Office Use Only

Project Code	
Project Type	

FINAL REPORT 2017

Applicants must read the *SAGIT Project Funding Guidelines 2017* prior to completing this form. These guidelines can be downloaded from www.sagit.com.au

Final reports must be emailed to admin@sagit.com.au as a Microsoft Word document in the format shown ***within 2 months*** after the completion of the Project Term.

PROJECT CODE	**:**	**SPAA114**

PROJECT TITLE (10 words maximum)
The H Sensor: a weed ID and mapping system

PROJECT DURATION

*These dates **must** be the same as those stated in the Funding Agreement*

Project Start date	**1 July 2014**					
Project End date	30 June 2018					
SAGIT Funding Request	2014/15		2015/16		2016/17	

PROJECT SUPERVISOR CONTACT DETAILS

The project supervisor is the person responsible for the overall project

Title:	**First Name:**	**Surname:**
Dr	Nicole	Dimos

Organisation:

SPAA Society of Precision Agriculture Australia Inc

Mailing address:

Telephone:	**Facsimile:**	**Mobile:**	**Email:**

ADMINISTRATION CONTACT DETAILS

The Administration Contact is the person responsible for all administrative matters relating to the project

Title:	First Name:	Surname:
Mrs	Kylie	Gove
Organisation:		
SPAA Society of Precision Agriculture Australia Inc		
Mailing address:		

Telephone:	Facsimile:	Mobile:	Email:

PROJECT REPORT

Provide clear description of the following:

Executive Summary (200 words maximum)

A few paragraphs covering what was discovered, written in a manner that is easily understood and relevant to SA growers. A number of key dot points should be included which can be used in SAGIT communication programs

The H sensor is an in crop weed identification system being developed by Agricon, Germany. The sensor is designed to detect 'green on green', that is green weeds in green crop. It is capable of mapping weed density and controlling on/off or variable rate spray applications, in real time or pre mapped. No variable rate spray applications were made during this project.

The H sensor discriminates crop and weeds based on plant and leaf shape characteristics. The accuracy of the H sensor is dependent on crop and weed types and their shape characteristics, crop and weed growth stage and the amount of leaf occlusion or overlap between plants. As crop and weed plants increase in size, leaf occlusion increases, reducing the ability of the sensor to determine leaf shape of individual plants and therefore plant type. This increase in leaf occlusion results in reduced accuracy and incorrect spray decisions.

It was found that the H sensor has the ability to identify grass weeds in broad leaf crops (pre canopy closure), particularly ryegrass. It also identified broadleaf weeds in pre tillering cereal crops, particularly rosette forming weeds. However, performance is highly sensitive to the crop and weed scenario. Several scenarios were tested where the system provided no value in weed patch identification.

The H sensor takes up to 10, 0.075m² images per second and the sensors are designed to run approximately 6 meters apart. The sensors can be placed closer together but are currently too expensive to do so for commercial application. Therefore, only a small percentage of the paddock is measured, up to 4.4% at 6m spacing and 12 km/h. For this reason the H sensor will not identify all isolated weeds, but will map weed patches provided the patch intersects the sensor transect.

Project Objectives

A concise statement of the aims of the project in outcome terms should be provided.

This project aims to provide growers with the tools needed to adopt site specific weed management (SSWM) strategies as a result of a commercially viable weed ID and mapping system being demonstrated. The adoption of SSWM strategies will result in more efficient use of herbicides, resulting in reduced herbicide usage while providing the desired weed control. This will provide economic benefits to growers through savings on herbicide use and potentially reduce the phytotoxic effect of some herbicides on the crop. It will also deliver environmental and social benefits through reduced herbicide load in cropping systems, resulting in reduced off target impacts on flora and fauna and reduced herbicide residue levels in food. This will benefit the general public and the consumer.

The expected output is a weed ID and mapping system with a demonstrated commercial viability. The benefits of this development will be derived primarily by Australian farmers and applicable to all grain growing regions across the country.

Commercial viability will be assessed based on the H sensors ability to accurately identify weeds in important crop and weed scenarios encountered in South Australia. This will allow weed control tactics to be targeted more precisely for more efficient use of resources without compromise to weed control.

Overall Performance

A concise statement indicating the extent to which the Project objectives were achieved, a list of personnel who participated in the Research Project including co-operators, and any difficulties encountered and the reasons for these difficulties.

Commercial viability has been difficult to demonstrate. Field trials demonstrated that the H Senor was able to accurately classify annual ryegrass in several broadleaf crops, including canola, faba bean, lentil and field pea. Other grass weeds such as brome grass and wild oats were also correctly identified as grasses in these crops. Broad leaf weeds were accurately classified in cereal crops, however this was more difficult due to the overlapping nature of the cereal crops at the time when the broadleaf weeds had emerged. Classification accuracy was lower for detection of grass weeds in cereal crops and broadleaf weeds in broadleaf crops, and these scenarios were not pursued for that reason.

However, good crop and weed feature classification accuracy does not necessarily translate to an accurate weed map or the correct spray decision. In a number of scenarios it was shown that small errors in classification of crop as weed can have a big impact on the spray decision resulting in significant over spray of weed free areas. In only one situation was the sensor found to identify every weed in an image series. As such, very rarely will the sensor be able to give 100% weed control. In using this system weed misses and over sprays would need to be accepted. Therefore, the number of useful situations that the H sensor could be deployed will be restricted to those where a surviving background weed population is acceptable and is not suitable for weeds that have nil tolerance for survivors.

Due to limitations on crop and weed size and leaf occlusion the period for generating accurate weed maps is restricted to a short window. For an end user this will be a logistical issue that requires operational capacity to map paddocks at the appropriate time.

With more training it is expected that the classification and mapping of both scenarios could be improved. However, due to sensor malfunctions early in the growing seasons of 2015, 2016 and 2017 and the need to return the sensor to Germany on all three occasions it meant that the sensing and processing time was limited. The ability of Agricon to produce new classifiers for our specific crop/weed scenarios was not possible due to restrictions placed on Agricon by the sensor manufacturer, Asentics Vision Technology.

Personnel who participated in the project, - Sam Trengove, Stuart Sherriff, Hermann Leithold (Agricon), Steffen Müller (Agricon), Adelaide University Weed Science Research Group, Co-operators - James Venning, Bill Trengove, Kenton Angel, Scott Weckert, Rod Sherriff, Neville Adams, Matt Dare, Hart Field Site Group,

Key Performance Indicators (KPI)

*Please indicate whether KPI's were achieved. The KPI's **must** be the same as those stated in the Application for Funding and a brief explanation provided as to how they were achieved or why they were not achieved.*

KPI	***Achieved (Y/N)***	***If not achieved, please state reason.***
Importation, setup and training on the H-Sensor: The H-Sensor was received in July 2014. Training was delivered by AgriCon via online means including GoTo Meeting and Skype and phone support. The H-Sensor was setup and used for data collection in the field during August 2014, with some software issues identified and addressed. Hermann Liethold from AgriCon travelled to Australia to deliver further training from 9th-13th February 2015 to provide more detailed instructions on image capture and image processing.	Y	
Implement stubble treatments for assessing effects on classification accuracy - 2 paddocks (wheat & canola stubble): Stubble treatments were implemented in canola stubble at the time of scanning. Wheat Stubble treatments were implemented by Hart Field Site in the long term Cropping Systems trial and the 2015 Stubble and Pre-emergent herbicide trial.	Y	
Crop and weed image collection from pot grown plants for building classification database: Plants were grown at the Waite Campus by the Adelaide University Weed Science Research Group (Agricultural Systems) including ryegrass, brome grass, barley grass, wild oat, mustard, radish, marshmallow,	Y	

bedstraw, medic, wild lettuce and sow thistle. Images of these plants were captured with the H sensor on four occasions and the data processed through the H sensor.		
H-Sensor trialed in 10 paddocks and accuracy assessed. Weed density will be measured at GPS points and the relationship trend between sensor and field measurements determined. Paddocks include 2 wheat, 2 barley, 1 canola, 1 lentil, 1 field pea, 1 faba bean, 1 chickpea and 1 lupin: During the initial use of the sensor in August 2014 data was collected from 1 wheat, 2 barley, 2 canola, 2 lentil, 1 field pea, 1 chickpea and 1 lupin crop. This data was used to start to asses existing classifiers, this is over and above the paddocks that were trialed in 2015. Images were collected from 19 paddocks or trials in 2015 with some paddocks being scanned 2 or 3 times to gather images at different crop and weed growth stages. Crops scanned include 4 canola paddock/timing combinations, 1 faba bean at 2 timings, 2 lupin, 4 wheat paddock/trials, 5 barley paddock/timings, 1 conventional and 2 semi leafless field pea, 1 oat, 1 chickpea and 1 lentil paddock. Plant counts were conducted in 10 of the 19 paddocks and analysis made between the physical count, a count from the sensor image and the sensor output. Maps of H sensor weed density and counted plant density have been created in canola and lupin, wheat and barley. Images were also collected under different weather conditions including under heavy dew compared to dry leaves and wet leaves from rain compared to dry leaves.	Y	
H-Sensor trialed in 2 paddocks with stubble treatments imposed: The first trial was conducted on wheat in standing canola stubble where images were collected in standing stubble and then stubble removed and images retaken over the same area with 3 replicates. The second trial utilised the cropping systems trial at the Hart field site which was sown to canola and grass weed species were present. Images of the 2016 Hart Stubble and Pre-emergent herbicide were also captured.	Y	
H Sensor images collected during 2015 analysed and classified to build new classifiers for Australian crop and weed scenarios. Analysis of the images captured in 2014, 2015 and 2016 has been conducted. H sensor training has been conducted including scenarios of ryegrass in faba bean, wild radish in 2 leaf barley, and tares and medic in 4	Y	

leaf wheat.		
Crop and weed image collection from pot grown plants for building classifiers. In 2015 only weed plants were grown and images captured. In early 2016 crop plants were grown and images were captured on four occasion to determine when crop growth stage becomes a limiting factor for sensing. These images were also used to determine the effects of light intensity and shadows on the ability of the sensor to classify plants.	Y	
H-Sensor trialed in 10 paddocks and accuracy assessed. Weed density will be measured at GPS points and the relationship trend between sensor and field measurements determined. Paddocks include 2 wheat, 2 barley, 1 canola, 1 lentil, 1 field pea, 1 faba bean, 1 chickpea and 1 lupin. The H sensor was trailed in 2 faba bean, 2 wheat and 1 canola paddock, plant counts were conducted in 3 of these paddocks to determine the accuracy. Analysis of these paddock images has also been conducted. An additional large scale soil amelioration field trial was also assessed using the H sensor , treatments include moulboard plough, spading and ripping. The sensor malfunctioned 12th June so no further scanning was conducted for 2016. The sensor was repaired in Germany but failed again with a separate fault in 2017 that prevented any image capture in that season.	Partial	Scanning of the remaining paddocks did not occur due to another sensor malfunction. The sensor is currently in Germany being repaired.
H-Sensor images collected during 2016 analysed and classified to build new classifiers for Australian crop and weed scenarios. Images collected in 2016 have been analysed, no further classifiers have been adjusted from images collected.	Partial	The development of new classifiers has not been possible due to restrictions between Agricon and the sensor manufacturer.
Collate all data into final analysis All data collected has been collated in a document summarising the findings for each assessment.	Y	
SAGIT final report	Y	

Technical Information (Not to exceed **three** pages)

Provide sufficient data and short clear statements of outcomes.

Relationships between weed density and sensor output.

The ability of the H sensor to effectively map a weed population depends on several factors. These include, crop growth stage and size, weed population, weed size, difference in leaf shapes between crop and weeds and location of weeds (crop row or inter-row). All of these factors contribute to the level of leaf occlusion or overlap that occurs within the sensor image. As the H Sensor relies on leaf shape, if the weeds are occluded by the crop or other weeds then the sensor is unable to determine the individual shapes and therefore identify them successfully.

The results below shows the variation in the sensors ability to identify weeds in crops (Table 1). In good scanning situations where there is separation of weeds and crop plants the sensor can be highly accurate, and is able to predict weed density (from quadrat counts) with R^2 values in excess of 0.8. However, where there is significant leaf occlusion the correlations are poor. Often there are a few images in a series that are poorly classified. If these are removed from the series as outliers such as in test 7 and 9 then the relationship can be improved significantly, however in a practical sense this would not be possible in a commercial use pattern. The weed density in the images in these cases is often very high so that the entire image is classified as one plant type.

The ability of the sensor to detect the weed plants at all also influences the accuracy. In test 3 and 10, the reason behind the poor relationship (R^2 = 0.04) is due to the 1.5 leaf ryegrass being too small to be detected.

Table 1: the relationship (R^2) between sensor classification and actual weed density.

Test	Crop	Weed	Classifier	R2 value	Comments
1	Canola	Ryegrass	WW3.0	0.84	
2	Lupin	Ryegrass	WW3.0	0.03	Lupin leaflets look similar to grass
3	Bean	Ryegrass	WW3.1	0.04	Small ryegrass could not be detected
4	Chickpea	Ryegrass	RAPS1.0	0.46	
5	Barley	Radish	WW2.0	0.66	
6	Barley	Radish	WW2.0	0.85	
7a	Wheat	Bifora, Medic, Tares	WW2.0	0.34	
7b	Wheat	Bifora, Medic, Tares	WW2.0	0.76	Outliers removed
8	Wheat	Radish	WW2.0	0.02	Too much leaf occulsion to identify radish
9a	Bean	Ryegrass	RAPS1.0	0.002	Thick ryegrass covering soil surface
9b	Bean	Ryegrass	RAPS1.0	0.43	Outliers removed
10a	Bean	Ryegrass	WW3.1	0.0003	Small ryegrass could not be detected and thick ryegrass areas idenified as dicot
10b	Bean	Ryegrass	WW3.1	0.05	Outliers removed, thick ryegrass areas identified as dicot

Improvements made to classifiers

Attempts were made to improve the existing classifiers however the accuracy of the original classifiers was not improved beyond the original capabilities.

Bean and ryegrass data sent to Agricon for improvement of classifier WW3.0. Steffen Müller returned an updated RAPS1.0 classifier which was able to improve classification of the beans but did not improve ryegrass classification.

Barley and radish images sent to Agricon with no improvement to existing classifiers.

Wheat and broad leaf weed data sent to Agricon for improvement of classifier WW3.1, Steffen Müller sent an updated WW1.0 to improve the identification of the tares. However overall accuracy was still not as good as the original WW3.1 classifier.

Lentil and Ryegrass data was sent to Agricon for improvement of classifier WW3.0 but it was unable to be improved.

Summary of analysis 1 - The Plant Feature Method

Analysis 1 is the process Agricon use to make assessments of there classifiers. It involves processing a series of images through the sensor software with a given classifier and then comparing that to the same series of images with identified plant features labeled manually. Manually labeling an image involves physically selecting each leaf shape segment in an image and putting it into the correct category. Overall accuracy of the sensor classifier can then be calculated and different classifiers objectively compared. Tables 2 and 3 show the results for the best classifier from analysis 1 for crops with ryegrass and broadleaf weeds, respectively. Accuracy levels for all segments range from 86 – 96% for image series containing ryegrass and from 47 – 84% for image series containing broadleaf weeds

Table 2: Classification accuracy for ryegrass in broadleaf crops. Percentage of crop and weed segments and pixels classified correctly.

Report section		1	2	3	4	5	6	13
Crop		Canola	Lupin	Faba bean	Field pea	Lentil	Chickpea	Canola
Weeds		Ryegrass	Ryegrass	Ryegrass	Ryegrass	Ryegrass	Ryegrass	Ryegrass
Best classifier		WW3.1	WW3.0	WW3.0	WW3.0	W3.0	WW3.0	WW3.1
	Type of segment							
Number of segments	**All**	**96**	**78**	**88.1**	**90**	**91**	**95**	**86**
	Weed	91	85	86	93	90	90	76
	Crop	99	72	98.5	91	93	97	96
	Undefined	*	64	*	*	53	97	95
Area of image (Pixel number)	**All**	**93**	**80**	**93**	**99**	**73**	**96**	**97**
	Weed	59	76	63	96	82	93	85
	Crop	97	86	99.9	99	98	97	98
	Undefined	*	32	*	*	3	55	100

Table 3: Classification accuracy for broadleaf weeds in cereal crops. Percentage of crop and weed segments and pixels classified correctly.

Report section		7	7	8	8	8	9	15	10	10
Crop		Barley (GS12)	Barley (GS22)	Wheat (GS22)	Wheat	Wheat	Oat	Wheat	Wheat in canola stubble	Wheat with canola stubble removed
Weeds		Wild radish	Wild radish	Tares, bifora, medic	Wild radish	Wild radish	Wild radish	Wild radish	Tares, bifora, medic	Tares, bifora, medic
Best classifier		WW2.0	WW2.0	WW3.1	WW3.0	WW1.0	WW3.0	WW2.1	WW2.0	WW2.0
	Type of segment									
Number of segments	**All**	**78**	**75**	**78**	**79**	**84**	**79**	**81**	**57**	**47**
	Weed	70	75	87	96	88	99	77	46	45
	Crop	96	78	74	66	61	56	82	69	49
	Undefined	*	5	36	23	0	66	6	5	43
Area of image (Pixel number)	**All**	**88**	**80**	**35**	**68**	**88**	**18**	**88**	**37**	**41**
	Weed	87	88	76	89	95	96	69	25	26
	Crop	91	66	86	51	52	9	95	87	84
	Undefined	*	1	6	39	0	75	0	3	4

Summary of analysis 2 - The Threshold Method

Analysis 2 is the process of making a visual assessment of an entire image, where weeds are observed the image is categorised as requiring spraying, where the image is weed free it does not require spraying. This is compared to the sensor output for the same image and this is repeated for the entire image series. The output from this analysis comes in the form of an over spray and under spray per cent. Over spray is where an image with no weeds is sprayed and under spray is where an image with weeds is not sprayed. In the perfect system over spray and under spray will both approach zero.

However, this is not attainable with the H-Sensor and a compromise between under spraying areas with weeds and over spraying areas without weeds has to be made, a threshold value can be moved to adjust the ratio. To simplify the analysis the threshold values are set to target an under spray level of 5 - 6%, that is, 5% of images that contain weeds will not be sprayed. In some series of images this cannot be achieved and in that case the classifier with the lowest under spray value is the best fit.

The results from this analysis demonstrate how much of a given paddock would be sprayed in an on/off decision. If a large proportion of the weed free images are classified incorrectly then most of the paddock would be sprayed and the variable rate application is pointless. Given that each image is $0.075m^2$, if an image contains a single weed this equates to 13.3 weeds/m^2 and this would trigger a spray 'on' decision.
Because this analysis looks at the entire image as opposed to individual features the results don't appear to be as successful as results from analysis 1.

The sensor performs best in broadleaf crops at detecting grass weeds, averaging 53% overspray of weed free images when targeting 5% under spraying (Table 4 and Table 5). In practice, this means that only 47% of the potential herbicide savings will be realised in weed free areas, while 5% of the area containing weeds will not be sprayed. The discrepancy between good feature classification accuracy in analysis 1 and poorer performance in spray decisions in analysis 2 can be explained by way of example. In field pea in test 4 the sensor correctly classified 99% of 5,207,944 field pea pixels with WW3.0, however the misclassified field pea pixels total 66,507 over 82 segments. While small in percent of field pea pixels, this is nearly equivalent to the entire pixel area identified as ryegrass at 73,362. The average field pea segment (n = 880) is 5,918 pixels, however the average misclassified field pea segment (n = 82) is 811 pixels. The average ryegrass segment (n = 137) is 535 pixels. Therefore the misclassified field pea segments are much smaller than the average field pea segment, but are still larger than the average ryegrass segment. Given there is an average of 1 misclassified field pea segment per image and each of these on average is larger than the ryegrass it will have a large weighting on overspray. The best classifier varied depending on the scenario, however the WW3.x classifiers were the best in most cases.

Results in cereal crops were not as good with an average of 74% overspray of weed free images (Table 5). This is due to leaf segments of cereal crops being classified incorrectly as broadleaf weeds. The misclassification is a result of the twist in the cereal leaf along its length, when the twist is edge on to the H sensor camera the sensor is unable to detect that part of the leaf as it is too thin. This effectively cuts the long leaf into short segments that often appear similar in shape to a small broad leaf weed.

Table 4: accuracy of spray decision for ryegrass in broadleaf crops from analysis two. Under spray % is calculated from images with weeds that are not sprayed and over spray % is calculated from images without weeds that are sprayed.

Report section	1	2	3	4	5	6	13
Crop	Canola	Lupin	Faba bean	Field pea	Lentil	Chickpea	Canola
Weeds	Ryegrass	Ryegrass	Ryegrass	Ryegass	Ryegrass	Ryegrass	Ryegrass, brome, wheat
Best Classifier	WW1.0	WW3.1	RAPS1.0Ud	WW3.0	WW3.1	WW3.0	RAPS1.0
Total images in series	256	161	437	80	299	60	216
Images under sprayed (%)	6	5	46	3	5	3	8
Images over sprayed (%)	53	55	14	53	70	54	75

Table 5: accuracy of spray decision for broadleaf weeds in cereal crops from analysis two. Under spray % is calculated from images with weeds that are not sprayed and over spray % is calculated from images without weeds that are sprayed.

Report section	7	7	8	8	9	16
Crop	Barley	Barley	Wheat	Wheat	Oat	Wheat
Weeds	Wild radish	Wild radish	Tares, bifora, medic	Wild radish	Wild radish	Field pea, tares, wild radish
Best Classifier	WW2.0	RAPS1.0	MAIS2.3	WW3.0	MAIS2.2	WW3.1
Total images in series	144	1000	500	998	300	300
Images under sprayed (%)	6	6	5	5	6	6
Images over sprayed (%)	59	90	68	88	81	57

Intellectual Property

Please provide concise statement of any intellectual property generated and potential for commercialisation.

Not Applicable

Application / Communication of Results

A concise statement describing activities undertaken to communicate the results of the project to the grains industry. This should include:

- *Main findings of the project in a dot point form suitable for use in communications to farmers;*
- *A statement of potential industry impact*
- *Publications and extension articles delivered as part of the project; and,*
- *Suggested path to market for the results including barriers to adoption.*

Note that SAGIT may directly extend information from Final reports to growers. If applicable, attach a list of published material.

The concepts of in crop weed identification and results to date have been presented at numerous industry events including;

- 3 GRDC adviser updates 2015 - Adelaide, Wagga Wagga, Ballarat,
- 2 GRDC grower updates 2015 - Moama, Naracoorte,
- Minnipa EPARF conference 2015,
- 2 x Australasian Precision Agriculture Symposium 2014 & 2015,
- BCG field day 2015,
- Peracto conference 2016,
- SPAA expo's and workshops at Wudinna, Loxton and Temora 2016,
- Wheatbelt NRM event, Northam 2017

Twitter has been used to share results in the social media sphere. This has been well received generating questions and numerous 'likes' and 'retweets'.

SPAA's magazine Precision Ag News featured an article on the H-Sensor and this project.

Meetings with other groups in Australia also working on in-crop weed ID have been held to share ideas and results. This includes ESRI (Electron Science Research Institute) at Curtin University and the NCEA (National Centre for Engineering in Agriculture) at the University of Southern Queensland.

In addition, several international linkages have been made and results shared. This includes with Lincoln Agritech (NZ), Precision Decisions (UK), Aarhus University (Denmark), University of Bonn (Germany) and Bayer (Germany).

POSSIBLE FUTURE WORK

Provide possible future directions for the research arising from the project including potential for further work and partnerships.

Improved plant recognition capabilities are required that can more accurately identify weeds in more complex scenarios where leaf occlusion and overlap occurs between plants. Applying 'Machine Learning' and 'Deep Learning' techniques to this problem may provide an opportunity to achieve this objective. A Fully Convolutional Neural Network - a deep learning technique - has been applied to this problem by Dyrmann *et al.*, the Department of Engineering at Aarhus University, Denmark. Weed classification results are promising and appear to be a significant improvement in the types of scenarios where the H-Sensor classification method produced errors.

Methodologies have been developed that could now be followed for use in Australian weed mapping scenarios. These processes require large amounts of images for training purposes.

Through this current project we have captured approximately 199,000 images, of which a significant number would be suitable for use in these new training methods. This work would require the appropriate computer science and engineering skills.

AUTHORISATION
Name: Dr Nicole Dimos
Position: Executive Officer
Signature:
Date: 01/02/2018

Submit report via email to admin@sagit.com.au as a Microsoft Word document in the format shown ***within 2 months*** after the completion of the Project Term.