

1 Potential of a terrestrial LiDAR-based system to characterize weed vegetation
2 in maize crops

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11 ABSTRACT

12 LiDAR (Light Detection And Ranging) is a remote-sensing technique for the measurement
13 of the distance between the sensor and a target. A LiDAR-based detection procedure was
14 tested for characterization of the weed vegetation present in the inter-row area of a maize
15 field. This procedure was based on the hypothesis that weed species with different heights
16 can be precisely detected and discriminated using non-contact ranging sensors such as
17 LiDAR. The sensor was placed in the front of an all-terrain vehicle, scanning downwards
18 in a vertical plane, perpendicular to the ground, in order to detect the profile of the
19 vegetation (crop and weeds) above the ground. Measurements were taken on a maize field
20 on 3m wide (0.45 m²) plots at the time of post-emergence herbicide treatments. Four
21 replications were assessed for each of the four major weed species: *Sorghum halepense*,
22 *Cyperus rotundus*, *Datura ferox* and *Xanthium strumarium*. The sensor readings were
23 correlated with actual, manually determined, height values ($r^2 = 0.88$). With canonical
24 discriminant analysis the high capabilities of the system to discriminate tall weeds (*S.*
25 *halepense*) from shorter ones were quantified. The classification table showed 77.7% of the

26 original grouped cases (i.e., 4800 sampling units) correctly classified for *S. halepense*.

27 These results indicate that LiDAR sensors are a promising tool for weed detection and

28 discrimination, presenting significant advantages over other types of non-contact ranging

29 sensors such as a higher sampling resolution and its ability to scan at high sampling rates.

30

31 *Keywords:* LiDAR technology. Precision crop protection. Site-specific weed management.

32 Weed discrimination.

33

34 **1. Introduction**

35 In spite of the fact that weed detection technologies have been widely explored, the

36 commercial uptake of these technologies has been very limited. Relatively simple

37 optoelectronic sensors have been used for weed mapping or patch spraying in non

38 cultivated areas and in row crops (Biller, 1998; Andújar et al., 2011a). However, these

39 sensors are not able to discriminate between different weed species, limiting their use to

40 broad-spectrum herbicide treatments. Numerous studies have shown the possibility to

41 discriminate different plant species based on their shape, texture and colour using vision

42 technologies (Slaughter et al., 2008; Weis & Sökefeld, 2010; Rumpf et al., 2012).

43 Although these technologies are accurate when weeds are small, their accuracies are

44 significantly reduced when plants get larger and their leaves start to overlap. Ultrasonic

45 sensors have been devised to characterize crop canopies, detecting structural differences in

46 the vertical distribution of crop leaves (Shibayama et al., 1985). Recent studies conducted

47 with this type of sensors have showed their potential for the automatic discrimination

48 between various monocotyledonous and dicotyledonous weeds based on height differences

49 (Andújar et al., 2011b). The use of these low-cost, fast-response sensors provides an

50 interesting opportunity for real-time spraying of row crops when the weed types to be

51 identified have different sizes. However, this technology has some limitations: a) the
52 scanned area (surface area explored) of these sensors is relatively small (20 to 50 cm,
53 corresponding to the footprint of a single sensor); consequently, a large number of sensors
54 would be needed to scan a representative portion of the field; b) because of this reduced
55 scanned area, the measurements do not include the crop row area; c) ultrasonic sensors are
56 not able to discriminate crop leaves that invade the scanned area in the inter-row space,
57 leading to false positives. In this regard, a higher spatial and temporal sampling sensor
58 could provide information on the crop row location and on the weed height in the inter-row
59 area. LiDAR sensing technologies have been used in some agricultural and forestry
60 applications, such as robotic guidance (Subramanian et al., 2006), estimation of cereal crop
61 volume (Saeys et al., 2009) and electronic measurement of canopy dimensions in woody
62 crops (Richardson et al., 2009; Llorens et al., 2011; Rosell & Sanz, 2012). The capabilities
63 of this type of devices to remotely detect objects and estimate distances, and its wider
64 scanning area make them very appropriate to detect and discriminate weeds in row crops.
65 This work assesses the usage of LiDAR for scanning ground vegetation in maize fields,
66 analysing its capabilities for row-crop identification and its possibilities for weed species
67 discrimination at the time of applying post-emergence herbicides.

68

69 **2. Materials and methods**

70 *2.1. LiDAR sampling system*

71 A Terrestrial Laser Scanner (TLS) sensor based on phase shift LiDAR technology was
72 used to estimate vegetation height. This sensor provides non-contact measurement of the
73 distance between the TLS and the object of interest. The sensor used was a Hokuyo URG-
74 04LX phase shift TLS. The LiDAR sensor contains a source of laser light (whose intensity
75 is modulated according to a sinusoidal signal of a certain frequency) and a photodetector to

76 detect the reflected beam from the object of interest. The distance between the object and
77 the sensor is determined from the measured phase shift between the emitted light beam and
78 the object's reflected beam detected by the photodetector. Possible distance ambiguities are
79 filtered by the sensor. The sensor estimates the distance to different points of the object of
80 interest by modifying the direction of the emitted laser beam by means of a rotating mirror
81 which deflects the beam in different directions within the same plane. Thus, the sensor
82 performs an angular scanning of the object within a plane, obtaining the distances from a
83 set of object points in the measurement plane as a result. Finally, moving the sensor in the
84 direction perpendicular to the scanning plane, distances to object points situated in adjacent
85 planes are obtained, to cover the whole object of interest.

86 The sensor was fixed in a metal frame scanning downwards in a vertical plane
87 perpendicular both to the ground and the travel direction in order to detect the vegetation
88 profile above the ground. The divergence of the laser beam emitted by the TLS results in a
89 certain footprint when impacting an object. In our study, the sensor was located 1.5 m in
90 height and, according to the manufacturer's technical specifications, the corresponding laser
91 beam diameter in the measurement range was 15 mm. This laser beam footprint may
92 contain ground, crop, weeds or mixtures of them. The frame supporting the TLS was fixed
93 to the front of an All Terrain Vehicle (Fig. 1). The software required to acquire and process
94 the LiDAR readings was developed using LabVIEW® (National Instruments) graphical
95 development environment.

96

97 2.2. Study site and procedure

98 The study was conducted in a maize field at La Poveda Research Farm (Arganda del
99 Rey, Madrid, Spain). Maize was planted with 75 cm row spacing and a density of 90.000
100 plants ha⁻¹. Natural weed infestations were composed of two dicotyledonous (*Datura ferox*

101 L. and *Xanthium strumarium* L.) and two monocotyledonous weeds, *Cyperus rotundus* L.
102 (Cyperaceae) and *Sorghum halepense* (L.) Pers. (Poaceae). Weeds were assessed on May
103 13 at maize growth stage BBCH 12-14 (16.0±3.0 cm height). Weed growth stages were
104 BBCH 14 (*D. ferox*, 6.5±2.5 cm height), BBCH 16 (*X. strumarium*, 9.0±5.0 cm height; and
105 *C. rotundus*, 9.0±3.5 cm height) and BBCH 24 (*S. halepense*, 17.0±10.0 cm height).

106 Based on the differential distribution of the various weed species in the field (weed
107 patches), four plots of 0.45 m² (300 cm wide × 15 cm) were located (as randomly as
108 possible) in patches where each species was dominant (accounting for more than 75% of
109 total weed density). Plants from the other weed species were removed manually. Two sets
110 of data were collected on these 16 plots (4 species × 4 plots per species). The first, aimed at
111 testing the reliability of the LiDAR system to accurately measure the vegetation height and
112 the soil profile, was obtained in the whole plot. For each cm of plot width, actual weed
113 height (Va) and LiDAR vegetation height (VL) were computed from vegetation height
114 profiles (see below) for a total of 300 sampling units per plot. Actual ground height (Ga)
115 and LiDAR ground height (GL) were also evaluated in the same way. The actual (Va and
116 Ga) profiles were drawn from digital images while LiDAR profiles were generated by
117 fitting the average line through nine LiDAR repeated measures per plot. A second set of
118 data, which was used to assess the relationship between LiDAR readings and weed density
119 and weed biomass, was obtained by dividing each plot into 12 (25 cm wide × 15 cm) sub-
120 plots where weed parameters were taken.

121 Nine separate LiDAR readings, i.e. nine repeated measures (effective beam footprint
122 of 15 mm) were taken from each plot in order to avoid errors from the sensing technique,
123 so that the sensor was positioned vertically to the plot. Afterwards, a panoramic view
124 composed of 4 (75 cm wide) digital images was obtained of each plot, using a Nikon D70
125 digital camera positioned at a distance of 120 cm from the plot and at ground level in order

126 to obtain a profile image of the vegetation. The vegetation between the **plot** and the camera
127 was removed in order to avoid interferences.

128 A modified version of the pin-microrelief method (Abd Elbasit et al., 2009) was used
129 to measure both plant height and ground surface level from digital images. A vertical metal
130 frame (300 cm × 60 cm) with 70 movable aluminium rods 4 cm equidistant from each
131 other as well as a graph paper background with a **cm scale** was placed in the back of the
132 **plot** (Fig. 2). The aluminium rods could move up and down through holes drilled on two
133 lateral metal bands attached to the frame allowing to measure **Ga profile**, i.e., the baseline.
134 Each aluminium rod had a red mark at the top rim which coincided with a zero elevation
135 line marked on the frame when the frame was placed on a flat surface. In a rough ground
136 surface, the red marks were above the baseline when the rods were supported on an
137 elevated surface and below the baseline when they were on a depression. Hence, **Va** was
138 determined in digital images by subtracting Ga (shown by the profile of the rods) from the
139 profile of maximum vegetation height.

140 After taking LiDAR readings and digital images, all plants present in a **plot** (i.e.,
141 belonging to the same weed species) were counted for weed density and **collected for** dry
142 weight biomass determination, dividing the **plot** into twelve **sub-plots** 25 cm long in the
143 direction perpendicular to rows and 15 cm wide in the row direction.

144 Afterwards, in order to obtain **the GL profile**, nine LiDAR **repeated measures** were
145 taken on the vegetation-free ground. The **VL profile** was obtained by subtracting GL to the
146 previous LiDAR readings.

147 Data were processed using AutoCAD 2012® (Autodesk, Inc). LiDAR measurements
148 were projected and trimmed at the edges so that only the 3 m corresponding to the **plot area**
149 were used. Profiles of maximum weed height and ground (**VL and GL, respectively**) were
150 created using the nine LiDAR **repeated measures** of each **plot**. Also, **the** panoramic view

151 created within each plot with the four digital images, was projected in the same software to
152 manually draw the actual vegetation height and ground profiles (V_a and G_a , respectively).
153 Afterwards, data from each centimetre (i.e., 300 sampling units in the 300 cm long plot)
154 were recorded in the four height profiles in order to obtain a database for point by point
155 comparisons. Additionally, a second set of data was obtained by calculating the average
156 VL height in each 25 cm sub-plot, so that 12 sampling units per plot were recorded.

157

158 2.3. Statistical Analysis

159 Before performing a regression analysis, we tested the normal distribution of residuals,
160 as well as the assumptions that residuals had a mean of zero and constant variance
161 (homoscedasticity). Pearson's correlation coefficient was used to analyse simple linear
162 relationships between V_a (actual weed heights as predictor/independent variable) and VL
163 (LiDAR measurements as outcome/dependent variable) using the database with 4800
164 sampling units (300 per plot) of both profiles. In addition, this database was used to
165 implement a canonical discriminant analysis (CDA) to classify and discriminate the four
166 groups, each of them belonging to a weed species (Kenkel et al., 2002) using the specific
167 V_a as interval variables and VL as classification variable. Although we did not observe an
168 overall canonical correlation, a trend was found for *S. halepense*. Consequently we
169 repeated CDA with only two groups, *S. halepense* and the rest of weed species, to predict
170 whether the individual species can be correctly classified from the rest. Finally, a multiple
171 linear regression analysis was performed to assess the relationship between average
172 LiDAR readings at the 25 × 15 cm sub-plots (response variable) and two explanatory
173 variables, weed biomass and weed density, using the database with 192 sampling units (12
174 per plot). All statistical analyses were performed using SPSS® v19.0 (IBM SPSS
175 Statistics).

176

177 3. Results and discussion

178 The measurements obtained with the system showed a high agreement for vegetation
179 and ground profiles. Indeed, Va and VL showed similar patterns, identifying the positions
180 of crop rows, vegetation free areas and weed infested areas (Fig. 2). In addition, Ga and
181 GL also showed high agreement, confirming the potential of this system to measure ground
182 surface topography or micro-topography (Abd Elbasit et al., 2009).

183 The high correlation between Va and VL heights obtained with the entire database for
184 the four weed species (Fig. 3; $r^2 = 0.88$) showed that LiDAR is a promising tool for the
185 assessment of vegetation height. The results varied for different weed species. Indeed, the
186 height of the short (*D. ferox*, 6.5 cm height, $r^2 = 0.48$), intermediate (*C. rotundus*, 9.0 cm
187 height, $r^2 = 0.55$; *X. strumarium*, 9.0 cm height, $r^2 = 0.80$) and tall species (*S. halepense*,
188 17.0 cm height, $r^2 = 0.86$) were correlated to different extents with LiDAR height.

189 Results of multiple linear regression analysis using the set of data obtained in sub-
190 plots of 25 × 15 cm showed weed biomass as the only explanatory variable related with
191 LiDAR readings (i.e., the dependent variable), with coefficients of determination ranging
192 from 0.21 to 0.68 for the different species (Table 1). In contrast, weed density was not
193 significantly related to LiDAR readings in any of the weed species studied.

194 The CDA showed the capabilities and limitations of the system. When performing a
195 four group (i.e., four weed species) discriminant analysis, canonical functions did not
196 discriminate correctly among groups. However, when CDA analysis was performed using
197 two groups, one for *S. halepense* and one for the other weed species, 77.7% of the original
198 grouped cases (also 77.7% of the cross-validated grouped cases) were correctly classified
199 for *S. halepense*. These results agree with those of Fig. 3 showing simple linear
200 relationships, where *S. halepense* points are clearly separated from the others, due to the

201 greater height of these plants. These predictions open the possibility of site-specific
202 treatments against *S. halepense*, one of the most problematic weeds in maize fields in the
203 Mediterranean region (Holm et al., 1977).

204 Although sensor readings did not allow discriminating the two dicotyledonous species,
205 this does not suppose a major practical problem: these species are generally controlled by
206 the same herbicides. In the case of *C. rotundus*, our results show that it can be easily
207 discriminated from the other monocotyledonous weed (*S. halepense*) due to its lower size.
208 However, in order to discriminate it from dicotyledonous weeds of similar size it would be
209 necessary to fuse LiDAR readings with the results obtained from a sensor based on
210 classification of leaf shapes (Weis & Sökefeld, 2010; Rumpf et al., 2012).

211 Previous studies have already shown that the different heights of different weed
212 species could be used as a basis for weed discrimination by using ultrasonic sensors
213 (Andújar et al., 2011b). Based on the results of our work, we can conclude that LiDAR
214 sensors can detect weeds in a maize field and discriminate taller (>18 cm) weeds located
215 within weed patches at the time of herbicide application. In addition, LiDAR sensors offer
216 several advantages over other types of non-contact distance sensors. The larger scanned
217 area of the laser beam and its ability to operate at high speed scanning mode make these
218 sensors ideal to be integrated in on-line operations for site-specific herbicide treatments.
219 Furthermore, LiDAR readings could be used in multi-purpose systems: detection and
220 discrimination of weeds for selective herbicide spraying, crop row identification for
221 automatic guidance and recognition of obstacles for fully automatic vehicle steering. For
222 this latter application, the LiDAR sensor should be mounted to scan in an intermediate
223 plane between vertical and horizontal planes.

224

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227

228 **References**

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270

271

Table 1. Standardized coefficients (β) and P -values after backward multiple linear regression analysis. LiDAR readings

272

(sub-plot averages) are related to weed density and weed biomass for each species.

	<i>Sorghum halepense</i>		<i>Datura ferox</i>		<i>Xanthium strumarium</i>		<i>Cyperus rotundus</i>	
	P	β	P	β	P	β	P	β
Constant	<0.001	–	<0.001	–	<0.001	–	<0.001	–
Weed biomass	0.001	0.456	<0.001	0.729	<0.001	0.826	<0.001	0.633
Weed density	–*	–*	–*	–*	–*	–*	–*	–*
Sig.	<0.001		<0.001		<0.001		<0.001	
R^2		0.208		0.532		0.682		0.401

273

* This variable has no significant effect in determining the LiDAR readings of the four weed species.

274

275 **Figure caption**

276

277 Fig. 1. Image of the ATV with a structure to support the terrestrial LiDAR sensor and the
278 data acquisition system ready to capture height readings from a single plot.

279

280 Fig. 2. Image of a *Sorghum halepense* plot showing height profiles. The green line
281 represents the actual vegetation profile (Va). The yellow line corresponds to the vegetation
282 profile calculated by integrating the multiple LiDAR measurements (VL). The brown line
283 shows the actual ground profile (Ga). The blue line corresponds to the LiDAR ground
284 profile (GL).

285

286 Fig. 3. Regression plot of plant height estimated by the LiDAR sensor versus actual plant
287 height measured from digital images. The symbols represent plant height for each weed
288 species: *Sorghum halepense* (L.) Pers., *Datura ferox* L., *Xanthium strumarium* L. and
289 *Cyperus rotundus* L.

Figure
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Fig. 1

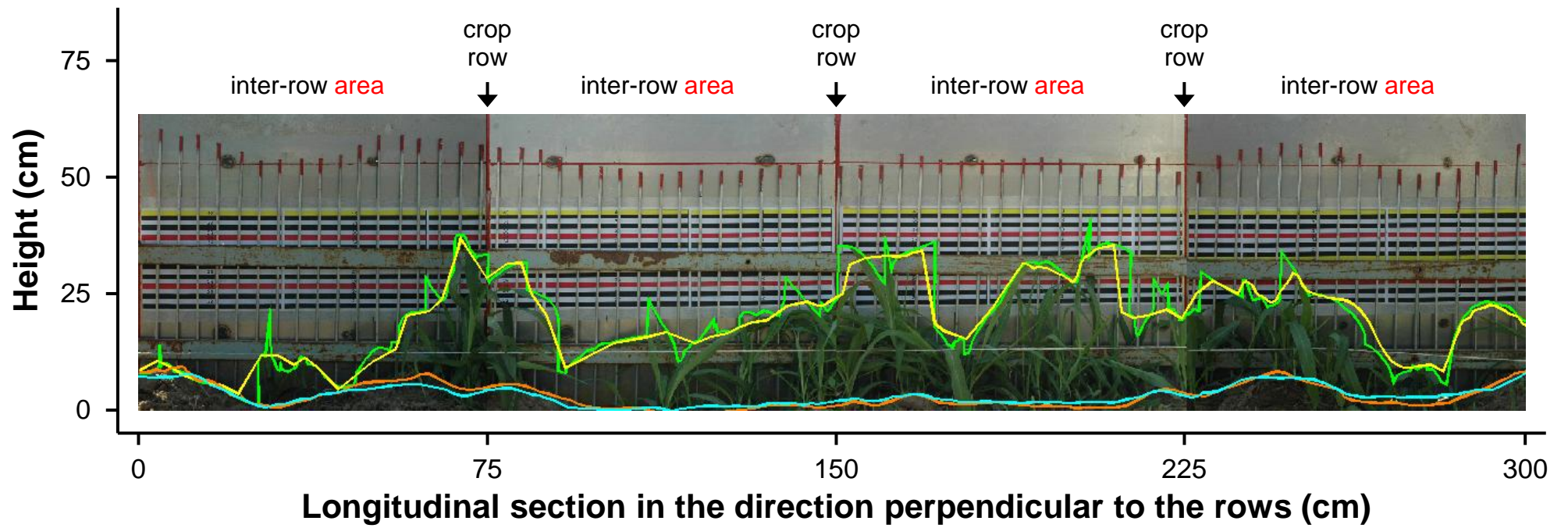


Fig. 2

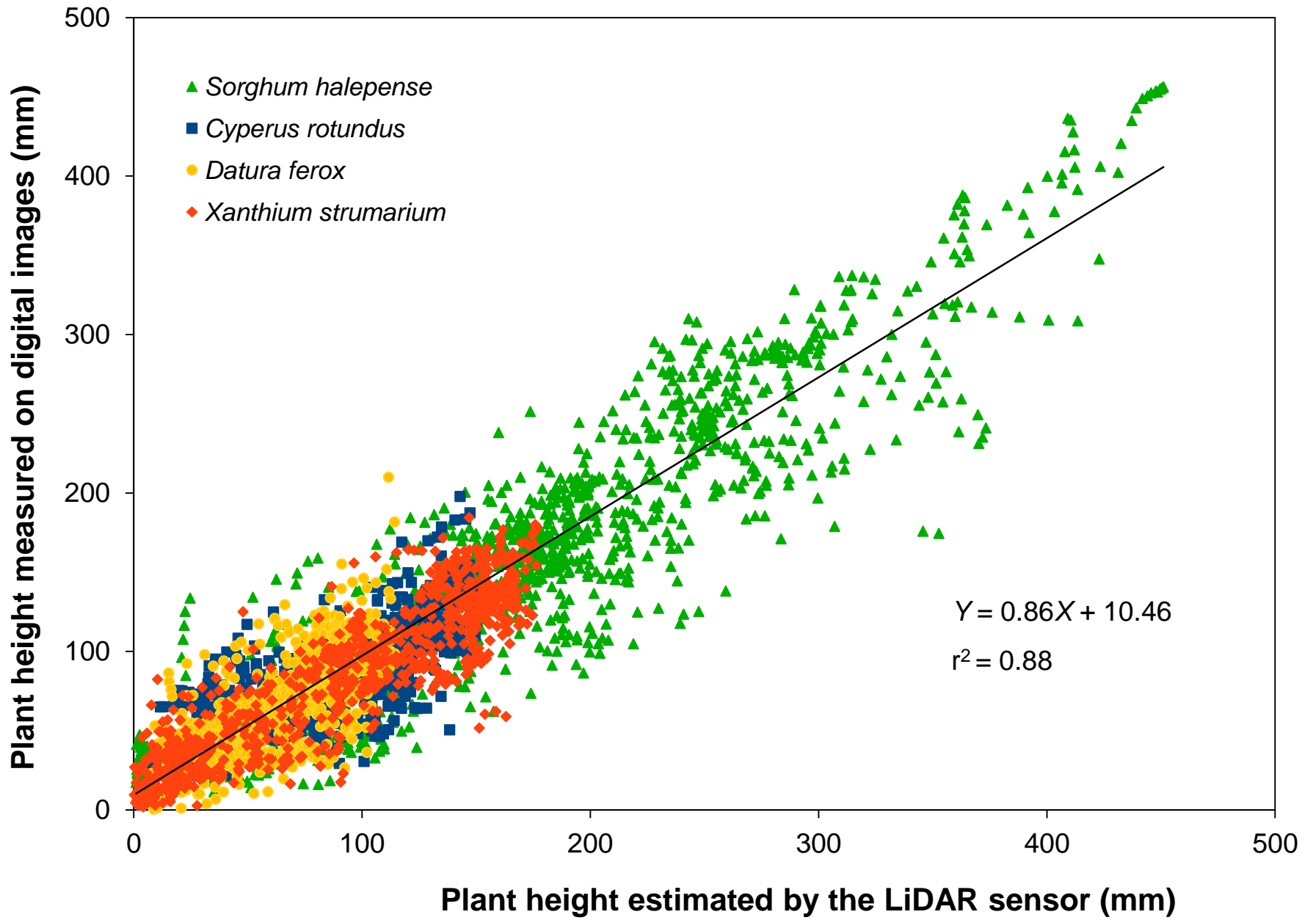


Fig. 3