Qualitative parameter analysis for *Botrytis cinerea* forecast modelling using IoT sensor networks

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This paper provides results of an evaluation of a fungal disease *Botrytis cinerea* forecast model (Model for *Botrytis cinerea* appearing) in vineyards for qualitative analysis of parameters which affect the development of the disease by using data from a network of connected sensors (air temperature and relative humidity, rain precipitation, and leaf wetness). The fungal disease model used by agronomists was digitalized and integrated into agroNET, a decision support tool, helping farmers to decide when to apply chemical treatments and which chemicals to use, to ensure the best growing conditions and suppress the growth of *Botrytis cinerea*. The temperature and humidity contexts are used to detect the risk of the disease occurrence. In this study, the impact of the humidity conditions (relative humidity, rain precipitation, and leaf wetness) is evaluated by assessing how different humidity parameters correlate with the accuracy of the *Botrytis cinerea* fungi forecast. Each observed parameter has its own threshold that triggers the second step of the disease modelling-risk index based on the temperature. The research showed that for relative humidity, rain precipitation, and leaf wetness measurements, a low-cost relative humidity sensor can detect, on average, 14.61% of cases, a leaf wetness sensor an additional 3.99% of risk cases, and finally, a precipitation sensor can detect an additional 0.59% of risk cases (in observed period the risk was detected in 19.19% (14.61%+3.99%0.59%) of the time), which gives a guide to farmers how to consider cost effective implementation of sensors to achieve good performance. The use of the proposed model reduced the use of pesticides up to 20%.

***Index Terms*—IoT, Fungal disease forecast, Botrytis cinerea, Precise agriculture, Decision support.**

I. INTRODUCTION

AGRICULTURE production has evolved throughout the years, from the family-based farms producing food mainly for themselves, to modern, well-equipped farms and agriculture companies that became the main food suppliers for the growing global population. The global smart agriculture market size is expected to reach $15.3 billion by 2025 [1], which is directly proportional to the increase of the number of Internet of Things (IoT) device installations in agriculture with a 20% annual growth [2]. However, the Food and Agriculture Organization (FAO) in [3] reports that 25% of the world's farmland is "highly degraded" with soil erosion, water degradation, and biodiversity loss, following with 8% being moderately degraded, 36% slightly degraded, and only 10% ranked as "improving". When it comes to higher yields, plant breeding, genetics, as well as production technologies, we have come to the point where introducing other knowledge and technologies is a necessity to enable crops to reach their maximum potential, while optimizing the use of chemicals and saving the soil.

Digital technology-based (IoT, ML/AI) solutions designed for the agriculture domain help farmers optimize their production by providing actionable insights generated through a combination of built-in agriculture expertise in form of disease models, best practices, etc., and rich sets of data acquired directly from multiple sources (primarily farms, but also third parties like weather forecast).

Manuscript received April 26, 2022; revised October 17, 2022. Corresponding authors: Dejan Drajić (email: dejan.drajic@dunavnet.eu).

Many crop disease models have been defined and researched over the years, tailored to different crop varieties and climate regions.

In this study, the focus was on fungal diseases in vineyards. The goal of the study was to analyze the influence of the qualitative parameters collected by low-cost sensors, on the fungal disease forecast accuracy. The existing expert model for fungal disease forecast (Model for Botrytis cinerea appearing [4]) is implemented as a rule-based algorithm and applied on the data collected from IoT sensor nodes to provide information and recommendations that will help farmers in the decision-making process.

The main contribution of this study is identification of the minimum technological requirements for an effective and reliable *Botrytis cinerea* disease forecast. The evaluation is done based on the sensor systems deployed in four vineyards in two countries (Serbia and Montenegro).

To the best of our knowledge, there are no studies that evaluated the impact of different types of sensors on the accuracy of fungal disease prediction models. The disease prediction uses a state-of-the-art "almost in real-time" model, where collected data are processed and quantified in short time windows of 1 hour.

The rest of the paper is organized in the following manner. In Section II, related work on fungal disease modelling using technology is provided together with an overview of the *Botrytis cinerea* academic work in the domain, including a background on wine production. The materials and methods, study sites, and data sources used in the study, as well as more details on the disease forecast model quantification are provided in Section III. In section IV, the evaluation results are provided, followed by the discussion in Section V. The paper is concluded in section VI.

II. Related work

Botrytis cinerea causes gray mold disease and is the most common among other fungi responsible for the rotting of grapes, which highly impacts the wine quality. There are certain wine types produced in specific regions which base the process of wine making solely on the controlled infection of the grape berries by the *Botrytis cinerea* (i.e. Botryzied wines) [5]. For those wines, the main process is based on changing the fruit composition, which is induced by *Botrytis cinerea*. For botrytized wines, remediation practice is a complex process of conservation, aging and stabilization, combining a number of parameters (e.g., very specific environmental conditions) [6]. Other wines require a *Botrytis cinerea*-free environment, which makes stopping the growth of this fungus a very necessary and demanding task. Air temperature and humidity are the two critical parameters which influence development of Botrytis. According to [7], the relation of the influence of temperature and humidity on the infection can be modelled as a multiple regression described the infection as a function of the interaction of wetness duration and temperature ($R^2 = 0.75$, where R^2 is square of correlation coefficient r, which represents the level of correlation between observed variables. The value of 0.75 shows a quite high correlation level). The presented field test showed the infection spreads after 4h of wetness at all temperatures between $12-30°\mathrm{C}$. In [8], non-real-time models were used, by monitoring if the temperature between 20–25°C and a relative humidity of 90% are present for a maximum of 15 h.

In [9], the authors proposed to improve the modelling impact of plant disease on agricultural systems by improving the quality and availability of data for model inputs and evaluation. The current trends in the prediction of crop pests using machine learning technology were analyzed in [10] with an emphasis on the use of SVM (Support Vector Machine), Multiple Linear Regression, Neural Network, and Bayesian Network based techniques.

In [8], the authors developed an IoT technology with four different disease models (Gray mold, Downy mildew, Powdery mildew, and Black rot) based on previous work and indications to create warnings for vineyard diseases [11]–[14]. In [8] disease warning models were adapted to run in (near) real-time, using meteorological variables generated by IoT devices, to inform farmers, and to enable them to tackle the infection with the appropriate treatments.

By taking into account the number of factors collected from low-cost sensors that could influence appearance of the disease, new topics for research in the multidimensional field of precision agriculture emerge. In this paper, we have selected one disease to quantify the accuracy of the first step of the forecast of fungal growth that bases its intelligence on the different humidity parameters (relative humidity, rain precipitation, and leaf wetness). To the best of our knowledge there is no previous research that shows, from the perspective of model accuracy, how humidity parameters from different types of sensors influence the potential outcome of the forecast.

III. Material and methods

A. Study sites and data sources

Presented work is done in the scope of DEMETER project [15]. DEMETER is large scale project focused on digital transformation of agrifood sector. Activities are organised through 20 pilots across 18 countries focusing on: arable crops, precision farming, fruits and vegetables, livestock and whole food supply chain. The key project objective is to empower farmers to improve their existing practice by introducing digital technologies. Under DEMETER project vineyards throughout Srem-Fruska Gora Mountain and 13. Jul-Plantaze vineyard are equipped with adequate devices providing inputs in expert modules as a basis for decision support to the farmers. Job orders/spraying configurations are sent to the orchard/vineyard sprayers in the field, and once executed, the result of the spraying operation is made accessible in the cloud. As mentioned, the observed and analyzed data sources in the paper are collected at the vineyard operated by the company 13. Jul-Plantaže located in the municipality of Podgorica in Montenegro (Fig. 1) and vineyards operated by members of the Association Srem-Fruška gora located on the Fruška gora mountain in Serbia (Fig. 2). 13. Jul-Plantaže, one of the largest wine producers in South-Eastern Europe, operates a huge vineyard in a single complex, covering an area of over 2300 ha. The Association Srem-Fruška gora gathered 77 members that operate around 700 ha of vineyards that are spread through the Fruška Gora Mountain. The microclimate diversity, from flat to hilly terrain across the Fruška Gora Mountain in Serbia, to the specific climate between rocky Montenegrin mountains provides a better verification of influence that the sensor measurements have on specific models.

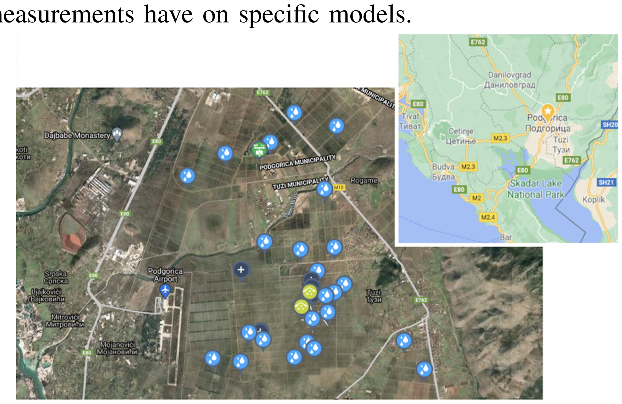

Fig. 1. The map showing the pilot site and agroNET sensor node locations at 13. Jul-Plantaže vineyard in Montenegro.

Within the research activities, weather station for monitoring the environmental parameters was deployed at an area of 50 ha covered with the Vranac variety at the 13 Jul-Plantaže vineyard. The weather station (marked with in Fig. 1 and 2) is equipped with sensors for monitoring air temperature, relative air humidity, precipitation, leaf wetness, solar radiation, and wind speed (Fig. 3.). In observed 13 Jul-Plantaže vineyard, the microclimatic conditions on this location are uniform and it was considered sufficient to deploy one weather station.

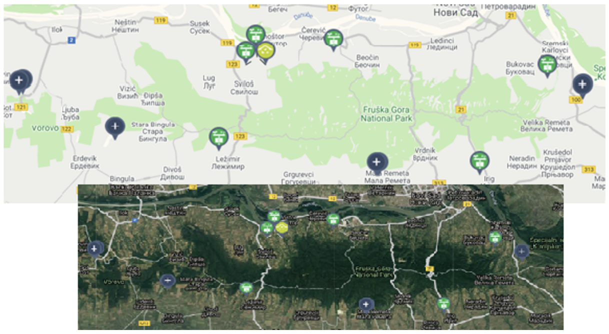

Fig. 2. Map showing the pilot site and agroNET sensor node locations at Association Srem vineyards in Serbia.

Fig. 3. Pictures of the sensor nodes installed at the pilot site, from left to right: a) weather station; b) soil moisture node; c) three types of soil moisture sensors.

At Association Srem, weather stations for monitoring air temperature (Operating temperature range: $-40°\mathrm{C}$ to $+125°\mathrm{C}$, Thermometer error $-10°\mathrm{C}$ to $+85°\mathrm{C} : +/-0.3°\mathrm{C}$), air humidity (Precision: $0-80\% : \pm 2\%, 81-100\% : \pm 3\%$) and precipitation (Sensitivity: 1 tip per 0.2 mm. Accuracy: $\pm 5\%$) were deployed at nine vineyards with calculated leaf wetness values. Additionally, similar weather stations with added sensors for measuring leaf wetness are deployed at three more vineyards and in Montenegro. While the total size of vineyards is much smaller than in Montenegro deployment, the actual spatial distribution (approx. 100 km between the vineyards at far ends) and the terrain configuration demanded a larger number of weather stations to account for varying microclimate conditions. The size of areas covered by one weather station varies in the range $1-100$ ha. Weather station uses LoRa communication for transferring data to the cloud where data is stored and processed.

The measurements from the weather stations are used as inputs for prediction model for gray mold (*Botritys Cinerea* [4]) disease appearance.

B. Disease prediction model for Botrytis cinerea

Different fungal diseases have a huge influence on grape production reflecting in the decrease of yield and grape quality. One of them is grey mold disease, caused by *Botrytis cinerea*. In order to avoid disease spreading, fungicides are applied. The most challenging part of treatment is defining the right moment for the spraying. The timing depends on the fungal life cycle, plant development phenophase, environmental conditions, sensitivity of different grape types, production goals, etc. There are different prediction models that represent a mathematical relationship between the pathogen life cycle, plant growing period, and environment conditions calculating the risk of disease appearance. These models are scientifically proven and validated by the end users over many years in different climate regions. However, their interpretation requires expertise, usually provided by agronomy consultants.

The development of sensors and IoT technology enable relevant data collection to the model which detect, and provide a timely reaction for controlling different diseases, minimizing the farmers' in-field effort. The model used in this study [4] quantifies a risk index (RI) used to identify the need for corrective measures, that triggers notifications, with adequate recommendations included, to farmers. The model takes into account temperature and humidity conditions which are specific for observed fungus, or even each phase in fungus development. The first step in the process, is assessment if the disease conditions are met based on the humidity parameters. Then, the RI quantification is done by measuring temperature over a period of time. The humidity parameters considered are the relative air humidity, precipitation (amount and/or duration), and the leaf wetness.

The model works in near real-time, calculating the infection risk every hour.

The grey mold disease model starts with the calculation of the infection risks once the following humidity conditions are met:

- the leaf is moist (LM) for at least 30 minutes during one hour or
- the relative air humidity (RH) is at least 90% or
- the duration of the rainfall (RF) is at least 30 minutes during one hour or
- the amount of rainfall (ARF) is greater than 0.4 mm during one hour.

When at least one of the above conditions is fulfilled, the model begins calculating the risk of infection. The risk increases when the temperature ranges from $10°\mathrm{C}$ to $23°\mathrm{C}$. However, the further air temperature increase decreases the disease risks. The model summarizes the risk percentage for each hour and the system creates instructions when the sum of the risk percentage reaches predefined threshold levels. If a humidity condition is not fulfilled in three hours after the risk calculation was initiated, the risk calculation is reinitiated and starts from 0, otherwise calculated sum is updated with new risk value. If one of the humidity conditions are met during these 3 hours, the risk percentage is taken from Table I and aggregated until it reaches 100%.

The used model is graphically presented in the form of algorithm in Fig. 4.

IV. Results

In this section, the collected data are analyzed to assess how different qualitative humidity parameters used for a fungal *Botrytis cinerea* disease forecast model correlate with the

TABLE I
RISK INDEX FOR TEMPERATURE ON ONE HOUR BASIS FOR BOTRYTIS CINEREA

Risk [%]	4	6	8	10	12	14
T [°C]	10	11-12	13	14-16	17-19	20-23
Risk [%]	12	10	8	6	4	2
T [°C]	24-26	27-29	30	31	32	33

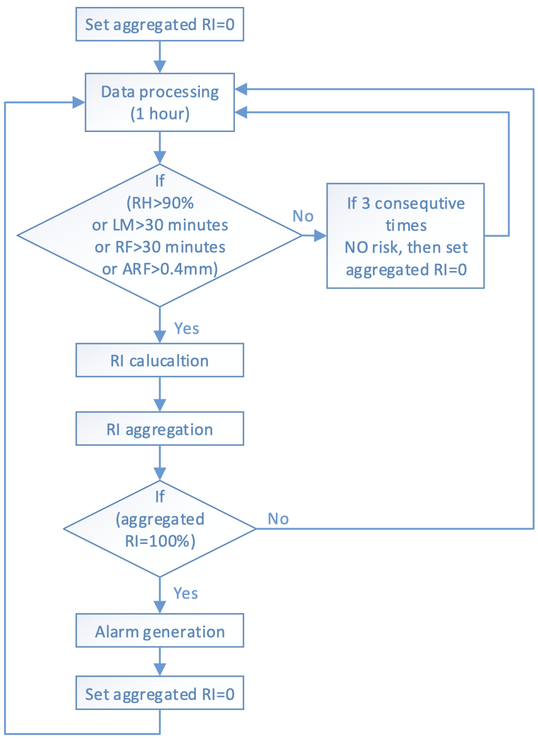

Fig. 4. Algorithm for risk index calculation.

model accuracy to provide information and help in decision making. In order to understand the influence of these sensors on the model accuracy it is of interest to analyze the influence of every single sensor, i.e. relative humidity, rain precipitation, and leaf wetness on the model.

In order to trigger the model, just one of three moisture measurements (relative air humidity, leaf wetness, precipitation) must be above the threshold level. Based on the experiment results in most of observed cases, relative air humidity was the trigger, i.e. above the threshold level. The other two parameters triggered the model less often. The leaf wetness measurements will trigger the model when reach threshold levels and the other two parameters did not. This is also the case when it comes to precipitation. Those cases show the influence of leaf wetness and precipitation sensors on the prediction model accuracy. As the analysis was done using data gathered from vineyards from different climatic conditions, better verification of the proposed model was secured.

The influence of different moisture measurements on triggering of the disease prediction model is shown in Figures (5-8) and Tables (II-V), respectively for all observed vineyards. The percentages in the tables give insight into influence of each parameter on triggering the model, i.e., when the risk is recognized by which sensor. The values shown in figures are averaged monthly values of the measurements given in the corresponding tables.

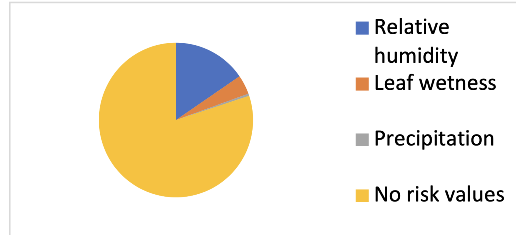

Fig. 5. Vineyard 1 Fruška gora, Serbia.

TABLE II
HUMIDITY RESULTS FOR VINEYARD 1 AT FRUŠKA GORA MOUNTAIN

Month	Relative humidity	Leaf wetness	Precipitation
April 2020	2.1%	0.7%	0.5%
May 2020	9.9%	4.9%	0.6%
June 2020	31.4%	8.1%	0.5%
July 2020	20.1%	4.3%	0.7%
August 2020	19.6%	2.9%	0.3%
Sept. 2020	9.4%	3.3%	0.2%

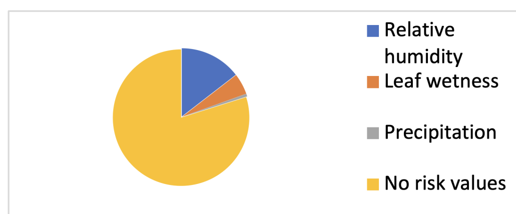

Fig. 6. Vineyard 2 Fruška gora, Serbia.

TABLE III
HUMIDITY RESULTS FOR VINEYARD 2 AT FRUŠKA GORA MOUNTAIN

Month	Relative humidity	Leaf wetness	Precipitation
April 2020	1.7%	1.39%	0.8%
May 2020	13%	7.3%	1.1%
June 2020	29.6%	8.9%	0.6%
July 2020	15.5%	3.6%	1,3%
August 2020	14.8%	4.7%	0.3%
Sept. 2020	12.6%	4%	0.4%

Looking at Figures 5-8, it can be noted that the average monthly values have almost the same behavior for all observed sites. It is also notable that the relative air humidity sensor triggers the risk calculation in the most cases (up to 33.9% of total observed time), the leaf wetness sensor is highly desirable to increase the number of risk cases (up to 10.5% of total observed time), while the precipitation sensor could be an added value, but its contribution is rather limited, up to 1.4%. It is obvious that the measurements highly depend on the

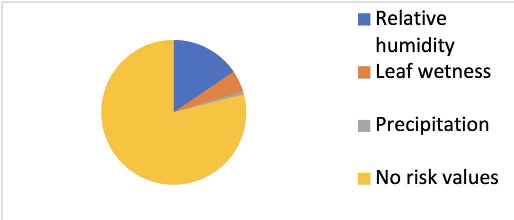

Fig. 7. Vineyard 3 Fruška gora, Serbia.

TABLE IV
HUMIDITY RESULTS FOR VINEYARD 3 AT FRUŠKA GORA MOUNTAIN

Month	Relative humidity	Leaf wetness	Precipitation
April 2020	2.2%	1.6%	1.4%
May 2020	6.5%	6.4%	1.1%
June 2020	33.9%	10.5%	0.6%
July 2020	19.8%	3.8%	0.4%
August 2020	20.2%	2.7%	0.3%
Sept. 2020	10.6%	4%	0.1%

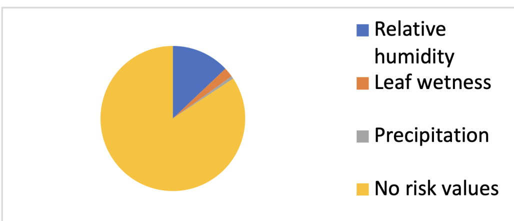

Fig. 8. Vineyard Montenegro.

TABLE V
HUMIDITY RESULTS FOR VINEYARD PLANTAŽE, MONTENEGRO

Month	Relative humidity	Leaf wetness	Precipitation
April 2020	13.1%	2.1%	0.4%
May 2020	11.9%	1.9%	0.4%
June 2020	21.6%	2.8%	1.1%
July 2020	5.4%	2.9%	0.5%
August 2020	9.2%	1.1%	0.6%
Sept. 2020	16.5%	2.1%	0.7%

observed months and vineyard locations, and it is not feasible to do a straightforward mutual comparison of the results. For example, the level of relative air humidity and leaf wetness per month are quite different in the Serbia and Montenegro vineyards. In Serbia, the relative air humidity is the lowest in April, while in Montenegro these values are moderate in April, whereas the relative air humidity is quite lower in July and August than in Serbia. In Montenegro, the contribution of the leaf wetness to the algorithm is almost the same throughout the period under the analysis and is much lower than in Serbia. In all the observed months, June is the month with the highest detected relative air humidity periods in both countries. The observed influence of precipitation on the algorithm is almost the same in all vineyards.

In the following Table, the results of analysis are presented for every vineyard, by averaging contributions per sensors per months per vineyard, and by averaging results from all vineyards (percentages given in table present the percentage of the observed time when model is triggered for risk calculation for monitored sensors, otherwise there is no risk).

TABLE VI
OVERALL AVERAGE VALUES

Month	Relative humidity	Leaf wetness	Precipitation
Vineyard 1, FG	15.42%	4.03%	0.47%
Vineyard 2, FG	14.53%	4.98%	0.64%
Vineyard 3, FG	15.53%	4.83%	0.65%
Vineyard, MN	12.95%	2.15%	0.62%
All vineyards	14.61%	3.99%	0.59%

Note. FG: Fruška Gora, MN: Montenegro.

The average values for all results are graphically shown as the pie charts in Fig. 9:

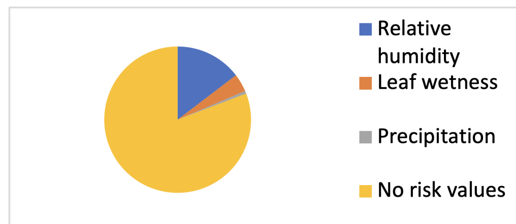

Fig. 9. Overall average values for all vineyards.

The average values are quite similar for vineyards in Serbia which was expected, since they are in the same area, but still micro climate conditions could affect monitored values. Also, the vineyard in Montenegro in average shows very similar behavior, although it is obviously a dryer area than in the Serbian vineyards. It is clear that air humidity is of huge importance for the accuracy of the prediction models (Table VI). The leaf wetness measurements increase the accuracy on average by $2.15 - 4.98\%$ (it is of interest to note that in the Serbian vineyards this sensor gives more contribution $3.99 - 4.98\%$ than in Montenegro 2.15%), while precipitation measurements have the lowest contribution.

V. DISCUSSION

Data gathering, as the first step of the smart agriculture approach, relies heavily on the accuracy of the data coming from devices deployed in the field.

For the fungal forecast models, temperature and humidity are the two contexts used i to predict if disease conditions are met. When humidity condition is met, risk percentage is calculated based on the measured temperature. This means, if there is no humidity condition met, there is no risk. If there is humidity condition met (section III-B), the risk is higher or lower, it depends on the temperature. In this study, we have collected data to assess humidity using relative air humidity, rain precipitation, and leaf wetness sensors.

One example illustrating the influence of relative air humidity, rain precipitation, and leaf wetness sensors on the model is the case of Vineyard 1 in Serbia in June 2020, where the model was triggered by relative air humidity measurements in 31.4% of the observed time, in 8.1% by leaf wetness sensor measurements, and finally, in 0.5% by precipitation sensor measurements. If the relative air humidity sensor is the only one used, the prediction model will be triggered in 31.4% cases of the observed time. When the leaf wetness sensor is added, an additional 8.1% cases when moisture condition is fulfilled were detected. Lastly, by adding the precipitation sensor 0.5% more cases were detected. So, for June 2020, the overall cases for triggering the model were in $31.4+8.1+0.5 = 40\%$ of the time, while in 60% of the time there were no risk detected.. It is obvious that vineyards in Fruška gora have quite similar results (although they are not collocated, but distanced 50 km), and that the vineyard in Montenegro shows similar behavior, with a slightly lower relative air humidity.

By averaging all the obtained results, the main conclusion of the study is that a cheap relative air humidity sensor in average will trigger risk calculations in 14.61% of the observed period, a leaf wetness sensor an additional 3.99% of risk cases, and finally, a precipitation sensor will detect only an additional 0.59% risk cases (it also means that in 80.81% of the time $(100\%-14.61\%-3.99\%-0.59\%)$ there were no risk conditions for disease appearance). It is obvious that the leaf wetness sensor provides more reliable risk detection as an additional sensor, while contribution of the precipitation sensor is rather low. On the other hand, these two sensors require more maintenance than the relative humidity sensor, especially the precipitation sensor, as it should be checked regularly and cleaned from leaves and similar plant pieces. Keeping in mind the low detection accuracy of the precipitation sensor, in the deployment scenario this sensor could be left out to optimize the final cost of the installation and service. Activities based on the analyzed data, can help farmers to optimize production, better use all of the inputs, increase product quality, predict potential problems, better plan activities, optimize costs, and consequently achieve higher profit.

In the conventional method of spraying vines, farmers mainly use general treatment recommendations created for the wider region, and use their experience to adapt the recommendations specifically for their plot. The application of the proposed method increased the precision of determining the optimal period of treatment and crop protection against disease, which is an improvement over the conventional method. Greater precision ensures the timely application of pesticides, which achieves savings and additionally positively affects the quality of the product. The use of data on leaf humidity increases the precision of the analysis of environmental conditions for the development of the disease, and it is desirable to use this sensor. The use of the proposed model reduced the use of pesticides by up to 20%, which resulted in a reduction in costs and an increase in crop quality.

VI. Conclusions

The precision agriculture concept is being increasingly adopted by large and medium size farmers. With the further reduction of the technology costs, it is expected that the smaller farmers will start adopting digital solutions on a larger scale.

The concrete and documented benefits achieved by introduction of digital solutions will further accelerate adoption. To maximize the benefits, it is important to optimize the amount of technology needed (e.g, the number and the type of sensors), i.e. to avoid deploying technological components (hardware or software) which do not bring additional value to farmers.

To that end, we have the outcomes of a study focusing on definition of a minimal set of sensors required to reliably predict the risk of appearance of the Botrytis cinerea disease. The impact of temperature, relative air humidity, rain precipitation, and leaf wetness measurements on the accuracy of the forecast modelling was evaluated. Validation was done using deployments in vineyards in two regions with different climate conditions and different terrain configurations. The study showed that using low-cost sensors for decision support was more accurate when a relative air humidity sensor was used: on average 14.61% risk values were detected; leaf wetness sensor detected additional 3.99% risk cases, and finally, the precipitation sensor detected only an additional 0.59% risk cases (in the observed period the risk was detected in 19.19% $(14.61\% + 3.99\%0.59\%)$ of the time). Application of the proposed model reduced the use of pesticides up to 20% which consequently reduced costs and increased crop quality.

Acknowledgment

The research leading to these results received funding from the European Union's Horizon 2020 — The EU Framework Programme for Research and Innovation 2014–2020, under Grant Agreement No. 857202-DEMETER.

We would like to express our gratitude to Daliborka Nedic, a software developer working on the agroNET platform for the data access and extraction. The authors would also like to thank the representatives of company 13. Jul-Plantaže in Montenegro and Association of Producers of Grapevine And Wines with Geographical Indication "Srem-Fruška Gora", Serbia for their help in the field.

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