

## SECTIONING AND ASSESSMENT REMOTE IMAGES FOR PRECISION AGRICULTURE: THE CASE OF *OROBANCHE CRENATE* IN PEA CROP

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### ABSTRACT

The software SARI® has been developed to implement precision agriculture strategies through remote sensing imagery. It is written in IDL® and works as an add-on of ENVI®. It has been designed to divide remotely sensed imagery into “micro-images”, each corresponding to a small area (“micro-plot”), and to determine the quantitative agronomic and/or environmental biotic (i.e. weeds, pathogens) and/or non-biotic (i.e. nutrient levels) indicator/s of each micro-plot.

Spatial patches aggregation of biotic/ non-biotic factors and their corresponding pesticide/ fertilizer variable rates application prescription maps can be achieved through SARI® from remote images and complementary ground-taken data. An example of SARI® implementation in the remote image of a pea’s field infested by the parasitic weed/ pathogen *Orobanche crenata* Forsk. at Montalban (Cordoba, Spain) is described. Infestation pressure between micro-plots greatly varies from virtually parasitic weed free micro-plots up to completely infested micro-plots. SARI® also provides geo-referenced and visualised herbicide prescription maps, which can be used in variable-rate application equipments. The work herein developed has shown that remotely sensed imagery managed with SARI® can play an important role in developing cost-effective precision agriculture.

**Keywords:** Spatial management, variable-rate prescription maps, *Orobanche crenata*.

## INTRODUCTION

Site-specific agriculture takes into account the spatial variability of biotic factors, such as weeds and pathogens, and of non-biotic factors, such as nutrients or water content, and uses diverse technologies to apply at variable rates fertilizers, pesticides or other inputs, fitted to the needs of each small area defined (Blackmore, 1996). Patchy distribution of pathogens/ weeds and non-biotic factors is visually observed in the fields and well documented (Krohmann et al., 2006; López-Granados et al., 2006). However, pesticides/ fertilizers are usually applied at a single rate over the entire agricultural field. To reduce the total amount of inputs applied, and to apply pesticide/ fertilizers only where biotic/ non-biotic patches demand them, site-specific management (SSM) techniques are being developed to treat only where weed/ pathogens/ nutrient levels densities exceed (or are lower than) the economic threshold, and to reduce application rates in patches where densities remain with low infestation levels. Potential economic and environmental benefits of SSM include reduced spray volume, application time and non-target spraying (Medlin et al., 2000).

Remote sensing is a useful tool to manage spatial variability of biotic/ non-biotic factors in agricultural fields. For example, late-season weed infestations were mapped through remote-sensed imagery (López-Granados et al., 2006; Peña-Barragán et al., 2007). Thus, taking into account that weed infestations can be relatively stable from year to year (Wilson and Brain, 1991), late-season weed detection maps can be used to design site-specific control methods in the coming years. The know-how of developing cost-effective weed infestation large-scale mapping in order to take full advantage of SSM needs to be achieved. A computerized decision method that estimates an economic optimal herbicide dose according to site specific weed composition and density was developed by Christensen et al., (2003). It consists in a competition model, an herbicide dose-response model and an algorithm that estimate the economically optimal doses. The software named Sectioning and Assessment of Remote Images® (SARI®) was developed to implement precision agriculture strategies through remote sensing imagery (García-Torres et al., 2008a and 2008b).

*Orobanche crenata* is a pathogen/ parasitic weed of winter legumes widely extended throughout the Mediterranean area. *Orobanche crenata* show a clear spatial distribution in the fields and is commonly controlled with herbicides (García-Torres et al., 1994). The aim of this work is to briefly describe the accomplishment of SARI® software in the site-specific management of a peas (*Pisum sativum* L.) field partly infested by *Orobanche crenata* through remotely sensed imagery.

## MATERIAL AND METHODS

### The SARI® software

ENVI® was the computer program used for visualizing and processing images; this is written in IDL®, a systematized computer language which permits integrated image processes. SARI® is written in IDL®, works as an add-on of ENVI®, and has been developed to implement precision agriculture strategies (García-Torres et al., 2008a & 2008b). Any waveband or vegetation index image in which the land uses can be discriminated is suitable for being processed by SARI®, as will be shown in this paper. First, a supervised classification of the main land uses in the plot image selected is needed, defining the boundary digital values (BDV) of each mentioned land use and its statistical accuracy. The BDV of the selected land uses, among other parameters, will then be SARI® software-implemented.

a) *Clustering parameters*: these are defined and implemented as follows: a.1) Boundary Digital Values (BDV): defines the selected land use  $Max.DV$  ( $DV_{MAX}$ )  $Min DV$  ( $DV_{MIN}$ ), and should be obtained by applying a preliminary classification algorithm; a.2) Cluster Merging Distance (CMD), or maximum distance to merge neighbouring clusters, which is defined in pixels; a.3) Minimum clustering size (MinCS): any cluster below the defined size (in number of pixels) is discarded; a.4) Maximum Clustering size ( $MaxCS$ ): defines a maximum number of columns (Width,  $W_{CMAX}$ ) and of rows (Height,  $H_{CMAX}$ ).

b) *ROI/ Micro-plot parameters* are defined as following: b.1) the maximum number of columns (Width/  $W_{RMAX}$ ), and b.2) the maximum number of rows (Height,  $H_{RMAX}$ ) in the regions of interest (ROI). Each ROI/ micro-plot is created in the geometric centre of each cluster.

c) *The classification of the ROIs/ micro-plots* formed can be based on c.1) The % of pixels of each ROI/ micro-plot with a  $DV \neq 0$ ; and/ or c.2) On the % of the integrated digital values (IDV) of each micro-plot as compared to the maximum IDV ( $IDV_{max}$ ) of a micro-plot.

Implementing by SARI® the same Clustering and ROI/ Micro-plot size parameters, the original image is divided into small images or micro-images, each of an equal size to the ROI or micro-plot defined. Each ROI defined by SARI® exhibits all the quantitative information provided by the ROI menu of ENVI, through the Statistics Sub-menu, for example, the number of pixels, mean and range of digital values, among others. Similarly, the ROIs or micro-images created by SARI® can be visually assessed in the original image, and/ or independently separated through adequate ENVI menus (*Subset Data via ROI*).

SARI® creates *ROI/ micro-plots* with a size defined by the maximum number of columns (Width/  $W_{RMAX}$ ), and of rows (Height,  $H_{RMAX}$ ) of the regions of interest (ROI), and each ROI/ micro-plot created is located in the geometric centre of each cluster. SARI® also classifies the *ROIs/ Micro-plots* using two alternative criteria, as follows: the % of pixels of each ROI/ micro-plot with a  $DV \neq 0$ ; and/ or the % of integrated digital values (IDV) of each micro-plot as compared to the maximum IDV ( $IDV_{max}$ ) of a micro-plot. The SARI®

operational flowchart and main interface is shown in Figure 1 and 2, respectively.

SARI® outcome shows the following parameters (Table 1):

$X_i$ ,  $Y_i$ : Geographic coordinates of the geometric centre of the cluster  $c_i$  or ROI $_i$

$NPAG_i$ : Number of pixels of the cluster  $c_i$  or ROI $_i$ .

$VDAG_i$ : Accumulated digital value of all the cluster pixels  $c_i$  or ROI $_i$ , calculated as the arithmetical sum of all DV;

$VDM_i$ : Average digital value of the cluster  $c_i$  or ROI $_i$ ;

Using these parameters, some others can be defined to characterize the whole image:

$NTAG$ : Total number of pixels of all clusters or ROIs;

$NTAG-NTP$ : Cluster density of the image;

$IVDA$ : Integrated digital value of all pixels of the clusters or ROIs in the image,

$VDAM$ : Average digital value of all cluster or ROIs in the image;

$No$ : Integrates the number of pixels in each ROI/ micro-image with DV  $\neq 0$ ;

$\%pixels$ : % of pixels with DV  $\neq 0$  over the total number of pixels in each micro-plot

$\%VDGA_{Max}$ : % of the integrated DV in each micro-plot over the maximum of a selected micro-plot ( $VDGA_{Max}$ ).

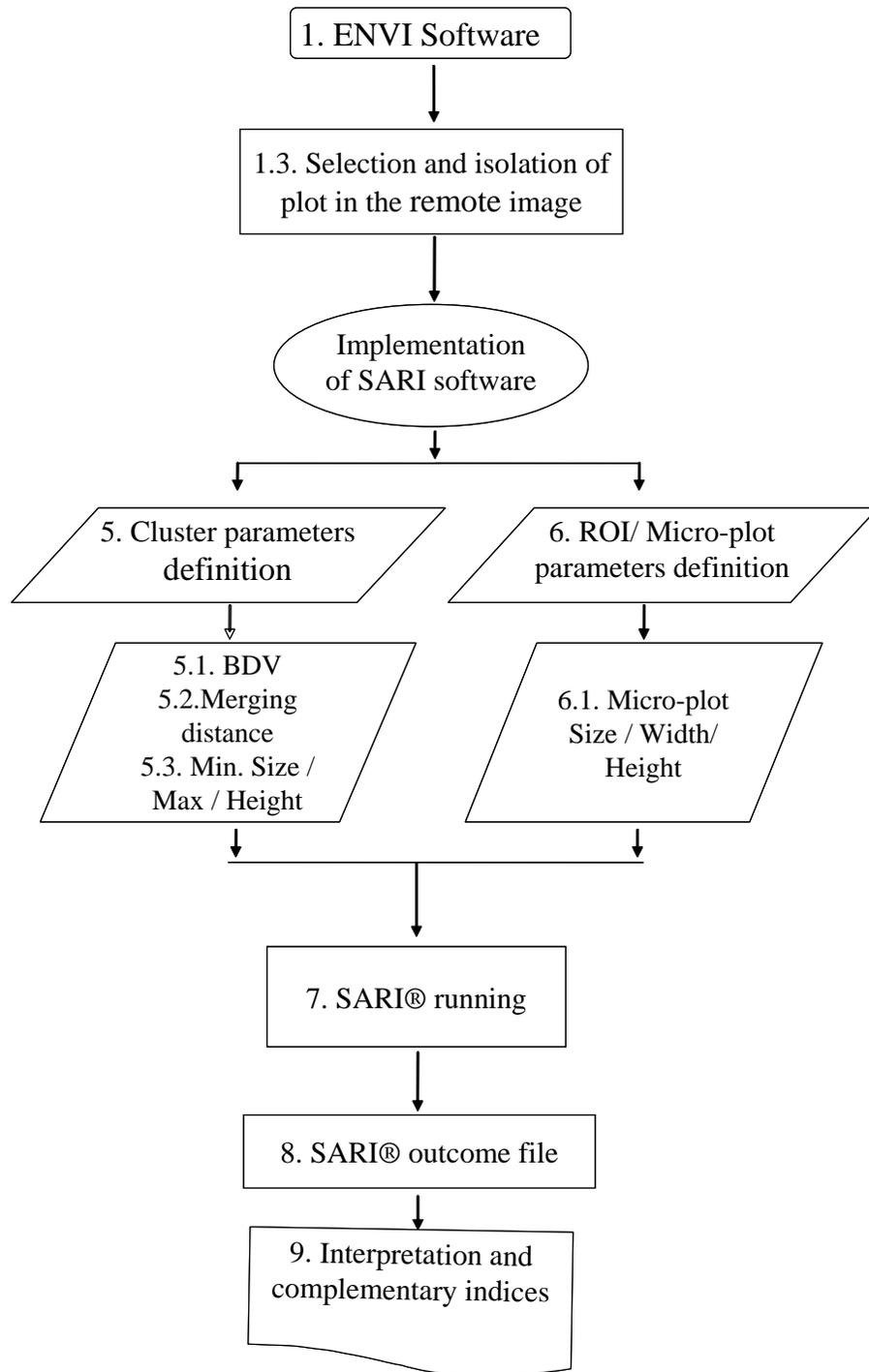
Class: classification of micro-plots can be achieved by SARI® as  $\%pixels$  or  $\%VDGA_{Max}$ . The resulting classes correspond to previously established percentages of pixels as defined in the interface; for example: classes 0, 1, 2, 3, 4, and 5 could be equal to 0-10%, 11-25%, 26-50%, 51-75%, 76-00%, respectively, or to whatever selected percentage is indicated. Further details of SARI® are described in García-Torres et al. (2008a and 2008b).

### **Case study: site-specific management of a pea's field infested by Orobanche**

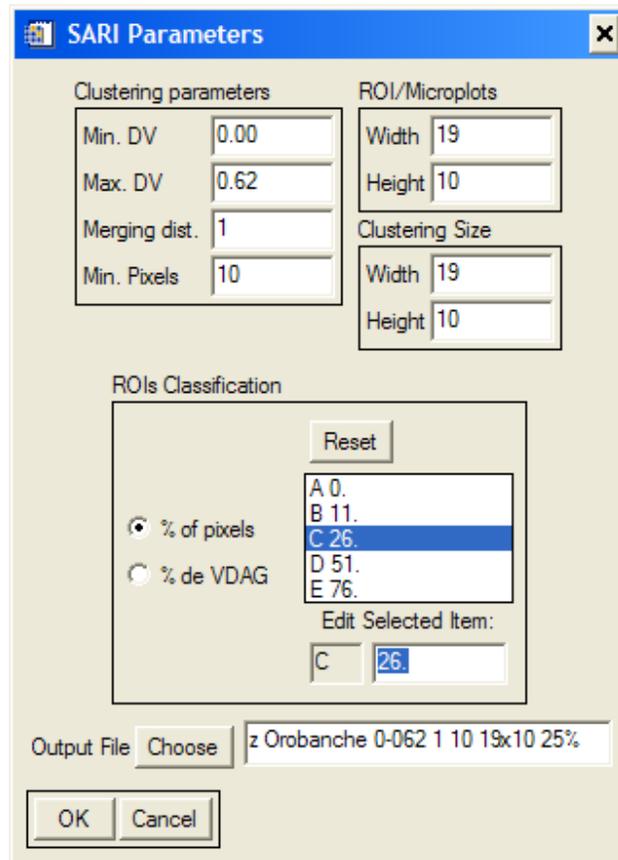
A multispectral remote image (Blue, B/Green, G/Red, R and Near-Infrared, NIR) was taken from an airplane at 1500 m above the soil surface at 26 April 2006 at Montalban (Cordoba, southern Spain. Pixel size was  $1 \times 1$  m. This image included a field of peas (*Pisum sativum* L.) of 0.7 ha ( $X = 311807$  m,  $Y = 4161192$  m). This pea's field was partly infested by the pathogen/ parasitic weed broomrape (*Orobanche crenata* Forsk.). In the date when the image was taken *Orobanche*-free crop was at an advanced fruiting stage and still completely green; while the *Orobanche*-infested crop patches showed the parasite *Orobanche* plants emerged from the soil surface and the crop plants exhibiting an anticipated senescence stage, colour brown-yellow. The vegetation index NDVI (NIR-R/ NIR+R) image was used to discriminate

*Orobanche*-free and *Orobanche*-infested areas through a supervised classification process. This was based on geo-referenced (DGPS) *Orobanche*-free and -infested ground data carried out one day before the aerial image was taken.

SARI® software was used to section the *Orobanche*-infested area (NDVI, VDF 0 to 0,619) image (Figure 1) into micro-images/ micro-plot of 19 m x 10 m, determining the percentage of infested pixels for each micro-plot. The herbicide prescription map was achieved with the criteria of applying herbicide where infested pixels in each micro-plot were over >25% (classes 2 a 5).



**Figure 1.** SARI® operation flowchart



**Figure 2.** Main interface of SARI® software, the parameters shown are those used in the *Orobanche* study described in the text.

## RESULTS

### Case study: site-specific management of a pea's field infested by *Orobanche*

*Orobanche*-free and -infested digital values (DV) were 0.62-0.74 and 0.21-0.62, respectively, determined with an overall accuracy (OA) of 0.93. In figure 3a the white and dark area is *Orobanche*-free (DV 0.62/0.74) and the grey-darker corresponded to *Orobanche*-infested area (DV 0.22- 0.62). Figure 3b shows in the same field only the isolated *Orobanche* patches (grey and light dark area). The quantitative information provided by SARI® for each microplot from the sectioning of the remote image is shown in Table 1. Figure 3c shows the prescription herbicide map.

**Table 1.** Quantitative information provided by SARI® outcome for each micro-plot from the sectioning of the remote image of the peas (*Pisum sativum* L.) field infested of broomrape (*Orobanche crenata* Forsk.) at Montalban (Cordoba, Southern Spain).

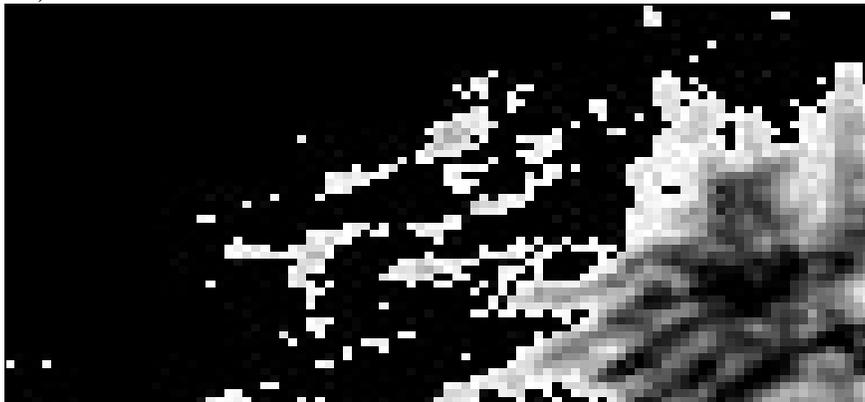
NTP* 5225						Classification criteria (> 25%)		
:								
AG	X	Y	NP AG	VDAG	VDAG/ NPAG	No.	%	Class
AG1	341839	4161179	190	0.00	0.00	0	0.00	1
AG2	341858	4161179	190	0.00	0.00	0	0.00	1
AG3	341877	4161179	190	1.23	0.01	2	1.05	1
AG4	341896	4161179	190	4.91	0.03	8	4.21	1
AG5	341915	4161179	190	6.61	0.03	11	5.79	1
AG6	341839	4161169	190	0.00	0.00	0	0.00	1
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AG25	341915	4161139	190	64.70	0.34	188	98.95	5
AG26	341839	4161132	95	0.00	0.00	2	1.05	1
AG27	341858	4161132	95	6.60	0.07	15	7.89	1
AG28	341877	4161132	95	19.52	0.21	38	20.00	1
AG29	341896	4161132	95	37.29	0.39	122	64.21	5
AG30	341915	4161132	95	35.54	0.37	133	70.00	5
NTA			787.					
G:	5225	IVDA:	22					
NTA								
G/NT								
P:	1.00	VDAM:	0.15					

\* See abbreviations in the text.

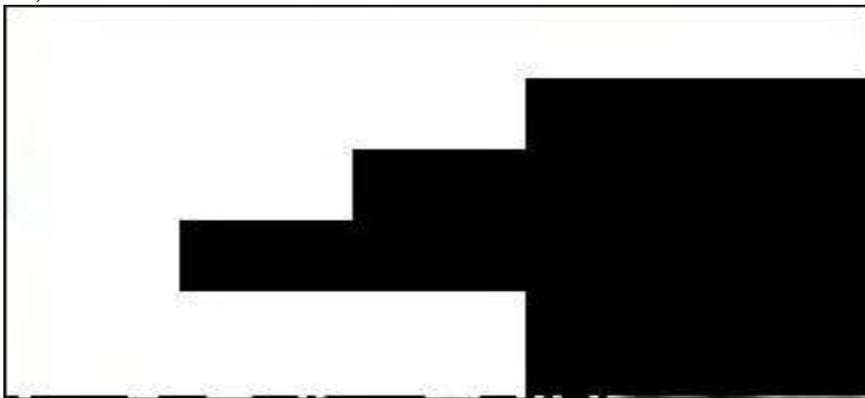
a)



b)



c)



**Figure 3.** a) NDVI image: white and dark area is *Orobanche*-free (DV 0.62/0.74) and *Orobanche*-infested (DV 0.21/0.62, respectively; b) the same field shown only the isolated *Orobanche* patches (DV 0-

0.62, grey and light dark area); and c) Prescription herbicide map achieved through SARI; micro-plot of 19 x 10 m; herbicide application criteria: over 25% infested pixels in each micro-plot.

## **DISCUSSION**

SARI® has shown being efficient software for sectioning remote images, assessment agri-environmental indicators and implementing weed/ pathogen-crop control strategies model in each micro-image/ micro-plot. In summary, SARI® software provides geo-referenced, quantitative and visual herbicide prescription application, and this can be transferred to variable-rate application equipment for practical SSM strategies

Remote images usually cover large areas, from several hundred hectares, if taken from airplanes, to dozens of square kilometres, if taken from satellites. Agriculture operations such as sowing, fertilization and pesticide application, among others, use to be programmed for individual plot of reduced area, normally smaller than 20-30 ha. So, a first step in programming such operations by remote sensing is isolating the image of the plot in which to implement the desired action. In addition, precision agriculture intend to determine the biotic/ non-biotic spatial variability of agricultural plots and then to apply at variable rates fertilizers, pesticides or other inputs, fitted to the needs of each small area defined (Blackmore, 1996). Consequently, planning site-specific operations by remote sensing requires sectioning the isolated plot image into small micro-images/ micro-plots, usually of a few hundred square meters, and interpreting for each micro-plot the adequate agro-environmental indicator for the desired operation.

Actually, SARI® is effective software sectionalizing plot images and assessing key agro-environmental characteristic of each micro-plot, regardless of the size of the original plot image and of the micro-images. In addition, SARI® software can work with any biotic factors and/or non-biotic factor that can be discriminated in the remote image. Moreover, the parameters characterizing the biotic/ non-biotic factor, such as the boundaries digital values and the distance and size of aggregates, can be implemented by SARI® in a very flexible way.

Spatial distribution biotic/ non-biotic factors patches studies on remote images and crop competition models implemented through SARI® software are much more cost-effective, this is requires much less ground and office work, than those achieved through conventional sampling ground techniques. Agricultural, environmental and economic objectives should be balanced in the final decision-making. From only a strict agricultural production point of view, the higher weed-infested herbicide-treated area the better, assuming that through this practice the maximum yield will be reached. While from an environmental view, the desirable goal can be to reduce the weed-free herbicide-treated area. Finally, the economic objective is likely to get the maximum benefit, taking into account weed-crop competition losses, input production costs and yield crop sailing price.

## **ACKNOWLEDGEMENTS**

This research was partially financed by the Spanish Commission of Science and Technology through the project AGL2007-60926.

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