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Influence of sensor calibration on forecasting models for vineyard disease detection

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Abstract. The evolution of vineyard diseases, such as downy mildew, are depending by temperature, humidity and rain. Fungicides are used to control these pathologies, with considerable economic costs, negative effects on environment, human health and wine quality. In order to identify fungicide sprays periods, several forecasting models were proposed. These tools require accurate knowledge of meteorological variables. These models give great contribution to farmers and technicians, nevertheless, do not consider the quality of the input data in terms of evaluation of measurement uncertainty and traceability to the reference sensors. The inclusion of the sensors' calibration and the influence of weather instrument positioning, affects the disease prediction up to 5 days. Therefore, the choice of instrument position and calibration procedure becomes a matter of importance in agriculture.

1. Introduction

The evolution of vineyard diseases, such as downy mildew, are depending by temperature (T), relative humidity (RH) and rain [1]. The pathologies are controlled with the use of fungicides, which has considerable economic costs, negative effects on environment, human health and wine quality [2,3]. Accurate meteorological data are needed to better predict vineyards diseases. Moreover, 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 [4]. Generally, the contributions of measurement uncertainties arising from these conditions are not considered. Metrological approach should be applied on agricultural studies.

1.1. Metrology.

As stated by the *Bureau International des Poids et Mesures* (BIPM)*, the metrology is "*The science of measurement, embracing both experimental and theoretical determinations at any level of uncertainty in any field of science and technology*" [5]. A task of the BIPM as well of the Metrology Institutes is to ensure worldwide uniformity of measurements and their traceability to the International System of Units (SI). Traceability, calibration and uncertainty are fundamental concepts in metrology.

1.1.1. Traceability. Involves the chain of measurements and accuracy transfers that connect the national standards, as maintained by National Metrology Institutes, with the measurements made in research, manufacturing and in field. Traceability is thus defined as the property of the result of a measurement

related to references through an unbroken chain of comparisons all having stated uncertainties. Traceability makes possible the comparison of accuracy of measurements worldwide, according to a standardized procedure for estimating measurement uncertainty.

1.1.2. Calibration. The term calibration means the act of comparison of an instrument to a reference standard with a known uncertainty and accuracy, and does not include any subsequent adjustment of the instrument. Accuracy is defined as an agreement between the measured value and the true value. The precision instead is the closeness of multiple measurements values. Thus, an instrument can be precise but not accurate.

1.1.3. Uncertainty. The Guide to the expression of Uncertainty in Measurement (GUM), define the uncertainty as the "Parameter, associated with the result of a measurement, that characterizes the dispersion of the values that could reasonably be attributed to the measurand" [6,7].
The GUM publishes by BIPM, asses that the word "uncertainty" means doubt, and thus in its broadest sense "uncertainty of measurement" means doubt about the validity of the result of a measurement. Therefore, we cannot take as valid the value measured by an instrument if this parameter is not associate with it. The parameter can be, for example, a standard deviation called standard uncertainty $u(x)$ of an interval having a probability of coverage established. The coverage factor k is a numerical factor typically in the range 2, where it is assumed that the values fall within an interval having a level of confidence of approximately 95 %. The uncertainty in not an error. Error is the difference between the measured value and the true value of the quantity being measured.

1.1.4. Metrology for agriculture. Since the quality of the measurements is determined by the development of metrology for the specific sector, the metrology can be usefully applied in agriculture field. Indeed, the main objectives of this research are:

- Improving both the meteorological observations and the forecasting models, achieved by inclusion of measurement uncertainties in the input values
- Disseminating techniques, methods and developing procedures for the calibration of weather stations sensors.
- The installation in the agricultural sites of calibrated and traceable automatic weather stations (AWS) and the evaluation of the uncertainty that may bring to optimize the use of pesticides with a positive impact on the environment, health and crops, towards a better management of agricultural risks.

These objectives are linked on the availability of reliable and accurate weather and climate measurements. Weather and climate data are also used in the Decision Support System (such as informational systems that supports farms, companies based on decision-making software). These systems were developed also in compliance with the European Directive n. 128 [8] that established rules for the use of pesticides in order to reduce the risks to human health and the environment.

1.2. Forecasting models
One important rule of the European Directive is the improvement of the forecasting models. These are tools able to transform the relations between crop, disease and the surrounding environment into mathematical equations. In general, the models provide information about the onset and evolution of a disease and alert farmers and technicians to a risk, so treatment can take on time. These tools require accurate knowledge of meteorological variables. Nevertheless, these models do not consider the quality of the input data in terms of evaluation of measurement uncertainty and traceability to the reference sensors [9]. Calibration of weather stations installed in agricultural sites is usually performed by comparison, positioning the reference sensors for a short period close to the station under calibration. This procedure was metrologically evaluated and showed relevant weak points [10,11].

Forecasting models have been developed world-wide in the last decades [12], in particular for diseases affecting viticulture, such as the grapevine downy mildew, an infection strictly depending by temperature, humidity and rain, caused by the fungus *Plasmopara viticola* [1].

The disease is defined by two kinds of infection: the primary infection will occur when specific conditions take place such as temperature at 10 °C or higher, at least 10 mm of precipitation over a 24-hour period. Spores released from the leaf litter germinates inside the leaves forming the characteristic oil spots symptoms. The secondary infection occurs during warm nights where the temperature is over 14 °C, humidity is greater than 90 %rh. The fungus appears as a white mould and spread still on grapes.

1.3. Agrometeorology

The objective of agrometeorology, the branch of meteorology that deals with the relationships among weather and climate on crop, soil management and the environment, as stated in the Guide n. 134 of World Meteorological Organization (WMO) [13], is to assist farmers the agricultural practices through agrometeorological services. The meteorology for agriculture – agro-meteorology – can play a significant role in reducing the negative impacts caused by pests and diseases. An appropriate, preferably integrated, pest management system using meteorological data can reduce losses appreciably.

There is a need for testing various types of sensors, their calibration, and to evaluate the measurement uncertainty related the meteorological quantities [14] in order to improve vineyard disease predictions and reduce the use of chemicals in agriculture.

2. Materials and Methods

Two AWS were installed in a vineyard located in Monferrato (North Italy) and the outcomes data were analysed metrologically in order to evaluate the uncertainty related to the positioning of the sensors and the influence on meteorological measurements. The meteorological data were also used as input values for an epidemiological forecasting model.

The two selected AWS (VA and VB) were specific for agricultural purpose and it composed by the following sensors: air temperature and relative air humidity (combined as thermo-hygrometer), rain gauge, solar radiation, soil temperature and soil moisture, wind speed and direction. The thermo-hygrometer was calibrated in the laboratories of the Italian Metrology Institute (INRiM).

2.1. Sensor's calibration

The calibration results for the temperature and relative humidity sensors are shown in Table 1 and Table 2, and in Figure 1a and 2b. The calibration curves (t_{calc} for temperature RH_{calc} for relative humidity) were obtained by applying a quadratic polynomial function to the data gathered from the sensor in calibration and the reference sensor (t_c), following the equation 1:

$$t_{calc} = a \, t_{AWS}{}^2 + (b+1)t_{AWS} + c \tag{1}$$

Where: t_{calc} is the calculated data, t_{AWS} is the sensors under calibration and a, b and c are the coefficients of the polynomial fitted equation.

The expanded uncertainties (U_t and U_{RH}) is expressed as standard uncertainty multiplied by the coverage factor $k = 2$. The U_t and U_{RH} evaluated were lower than the calibration target uncertainties proposed for the temperature and humidity, that was in the order of 0.3 °C and 5%, respectively. The statistical contribution U_t was calculated following the Equation 2:

$$U_t = \left(\frac{\sum(t_{calc}-t_c)^2}{d}\right)^{1/2} \tag{2}$$

Where: t_c is the reference sensor, (t_{calc} - t_c) is a residue (the differences between the measured values and those calculated with the polynomial function) and d the degrees of freedom.

Table 1. Components of the calibration uncertainty budget for the temperature sensors

Source of uncertainty budget (T)	Contribute (°C)
Resolution of sensor in calibration	0.1
Uncertainty related to the position	0.03
Reference sensor uncertainty (t_c)	0.01
Interpolation uncertainty	0.035
Standard uncertainty U_t	0.055
Expanded uncertainty U_t ($k = 2$)	0.11

Table 2. Components of the calibration uncertainty budget for relative humidity sensors

Source of uncertainty budget (RH)	Contribute (%rh)
Resolution of sensor in calibration	0.1
Repeatability of sensor in calibration	0.08
Reference sensor uncertainty (RH_c)	0.01
Interpolation uncertainty	0.70
Standard uncertainty U_{RH}	1.23
Expanded uncertainty U_{RH} ($k = 2$)	2.5
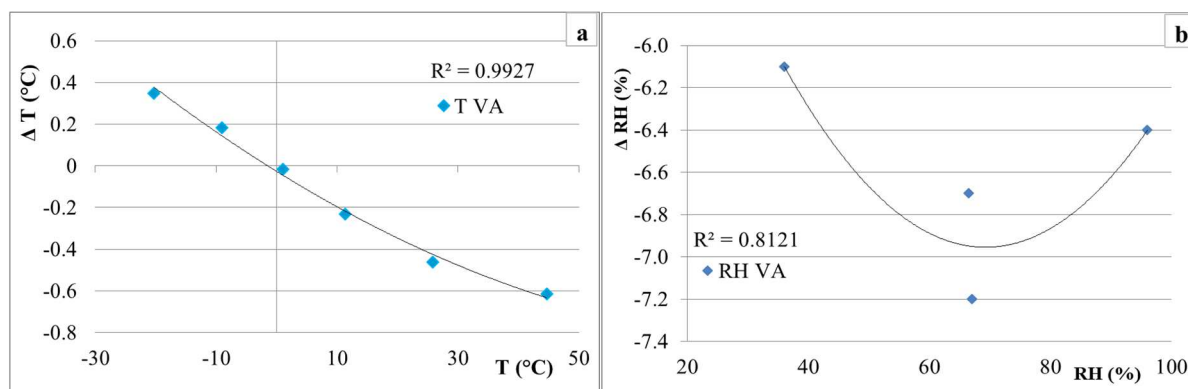
Figure 1. Calibration curve obtained by a polynomial fitted equation for temperature (a) and relative humidity sensors (b) in VA (as example)

2.2. Forecasting model

For this study, the forecasting models choose was the EPI - État Potentiel d'Infection [15], one of the most studied models and still widely used; This model, like others, has improved the quality of the output data, but do not considers the quality of the input data in terms of evaluation of measurement uncertainty and sensors calibration. The model follows the whole life cycle of the pathogen, the EPI index value depends on the sum of a component called "potential energy" that needs climate data and another called "kinetic energy" which use weather data. A risk situation is marked when the index is greater than -10 and this increases constantly in the following three days. The situation risk alerts farmer

on a potential infection, in order to make a treatment in the vineyard. The model equation were validated based on the meteorological trend of the last 15 years, using the data provided by the *Servizio fitosanitario della Regione Piemonte*.

In order to presume the period of spores' germination and the period of primary infection (PPI), the length of incubation period was calculated going backward from the date of primary infection symptoms (DPIS) onset (Figure 2a). An equation temperature and humidity dependent was used (Figure 2b). Taking into account also the precipitations that give the right conditions to spores to spread in the leave, the germination was calculated between the 6 and 7 of April (Table 3).
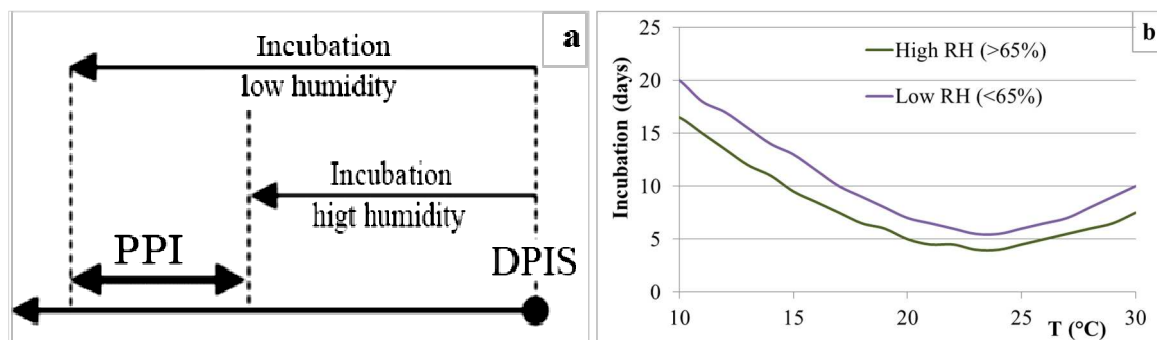

Figure 2. Scheme of period of primary infection (PPI) and date of primary infection symptoms (DPIS) calculation (a); temperature and humidity dependent equation (b).

Table 3. Event that lead to infection (precipitations), period of primary infection (PPI) and date of primary infection symptoms (DPIS) onset.

| Precipitation | PPI | | | DPIS |
	Beginning of germination	Sporangia formed	Day of infection	
4 April	6 April	30 April	1 May	9 May
5April	7 April	1 May	1 May	10 May

3. Results

3.1. Simulation and forecast

In Figure 3 and Table 4 are represented the seven scenarios focused on period in which is recommended to make a treatment. The seven simulations were with or without the inclusion, in the input values of the model, of the measurement uncertainties in the upper and lower limits of the confidence interval, for temperature and humidity, and the outcomes are very different among the scenarios. The simulation that better predicted the germination was that one which include uncertainties in upper limit for both temperature and relative humidity.
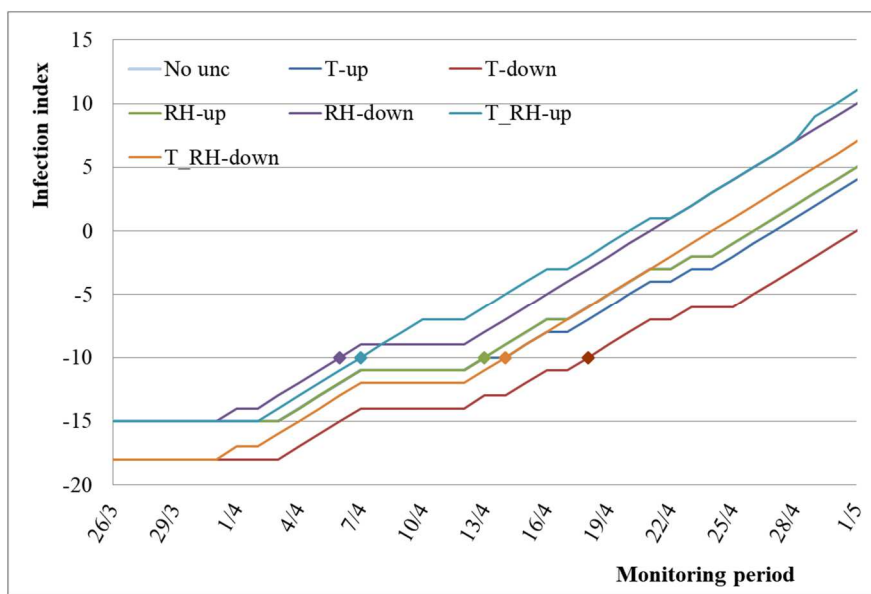
Figure 3. EPI indexes that reached the values -10 for each simulation, the rhombus marks highlighted the day in which is highly recommended starts the treatment.

Table 4. EPI index value focused on period in which is highly recommended make a treatment, data used are without uncertainty (column 2) and with uncertainty in input values (columns 3-4-5-6-7-8). Dark grey boxes indicate the day in which EPI index reached value -10; light grey boxes the days in which the values increases progressively. Red frame cells pointed at the better simulation.

DATA	No unc	T-up	T-down	RH-up	RH-down	T_RH-up	T_RH-down
05-apr	-13	-13	-16	-13	-11	-12	-14
06-apr	-12	-12	-15	-12	-10	-11	-13
07-apr	-11	-11	-14	-11	-9	-10	-12
08-apr	-11	-11	-14	-11	-9	-9	-12
09-apr	-11	-11	-14	-11	-9	-8	-12
10-apr	-11	-11	-14	-11	-9	-7	-12
11-apr	-11	-11	-14	-11	-9	-7	-12
12-apr	-11	-11	-14	-11	-9	-7	-12
13-apr	-10	-10	-13	-10	-8	-6	-11
14-apr	-9	-10	-13	-9	-7	-5	-10
15-apr	-8	-9	-12	-8	-6	-4	-9
16-apr	-7	-8	-11	-7	-5	-3	-8
17-apr	-7	-8	-11	-7	-4	-3	-7
18-apr	-6	-7	-10	-6	-3	-2	-6
19-apr	-5	-6	-9	-5	-2	-1	-5
20-apr	-4	-5	-8	-4	-1	0	-4
21-apr	-3	-4	-7	-3	0	1	-3
22-apr	-3	-4	-7	-3	1	1	-2
23-apr	-2	-3	-6	-2	2	2	-1

If the predictions of the simulation without uncertainties was followed, the pesticide treatments would be carried out a week later, when germination was already begun. Moreover, considering to the potentially washout rains of the following days, the fungicide sprays would have been useless, with significant costs in terms of loss of fungicides, human labour and the final product.

3.2. Position simulation and forecast

Vineyards or other cultures sometimes are positioned on slopes that force a non-ideal positioning of weather instruments. Therefore, we investigated on the temperature and humidity measurements effects on pathogen growth, due to the weather station positioning. In the same vineyard was installed a second calibrated AWS, the first (coded VA) was installed in a sun-exposed place while the second (coded VB) was installed in proximity of trees (approx. 8 and 17 m), where the canopy influenced weather measurements.

Based on the observed symptoms for this second season, the beginning of germination was calculated around 28 and 29 April. The simulations performed were four, considering the two position and data with or without the inclusion of the calibration curve: VA and VB without inclusion of calibration uncertainties in the input values (VA-NC and VB-NC, respectively); VA and VB with inclusion of the calibration uncertainty for temperature and relative humidity (VA-C and VB-C, respectively). A fifth simulation were performed (V-SP) as a control, using the data gathered from an AWS handled by the *Servizio Fitosanitario della Regione Piemonte*, close to the vineyard.

The results of the simulations shown that forecasting without inclusion of the calibration curves predict from four to five days in advance the real spore germination (Figure 5Figure 4), while the simulations with inclusion of calibration curves overlapped at the estimate period of infection.
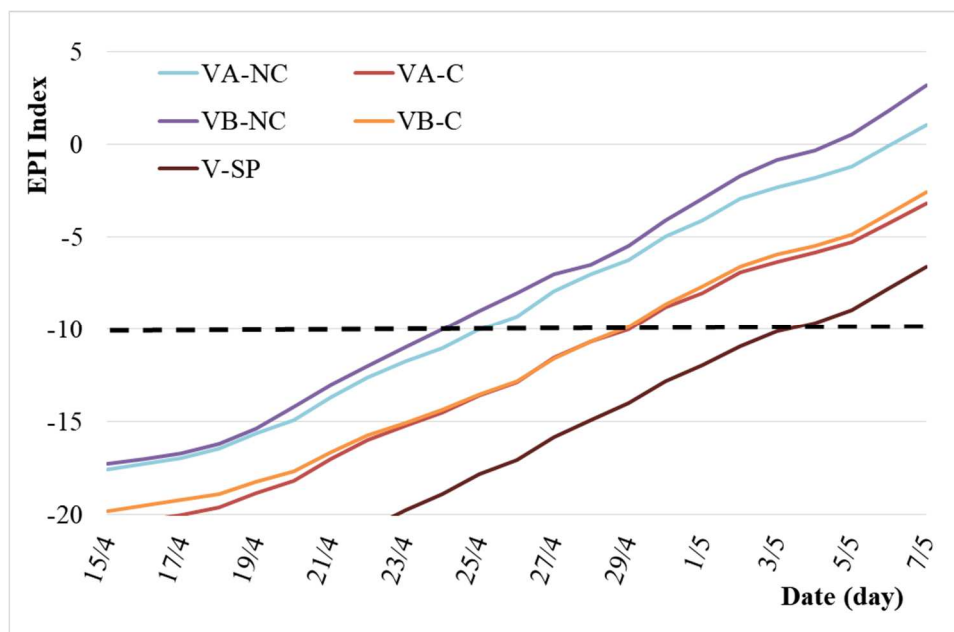

Figure 4. EPI indexes which give estimates of risk for the primary infections. The dashed line is the threshold in which the value reached the critical point -10.

Pesticide treatments carried out when the risk of spores' germination was not occurred yet or was already occurred by a week if we consider the simulation with the data gathered from the phytosanitary service network.

3.3. Secondary infection

In previous studies, the model shown a tendency to overestimate the risk for the secondary infection [16]. In this study, we decide to investigate also this aspect. It could be noticed that using as input values of the model the data from calibrated sensors this overestimation was reduced. Indeed, the symptoms observed around 19-20 June were classified of degree 3 on the base of the European for Plant Protection scale [17], that correspond to a severity of disease of 5-25%.

In the same period, the EPI index produces a value of about 47 and 35 in VB-NC and VA-NC, respectively, compared to the lower values obtained with the calibrated data of 29 and 33 in VA-C and VB-C, respectively (Figure 5). The severities of the disease foreseen are listed in Table 5:

Table 5. EPI index values, percentage of infection and severities of the disease foreseen based on EPPO scale for the four scenarios.

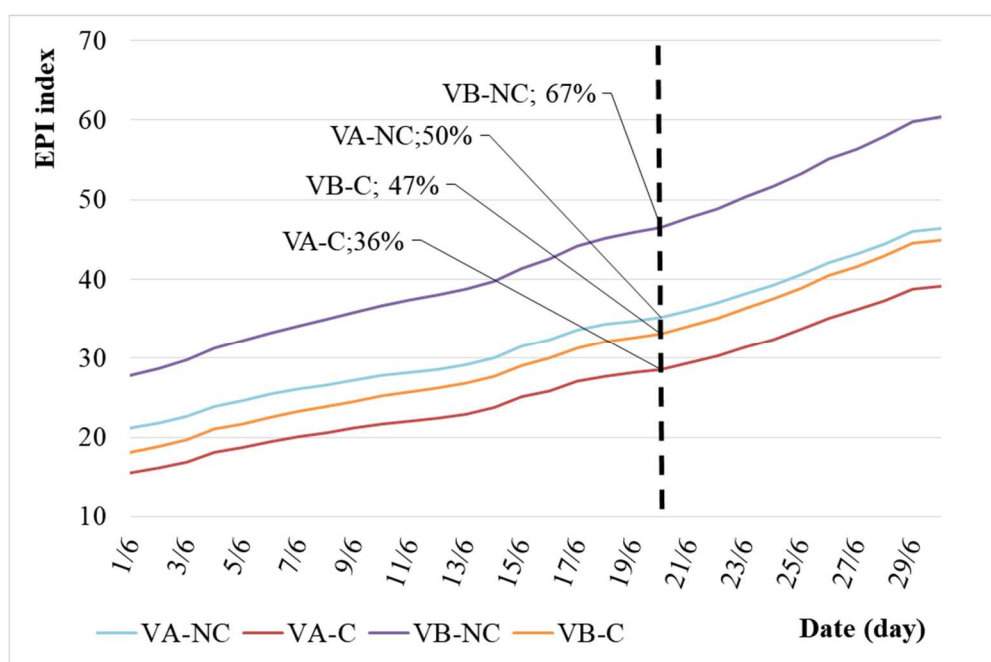| Simulation	Epi index	Infection	EPPO degree
VB-NC	46	67%	5
VA-NC	37	50%	5
VB-C	33	47%	4
VA-C	28	36%	4

Figure 5. EPI index values and percentage of secondary infection for the four scenarios: VA and VB without inclusion of calibration uncertainties in the input values (VA-NC and VB-NC, respectively); VA and VB with inclusion of the calibration uncertainty (VA-C and VB-C, respectively) for temperature and relative humidity.

The simulation with calibrated data reduced the risk in VA and in VB of 20 and 14%, respectively. Considering the position only, the reduction is at about 11%.

4. Conclusions and Future works

The forecasts provided by calibrated data overlapped the estimated period of infection, confirming that the inclusion of measurement uncertainties produce data closer to the real value of the measurand.

Focusing on the simulations without inclusion of the uncertainties and calibration curves in the input data, the pesticide treatments will be carried out when the diseases was already occurred or not occurred yet, that can be translated in more costs in terms of labour, chemicals waste, with consequences for the human health and environment. Moreover, using accurate data, the overestimation of secondary infection risk was reduced.

The inclusion of the sensors calibration and weather instrument positioning contributions, affects the disease prediction up to 5 days. Therefore, the choice of instrument position and calibration procedure becomes a matter of importance in agriculture. Measurements should be based on fully documented traceability and forecasting models should include measurement uncertainties in the input values, to improve output data reliability

The WMO Guide to Agricultural Meteorological practices n. 134 has valuable information on basic aspects of agrometeorological observations but there is a lack of metrological approach on data analysis, instrument calibration, traceability, and uncertainty evaluations.

The establishment of the metrological requirements for the agrometeorological services and observing systems might allow improving the accuracy in monitoring of local meteorology changes. This is particular true in the vison of a potential creation of a *Reference surface-based observing network*: Measurements performed at different times and sites would be reliably comparable since all measurements would be traceable to the SI.

Metrological approach is needed, also for accurate measurement of soil moisture for a better management of the water supply to the crops as well as for Land-surface temperature and soil temperature. Potential variables to be included in the list of the Essential Climate Variables (ECVs). That critically contributes to the characterization of Earth's climate as defined by the Global Climate Observing System (GCOS).

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