinery and New Technologies, UniLaSalle, France; ⁴AGHYLE (UP 2018.C101), UniLaSalle, France; ⁵Department of Civil, Chemical, Environmental, and Materials Engineering (DICAM), University of Bologna, Bologna, Italy; ⁶Geolab, UniLaSalle, France; ⁷Archetipo s.r.l., Padova, Italy

Correspondence: Nebojša Nikolić, Department of Agronomy, Food, Natural resources, Animals and Environment (DAFNAE), University of Padova, Viale dell'Università 16, 35020 Legnaro (PD), Italy.

E-mail: nebojsa.nikolic@phd.unipd.it

Key words: Precision weed control; remote sensing; predicting weed emergence; *Sorghum halepense*; maize.

Highlights

- *Efficacy of UAVs and emergence predictive models for weed control has been confirmed.*
- *Combination of time-specific and site-specific weed control provides optimal results.*
- *Use of timely prescription maps can substantially reduce herbicide use.*

Abstract

Remote sensing using unmanned aerial vehicles (UAVs) for weed detection is a valuable asset in agriculture and is vastly used for site-specific weed control. Alongside site-specific methods, time-specific weed control is another critical aspect of precision weed control where, by using different models, it is possible to determine the time of weed species emergence. In this study, site-specific and time-specific weed control methods were combined to explore their collective benefits for precision weed control. Using the AlertInf model, which is a weed emergence prediction model, the cumulative emergence of *Sorghum halepense* was calculated, following the selection of the best date for UAV survey when the emergence was predicted to be at 96%. The survey was executed using a UAV with visible range sensors, resulting in an orthophoto with a resolution of 3 cm, allowing for good weed detection. The orthophoto was post-processed using two separate methods: an artificial neural network (ANN) and the visible atmospherically resistant index (VARI) to discriminate between the weeds, the crop and the soil. Finally, a model was applied for the creation of prescription maps with different cell sizes (0.25 m², 2 m², and 3 m²) and with three different decision-making thresholds based on pixels identified as weeds (>1%, >5%, and >10%). Additionally, the potential savings in herbicide use were assessed using two herbicides (Equip and Titus Mais Extra) as examples. The results show that both classification methods have a high overall accuracy of 98.6% for ANN and 98.1% for VARI, with the ANN having much better results concerning user/producer accuracy and Cohen's Kappa value (k=83.7 ANN and k=72 VARI). The reduction percentage of the area to be sprayed ranged from 65.29% to 93.35% using VARI and from 42.43% to 87.82% using ANN. The potential reduction in herbicide use was found to be dependent on the area. For the Equip

herbicide, this reduction ranged from 1.32 L/ha to 0.28 L/ha for the ANN; with VARI the reduction in the amounts used ranged from 0.80 L/ha to 0.15 L/ha. Meanwhile, for Titus Mais Extra herbicide, the reduction ranged from 46.06 g/ha to 8.19 g/ha in amounts used with the ANN; with VARI the reduction in amounts used ranged from 27.77 g/ha to 5.32 g/ha. These preliminary results indicate that combining site-specific and time-specific weed control, has the potential to obtain a significant reduction in herbicide use with direct benefits for the environment and on-farm variable costs. Further field studies are needed for the validation of these results.

Introduction

Since its early beginnings, agriculture has been constantly changing and evolving, and the same trend continues to this day (Thrall *et al.*, 2010). Throughout the ages, the human population has been cultivating plants, always searching for an economic and environmentally sustainable way to produce. For this purpose, different tools, equipment, and crop management practices have been created (Lobley and Potter, 2004; Gaillard, 2005; Paul and Nehring, 2005; Ricroch *et al.*, 2014). Weeds, the unwanted plants that spontaneously emerge alongside crops, are one of the biggest constraints to crop production. Because of their biology and evolutionary path, they are more competitive than traditional crops and therefore, they have a detrimental effect on crop yield (Radosevich *et al.*, 2007; Holt, 2013; Lingenfelter and Hartwig, 2013). Weeds can cause serious losses by competing for natural resources, but can also serve as potential hosts for a variety of harmful organisms (Radosevich *et al.*, 2007; Zimdahl, 2007; Cerrudo *et al.*, 2012). In some cases, the percentage of yield loss caused by weeds can reach up to 84% (Imoloame and Omolaiye, 2017). In light of the fact that the negative economic impact is measured in billions per year (Soltani *et al.*, 2016), it is not surprising that significant effort has been placed into finding the best way to control these unwanted plants. Today, the measures used for weed control can mostly be grouped into two categories. Mechanical control, which involves the use of different tools and machines to mechanically remove and/or destroy weeds; and chemical control, which involves the use of different chemical formulations (herbicides), with the same aim

(Arriaga *et al.*, 2017; Peruzzi *et al.*, 2017; Zimdahl, 2018). Other important weed controlling techniques include also agronomic, physical and cultural weed control. For agronomic techniques it is important to mention crop rotation and row spacing, while physical methods may include using the heat for weed control such as using the flames or steam (Astatkie *et al.*, 2007). Finally, cultural methods involve selecting the right variety, cultivar or hybrid that can compete with plants and maybe even help the weed suppression, for example growing faster and creating the canopy that can shade the weeds (Melander *et al.*, 2005). Although mechanical agronomic, physical and cultural weeding measures can be very efficient, they are not as effective as chemical weed control methods and should be used as a part of a holistic approach (Mohler, 1996; Weis *et al.*, 2008). Further on, mechanical measures tend to be reduced or completely removed from newer production management systems, such as conservation agriculture, due to negative impacts such as soil compaction and disturbance. In addition, these operations may raise the production costs (e.g. machine maintenance, fuel) and can also lengthen the times of agricultural production, considering different tillage operations that are necessary for the soil preparation before sowing (Raghavan *et al.*, 1990; Idowu and Angadi, 2013; FAO, 2014; Arriaga *et al.*, 2017; Hussain *et al.*, 2018). Therefore, use of chemical control methods has become the dominant technique for weed control, and in cases like for example in conservation agriculture, it is one of the few effective means of weed control. This means that the use of herbicides is always on the rise, and has been on an upward trend since their introduction (FAO, 2014; Vats, 2015; Zimdahl, 2018). The use of herbicides, however, has a number of negative effects on the environment brought on by leaching into soil and groundwater (Tiktak *et al.*, 2004; Gimsing *et al.*, 2019). This potentially leads to soil and water contamination, putting wildlife biodiversity at risk, and it can also be harmful for humans (Morales *et al.*, 2013; Hasenbein *et al.*, 2017; Gupta, 2018; Beasley, 2020). Herbicides can also enter the food chain via residues found on food, and may have serious adverse implications (Morales *et al.*, 2013; European Food Safety Authority, 2018). Today, the process of creating new herbicides is very slow due to the strict protocols imposed by the international organizations legislations such as FAO/WHO (FAO/WHO, 2016a, 2016b), and by national and

supranational laws regulating production and the use of pesticides, e.g. European Parliament (2009). In order to reduce the negative effects that future herbicides may have (Lyon *et al.*, 1996; Kudsk and Streibig, 2003). However, this has an adverse impact on traditional herbicide application, due to the development of weed resistance to herbicides currently in use (Heap and LeBaron, 2001; Holt, 2013; Sherwani *et al.*, 2015). All things considered, the use of herbicides in agriculture needs to be reshaped in order to guarantee not only their effectiveness, but also the stability of agricultural production, and reduce environmental impact. One of the possible solutions to this problem could be the implementation of precision agriculture, which could enable the reduction of herbicides by applying them only where and when needed, thanks to the technological progress and innovative tools available for weed detection (Lyon *et al.*, 1996; Zarco-Tejada *et al.*, 2014). Current limitations to the use of precision weed control in the field are the identification of weeds and the associated decision support systems. However, among precision farming adopters, Ayerdi Gotor and colleagues (Ayerdi Gotor *et al.*, 2020) have demonstrated that there is still poor use of these techniques for weeding. Given that weeds do not appear uniformly in space nor in time (Radosevich *et al.*, 2007; Zimdahl, 2007; Martín *et al.*, 2015; Santín-Montanyá *et al.*, 2015), it is important to address this issue from both the spatial and temporal points of view (Forcella *et al.*, 2000; Gerhards, 2013). Mapping the weeds in space has never been easy (Hanzlik and Gerowitt, 2016), but the development of unmanned aerial vehicles (UAVs) simplifies this task (Herwitz *et al.*, 2004; Giacomo and David, 2017). For this purpose some additional aspects could be exploited such as 3D model (Digital Surface Model), where different height of weeds and crops are used to discriminate between them (Stroppiana *et al.*, 2018). In fact, a number of studies worldwide have started implementing UAVs for weed mapping as a part of precision agriculture, with very promising results (López-Granados, 2011; Ballesteros *et al.*, 2014; Hassanein and El-Sheimy, 2018; Huang *et al.*, 2018; Lambert *et al.*, 2018; Maes and Steppe, 2019). Depending on the flight altitude and the sensors used, UAVs can provide images with a resolution of a few centimeters or less than a centimeter, allowing for useful weed classification (Torres-Sánchez *et al.*, 2013; Koot, 2014; Bareth *et al.*, 2015; Candiago *et al.*, 2015; Pérez-Ortiz *et al.*, 2015).

Moreover, images obtained in this way can serve as a basis for further analysis of weed spatial distribution (Borra-Serrano *et al.*, 2015; Pérez-Ortiz *et al.*, 2016). Weed emergence models have already been developed (Myers *et al.*, 2004; Colbach *et al.*, 2007; Dorado *et al.*, 2009), to identify correct time for an effective weed control. The introduction of such models in decision support programs can reduce herbicide use and weed control costs when compared with standard management practices (Forcella *et al.*, 2000). These models provide the percentage of cumulated emergence reached every day by weed species, and this information can be used to select the best timing for mechanical or chemical weed control methods to achieve maximum efficacy. One of these models, named “AlertInf” was developed in Italy by Masin and colleagues (Masin *et al.*, 2010). It uses the hydrothermal time concept (Bradford, 2002), in which the combination of soil temperature and soil water potential is the main factor driving germination (Masin *et al.*, 2010, 2012, 2014).

To our knowledge, no study (or very few studies) in the scientific literature so far have addressed the combination of spatial and temporal weed detection. This study aims to bridge this gap and to investigate the possible benefits of combining spatial and temporal approaches for precision weed control. In this experiment, UAVs were used to map the weeds present in a field, which were later identified with the help of spatial analysis software within a geographic information system (GIS). Afterwards, based on the weed location results, prescription maps were created to support site-specific weed control. The main novelty of our approach was to use the AlertInf model to predict the cumulative emergence of weed species present in the field, providing time-specific weed control, thereby allowing us to define the best flight date to map the weeds. Eventually, by implementing and combining site-specific and time-specific weed control techniques, the possible reduction of herbicide use was assessed.

Materials and methods

Study site

The experiment was conducted at the experimental farm “Lucio Toniolo” of the University of Padova

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at Pozzoveggiani locality, within the province of Padova in the Veneto region (northeastern Italy). The field morphology is flat and the soil is classified as Fluvic Cambisol (FAO, 2006). The local climate is sub-humid with an average temperature of 12 °C and 800–850 mm of rainfall, mostly during the autumn and spring months, based on the data from the Regional Agency for Environmental Protection (ARPA). In this field, a hybrid of maize (DKC 5530) was sown on the 7th of June 2019 with 75 cm interrow and 15 cm in-row spacing, while the previous culture was soybean Pioneer hybrid PR92M22, harvested on 11.10.2018. This late sowing date was due to very unfavorable meteorological conditions during the late spring/early summer period. Prior to sowing, different tillage operations, commonly employed for soil preparations, were performed. On the 9th of January 2019 weeding was performed using a grubber, on the 26th of February 2019 53 kg N/ha was applied as manure, corresponding to 36 Mg/ha of raw manure, on the 4th of March 2019 false sowing was executed using the rotary harrow, on the 4th of June 2019 shredding was implemented using a tiller, and on the 5th of June 2019 a rotary harrow was used.

UAV Survey

The flight was performed with the Matrice 100 UAV, coupled with DJI X3 and DJI X5 visible sensors (DJI Sciences and Technologies Ltd., Shenzhen, China), on the 19th of June 2019 when maize was at 10-11 BBCH stage. The flight was executed at a height of 35 m from the ground over an area of 1 ha, providing an orthophoto with a resolution of 3 cm. The orthomosaic was created with Pix4D software using the Gauss Boaga Monte Mario Italy Zone 1 (EPSG:3003) projected coordinate system. The result was an accurate orthophoto allowing a rather easy distinction between weed species and the surrounding elements (Figure 1).

Weed classification methodologies

Two different approaches were tested for weed classification: an artificial neural network (ANN) (OpenCV) using the SAGA GIS open source software (version 7.6.2), and the visible atmospherically

resistant index (VARI) using ArcGIS Pro software (version 2.2.0 ESRI - Environmental Systems Research Institute, Redlands, CA).

The OpenCV algorithm operates by performing a backpropagation, which is one of the most widely used methods for training artificial neural networks for diverse purposes (Sözen *et al.*, 2004; Murat and Ceylan, 2006; Elmolla *et al.*, 2010; Turan *et al.*, 2011). Backpropagation is an iterative process that consists of making a backward pass after each forward pass through the network, while making the relevant adjustments to the model's parameters, namely weights and biases (Rumelhart *et al.*, 1986). These adjustments are performed based on the training dataset; meaning, the classification process is stopped when the difference between the neural network classification and the training dataset is minimized. From an operational point of view, this is achieved when the difference between two subsequent iterations is lower than a certain threshold, or the prearranged maximum number of iterations is reached. The algorithm requires two inputs: (1) grid (raster) data, which are represented by the red, green, and blue (RGB) bands of the orthophoto obtained from the drone survey; and (2) the vector data defining the training areas, which are the detection targets. The detection targets (or labeled samples) were defined by manually tracing some of the weed spots as a polygon shapefile, in particular 11 polygons were traced scattered across the field comprising both single weeds and group of weeds in cases where they emerged closely, and a single weed couldn't be traced, the total area of these polygons was 2.21 m². The parameters to be set are: (i) the number of hidden layers of the neural network, (ii) the number of neurons of the hidden layers, (iii) the process stopping criteria (i.e., the maximum number of iterations and the minimum difference between the iteration threshold), and (iv) the activation function and learning rate parameters. Altogether, these parameters determine the structure and functioning of the OpenCV ANN (OPEN CV, 2014).

The VARI index was developed by a group of scientists at the University of Nebraska and its main purpose is to calculate the vegetation indices, whilst reducing the influence of atmospheric interference. It is based on a combination of the visible spectral bands (Formula 1) (Gitelson *et al.*, 2002).

$$\text{VARI} = (\text{Green}-\text{Red})/(\text{Green}+\text{Red}-\text{Blue}) \quad (1)$$

The VARI index is used for different purposes, mostly for measuring leaf area index (LAI) (Gitelson *et al.*, 2003), as well as for monitoring crop health and even estimating fire hazard potential (Schneider *et al.*, 2008; McKinnon and Hoff, 2017). However, in our research, the authors have not found references for the use of this index in weed detection. Similar to the OpenCV ANN, VARI was also computed on grid (raster) data, that is, RGB bands of the orthophoto obtained from the drone survey. The VARI index is designed to be minimally sensitive to atmospheric effects (Gitelson *et al.*, 2002; Schneider *et al.*, 2008). As so, we computed it directly on the raw digital number values of the UAV images, i.e., without converting to reflectance. In addition, the flight conditions were constant. However, for further comparison the illumination conditions might be considered to test transferability of the method.

In the derived raster each pixel was attributed with a VARI value ranging from -0.16 to 1.67. The raster was then classified into five classes using the optimization algorithm defined by Jenks. This algorithm minimizes the standard deviation within the single classes (i.e., the differences within each class) and maximizes the differences among classes, thus identifying so called "natural breaks". The Jenk's algorithm is suggested to provide neutral class delineation in early spatial data mining (Murray and Shyy, 2000; Irigaray *et al.*, 2007). Following, it was necessary to conduct a reclassification to achieve only two categories: non-weed and weeds. To this end, we identified the threshold value for pixels identified as weeds, by visually comparing the original orthophoto to the one with VARI values. Non-weed categories were the first three classes, corresponding to the interval of values $-0.16 \leq \text{non-weed} < 0.08$, while the weed categories were the last two classes, corresponding to the interval $0.081 \leq \text{weed} \leq 1.67$. The, Reclassify (Spatial Analyst) tool integrated in ArcGIS Pro was used to reclassify the pixels into the two categories, non-weed and weed.

Accuracy assessment

Image classification is one of the most frequently performed analysis on remote sensing data; because of this, classification accuracy has been widely addressed in literature (Foody, 2008). Nonetheless, there is still an open debate in the scientific community about the multiple accuracy methods developed so far. A widely established method for accuracy assessment is the confusion matrix (Foody, 2002), which essentially allows the comparison of classified values with reference values (called “field truth” or “ground truth”) by means of a contingency table (Cohen, 1960). In this study, the confusion matrix was computed within the SAGA GIS open source software (version 7.6.2). For each class, two in this case (i.e., weed and not-weed), the number of pixels is compared with the ones from the reference data (Story and Congalton, 1986). Reference data were produced by an expert classification through photointerpretation on the orthomosaic and was used for the assessment of both methods. The accuracy assessment based on the confusion matrix included the computation of the overall accuracy, the commission error (false positive rate) and the omission error (false negative rate), as well as Cohen’s Kappa that estimates the accuracy net of values due to chance (Congalton, 1991).

Estimation of weed emergence percentage

From the data gathered during the ground surveys seven days after sowing, when maize was in the initial growing stage (9-10 BBCH scale), that included the scouting for the weed species present, it was determined that plant infestation in the field was composed almost exclusively of *Sorghum halepense*. In order to determine the best time for a UAV survey, an AlertInf emergence predictive model was used. The soil temperature and daily precipitation levels comprised the AlertInf input data. Both the soil temperature, at 5 cm depth, and precipitation data were obtained from the meteorological stations of the Regional Agency for Environmental Protection (ARPA), located near the experimental field. Based on the data concerning the biology of *Sorghum halepense* and the meteorological data, AlertInf produced a cumulative emergence curve, showing the percentage of seedling emergence

reached by the species relative to each day (Figure 2).

Prescription maps

The creation of prescription maps was a three-stage process performed with ArcGIS Pro ModelBuilder, integrated in the ArcGIS Pro software (Figure 3). The first stage consisted of creating a precision spraying grid by dividing the field into regular cells. The cell size was chosen after considering the fundamental factors that determine the base area coverage for a sprayer: (i) the spraying angle, (ii) the altitude of the boom, and (iii) the possibility of controlling a single nozzle or a boom section (Bajwa, 2014; Gonzalez-de-Soto *et al.*, 2016; Kluza *et al.*, 2019; Partel *et al.*, 2019).

Three different cell sizes were defined based on the technical specifications of the most common models of sprayers for precision spraying available in the region (TOSELLI Srl; KUHN ITALIA S.R.L.; LEMKEN GmbH & Co. KG). These cell sizes were: 3.00 m², 2.00 m², and 0.25 m² (Figure 4).

The second stage comprised selecting the pixels classified as weeds in the outputs of the two weed classification methods (i.e., OpenCV ANN and VARI). Finally, in the third stage, each of the three precision spraying grids was intersected with the weed classification output to quantify weed infestation per cell. From here, each cell was classified (i) to be sprayed or (ii) not to be sprayed according to the weed infestation ratio. This classification was based on the three decision-making thresholds for spraying: more than 1%, more than 5%, and more than 10% of the pixels within a cell identified as weeds.

Herbicide use assessment

The prescription maps issued from the previous step were used to assess the potential herbicide use reduction for the different classification methods and decision-making scenarios. For this purpose, two herbicides were considered, both registered in Italy for use in maize fields and for the chemical control of *Sorghum halepense* ('Banca dati dei prodotti fitosanitari', 2020). The first one was Equip

(Foramsulfuron 2.33% = 22.5 g/L, Isoxadifen-etile 2.33% = 22.5 g/L), with a recommended dose of 2.3 L/ha, corresponding to 53.75 € on the market, and the second one was Titus Mais Extra (Nicosulfuron p.a. pure 30 g, Rimsulfuron p.a. pure 15 g, Coformulants q.b. 100 g), with a recommended dose of 80 g/ha, corresponding to 37.50 €. The prices are indicative of the 2020 market price. The quantity for each of the two herbicides (liters and grams) was calculated based on the area to be sprayed according to prescription maps and knowledge of how much product is needed for the whole field area, by using simple proportions. Following the same procedure, treatment costs were calculated. In this way, both the reduction in the quantity of herbicides used and the related variable costs were obtained.

Results and discussion

Using the AlertInf model, the cumulative emergence percentage for *Sorghum halepense* in the experimental field was obtained. It was decided to carry out the survey with the UAV on the date that AlertInf predicted 96% of species emergence, allowing for a good mapping and efficient weed control operations. The date was also suitable considering meteorological parameters for the drone flight, phenological stage of the crop, and planned agronomical operations.

The OpenCV ANN method outperformed the VARI method in weed classification. In particular, the ANN showed a commission error (false positive) for weed classification almost five times lower than the VARI. However, the OpenCV ANN algorithm underestimated the weed occurrence compared to VARI, with an omission error (false negative) of 19.4% versus 6.0%, respectively. The difference in commission/omission error between the two methods could also be one of the reasons to impact the choosing of one method over the other. From the environmentalist point of view it is probably better to use the OpenCV ANN that would indicate lesser use of herbicides even if it means letting some of the weed plants survive. From the farmers point of view however, it is probably better to use the VARI method, that although proposes the higher use of herbicides, it would also eliminate more weed, that could have a negative impact on the final yield if they are left untreated. Altogether, the

overall accuracy of both classification methods is very high and quite similar, with 98.6% for OpenCV ANN and 98.1% for VARI classification. However, Cohen's Kappa indicated that the OpenCV ANN stands a greater chance at being accurate than the VARI thresholding (Table 1).

The combination of three precision spraying grids and three spraying thresholds, produced nine prescription maps for each of the two orthomosaic classification methods: OpenCV ANN (Figure 5) and VARI (Figure 6).

Decision-making thresholds were chosen arbitrarily, considering the format of the data used, the weed species present, and agronomic information available. There are different kinds of thresholds and it is important to choose the one that is most suitable for the data being used (Coble and Mortensen, 1992). The most commonly used threshold is based on weed density, where the decision to spray is based on the number of weeds per area, which can be as low as 0.05 weeds/m² for some weed species (Auld and Tisdell, 1987; Zanin *et al.*, 1994; Sartorato *et al.*, 1996). For *Sorghum halepense*, this threshold is one plant per square meter (Roberts and Hayes, 1989; Ghoshen *et al.*, 1996). Due to the inability to effectively count plants, considering that the data is expressed in pixels, the thresholds have been translated into percentage of pixels that have been marked as weeds in a certain area. This was performed in a manner similar to that used in the study done by López-Granados and colleagues (López-Granados *et al.*, 2016), where thresholds chosen ranged from 0% to 15% of the pixels marked as weed/m². The three thresholds chosen are also very low because the cell sizes are either smaller or greater than 1 m², which is not an isolated case (Mortensen *et al.*, 1995; Keller *et al.*, 2014). Nevertheless, it requires thoroughly considering the thresholds to use, making them also comparable between different prescription maps created. These maps allowed for a comparison not just between the different cell sizes and decision-making thresholds, but also between the two classification methods. The possible reduction of the area to be sprayed and the differences in the area classified for spraying between the two classification methods were calculated for a field 1 ha large (Table 2). The reduction in the area to be sprayed using the prescription maps is significant compared to traditional spraying, which comprises spraying the entire field. Depending on the cell size and the

threshold percentage for decision making, the area reduction for spraying can go from 65.29% to 93.35% with the VARI classification, and from 42.43% to 87.82% with the OpenCV ANN classification. However, these data should be considered with caution, taking into account the classification precision, the level of infestation where, in the case of complete coverage by the weeds, blanket spraying might be the only option; and the potential damage that can be caused by the plants that could be skipped during the field treatment using this method. This may result in possible damage to crops caused by inadequate herbicide targeting (Hall *et al.*, 2000; Kudsk and Streibig, 2003; Wolf, 2009; Lottes *et al.*, 2017).

It is also important to emphasize that the decision-making thresholds have been set arbitrarily by the authors based on their experiences, in order to observe the changes in the area to be sprayed. Therefore, while they could, they should not necessarily be considered as thresholds to use. The progress in spatial detection of weeds is also followed by the progress in technologies for precise herbicide application, which is one of the key points allowing the creation of prescription maps and the reduction in the quantity of herbicides used (Gopalapillai *et al.*, 1999; Baillie *et al.*, 2013; Gerhards, 2013; Gonzalez-de-Soto *et al.*, 2016; Partel *et al.*, 2019). By modeling the possible reduction in cost and amount of the two herbicides used, it is evident that a reduction in their use is dependent on the reduction of the area to be treated. Therefore, it is also highly dependent on the classification precision and on the precision of systems for herbicide application, translated to cells of prescription maps. As so, we computed the reduction in the quantity and costs comparing the two classification methods, whilst considering different decision-making thresholds, both for Equip (Table 3) and Titus Mais Extra (Table 4). In the tables the cost of effective quantity needed for treatment of the area proposed by the methods is shown in the columns 'cost', while in the columns 'savings' it is shown how much money can be saved by treating only the area proposed by the methods compared to the cost of herbicides quantity necessary for the treatment of the whole field.

For Equip (Table 3), it is possible to see that there are great differences in the reduction of quantity used and in savings, between both the classification methods and decision-making thresholds. For the

OpenCV ANN classification, the quantity used can go from 1.32 L/ha to 0.28 L/ha, a significant reduction considering that with blanket spraying, the quantity used would be 2.3 L/ha. As a consequence, the savings can go from 22.81 €/ha to 47.2 €/ha, again an important cost reduction considering that for the traditional spraying, the cost would be 53.75 €/ha. As for the VARI classification, the quantity used can go from 0.80 L/ha to 0.15 L/ha, which is very notable considering the quantity needed for traditional spraying. Moreover, the savings are also very significant for VARI, going from 35.09 €/ha to 50.18 €/ha. Also for Titus Mais Extra (Table 4) is possible to observe important differences in the reduction of the quantity of herbicides used and in the associated savings, between both the classification methods and decision-making thresholds. For the OpenCV ANN classification, the quantity used can go from 46.06 g/ha to 8.19 g/ha, a very notable reduction considering that for traditional spraying, the quantity used would be 80 g/ha. Meanwhile, the savings can go from 15.91 €/ha to 32.93 €/ha, which is also very important considering that the cost would be 37.5 €/ha, for traditional spraying. For VARI classification, the quantity can go from 27.77 g/ha to 5.32 g/ha, both much lower than the 80 g/ha required for blanket spraying. Furthermore, the savings are also high, ranging from 24.48 €/ha to 35.01 €/ha. All prices are indicative of the 2020 market value.

It is important to note that even though there are differences in the quantity of spraying required between the two methodologies used and different decision-making thresholds, they each offer a substantial reduction in herbicide use compared to traditional spraying. Consequential cost reduction can also be very important, especially if the area to be treated is very large. These results are similar to the results from different studies done worldwide. For example, in their work, Slaughter *et al.* (1999) found that by implementing precision spraying, the area to be sprayed can be reduced from 100% to approximately 57%, making the chemical weed control 3.7 times more efficient. Additionally, Hamouz *et al.* (2013) found that the reduction in herbicide application can increase from 15.6% to 100%, depending on the different methodologies and thresholds used. The authors also agree that a higher decision-making threshold equates to more herbicide savings. Other works,

such as that done by Takács-György (2008), indicate that by implementing precision weed controlling tactics, the reduction of herbicide usage can be substantial and so can the savings. This author also implies that the initial investments in precision agriculture are paid off in a few years due to the savings they allow.

Conclusions

Because of the herbicide traits that make them harmful to the environment and health, their application must be improved, and their use reduced. In this study, an innovative approach that combines site-specific and time-specific weed management methods is presented. As is, the method could improve the performance of UAV image classification for weed detection. Moreover, by implementing the proposed method, it is possible to reduce the amount of herbicide used, which also results in the reduction of agricultural production costs. Overall, the two classification approaches used have both positive and negative traits. On the one hand, while the OpenCV ANN produced a better classification than VARI, it required more training and was, therefore, more time consuming. On the other hand, the VARI algorithm showed some limitations in weed classification, yet it was much more straightforward to use and thus required much less time. As stated before, the efficacy of the treatment depends on the threshold for decision making and the cell size chosen. It is, therefore, up to the end user to decide which combination could suit his/her needs better. However, as a general rule for better efficacy, one should consider using lower thresholds with bigger cells, while from an economic perspective using higher thresholds with smaller cells could also give good results. We have shown that adding a temporal component to precision weed detection could be very useful for herbicide reduction, as it offers information about the percentage of weed emergence in time. Indeed, with the temporal AlertInf weed detection model, it was possible to better organize the UAV survey in order to map the maximum number of weeds possible according to the percentage of weed emergence, and the development stage of the crops. Moreover, if the correct timing for UAV surveys is chosen, the resulting prescription maps will then contain a majority of weed plants that could

possibly infest the field, thus potentially improving the spatial detection of the most relevant weed(s). As a consequence, given the proper use of herbicides, it might be possible to reduce not only the herbicide amount used, but also eliminate the need for subsequent chemical herbicide treatments. This could be a leap forward, considering that with the traditional weed controlling methods, the percentage of emerged weeds is not considered. Consequently, in some cases, after the first spraying, the weeds that have not yet emerged create a second flush of infestation, compelling the farmers to undergo a second round of herbicide treatment in order to prevent reduced crop yield. However, with fewer and more efficient treatments, the problem of herbicide resistance could be attenuated. Nevertheless, consider that the present experiment is modular and theoretical; therefore, it is necessary to transfer it to real situations by conducting field trials. With the field trials, it will be possible to understand how applicable these methods are and determine if the efficacy achieved corresponds to the one simulated. It would also be possible to better understand the problems that may occur in real-life applications and resolve them. Finally, comparing the final yield from a field in which precision weed control methods were applied with one in which they were not applied, would provide valuable insight for a cost-benefit analysis. Other than what has been mentioned before, further studies are required in order to be able to address different production methods, with more cultivated species and more weed species, in order to meet market demands. It could also be very useful to collaborate with the sprayer production industry in order to develop increasingly more precise spraying systems. Additionally, calibration of weed emergence predictive models for use in different parts of the world must also be performed, so that they may be able to apply the techniques presented in this work beyond the Veneto region.

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Table 1. Accuracy assessment of the OpenCV ANN and VARI weed classification methods.

Classification method	Classes	Commission error (false positive, %)	Omission error (false negative, %)	Overall accuracy (%)	Cohen's Kappa (%)
OpenCV ANN	Weed	11.8	19.4	98.6	83.7
	No-weed	1.0	0.5		
VARI	Weed	40.2	6.0	98.1	72.0
	No-weed	0.2	1.8		

Table 2. Possible spraying area reduction in a field of 1 ha.

VARI						
	1% infestation		5% infestation		10% infestation	
Cell size	Area to be sprayed (ha)	Reduction %	Area to be sprayed (ha)	Reduction %	Area to be sprayed (ha)	Reduction %
0.25 m ²	0.35	65.29	0.19	80.59	0.15	85.36
2.00 m ²	0.15	85.33	0.15	84.82	0.11	88.88
3.00 m ²	0.12	88.05	0.09	91.42	0.07	93.35
OpenCV ANN						
	1% infestation		5% infestation		10% infestation	
Cell size	Area to be sprayed (ha)	Reduction %	Area to be sprayed (ha)	Reduction %	Area to be sprayed (ha)	Reduction %
0.25 m ²	0.58	42.43	0.30	69.97	0.21	78.94
2.00 m ²	0.50	49.7	0.26	73.72	0.17	83.00
3.00 m ²	0.22	77.57	0.16	84.03	0.12	87.82

Table 3. Possible savings associated with various degrees of quantity reductions of herbicide (Equip).

OpenCV ANN									
Cell size	1%			5%			10%		
	Quantity (L/ha)	Cost (€/ha)	Savings (€/ha)	Quantity (L/ha)	Cost (€/ha)	Savings (€/ha)	Quantity (L/ha)	Cost (€/ha)	Savings (€/ha)
3.00 m ²	1.32	30.94	22.81	0.69	16.14	37.61	0.48	11.32	42.43
2.00 m ²	1.16	27.04	26.71	0.60	14.13	39.63	0.39	9.14	44.61
0.25 m ²	0.52	12.06	41.70	0.37	8.58	45.17	0.28	6.55	47.2
VARI									
Cell size	1%			5%			10%		
	Quantity (L/ha)	Cost (€/ha)	Savings (€/ha)	Quantity (L/ha)	Cost (€/ha)	Savings (€/ha)	Quantity (L/ha)	Cost (€/ha)	Savings (€/ha)
3.00	0.80	18.66	35.09	0.45	10.43	43.32	0.34	7.87	45.88

m ²									
2.00 m ²	0.34	7.89	45.87	0.35	8.16	45.6	0.26	5.98	47.77
0.25 m ²	0.28	6.42	47.33	0.20	4.61	49.14	0.15	3.57	50.18

Table 4. Possible savings associated with various degrees of quantity reductions of herbicide (Titus Mais Extra).

OpenCV ANN									
Cell size	1%			5%			10%		
	Quantity (g/ha)	Cost (€/ha)	Savings (€/ha)	Quantity (g/ha)	Cost (€/ha)	Savings (€/ha)	Quantity (g/ha)	Cost (€/ha)	Savings (€/ha)
3.00 m ²	46.06	21.59	15.91	24.02	11.26	26.24	16.85	7.90	29.60
2.00 m ²	40.24	18.86	18.64	21.02	9.86	27.65	13.60	6.38	31.13
0.25 m ²	17.94	8.41	29.09	12.78	5.99	31.51	9.74	4.57	32.93
VARI									
Cell size	1%			5%			10%		
	Quantity (g/ha)	Cost (€/ha)	Savings (€/ha)	Quantity (g/ha)	Cost (€/ha)	Savings (€/ha)	Quantity (g/ha)	Cost (€/ha)	Savings (€/ha)
3.00 m ²	27.77	13.02	24.48	15.53	7.28	30.22	11.71	5.49	32.01
2.00 m ²	11.74	5.50	32.00	12.14	5.69	31.81	8.90	4.17	33.33
0.25 m ²	9.56	4.48	33.02	6.87	3.22	34.28	5.32	2.49	35.01



Figure 1. Sample of the orthophoto obtained (06.19.2019).

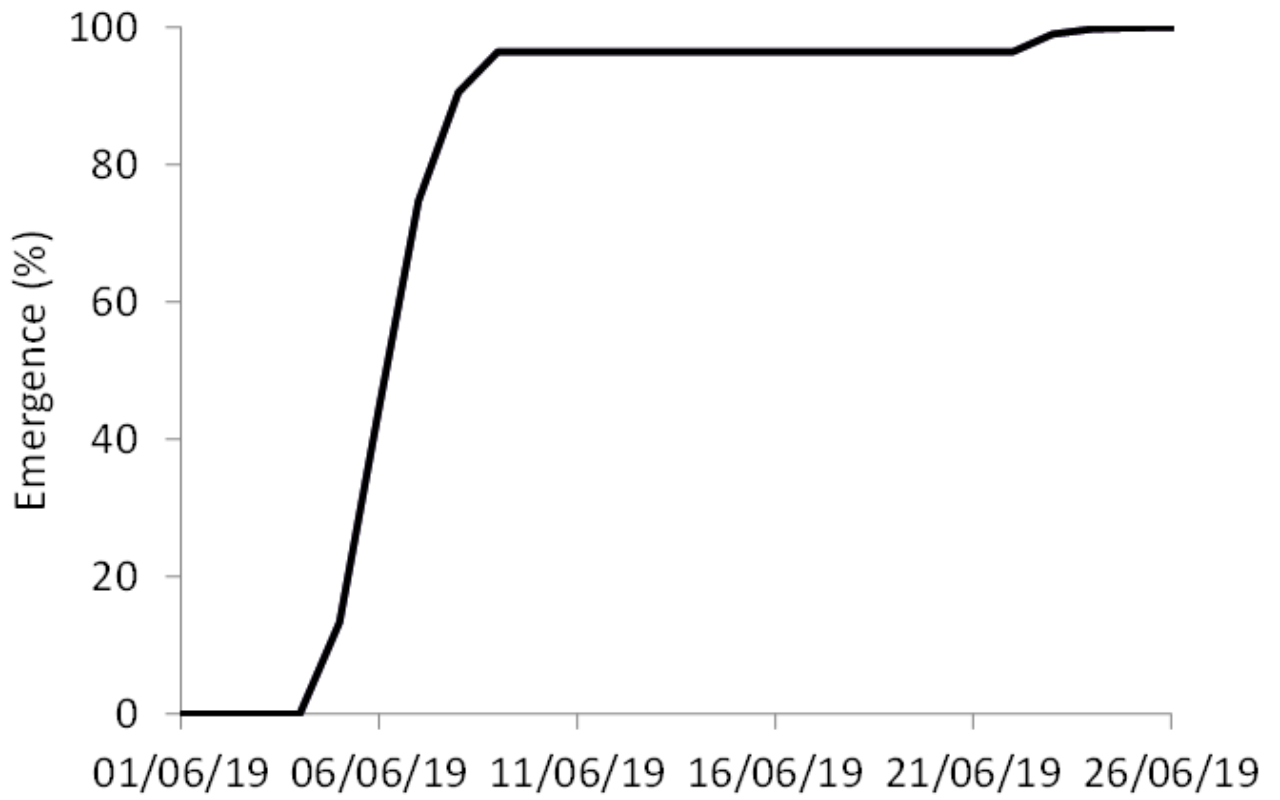


Figure 2. Cumulated emergence (%) of *Sorghum halepense* in the field in 2019, simulated by the Alertinf model.

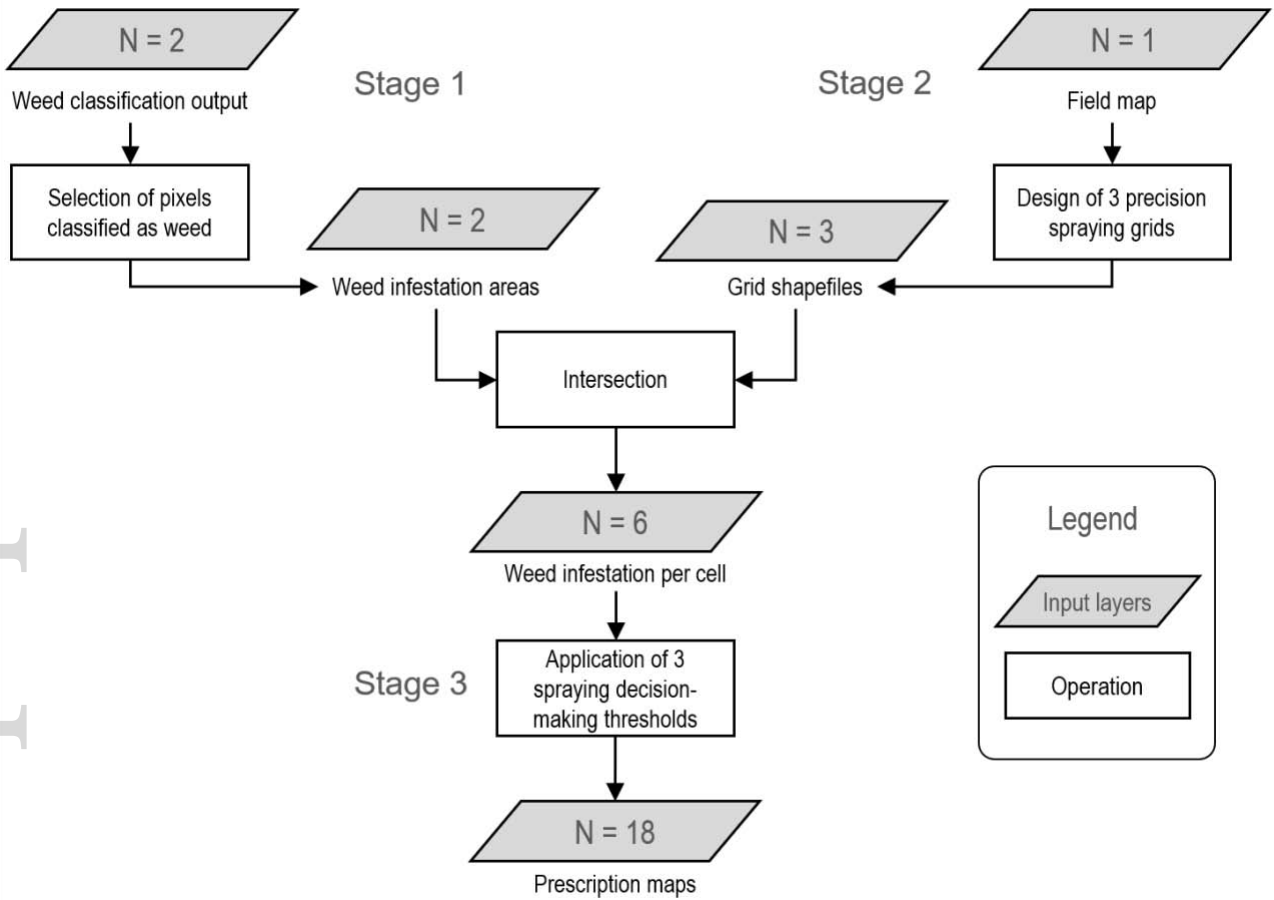


Figure 3. Prescription map creation workflow, N is the number of inputs/outputs used/produced during the creation of prescription maps.

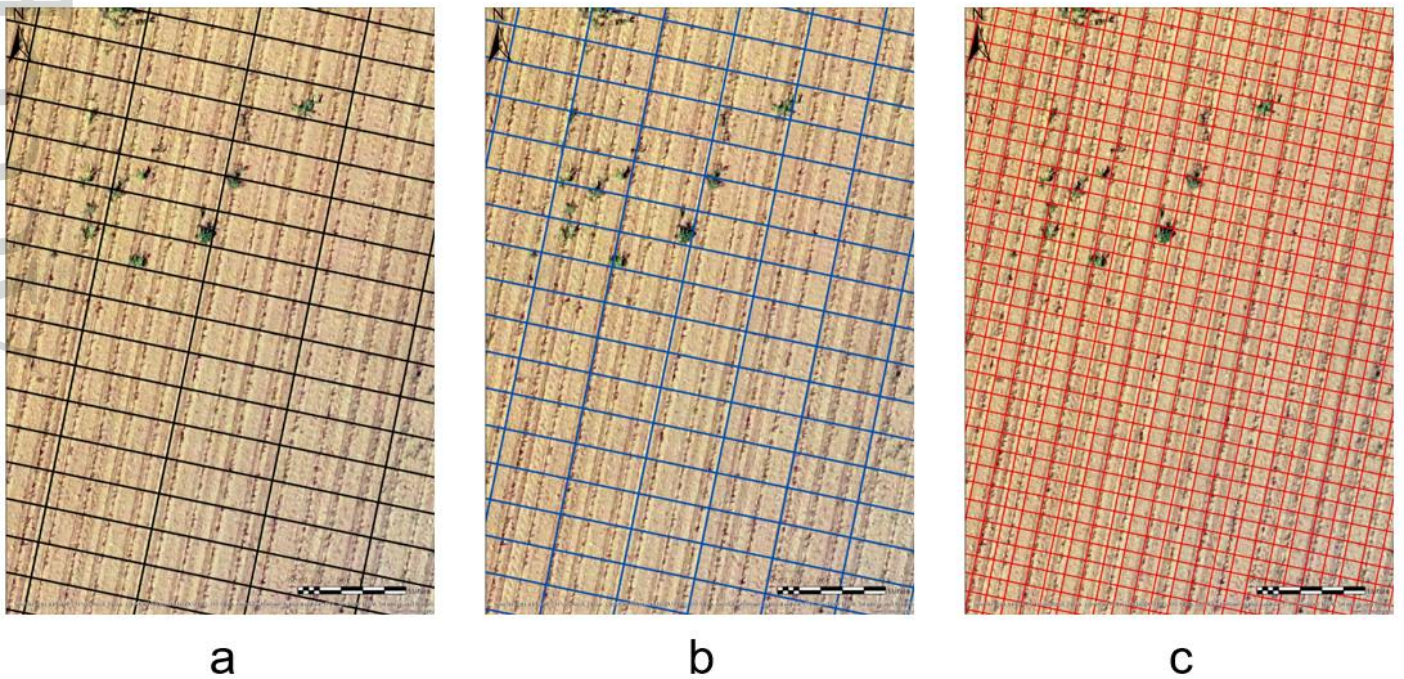


Figure 4. Sample of precision spraying grid with three cell sizes: 3.00 m² (a), 2.00 m² (b), and 0.25 m² (c).

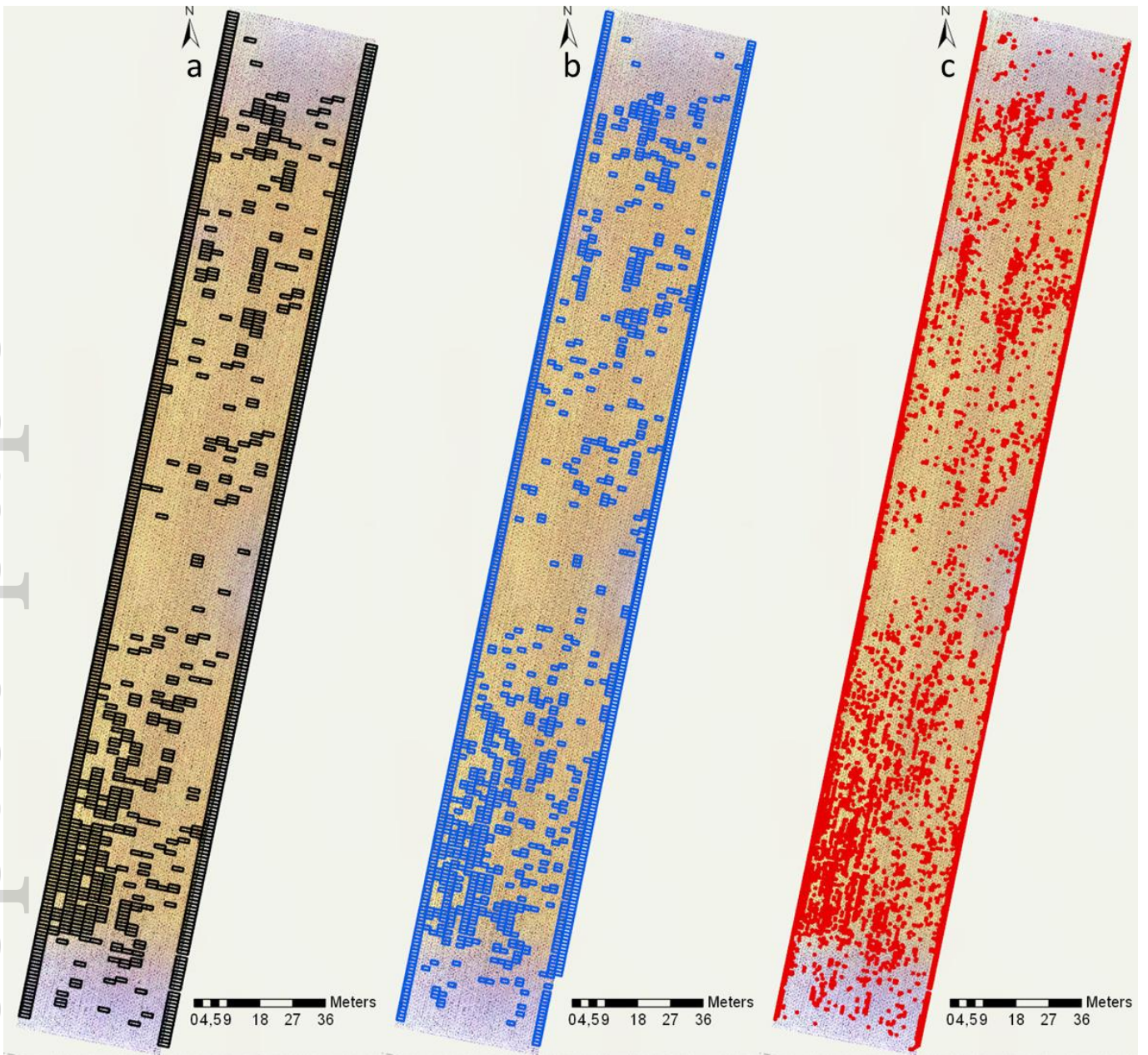


Figure 5. Comparison of the prescription maps for the OpenCV ANN classification method. Examples for the 5% threshold for three cell sizes to be sprayed, namely: 3.00 m^2 (a), 2.00 m^2 (b), and 0.25 m^2 (c).

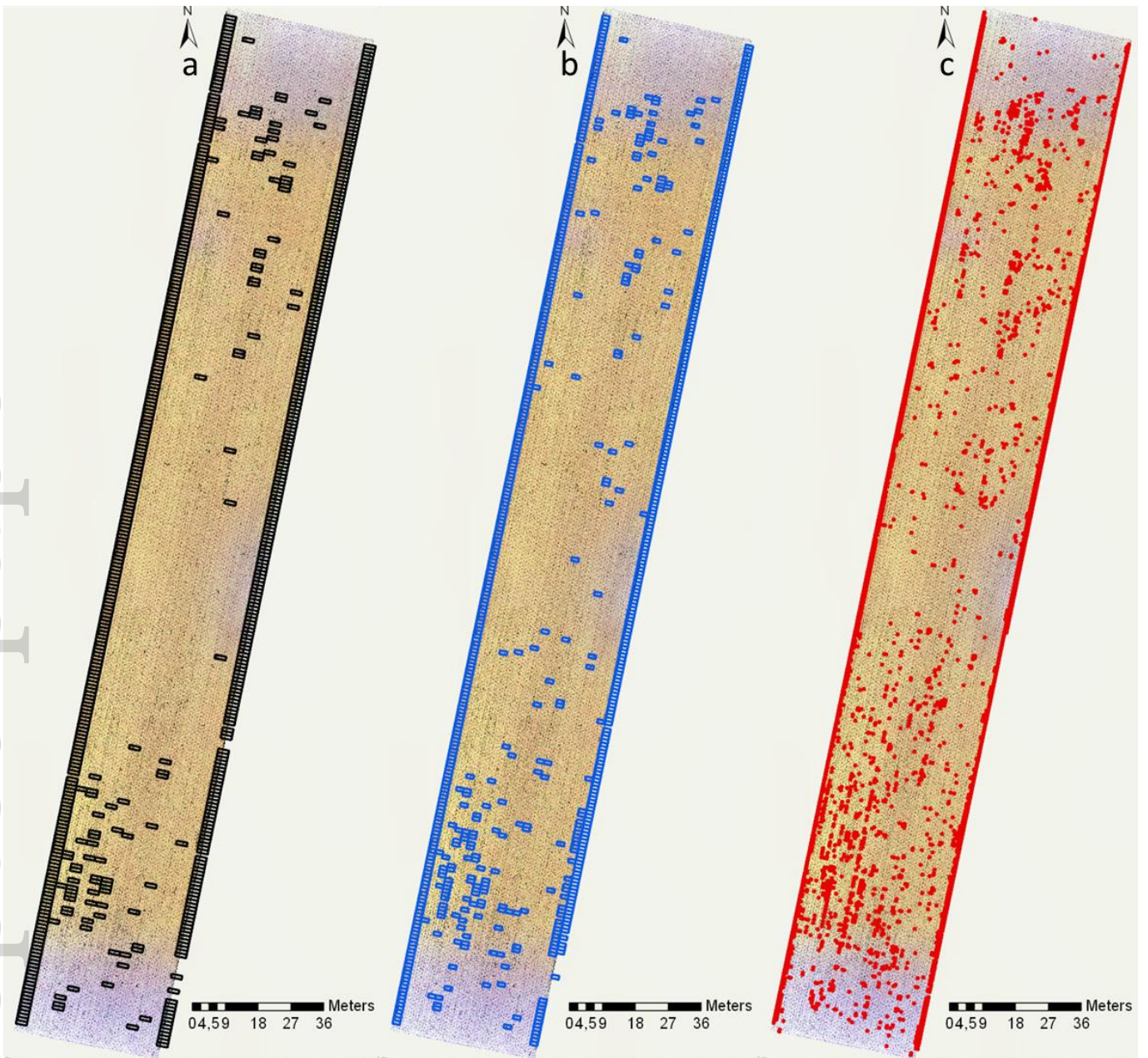


Figure 6. Comparison of the prescription maps for the VARI classification method. Examples for the 5% threshold for three cell sizes to be sprayed, namely: 3.00 m² (a), 2.00 m² (b), and 0.25 m² (c).