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Complete List of Authors: Sanna, Francesca; Università di Torino, Scienze Agrarie, Forestali e Agroalimentari; Istituto Nazionale di Ricerca Metrologica, Metrologia per la qualità della vita
Calvo, Angela; Università di Torino, Scienze Agrarie, Forestali e Agroalimentari
Deboli, Roberto; Istituto per le Macchine Agricole e Movimento Terra, IMAMOTER-CNR
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Vineyard diseases detection: a case study on the influence of weather instruments' calibration and positioning

Francesca Sanna a,c,1, Angela Calvo a,b, Roberto Deboli b, Andrea Merlone c

a DiSAFA Dipartimento di Scienze Agrarie, Forestali e Alimentari, Università degli Studi di Torino, Largo Paolo Braccini, 2, 10095 Grugliasco (TO), Italy
b IMAMOTER-CNR – Istituto per le Macchine Agricole e Movimento Terra – Consiglio Nazionale Ricerche, Strada delle Cacce, 73, 10135, Torino, Italy
c INRiM – Istituto Nazionale di Ricerca Metrologica, Strada delle Cacce 91, 10135, Torino, Italy

Abstract
Weather monitoring instruments installed on hill and mountain agricultural sites are often forced into non-ideal positioning due to slopes, tree proximity and other obstacles such as rivers and rocks that primarily affect relative humidity, temperature, and solar radiation. Moreover, data from these weather stations do not take into account the measurement uncertainties related to these influences.

The aim of this study is to investigate weather instruments’ calibration and positioning in a vineyard located in the Monferrato region in north-western Italy.

Meteorological data from two weather stations were analysed metrologically, in terms of evaluation of calibration uncertainty and traceability to the International System of Units, and using a statistical test, with the purpose of evaluating primarily the effect of the sensors’ calibration and positioning on sloping hills.

To better understand these influences, and in order to improve vineyard disease predictions reducing the use of chemicals in agriculture, the data recorded from the weather stations were included with the calibration uncertainties and used as input values of an epidemiological forecasting model. The inclusion of the calibration uncertainties and positioning contribution affected disease prediction up to five days; this can be explained by the effect of the tree canopy’s spatial arrangement, which tends to alter the vineyard's microclimate.

Keywords Weather station; positioning; agriculture; calibration; uncertainty; metrology for meteorology

1 Corresponding author: Francesca Sanna: DiSAFA- Università degli Studi di Torino, Tel.: +390116708592; E-mail address: francesca.sanna@unito.it
1. Introduction

Vineyards and other agricultural sites are often positioned on slopes and close to forests where the canopy influences weather conditions in the vicinity. This enforces a non-ideal position for installing weather instruments and the resulting data do not take into account the effect of slope, the proximity of trees or intensity of solar radiation (Matese et al., 2014). The contribution of measurement uncertainty arising from these conditions is not generally considered; in addition, there is a lack of sensor calibrations.

The calibrations of weather stations are generally performed by comparison, positioning the reference sensors for a short period close to the station under calibration (Rana et al., 2004). This procedure has shown relevant weak points (Sanna et al., 2013). Reference sensors are not always made to operate in open air and it is not possible to cover the entire range for the quantities, thus, evaluating the mutual influences among parameters is not achievable.

In 2010, the World Meteorological Organization (WMO) signed the Mutual Recognition Arrangement (MRA) of the International Committee for Weights and Measures (Comité International des Poids et Mesures - CIPM) during a workshop with the Bureau of Weights and Measures (Bureau International des Poids et Mesures - BIPM) (WMO-BIPM, 2010). The signing of the MRA by WMO lead to closer liaising and cooperation with the metrology community, encouraging the National Metrology Institute to face new perspectives, needs, projects and activities related to traceability, quality assurance, calibration procedures and definitions for those quantities involved in climate studies and meteorological observations.

In relation to agriculture, metrology can be usefully applied in the measurement of meteorological quantities for sustaining Decisions Support Systems. A case in point is the epidemiological forecasting model for vineyard diseases detection, such as grapevine downy mildew, one of the most important infections affecting viticulture (Lafon and Clerjeau, 1988). This disease strictly depends on temperature, humidity, rain and solar radiation. Indeed, the fungus *Plasmopara viticola*, causing the infection, releases the zoospores in a minimum temperature of 10 °C and up to a maximum of 32 °C, with an optimum of 23 °C - 24 °C, (Blaeser and Weltzien, 1978). Further, needs at least four hours of darkness, during which the temperature must be at least 13 °C and the relative humidity at 92 %rh, in order to sporulate (Vercesi, 1994).

With the purpose of relating meteorological quantities to the biological cycle of this pathogen, several forecasting models have been developed that provide information on the progress and evolution of infection. The forecasting models proposed –both empirical types (Stryzik, 1983; Hill, 1990; Magarey et al., 1991; Rosa et al., 1993; Blaise et al., 1999) and dynamic types – (Rossi et al., 2008), use as input values meteorological data collected from sensors not calibrated, or calibrated without traceability and...
without inclusion of measurement uncertainties. In general, these models do not consider the quality of input data (Sanna et al., 2014). Indeed, considering the quality of input data and the calibration of sensors used in meteorological application are important aspects for ensuring the reliability of the measurements performed over time (Begeš et al. 2015).

The aims of this study are to investigate weather instruments’ calibration and positioning, to achieve a metrological approach applied to agrometeorological studies and to implement the traceability of weather measurements. Specifically, this work investigated metrological processes’ effect on meteorological measurements as a result of automatic weather stations’ (AWS) positioning in a vineyard located on a hilly agricultural site for downy mildew detection, in order to improve vineyard disease predictions and reduce the use of chemicals in agriculture.

2. Material and methods

2.1 Field site

The vineyard locality is Vezzolano (Monferrato, north-western Italy) at an altitude between 416 m and 437 m, at an average slope of 28 % (maximum 35 %). It is surrounded by lawn to the east, from the copse to the west and south, and by other vineyards in the north. The vineyard selected is representative of vine-growing area, cultivar, position, slope, solar exposure and proximity of trees.

The two vine variety assayed were Arneis and Sauvignon and two clones for each vine, susceptibility to infection of downy mildew; these were distributed in three rows for vine clone with alternating every two rows in order to have a homogeneous system.

Meteorological data and surveys on the evolution of the *P. viticola* were carried out from 1 October 2013 to 30 June 2014. Data from the Regione Piemonte - Servizio fitosanitario database, gathering from an AWS placed in sun-exposed place, installed at about 500 m distance from the vineyard under study (called V-SP), were also used in order to calculate the climate trend and for the model’s simulation.

2.2 Instrumentation

Two AWSs, (provided by MTX S.r.l, Italy), were installed in the vineyard, both composed by sensors for measuring air temperature, relative humidity, photosynthetically active radiation (PAR) and a tipping bucket rain gauge for precipitation. The first AWS, called VA, was placed in sun-exposed place, in conformity to WMO recommendations and class 4 of the Siting classification of surface observing stations (WMO – ET-AWS, 2008). The second, called VB, was installed in proximity of trees (approx. 8 and 17 m), where the tree canopy influenced weather measurements.
The air temperature and relative humidity sensors were calibrated using the “EDIE – Earth Dynamics Investigation Experiment” facility (Lopardo et al., 2015), developed under the European ENV07 MeteoMet project (Merlone et al., 2015).

The chamber (Fig. 1 a-c) is equipped with the reference sensor 25Ω Capsule type Standard Platinum Resistance Thermometers (C-SPRT), where the measurand (W) consists by the ratio between the electrical resistance of the thermometer measured at the fixed points temperatures (t_{90}) of the International Temperature Scale (ITS-90) (Preston-Tomas, 1990), with respect to the electrical resistance measured at triple point of water (TPW):

\[ W = \frac{R(t_{90})}{R(TPW)}. \]

The fixed points involved in the calibration are: mercury, water, gallium and indium.

The nominal ranges of the chamber are: absolute pressure from 50 kPa to 110 kPa, and temperature from -25 °C to 50 °C. The expanded uncertainty \( (k = 2) \) of pressure and temperature reading inside the chamber are 10 Pa and 0.076 °C, respectively. This apparatus was also designed to allow the humidity control to complete the characterization of the whole AWS pressure-temperature-humidity modulus. The independent control of the three quantities allows AWS calibration in a large atmospheric variability range and the study of the mutual influence effects on sensors response.

**Fig. 1** Transportable calibration chamber EDIE. a) project drawing, b) external and c) internal configuration

### 2.2.1 Air temperature

The calibration of the air temperature sensors were performed by positioning the sensor into the calibration chamber equipped with the C-SPRT used as reference sensor.

The calculated calibration curve \( t_{\text{calc}} \) was obtained through a polynomial fit on the differences between the readings of the sensors in calibration \( (t_{\text{AWS}}) \) and the reference sensor \( (t_c) \).
Concerning both the temperature sensors, the contribution of the calibration uncertainty included also:

- the resolution of $t_{\text{AWS}}$ (0.028 °C), the vertical uniformity (0.021 °C); the axial uniformity (0.028 °C) and
- the stability (0.01 °C) of the chamber, the calibration of $t_C$ (0.011 °C), and the nanovoltmeter readings
  (0.004 °C) (Lopardo et al. 2015).

The statistical expanded uncertainty ($U_t$) for the final temperature calibration was different for the two sensors and was given by Equation (1).

$$U_t = \sqrt{\frac{\sum (t_{\text{calc}} - t_C)^2}{d}} \quad \text{Eq. (1)}$$

Where:

- $(t_{\text{calc}} - t_C)$: residue,
- $d$: degrees of freedom.

2.2.2 Air relative humidity

A similar procedure (T/07/06 REV00, INRiM internal procedure) was applied to the air relative humidity sensors. The sensors were placed in the calibration chamber and the calibration was done using the direct method by comparing the relative humidity reference sensor ($RH_c$), where the physical quantity is produced by a generator of air humidity secondary calibration reference standard, with the reading of the sensors in calibration ($RH_{\text{AWS}}$). For each points of calibration was calculated: the mean of the standard hygrometer’s measures, the mean of the standard thermometer’s measures, the RH mean and the standard deviation readings of the instrument being calibrated. To determine the calibration uncertainty occurs: stability (0.06 %) and uniformity (0.02 %) of the climatic chamber, resolution (0.05 %) and sensibility (0.05 %) of the instrument being calibrated, repeatability (0.08 %). The expanded uncertainty $U$ is expressed as the standard uncertainty multiplied by the coverage factor $k = 2$, corresponding to a confidence level of ~ 95.45 % (GUM, 1995). In evaluating the standard uncertainty is considered the long-term stability of the instrument being calibrated.

2.3 Forecasting model

The selection of the forecasting model used in this research falls into EPI - Plasmopara (État Potentiel d’Infection) model, proposed by Stryzik (1983), modified by Vercesi (1997).

The model follows the entire life cycle of the pathogen; the index of risk infection is the sum of a component called “potential energy” ($P_e$), which requires climate data during the October-March period and a second component, “kinetic energy” ($K_e$), which uses weather data during the March-August period, and provides estimates for the risk of a severe epidemic by accumulating favourable conditions for primary and secondary infections.
The EPI model was validated with respect to the climate and weather conditions of the site under study. The $P_e(t_i)$ and $K_e(t_i)$ contributions, as described in Sanna et al. (2014), were calculated according to deviations from the means of the climate values of air temperature and rainfall, and the equations refer to the contribution per unit of potential energy in a generic time interval.

### 2.3.1 The EPI value

The EPI($t_i$) value is therefore given by Equation (2).

$$EPI(t_i) = P_e(t_i) + K_e(t_i) \quad \text{Eq. (2)}$$

The risk situation was marked when the value of EPI was greater than -10 (threshold) and when a progressive increase in the value occurred for the following three days. Following the alert, a preventive fungicide intervention was recommended. In order to detect the EPI value, the most likely period of infection was calculated using a linear regression both temperature and relative humidity dependent, as per Giosuè et al. (2002) and modified as in Caffi et al. (2011), working backward from the date of the emergence of the first onset of downy mildew symptoms.

### 2.4 Experimental design

Simulations were carried out using the EPI forecasting model with data from the two automatic weather stations VA and VB. Four different conditions were simulated: (i) VA without inclusion of calibration uncertainties in the input values for temperature and relative humidity (VA-NC); (ii) VA with inclusion of the calibration uncertainty (VA-C); (iii) VB without inclusion of calibration uncertainties (VB-NC); (iv) VB with inclusion of the calibration uncertainty (VB-C).

### 2.5 Data analysis

Mean data of temperature, solar radiation and relative humidity from the same AWS (calibrated/not calibrated) and between the two AWS (VA/VB) were analysed using the statistic Kruskal-Wallis non parametric test in order to compare the mean daily meteorological value for temperature and relative humidity, using the statistical software package SPSS (IBM, release 22.0.0). Meteorological data, focused on the potential risk period, were collected hourly. The ANOVA was not used because the variance homogeneity was not verified.

### 3 Results and discussion

#### 3.1 Statistic evaluation

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From a statistic point of view, given the considerable amount of information and slightly hourly differences among the registered data in comparison to the daily variation, the mean daily temperature and relative humidity were always statistically different (Kruskal-Wallis non parametric test) both inside each AWS (calibrated and not calibrated) and between the two AWS (VA/VB).

Data representation was more useful for appreciating the environmental influences on the positioned sensors (temperature, humidity and solar radiation), as the VA sensor was placed in a sunny area, whereas the VB was installed in the proximity of tree canopies. A slight difference was evident in the information recorded by the two AWS positioned in the different areas (both calibrated and not calibrated couples) with regard to both temperature and the humidity (Fig. 2a and Fig. 2b), relationship among the calibrated AWS). The difference was also confirmed by the high coefficient of variance in their ratios, measured hourly. The relative humidity registered in VB-C was greater than in VA-C, thus confirming the influence of sensor positioning.

**Fig. 2** a) Temperature (in K) and (b) relative humidity (in %) comparison between VA-C and VB-C

### 3.2 Air temperature sensors calibration

The reference temperature was the result of 20 repeated measures taken from the nanovoltmeter, (Agilent A34420A), one every 30 s for each of the six points from -20 °C to 45 °C. The calculated calibration curve $t_{\text{calc}}$ was obtained through a polynomial fit on the differences between the readings of the sensors in calibration ($t_{\text{AWS}}$) and the reference sensor ($t_c$) (Fig. 3a and Fig. 3b). The statistical expanded calibration uncertainty ($U_e$) was different for the two sensors.
The Equation (3) reports the temperature calibration curve.

\[ t_{\text{calc}} = a \ t_{\text{AWS}}^2 + t_{\text{AWS}}(1 + b) + c \tag{3} \]  

Eq. (3)

Where: a, b and c are the coefficients of the polynomial fitted.

Fig. 3 Calibration curve obtained by the polynomial fitted equation for temperature sensors in (a) VA and (b) VB

The sensor installed in VA had an expanded calibration uncertainty of 0.11 °C, similar to the uncertainty of the sensor installed in VB, which had a value of 0.13 °C, both inclusive of residues with coverage factor \( k = 2 \). These values are to be considered components of the measurement uncertainty.

Considering the mean daily temperature during the interval of time considered in this study, the measurement uncertainty had a minimum of 0.13 °C and a maximum of 0.53 °C for VA, and a minimum of 0.14 °C and a maximum of 0.57 °C for VB.
3.3 Relative air humidity sensors calibration

The reference relative humidity was the result of four repeated measures from 30 %rh to 90 %rh and a return point at 60 %rh to evaluate hysteresis. The standard measurement uncertainty associated with hysteresis was within 1.0 %. The relative humidity calibration uncertainty ($U_{RH}$) was obtained by taking into consideration the resolution, measurement repeatability, hysteresis and the uncertainty in the determination of the conditions applied to the sensor under calibration $RH_{AWS}$. The corresponding relative humidity calibration curves were obtained (Fig. 4a and 4b).

**Fig. 4** Calibration curve obtained by the polynomial fitted equation for the relative humidity sensors in (a) VA and (b) VB.
The calibration of the relative humidity sensors return dissimilar results: the uncertainty of the sensor in VA had a minimum value of 0.9%, a maximum of 2.1% and a calibration curve with $R^2$ of 0.6534 (Fig. 4a), while for the sensor in VB, the minimum value was 1.0%, the maximum 2.1% and a calibration curve with $R^2$ of 0.4020 (Fig. 4b). In this last case, the standard calibration uncertainty associated with hysteresis was within 1.0%, evaluated at the point of return. As a result, the difference range of relative humidity calibration uncertainty reached up to 6.7% for VB.

The analysis carried out in this work showed that sensors of the same type, purchased from the same supplier and with the same resolution and accuracy, guaranteed by certificates released by the manufacturers produced dissimilar values if they were not properly calibrated.

3.4 Forecasting model

In this study, the date of emergence of the first symptoms was observed between 10 and 11 May and the most probable period of infection was calculated to be around 28 and 29 April, as previously explained in paragraph 2.3.1. During these days, the AWS registered seven rain events (a total of 38.9 mm of rainfall) as necessary for triggering the infection.

The five simulations of pathogen infection delivered different results. The forecast for VA-C and VB-C overlapped at the estimate period of infection, on 29 April and between 28 and 29 April, respectively. The prediction of VA-NC anticipated the estimate period of infection four days in advance, on 25 April, while V-SP simulation postponing the estimate period to 4 May, due the position of the AWS. The simulation on VB-NC amplifying the prediction up to roughly five days, on 24 April, overestimating the risk of primary infection (Fig. 5).
Fig. 5. EPI index focused on period in which is highly recommended to make a treatment. The boxes explained the day in which EPI value reached the critical value -10 (threshold).

The EPI model proposed by Stryzik (1983) has been widely modified during the last decades, due to its difficulty to reach an exhaustive definition of the rules concerning the system plant-pathogen-environment. Nevertheless, EPI is still one of the most used and validated forecasting model.

The model modified by Vercesi (1997) is accurate in predicting the level of risk during the primary infection but less accurate in predicting the level of secondary infection cycle. In studies related the efficiency, Fronteddu and Cossu (2002), argue that in general terms EPI showed the typical gaps of an empirical model and the inaccuracies of the simulations are due, at least in part, to a limited database of climate parameters. Fremiot et al. (2008) state that EPI model returns promising results, but remark the importance to used more reliable data to obtain better and robust simulations. The need for more reliable data was also observed in studies in hillside vineyards. The simulation provided by EPI has shown a tendency to overestimate the risk, especially for secondary infection, compared to studies conducted on ground level and allowed to develop more rational intervention strategies (Vercesi et al., 2012).

In this study, it could be noticed that using as input values of the model the data from calibrated sensors this overestimation was reduced (Fig. 6). As a result of infectious rains of 13 to 17 June, in which the mean daily relative humidity has reached and exceeded 90% (data not shown), it have created the ideal conditions for secondary infection which has led to the emergence of slight symptoms observed around 19-20 June. In the same days the EPI index produces a value of about 46 and 37 in VB-NC and VA-NC, respectively, compared to the lower values obtained with the data from calibrated sensors of 28 and 33 in VA-C and VB-C, respectively.
Vineyard diseases detection: influence weather inst. calib. posit.

Fig. 6 EPI index focused on the first period of $K_e$ phase, in which gives estimates of risk for the primary and secondary infections

3.5 Effects of the calibration and position on output recorded data

In order to improve the understanding of the influences of the temperature and the relative humidity on pathogen growth, comparisons among the four scenarios were carried out, focused around the period in which the EPI model marks a potential infection onset and evolution.

Comparing the four scenarios (VA-NC, VA-C, VB-NC and VB-C), as expected, the differences ($\Delta_t$) between the data with inclusion of uncertainties are lower than the data without inclusion. As well as the data recorded in VB are lower than the data collected from the AWS in VA. This difference is more marked for the recorded relative humidity values with respect to the temperature values.

In the specific, as showed in Figure 7, VA-NC always records higher temperatures, while VB-NC always lower, with a $\Delta_t$ up to 1.07 °C. Generally, $\Delta_t$ values over 0.50 °C are recorded in particular when the temperature is over 16 °C (mean daily temperature).

Comparing VA-NC and VB-C, the lower values of the latter, are recorded in 97 days of the considered period, with a $\Delta_t$ ranging up to 1.12 °C. In the third comparison carried out, the days in which the recorded data of VB-C are lower than VA-C is reduced at 53 with a maximum $\Delta_t$ of 0.74 °C. In the comparison between VA-NC and VB-NC the number of days in which VB-NC is lower is 45 with a maximum $\Delta_t$ of 0.74 °C, but in 27 days the two mean values are equal, while comparing VB-NC with VA-C, in contrast to the others results, the values of the latter are lower in 89 days with a $\Delta_t$ that reach up to 1.07 °C.
Fig. 7 Comparison among the four scenarios of air temperature measurements, focus on the period in which the EPI model marked a potential infection onset (mean daily data). Grey box shows the range of values of temperature where treatments of plants are not efficient.

The result comparisons of the four scenarios for the relative humidity measurement are shown in Figure 8. In this case, unlike the temperature comparisons, the differences ($\Delta_{RH}$) between the data with inclusion of uncertainties are lower than the data without inclusion and the value of the data recorded in VB are higher than the value recorded in VA.

In particular, VB-NC always records higher values of humidity, with a $\Delta_{RH}$ from 3.0 % up to 14.0 % as respect VA-NC and from 4.0 % to 16.0 % as respect VA-C. Generally, $\Delta_{RH}$ over 10.0 % is recorded when the relative humidity is under 70 % (mean daily).

Comparing VA-C and VB-C, the higher values of the latter, are recorded in 93 days of the considered period, with a $\Delta_{RH}$ ranging up to 9.5 %, indeed, in the remaining 9 days the $\Delta_{RH}$ ranged from 0.1 % to 2.3 %. In the fourth comparison carried out, the days in which the recorded data of VB-C are lower than VA-NC is reduced at 88 with a maximum $\Delta_{RH}$ of 7.5 %; in 14 days VA-NC values are higher, with $\Delta_{RH}$ from 0.5 % to 3.4 % but this values are usually recorded when the relative humidity is over 90 %.
Fig. 8 Comparison among the four scenarios of air relative humidity measurements, focus on the period in which the EPI model marks a potential infection onset (mean daily data). Grey box shows the range of values of relative humidity where treatments of plants are efficient.

As far as the siting is concerned, VB-C, VB-NC and V-SP simulations including intrinsically the position contribution, since for VB-C and VB-NC the tree canopy’s spatial arrangement tended to alter the vineyard's microclimate, while for V-SP, the distance from the vineyards is the predominant factor that tamper with the estimate period of infection. VB-C simulation estimated the period of infection one day in advance, although VB-NC and V-SP forecasts amplifying the prediction up to five days. Considering that calibration contribution affects the prediction up to four days we could suppose that the position contribution is about of one day. In terms of temperature and relative humidity, the contribution is up to 0.33 °C and 6.5 %rh, respectively.

It is worth considering the scenario that will arise if the choice of fungicide spray programme falls within the simulation carried out where no data were calibrated. The risk of a failed treatment will be high in the case of no zoospores having been released or during washout rainy days, with the implication of soil poisoning (hypertrophication), costs of labour man and products as a consequence. These encouraging results lead to the conclusion that further studies are needed using traceable data, both on vineyards with the same characteristics, as well as those that differ from one another. Such a Decision Support System must also take into consideration support of the environment.
4 Conclusions

In this study, the forecasts provided by the epidemiologic model with data inclusive of uncertainty overlapped around the estimate period of infection, confirming that the inclusion of calibration uncertainties produces data closer to the real value of the measurand. Moreover, the inclusion of the instrument positioning contribution affected disease prediction up to five days. This can be explained by the effect of the distance and the vine canopy’s spatial arrangement, which tended to alter the vineyard's microclimate.

Therefore, calibration procedures and instrument positioning are important factors in agrometeorology, although further in-depth studies are needed in this field focus in particular to define a reference grade sensor, within regional baseline observing networks, for agricultural sector. Measurements should be based on fully documented traceability and forecasting models should include measurement uncertainties in their input values to improve output data accuracy.

5 Acknowledgement

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6 References


Fig. 1 Transportable calibration chamber EDIE, a)
Fig. 1a
47x43mm (300 x 300 DPI)
Fig. 1 project drawing external configuration b)

Fig. 1b

18x28mm (300 x 300 DPI)
project drawing internal configuration c)  
Fig 1c  
41x39mm (300 x 300 DPI)
Fig. 4a Calibration curve obtained by the polynomial fitted equation for the relative humidity sensors in VA

\[ y = 0.0009x^2 - 0.1122x + 1.4430 \]

\[ R^2 = 0.6534 \]

\[ \Delta RH \] (%) vs.

20 40 60 80 100

\[ \begin{array}{c}
\text{RH Vezzolano A --- Poli. (RH Vezzolano A)}
\end{array} \]
Fig. 4b Calibration curve obtained by the polynomial fitted equation for the relative humidity sensors in VB

\[
y = 0.0006x^2 - 0.0832x - 3.7984 \\
R^2 = 0.4020
\]

50x34mm (300 x 300 DPI)
Fig. 2 a) Temperature (in K) comparison between VA-C and VB-C
Fig. 2a
63x51mm (300 x 300 DPI)
Fig. 2 b) relative humidity (in %) comparison between VA-C and VB-C

39x31mm (300 x 300 DPI)
Fig. 3 Calibration curve obtained by the polynomial fitted equation for temperature sensors in (a) VA

Fig. 3a

55x33mm (300 x 300 DPI)
Fig. 3 Calibration curve obtained by the polynomial fitted equation for temperature sensors in (b) VB

$y = -0.00003x^2 - 0.0163x + 0.0430$

$R^2 = 0.9896$

Fig. 3b

55x33mm (300 x 300 DPI)
Fig. 5. EPI index focused on period in which is highly recommended to make a treatment. The boxes explained the day in which EPI value reached the critical value -10 (threshold)

Fig. 5

94x57mm (300 x 300 DPI)
Fig. 6 EPI index focused on the first period of Ke phase, in which gives estimates of risk for the primary and secondary infections

Fig. 6
94x57mm (300 x 300 DPI)
Fig. 7 Comparison among the four scenarios of air temperature measurements, focus on the period in which the EPI model marked a potential infection onset (mean daily data). Grey box shows the range of values of temperature where treatments of plants are not efficient.

Fig. 7
66x41mm (300 x 300 DPI)
Fig. 8 Comparison among the four scenarios of air relative humidity measurements, focus on the period in which the EPI model marks a potential infection onset (mean daily data). Grey box shows the range of values of relative humidity where treatments of plants are efficient.

Fig. 8

65x45mm (300 x 300 DPI)