

Article

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

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Abstract: This paper presents the evaluation of a fungal disease forecast model in vineyards for qualitative parameter analysis using the data from off the shelf sensors, i.e. temperature and air relative humidity, rain precipitation, and leaf wetness. The rules for the fungal disease models are digitalized as a decision support tool that serve as an indicator to farmers for the need of spraying of the chemical substances to ensure the best growing condition and suppress the level of parasites. The temperature and humidity contexts are used interchangeably in practice to detect the risk of the disease occurrence. By taking into account a number of influences on these parameters collected from the shelf sensors, new topics for research in the multidimensional field of precision agriculture emerge. In this study, the impact of the humidity is evaluated by assessing how different humidity parameters correlate with the accuracy of the *Botrytis cinerea* fungi forecast. Each humidity parameter has it's own threshold that triggers the second step of the disease modelling - risk index based on the temperature. The research showed that for humidity a low-cost relative humidity sensor can detect in average 14.61% risk values, a leaf wetness sensor an additional 3.99% risk cases, and finally, a precipitation sensor will detect only an additional 0.59% risk cases.

Keywords: IoT; Fungal disease forecast; *Botrytis cinerea*; Precise agriculture; Decision support

1. Introduction

Agriculture production has changed throughout the years, from family-based farms able to produce food mainly for themselves, to modern, well-equipped smart farms and agriculture companies that became the main food suppliers for billions of inhabitants. The global smart agriculture market size is expected to reach \$15.3 billion by 2025 [1], which is directly proportional to the number of Internet of Things (IoT) device installations increase in agriculture with 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% is slightly degraded, and only 10% is ranked as "improving". When it comes to higher yields, plant breeding, genetics, as well as production technologies, we came 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.

IoT makes the application of science into practice possible, helping farmers optimize their production by converting agriculture expertise into actionable knowledge. Farm management optimization and precise agriculture facilitates technologies like big data, cloud, IoT and machine learning to enhance on-farm processes and improve the decision support. The focus is on monitoring all farm operations, having a deeper insight into weather conditions, soil characteristics, resources, machinery, labour, etc. Accordingly, farmers can make better decisions supported by concrete data instead of searching for an expert advice or using their own intuition. The main innovation in agriculture is focused on precise measurements and enabling autonomous forecast modelling, early disease detection, and prevention. This innovation implies using sophisticated technology such as

sensors, robots, satellite images, drones, GPS navigation, and other data sources to gather rich sets of data and make them available for the analysis.

In this study, the collected data is analysed to assess the qualitative parameters used for fungal disease forecast. The existing expert models for fungal disease forecast and newly developed one, implemented as a rule-based algorithm, are applied on the data collected from IoT sensor nodes in order to provide information and knowledge that will help farmers in the decision-making process.

The main contribution of this research is the evaluation of the use of technology, spatial, and temporal measurements from low-cost devices to identify minimum technological requirements for *Botrytis cinerea* disease forecast sensing scenario: a selection of humidity parameters from the available sensorial technology necessary to achieve a good performance. The evaluation is done based on the service deployed in four vineyards in two countries (Serbia and Montenegro, the one in Montenegro being one of the largest vineyards in Europe).

To the best of our knowledge, there are no studies that show the evaluation of humidity sensors' accuracy for decision support for farmers used to quantify the disease forecast risk. The prediction is using the state-of-the-art "almost in real-time" model, collecting the data, quantified in short time windows of 1 hour.

The rest of the paper is organized in the following manner. In Section 2, related work on fungal disease modelling using technology is provided together with an overview of the *Botrytis cinerea* academic work in the domain, including background on the 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 3. In section 4, results on the evaluation on humidity sensors accuracy is provided, followed by the discussion in Section 5. The paper is concluded in section 6.

2. Related work

Botrytis cinerea causes grey mould disease and is the most common among other fungi responsible for the grapes rotting, which highly impacts the wine quality. There are some 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. Botrytized wines) [4]. For those wines, the main process is based on changing the fruit composition 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) [5]. Other wines require an environment free from the *Botrytis cinerea* which makes the struggle against this fungus a very necessary and demanding task. Temperature and humidity are the two critical parameters which influence the development of *Botrytis*. According to the study [6], the relation of the influence of temperature and humidity on the infection can be modelled as a multiple regression described the logit of infection as a function of the interaction of wetness duration and temperature ($R^2=0.75$). The field test shown the infection spreads after 4h of wetness at all temperatures between 12-30C. In [7], a non real-time models are used, by monitoring if temperature of 20–25 C and a relative humidity of 90% are present for a maximum of 15 h.

In [8], authors proposed to improve 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 is done in [9] with the emphasis on the use of SVM (Support Vector Machine), Multiple Linear Regression, Neural Network, and Bayesian Network based techniques. The paper [10] proposes interoperability architecture for IoT platform to increasing scalability, stability, interoperability, and reusability deployed for evaluation in wine production.

There is prior work on the topic of fungal disease monitoring using technology, targeting a proprietary platform for precise agriculture. In [7], authors developed IoT technology with four different disease models (Gray mould, Downy mildew, Powdery mildew, and Black rot) based on previous work and indications to warn for vineyard diseases [11-14]. In [15] disease warning models

are adapted to run in (near) real-time over meteorological variables generated by IoT devices, to inform farmers, and to enable them to tackle the infection with the appropriate treatments.

In this paper, we have selected one disease in order to quantify the accuracy of the first step of the fungal forecast that bases its intelligence on the different humidity parameters. To the best of our knowledge there is no previous research that shows, from the sensors' accuracy perspective, how humidity parameters from different types of sensors influence the potential outcome of the forecast. This represents a potential threat to a system relying on a specific humidity sensor.

3. Material and methods

3.1. Study sites and data sources

The data sources are collected at four different vineyards in Serbia and Montenegro (three in Serbia and one in Montenegro), during the vegetation period when crop diseases are expected to appear. The microclimate diversity, from flat to hilly land across the Fruška gora mountain in Serbia, to the specific climate between rocky the Montenegrin mountains allows a better verification of influence that sensor measurements have on specific models. The vineyards in the Fruška gora are mutually distant for about 50 km.

For the precision viticulture the data was collected at the vineyard operated by the company „13. jul Plantaže“ located in the municipality of Podgorica in Montenegro (Figure 1) and vineyards operated by members of Association Srem-Fruška gora located on the Fruška gora mountain in Serbia (Figure 2). „13. jul Plantaže“ operates a huge vineyard in a single complex, covering an area of over 2300 ha. The company is one of the largest wine producers in the South Eastern Europe, producing around 22 million kilos of grapes and more than 16 million bottled products annually. Association Srem-Fruška gora gathered 77 members that operates around 700 ha of vineyards that are spread through the Fruška gora mountain.

The deployment and installation included devices for measuring environmental parameters (air temperature, relative air humidity, rainfall, leaf wetness, radiation, wind speed); as well as data about the crop (crop type and planting date). Further, 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.



Figure 1. Map showing the pilot site and agroNET sensor node locations at Plantaže vineyard in Montenegro (left) and Association Srem vineyards in Serbia

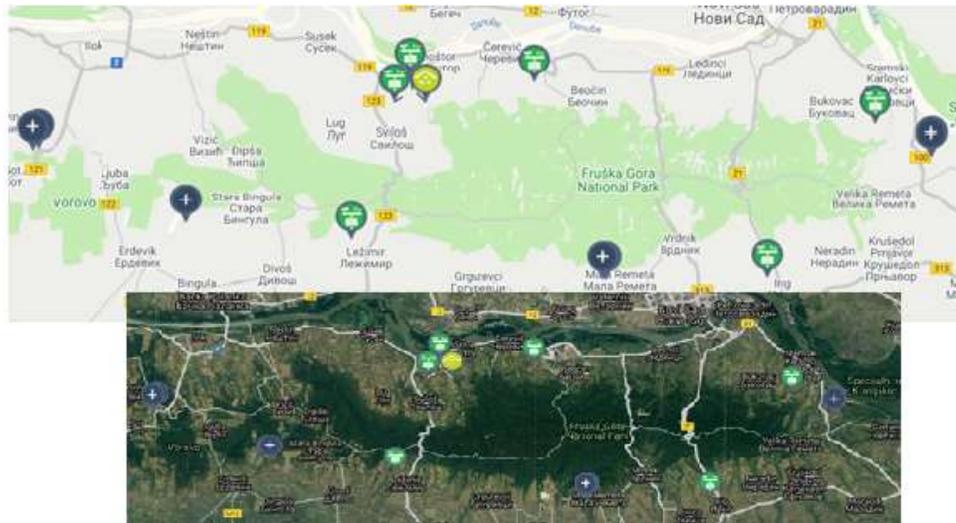


Figure 2. Map showing the pilot site and agroNET sensor node locations at Association Srem vineyards in Serbia

Under research activities, weather stations for monitoring the environmental parameters were deployed at an area of 50 ha covered with the Vranac variety at the Plantaže vineyard. Half of the area is considered as control area, while the other half is experimental site. The weather station is equipped with sensors for monitoring air temperature, relative air humidity, barometric pressure, precipitation, leaf wetness, solar radiation and wind speed. Devices for monitoring soil conditions are equipped with three types of sensors. Four devices are aimed to measure the soil moisture with sensors installed at two different depths covering the main root zone and two devices are equipped with sensors for monitoring soil moisture, soil temperature, and salinity at six different depths.

At Association Srem, weather stations for monitoring air temperature, air humidity and precipitation were deployed at nine vineyards with calculated leaf wetness values. Additionally, a similar weather station with added sensors for measuring leaf wetness are deployed at three more vineyards.

The measurements from the weather stations are used as inputs for prediction models for pests and disease. For the purpose of this research, humidity sensors data were used for the quantification of the influence on disease prediction.



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

3.2. Disease prediction model for *Botryotinia fuckeliana*

Different fungal diseases have huge influence on grape production reflecting in decreasing of yield and grape quality. One of them is *Botrytis cinerea* or grey mould disease. In order to avoid disease spreading, fungicides should be applied, but the most challenging part is defining the right time for spraying. This depends on the fungal life cycle, plant development phenophase, environmental conditions, sensitivity of different grape types, production goals, etc. There are different prediction models for the disease appearing, already available, scientifically proven and validated by end users through a number of years in different climate regions, but their interpretation requires expert knowledge. Those empirical models represent a mathematical relationship between the pathogen life cycle, plant growing period, and environment conditions.

The development of sensors and IoT technology enable these models to be developed to collect, detect, and provide a timely reaction for controlling different diseases, minimizing the farmers' in-field effort. The model provided in this study quantifies risk index (RI) used to identify the need for corrective measures, that drives the decision support provided to farmers. The first step is to assess if disease conditions are met using humidity, then it starts with quantifying the risk index of the disease by measuring temperature in different time frames. Humidity conditions encompass leaf wetness, relative air humidity, and precipitation (amount and/or duration).

For our purpose, the models are developed to work in near real-time, calculating the risk for infection every hour. The models take into account temperature and the humidity conditions which are specific for each fungus, or even each phase in fungus development.

The model for grey mould disease starts with summarizing the risk of infection when humidity conditions as described below are met:

- the leaf is moist at least 30' for one hour or
- the relative air humidity is at least 90% or
- the duration of the rainfall is at least 30' for one hour or
- the amount of rainfall is greater than 0.4mm for one hour.

When at least one of stated conditions is fulfilled, the model begins calculating the risk of infection which depends on air temperature. The risk increases when the temperature increases from 10°C to 23°C, however further increasing of temperature decreases the risk. The model summarizes the risk percentage for each hour and the system creates instructions when the sum reaches predefined threshold levels. If the humidity condition is not fulfilled for three hours, the risk calculation is reinitiated. In the case that rainfall, leaf wetness, or relative humidity are present in the time window of 3 hours, the risk percentage is taken from the table and aggregated until it reaches 100%.

Table 1. Risk index for temperature on one-hour basis for *Botryotinia fuckeliana*

Risk [%]	4	6	8	10	12	14	12	10	8	6	4	2
Temperature	1	11-	1	14-	17-	20-	24-	27-	3	3	3	3
e	0	12	2	16	19	23	26	29	0	1	2	3

There are many factors that needs to be taken into account for the decision-making process for *Botryotinia fuckeliana*. It is hard to develop a one-fit-all scenario for all wine types. The decision depends on the type of grape, development phenophase, type of wine (sour, semi - sweet, sweet), and in-field experience with the behaviour of the fungus in the given vineyard. Therefore, we have developed our decision support models to create instructions based the environmental parameters, which are further interpreted based on the end-user needs for the specific region.

The fungal disease models are developed for two different plant growing periods as follows: 1) during blooming and 10 days after blooming; and 2) beginning of the ripening until harvest. In first case (1), during blooming and after blooming instructions are given if risk index is $> 50\%$ and $< 100\%$. In second case (2), beginning of the ripening differentiates for different grape sorts. The general period for all sorts and grape secondary usage for monitoring of the risk is from the middle of July to the end of October. The instructions are given to the farmer when the risk index reaches 50% and 100% for sensitive sorts and tolerant sorts.

4. Results

In this study, the collected data are analysed to assess qualitative humidity parameters used for fungal disease forecast based on the predefined expert models to provide information and help in decision making. The fungal models calculate the risk for crop diseases appearance based on the fulfilment of the air temperature and the humidity conditions. The humidity conditions take into account the measurements of the following sensors: relative humidity, rain precipitation, and leaf wetness. If at least one of these measurements is above the predefined value, then it is considered that the first condition is met, and the temperature is monitored to assess the risk of disease. In order to understand the influence of these sensors on the model accuracy it is of interest to analyse the influence of every single humidity sensor on the model.

In order to trigger the model, just one of three moisture measurements (relative air humidity, leaf wetness, precipitation) must be above threshold level. In most cases, the relative air humidity is the trigger. The other two parameters were higher than the threshold levels when relative air humidity is below threshold in only a few cases. On the other hand, the leaf wetness measurements reach threshold levels even in the case when 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. The analysis is done on the four different vineyards (three in Serbia and one in Montenegro) and under different climatic conditions during six months of interest (during vegetation period when crop diseases are expected to appear). Thus, we have good climatic diversity which allows for better verification of the proposed model.

The influence of different moisture measurements on triggering of the disease prediction model is shown in the figures and tables below, respectively for all observed vineyards.

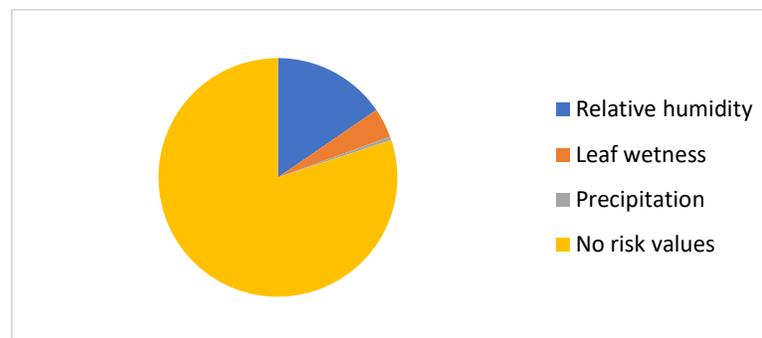


Figure 4. Vineyard 1 Fruška gora, Serbia

Table 2. 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%

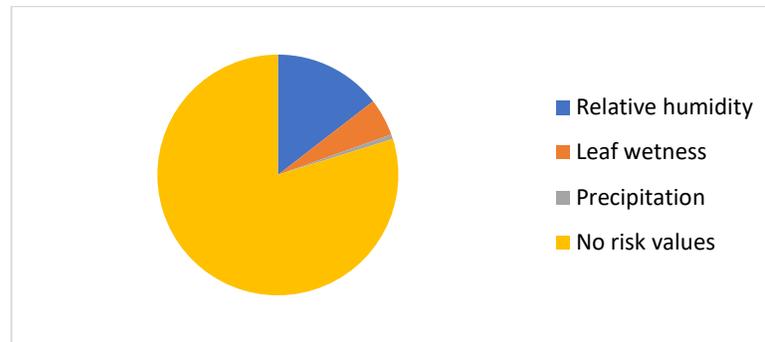


Figure 5. Vineyard 2 Fruška gora, Serbia

Table 3. 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%

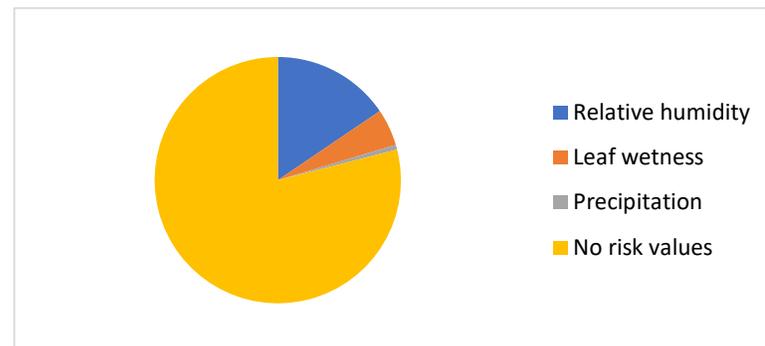


Figure 6. Vineyard 3 Fruška gora, Serbia

Table 4. 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%

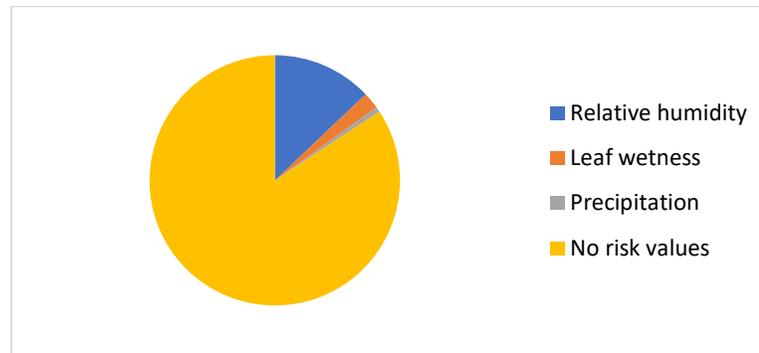


Figure 7. Vineyard Montenegro

Table 5. 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%

From the tables it is notable that the relative air humidity sensor provides the most of values for the model (up to 33.9%), the leaf wetness sensor is highly desirable to increase the number of risk cases (up to 10.5%), while the precipitation sensor could be value added, but its contribution is rather limited, up to 1.4%. It is obvious that the measurements highly depend on the 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 most 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.

Table 6. Overall average values

	Relative humidity	Leaf wetness	Precipitation
Vineyard 1 at Fruška gora	15.42%	4.03%	0.47%
Vineyard 2 at Fruška gora	14.53%	4.98%	0.64%
Vineyard 3 at Fruška gora	15.53%	4.83%	0.65%
Vineyard at Montenegro	12.95%	2.15%	0.62%
All vineyards	14.61%	3.99%	0.59%

The average values for all results are graphically shown as the pie charts:

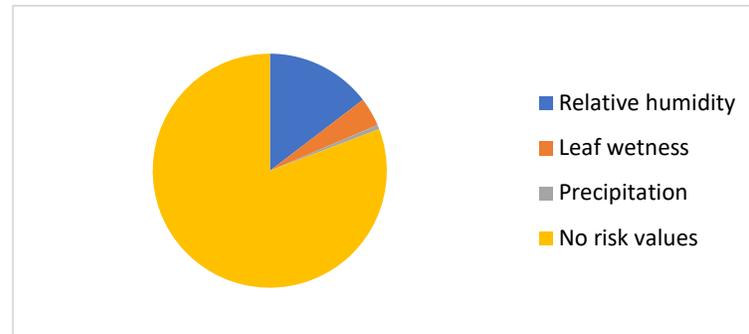


Figure 8. Overall average values for all vineyards

The average values are quite similar for vineyards in Serbia (which was expected, since they are in the same area – Fruška gora, but still micro climate conditions could affect monitored values). Also, the vineyard in Montenegro in average shows very similar behaviour, 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 6). 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.

5. Discussion

Data gathering, as the first step of the smart and precise agriculture process, relies heavily on the accuracy of the data coming from different IoT devices and sensors deployed in the field, meteorological stations, and satellite data. These data are used to drive pesticide application and irrigation and its accuracy is of particular importance, as it mitigates the influence of external factors such as wind direction, clouds, and structure of the terrain.

For fungal forecast models, temperature and humidity are the two contexts used interchangeably to predict if disease conditions are met. When the first is not available, – the other is used instead for providing decision support to a farmer. 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 cases, in 8.1% by leaf wetness sensor measurements, and finally, in 0.5% by precipitation sensor measurements. If only relative air humidity sensor is used, the prediction model will be triggered in 31.4% cases. 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. The overall cases for triggering the model are $31,4+8,1+0,5=40\%$. It is obvious that vineyards in Fruška gora have quite similar results (although they are not collocated, but 50km distanced), and that the vineyard in Montenegro shows similar behaviour, with a slightly lower relative air humidity.

By averaging all obtained results, the main conclusion of the study is that a cheap relative air humidity sensor in average will detect 14.61% risk values, a leaf wetness sensor an additional 3.99% of risk cases, and finally, a precipitation sensor will detect only additional 0.59% risk cases. It is obvious that a 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 relative humidity sensor, especially the precipitation sensor, as it should be timely checked 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 final cost of the installation and service. Activities based on the analysed data, can help

farmers to optimize production, better use of all inputs, increase product quality, predict potential problems, better plan activities, optimize costs, and consequently achieve higher profit.

6. Conclusions

The precise agriculture concept is becoming a commonly used, affordable for both large-scale and small-scale farms. This is mainly due to the application of the sensor devices, machine learning algorithms, and decision support that can increase the efficiency of the crop production. The main potential problem in precise agriculture is obtaining accurate information on when to irrigate, when to apply pesticides, and other preventive measures. The accuracy of this decision depends directly on the accuracy of the collected data from IoT devices. The data should be in correlation with the two main factors used for disease prediction: humidity and temperature. In this paper, we have presented decision support instructions for farmers against the *Botrytis cinerea* disease based on the data collected from IoT sensors – temperature, relative air humidity, rain precipitation, and leaf wetness. The impact of usage these sensors on the accuracy of the forecast modelling is done based on data from in-situ sensors deployed in four vineyards in two countries during the period of six months. The study showed that using low-cost sensors for decision support was more accurate when a relative air humidity sensor was used: in average 14.61% risk values were detected; leaf wetness sensor detected additional 3.99% risk cases, and finally, the precipitation sensor detected only additional 0.59% risk cases.

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Conflicts of Interest: The authors declare no conflict of interest.

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