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Abstract

One strategy to optimise spraying is to adjust the spray rate according to local vegetative characteristics. Mobile 2D LiDAR proximal sensor data and local measurements of deposition rates from a side-by-side sprayer were made across eleven narrow inter-row fields in three French vineyards at three dates in 2021. Primary canopy attributes (height, width and porosity) and an integrated indicator of canopy geometry (leaf wall area) were calculated from the LiDAR data using a Bayesian Point Cloud Classification algorithm. Multivariate models to predict the deposition distribution, as deciles, using the primary canopy attributes were constructed and calibrated using data from five of the fields and validated against the data from the six other fields. The models are based on log-lin regression for data acquired at three growth stages covering the whole season. The prediction quality and uncertainty of these multivariate statistical models at different growth stages were evaluated by comparison with previously proposed univariate deposition models based on integrated indicators at the same growth stages. The results showed that multivariate models can predict the distribution of deposits from a typical face-to-face sprayer more accurately (0.79 < R^2 < 0.91), and robustly (11.2% < nRMSEp < 25.3%) than univariate prediction models based on integrated indicators. These predictive multivariate models could enable variable-rate sprayers to adjust the spray rate according to local vegetative characteristics in an automated way. This work is an extension of previous work made on vineyards with wider inter-rows.

Keywords: 3D point clouds, Variable-rate spraying, Precision viticulture

INTRODUCTION

The control of the quantities of pesticides is a major challenge, particularly in viticulture. Achieving the objective of reducing pesticides will require the implementation of complementary approaches, including optimisation of spraying technologies and adjustment of plant protection products (PPP) doses according to vegetation architecture (Walklate et al., 2011). The current system used in France for expressing doses of PPPs in viticulture is per hectare of ground and is thus independent of the quantity of vegetation to be treated (growth stage, vigour). Developing a system for expressing PPP dose rates that explicitly take into account the evolution of the structure of the plant to be protected would be an important step toward precision agriculture (Solanelles et al., 2006). This requires the definition and selection of suitable crop parameters to be used for locally adjusting dose rates to canopy architecture. To address this need, recent experiments in vineyards with 2D LiDAR have been reported to be effective for site-specific measurements of canopy size and shape (Rosell et al., 2012). LiDAR sensors allow a digitalisation of the canopy geometry in the guise of point clouds. From these point clouds, primary canopy attributes can be obtained, such as canopy height and the width of the trellised vine. Another useful primary canopy attribute is apparent porosity, which is the ratio of the number of LiDAR beams that are intercepted by the vine to the total number of emitted LiDAR beams toward the vine (Llorens et al., 2011). Subsequently, these primary canopy attributes can be used for the calculation of integrative indicators, such as the leaf wall area (LWA), at high spatial resolutions. So far, these integrative indicators have been used as input data to build univariate empirical models to predict mean foliar pesticide deposition (Bastianelli et al., 2017). However, these univariate empirical models do have limitations, particularly when the objective is to adjust dose rates under a wide variety of vineyard conditions and training systems (Bastianelli et al., 2017). In response, Cheraiet et al. (2021) proposed a multivariate statistical modelling approach, based on primary canopy attributes, to predict the distribution of deposition over the entire growing season. These models were built and validated in vineyards that are typical and representative of warm-climate viticulture in southern France, with a typical inter-row spacing of between 2 and 3 meters.

However, row spacings in viticulture do vary and for various reasons some vineyards may be established as narrow-row vineyards with inter-row spacings of 0.9-1.2 m. Such an approach is very common in cooler climate viticulture, e.g. in north-eastern France. Narrow inter-rows have the effect of generating a higher density of vegetation per hectare, with LWA values up to 24 000 m^2 ha^{-1} in narrow inter-row vineyards, against 12 000 m^2 ha^{-1} in systems with 2-3 m spacings. A further consequence of this change in row spacing and vine density is a change in canopy architecture, which may affect the ability of LiDAR sensing systems to characterise the canopy and/or the ability of existing models to predict spray deposition in the canopy.

Therefore, in order to validate and facilitate the optimisation of spraying efficiency in narrow inter-row vineyards, the research presented here aims to investigate if LiDAR observations in narrow-row vineyards can also be used, with the previously proposed multivariate modelling approach, to predict deposition distribution as a function of primary canopy attributes (dimensions, porosity). The specific objectives are to (i) calibrate and validate multivariate models specific to narrow inter-row vines, to predict the distribution of intercepted deposits in vineyard canopies applied by a face-to-face sprayer at several growth stages during the growing season and; (ii) evaluate the predictive quality and uncertainty of these multivariate models compared to a previously proposed univariate model (based on LWA).

MATERIALS AND METHODS

Field trials

Three vine estates with blocks of different varieties and contrasting vigour were chosen for experimentation in 2021. They are located in Plumecoq (Marne, France, Lat. 49.022067; Long. 3.985409), Beaune (Côte-d'Or, France, Lat. 4,827183; Long. 47,036943) and Rully (Saône-et-Loire, France, Lat. 4.745191; Long. 46.866283). The training system, vine vigour and grape varieties in the three estates are characteristic of narrow inter-row vineyards in northern France. Vines were trellised in 1.1 m spaced rows with a 1.0 m vine spacing within rows. Sensor and spray deposition measurements were performed on 11 blocks with 4 different *Vitis vinifera* varieties (Chardonnay, Pinot noir, Aligoté and Meunier) at 3 dates (T1, T2 and T3). However, due to accessibility problems (waterlogged soil) at T1, not all blocks were sampled. This sampling design generated a range of growth stages due to phenological differences between varieties on a given date. These 3 dates corresponded to the following BBCH growth stages (Lorenz et al., 1994): 7

leaves spread out (T1: 18/05/2021), green pea stage (T2: 16/06/2021), bunch closure (T3: 22/07/2021).

Measurements of Standardised spray deposition

According to the method defined by Codis et al. (2018), for each date and each block, a 15 m section, composed of 16 vines that were as homogenous as possible, was chosen to represent typical growth for the phenological stage. In each of the 15 m sections, 2 series of 3 consecutive vines (termed a "trio") were sampled for deposition rates. Within each trio, 40 cm^2 PVC collectors were positioned on the leaves inside the canopy on a regular cross-sectional grid, with cells 0.4 m high and 0.1 m wide. Tartrazine, a colorimetric tracer (E102), was mixed with water and sprayed with a side-by-side sprayer. Two sprayers were used, depending on the site: a Precijet (Tecnoma, France) and an Ideal+ (Ideal, Italy). Both were equipped with TXA800067VK nozzles (Teejet, USA). After the tracer had completely dried, each PVC collector was collected and the concentration of E102 on each collector was measured in a laboratory with a spectrophotometer. Spray deposition was normalised to the collector area and the dose rate of tartrazine ha^{-1} per hectare and was expressed as nanograms per square decimetre of leaves per 1 g sprayed per hectare (ng dm^2 per 1g ha^{-1}) (see Cheraiet et al., 2020 for further details).

LiDAR 2D data collection

A 2D LiDAR sensor (LMS100, SICK AG, Germany) coupled with a RTK GNSS (Teria GSM, France) and a data logging system (Effidence, France) were mounted on a purposely built stainless-steel mast fixed on an electric wheelbarrow. The procedure was similar to the tractor-mounted system described previously (Cheraiet et al., 2020). The 2D LiDAR data were acquired at an angular resolution of 0.5°, at 50 Hz and with an angular range of 270°. The wheelbarrow's forward speed was 4 km h^{-1}. A full scan with 541 values (distances from the LiDAR to the vegetation) was obtained every 21 mm along the row. Once the starting point was set, scans were aggregated using this fixed forward distance and direction to generate a 3D point cloud reconstruction of the vine environment. Portions of these 3D point clouds corresponding to each trio were extracted. A total of 54 vines trio were assessed during the whole season.

Calculation of LiDAR primary attributes

For each trio at each date, primary canopy dimensions, height (VH), width (VW) and canopy porosity (intercepted beam rate, IBR) were determined from the extracted and filtered LiDAR data using the Bayesian LiDAR point cloud classification algorithm (BPCC) and the method proposed by Cheraiet et al. (2020). The VH and VW were estimated using an adjustable statistical threshold to account for the development of the canopy along the season, as well as the different cultural operations, i.e. topping, trimming, trellising. The IBR was calculated as the ratio between the number of beams intercepted between the angles that define the height range of the canopy area and the total number of beams emitted over the same angular range, expressed in %.

Calculation of LiDAR integrated indicator

The LWA (Eq. 1) is the projected area of vegetation on a vertical plane. The LWA has been chosen at the EU level as the metric to support dose rate expression in 3D cropping systems when conducting efficacy trials for PPP registration (EPPO, 2016). It is expressed in square metres per hectare (m^2 ha^{-1}) and derived using the height of the vegetation (VH) and the inter-row distance (RS), with the latter being generally a constant in vineyards.

$$LWA = \frac{2 \times \mathrm{VH} \times 10{,}000}{\mathrm{RS}} \quad \text{(Eq. 1)}$$

Where VH = vegetation height and RS = inter-row spacing

Calibration and validation of the local model for predicting the statistical distribution of deposits

The intent here is to model the statistical distribution of intercepted deposition. For this purpose, as proposed by Cheraiet et al. (2021), log-lin regression models were used for each decile (D1 - D9) of the deposition distribution, in order to improve model behaviour and fitting at the upper and lower limits of the distribution.

Calibration

To build the model, a subset of 5 fields was chosen that maximised the coverage of possibilities in terms of canopy structure in the study area, regardless of the estate considered. These 5 fields (Pinot 1, Pinot 2, Chardonnay, Aligoté and MHCS) were selected on the basis of primary canopy dimensions (VH and VW) derived from the LiDAR data. The calibration data were used to develop univariate and multivariate regression models to predict leaf deposition distributions at T1, T2 and T3. In this calibration stage, a distinction was made between univariate and multivariate prediction models. Using the integrative indicator (LWA) as the sole predictor, a univariate empirical model was derived to predict the distribution of leaf deposition (Table 1). Multivariate models for prediction of decile deposition as a linear combination of primary canopy attributes (VH, VW and IBR) were similarly constructed using the log-lin model form (Eq. 2). The coefficient of determination (R^2) and the normalised root mean square error (nRMSE) were used to evaluate the fit of the calibration models.

$$y_{i,j} = M_j e^{-(\alpha_j * VH_i + \beta_j * \mathrm{VW}_i + \gamma_j * \mathrm{IBR}_i)} \quad \text{Eq. 2}$$

Where: $y_{i,j}$ represents the value of the jth decile of spray deposit present in the ith vine trio with $\forall \mathrm{i} \in [1, 54]$ and $\forall \mathrm{j} \in [1,9]$, VH_i, VW_i, IBR_i are the mean value of vegetation height, width and porosity measured at the ith vine trio, M_j, α_j, β_j and γ_j are real unknown parameters to be estimated, where M_j is the intercept and $\alpha_j, \beta_j, \gamma_j$ are the slopes corresponding respectively to VH, VW and IBR in the model equation for the prediction of jth decile.

Validation

The data acquired on the blocks Toussaints, Grèves, Tue-bœuf, Aigrots, Meunier and Pinot 3 were used as the validation set to evaluate the performance of the developed models. To do this, a comparison between observed and simulated deposition was performed for each of the two prediction models using a 1:1 linear regression. The performance of the univariate and multivariate decile models, when applied to the validation data, was assessed by analysing the observed vs. predicted values by the R^2 of a 1:1 linear regression fit, the normalised root mean square

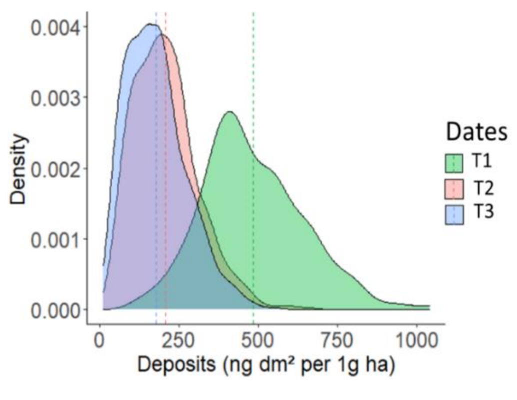

Figure 1. Empirical density curves of deposition values as a function of spray date (T1, T2, T3) obtained from calibration data. (The dashed lines indicate the mean value of the deposits observed for each date).

error of prediction (nRMSEp) (normalised by the mean of the predicted decile deposit values) and model bias (%).

RESULTS AND DISCUSSIONS

Description of data

1. **Deposition**

Spray deposition measurements were used to assess the amount of PPP deposited on vegetation by a given sprayer over the entire growing season. Figure 1 shows the empirical density curves of the deposition values observed at the trio of vines used for model calibration, for a given date. The deposition distributions followed a Poisson-like shape and the shape of the distribution changed with time, with the mean and variance decreasing as the season progressed. There was a clear tendency for the deposition values to decrease with time, associated with the growth of the vine over time that was being sprayed with a constant quantity of tracer. It can be observed that the average deposition value was reduced by a factor of 2.17 between the beginning (T1) and the end (T3) of the growing season. Furthermore, due to the differences in the timing of bud-burst and the different management methods from one field to another, it was observed that the deposition was very variable between vineyard blocks at a given date. On average, this inter-block variability was highest at the start of the season (T1, 39%) and lowest at the end (T3, 26%).

2. ***LiDAR***

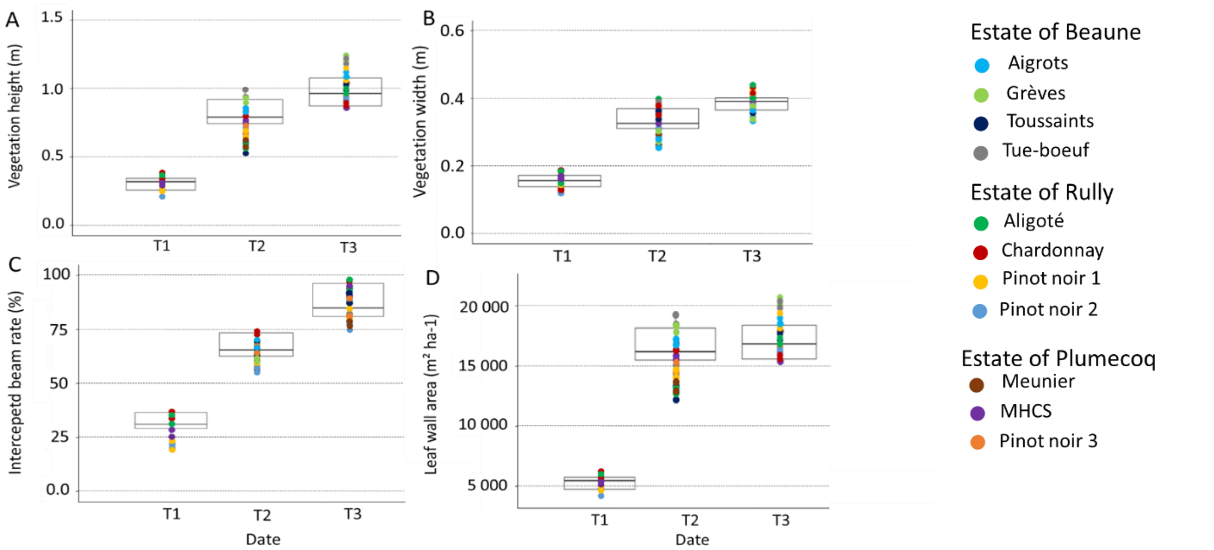

Figure 2. Evolution of primary canopy attributes VH (A), VW (B), IBR (C) and the integrated indicator LWA (D) at the vine trio scale (shown as a dot on graphs) by blocks over the entire growing season (T1 to T3).

The dynamics and variability of the primary canopy attributes (VH, VW, IBR) and the integrated indicator (LWA) derived from the LiDAR survey in the 11 study blocks, at a resolution scale of the trio of vines are presented in Figure 2. The VH, VW and LWA (respectively Figs. 2A, 2B and 2D) increased almost linearly from bud break (T1) to the green pea stage (T2), which corresponded approximately to the date of the first canopy trimming and topping operation. These cultural operations tended to stagnate any further growth. This was reflected in the slower rate of advancement of the VH, VW, and LWA values between T2 and T3 compared to between T1 and T2. This was an indication that these parameters were less likely to be informative about changes in canopy conditions towards the end of the season. On average, over the study period (T1-T3), the inter-block variability was 19.5% for VH, 13.4% for VW, 19.2% for LWA. This showed that there were real differences between the blocks during the growing season. In contrast to VW, VH and LWA, the rate of change of the IBR was still relatively high at T3 (Fig. 2C). It was also observed that the variability (expressed as a coefficient of variation in %) of the IBR increased as the season progressed, from 7.3% at T1 to 14.7% at T3. It appeared that the IBR provided more differentiation of the canopy structure at the mid to late-season stages, when deposits were lowest. It is important to note that the LWA indicator depends on the row spacing and not on canopy width or porosity. Thus, for different vegetation densities, the same LWA value can be obtained and its use as a predictor of linear application rates has a potential risk for the biological effectiveness of the PPP (Rüegg et al., 2001).

Assessment of the performance of multivariate models compared to univariate models

1. **Univariate models**

The results of univariate models construction for deciles D1 to D9 with the calibration dataset showed a relationship with a relatively stable fit ($0.67 < R^2 < 0.83$) for the prediction of leaf deposition using the LiDAR derived LWA indicator (Table 1). Deciles D1 and D3 had the lowest prediction quality and the highest error of the prediction models with nRMSE values of 29.4% for D1 and 27.9% for D3. The application of the calibrated model to the validation data obtained on 6 different blocks generated prediction accuracy for the univariate decile models that followed the same trend as the calibration models with R^2 1:1 values between 0.65 and 0.80 (Table 1). Similar to what was observed by Cheraiet et al. (2021) on data acquired in 2016 and 2017 on vineyards with wider inter-rows, the predictive quality of the models was lower for the lower decile models. The lower deciles (D1-D5) represented areas of the canopy where lower than average levels of deposition had been achieved, which may be insufficient for effective crop protection. However, it was observed that the prediction models for deciles D3, D4 and D5 had positive bias values (Table 1), which meant that these univariate models overestimated deposition in already poorly covered areas (low deposition). Underestimation is preferable to overestimation under these conditions, although a correct estimate is preferable. The ability of the univariate model to robustly predict the lower deciles (D1- D5) of leaf deposition was not assured. This was explained by the fact that the univariate approach only took into account the VH in the LWA, but not the VW or the canopy porosity (IBR). For systems where the dose expression is adjusted to the expected canopy structure, overestimation may be a problem and using the LWA to determine the dose to be applied with a linear model presents a potential risk of under-dosing with potential consequences for the effectiveness of the PPP (Rüegg et al., 2001).

Table 1. Parameters and quality indicators of univariate models for prediction of decile deposition over the entire growing season: including model coefficients (U and λ) and quality indicators for each decile model for both the calibration and validation stages.

Deciles distribution deposit	Model equation parameters		Calibration (n = 30 vines trio)		Validation (n = 24 vines trio)		
	U	λ	R^2	nRMSE (%)	R^2 of 1:1 line	nRMSEp (%)	Bias (%)
D_1	859.57	1.02E-03	0.67	29.4	0.65	42	-6.3
D_2	496.07	1,54E-04	0.72	18.2	0.69	35	-5.4
D_3	458.87	1,61E-04	0.69	27.9	0.67	31	4.1

D_4	530.97	1,58E-04	0.82	23.5	0.74	27	2.6
D_5	474.89	1,47E-04	0.83	21.3	0.8	22	2
D_6	552.15	1,35E-04	0.77	26.6	0.78	20	3.4
D_7	601.71	1,30E-04	0.72	24.3	0.73	21	3.9
D_8	696.04	1,25E-04	0.73	23.4	0.72	24	3.7
D_9	725.5	1,19E-04	0.75	21.4	0.73	27	4.2

2. Multivariate models

The parameters of the fitted multivariate calibration models and the results for both the calibration and validation models are presented in Table 2. For all deposition deciles models (D1-D9), the prediction quality was good for the calibration data sets ($0.79 < R^2 < 0.91$) and for the validation data sets ($0.77 < R^2$ 1:1 < 0.87). In trends, the fit (nRMSE and nRMSEp) of the models was observed to be weaker for the lower deciles (D1-D5). The nRMSE ranged from 16.3% to 12.2% for calibration and from 25.3% to 11.2% for validation (Table 2). The validation bias was negative for all nine prediction models, indicating that the multivariate deposition decile models underestimated deposition for all deciles of the distribution. A worst-case risk management modelling approach should encourage underestimation rather than overestimation of the deposition, to ensure that PPPs are applied in sufficient quantity. For all decile levels, the multivariate model performed better than the univariate model (higher R^2, lower nRMSE) (Tables 1 and 2). The improved performance of the multivariate models over the entire growing season was attributed to its ability to account for the differential contribution of VH, VW and IBR to depositions as the canopy develops. The bias of the multivariate models was always negative (Table 2), in contrast to the univariate prediction models for deciles D3 to D9 that had a positive bias (Table 1). It appeared that the functional unit of the vine trio could be a relevant spatial scale to adjust the doses according to the vegetation architecture, for sprayers that have real-time control functionalities.

Table 2. Parameters and quality indicators of multivariate models for prediction of decile deposition over the entire growing season: including model coefficients (M and α, β, γ) and quality indicators for each decile model for both the calibration and validation stages.

Deciles distribution deposit	Model equation parameters				Calibration (n = 30 vines trio)		Validation (n = 24 vines trio)		
	M	α	Β	γ	R^2	nRMSE (%)	R^2 of 1 :1 line	nRMSEp (%)	Bias (%)
D_1	966.29	0.86	0.06	0.72	0.79	13.9	0.77	25.3	-1.3
D_2	617.99	0.54	1.53	1.25	0.81	12.5	0.79	24	-1.8
D_3	683.71	0.53	0.83	1.26	0.83	12.2	0.81	19	-2.1
D_4	826.53	0.92	0.37	0.75	0.86	13.1	0.83	15	-2.0
D_5	827.63	0.81	0.09	0.82	0.91	13.6	0.87	14	-1.9
D_6	885.98	0.74	0.13	0.81	0.90	16.3	0.86	11.2	-2.8
D_7	1031.72	0.79	0.07	0.80	0.88	15.1	0.82	13	-2.9
D_8	1197.76	0.95	0.16	0.51	0.84	15.6	0.80	16	-2.5
D_9	1258.44	0.93	0.15	0.56	0.83	15.1	0.79	19	-3.0

CONCLUSIONS

The results obtained from data collected over one year, on three estates managed with narrow inter-rows, showed that the proposed multivariate statistical models predicted the distribution of depositions of a typical face-to-face sprayer more accurately and robustly than univariate prediction models based on a calculation of leaf wall area, the current industry standard. This reflected results from other systems in southern France on wider row spacings (and lower vegetation density ha^{-1}). The LiDAR-derived canopy attributes appeared useful for deposition prediction in these systems. In a more general sense, these multivariate statistical models offer the possibility of reacting to the evolution and variability of vegetation during the season in narrow inter-row vineyards, so that it is possible to consider reducing the use of PPPs while offering a margin of safety to producers in terms of crop protection. As such, these models could be used as a reference to propose adaptation charts for phytosanitary treatment doses based on vegetative indicators that are easy to measure in the vineyard, for a revision of the mode of expression of doses. Further studies are still needed to validate these results, especially under different seasonal conditions and to further examine if such a multivariate statistical model can be extrapolated to other vineyards with different canopy management practices. More research is certainly needed to continue to develop approaches to spatialise in 3D the distribution of deposits within the canopy.

ACKNOWLEDGMENTS

This research was partially funded under CASDAR TECHNODOSEVITI and EcoPhyto PULVETROIT projects. The authors want to thank all their colleagues for their assistance in the research for this paper (UMT Ecotech, Chambre d'agriculture 21, Chambre d'agriculture 71, Comité interprofessionnel du vin de champagne).

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