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Influence of micrometeorological factors on pesticide loss to the air during vine spraying: Data analysis with statistical and fuzzy inference models

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Upward spray losses over vines were assessed during a typical air-assisted application using a fluorescent tracer dye and PVC lines as samplers. Linear multiple regression and fuzzy logic inference models were used to evaluate the effects of micrometeorological conditions on pesticide application for two spray qualities (fine and very fine). For the fine spray application (volume median diameter [VMD] 134 μm), the significant variables for the multiple regression were wind speed, air temperature and wet bulb temperature depression, with a coefficient of determination of 0.70. For the very fine spray application (VMD 65 μm), atmospheric stability was also significant, with a coefficient of determination of 0.82. Spray losses were also predicted using fuzzy inference systems, and high coefficients of determination were obtained ($R^2 = 0.72$ for the fine spray and 0.66 for the very fine spray). Interpretable rules were established for the characterisation of micrometeorological parameters using the two sprays. Both analysis tools can be combined with mathematical modelling in order to evaluate air pollution and spray drift from simplified field tests.

1. Introduction

Pesticide use in intensive agriculture has generated increasing public concern the public, which in turn has increased the pressure on agricultural and environmental planning authorities. Spray drift, i.e., pesticide that leaves the treated area by the action of atmospheric factors, is one of the most critical problems to be dealt with by farmers when applying chemicals. Research is strongly focussed at mitigating drift. As part of this it is important to quantify the amount of pesticide lost to the atmosphere in order to predict downwind contamination and the risk of damages to crops and livestock.

In many field crops and orchards, including vines, sprays are often assisted by fan-produced airflows to aid the transport of the droplets towards the target. Aubertot et al. (2006) indicated that air assistance is often accompanied by losses to the ground and to the atmosphere, and that differences in velocity between the air stream and droplets can increase evaporation. They found that losses to the air can be between 10% and 20% during a typical application.

The production of drift during air-assisted spraying using radial fans in orchards is a complex process that was well described by Xu et al. (1998). The flow-field that comes from the air-jet outlet extends beyond the air–crop interface and affects spray penetration into the crop. The droplets are

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Nomenclature

A_i^j	branch of a fuzzy decision tree
b	node of a fuzzy decision tree
C_b	rule conclusion in a fuzzy decision tree
d	PVC lines diameter, mm
D_j^i	deviance of a node for the fuzzy set j of the variable i
E^i	entropy of the variable i
f	fuzzy set
g	gravitational acceleration, $\mathrm{m\,s^{-2}}$
I_e	turbulence intensity, adimensional
i, j, k	indices
L	Monin–Obukhov length, m
Q	airborne spray volume, ml
R^2	coefficient of determination
S_i	time-integrated flux, $\mathrm{ml\,mm^{-1}}$
T	absolute temperature, K
T'	temperature fluctuation, K
U, V, W	wind averaged velocities, $\mathrm{m\,s^{-1}}$
u^*	friction velocity, $\mathrm{m\,s^{-1}}$
u', v', w'	wind velocity fluctuations, $\mathrm{m\,s^{-1}}$
V_i	spray volume removed from collector i, ml
W	distance between two PVC lines, m
$w_k{}^b$	"Fire-strength" of the rule associated with node b, for the input k
x	fuzzy variable
Y_i	statistical dependent variable
y_k	measured output corresponding to the input k
$y_j{}^i$	weighted output of a node for the fuzzy set j of the variable i
$\hat{y}_i$	predicted value for the variable Y_i
Z	height, m
β_i	constants
ΔT	wet bulb depression, K
κ	Von Karman constant
$\mu()$	membership function

deposited onto leaves but they may then be re-entrained. Airstreams produced by the sprayer and its deflectors can interact with the crop and generate large eddies. These eddies can entrain spray droplets causing them to be advected above the top of the canopy where they are subsequently dispersed and transported by the wind.

Because of the costs of field tests, and the inherent variability of micrometeorological conditions, modelling the effect of the variables acting on environmental pollution is an attractive alternative. Because of the numerous factors related to application, equipment and meteorological and geographical conditions, tools have been developed to model air drift from a few key parameters (Hewitt et al., 2002). In particular, computational fluid dynamic (CFD) codes have frequently been used to solve the Reynolds average flow equations, most often with a standard k–ε turbulence model (e.g. Weiner and Parkin, 1993; Brown and Sidahmed, 2001; Tsay et al., 2002).

Although CFD codes can describe complex flow fields with some degree of precision, they require as input either an accurate description of the source or the source and its near field. A detailed review of factors influencing emissions of pesticide into the air can be found in Gil and Sinfort (2005). Quantification of the source can be obtained from measurements of the emissions close to the sprayer during small-scale field tests (Cross et al.,2001) or even from other simulation models (Walklate, 1992). Various methods have been proposed and validated for source measurements (Herbst and Molnar, 2002). Among them, the use of a tracers combined with passive collectors is the most common method to assess the movement of sprayed liquid plumes since it is both simple and inexpensive.

Although there are some limitations related to the collection efficiency of passive collectors, they can be determined both theoretically (Aylor, 1982; Walklate, 1992; Parkin and Young, 2000) and experimentally (Fox et al., 2004, Gil et al., 2005). It has also been shown that passive collectors may underestimate pesticide loss to the air when very fine droplets evaporate close to the emission source (Gil et al., 2007). However, suitable analysis methods can help interpret the results and identify the influence of the variables acting on spray loss.

Statistical modelling has also been widely used to describe spray drift. Goering and Butler (1975) used regression analysis to examine spray drift deposits during ground applications and concluded that this method could allow the effects of meteorological and application variables on the drift to be assessed. Smith et al. (2000) developed empirical models to determine the significant variables related to the drift in boom sprayer applications and found a close agreement between predicted and measured drift deposits. The AgDRIFT® model, developed by the Spray Drift Task Force (Teske et al., 2002), is also partly based on a statistical model established from empirical observations during ground spraying. Nevertheless, to date, no regression models have been developed that predict spray losses above a crop under various meteorological conditions. In most cases, the amount of spray drifting downwind has been predicted.

Fuzzy inference methods have recently been proposed as suitable tools for building environmental indicators that may help analyse complex situations. They provide a stable basis to improve the development of transferable indicators for agricultural and environmental systems (Ferraro et al., 2003, Ocampo-Duque et al., 2006). Fuzzy logic is well known for its natural language modelling ability; inference systems allow rules to be built of the form "*If X is A then Y is C*", where A is a fuzzy set defined in the X universe and C is either a scalar or a fuzzy set defined in the Y universe. These rules can either be written by a domain expert or induced from data. In the latter case, severe constraints have to be superimposed to the algorithm inducting the rules so that the system remains linguistically interpretable by a human expert.

Thus, both statistical and fuzzy inference systems can be used to assess the complex relationships between environmental factors, spraying techniques and spray losses from simplified and reproducible tests.

This paper aims to compare these two methods by analysing the test results and classifying the main micrometeorological conditions that affect potential losses above the crop during a typical application air-assisted application. The two methods will be compared using previously published data obtained in 2004 (Gil et al., 2007). These data were obtained from experiments related to air-assisted applications in vines where the amount of spray moving upwards above a simulated crop was measured using a fluorescent tracer dye that was collected on standard 2 mm diameter passive collectors. The evaluation of the methods focuses on the use of the passive collector technique, the relationship between the main micrometeorological variables, and the performance of the analysis methods.

2. Material and methods

All the experimental conditions were described and discussed in Gil et al. (2007). In Sections 2.1–2.3 their main characteristics are summarised.

2.1. *Field test setting*

The experiments were performed from June 10 to July 20, 2005 in Montpellier (Southern France), during the vine spraying period. These dates were selected so as to maximise the variability in weather conditions.

An artificial vineyard was built from shade nettings chosen to have similar droplet capture properties as those of vines. Raupach et al. (2001) showed how such properties could be derived from the apparent porosity of the netting (34% here) and the crop row (Gil et al., 2007). The energy loss coefficient and the global efficiency factor of this net have been measured as a single-layer using tests in a wind tunnel. Row spacing and crop height were 2 m each, a standard size for vineyards in this region. The artificial plot was built with four 8 m long rows oriented along the north–south direction. An axial air-assisted sprayer Fisher Turbo 561 (Berthoud Ltd., France) was used.

Table 1 – Droplet diameter, μm, for 10% ($D_{V.10}$), 50% ($D_{V.50}$) and 90% ($D_{V.90}$) of the cumulative volume

Nozzle	$D_{V.10}$	$D_{V.50}$	$D_{V.90}$	Spray quality
Green	72	134	180	Fine
White	28	65	135	Very fine

The $D_{V.50}$ is also the volume median diameter (VMD). Spray quality is derived from the BCPC classification system. All information was obtained from manufacturer reports. All measurements were performed with a laser diffraction instrument

Two sets of nozzles were used in the experiments. Both were operated at a 1000 kPa operating pressure: Albuz ATR white hollow-cone nozzles (0.38 l min^{-1}) and Conejet green hollow-cone nozzles (1 l min^{-1}). Manufacturer's data using water and laser diffraction (Table 1) gives the volume median diameters (VMDs) as 65 μm for the white nozzle and 134 μm for the green nozzle. According to the British Crop Protection Council (BCPC) classification (Southcombe et al., 1997), the spray quality for the green nozzle is fine and that for the white nozzle is very fine. All tests were carried out using the same two nozzle sets and the same air deflection settings. Characterisation of the air stream was obtained with a 3D ultrasonic anemometer (Young 81000, R.M. Young Co., USA). To ensure proper sampling, air velocities were measured 500 mm from the nozzles where the air jets are wider than the diameter of the anemometer sample volume (100 mm). For all tests the PTO rotational speed was 540 rev min^{-1}. This gave a mean air volumetric flow rate of 3.3 m^3 s^{-1} and a mean air velocity of 12.8 m s^{-1}. The forward speed of the tractor was set to 5.1 km h^{-1}.

So as to obtain results from a range of atmospheric conditions for both spray qualities, Sixty-three tests were carried out (33 runs for the fine spray and 30 for the very fine spray). These meteorological conditions are described in Section 2.3. During all of these tests, the set-up of the sprayer was carefully conserved with only the set of nozzles being changed.

2.2. *Upward spray flow estimation*

The sprayed liquid was an aqueous solution of 1 g l^{-1} of Brilliant Sulphoflavine (BSF) as a fluorescent tracer dye and 0.1% of a non-ionic surfactant.

In order to quantify the upward spray losses above the simulated crop, five 12 m long 2 mm diameter PVC lines were

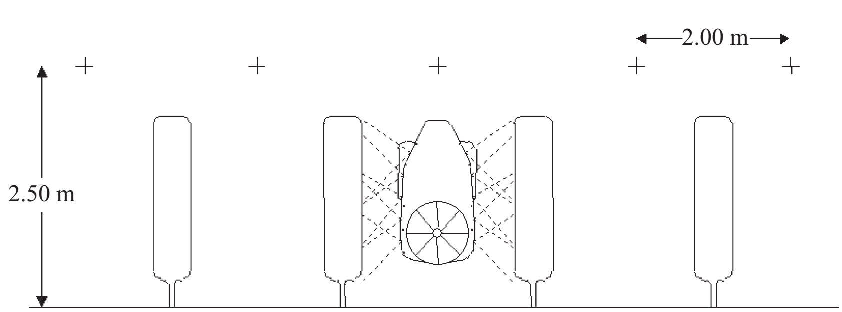

Fig. 1 – Schematic plane of PVC lines, with their positions above four artificial crop rows. The sprayer circulates along the central inter-row.

positioned at 2.5 m above the soil surface (Fig. 1). Three lines were placed over the three inter-rows and two lines at 1 m away from the first and the last plot rows. This arrangement created a reference plane through which the upward moving spray could be measured. Spray moving horizontally below the lines was not measured. During each run, the sprayer was driven four times along the central inter-row in order to increase the amount of deposited spray and reduce the effects of random variations.

The volumes of spray liquid-captured liquid on the lines were estimated from the amounts of liquid collected by the 2 mm diameter lines. Once the spray liquid on the lines had dried, each line was washed using 200 ml of tap water. The spray volume removed from the lines (V_i, ml) was determined from the concentration of dye in the spray liquid, the amount of water used to elute the dye and the concentration of dye in the elution which was obtained by fluorimetry. The time-integrated flux through the reference plane (S_i, ml mm^{-1}) was then calculated as

$$S_i = \frac{V_i}{d} \tag{1}$$

where d is the collector diameter in mm. The airborne spray quantity (Q, in ml) crossing the reference plane during the spraying was calculated by

$$Q = \sum_{i=1}^{5} S_{i.} \times W \tag{2}$$

where W represents the distance between the lines (in this case 2 m). The amount of spray moving through the reference plane was then normalised by the amount of spray applied to the crop so that the atmospheric loss was defined as a percentage of the total amount of spray used in each experiment.

2.3. Determination of micrometeorological variables

Mean hourly values of relative humidity were obtained from a nearby standard meteorological station. Wind speed components and temperature fluctuations were sampled at 10 Hz with a 3D ultrasonic anemometer positioned at a height of 4 m on a meteorological mast located at the edge of the plot. Results showed that the wind speed measurements were not affected by the movement of the sprayer.

The friction velocity (u^* in m s^{-1}) was estimated from the following equation, using the surface kinematic momentum fluxes ($\overline{u'w'}$ and $\overline{v'w'}$, respectively), calculated from wind velocity fluctuations (u' and v', defined in the directions perpendicular and parallel to the rows, respectively, and w' in the vertical direction):

$$u^* = \left[\overline{u'w'}^2 + \overline{v'w'}^2\right]^{1/4} \tag{3}$$

The Monin–Obukhov length (L in m) was calculated by

$$L = \frac{-u^{*3} \times T}{\kappa \times g \times \overline{T'w'}} \tag{4}$$

where κ is the von Karman constant (0.41 here), g is the acceleration due to gravity, T is the absolute temperature and T' stands for the air temperature fluctuations (Stull, 1988). The stability parameter (z/L) was evaluated at the height of the 3D anemometer ($z = 4$ m). It should be noted that, given the size of the plot, the micrometeorological variables derived from the sonic anemometer are more representative of its surroundings; however, the roughness values are similar in magnitude. All micrometeorological variables were calculated over 20-min measurement periods centred on each spraying operation, whose effective duration was about 2 min.

Turbulence intensity (I_e, dimensionless) was calculated for each test using the following equation, from standard deviations ($\overline{u'^2}$, $\overline{v'^2}$ and $\overline{w'^2}$) and averaged values (U, V and W) of air velocity components (Chassaing, 2000):

$$I_e = \frac{\sqrt{\overline{u'^2} + \overline{v'^2} + \overline{w'^2}}}{\sqrt{U^2 + V^2 + W^2}} \tag{5}$$

The main micrometeorological variables observed during the experiments are shown in Table 2 (White nozzle tests) and Table 3 (Green nozzle tests).

2.4. Multiple-regression analysis

Spray loss, expressed as a percentage, was taken as the dependent variable (Y_i) for the multiple-regression analysis. Mean wind speed, stability parameter (z/L), wet bulb temperature depression (ΔT), air temperature and turbulence intensity (Gil et al., 2007) were selected a priori, from our knowledge of the micrometeorological variables (independent variables) suspected to influence spray losses to the air.

The experimental data set was used to test the "full interactions" (between two variables) model described by the following standard equation (Cook and Weisberg, 1994):

$$\hat{Y}_i = \beta_0 + \beta_1\theta_1 + \cdots + \beta_n\theta_n + \beta_{12}\theta_1\theta_2 + \cdots + \beta_{(n-1)n}\theta_{n-1}\theta_n \tag{6}$$

β_0 is the offset term; $\beta_1 \ldots \beta_n$ are the linear effect terms; and $\beta_{12} \ldots \beta_{(n-1)n}$ are the interaction effects. The independent variables, such as those mentioned above, are represented as θ_i. The proportion of variance explained by the resulting polynomial model is given from a variance analysis (ANOVA) as the multiple coefficient of determination R^2. The significance of each coefficient was determined using the t-value and p-value of a Student test, determining the probability that the β_i are equal to zero. A stepwise procedure was applied (Smith et al., 2000), starting with an empty model. Variables were added one at a time as long as their p-value was small enough. The significance criterion for the p-value was set to 0.05. Finally, a leave-one-out cross-validation assessment was carried out to validate the regression model (Martinez and Martinez, 2002).

2.5. Fuzzy inference systems

Fuzzy Inference Systems (FIS) are one of the most well-known applications of fuzzy logic and fuzzy set theory (Zadeh, 1965). The strength of FIS relies on their two-fold identity: on the one hand, they are able to handle linguistic concepts such as *High* or *Low*; on the other, they are universal approximators able to perform non-linear mappings between inputs and outputs through automatic learning procedures.

However, applying this type of procedure only for the sake of numerical performance conflicts with the unique quality of

Table 2 – Very fine spray data: micrometeorology variables at 4 m above the ground and measured spray losses

Test reference	Wind speed, $m\,s^{-1}$	z/L	ΔT, °C	Temperature, °C	I_e	Spray losses, %
W-01	0.68	−0.25	3.73	16.55	0.75	9.58
W-02	1.00	3.17	4.42	17.17	1.03	11.23
W-03	0.49	0.06	5.25	18.41	1.21	9.59
W-04	1.38	−0.08	9.60	18.51	0.94	9.63
W-05	0.89	0.34	6.85	19.65	0.76	8.23
W-06	0.26	−4.80	4.11	19.97	2.13	6.61
W-07	0.68	−0.23	4.98	20.21	1.24	7.77
W-08	2.21	−0.11	8.64	20.95	0.46	9.89
W-09	0.68	−2.58	7.74	21.02	1.03	8.24
W-10	1.61	−0.43	9.27	21.13	0.61	9.02
W-11	2.68	−0.48	5.91	21.52	0.44	11.36
W-12	4.15	−0.07	9.77	21.58	0.36	10.33
W-13	1.62	−0.22	8.49	22.02	0.59	7.92
W-14	0.61	−0.62	5.27	22.25	1.06	5.96
W-15	2.53	−0.14	10.04	22.52	0.60	9.91
W-16	3.26	−0.08	7.61	22.87	0.41	7.60
W-17	3.26	−0.19	7.61	23.34	0.46	8.98
W-18	3.66	−0.96	7.65	23.55	0.36	9.50
W-19	2.79	−0.13	10.33	23.60	0.59	11.02
W-20	3.83	−0.14	8.84	23.89	0.40	11.65
W-21	0.51	−1.44	5.98	24.08	1.55	5.35
W-22	1.00	−0.23	10.66	25.28	0.56	7.22
W-23	0.25	−2.25	6.88	25.89	2.18	5.26
W-24	1.83	−0.49	10.93	26.20	0.81	8.63
Mean	1.74	−0.51	7.52	21.76	0.86	8.77
SD	1.24	1.37	2.19	2.57	0.51	1.82
Min	0.25	−4.80	3.73	16.55	0.36	5.26
Max	4.15	3.17	10.93	26.20	2.18	11.65

Mean, standard deviation (SD), minimum (Min) and maximum (Max) values obtained over the whole experiment

fuzzy logic: its interpretability. In this study, FIS were implemented through the use of the software program, FisPro 3.0 (Guillaume, 2001, www.inra.fr/internet/Departements/MIA/M//fispro/). Among the available methods for fuzzy rule induction, FisPro implements those yielding interpretable fuzzy rules.

The goal of this section is not to give an extensive introduction to fuzzy logic (see Zadeh, 1965; Dubois and Prade, 2000; Bouchon-Meunier and Marsala, 2003 for more details), but to provide the reader with the basic elements of fuzzy linguistic modelling. We first recall how fuzzy sets are used to model linguistic concepts, and then detail the two main steps of rule generation: variable fuzzy partitioning design and rule induction.

2.5.1. *Fuzzy sets and linguistic terms*

A fuzzy set is defined by its membership function. A point x in the X universe belongs to a fuzzy set A with a membership degree $0 \leqslant \mu_A(x) \leqslant 1$. Fig. 2 shows a triangle membership function.

Fuzzy sets can be used to model linguistic concepts. If A is the set of *High* temperatures, the membership degree of a given temperature x, $\mu_A(x)$ indicates to which degree the value x belongs to the set A on a scale from 0 to 1.

The rule "*If Temperature is High then …*" is implemented as "*If X is A then …*". For the x value of temperature the matching degree of the rule is given by its membership degree, $\mu_A(x)$. Usually, several variables are involved in the rule description. In such a case the membership degrees are combined using an *AND* operator, the minimum and the product being the most common ones.

Several fuzzy sets corresponding to linguistic concepts can be defined on the same universe, e.g., *Low*, *Mean*, *High*. The set of the fuzzy sets defined on the same universe forms a fuzzy partition of the variable.

2.5.2. *Fuzzy partitioning*

The readability of fuzzy partitioning is a pre-requisite condition to building an interpretable rule base. The necessary conditions for interpretable fuzzy partitions have been studied by several authors (e.g. Ruspini, 1969; De-Oliveira, 1999; Glorennec, 1999). One condition, for example, is that there must not be too many distinguishable fuzzy sets. The latter must directly correspond to linguistic concepts, and entirely cover the variable domain.

In FisPro these constraints are implemented as follows:

$$\left\{ \begin{array}{ll} \forall x, & \sum_{f=1,2,\ldots,m} \mu^f(x) = 1 \\ \forall f, & \exists x / \mu^f(x) = 1 \end{array} \right\} \tag{7}$$

where m is the number of fuzzy sets in the partition and $\mu^f(x)$ is the membership degree of x to the fth fuzzy set.

Fuzzy sets are of triangular shape, except at the domain edges, where they are semi-trapezoidal. Conditions from

Table 3 – Fine spray data: micrometeorology variables at 4 m above the ground and measured spray losses

Test reference	Wind speed, $m\,s^{-1}$	z/L	ΔT, °C	Temperature, °C	I_e	Spray losses, %
G-01	0.22	−1.25	2.98	17.00	2.02	5.87
G-02	0.39	−0.34	2.37	17.33	1.25	5.37
G-03	0.30	0.77	1.89	17.80	0.85	5.84
G-04	1.67	−0.10	6.90	19.71	0.69	7.56
G-05	0.22	−0.19	8.20	19.80	2.20	5.00
G-06	0.88	−0.16	7.25	20.05	1.11	7.44
G-07	1.52	−0.13	7.76	20.26	0.82	6.45
G-08	1.75	−0.03	9.31	21.10	0.95	6.06
G-09	2.80	−0.09	9.36	21.30	0.59	7.02
G-10	0.71	−0.39	8.91	21.45	0.76	5.64
G-11	1.87	−0.05	7.51	22.03	0.77	5.42
G-12	3.33	−0.03	8.11	22.29	0.51	7.76
G-13	0.61	−2.32	9.40	22.37	1.23	5.32
G-14	0.92	−0.07	7.77	22.71	0.91	4.57
G-15	0.17	−5.51	9.93	22.88	2.55	4.81
G-16	0.80	−0.10	7.72	22.92	1.40	4.53
G-17	3.32	−0.08	8.49	22.98	0.40	7.65
G-18	3.10	−0.04	8.52	23.12	0.41	8.22
G-19	0.72	−0.69	10.59	23.82	0.93	4.35
G-20	1.07	−0.58	5.82	24.62	0.56	4.80
G-21	0.81	−0.34	4.87	24.69	0.92	3.84
G-22	0.95	−0.24	4.49	24.69	0.87	3.69
G-23	0.65	−0.59	11.27	24.95	1.17	4.96
G-24	0.20	−1.79	5.36	25.14	2.85	5.21
G-25	0.92	−2.02	5.36	25.22	1.01	4.49
G-26	1.23	−0.21	11.89	25.65	0.85	5.43
G-27	0.44	−3.15	6.23	25.93	1.36	4.87
G-28	1.40	−0.13	7.82	26.28	0.81	4.81
G-29	2.61	−0.12	8.63	26.31	0.37	5.33
G-30	1.63	−0.39	12.38	26.46	0.84	6.79
G-31	1.52	−0.35	8.38	26.58	0.92	5.60
G-32	1.01	−0.54	12.92	27.37	1.16	4.43
Mean	1.24	−0.66	7.76	22.96	1.06	5.60
SD	0.92	1.18	2.70	2.82	0.59	1.19
Min	0.17	−5.51	1.89	17.00	0.37	3.69
Max	3.33	−0.77	12.92	27.37	2.85	8.22

Mean, standard deviation (SD), minimum (Min) and maximum (Max) values obtained over the whole experiment

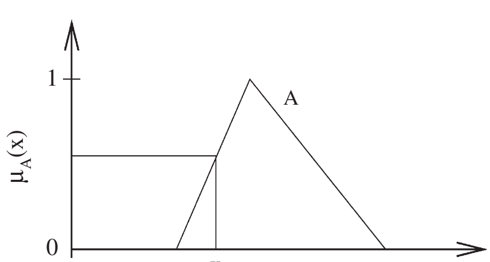

Fig. 2 – A triangle membership function.

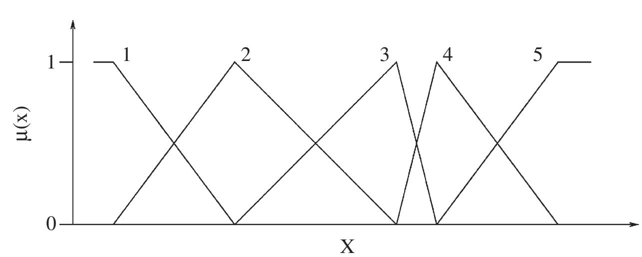

Fig. 3 – A standardised fuzzy partition with five fuzzy sets and standardised membership degree, $\mu(x)$, between 0 and 1. X is the universe variable.

Eq. (7) allow us to define each fuzzy set with only one point, as shown in Fig. 3. For instance, as described in Section 3.2 (Fig. 6), for the variable "*Wind speed*", there are three fuzzy sets ($m = 3$), named, respectively "*Low*", "*Mean*" and "*High*".

Various methods are available within FisPro to build fuzzy partitions automatically (according to input data) or from expert knowledge.

2.5.3. *Fuzzy rule generation*

The next phase of FIS design consists of generating rules to be applied to the multi-variable inputs. The goal is to produce a small number of general rules. In the present case the rule induction was accomplished with a fuzzy decision tree algorithm.

Fuzzy decision trees (Ichihashi et al., 1996) are an extension of classical decision trees (Breiman et al., 1984; Quinlan, 1986). They can be used either for classification or regression. Tree building is an iterative process. The root node is the starting point of the decision process. At each step a new level is added, on which each node corresponds to a split in the values of a new input variable, according to its partition. This variable is chosen while computing a selection criterion, called entropy, in order to reach a maximum of homogeneity amongst the examples that belong to each node relative to the output variable (response variable). The process is achieved when the selection criterion cannot be further improved. In this way, each terminal node corresponds to a particular path through the possible fuzzy sets of all variables.

The fuzzy rule associated with a given node b is written as

$$\text{IF}\quad x_{i1} \text{ is } A_{i1}^{j1} \quad \text{AND} \quad x_{i2} \text{ is } A_{i2}^{j2} \ldots \text{THEN } y \text{ is } C_b$$

A_{i1}^{j1} corresponds to the first branch of the path starting from the root and leading to node b, meaning that the first selected variable has the label i_1 (for instance, i_1 stands for *wind speed* or *temperature*, etc.), and the sub tree leading to node b starts from the j_1 label of this variable (for instance, j_1 stands for "*low*" or "*high*"). y is the output variable (in our case, it is the percentage of upward losses). C_b is the rule conclusion. An illustration is shown in Fig. 4.

The premise of the rule corresponding to node b is defined by the couples (i,j), the jth label of the ith input variable, along the branch from the root to node b. The induction process relies on minimising the entropy computed at each node for each variable.

Every sample k is characterised by its membership degrees, $\mu_j^i(x_k^i)$, for all the variables i and all their labels j. For instance, for the test W-03 (Table 2), the computed membership degrees are:

for the variable "*Wind Speed*",

$$\mu_{low}^{wind\ speed}(x_{W03}^{wind\ speed}) = \mu_{low}^{wind\ speed}(0.49\,\mathrm{m\,s^{-1}}) = 0.833$$
$$\mu_{mean,}^{wind\ speed}(x_{W03}^{wind\ speed}) = \mu_{mean,}^{wind\ speed}(0.49\,\mathrm{m\,s^{-1}}) = 0.167$$
$$\mu_{high,}^{wind\ speed}(x_{w03}^{wind\ speed}) = \mu_{high,}^{wind\ speed}(0.49\,\mathrm{m\,s^{-1}}) = 0$$

and for the variable "*Temperature*",

$$\mu_{low}^{temperature}(x_{W03}^{temperature}) = \mu_{low}^{temperature}(18.41\,^\circ\mathrm{C}) = 1$$
$$\mu_{high,}^{temperature}(x_{W03}^{temperature}) = \mu_{high,}^{temperature}(18.41\,^\circ\mathrm{C}) = 0$$

and the output is $y_{W03} = 9.59$ (%).

For a given node, b, and for each sample, k, the validity of the rule associated with the node is evaluated through an indicator, called "fire-strength", defined as

$$w_k^b = \underset{(i,j)\in b}{\Lambda} \mu_j^i(x_i^k) \tag{8}$$

where Λ is an AND operator (usually the minimum or the product) and $(i,j\in b)$ defines the rule associated with the node b. For instance, for the node associated with the rule R: "*Wind speed is low and temperature is low*", the fire-strength of the rule R for the input W-03 may be:

$$w_{W03}^R = \min(0.833, 1) = 0.833$$

To compute the entropy of a given variable i, we first calculate the weighted output for each possible branch (i.e., each label of the variable), j:

$$\overline{y_j^i} = \frac{\sum_k w_k^b \times y_k}{\sum_k w_k^b} \tag{9}$$

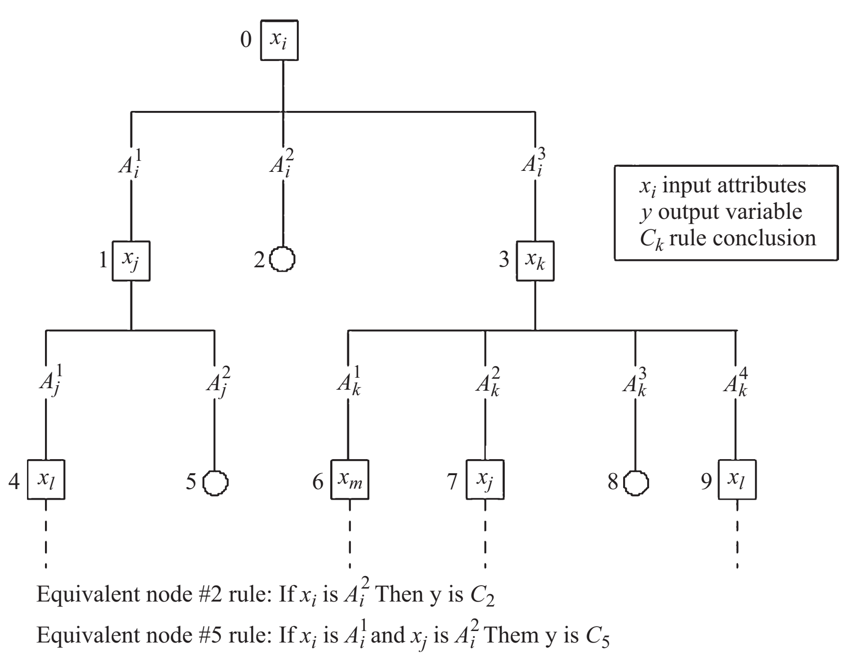

Fig. 4 – An illustration of a fuzzy decision tree.

Then, we compute a deviation index, called "deviance":

$$D_j^i = \frac{\sum_k w_k^b \times (y_k - \overline{y_j^i})^2}{\sum_k w_k^b} \quad (10)$$

For the root node, the entropy E_i of the ith variable is the sum of the deviances of this variable:

$$E^i = \sum_j D_j^i \quad (11)$$

and the variable with the lowest entropy is retained to define the next sub-nodes (for instance, in Fig. 7, the first variable is "*Wind speed*"). The tree is then split into *m* branches where *m* is the number of labels of the variable.

At the next sub-nodes, the entropy of the variable i' entropy is the weighted sum of the deviances:

$$E^{i'} = \sum_j q_j \times D_j^{i'} \quad \text{with} \quad q_j = \sum_k w_k^{bj} \Big/ \sum_k w_k^b \quad (12)$$

where *bj* stands for the possible branches (one per label) of the variable i' at the sub-node *b*. For instance, if we consider the sub-node associated with the rule "*wind velocity is low*" and the variable "*temperature*", entropy is computed with two weighting values, q_{low} and q_{high}, obtained from the fire-strengths ${w_k}^{b\text{-}low}$ and ${w_k}^{b\text{-}high}$ of the *rules* "*wind velocity is low and temperature is low*" and "*velocity is low and temperature is high*" (${w_k}^b$ is the fire-strength of the rule "*wind velocity is low*"). The weighting values q_j stand for the part of the training set falling into the corresponding branches *j*.

The gain of entropy is the difference between the entropy of the node and the entropy of the new variable. The entropy of the node is computed with the relation of the deviance given in (10). For the root node, all the ${w_k}^b$ are equal to 1, thus, the entropy is the variance of the outputs. The process is stopped when the gain is lower than a user-selected threshold.

Once the tree is built, the output values are the weighted average outputs at the ending nodes. The final step consists of a rule conclusion optimisation using a least square minimisation criterion (OLS, Destercke et al., 2007).

The main advantage of the decision trees is to generate incomplete rules, only defined by a subset of the available input variables. The generated rules are informative for experts under the condition that the partitioning is carefully defined.

3. Results

3.1. *Regression model fitting*

After a few possible outliers were first identified using the Welsh–Kuh method (Cook and Weisberg, 1994), the multiple-regression analysis described in Section 2.4 was performed on a set of 56 runs selected out of the initial 63 (32 runs for the fine spray and 24 for the very fine spray). The rejected runs are given in Table 4. No relationship could be determined between them.

A correlation matrix was used to check the colinearity effects between the variables. The variable used for atmospheric stability was the inverse of the stability parameter (*z*/*L*), which turned out to improve the prediction.

3.1.1. *Fine spray*

For the fine spray data, the stepwise approach suggested two significant variables for the model: the linear term for air temperature (*T*), followed by the interaction effect of wind speed and wet bulb temperature depression ($V\Delta T$). Table 5 shows the significance of each coefficient determined using the Student test as explained in Section 2.4. The resulting model assessed upward spray losses during standard air-assisted spraying through the following expression:

$$\hat{Y}_i = 9.719 - 0.229 \times T + 0.109 \times V\Delta T \quad (13)$$

The interaction effect for the product of wind speed, *V*, and ΔT is positive, indicating that, as wind speed and ΔT increased, spray losses also increased. The negative sign of the air temperature effect (*T*) indicates that spray losses were lower for high temperatures. The determination coefficient (R^2) was 0.70.

3.1.2. *Very fine spray*

The results from using a very fine spray are shown in Table 6, and Eq. (13) shows the selected regression model. The stepwise procedure determined the statistical significance of two variables and two interactions in the model. The first variable was the linear effect of wind speed, *V*, with a positive sign. The second variable is temperature, *T*, with a negative sign. This corroborates the results obtained with the other data set. However, the factor β was larger with this test series, revealing that the air temperature effect was more important. The interaction between ΔT and *T* was also significant, with a

Table 4 – Rejected runs from the linear regression model

Nozzle	Wind speed, $m\,s^{-1}$	z/L	ΔT	T, °C	Spray losses, %
F	4.41	−0.05	9.21	20.76	6.07
VF	2.78	−0.09	9.51	18.54	7.28
VF	1.36	−0.26	9.23	17.88	5.66
VF	3.12	−0.03	10.96	25.68	5.99
VF	1.29	−0.31	9.01	21.17	12.23
VF	1.97	−0.15	8.68	23.80	14.44
VF	1.97	−0.07	8.64	23.62	12.50

F: fine spray and VF: very fine spray.

Table 5 – Results of the stepwise variable selection for fine spray data

Variable and interactions	β	SD of β	*t*-Value	*P*-Value
Offset	9.719	0.997	9.748	0.0000
Wind speed × ΔT	0.109	0.015	7.437	0.0000
Temperature	−0.229	0.044	−5.181	0.0000

β, regression predictor; SD standard deviation of the predictor; *t*-value, Student statistical test; *p*-value, probability that β is zero.

Table 6 – Results of the stepwise variable selection for very fine spray data

Variable and interactions	β	SD of β	*t*-Value	*p*-Value
Offset	18.732	1.965	9.534	0.000
Wind speed	1.488	0.257	5.788	0.000
Temperature	−0.672	0.117	−5.744	0.000
ΔT × temperature	0.016	0.005	2.911	0.009
Wind speed × $(z/L)^{-1}$	0.058	0.02	2.838	0.011

β, Regression predictor; SD standard deviation of the predictor; *t*-value, Student statistical test; *p*-value, probability that β is zero.

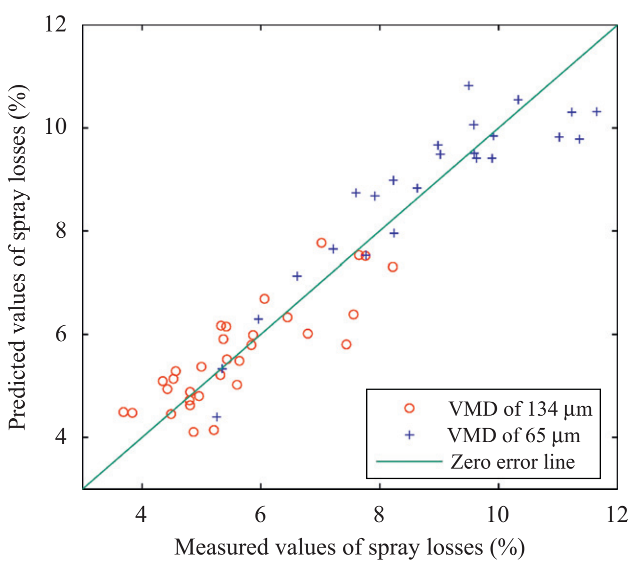

Fig. 5 – Normalised losses (%) at 2.5 m above the ground; measured and estimated values obtained by the multiple-regression model.

positive sign. Finally, the interactions between wind speed (*V*) and stability conditions, $(z/L)^{-1}$ were also significant, with a positive sign. The model for very fine spraying was therefore:

$$\hat{Y}_i = 18.732 + 1.488 \times V - 0.672 \times T + 0.016 \times (T\Delta T) + 0.058 \times (V(z/L)^{-1}) \quad (14)$$

3.1.3. *Prediction from statistical modelling*

A comparison of the values obtained by the model with the measured values is shown in Fig. 5. The overall coefficient of determination R^2 is 0.90 (including both fine and very fine data series). Using a cross-validation procedure, the coefficient of determination becomes 0.83, which provides evidence of the reliability of the statistical model for the data set considered.

3.2. *Fuzzy inference*

Fuzzy sets were defined according to the expected physical influence of various variables on spray losses (Fig. 6). Three representative sets were defined according to the wind speed variable, using the Beaufort scale reference: *Low* was set to 1 when velocities were lower than Beaufort level 1 ($<0.3\,\mathrm{m\,s^{-1}}$), *Mean* was defined with the higher value of level 1 ($1.5\,\mathrm{m\,s^{-1}}$) and *High* was set to 1 when velocities were higher than level 2 ($>3.3\,\mathrm{m\,s^{-1}}$). As for air temperature, wet bulb temperature depression, ΔT, and the stability parameter, fuzzy sets were described by only two levels (*Low* and *High*), according to the atmospheric conditions that favour spray emissions (PISC, 2002). For air temperature, the breakpoint values were set to 19 and 25 °C, whereas for ΔT they were set to 5 and 10 °C. The reference values for the stability parameter $(z/L)^{-1}$ were set to −10 and +10. The lower and higher limits of the domains optimise the classification of the registered values expressed in Tables 2 and 3.

3.2.1. *Fine spray*

The induction process for the fine spray data determined that three variables influenced spray losses: wind speed, air temperature and ΔT (Fig. 7). The most influential variable was wind speed, followed by air temperature and ΔT. The rules are of a general type and each one was activated by at least 7 examples.

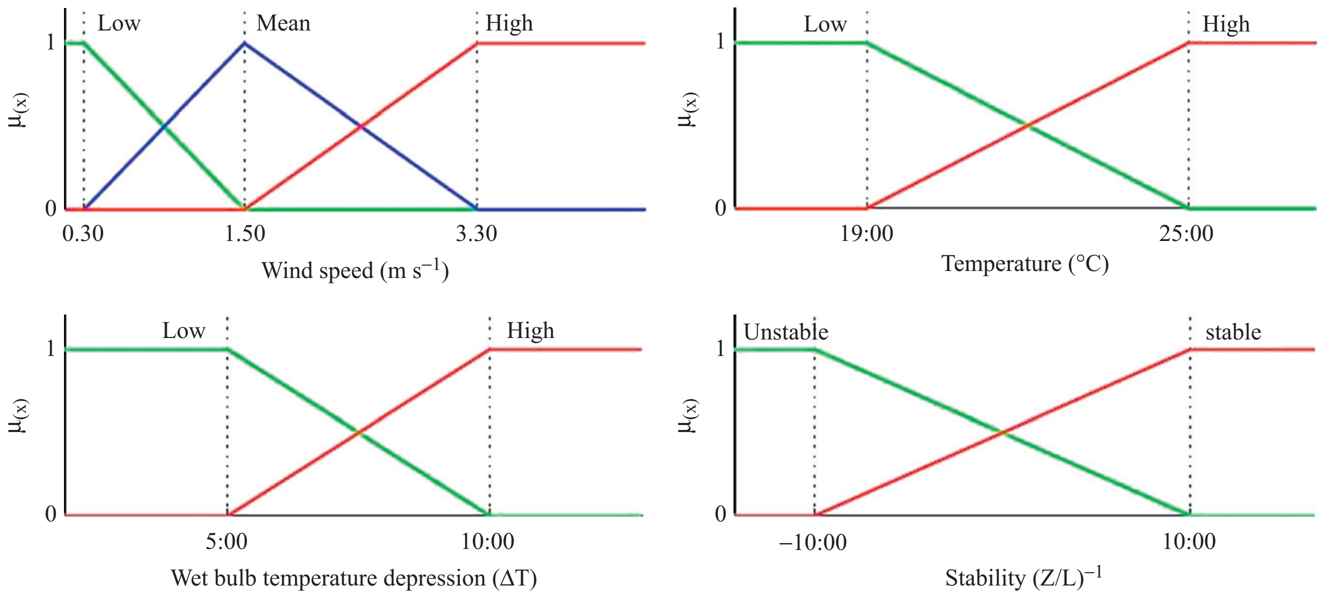

Fig. 6 – Selected fuzzy partitions for wind speed, air temperature, wet bulb temperature depression and stability parameter. $\mu_{(x)}$, normalised membership degree.

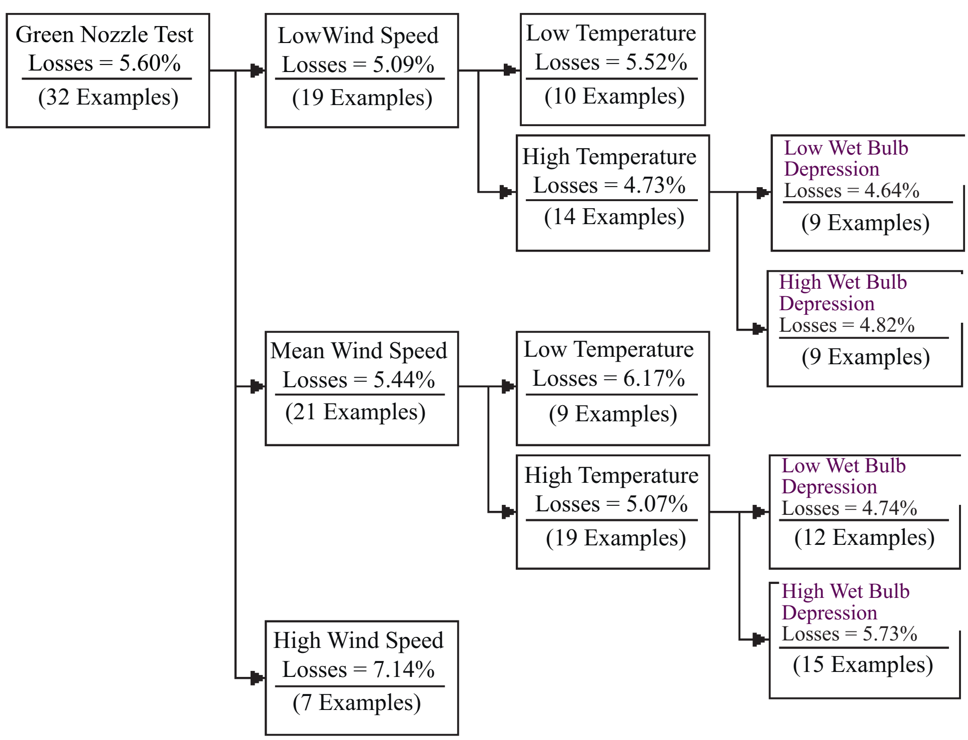

Fig. 7 – Decision tree from fine spray data (VMD 134 μm). The induction process sets the variables according to their contribution to entropy minimisation.

From this decision tree a Rule Base was defined (Table 7). It included five rules giving different values of spray losses. Optimised output values were computed with the least square optimisation given. This optimisation improved the correlation between measured and predicted values. Spray losses increased with wind speed. *Low* and *High* wind speed labels each defined a level of losses of their own (see rules 01 and 05). The *Mean* value category was subdivided into two levels, defined by air temperature partition (rules 02 and 03 for High temperatures and rule 04 for *Low* temperature). Here, spray losses were larger when the temperature is *Low*. Finally, when the temperature was *High*, the two sets of ΔT defined different spray losses; evaporative conditions (*High* ΔT) weakly increased spray losses. Spray loss inference predicted the losses with a coefficient of determination (R^2) of 0.72.

Table 7 – Rule base for spray loss estimation from fine spray data

Rule Id	Wind speed, $m\,s^{-1}$	Temperature, °C	ΔT, °C	Losses, %		
				RC	OC	LM
Rule 01	Low			5.09	5.27	Mean
Rule 02	Mean	High	Low	4.75	3.13	Low
Rule 03	Mean	High	High	5.33	5.27	Mean
Rule 04	Mean	Low		6.17	7.70	Strong
Rule 05	High			7.14	7.70	Strong

ΔT is the wet bulb temperature depression. Spray loss values for rule conclusion (RC), optimised conclusion (OC) and linguistic mean (LM).

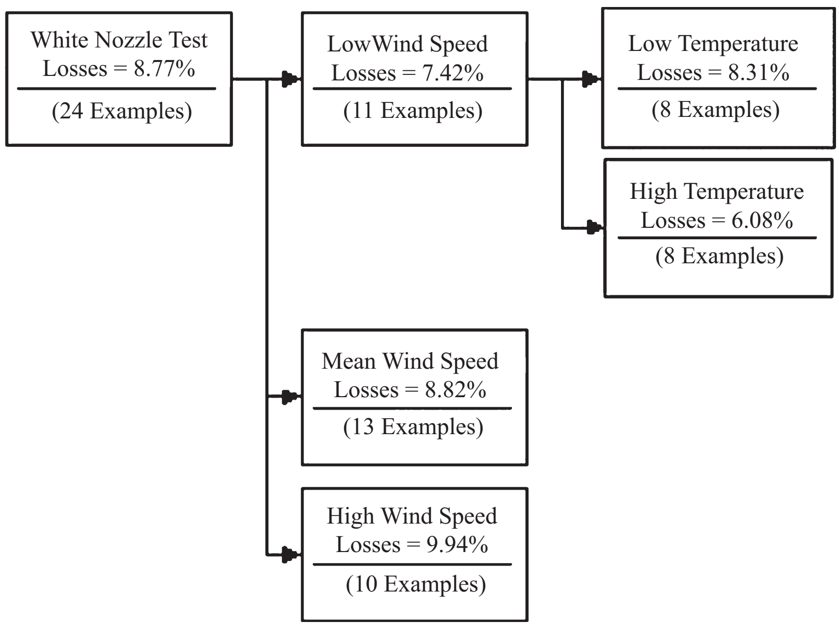

Fig. 8 – Decision tree from very fine spray data (VMD 65 μm).

Table 8 – Rule base for spray loss estimation from very fine spray data

Rule Id	Wind speed, $m\,s^{-1}$	Temperature, °C	Losses, %		
			RC	OC	LM
Rule 01	Low	High	6.08	4.28	Low
Rule 02	Low	Low	8.31	9.03	Mean
Rule 03	Mean		8.82	9.03	Mean
Rule 04	High		9.94	10.00	Strong

ΔT is the wet bulb temperature depression. Spray loss values for rule conclusion (RC), optimised conclusion (OC) and linguistic mean (LM).

3.2.2. *Very fine spray*

According to the decision tree from fuzzy inference (Fig. 8), the system can be modelled with only two variables: wind speed and air temperature. Similar to the fine spray data, the most influential variable was wind speed.

Table 8 shows the obtained rule base including four rules. Averaged spray losses increased with the wind speed. When the wind speed was *Low* two subdivisions were possible according to air temperature values. As with fine sprays the amount of spray collected on the PVC lines decreased when the air temperature increased. The resulting coefficient of determination was an (R^2) of 0.66.

3.2.3. *Prediction from Fuzzy Inference*

Fig. 9 shows the values predicted by fuzzy inference. From a training data set of 75% of each record set, which was tested on the 25% remaining, the cross-validation procedure generated a coefficient of determination (R^2) of 0.80.

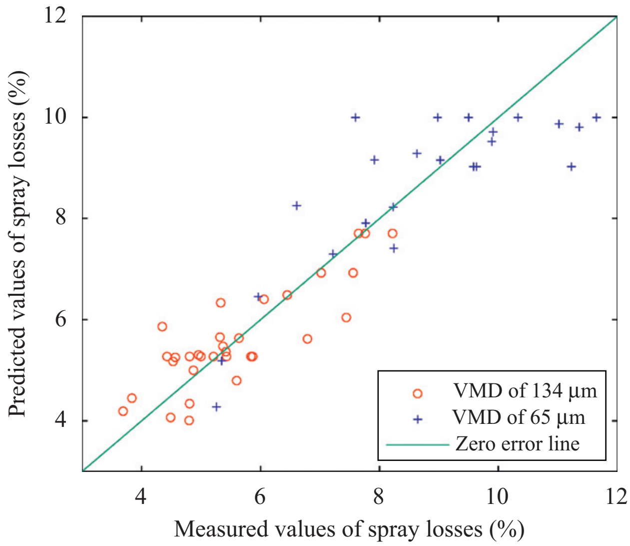

Fig. 9 – Upward spray losses (%) predicted by fuzzy logic. Comparison with the zero error line.

4. Discussion

4.1. *Micrometeorological effects on upward spray losses*

Multi-regression analysis revealed that wind velocity was the most influential factor for very fine sprays. The predictor had a positive sign, showing that increasing wind produces greater upward losses. For fine spraying, the influence of wind interacted with wet bulb depression. Fuzzy inference shows that wind speed was the most important factor for both fine and very fine sprays. The use of the Beaufort scale for partitioning the fuzzy set provided a good classification of predicted spray losses.

Spray losses are influenced by the evaporation process and are driven by the wet bulb temperature depression (ΔT). It must be considered that, as the tracer is a solution, only the water evaporated from the spray and the droplets became more and more concentrated until the carrier (water) was totally dissipated. Thus, collected amounts are only affected if the droplets do not reach the lines. When the droplet size decreases, they are more easily transported by mechanical effects and the wind speed becomes more influential. This phenomenon can explain the interaction between ΔT and wind speed during fine spraying, with positive effects on upward spray losses (note that the wind speed measurements are not affected by the sprayer). Fuzzy inference also demonstrates this effect, although it was only present with fine sprays when the wind speed is *Mean*.

Atmospheric stability does not appear to be an influential variable, except for fine spraying, in interaction with wind velocity and with a weak coefficient. It also does not appear with fuzzy inference. We can assume that stability does not play a role because the collecting lines were too close to the emission (only 1 m above the "crop") for any temperature gradients to significantly alter turbulence. The interaction with U may not have any logical explanation. Nevertheless, the determination coefficient was lower when this variable was not considered.

4.2. *Air temperature effect on spray quantities trapped by the lines*

Multiple-regression analysis shows that air temperature affects the quantities collected on the lines during spraying with both spray qualities. Indeed, as air temperature increased a decrease in spray losses was observed, and this was more significant with the very fine spray. The analysis cannot explain this effect and it is not possible to determine whether air temperature had an effect on either the spray emitted or on the performance of drift collectors. Fuzzy inference revealed that air temperature only affected the emissions with *Low* wind speed and very fine sprays, and with *Mean* wind speed for fine sprays.

4.3. *Collector efficiency and losses by evaporation*

Particle impaction efficiency on cylinders depends on the particle Stokes number (Aylor (1982); Walklate (1992); Parkin and Young (2000). Hence, the collection efficiency of the lines is expected to be a function of both droplet diameter and velocity.

The collector efficiency was evaluated in a wind tunnel (Gil et al., 2005), and was about 80% with a wind speed of 3.5 m s^{-1} and with sprays with VMDs between 146 and 255 µm.

The impaction efficiency was also estimated from the Stokes number for the $D_{V.10}$ and $D_{V.90}$ droplet diameters (the observed range in our conditions was 28 to 180 µm). The particle Reynolds number was calculated with a relative velocity between the droplets and the air of 0.1 m s^{-1}. Using three different models, the following efficiency values were obtained: 86% (Aylor, 1982), 100% (Walklate, 1992) and 78% (Parkin and Young, 2000); these are in fact the asymptotic values for each of these models. They all lie in the same range and, at least for two of them, they agree well with the wind tunnel measurements. If we assume a smaller wind velocity (0.5 m s^{-1}), the efficiency slightly decreases, down to 70–100% depending on the model used, considering all droplet diameters. Thus, taking into account that in most cases the wind velocity was higher than 0.5 m s^{-1} and the size of droplets encountered in our experiments, we can consider that the PVC lines act as good collectors even under relatively low wind conditions and that the measured value for efficiency (80%) could be used to analyse our data.

5. Conclusions

The main factors influencing the upward movement of spray above crops can be assessed using the proposed test protocol. Experiments, such as those presented here, are able to provide important information to validate and improve current diffusion and pollution models. However, additional information is required to better understand the effects of air temperature on droplet movement and the sampling process.

Statistical and fuzzy inference approaches can characterise the influence of micrometeorological factors on upward losses from a crop. The dynamics of spray emission, and its relationship with the main environmental variables, vary with spray quality (droplet spectra). Both methodologies were used with two sprays and produced high coefficients of determination. The most influential factors were wind speed, air temperature and wet bulb temperature depression for both spray qualities, whereas atmospheric stability appeared not to have an influence.

The loss process may also be modelled using a fuzzy inference system that includes expert knowledge related to the influential variables. Using such a method may improve the understanding of pesticide dynamics into the air. Additionally, a classification of influential variables on spray emissions can be achieved and linked to pesticide emission risk levels. This would provide an interesting tool for environmental management.

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