

1 **Digital imaging outperforms traditional scoring methods of spittlebug tolerance in**
2 ***Urochloa humidicola* hybrids**

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13 Running title: Phenotyping spittlebug tolerance in *Urochloa humidicola* using digital images

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1 **Highlight**

2 Digital imaging outperformed standard scoring method of spittlebug tolerance in *Urochloa*
3 *humidicola*, suggesting that this method might improve the efficiency of breeding for such stress.

4
5 **Abstract**

6 American spittlebug complex (Hemiptera: Cercopidae) is a critical pest for existing *Urochloa*
7 *humidicola* cultivars in the neotropical savannas. The *U. humidicola* breeding program of the
8 International Center for Tropical Agriculture aims to increase tolerance to spittlebugs. To develop *U.*
9 *humidicola* genotypes with superior tolerance to spittlebugs than existing cultivars, adequate
10 screening methods ought to be deployed. Currently, visual scores of plant damage by spittlebugs is
11 the standard method to screen for variation in plant tolerance. However, visual scoring is prone to
12 human bias, is of medium throughput and relies of the expertise of well-trained personnel. In this
13 study, we compared estimations of plant damage from two alternative methods (SPAD
14 measurements and digital images) and visual scoring from an inexpert evaluator with the plant
15 damage estimated from an expert. This information should instruct if different methods could be
16 implemented in the *U. humidicola* breeding program. Time needed to evaluate damage was
17 recorded for each method. Lin's correlation coefficient, Pearson's correlation coefficient and broad
18 sense heritability values were also calculated. Overall, damage estimated from digital images
19 showed the highest throughput (twice as fast as visual scoring from an expert); high correlations with
20 visual scoring ($r > 0.80$, $p < 0.0001$); and heritability values for plant damage as good or better ($>$
21 0.7) than those obtained by visual scoring from an expert. Our results indicate that digital imaging is
22 a phenotyping method that might improve the efficiency of breeding for increased tolerance to
23 spittlebugs in *U. humidicola*.

24
25 **Keywords:** High-throughput phenotyping; sensors; Host-Plant Resistance; *Aeneolamia varia*;
26 tropical forage grasses.

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2 **Introduction**

3 *Urochloa humidicola* is an important forage grass in the tropical savannas of America (Vasques
4 Berchembrock et al. 2020). The productivity of current cultivars of *U. humidicola* is challenged by
5 the American spittlebugs complex (Valério et al. 2001). Increasing tolerance to spittlebugs
6 complex in *U. humidicola* is a major target for the *Urochloa* breeding program of the International
7 Center for Tropical Agriculture (CIAT, Colombia). To develop *U. humidicola* genotypes with
8 superior tolerance to spittlebugs than current available cultivars, adequate screening methods
9 ought to be deployed. Currently, visual scoring of plant damage is the standard phenotyping
10 method to evaluate plant tolerance to spittlebug complex in *Urochloa* grasses. Visual scores rely
11 on estimates of percentages of dead leaf tissue (Parsa et al. 2011). Overall, visual scoring is a
12 low cost and medium throughput phenotyping method that has proven successful in the *Urochloa*
13 breeding program of CIAT (Cardona et al. 1999; Miles et al. 2006).

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15 Visual scoring is nonetheless prone to the subjectivity of any given evaluator and may not be
16 accurate enough (Walter et al. 2012). Among factors that can affect scoring of plants are the
17 expertise of the evaluator (i.e., different scores from different evaluators) and fatigue over
18 working hours. To overcome this, sensor based measurements are gaining momentum in the
19 *Urochloa* breeding program (Cardoso & Rao 2019). Hand-held devices such as the SPAD
20 series meters are used to non-destructively record greenness of leaves. Measurements of
21 SPAD have been shown to be positively and linearly correlated with percentages of dead tissue
22 in *Urochloa* grasses (Cardoso et al. 2013). Another method used to record percentages of dead
23 leaf tissue in *Urochloa* grasses is digital imaging (Jiménez et al. 2017).

24

25 Albeit sensor based measurements are currently used in the *Urochloa* breeding program, their
26 use have been limited to evaluations different to those of tolerance to spittlebugs (e.g., Jiménez

1 et al. 2017; Cardoso & Rao 2019; Mazabel et al. 2020; Jiménez et al. 2020). Therefore, the
2 main objective of the present work was to compare how well alternative phenotyping methods
3 (SPAD measurements and digital images) or a visual scoring from an inexperienced evaluator
4 related to the traditional evaluation based on visual scoring of damage from an expert. For that
5 purpose, a set of 24 *U. humidicola* hybrids (plus seven *U. humidicola* genotypes with known
6 tolerance to spittlebugs) were used and evaluated under greenhouse conditions. Estimations of
7 plant damage using different methods were carried out and calculations of agreement (Lin's
8 concordance index) and Pearson correlation coefficient were performed. Broad sense
9 heritability value was calculated to provide an indication of the efficiency of the selection
10 process from the different phenotyping methods. This information should instruct which
11 screening methodology is the most appropriate (in terms of ease, accuracy and throughput), but
12 also guide further refinements needed in any screening method used. Improved screening
13 methods should allow more accurate and intense selection, and hence, greater genetic gain for
14 tolerance to spittlebugs in *U. humidicola* hybrids.

15

16 **Materials and Methods**

17 Thirty-one *U. humidicola* genotypes were used in the present study, which was conducted at
18 CIAT (Palmira, Colombia, latitude 3°31'N; longitude 76°19'W; altitude 965 m). Genotypes
19 included 24 hybrids originated from the *U. humidicola* breeding Program of CIAT, and seven
20 plant checks with known tolerance to spittlebugs. Plant checks consisted of three tolerant
21 genotypes (cvv. Llanero and Tully and one germplasm accession, CIAT/16888) and three
22 sensitive ones (two germplasm accessions, CIAT/26146, CIAT/26375 and a hybrid, Bh13/2768).
23 The germplasm accessions CIAT/16888 and CIAT/26146 are the foundation parents of the *U.*
24 *humidicola* breeding program. All genotypes were obtained from vegetative material
25 (propagation plants) that were maintained under greenhouse conditions [28°C; 80% RH]. For
26 each genotype, ten vegetative propagules (plant units) of one single tiller were harvested from

1 propagation plants and then immersed for five minutes in a 1% sodium hypochlorite solution.
2 Plants were rinsed from sodium hypochlorite prior to planting. Each plant unit was planted in a
3 cylindrical polyvinyl chloride (PVC) unit (5.3 cm wide X 6.5 cm deep) that contained 40 g of
4 sterilized soil (3:1 weight soil: weight sand). Plants were watered daily and fertilized with 30 mL
5 of nutrient solution prepared with a 15% N-15% P-15% K soluble fertilizer at 3 g L⁻¹ two weeks
6 after planting. One month after planting, when sufficient superficial roots were available to serve
7 as feeding sites for the nymphs, five plants/genotype were infested with six mature eggs of
8 *Aeneolamia varia* as previously described by (Cardona et al. 1999). The other five
9 plants/genotype were not infested and used as controls. The eggs were previously obtained
10 from the CIAT spittlebug mass rearing colony, selected for viability by visual inspection and
11 incubated under controlled conditions (28C, 85% RH) (Parsa et al. 2011). Plants were
12 organized in a randomized complete block with two treatments (infested with *A. varia* and
13 uninfested) and five replicates.

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15 *Plant Damage evaluation*

16 Three phenotyping methods for plant damage were carried out at weekly intervals for five
17 weeks: 1) visual scoring from an expert and an inexperienced evaluator; 2) SPAD measurements and,
18 3) digital images. Plant damage was estimated and expressed in percentage as described
19 below. Also, time spent during plant damage evaluation under the different methods was
20 recorded.

21

22 *Visual scoring*

23 Visual scoring for plant damage consisted on the assessment of the proportion of green to
24 senescing leaf tissue (yellow to brown) of the whole plant. Visual scoring used a 11-point scale
25 as follows: 0 = all leaves are green; 1= 10% of senescent leaves; 2 = 20% of senescent leaves;
26; 10 = 100% of senescent leaves. To test whether the visual scoring was affected by a given

1 person during an evaluation, an expert and an inexperienced evaluator carried out visual scorings
2 independently.

3

4 *SPAD measurements*

5 SPAD meters (SPAD-502, Konica Minolta, Japan) were used to estimate greenness of different
6 leaves. SPAD units were recorded on three fully expanded leaves for each plant and their
7 values averaged. Plant damage was estimated from the difference in SPAD measurements
8 between consecutive weeks as follows; $[(SPAD_n - SPAD_{n+1})/SPAD_n] * 100$. where $SPAD_n$ is a
9 SPAD recording at any given week, and $SPAD_{n+1}$, the recording of SPAD the week after.

10

11 *Digital imaging*

12 For image acquisition, individual plants were placed within a closed chamber (dimensions:
13 2x1.5x1 m) and illuminated from above with a T8 led tube 32w 120 cm. Images were then
14 acquired with a digital color camera (Nikon Coolpix P6000, Nikon, Japan) with the following set
15 up: F-stop: f/2.7, Exposure time: 1/60, and ISO speed ISO-89 and from a Nadir view of the
16 plant. Images were saved in a 4224 x 3168 pixel JPEG format. To account for difference in
17 illumination throughout acquisitions and thereby influencing color tones in images and
18 greenness estimates, images were pre-processed with GIMP software (GIMP 2.10). GIMP
19 software was used to apply a pre-saved color tone matching curve to all JPEG files. After that,
20 images were processed and analyzed using ImageJ (ImageJ 1.51). Image processing consisted
21 on splitting the images onto their color channels (Red, Green and Blue), and then normalizing
22 the blue channel (Blue channel / Red channel + Green channel + Blue channel). The
23 normalized blue channel was used for image segmentation using the default threshold method
24 of ImageJ. Image segmentation consisted on the separation of shoot (white pixels) from
25 background (black pixels). Once the image was segmented, a mask was laid onto the original
26 unsegmented image using the AND logic operation. The masked image was then used to

1 calculate the difference between green and red channels, which enhances contrast between
2 green tissue and senescing (yellow to brown) tissues. Once the normalized green red difference
3 index was calculated, K-means clustering was used to create three clusters of colors in the
4 image: background, green tissue and senescing (yellow to brown) tissue. The number of pixels
5 for each cluster was then quantified and plant damage was calculated as $[\text{SP}/(\text{SP}+\text{GP})]*100$;
6 where SP = number of pixels clustered as senescing tissue and GP = number of pixels
7 clustered as green tissue. Figure 1. summarizes the image processing pipeline.

8

9 *Statistical analysis*

10 Mean values and standard deviations were calculated for estimations of plant damage for different
11 dates and evaluation methods. Two-way analyses of variance were calculated. Analyses were
12 performed only in infested plants and conducted in R (R Development CoreTeam 2015).
13 Calculations of agreement (Lin's concordance index; Lin, 1989) and Pearson correlation
14 coefficient were performed between estimates of plant damage from alternative methods (SPAD
15 meter and digital imaging) and visual scores from an inexperienced evaluator with the standard
16 evaluation of visual scoring of plant damage from an expert. Broad sense heritability was
17 calculated for each of the different evaluation methods (Piepho & Möhring 2007).

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19 **Results and discussion**

20 *Comparison of throughput and estimated damage from phenotyping methods*

21 The present study aimed to compare how well alternative phenotyping methods (SPAD meter
22 and digital images) or a visual scoring from an inexperienced evaluator related to the standard
23 evaluation of visual scoring of plant damage from an expert. Among them, the throughput of
24 each method (in terms of time consumed by one person to evaluate plants) was compared
25 (Table 1). Overall, capture of digital images was the fastest method to record plant damage
26 (twice as fast as second fastest, i.e., visual scoring from expert evaluator). Similar results were

1 previously shown by several authors (Büchi et al. 2018; Jiménez et al. 2020). Reduction of time
2 is among the improvements sought by most phenotyping methods (c.f., Shakoor et al. 2017;
3 Araus et al. 2018). Faster phenotyping could allow the increment of number of plants to be
4 evaluated for plant damage and/or to reduce the time dedicated to such activity; or allow more
5 intensive phenotyping (recording of additional traits that might be of interest).

6
7 Estimations of plant damage using different phenotyping methods are shown in Figure 2. Our
8 results showed that there were not significant differences between estimates of damage from
9 visual scoring from an expert and an inexpert evaluator. This suggests that the inexpert
10 evaluator followed well instructions given by the expert evaluator. However, this might not
11 always be the case for every training of new evaluators. The success of training of a new
12 evaluator is dependent to inherent characteristics of such individual (e.g., previous knowledge of
13 the plants; this case), which likely affects the accuracy of any evaluation. Bock et al. (2020)
14 recently reviewed inter-rater variability and success of training among drawbacks of visual
15 estimates of plant damage. Albeit estimates of damage from the expert and inexpert evaluators
16 were similar, measures of data variability (i.e., standard deviation) from the inexpert evaluator
17 were greater than those from the expert evaluator. Similar results were found by (El Jarroudi et
18 al. 2015) when comparing estimates of septoria leaf blotch severity (and measures of data
19 variability) in winter wheat from different evaluators.

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21 Differences in estimates of damage between visual scores (from expert and inexpert evaluators)
22 and the other two methods (SPAD measurements and digital images) were found from the first
23 week of evaluation (Table 2). Throughout the experiment, it was notable that estimates of
24 damage were greater in visual scores compared to those obtained from SPAD meters (~ 1.5-
25 fold greater) and digital images (~1.3-fold greater). Furthermore, development of damage
26 appeared faster under the visual scoring method. Since the magnitude and speed of damage

1 were greater under the visual scoring method (for both experienced and inexperienced
2 evaluators), it is likely that visual scores over-estimated damage. Over-estimation of damage by
3 visual scoring compared to other methods, including digital imaging, was previously identified by
4 (Bock et al. 2010).

5

6 *Concordances, correlations, and heritability*

7 Highest concordances (Lin's concordance coefficient, CCC) and correlations (r) were observed
8 between visual scoring from the expert and inexpert evaluators (Table 2). Our results showed
9 increasing values of CCC and r between visual scores from an expert and inexpert evaluator
10 with each passing week until the end of the evaluation period (data not shown). This suggests
11 that the inexpert evaluator got better with time in the visual scoring of plant damage, as shown
12 elsewhere (Bock et al. 2016; Bock et al. 2020). Albeit the improvement gained by the inexpert
13 evaluator, this one was not able to distinguish percentages of damage below 20% intervals,
14 whereas the expert evaluator could do it at 10% intervals (data not shown). Similar results were
15 found when experienced and inexperienced evaluators assessed severity of Phomopsis leaf
16 blight of strawberry (Nita et al. 2003). Second best values of CCC (0.82) and r (0.87) were
17 between visual scoring from expert evaluator and digital images (Table 3). Such level of
18 agreement between estimates of damage from visual scoring and digital images is considered
19 low (c.f., McBride, 1985). This is not surprising as 1) estimates of damage from visual scoring
20 were discrete values vs. continuous values of plant damage estimated from digital images (c.f.,
21 McBride, 1985); and 2) a likely overestimation of damage from visual scoring (Figure 2) as
22 mentioned before.

23

24 Table 4 summarizes broad sense heritability (H^2) values according to evaluation method,
25 treatment and sampling day. Greater values of H^2 (values closer to 1) were obtained using the
26 digital images method. Similar results for H^2 were obtained by other authors when comparing

1 image based phenotyping methods to visual evaluations (Makanza et al. 2018; Singh et al.
2 2019). A phenotyping procedure (e.g., digital imaging) that detects high heritability of any given
3 trait allows a broader selection process, hence, the genetic advance through the breeding
4 cycles is faster (Holland et al. 2003).

5

6 *Conclusions*

7 The present work showed that estimation of plant damage from digital images yielded similar
8 results to those obtained by the standard method of visual scoring by an expert evaluator. One
9 of the major drawbacks of visual scoring is the dependence of an expert evaluator. Training of
10 new evaluators for visual scoring of plant damage might be a straightforward mechanism to
11 ensure continuity of such method over time. However, as argued before, inter-rater variation
12 represents a major drawback for this method. Overall, SPAD measurements provided the less
13 throughput and less agreement (CCC) and correlation with the standard evaluation of visual
14 scoring from an expert, which makes this method an unattractive one to a breeding program.
15 Higher values of broad sense heritability and faster recording of plant damage from digital
16 images suggests that this phenotyping method might improve the efficiency of breeding for
17 increased tolerance to spittlebugs in *U. humidicola*.

18

19 **Acknowledgments**

20 We would like to thank William Mera, Ximena Bonilla, Jeison Velasco and Miller Escobar of the
21 Tropical Forages Program (Alliance Bioversity-CIAT) for their technical support. This study was
22 supported by the CGIAR Research Program 3.7 (Livestock and Fish).

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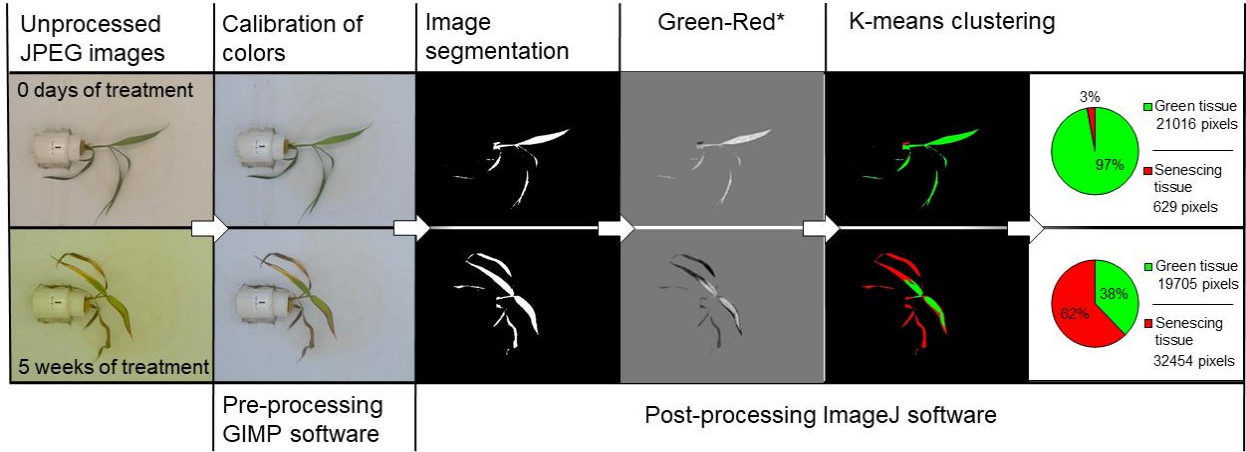
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2 **Figure 1.** Summary of the image processing pipeline. Green-Red* is the product of the green

3 minus red channel.

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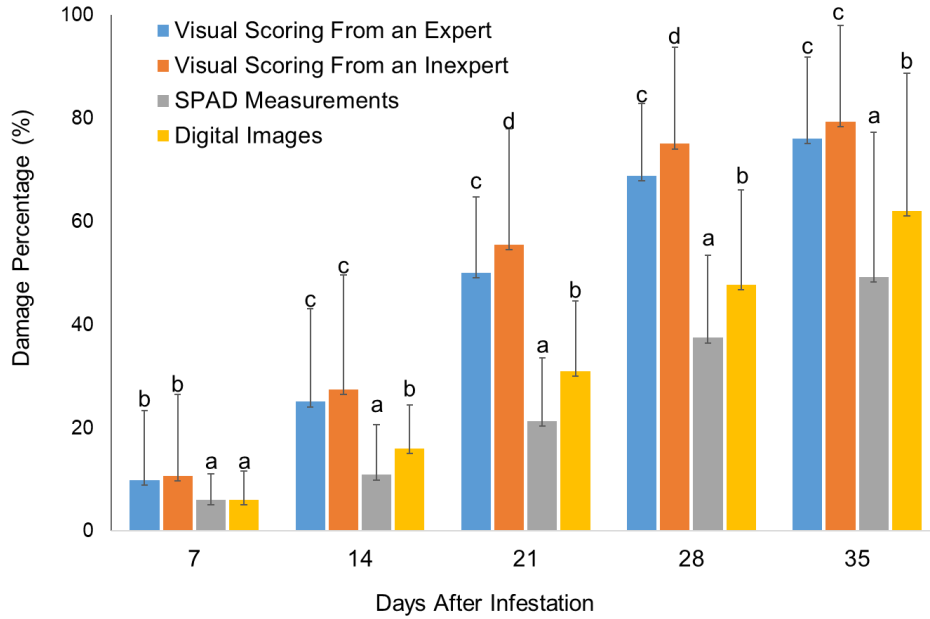
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2 **Figure 2.** Comparison of damage percentage of three plant damage evaluation methods
3 assessed over Bh16 genotypes at 7, 14, 21, 28, and 35 days after infestation with spittlebug
4 nymphs *Aeneolamia varia*. Letter over bars indicated the differences by evaluation method at 7,
5 14, 21, 28 or 35 days after infestation. Column bars represent means and error bars indicate the
6 standard deviation. Columns with different letter are significantly different ($\alpha < 0.05$).

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- 1 **Table 1.** Average values of five evaluations showing the time required to perform evaluations.
2 Values denote means \pm standard deviations. Different letters next to standard deviation values
3 denote significant differences at $\alpha = 0.05$.

	Number of plants/hour
Visual scoring (expert)	58 \pm 13b
Visual scoring (inexpert)	71 \pm 25c
SPAD measurements	80 \pm 15bc
Digital images	113 \pm 15a

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1 **Table 2.** Results of analysis of variance (two-way ANOVA) for 27 genotypes from *Urochloa*
 2 *humidicola* Bh16 population breeding program evaluated against spittlebug nymph *Aeneolamia*
 3 *varia*.

DAI [†]	Source	Df	Sum of Square	Mean of Square	F value	P value	
7	Genotype	29	13869	478.2	4.849	7.06E-14	***
	Method	3	2471	823.7	8.352	0.000021	***
	Genotype:Method	87	9659	111	1.126	0.225	
	Residuals	416	41026	98.6			
14	Genotype	29	33021	1139	5.712	<2e-16	***
	Method	3	24089	8030	40.276	<2e-16	***
	Genotype:Method	87	15286	176	0.881	0.761	
	Residuals	416	82935	199			
21	Genotype	29	48623	1677	8.695	<2e-16	***
	Method	3	103661	34554	179.185	<2e-16	***
	Genotype:Method	87	12537	144	0.747	0.951	
	Residuals	416	80220	193			
28	Genotype	29	64296	2217	11.771	<2e-16	***
	Method	3	124900	41633	221.037	<2e-16	***
	Genotype:Method	87	9217	106	0.562	0.999	
	Residuals	416	78355	188			
35	Genotype	29	121290	4182	12.627	<2e-16	***
	Method	3	76836	25612	77.323	<2e-16	***
	Genotype:Method	87	20665	238	0.717	0.97	
	Residuals	416	137794	331			

4 ***Significant at the 0.001 probability level.

5 [†]DAI, days after infestation.

1 **Table 3.** Lin's concordance coefficient and Pearson correlation analysis between damage
 2 percentages obtained from the evaluation methods. CCC: Lin's concordance correlation
 3 coefficient, CI: confidence interval (95%), r = Pearson correlation coefficient, *** correlation
 4 significance ($p < 0.001$).

DAI*	Index	Visual Scoring From an Expert	Visual Scoring From an Expert	Visual Scoring From an Expert
		vs. Visual Scoring From an Inexpert	vs. SPAD Measurements	vs. Digital Images
7	CCC	0.89	0.16	0.29
	CI	0.86 - 0.91	0.09 - 0.24	0.22 - 0.36
	r	0.9***	0.25***	0.44***
14	CCC	0.89	0.24	0.42
	CI	0.86 - 0.91	0.17 - 0.32	0.36 - 0.49
	r	0.91***	0.36***	0.59***
21	CCC	0.89	0.34	0.58
	CI	0.87 - 0.91	0.28 - 0.4	0.52 - 0.64
	r	0.92***	0.6***	0.76***
28	CCC	0.93	0.56	0.75
	CI	0.91 - 0.94	0.5 - 0.61	0.71 - 0.79
	r	0.94***	0.82***	0.88***
35	CCC	0.94	0.70	0.86
	CI	0.93 - 0.95	0.64 - 0.75	0.83 - 0.89
	r	0.95***	0.83***	0.9***

1 **Table 4.** Broad sense heritability according treatment, evaluation method, and days after
2 infestation for damage percentage. DI: Digital images; SM: SPAD measurements; VSI; Visual
3 evaluation from expert; VS2: Visual evaluation from inexpert. DAI: Days after infestation.

Method	7 DAI		14 DAI		21 DAI		28 DAI		35 DAI	
	<i>H2</i>	<i>Pvalue</i>	<i>H2</i>	<i>Pvalue</i>	<i>H2</i>	<i>Pvalue</i>	<i>H2</i>	<i>Pvalue</i>	<i>H2</i>	<i>Pvalue</i>
DI	0.6	0.007	0.7	0.001	0.8	0.001	0.8	0.001	0.8	0.001
SM	0.4	0.13	0.5	0.04	0.7	0.001	0.7	0.001	0.8	0.001
VS1	0.6	0.0024	0.6	0.0077	0.7	0.001	0.8	0.001	0.8	0.001
VS2	0.5	0.0083	0.5	0.0077	0.5	0.0079	0.5	0.0212	0.5	0.0088

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