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# Predicting the site-specific distribution of agrochemical spray deposition in vineyards at multiple phenological stages using 2D LiDAR-based primary canopy attributes

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1           **Predicting the site-specific distribution of agrochemical spray deposition in vineyards at**  
2           **multiple phenological stages using 2D LiDAR-based primary canopy attributes**

3  
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10  
11 **Abstract**

12  
13 Predicting the dose to be applied on the basis of the structural characteristics of the plant canopy is a  
14 crucial step for the optimization of the spraying process. Mobile 2D LiDAR sensor data and local  
15 measurements of deposition rates from a face-to-face sprayer were made across eight fields in two  
16 Mediterranean vineyards at four dates in 2016 and 2017. Primary canopy attributes (height, width and  
17 density) were calculated from the LiDAR sensor data and the leaf wall area (LWA) determined.  
18 Multivariate models to predict the deposition distribution, as deciles, as a function of the primary  
19 canopy attributes were constructed and calibrated using the 2017 data and validated against the 2016  
20 data. The prediction quality and uncertainty of these multivariate statistical models at various stages of  
21 growth was evaluated by comparison with a previously proposed univariate deposition models based  
22 on LWA at the same growth stages. The results showed that multivariate models can predict the  
23 distribution of deposits from a typical face-to-face sprayer more accurately ( $0.76 < R^2 < 0.94$ ), and  
24 robustly ( $10\% < nRMSEp < 24\%$ ) than LWA-based univariate prediction models over the whole  
25 growing season. This improvement was especially clear for the lowest deciles (D1 to D5) of the  
26 deposition distribution. Results also demonstrated the importance of canopy density to provide  
27 relevant and complementary information to canopy dimensions when predicting deposition deciles  
28 with the multivariate models. The improved ability of multivariate models to predict underestimated  
29 deposition ( $-1.5\% < bias < -3.2\%$ ) when compared to univariate models makes it possible to consider a

30 reduction in the plant protection products while guaranteeing a safety margin for winegrowers when  
31 spraying. These predictive multivariate models could enable variable-rate sprayers to modulate doses  
32 at an intra-plot scale, which would allow a potential reduction in the quantities of plant protection  
33 products to be applied.

34

35 **Keywords:** Canopy density; Variable-rate spraying; 3D vine; Leaf Wall Area; Log-linear models

36

## 37 **1. Introduction**

38

39 The current regulatory context, and the very high societal demand for a reduction in the use of  
40 pesticides in viticulture, has led to a reconsideration of the entire plant protection process (EPPO,  
41 2016). Achieving the objective of reducing pesticides will require the implementation of different and  
42 complementary approaches, including biological control (Flint and van den Bosch, 1982), the  
43 selection of resistant varieties (Vivier and Pretorius, 2002), optimization of spraying technologies  
44 (Llorens et al., 2011a) and adjustment of plant protection product (PPP) doses according to vegetation  
45 architecture (Walklate et al., 2011). Dose adjustment based on varying canopy size and shape, has  
46 been widely discussed in previous research (Gil et al., 2019), and seems especially important in  
47 countries, like France, where the registered dose rates of PPPs are still based on a fixed value per  
48 hectare (Codis, 2016) and calculated independently of the quantity of vegetation to be treated. There  
49 are two interrelated issues concerning dose reasoning. The first is dose expression. Some authors  
50 believe that a new dose expression that explicitly takes into account canopy development, which will  
51 be mostly influenced by growth stages, training systems and varietal characteristics, would be an  
52 important step toward a more efficient use of PPPs (Solanelles et al., 2006). The second issue is to  
53 define and select the most suitable crop parameters to be used for locally adjusting dose rates to  
54 canopy architecture (Walklate et al., 2011).

55

56 Historically, simple manual measurements of primary canopy attributes, such as height, width and the  
57 distance between rows, have been used to generate integrative indicators of canopy geometry, such as

58 the leaf wall area (LWA) (Koch, 1993) or tree row volume (TRV) (Byers et al., 1971). These  
59 integrative indicators have become widely used as they provide a simple expression of the complex  
60 architecture of the vegetation for modelling the PPP dose to be applied (Walklate and Cross, 2012). In  
61 particular, the LWA has been identified as a good compromise between accuracy and simplicity to  
62 establish a linear relationship between canopy geometry and the recommended amount of PPP  
63 (Walklate and Cross, 2012) and it is now used to standardise PPP trials. However, the derivation of  
64 these integrative indicators has two disadvantages: (i) they are too simplistic to properly model foliar  
65 deposition (Cheraïet et al., 2019) under variable production conditions as the same LWA or TRV  
66 value may reflect very different vegetation characteristics and PPP needs; and (ii) they are typically  
67 based on measurements at only a few points within a vineyard with an assumption of a homogeneous  
68 canopy structure over the entire area. When sampling is scarce, then local, site-specific variations in  
69 canopy geometry cannot be taken into account when applying PPP.

70

71 To address the limitation in the spatial resolution of manual measurements, different high-resolution  
72 spatial sensing systems have been proposed in recent years (Rosell and Sanz, 2012). Among these,  
73 LiDAR systems have been reported to be effective for site-specific measurements of canopy size and  
74 shape (Colaço et al., 2018). LiDAR sensors make it possible to obtain digitalised 3D point clouds,  
75 from which a large amount of plant architecture information, such as canopy height, width (Rosell et  
76 al., 2009;) and density (Walklate et al., 2002; Llorens et al., 2011b) can be obtained with a high level  
77 of accuracy and repeatability (Moorthy et al., 2011). Due to the high spatial resolution of these LiDAR  
78 data, these attributes can be calculated at any scale, from individual vines to entire vineyards.

79

80 Obtaining primary canopy dimensions from sensors, including LiDAR sensors, enables the calculation  
81 of integrative indicators, such as the TRV or LWA, at high spatial resolutions. So far, this ability has  
82 been used to build univariate empirical models to predict the mean foliar pesticide deposition (Llorens  
83 et al., 2010), typically using power or logarithmic regression models (Siegfried et al., 2007; Bastianelli  
84 et al., 2017). Bastianelli et al. (2017) highlighted the ability of these univariate empirical models to  
85 discriminate between different types of spraying equipment and noted that the prediction quality for a

86 side-by-side sprayer using a univariate empirical based on LWA was sufficient to be considered for  
87 production applications.

88

89 However, empirical models that are based on a unique integrative indicator do have limitations,  
90 particularly when the objective is to adjust dose rates under a wide variety of vineyard conditions and  
91 training systems (Llorens et al., 2010). Vine management and pruning is normally standardised within  
92 blocks, which results in a strong correlation between canopy height and width. However, across  
93 different blocks, vineyards and regions, the relationship between primary canopy attributes differs  
94 according to local trellising systems, management strategies and vine varieties. Cheraïet et al. (2019)  
95 demonstrated that the prediction uncertainty of univariate empirical models varied greatly between  
96 vineyards in southern France, especially in the early stages of vegetation development when correct  
97 PPP is needed for effective crop protection. Moreover, univariate empirical models have only been  
98 used to predict the mean deposition, and not the distribution of deposition within the canopy. The  
99 distribution of deposition within the canopy will be dependent on both the characteristics of the  
100 canopy (Palleja and Landers, 2015) and the characteristics of the sprayer (type and settings: nozzle  
101 type, size and pressure, air velocity and airflow direction) (Derksen et al., 2007).

102

103 Therefore, whilst integrative indicators have proved useful for the industry when used with low-  
104 resolution measurements, their suitability for the development of precision spraying approaches using  
105 high-resolution information from sensing systems is questionable, especially when knowledge of  
106 deposition distribution rather than mean deposition is desirable. Sensor systems are now capable of  
107 generating high-resolution spatial and temporal information on primary canopy attributes, including  
108 height, width and some indication of density. However, so far, canopy density information has not  
109 been well incorporated into deposition prediction models within a vegetation canopy, even though the  
110 literature highlights the importance of this attribute (Pergher and Petris, 2008). It follows that  
111 multivariate statistical modelling approaches to predict the distribution of deposits at different stages  
112 of canopy development that are based on primary canopy attributes should be investigated, and are

113 hypothesised to be better than previously used univariate modelling approaches based on an  
114 integrative indicator of canopy architecture.

115

116 In order to test this hypothesis and to facilitate the optimization of spraying efficiency, the research  
117 presented here aims to investigate the use of multivariate statistical models to predict the distribution  
118 of deposits based on primary canopy attributes (dimensions, density) derived from a LiDAR sensing  
119 system. The specific objectives are to:

120 (1) Propose a primary canopy density attribute, based on 2D LiDAR data, that can be included in the  
121 modelling;

122 (2) Construct, calibrate and validate multivariate models, based on primary canopy attributes, to  
123 predict the distribution of intercepted deposits in vineyard canopies applied by a side-by-side sprayer  
124 at multiple growth stages over the growing season;

125 (3) Assess the prediction quality and uncertainty of these multivariate models relative to a previously  
126 proposed univariate model that is based on an integrated indicator of canopy size (LWA).

127

## 128 **2. Materials and Methods**

129

### 130 ***2.1. Fields trials***

131

132 Two vine estates with blocks of different varieties and contrasting vigour were chosen for the study in  
133 2016 and 2017. The 2016 trials were at the Mas Piquet Estate in Grabels, close to Montpellier,  
134 Hérault, France, and the 2017 trials at the Domaine Chapitre Estate in Villeneuve les Maguelone,  
135 Hérault, France. The training system, vine vigour and grape varieties in the two estates are  
136 characteristic of vineyards in southern France. Vines were trellised in 2.5m rows with a 1.0m vine  
137 spacing within rows using a cordon Royat or Guyot system that comprised a cordon wire and at least  
138 one trellising wire.

139

140 In 2016, spray deposition measurements and 2D LiDAR sensor canopy characterization was  
 141 performed on four plots with four different varieties, while in 2017, measurements were performed on  
 142 five plots with five different varieties. In both years there were 4 surveys (dates of measurements) that  
 143 generated a range of growth stages (BBCH scale, Lorenz et al., 1994) due to phenological differences  
 144 between varieties on a given date. These were: 3rd leaves unfolded (14), inflorescences clearly visible  
 145 (53), inflorescences swelling and flowers closely pressed together (55), inflorescences fully developed  
 146 and flowers separating (57), beginning of flowering: 10% of flowerhoods fallen (61), flowering (70),  
 147 berries pea-sized and bunches hang (75), berry development (76), berries beginning to touch (77) and  
 148 beginning of ripening (81). Full details of varieties, dates of measurements and growth stages are  
 149 given in Table 1.

150

Table 1. Plot characteristics and phenological stages (BBCH scale) for each measurement dates 2016 and 2017 trials.

Block ID	Variety	Dates – 2016			
		T1: 03/05/2016	T2: 25/05/2016	T3: 23/06/2016	T4: 18/07/2016
Collection	<i>Marselan</i>	55	57	75	77
Faysse	<i>Chardonnay</i>	53	57	77	77
Franquet	<i>Cabernet Sauvignon</i>	14	55	75	77
Verdot	<i>Petit Verdot</i>	53	57	75	77
		Dates – 2017			
		T1: 28/04/2017	T2: 22/05/2017	T3: 14/06/2017	T4: 31/07/2017
Aranel	<i>Aranel</i>	57	62	75	81
Marselan	<i>Marselan</i>	57	61	75	81
Caladoc	<i>Caladoc</i>	57	61	75	81
PetitVerdot	<i>Petit Verdot</i>	57	62	75	77
Syrah	<i>Syrah</i>	57	61	75	85

151

## 152 2.2. *Sprayer characteristics*

153

154 An air-assisted side-by-side sprayer (Precijet, Tecnomatix®, Epernay, France) with nozzles set on  
 155 vertical booms in front of each side of the canopy was used for all trials. Each boom was fitted with  
 156 four hollow cone nozzles (TXA800067VK, Teejet, Wheaton, USA) aligned in a vertical plane to spray

157 the entire canopy. The Precijet is a more efficient sprayer than the pneumatic arch-type sprayers more  
158 commonly used in the vineyards of southern France. For each spraying date and each block, sprayer  
159 settings (number and direction of nozzles) were adapted according to the canopy size following good  
160 agricultural practices and were not altered from one sampling site to another during block spraying. At  
161 all dates and blocks, the working pressure was 0.5 MPa and the total flow rate was 5.5 L min<sup>-1</sup>. At a  
162 forward speed of 5 km h<sup>-1</sup> the spray volume was 150 L ha<sup>-1</sup>.

163

## 164 **2.3. Data collection**

165

### 166 *2.3.1. Measurements of spray deposition*

167

168 For each date and each block, a 15 m section of a vineyard row was chosen under two constraints; i)  
169 that it represented typical growth for the phenological stage and ii) that it was as homogeneous as  
170 possible, i.e. sections with missing, over vigorous or under vigorous vines were avoided. Spray  
171 deposition for each application was determined by including a chemical tracer in the spray application  
172 and embedding part of the 15m section with artificial collectors. Different 15 m long sections were  
173 chosen from one date to another to ensure that measurements were not affected by previous survey  
174 activities.

175

176 The deposition sampling scheme differed slightly for the two years. In 2016, four consecutive vines  
177 segments were sampled within each 15 m section. On each vine segment, 0.004 m<sup>2</sup> polyvinyl chloride  
178 (PVC) collectors were positioned on the leaves inside the canopy in several planes according to a  
179 profile perpendicular to the row according to a cell grid 0.2 m high and 0.1 m wide. In 2017, two  
180 three-vine segments (that were termed a “trio”) were sampled within each 15 m section. Within each  
181 trio, a regular grid of the 0.004 m<sup>2</sup> PVC collectors was established in several planes; however, at a  
182 lower density with a spacing of 0.4 m vertically and 0.1 m horizontally. Each trio in 2017 and each  
183 four-vine section in 2016 will be called hereafter a “sampling unit”. Details of the number of collectors  
184 analysed for each sampling unit at each sampling date are given in Table 2.



Table 2. Number of collectors sampled (with spray deposits) in 2016 and 2017 for each sampling unit selected within the 15 m long plots. In 2016 there was one 4-vine section per 15 m and in 2017 there were two 3-vine sections sampled per 15 m of vine row.

Block ID	Sampling unit ID	Dates - 2016			
		T1: 03/05/2016	T2: 25/05/2016	T3: 23/06/2016	T4: 18/07/2016
Collection	A	28	95	109	117
Faysse	B	30	61	65	101
Franquet	C	30	52	95	121
Verdot	D	30	62	120	101
		Dates - 2017			
		T1: 28/04/2017	T2: 22/05/2017	T3: 14/06/2017	T4: 31/07/2017
Aranel	A1	34	37	71	66
	A2	29	51	69	72
Marselan	B1	24	46	68	66
	B2	27	50	66	67
Caladoc	C1	32	47	67	69
	C2	28	48	65	59
PetitVerdot	D1	22	38	48	47
	D2	22	36	53	47
Syrah	E1	21	NA <sup>†</sup>	67	67
	E2	25	NA <sup>†</sup>	64	69

186 <sup>†</sup> No deposition data on the Syrah block on 22/05/2017 following a problem of accessibility to the  
187 block due to phytosanitary treatments.

188  
189 A quantitative assessment of the spray distribution in the canopy was made by measuring the  
190 deposition of a colorimetric tracer, Tartrazine E-102 (Sigma, St. Louis, MO, USA) on the PVC  
191 collectors (Codis et al., 2018). For each spray campaign, the sprayer was filled halfway with distilled  
192 water and the necessary amount of Tartrazine was added to achieve a target concentration of 10 g. L<sup>-1</sup>.  
193 This solution was then sprayed, reproducing normal spraying procedures. After the tracer had  
194 completely dried, all PVC collectors were retrieved and placed in individual bags. In the laboratory,  
195 each individual PVC collector was rinsed in a known volume of distilled water to recover the  
196 Tartrazine and the concentration was measured with a spectrophotometer at 427 nm (Uviline 9100,  
197 resolution: 0.001, accuracy  $\pm$  0.003, Secomam, Champigny sur Marne, France). Deposition was  
198 normalised according to the collector surface and to the Tartrazine dose rate ha<sup>-1</sup>. Spray deposits were

199 expressed in nanograms per square decimetric of leaves for 1 g sprayed ha<sup>-1</sup> (ng dm<sup>2</sup> per 1g ha<sup>-1</sup>)  
200 (Codis et al., 2018).

201 It should be noted that many physical effects influence deposition values, including variation in the  
202 spray trajectory angle, anisotropic leaf area distribution, streamlining of leaves in the air flow and  
203 small-scale aerodynamics of spray droplets (Walklate et al., 2011). These effects are either considered  
204 constant or impractical to measure. The sampling design, based on a regular 2D grid across the canopy  
205 row along a minimum length of 3 m of vine row, was designed to minimise any of these potential  
206 effects.

207  
208 Artificial collectors are often used as replacements for natural foliage in research studies as the  
209 recovery of sprayed tracer retained on natural plant surfaces is more difficult and more expensive than  
210 from artificial targets. Furthermore, research using natural targets is always limited by the size and  
211 spatial heterogeneity of the sample, and these parameters play an important role in the unbiased  
212 estimation of deposition in vegetation (Forster et al., 2014). PVC collectors have been demonstrated to  
213 have a good recovery rate and are efficient in recovering the spray deposits (Garcerá et al., 2012).  
214 From the results presented in the literature, this study used the hypothesis that the distribution of  
215 deposits intercepted on PVC collectors is near to the distribution actually observed on vine leaves.

216  
217 Historically, deposits onto vine leaves or PVC collectors (Codis et al., 2018), have been aggregated to  
218 give a mean deposition per sampling unit, without taking into account the variability or spatial  
219 distribution of deposition rates within the sampling unit. However, in order to ensure optimal crop  
220 protection, it is assumed here that the attribute space can be characterised more precisely by a  
221 statistical distribution rather than a mean. Using the statistical distribution, rather than a mean of  
222 deposition, makes it possible to account for the variability of locally intercepted deposits and to avoid  
223 PPP under-dosing, regardless of the area in the canopy where this under-dosing may occur.

224  
225 As the intent here is to examine if and how spray deposition varies within the canopy, the distribution  
226 of deposits across all vineyards for each individual survey (date) were aggregated and described using

227 deciles. It is worth noting that although the PVC collectors were located in a regular 2D grid across the  
228 canopy, their physical location has not been explicitly used in the modelling. The crop management  
229 hypothesis is that if the attribute space can be modelled more accurately with a statistical distribution  
230 rather than a mean, then management can be altered to avoid under-dosing, regardless of where it  
231 occurs in the canopy.

232

### 233 *2.3.2. 2D LiDAR information of canopy structure*

234

235 A Sick LMS100 (SICK AG, Düsseldorf, Germany) 2D LiDAR sensor was used in the study. The  
236 LMS100 is a fully-automatic divergent laser scanner based on time-of-flight (TOF) measurement with  
237 a typical error of  $\pm 30\text{mm}$ , a selectable angular resolution ( $\Delta\theta$ ) set to  $0.5^\circ$  and a range of  $270^\circ$ . With  
238 these settings, there were 541 distances recorded for one complete laser rotation, which is hereafter  
239 referred to as a “scan”, and scans were obtained at 50 Hz. The LMS100 and data logging system were  
240 mounted on a purposely-built stainless-steel mast fixed behind the tractor operating the sprayer,  
241 according to a previously described procedure (Cheraïet et al., 2020). The LMS100 sensor height  
242 ranged from 1.0 – 1.4m above ground level and was adjusted up during the season to account for  
243 increasing canopy height. The tractor was driven along the vineyard rows at a constant forward travel  
244 speed of  $5\text{ km h}^{-1}$ , with a typical error of  $\pm 0.21\text{ km h}^{-1}$  (IFV, internal report, October, 2018).

245

246 This sensing system was coupled to a Real Time Kinematic (RTK) GNSS receiver (Teria GSM  
247 correction, Vitry-sur-Seine, France) to identify the start and end point of the sampling units. Once the  
248 starting point was set, scans were aggregated using a fixed forward distance based on the constant  
249 tractor speed to generate a 3D point cloud reconstruction of the vine environment. The sprayer  
250 replicated commercial operations, i.e. the tractor only traversed every second row so that the canopy  
251 was only scanned from one side. This differs to most previous research activities with LiDAR sensors,  
252 but was deliberately done to approximate commercial conditions. Full details of the system set-up are  
253 given in Cheraïet et al. (2020).

254

255 *2.3.2.1. Derivation of primary canopy attributes*

256

257 The determination of primary canopy dimensions (height and width) from the filtered LiDAR data was  
258 performed using the LiDAR bayesian point cloud classification algorithm (BPCC) (Cheraiet et al.,  
259 2020). This is achieved by (a) a 1D cluster analysis of the LiDAR point clouds to identify different  
260 components of the vine and trellis system (trunk, vegetation zone, trellis wire), followed by a Bayesian  
261 classification, and (b) an estimation of canopy height and width using an adjustable statistical  
262 threshold to improve canopy dimension estimates as the canopy develops. For canopy width, the  
263 method derives a half-vine width, as only one side of the canopy is scanned, and assumes symmetry to  
264 derive the full vine canopy width. Full details of the BPCC method are in Cheraiet et al. (2020).

265

266 Several indicators for vegetation density based on 2D LiDAR acquisition have previously been  
267 proposed but have drawbacks for use in predicting deposition distributions in the canopy. The density  
268 metric proposed by Llorens et al. (2011b) exhibits a strong collinearity with vegetation height and is  
269 discrete in nature (5 classes), making it less suitable for modelling. The tree area index (TAI) proposed  
270 by Walklate et al. (2002) has been shown to be sensitive to the length of the vine row section scanned  
271 and is only recommended for > 1 m row sections (Arnó et al., 2013). This limits its usefulness for  
272 multi-scale dose modulation methods, especially if real-time and high resolution dose modulation are  
273 to be considered. Therefore, an adapted estimation of canopy density using LiDAR data, called the  
274 intercepted beam rate (IBR), is proposed here. The IBR is similar to the metric of Llorens et al.  
275 (2011b) except that it is restricted to interceptions in the canopy zone defined by the BPCC algorithm.  
276 It is expressed as a continuous value, not a class, generating more degrees of freedom to characterise  
277 heterogeneity in the canopy density. The IBR (%) is defined as (Eq. 3):

278

279 
$$\text{IBR} = \frac{\text{NBI}}{\text{NBE}} * 100 \quad \text{Eq. 3}$$

280 Where: NBI is the number of beams intercepted between angles that define the range of the canopy  
281 zone height along a trellis and NBE is the total number of beams emitted over the same angular range.  
282 The mean IBR was calculated for each sampling unit.

283

#### 284 *2.3.2.2. Integrated indicator: Leaf Wall Area*

285

286 The LWA is the area of leaf based on the assumption that the canopy sides are completely flat, and  
287 hence, form a “wall”. The LWA has been chosen at the European Union level as the new metric to  
288 support dose expression in 3D cropping systems when performing efficacy trials during registration  
289 processes (EPPO, 2016). The LWA is expressed in square metres per hectare (m<sup>2</sup> ha<sup>-1</sup>) and defined as  
290 (Eq. 4):

291

$$292 \quad LWA = \frac{2 \times VH \times 10,000}{RS} \quad \text{Eq. 4}$$

293 Where: VH is canopy height (m); 10,000 is the ground area (m<sup>2</sup>) and RS is the row spacing (m).

294

295 The LWA is derived from canopy height and row spacing only, with the later usually a constant in  
296 vineyards. Therefore, while LWA is considered an integrative metric, it is directly correlated to  
297 canopy height. Canopy width and density information is not included.

298

#### 299 **2.4. Modelling**

300

301 Previous approaches to modelling intercepted spray deposits within a crop canopy have used power  
302 (Bastianelli et al., 2017) or logarithmic (Siegfried et al., 2007) laws to model mean depositions. As the  
303 intent here is model deposition distribution, not mean deposition, log-lin regression models were used  
304 to improve model behaviour and fitting at the upper and lower limits of the distribution.

305

306 The data acquired on the 2017 and 2016 plots were used as calibration and validation sets respectively.  
 307 The 2017 data was used for calibration as it had a higher number of PVC collectors per sampling unit  
 308 (Table 2) and the 2017 survey encompassed a longer phenological period (Table 2). The calibration  
 309 data were used to develop both univariate and multivariate regression models for predicting foliar  
 310 deposits distributions, while the validation data were used to evaluate the performance of the  
 311 developed models.

312

313 Univariate empirical models for the prediction of foliar deposit distributions were derived using the  
 314 integrative indicator (LWA) as the sole predictor. This formed a “standard” model based on the  
 315 current European standard. For each decile of the deposition distribution, a log-lin regression model  
 316 was used (Eq. 5).

317

$$318 \quad y_{i,j} = U_j e^{-(\eta_j * LWA_i)} + e_{i,j}, \quad y_{i,j} > 0 \quad \text{Eq. 5}$$

319 Where:  $y_{i,j}$  represents the value of the  $j^{\text{th}}$  decile of spray deposit in the  $i^{\text{th}}$  vine trio with  $\forall i \in [1, 40]$   
 320 and  $\forall j \in [1, 9]$ ,  $e_i$  are random variables, it is assumed that  $e_i$  are independent and  $\varepsilon_i \sim N(0, \sigma^2)$ ,  $LWA_i$   
 321 is the leaf wall area for the sample site in the  $i^{\text{th}}$  sampling unit,  $U_j$  and  $\eta_j$  are real unknown parameters  
 322 that will have to be estimated, where  $U_j$  is the intercept and  $\eta_j$  is the slope of the model equation for  
 323 the prediction of  $j^{\text{th}}$  decile.

324

325 Multivariate models for prediction of decile deposition as a linear combination of primary canopy  
 326 attributes (VH, VW and IBR) were similarly constructed using the same log-lin model form (Eq. 6).

327

$$328 \quad y_{i,j} = M_j e^{-(\alpha_j * VH_i + \beta_j * VW_i + \gamma_j * IBR_i)} + e_{i,j}, \quad y_{i,j} > 0 \quad \text{Eq. 6}$$

329 Where:  $y_{i,j}$  represents the value of the  $j^{\text{th}}$  decile of spray deposit present in the  $i^{\text{th}}$  vine trio with  $\forall i \in$   
 330  $[1, 40]$  and  $\forall j \in [1, 9]$ ,  $e_i$  are random variables, it is assumed that  $e_i$  are independent and  
 331  $\varepsilon_i \sim N(0, \sigma^2)$ ,  $VH_i$  is the mean value of vegetation height measured at the  $i^{\text{th}}$  vine trio,  $VW_i$  is the mean  
 332 value of vegetation width measured at the  $i^{\text{th}}$  vine trio,  $IBR_i$  is the mean value of intercepted beam rate

333 measured at the  $i^{\text{th}}$  vine trio,  $M_j, \alpha_j, \beta_j$  and  $\gamma_j$  are real unknown parameters to be estimated, where  $M_j$   
 334 is the intercept and  $\alpha_j, \beta_j, \gamma_j$  are the slopes corresponding respectively to VH, VW and IBR in the  
 335 model equation for the prediction of  $j^{\text{th}}$  decile.

336  
 337 A stepwise forward approach was used to identify the most parsimonious prediction model (uni-, bi-  
 338 or tri-variate) as well as the statistical weight of each predictor in the models. Models for each  
 339 deposition decile were ranked using the corrected Akaike's Information Criterion (AICc) as the  
 340 number of data were limited ( $\leq 40$  data points) (Hurvich and Tsai, 2001).

341  
 342 Multicollinearity among the explanatory variables was tested using the variance inflation factor (VIF)  
 343 (Akinwande et al., 2015) (Eq. 7): The VIF was calculated for each multivariate model used to predict a  
 344 decile deposition and  $VIF > 5$  set as a threshold to indicate relatively high levels of multicollinearity in  
 345 the models.

346  
 347 
$$VIF = \frac{1}{1-R^2} \quad \text{Eq. 7}$$

348 Where:  $R^2$  is the coefficient of determination of the prediction model.

349

### 350 **2.5. Model Evaluation**

351

352 The coefficient of determination ( $R^2$ ) and the normalised root mean square error (nRMSE) were used  
 353 to evaluate the fit of the calibration models (2017 data). The nRMSE was used to facilitate comparison  
 354 between models of all the deposition deciles and is defined as a percentage (Eq. 8):

355

356 
$$nRMSE_j = \frac{\sqrt{\frac{\sum_{i=1}^N (\hat{y}_{i,j} - y_{i,j})^2}{N}}}{\bar{y}_{i,j}} * 100 \quad \text{Eq. 8}$$

357 Where:  $\hat{y}_{i,j}$  are estimated values for the  $j^{\text{th}}$  decile,  $y_{i,j}$  are observed values for the  $j^{\text{th}}$  decile and  $\bar{y}_{i,j}$  are  
 358 the mean of observed values for the  $j^{\text{th}}$  decile, and  $N$  is the number of observations.

359

360 The performance of the univariate and multivariate decile models, when applied to the validation data,  
361 was assessed by analysing the observed vs. predicted values by the (i) R<sup>2</sup> of a 1:1 linear regression fit,  
362 (ii) model bias (%) and, (iii) normalised root mean square error of prediction (nRMSEp) (normalised  
363 by the mean of the predicted decile deposit values). Again the nRMSEp is defined as a percentage (Eq.  
364 9):

365

$$366 \quad nRMSEp_j = \frac{\sqrt{\sum_{i=1}^N \frac{(Y_{i,j} - y_{i,j})^2}{N}}}{Y_{i,j}} * 100 \quad \text{Eq. 9}$$

367 Where:  $Y_{i,j}$  are predicted values for the  $j^{\text{th}}$  decile,  $y_{i,j}$  are observed values for the  $j^{\text{th}}$  decile and  $\bar{y}_{i,j}$  are  
368 the mean of predicted values for the  $j^{\text{th}}$  decile, and  $N$  is the number of observations.

369

370 All analyses were performed using the open source statistical R Software® (Version 1.2.5001) (R  
371 Development Core Team, 2020). Respectively, for the AIC, nRMSE and VIF calculations, the stats4  
372 (version 3.6.2), Metrics (version 0.1.4), car (version 3.0.10) packages were used.

373

### 374 **3. Results and discussions**

375

#### 376 **3.1. Data description**

377

##### 378 *3.1.1. Description of the deposition data*

379

380 The deposition distributions exhibited a positive skewness, associated with very high deposition rates  
381 on the external canopy PVC collectors. The 10<sup>th</sup> decile skewed the distribution and was characterised  
382 by oversaturation relative to the target dose. It is commonly accepted by growers and experts that the  
383 external canopy layers that face the sprayer will exhibit this phenomenon to achieve adequate  
384 deposition in the internal layers. As oversaturation is assumed to ensure protection, the 10<sup>th</sup> decile was  
385 excluded from subsequent analyses and only the first nine deciles were used for modelling.

386



387 The empirical density curve of the depositions recorded by the PVC collectors positioned within the  
388 vine trios in 2017 showed a clear trend towards a decrease in mean deposition associated with  
389 increasing vine growth over time that is being sprayed with a constant quantity of tracer (Fig. 1). The  
390 deposition distributions followed a Poisson-type form and the shape of the distribution changes over  
391 time, with the mean and the variance decreasing as the season progresses. The median foliar  
392 deposition ranged from 500 ng dm<sup>2</sup> per 1g ha<sup>-1</sup> in T1 to 195 ng dm<sup>2</sup> per 1g ha<sup>-1</sup> in T4.

393

394 Figure 1 near here

395

396 The Poisson distributions indicated that a unique and central statistic (mean or median) of the deposit  
397 was insufficient to describe the data, even if completed by a quantification of variance. This highlights  
398 the problem of modelling deposition using the mean and supports the use of the decile by decile  
399 analysis in order to take into account the statistical dispersion of deposition values.

400

401 Deposition rates also varied between varieties at a given date, with inter-block variability being  
402 greatest early in the season (at T1, 38%) and lowest at the latest observation (T4, 11%) (data not  
403 shown). This can be explained by differences in the timing of bud-burst and shoot development  
404 between the grape varieties early in the season (Table 1). Even at full canopy development (T3-T4),  
405 some differences in shoot length, leaf size and shape and vine morphology between varieties still  
406 existed, despite the common trellising systems between vineyards.

407

### 408 *3.1.2. LiDAR-derived canopy data*

409

410 Summary plots of the primary canopy attributes (VH, VW and IBR) derived from the LiDAR sensor  
411 survey in the 2017 survey blocks, at a resolution scale of 3 m (same as vine trio scale used for  
412 sampling deposits) are shown in Figure 2.

413

414 Figure 2 near here

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Table 3. Summary of canopy height (VH) and width (VW) and density (IBR) data obtained at the four LiDAR acquisition dates in 2017.

	T1	T2	T3	T4
Vegetative parameters	Mean			
VH (m)	0.65	0.99	1.24	1.19
VW (m)	0.38	0.59	0.83	0.81
IBR (%)	28.2	45.3	59.1	72.4
	CV (%)			
VH	13.1	14.5	16.2	17.1
VW	10.2	16.6	11.5	5.3
IBR	9.4	12.7	12.3	19.6

Vegetation height and width (Figs. 2a-b) increased almost linearly from bud break (T1) to green pea stage (T3), which is approximately the date of the first canopy trimming operation. Trimming, combined with increasing water stress over summer, tends to stagnate any further growth. This is reflected in a plateauing of VH and VW between T3 and T4 (Table 3), which indicated that these parameters were likely to be less informative about changes in canopy conditions towards the end of the season. Overall, the earlier varieties (Aranel, Marselan and Caladoc) had larger dimensions than the later developing variety (Petit Verdot) that never caught up in size to the other varieties (Figs. 2a-b). On average, over the survey period (T1-T4), the inter-block variability was 15.2% and 11% for VH and VW respectively. This showed that there were real differences between blocks during the growing season (Table 3).

In contrast to VH and VW, the IBR canopy density metric (IBR) did not plateau in any block between T3 and T4, despite the in-season canopy trimming operations (Fig. 2c). This indicated that IBR could provide relevant information to characterise the canopy later in the season. The variability of the IBR metric also increased as the season progressed, with the IBR parameter having a CV of 9.4% in T1, 12.7% in T2, 12.3% in T3 and 19.6% in T4 (Table 3). This higher variability of the mid- to late-season IBR corresponds to the period when mean deposits were lowest (Fig. 1).

437 **3.2. Modelling**

438

439 **3.2.1. Univariate models**

440

441 The results of the univariate model construction for deciles 1-9 (D1-D9) with the calibration data set  
 442 showed a relatively stable relationship ( $0.69 < R^2 < 0.82$ ) for the prediction of foliar deposition using  
 443 the LiDAR-derived LWA indicator (Table 4). The first two deciles (D1-D2) had the lowest prediction  
 444 quality ( $R^2$ ) and the greatest error of the prediction models (nRMSE) (Table 4). The mean deposition  
 445 was also modelled, which is the current recommended approach, and explained 80% of the variance in  
 446 the mean deposition in the canopy.

447

Table 4. Parameters and quality indicators of univariate models for prediction of decile deposition over the entire growing season: indicating model coefficients (U and  $\lambda$ ) and quality indicators for each decile model for both the calibration ( $R^2$  and nRMSE) and validation ( $R^2$  of 1:1, nRMSE and bias) stages. The equivalent mean model (current standard reference) parameters and quality indicators are also shown.

Deciles distribution deposit	Model equation		Calibration (2017) (n=40)		Validation (2016) (n=16)		
	U	$\lambda$	$R^2$	nRMSE (%)	$R^2$ of 1:1 line	nRMSEp (%)	Bias (%)
D <sub>1</sub>	740.6	2.35E-04	0.69	46	0.66	45	-5.8
D <sub>2</sub>	935.39	2.54E-04	0.75	36	0.77	41	-4.8
D <sub>3</sub>	1282.13	2.61E-04	0.79	28	0.80	37	-3.9
D <sub>4</sub>	1524.34	2.58E-04	0.81	25	0.75	34	-2.3
D <sub>5</sub>	1702.88	2.47E-04	0.81	19	0.80	30	2
D <sub>6</sub>	1820.63	2.35E-04	0.78	17	0.82	27	2.9
D <sub>7</sub>	2100.3	2.30E-04	0.80	18	0.83	25	2.1
D <sub>8</sub>	2474.84	2.25E-04	0.79	20	0.85	29	7.6
D <sub>9</sub>	3045.88	2.19E-04	0.82	21	0.81	34	8.4
mean	1789.88	2.40E-04	0.80	18	0.79	26	2.2

448

449 Applying the calibrated model to the independent validation data (2016) generated prediction  
 450 accuracies for the univariate decile models that were similar to and followed the same trend as the  
 451 calibration models ( $0.66 < R^2 < 0.85$ ), with lower deciles being associated with lower prediction

452 quality (Table 4). The bias values were negative for the validation models predicting deciles D1 to D4  
453 and positive for deciles D5 to D9 (Table 4). The lower deciles represent areas of the canopy where a  
454 below mean level of deposition was achieved, which may be insufficient for effective crop protection.  
455 In these deciles, the univariate model underestimated (negative bias) depositions in the already poorly  
456 covered (low deposition) areas.

457

458

459 Figure 3 near here

460

461 The model fit for the median deposition (D5) is shown as an example (Fig. 3). The overestimation at  
462 higher deposition rates, associated with T1 (red squares; early season), is evident. Correct application  
463 of early season PPPs is important for prophylactic protection of the plant and a systematic  
464 overestimation of deposition is undesirable. However, when the canopy is small (early season), the  
465 median depositions were very high (Fig. 1), so with a fixed dosage per hectare there is little risk of  
466 under-application. This may change if dose expression regulations are altered in the future to minimise  
467 the risk of early season over-applications and to improve the use-efficiency of PPPs. For T2, T3 and  
468 T4, the median deposition from the model underestimated real conditions, i.e. it was likely that there  
469 was more being applied than was being modelled. However, under the fixed dose expression  
470 regulations, the amount of deposition per canopy surface area was dropping as the canopy increased,  
471 so under-applications are more likely. Underestimation is preferable to overestimation under these  
472 conditions, although correct estimation is preferred. The ability of the univariate model to robustly  
473 predict median foliar deposition throughout the growing season was not assured. This can be  
474 explained by the fact that the univariate approach only accounted for VH in the LWA, but not VW or  
475 canopy density.

476

477 *3.2.2. Multivariate models*

478

479 The VIF analysis indicated that there was no multicollinearity ( $VIF < 5$ ) between the primary canopy  
 480 attributes (VH, VW and IBR) in the multivariate decile deposition models. The stepwise parameter  
 481 selection showed that the IBR metric had the strongest contribution to the D1-D3 models, followed by  
 482 VW and then VH. Thus for low deposition values, which are more common at the end of the growing  
 483 season (T3 and T4), the IBR was dominant for predicting deposition (Table 5). For the D7-D8  
 484 prediction models, which corresponded to high deposition values, VH and VW were the strongest  
 485 predictors, followed by IBR (Table 5). Therefore, when the canopy was developing (T1 and T2)  
 486 information on VH and VW was important for modelling deposition. Once the canopy had reached  
 487 full size (T3 and T4) and VH and VW had stabilised, the importance of VH and VW diminished.  
 488

Table 5. Multivariate models for predicting of decile deposition: comparison of the relative weight (order of occurrence in the model (1, 2 or 3)) of the primary canopy attributes (VH, VW and IBR) according to the conditional Akaike information criterion and study of the multi-collinearity between the primary canopy attributes by variance inflation factor (VIF).

Deciles model	Primary canopy attributes					
	vegetation height (VH)		vegetation width (VW)		Intercepted beam ratio (IBR)	
	order of occurrence in the model	VIF	order of occurrence in the model	VIF	order of occurrence in the model	VIF
1	3	1.63	2	1.59	1	2.09
2	3	2.13	2	2.34	1	2.02
3	3	1.81	2	2.98	1	2.67
4	2	3.22	1	3.74	3	3.06
5	2	3.32	1	3.45	3	2.06
6	2	3.35	1	3.75	3	1.61
7	1	2.78	2	2.1	3	1.94
8	1	2.37	2	3.36	3	1.62
9	1	3.53	2	3.74	3	2.53

489 The parameters for the fitted multivariate calibration models and model statistics for both the  
 490 calibration and validation models are shown in Table 6. Prediction quality was very good for both the  
 491 calibration ( $0.81 < R^2 > 0.93$ ) and validation ( $0.79 < R^2 > 0.94$ ) data sets and these followed the same  
 492 trend as the univariate approach, with lower fits at lower deciles. The nRMSE ranged from 22% to 7%  
 493

494 for calibration and 24% to 10% for validation (Table 6). The validation bias was negative for all nine  
 495 prediction models (Table 6), indicating that the multivariate deposition decile models underestimated  
 496 deposition for all deciles in the distribution. While underestimation was not desirable, a "worst-case"  
 497 risk management modelling approach should encourage underestimation rather than overestimation of  
 498 deposition, in order to ensure that PPPs are applied in sufficient quantity. Figure 4a shows the  
 499 relationship between the observed and predicted median (D5) deposition for the multivariate case  
 500 (comparable to the univariate case in Fig. 3). The data plots close to the 1:1 line, over the entire period  
 501 of the study (T1 – T4), but consistently slightly underestimates depositions (Fig. 4a). The ability of the  
 502 multivariate model to reliably predict median foliar deposition throughout the growing season was  
 503 explained by its ability to account for the differential contribution of VH, VW and IBR to deposition  
 504 as the canopy develops. The actual log-lin regression for the median deposition prediction model (D5),  
 505 using the model parameters in Table 6, is shown in Figure 4b as an example.

506

Table 6. Parameters and quality indicators of multivariate models for prediction of decile deposition over the entire growing season: including model coefficients (M and  $\alpha$ ,  $\beta$ ,  $\gamma$ ) and quality indicators for each decile model for both the calibration ( $R^2$  and nRMSE) and validation ( $R^2$  1:1, nRMSE and bias) stages (same as Table 4). Decile 10 is not shown.

Deciles distribution deposit	Model equation				Calibration (2017) (n=40)		Validation (2016) (n=16)		
	M	$\alpha$	$\beta$	$\gamma$	$R^2$	nRMSE (%)	$R^2$ of 1:1 line	nRMSEp (%)	Bias (%)
D <sub>1</sub>	847.32	1.06	0.3	1.28	0.81	22	0.79	24	-1.5
D <sub>2</sub>	1057.31	0.97	0.48	1.13	0.83	20	0.81	21	-2.1
D <sub>3</sub>	1506.97	0.82	0.37	1.54	0.88	10	0.83	15	-2.2
D <sub>4</sub>	1819.9	0.7	0.36	1.69	0.92	9	0.87	12	-2.5
D <sub>5</sub>	2055.62	0.55	0.34	1.81	0.93	9	0.94	13	-2.1
D <sub>6</sub>	2154.46	0.52	0.47	1.59	0.88	7	0.91	10	-2.6
D <sub>7</sub>	2530.31	0.38	0.43	1.77	0.91	8	0.9	12	-3.1
D <sub>8</sub>	2976.56	0.34	0.46	1.75	0.9	10	0.9	13	-2.8
D <sub>9</sub>	3578.82	0.39	0.55	1.5	0.91	11	0.89	14	-3.2

507

508

509

Figure 4 near here

### 510 *3.3. Assessment of the performance of multivariate models compared to univariate models*

511

512 For all decile levels, the multivariate model outperformed the univariate model (higher R<sup>2</sup>, lower  
513 nRMSE) (Tables 4 and 6). The improved performance of the multivariate models was attributed to the  
514 additional information on canopy width and density available to the model, both of which influence  
515 deposition. The bias of the multivariate models was always negative (Table 6), unlike the univariate  
516 prediction models of deciles D5 to D9 that had a positive bias (Table 4). The overestimation of  
517 deposition at the early stages of the growing season, when the risk of pathogen occurrence and  
518 development is highest, is not problematic under current fixed dose regulations, as the real deposition  
519 rates are very high (Fig. 1). For systems where the dose expression is adjusted to expected canopy  
520 size, overestimation may be an issue and the use of the LWA to determine the dose to be applied  
521 presents a potential risk of underdosing (Rüegg et al., 2001). This would have potential consequences  
522 on the efficacy of PPP. These models need to be tested under these conditions, but the results here  
523 indicated that the multivariate model provided a more risk-adverse model for managing plant  
524 protection risk throughout all stages of the growing season. Thus, multivariate statistical models offer  
525 the possibility to react to the evolution and variability of vegetation during the season, so that it is  
526 possible to consider reducing the use of PPPs while providing a margin of safety to growers in terms  
527 of crop protection.

528

529 The low deposition values that constituted (D1-D4) were found at all four dates (T1 to T4) (Fig. 1).  
530 Therefore, the prediction models for D1-D4 take into account deposition data from all dates (T1 to  
531 T4), which may lead to these prediction models having poorer quality with regards to accuracy and  
532 uncertainty. In contrast, higher deposition values (greater than 500 ng dm<sup>2</sup> per 1g ha<sup>-1</sup>) were only  
533 found at T1 and T2.

534

### 535 *3.4. Potential uses of multivariate deposit prediction models*

536

537 The current use of a fixed dose expression under European guidelines, which is independent of canopy  
538 size, is problematic. Guidelines are evolving and a first step toward this was the introduction of the  
539 LWA metric into calculations of dose expression in all situations (EPPO, 2016). However, this new  
540 LWA-based dose expression is based on the unproven hypotheses that (i) dose requirements are a  
541 function of a single integrative indicator and (ii) there is a strictly linear relationship between  
542 intercepted deposits and the quantity of vegetation canopy to be protected. The results from this study  
543 indicated that this relationship was not necessarily linear and that using individual canopy attributes in  
544 a multivariate model, rather than an aggregated canopy metric, provided more flexibility in the  
545 modelling process. As vine canopies evolve, the relative importance of different canopy dimensions  
546 for modelling depositions also changed. This flexibility and improve modelling will become more  
547 important if dose expression shifts from an analysis of mean deposition rates to an analysis of the  
548 expected distribution of deposition rates within a canopy. From the perspective of commercial  
549 applications, this is unlikely to become the norm in the near future; however, from a regulatory  
550 perspective and for testing and grading the performance of new commercial sprayers, the ability to  
551 better model the distribution of depositions will be very useful in promoting more effective and  
552 efficient spray systems.

553

554 Ultimately the ability of these, or similar, multivariate models will make it possible to consider a step  
555 change in the spray management paradigm from managing a mean deposition (Walklate et al., 2011)  
556 to managing the deposition distribution at any given time over the season. This will allow deposition  
557 in areas of the canopy that are least well treated (D1-D2) during a spray operation to be taken into  
558 account. The decomposition of the overall deposition into a distribution will be critical to a better  
559 epidemiological understanding of resistance and pathogen pressure after phytosanitary treatments have  
560 been carried out. In this study, the distribution has only been described in the attribute space, and not  
561 in the geographical (canopy) space. It is expected that the areas of lower deposition will be located in  
562 denser areas of the canopy with greater numbers of leaf layers between the target point and the  
563 sprayer; however, more research is certainly needed to develop approaches to spatialise the  
564 distribution of deposits within the canopy.



565

566 Furthermore, in view of the quality of the prediction models developed in this study at a trio scale (3m  
567 of trellised vineyard row), the application of these multivariate prediction models at such a small  
568 spatial scale offers interesting possibilities for the optimization of spraying in viticulture. If high-  
569 resolution spatial canopy dimensions, including density, are generated, then differential or variable-  
570 rate spraying could be performed in real-time. This can be achieved by sensing pre-spraying to  
571 develop prescription spray maps, or by sensing directly in front of a sprayer to perform real-time dose  
572 modulation (Llorens et al., 2010). The proposed modelling approach here, when tuned to sprayer  
573 characterisers, could be used to model and optimise deposition coverage whilst minimising the  
574 quantity of PPP applied. This is a clear objective for the industry (EPPO, 2016) and is not just  
575 dependent on good sensing and variable-rate technology but also on good decision support systems  
576 that require accurate predictive modelling capabilities. In addition to supporting differential spraying,  
577 improved deposition models could be applied site-specifically post-application to identify areas where  
578 the PPP application may have been sub-optimal i.e. where there is a disagreement between the amount  
579 applied and the amount modelled.

580

#### 581 **4. Conclusions**

582

583 Optimization of the use of crop protection inputs in viticulture should take into account the structural  
584 characteristics of the vegetation. In this study, a multivariate statistical modelling approach was  
585 proposed to predict the mean and distribution of spray depositions as a function of primary vine  
586 canopy attributes (height, width and density) that were derived from a LiDAR sensor system. Results  
587 obtained from data collected over two years, on seven grape varieties and on two trellising systems,  
588 showed that the proposed multivariate statistical models can predict the distribution of depositions of a  
589 typical face-to-face sprayer more accurately and robustly than univariate prediction models based on a  
590 calculation of leaf wall area, the current industry standard. This ability to predict deposition  
591 distributions will allow areas of the vine canopy that are poorly treated (unprotected) after spraying to  
592 be taken into account and will provide a better understanding, from an epidemiological point of view,

593 of resistance and pathogen pressures in vineyards. In addition, the results provided clear indications of  
594 the ability of multivariate statistical models to react to changing canopy attributes over the season and  
595 spatially in the vineyard, such that it is possible to envisage using these models for a site-specific  
596 reduction in the PPP expected by the wine industry while guaranteeing a safety margin for growers  
597 when spraying.

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## 609 **References**

- 611  
612 Akinwande, M. O., Dikko, H. G., Samson, A. (2015). Variance inflation factor: as a condition for the  
613 inclusion of suppressor variable (s) in regression analysis. *Open Journal of Statistics*, 5(07), 754.  
614 <https://doi.org/10.4236/ojs.2015.57075>
- 615 Arnó, J., Escolà, A., Vallès, J. M., Llorens, J., Sanz, R., Masip, J., Palacín, J., Rosell-Polo, J. R., 2013.  
616 Leaf area index estimation in vineyards using a ground-based LiDAR scanner. *Precision*  
617 *Agriculture*, 14(3), 290-306. <https://doi.org/10.1007/s11119-012-9295-0>
- 618 Bastianelli, M., Rudnicki, V. D., Codis, S., Ribeyrolles, X., Naud, O., 2017. Two vegetation indicators  
619 from 2D ground Lidar scanner compared for predicting spraying deposits on grapevine.  
620 *Proceedings of the 2017 EFITA WCCA conference, Montpellier, France, 153-154.*

621 Byers, R. E., Hickey, K. D., Hill, C. H., 1971. Base gallonage per acre. *Virginia Fruit*, 60(8), 19-23.  
622 <https://doi.org/10.1590/S0103-90162013000600003>

623 Cheraïet, A., Carra, M., Lienard, A., Codis, S., Vergès, A., Delpuech, X., Naud, O., 2019.  
624 Investigation on LiDAR-based indicators for predicting agrochemical deposition within a vine  
625 field. In 12th European Conference on Precision Agriculture, Precision Agriculture '19 (July),  
626 (Eds). J.V. Stafford, Wageningen Academic Publishers, 157-164. [https://doi.org/10.3920/978-90-8686-888-9\\_18](https://doi.org/10.3920/978-90-8686-888-9_18)

627

628 Cheraïet, A., Naud, O., Carra, M., Codis, S., Lebeau F., Taylor J. A., 2020. An algorithm to automate  
629 the filtering and classifying of 2D LiDAR data for site-specific estimations of canopy height and  
630 width in vineyards. *Biosystems Engineering*, 200, 450-465.  
631 <https://doi.org/10.1016/j.biosystemseng.2020.10.016>

632 Codis, S., 2016. Stakes for a new model of dose expression in viticulture: advantages and points to be  
633 taken into consideration. In Proceedings of the EPPO Workshop on harmonized dose expression  
634 for the zonal evaluation of plant protection products in high growing crops, Austrian Agency for  
635 Health and Food Safety Vienna, 12-13.

636 Codis, S., Carra, M., Delpuech, X., Montegano, P., Nicot, H., Ruelle, B., Ribeyrolles, X., Savajols, B.,  
637 Vergès, A., Naud, O., 2018. Dataset of spray deposit distribution in vine canopy for two contrasted  
638 performance sprayers during a vegetative cycle associated with crop indicators (LWA and TRV).  
639 *Data Brief*, 18, 415–421. <https://doi.org/10.1016/j.dib.2018.02.012>

640 Colaço, A.F., Molin, J.P., Rosell-Polo, J.R., Escolà, A., 2018. Application of light detection and  
641 ranging and ultrasonic sensors to high-throughput phenotyping and precision horticulture: Current  
642 status and challenges. *Horticultural Research* 5, 35. <https://doi.org/10.1038/s41438-018-0043-0>

643 Derksen, R. C., Zhu, H., Fox, R. D., Brazee, R. D., Krause, C. R., 2007. Coverage and drift produced  
644 by air induction and conventional hydraulic nozzles used for orchard applications. *Transactions of*  
645 *the ASABE*, 50(5), 1493-1501. <https://doi.org/10.13031/2013.23941>

646 EPPO (European Plant Protection Organization), 2016. Conclusions and recommendations.  
647 Workshop on harmonized dose expression for the zonal evaluation of plant protection products in  
648 high growing crops. Vienne, 18–20 October 2016. Available online :

649 [https://www.eppo.int/media/uploaded\\_images/MEETINGS/Conferences\\_2016/dose\\_expression/Co](https://www.eppo.int/media/uploaded_images/MEETINGS/Conferences_2016/dose_expression/Conclusions_and_recommendations.pdf)  
650 [nclusions\\_and recommendations.pdf](https://www.eppo.int/media/uploaded_images/MEETINGS/Conferences_2016/dose_expression/Conclusions_and_recommendations.pdf) (accessed on 11 November 2020).

651 Flint ML, van den Bosch R (1981) A history of pest control. In: Flint ML, van den Bosch R  
652 (eds) Introduction to integrated pest management. Springer, Boston, 51–81. [https://doi.](https://doi.org/10.1007/978-1-4615-9212-9_4)  
653 [org/10.1007/978-1-4615-9212-9\\_4](https://doi.org/10.1007/978-1-4615-9212-9_4)

654 Forster, W. A., Gaskin, R. E., Strand, T. M., Manktelow, D. W. L., Van Leeuwen, R. M. (2014).  
655 Effect of target wettability on spray droplet adhesion, retention, spreading and coverage: artificial  
656 collectors versus plant surfaces. *NZ Plant Protection*, 67, 284-291.

657 Garcerá, C., Moltó, E., Zarzo, M., Chueca, P. (2012). Modelling the spray deposition and efficacy of  
658 two mineral oil-based products for the control of *Aonidiella aurantii* (Maskell). *Crop Protection*,  
659 31(1), 78-84. <https://doi.org/10.1016/j.cropro.2011.10.004>

660 Gil, E., Campos, J., Ortega, P., Llop, J., Gras, A., Armengol, E., Salcedo, R., Gallart, M., 2019.  
661 DOSAVIÑA: Tool to calculate the optimal volume rate and pesticide amount in vineyard spray  
662 applications based on a modified leaf wall area method. *Computers and Electronics in Agriculture*,  
663 160, 117-130. <https://doi.org/10.1016/j.compag.2019.03.018>

664 Hurvich, C. M., Tsai, C. L., 1993. A corrected Akaike information criterion for vector autoregressive  
665 model selection. *Journal of Time Series Analysis*, 14(3), 271-279. [https://doi.org/10.1111/j.1467-](https://doi.org/10.1111/j.1467-9892.1993.tb00144.x)  
666 [9892.1993.tb00144.x](https://doi.org/10.1111/j.1467-9892.1993.tb00144.x)

667 Koch, H., 1993. Application rate and spray deposit on targets in plants. In: ANPP/BCPC 2nd  
668 International Symposium on Pesticides Applications, Strasbourg, France, 1, 175–182.

669 Llorens, J., Gil, E., Llop, J., Escolà, A., 2010. Variable rate dosing in precision viticulture: Use of  
670 electronic devices to improve application efficiency. *Crop Protection*, 29(3), 239-248.  
671 <https://doi.org/10.1016/j.cropro.2009.12.022>

672 Llorens, J., Gil, E., Llop, J., Escolà, A., 2011a. Ultrasonic and LiDAR Sensors for Electronic Canopy  
673 Characterization in Vineyards: Advances to Improve Pesticide Application Methods. *Sensors*,  
674 11(2), 2177-2194. <https://doi.org/10.3390/s110202177>

675 Llorens, J., Gil, E., Llop, J., Queraltó, M., 2011b. Georeferenced LiDAR 3D Vine Plantation Map  
676 Generation. *Sensors*, 11(6), 6237-6256. <https://doi.org/10.3390/s110606237>

677 Lorenz, D. H., Eichorn, K. W., Bleiholder, H., Klose, U., Meier, U., Weber, E., 1994. Phänologische  
678 Entwicklungsstadien der Weinrebe (*Vitis vinifera* L. spp. *Vinifera*). (Phenological stages of  
679 grapevine (*Vitis vinifera* L. spp. *Vinifera*)). *Viticultural and Enological Science* 49, 66-70.  
680 <https://doi.org/10.1111/j.1755-0238.1995.tb00085.x>

681 Moorthy, I., Miller, J. R., Berni, J. A. J., Zarco-Tejada, P., Hu, B., Chen, J., 2011. Field  
682 characterization of olive (*Olea europaea* L.) tree crown architecture using terrestrial laser scanning  
683 data. *Agricultural and Forest Meteorology*, 151(2), 204-214.  
684 <https://doi.org/10.1016/j.agrformet.2010.10.005>

685 Palleja, T., Landers, A. J., 2015. Real time canopy density estimation using ultrasonic envelope signals  
686 in the orchard and vineyard. *Computers and Electronics in Agriculture*, 115, 108-117.  
687 <http://dx.doi.org/10.1016/j.compag.2015.05.014>

688 Pergher, G., Petris, R., 2008. Pesticide dose adjustment in vineyard spraying and potential for dose  
689 reduction. Manuscript ALNARP 08 011. *Agricultural Engineering International CIGR Journal*, 10,  
690 1-9.

691 R Core Team., 2020. R: A language and environment for statistical computing. R Foundation for  
692 Statistical Computing, Vienna, Austria. URL <http://www.R-project.org/>

693 Rosell, J. R., Llorens, J., Sanz, R., Arnó, J., Ribes-Dasi, M., Masip, J., Escolà, A., Camp, F.,  
694 Solanelles, F., Gràcia, F., Gil, E., Val, L., Planas, S., Palacín, J., 2009. Obtaining the three-  
695 dimensional structure of tree orchards from remote 2D terrestrial LiDAR scanning. *Agricultural  
696 and Forest Meteorology*, 149(9), 1505-1515. <https://doi.org/10.1016/j.agrformet.2009.04.008>

697 Rosell, J.R., Sanz, R., 2012. A review of methods and applications of the geometric characterization of  
698 tree crops in agricultural activities. *Computers and Electronics in Agriculture*, 81, 124-141.  
699 <https://doi.org/10.1016/j.compag.2011.09.007>

700 Rüegg, J., Siegfried, W., Raisigl, U., Viret, O., Steffek, R., Reisenzein, H., Persen, U., 2001.  
701 Registration of plant protection products in EPPO countries: Current status and possible approaches  
702 to harmonization. *EPPO Bulletin*, 31(2), 143-152. [https://doi.org/10.1111/j.1365-  
703 2338.2001.tb00983.x](https://doi.org/10.1111/j.1365-2338.2001.tb00983.x)

704 Siegfried, W., Viret, O., Huber, B., Wohlhauser, R., 2007. Dosage of plant protection products  
705 adapted to leaf area index in viticulture. *Crop Protection*, 26(2), 73-82.  
706 <https://doi.org/10.1016/j.cropro.2006.04.002>

707 Solanelles, F., Escolà, A., Planas, S., Rosell, J. R., Camp, F., Gràcia, F., 2006. An Electronic Control  
708 System for Pesticide Application Proportional to the Canopy Width of Tree Crops. *Biosystems  
709 Engineering*, 95(4), 473-481. <https://doi.org/10.1016/j.biosystemseng.2006.08.004>

710 Vivier, M. A., Pretorius, I. S., 2002. Genetically tailored grapevines for the wine industry. *Trends in  
711 Biotechnology*, 20(11), 472-478. [https://doi.org/10.1016/S0167-7799\(02\)02058-9](https://doi.org/10.1016/S0167-7799(02)02058-9)

712 Walklate, P. J., Cross, J. V., Richardson, G. M., Murray, R. A., Baker, D. E., 2002. Comparison of  
713 different spray volume deposition models using LIDAR measurements of apple orchards.  
714 *Biosystems Engineering*, 82 (3), 253–267. <https://doi.org/10.1006/bioe.2002.0082>

715 Walklate, P. J., Cross, J.V., Pergher, G., 2011. Support system for efficient dosage of orchard and  
716 vineyard spraying products. *Computers and Electronics in Agriculture* 75, 355–362.  
717 <https://doi.org/10.1016/j.compag.2010.12.015>

718 Walklate, P. J., Cross, J. V., 2012. An examination of Leaf-Wall-Area dose expression. *Crop  
719 Protection*, 35, 132-134. <https://doi.org/10.1016/j.cropro.2011.08.018>

720

## 721 **Figures caption**

722

723 Figure 1. Empirical density curves of deposition values as a function of spray date (T1, T2, T3, T4)  
724 obtained from 2017 calibration data.

725

726 Figure 2. Evolution of primary canopy attributes VH (A), VW (B) and IBR (C) at the vine trio scale  
727 (shown as a dot on graphs) by blocks (Aranel (red), Caladoc (brown), Marselan (green), Petit verdot  
728 (blue) and Syrah (purple)) over the entire growing season (T1 to T4) in 2017. At each date, a box plot  
729 is presented in order to summarise the information obtained for the relevant primary canopy attribute.

730

731 Figure 3. Relationship between the median deposition observed in 2016 and the median deposition in  
732 2016 predicted from of univariate models for prediction of median deposition calibrated in 2017 on  
733 the Collection, Faysse, Franquet and Petit Verdrot blocks over the entire growing season (T1 red  
734 square, T2 green triangle, T3 blue dot and T4 purple cross), coefficient of determination ( $R^2$ ) of 0.79,  
735 normalised root mean square error of prediction (nRMSEp) of 30% and bias of + 2.0%. The black  
736 curve represents a 1:1 linear curve.

737

738 Figure 4. a: Relationship between the median deposition observed in 2016 and the median deposition  
739 predicted from multivariate models for prediction of median deposition calibrated in 2017 (T1 red  
740 square, T2 green triangle, T3 blue dot and T4 purple cross),  $R^2 = 0.94$ , nRMSE = 13% and bias = -  
741 2.1%. The black curve represents a 1:1 linear fit.

742 b: Evolution of D5 median spray deposits as a linear combination of primary canopy attributes  
743 measured over the entire field and growing season (T1 red square, T2 green triangle, T3 blue dot and  
744 T4 purple cross) in 2017. The dotted black curve represents the multivariate model for prediction of  
745 median deposition (see D5 in Table 6 for parameters and statistics).

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