

Article

Grapevine Downy Mildew Warning System Based on NB-IoT and Energy Harvesting Technology

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Abstract: One major problem that affecting grape production is that of infestations by fungal pathogens, among which *Plasmopara viticola* is one of the worst, causing grapevine downy mildew. This can cause substantial damage to a vineyard, which leads to economic losses. Methods of predicting disease outbreak rely on the monitoring of meteorological parameters. With the recent development of Internet of Things (IoT) technologies, in situ data can be efficiently collected on a large scale. In this paper, a new model with early warning system implementation for grapevine downy mildew based on Narrow Band IoT (NB-IoT) and energy harvesting is presented. Models of downy mildew warning systems have evolved from the early temperature-based (and later, humidity-based) models to the latest mechanistic models which include rainfall/leaf wetness and hourly monitoring. We added parameters such as 'favorable night condition' and 'wind speed' as critical for sporangia spreading. The comparison of the model with the commercial iMetos[®] warning system and the latest mechanistic model for three specific vineyard locations indicates a high correlation between alarms.



Citation: Mezei, I.; Lukić, M.; Berbakov, L.; Pavković, B.; Radovanović, B. Grapevine Downy Mildew Warning System Based on NB-IoT and Energy Harvesting Technology. *Electronics* **2022**, *11*, 356. <https://doi.org/10.3390/electronics11030356>

Academic Editors: José Santa, Andrés Muñoz and Juan Antonio Martínez Navarro

Received: 20 December 2021

Accepted: 17 January 2022

Published: 25 January 2022

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Keywords: NB-IoT; energy harvesting; grapevine downy mildew; decision support; early warning

1. Introduction

Downy mildew is among the most harmful diseases to grapevine [1,2]. It is caused by the fungi *Plasmopara viticola*. The fungi overwinter in infected leaves and litter in the soil as oospores that germinate in the spring and produce a sporangium. Rainfall and wind can disperse the primary zoospores to grapevine leaves. Zoospores can swim through water and only penetrate through the stomata. The process of sporangia production occurs at night (for at least 4 h) under very humid conditions (relative humidity of 95 to 100%) and at a favorable temperature (an optimal temperature for growth is approximately 25 °C).

The number of infestations varies from one year to the next, primarily depending on the weather conditions. Under favorable weather conditions, the disease can cause huge losses due to the infection of the entire grapevine canopy (green parts). The worst epidemics occur in years with wet winters and wet springs followed by a hot summer with occasional rain showers. Meteorological parameters such as temperature, precipitation and relative humidity should be known in order to take proper measures against the disease. These parameters are used to determine the incubation period, which allows immediate actions to be taken.

Plasmopara viticola has two cycles of infestation. The first infestation cycle develops following the widely known 3–10 (three tens) rule [3]. The rule is based on the simultaneous occurrence of the following conditions: vine shoots at least 10 cm long, a minimum of 10 mm of rainfall within 24–48 h and average daily air temperature equal to or greater than 10 °C. Persistent rain, high humidity, and average daily temperatures higher than 11–14 °C (depending on region and authors) are critical to primary infections cycles. Secondary infections only occur if the primary infection has already spread. Primary infection spread

is directly observed in the form of the so-called “oil stains” found on grapevine leaves. Secondary infection can only occur under favorable night conditions, i.e., in humid, wet, and wind conditions, with temperatures higher than 12 °C. Various simulation models can provide the basis for the development of useful systems for timely disease warning and forecasting [2]. The winemaker can therefore optimize the number and timing of treatments. It is generally assumed that under favorable conditions, *Plasmopara viticola* can inoculate one primary infection and several secondary infections. However, Kennelly et al. [4] have shown that multiple primary infections can occur during a single season. The disease prevention strategies include treating the primary infection immediately before rainfall. A good weather forecast service is required in order to take as timely action as possible. If the infection has already occurred, a percentage of affected area will influence the method of treatment. Most of present disease treatment strategies include applying proper chemical sprays (copper-based fungicides or systematic fungicides, etc.). The application of sprays generally follows a fixed calendar schedule which results in a number of unnecessary treatments and large associated economic, health and environmental impacts. A more up-to-date approach in precision agriculture involves using precise data on environmental conditions (for example, on weather, soil or plants) and predicting infection periods. Precise data can enable the provision of timely warnings for both primary and secondary infections. A new model of the warning system with additional parameters that can replace conventional models is proposed in this paper.

Wireless sensor networks (WSNs) have been used in short-range communication for decades. In the last decade, these have evolved into new systems such as massive machine to machine (M2M) and the Internet of Things (IoT) [5]. New technologies have recently emerged for scenarios where low power and a wide area are required. Technologies such as LoRaWAN [6] and Sigfox are used in non-licensed bands of the frequency spectrum. In the licensed spectrum covered by mobile network operators (MNOs), the Narrowband Internet of Things technology (NB-IoT) [7,8] has emerged, with the advance of the Long Term Evolution (LTE) and issuing of 3GPP standard Release 13 [9]. NB-IoT has been in use for a few years, with several hardware platforms available (for example, U-blox SARA-R410 and Quectel BC-68/95 modules).

NB-IoT uses star topology where all the sensor nodes are directly connected to the LTE cellular base station acting like a concentrator or the ‘sink node’ in WSN terminology. The underlying network core performs all the necessary data processing. On the other hand, the WSN uses multi-hop communications and distributed systems in most applications. Figure 1 illustrates an example of the NB-IoT system. This shows the end-to-end NB-IoT details of connection for a reliable and efficient communication system between the two end points: a wireless sensor node and a cloud application. At the physical level, the wireless sensor node receives all the information on environmental conditions (e.g., temperature, humidity, etc.) and transfers the information to the mobile operator eNB (Evolved Node B) using the User Datagram Protocol (UDP) or Transmission Control Protocol (TCP) with higher overhead. All the NB-IoT signals are managed within the mobile network operator premises by using various protocols (e.g., radio resource controls (RRC), non-access stratum (NAS), and mobility management entity (MME)). The received data are forwarded through a packet gateway (PGW) to an IoT platform that manages the cloud application. With regard to the application level, there are several options such as MQTT or CoAP.

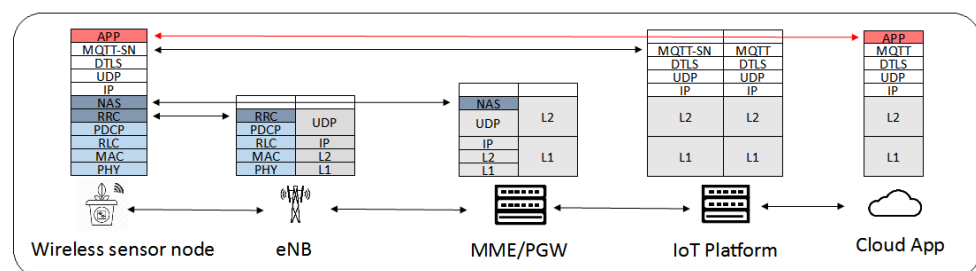


Figure 1. NB-IoT system overview with an exemplary protocol stack.

Energy efficiency [10] is crucial for all the low-power IoT and M2M communication technologies including the NB-IoT. Long battery life is fundamental to extending the system life to the final goal of 10 years. A decrease in service and maintenance costs can also be achieved. Cellular technologies do not feature low power and energy efficiency by default. The NB-IoT uses LTE cellular technologies with some modifications and simplifications in order to decrease power consumption. The list of NB-IoT characteristics and assumptions is provided below:

- Infrequent data transmissions;
- Low data rates;
- Specific dataflow;
- Extended coverage (due to the 20 dB boost of maximum losses);
- Battery and system lifetime extension by low-power device design;
- Reduced signaling compared to ‘conventional’ cellular technologies;
- High scalability.

Feltrin et al. [11] provided more technical details and explanations on potential NB-IoT configurations and the data exchange procedures (both uplink and downlink). Lukic et al. [12] explained the specific non-IP and IP-based data flow in the NB-IoT networks. Most of the early warning systems and decision support and forecasting systems for grapevine diseases currently use the well-established communication technologies such as SMS or GPRS but some alternative solutions with LoRaWAN or the NB-IoT were recently developed (e.g., Metos [13]).

Where a large number of sensor devices are needed to monitor a particular area, the operation of these devices with minimum maintenance requirements should be provided. In this regard, we applied energy-saving techniques to ensure uninterrupted operation over a long time without having to recharge or replace batteries. A photovoltaic cell and a LiPo battery with a charging circuit were added to complement the usual NB-IoT power preserving methods such as the power saving mode (PSM) and the microcontroller unit sleep mode during periods of inactivity. The used energy harvesting feature enables the compensation of energy discharged by measure-and-transmit cycles, which was confirmed by measurements and calculations, as discussed in Section 2.3.

1.1. Related Work

A review of the related works on the two research areas, downy mildew models and the warning and forecasting systems, is provided in this section.

Early downy mildew warning system models were based on incubation methods. After the conditions for primary infection are met (e.g., as indicated by the 3–10 method [3]), Miller’s incubation method [14] can be used to estimate the incubation period of time (number of days). This incubation method resulted from many decades of research in central Europe [15]. The incubation curve is interpreted in the form of a table in order to enable the estimation of the incubation period based on average daily temperatures. The main drawback of this method is that it predicts the duration of the incubation period from the average daily temperature at the time of the beginning of incubation. A more precise method has been developed [15] to account for daily averages. It can be given by Equation (1), which corrects the estimation of the incubation period on a per-day basis. Note that Miller’s method does not take into account days with average daily temperatures below 12 °C:

$$c = \frac{a}{b} - b \quad (1)$$

where c is the number of days before the incubation is completed, b is the number of days that have passed after the infection started (the days with average daily temperatures below 12 °C are not taken into account), and a is the sum of the estimated duration of incubation period for every day that has passed after the infection started.

A similar method is that of Shatsky’s incubation method, in which the incubation time is taken as a daily ratio based on the average daily temperature. When the daily ratios sum

up to 100%, the incubation period can be considered completed. Only days with a new temperature threshold (8 °C, instead of 12 °C) qualify for the estimation. The actual daily add-ons to the sum based on the average daily temperature are given in a table in [15].

Russian scientists Mersanin and Lipitskaya found that the incubation period calculated as a sum of effective temperatures could be considered during the period when the sum was 61 °C. Here, the temperature threshold is set to 8 °C.

The Goidanich index (GI) [16] is applied where the 3–10 requirements are met, and an observation of the evolution of primary infection can start. Unlike the early methods that only use average daily temperatures, the GI is based on monitoring the average daily temperature (T_m), the average relative humidity (H_m), and precipitation. In addition, low and high humidity values are distinguished with the GI. The Goidanich table-based model [16] can be described as a more practical version of the two equations [17].

One of the early mechanical models [18] (we designate it as mechanical model 1) simulated the monitoring of the entire infestation spread during the season. To calculate the incubation period, the hydro-thermal time from the temperature, humidity, and precipitation data including hourly monitoring was used.

A more recent simulation model [19] of downy mildew epidemics was based on a complex set of parameters to simulate epidemics throughout the entire season. However, the incubation period was set to two discrete values in correlation with the levels of temperature (cold and warm) and humidity (wet, partly wet, dry, and very dry). Temperature is considered cold at below 13 °C and warm at above 13 °C. The daily precipitation is added for the wet and partly wet parts in the next model [20] (we designate it as mechanical model 2).

Present early warning systems (EWSs) for the disease forecasting generally consist of (1) a module for collecting environmental and weather information (from on-site sensors or meteorological services); (2) a model for disease prediction; (3) a hardware and communication module; and optionally (4) a cloud-based platform service. The early EWS was designed to operate offline on a desktop computer [21,22]. Systems with fundamental communication based on the SMS were subsequently introduced [23]. With the growth in wireless sensor networks, Web technologies, and especially the Internet, the early warning systems and forecasting systems for grape diseases have begun to use widely available communication technologies (such as the Web [24], GSM/GPRS [25] and WiFi [26]). Some commercial solutions that use modern low-power technologies such as LoRaWAN or NB-IoT, have recently emerged (e.g., Metos [13]). Two examples of a platform-based approach consist of a weather station net, disease models, and the Internet website with specific tools and features [27]. A new line of research suggests using a machine learning approach to downy mildew forecasting [28].

1.2. Contributions

The contributions of this paper are as follows:

- A new algorithm for the warning system and a model for the early prediction of downy mildew of grapevines (primary and secondary infections) in the vineyard use-case were developed and presented. In addition to temperature and relative humidity, it uses additional sensor data (hourly based data, wind speed, and day/night period) to make the model more accurate than traditional methods.
- A complete design and overview of the implementation of the NB-IoT and energy harvesting-based early warning system (called Winet) with a wireless sensor node for monitoring several environmental parameters are presented, including both hardware and software (cloud-based front-end, back-end, and mobile application). To the best of our knowledge, there has not been any published scientific research to date using the NB-IoT technology in downy mildew EWS implementation.
- The proposed model is compared with the alarms provided by the commercial Field-Climate system [29] that uses iMetos1 and iMetos3.3 data collection system, for the three particular vineyard locations of Vršački Vinogradi, Serbia, Rimski Šančevi, Serbia,

and Trient, Switzerland, during the 2020 season. The results show a full correlation with iMetos[®] alarms in the case of severe infection warnings for all given locations. The correlation ranges between 0.4 and 1 for moderate and light infection alarms.

- In addition, the proposed model is compared with the latest mechanistic model [20]). The correlation ranges between 0.55 and 0.71 for the secondary alarms.

The paper is organized as follows. A detailed system overview is provided in Section 2. The research results are presented in Section 3 while the discussion related to obtained results is in Section 4. Finally, the conclusions and future research directions are discussed in Section 5.

2. System Overview

In this section, the components of the designed system are explained in detail.

In Figure 2, the same icons as in Figure 1 are used to illustrate the hardware and the software components of the designed Winet system. The algorithm of the Winet warning system runs in the Cloud. Data from the sensor are sent by microcontroller board with the NB-IoT communication and energy-harvesting module. There is also an in-house developed add-on board with a display connecting all environmental sensors. The end-user reads the results and gets warnings from the provided cloud front-end and back-end application with appropriate dashboard and visualizations. In addition, a mobile application was also developed.

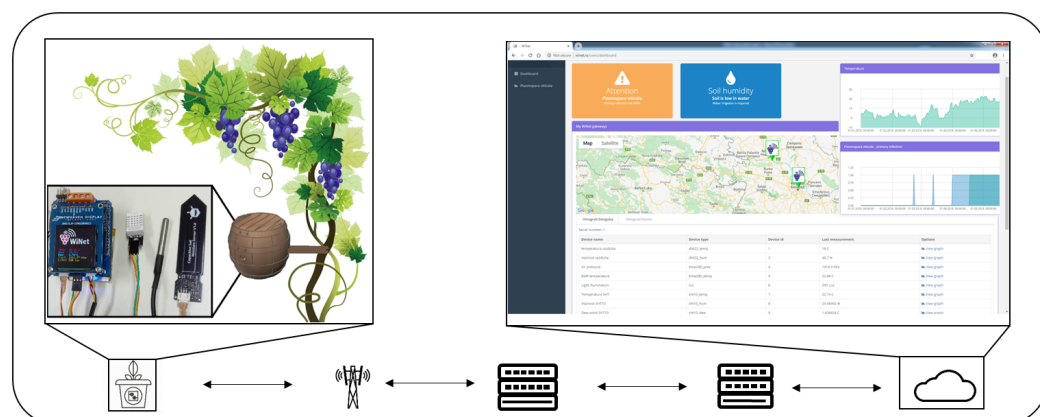


Figure 2. The Winet system overview focusing on hardware and software components: the barrel-like casing holds the NB-IoT module (left); Web user interface for vineyard mildew monitoring (right).

2.1. Warning System Algorithm and Model Overview

The proposed model for primary infection warning starts when the grapevine shoots are in stage 13 of the BBCH scale (i.e., the shoots are at least 10 cm long, or a few unrolled leaves) at minimum [30]. Then, the average daily air temperature, precipitation, wind, and daytime/nighttime are monitored. When the average daily temperature exceeds 10 °C and the precipitation within the last 48 h reaches 10 mm, conditions for winter spores germination are met (designated as 3–10 flag = 1 in our model). If rainfall or gentle breeze (i.e., wind of speed greater than 3.4 m/s according to the Beaufort scale) occurs at night within the following 48 h, primary infection has presumably occurred, causing the start of the incubation period of *Plasmopora viticola*. When 48 h without rainfall elapse, the 3–10 flag is reset to zero. The incubation period is calculated on daily basis according to:

$$f(t) = 0.076t^2 - 3.453t + 42.925 \quad (2)$$

fitted using Miller's incubation tables [15] (with 99.7% correlation), followed by Equation (1). When the incubation period has been completed, the algorithm for secondary infection starts monitoring weather conditions and updates the warning system. Because primary infection can occur multiple times in a year [4], the algorithm for primary infection con-

tinues to monitor and update the warning system until the end of the current season. The primary infection warning system algorithm is shown in Figure 3.

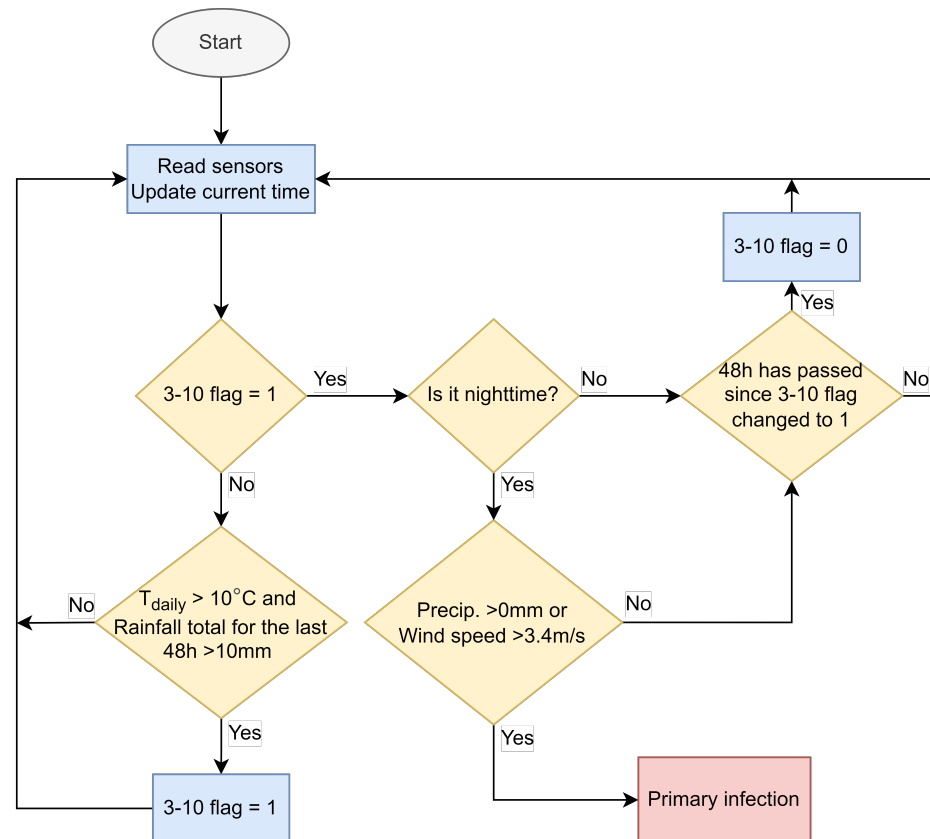


Figure 3. Algorithm for primary infection alarms.

In order to provide a timely alert for secondary infection, sporulation on downy mildew lesions were assessed. Favorable night conditions (FNCs) are monitored. Night conditions are considered favorable if the weather is humid (relative humidity (RH) > 80%) and the temperature is higher than 12 °C for at least 2 h. The secondary infection warning is triggered when the following conditions occur: an additional 2 h of uninterrupted leaf wetness (LW) and average temperature (T) above 10 °C (similar weather assumptions [31]), with precipitation or strong wind that can increase spore spread. Night conditions are no longer favorable (FNC = 0) if relative humidity (RH) drops below 60% for at least two hours. The secondary infection warning algorithm is illustrated in Figure 4.

The main novelties of our algorithm are the monitoring of wind speed for both primary and secondary alarms and observing favorable night conditions (FNCs) for the secondary alarms. Wind and FNC as crucial parameters for sporangia dispersion are reported in several works. The latest is in [20]. However, the wind is not a part of their model.

2.2. The Sensor Node

The sensor node we used for the on-site data collection (Figure 5) is designed based on the off-the-shelf module Sodaq SARA AFF [32] featuring the NB-IoT module from uBlox ATSAM21J18 and the 32-Bit ARM Cortex M0+ microcontroller. The shield is designed to support various onboard and external sensors as specified in Table 1.

It is planned to include a leaf wetness sensor and an anemometer in the next version of the sensor node.

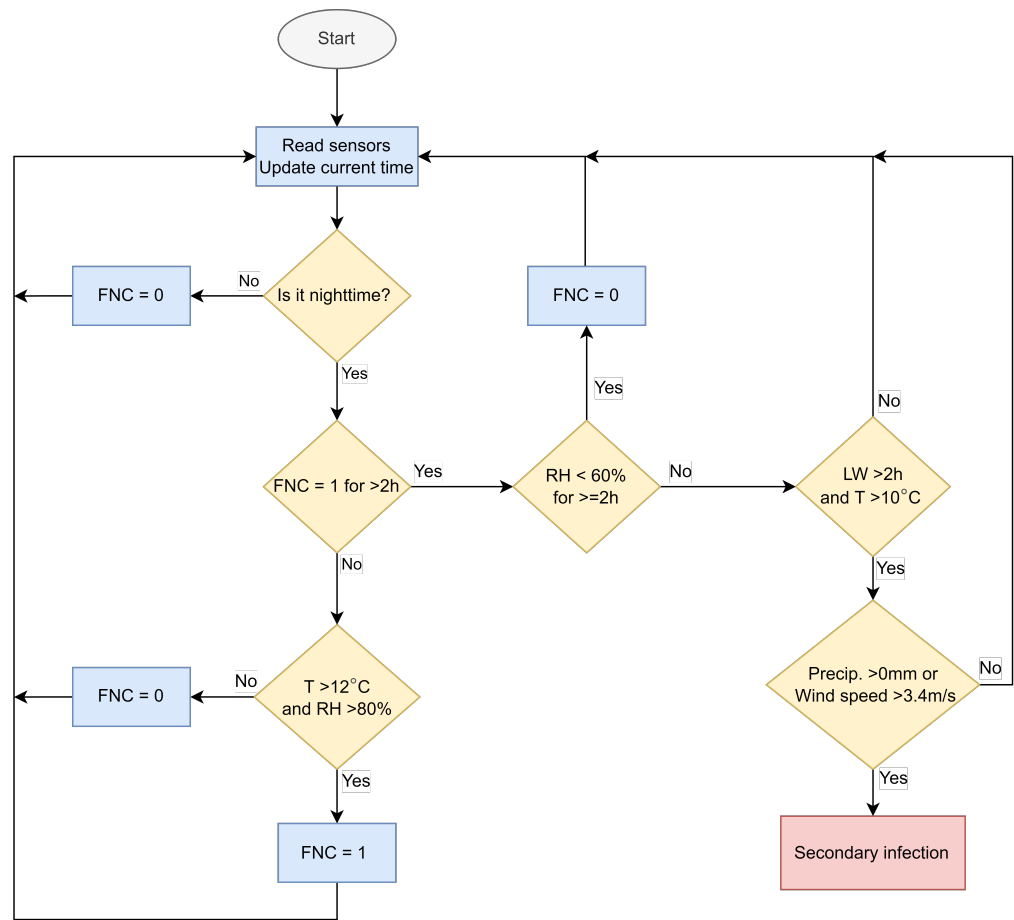


Figure 4. Algorithm for secondary infection alarms.

Table 1. Sensor specifications.

Sensor Type	Operational Range	Unit
Air temperature	−40 to 85	°C
Air pressure	−300 to 1100	hPa
Relative air humidity	0 to 100	%
Ambient light	1 to 65,535	lx
Soil temperature	−55 to 125	°C
Soil moisture	0 to 100	%

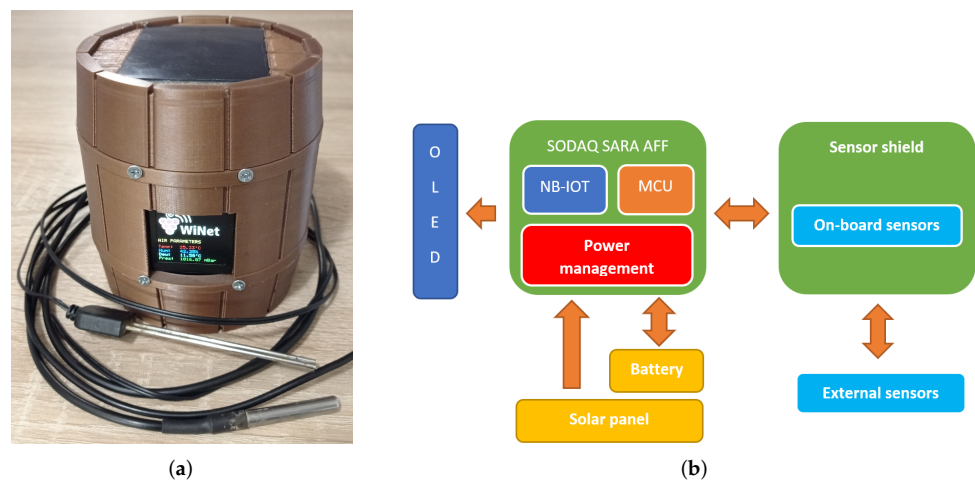


Figure 5. Sensor device: (a) physical appearance; and (b) block diagram.

2.3. Energy Harvesting

The in-depth evaluation of power consumption was performed by monitoring the current consumed by the device, as shown in Figure 6. With a typical LiPo battery (3.6 V, 1000 mAh), the total energy budget is $E_{total} = 3.6 \text{ V} \times 1000 \text{ mAh} = 3600 \text{ mWh}$. The average power consumed during a single measure-and-transmit cycle is approximately $E_{TX} = 650 \text{ } \mu\text{Wh}$, and the average time required to complete the cycle is $T_{TX} = 8 \text{ s}$. On the other hand, when the device is in low-power mode between two measurements, the average power consumption is $P_{sleep} = 26 \text{ } \mu\text{A} \times 3.6 \text{ V} = 93.6 \text{ } \mu\text{W}$. When n cycles of data collection are performed per day, a total daily energy consumption is calculated, as shown in Equation (3):

$$E_{daily} = n \times E_{TX} + (24h - n \times T_{TX}) \times P_{sleep} \quad (3)$$

Accordingly, the total lifetime of the system (in days) can be calculated as $\frac{E_{total}}{E_{daily}}$. Table 2 shows the estimation of battery life for various numbers of daily measurement cycles, with an assumption that no energy-harvesting techniques are applied whatsoever.

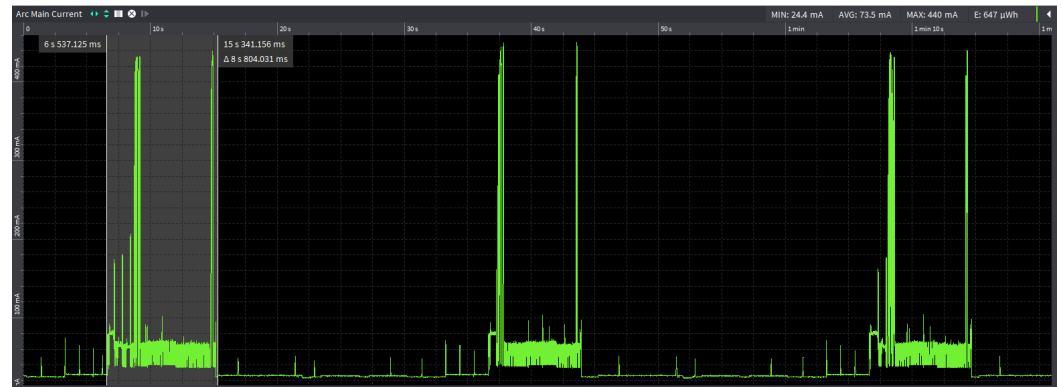


Figure 6. Current consumption log.

Table 2. Battery lifetime depending on the number of daily sampling cycles.

Sampling Period	n (nb. of Daily Cycles)	E_{daily} (mWh)	Battery Lifetime (Days)
24 h	1	2.90	146.06
12 h	2	3.55	142.32
8 h	3	4.20	138.76
6 h	4	4.85	135.38
4 h	6	6.15	129.09
3 h	8	7.44	123.36
2 h	12	10.04	113.30
1 h	24	17.84	91.03
30 min	48	33.44	65.34
20 min	72	49.03	50.96
15 min	96	64.63	41.77
10 min	144	95.82	30.70
5 min	288	189.39	17.10
2 min	720	470.10	7.34
1 min	1440	937.95	3.76

The solar panel used in the model for the battery recharge has the output power $P_{solar} = 400 \text{ mW}$ with the reference value of solar radiation of $\frac{1 \text{ kW}}{\text{m}^2}$. Under the most unfavorable operating conditions (1 transmission per minute), it takes $\frac{E_{daily}}{P_{solar}} = 2.34 \text{ h}$ to fully compensate for daily consumption. Statistical data available online [33] indicate that in all grapevine growing regions, the daily amount of solar radiation is large enough to provide the uninterrupted operation of the edge node with no need to recharge, even under the most demanding operating conditions.

2.4. Server Back-End

The data collected at the sensor node are transmitted through the NB-IoT network and the Internet to the WiNet application back-end server, as illustrated in Figure 7.

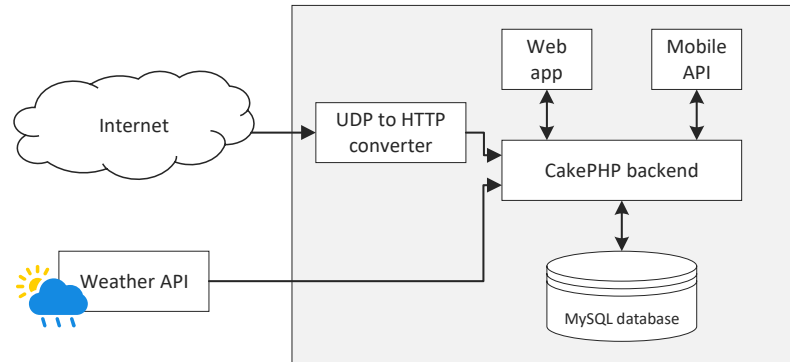


Figure 7. The Winet server.

The server application was developed using the CakePHP software framework. The data were sent from the sensor node to the server by using the UDP protocol. The Python service translates the UDP packets into an HTTP request. Each time a new message conveying the sensor measurements is received, a corresponding HTTP request is created, which is then received by the CakePHP back-end. The specific API endpoint developed within the back-end checks the data and if the format is correct, the measurements are stored in a MySQL database, as illustrated in the diagram in Figure 8. It can be seen in the diagram that every user in the system has a connected gateway device.

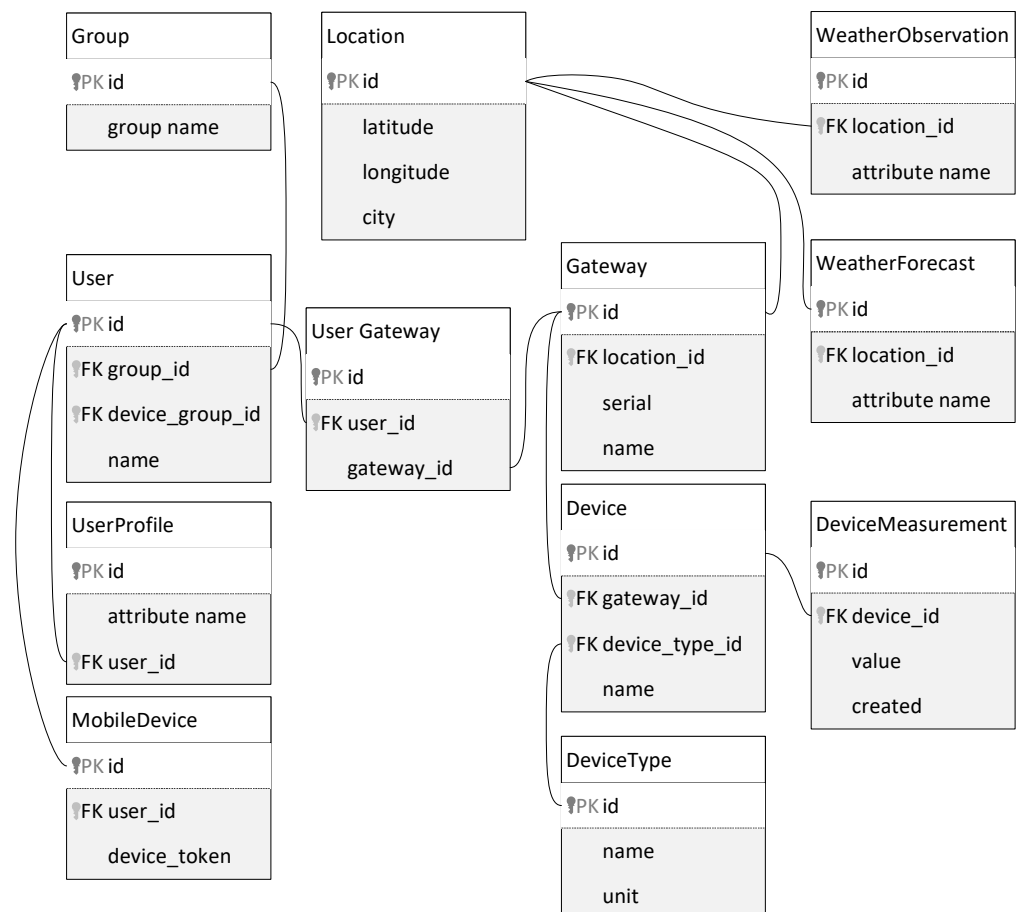


Figure 8. The Winet MySQL database schema.

The server collects data from the sensor node and also takes over the data from the external weather forecast API. The weather data are collected from the Weatherbit.io API that provides current weather observations as well as weather forecasts on an hourly basis. The algorithms discussed in the previous sections are periodically run for the collected data to enable predictions. The user has the following options to access the data: the Web application and the Android mobile application, which are described in the following subsection.

2.4.1. Web Application

The Winet Web application is designed on the top of the Web server back-end (see Figure 9). It supports authentication and authorization options with different user roles. The super-administrator account has the right to administer the entire Winet Web platform, manage users, define new measuring device types (see Figure 10), etc. When the vineyard owner/administrator logs into the platform, they can see the graph of various measurements and obtain the alert from the platform, as illustrated in Figure 10.

The Web user interface allows registered users to verify the data for the assigned sensor nodes in addition to the prediction results of the algorithms, as shown in Figure 11.



Figure 9. The Winet Web application—home page.

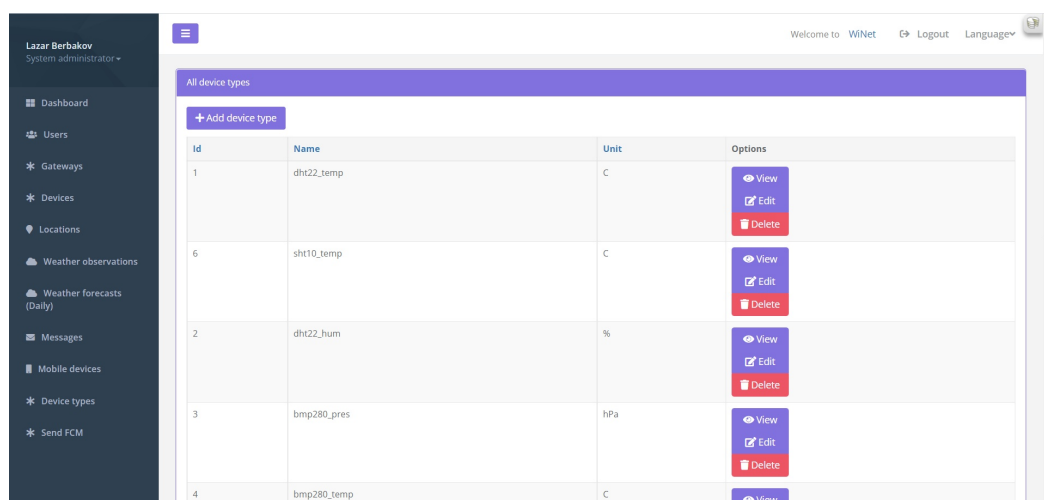


Figure 10. The Winet Web application—sensor type configuration.

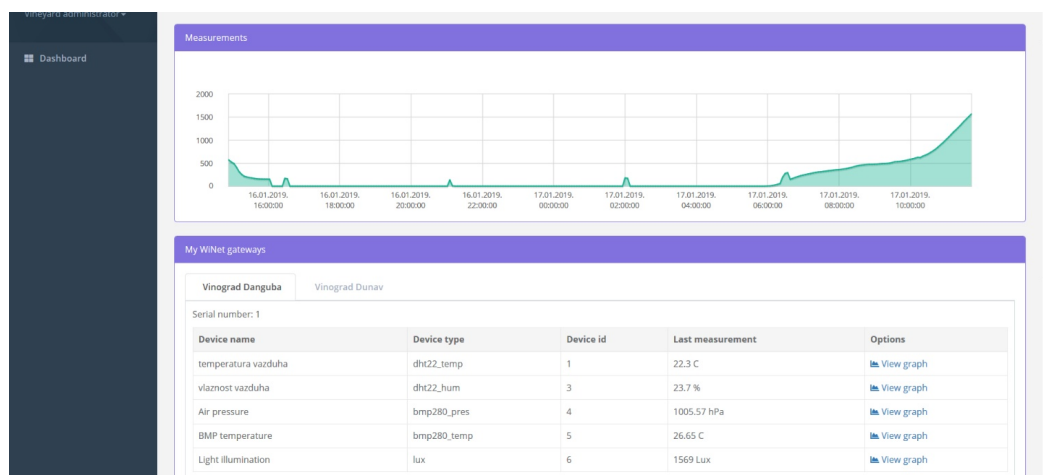


Figure 11. The Winet Web application—measurement graph.

2.4.2. Android Mobile Application

In addition to the Web application, a mobile Android application has also been developed. While the Web interface is more suitable for the deep analysis of the data, the Android interface provides real-time notifications of the predefined alarms (see Figure 12). The Android application visualizes the data measurements in real time as well as displays present the weather observations and weather forecasts obtained from the weather service weatherbit.io.

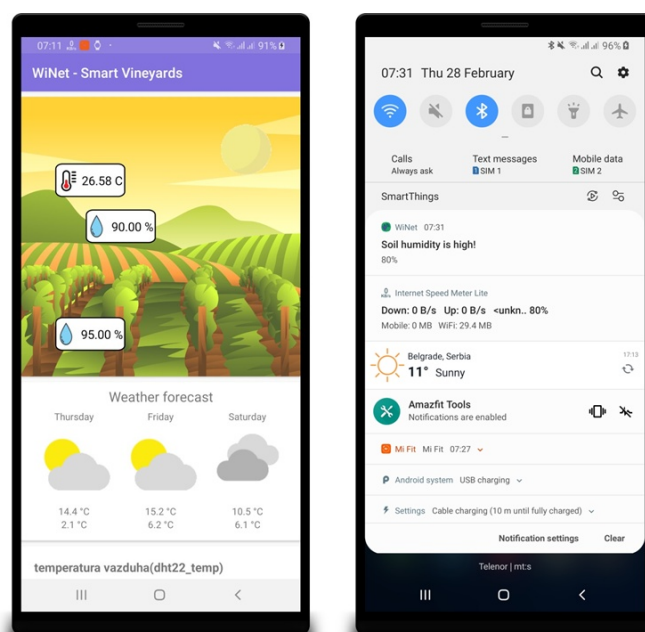


Figure 12. The Winet mobile application.

3. Results

In this section, the results obtained for the primary and secondary alarms for the three locations during the 2020 season are provided and discussed. The first two locations, Rimski Šančevi (RS) and Vršački Vinogradi (VV), are in Serbia. The third location is in Trient (T), Switzerland. The results for the primary infection warning alarms for all three locations are presented in Figures 13–15, respectively. All the results are provided together with the meteorological data. The top part of the figures illustrates relative humidity and precipitation. The leaf wetness and average daily temperatures are displayed in the middle part of the figures. Data on the wind are also included for the location of Trient. For both RS and VV locations, the anemometer was missing and the dataset does not have a wind speed

parameter. iMetos[®] alarms for primary or secondary infections as well as mechanistic model 2 [20] alarms for secondary infections are compared with the alarms provided by the proposed model in the bottom part of the figures. The iMetos[®] system sends alarms for light, moderate, and severe infections, while our model and mechanistic model 2 provide alarms at a single level.

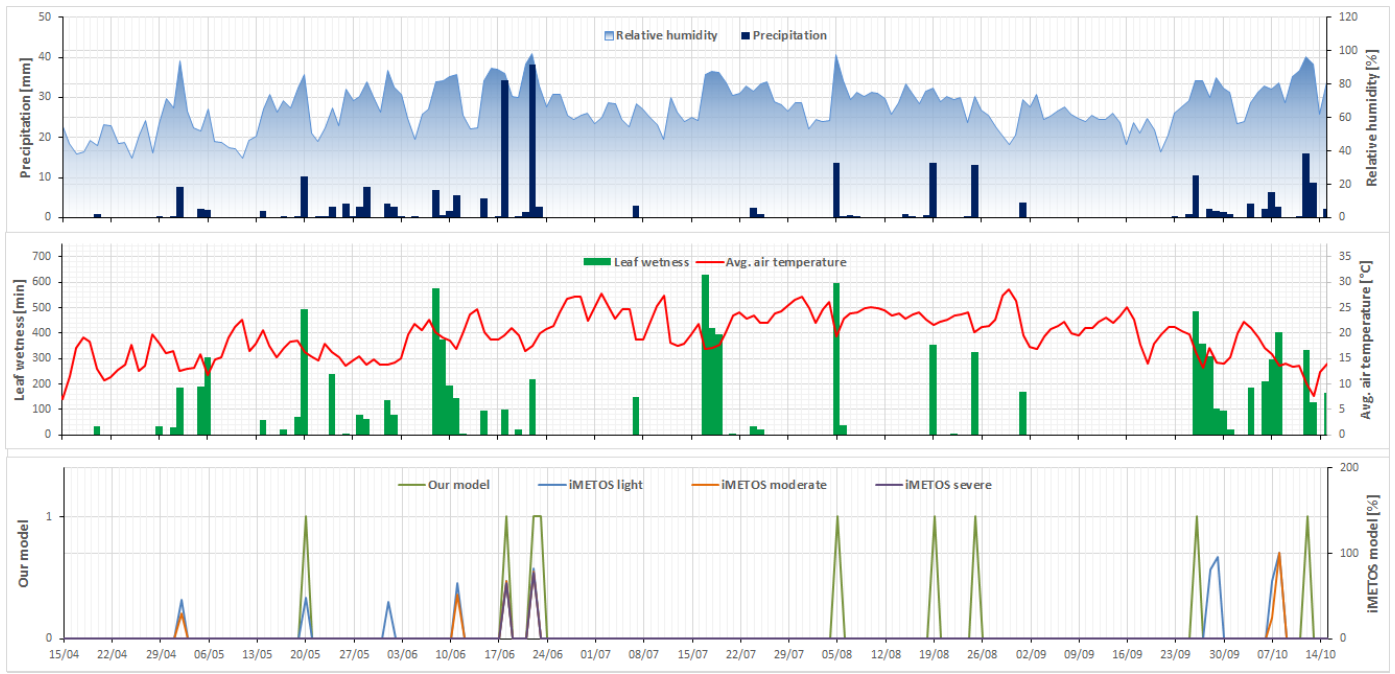


Figure 13. Primary infection alarms for the location 'Rimski Šančevi'.

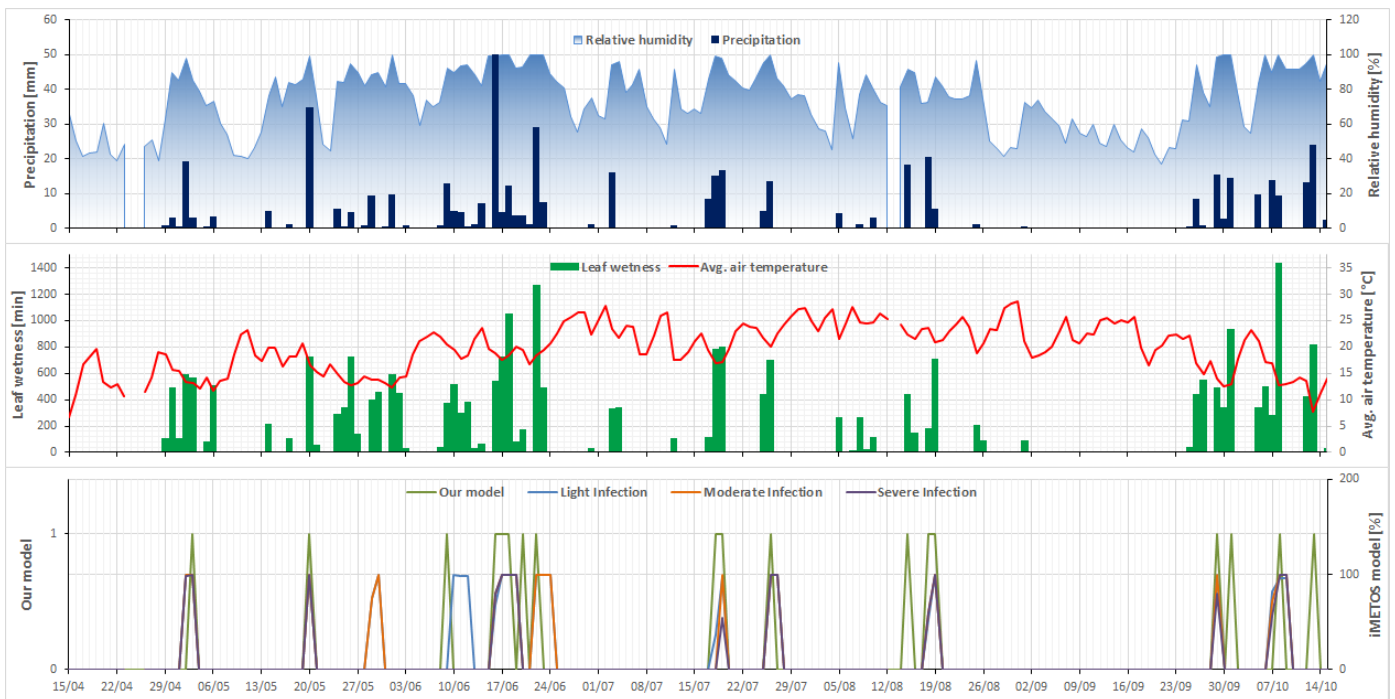


Figure 14. Primary infection alarms for the location 'Vršački vinogradi'.

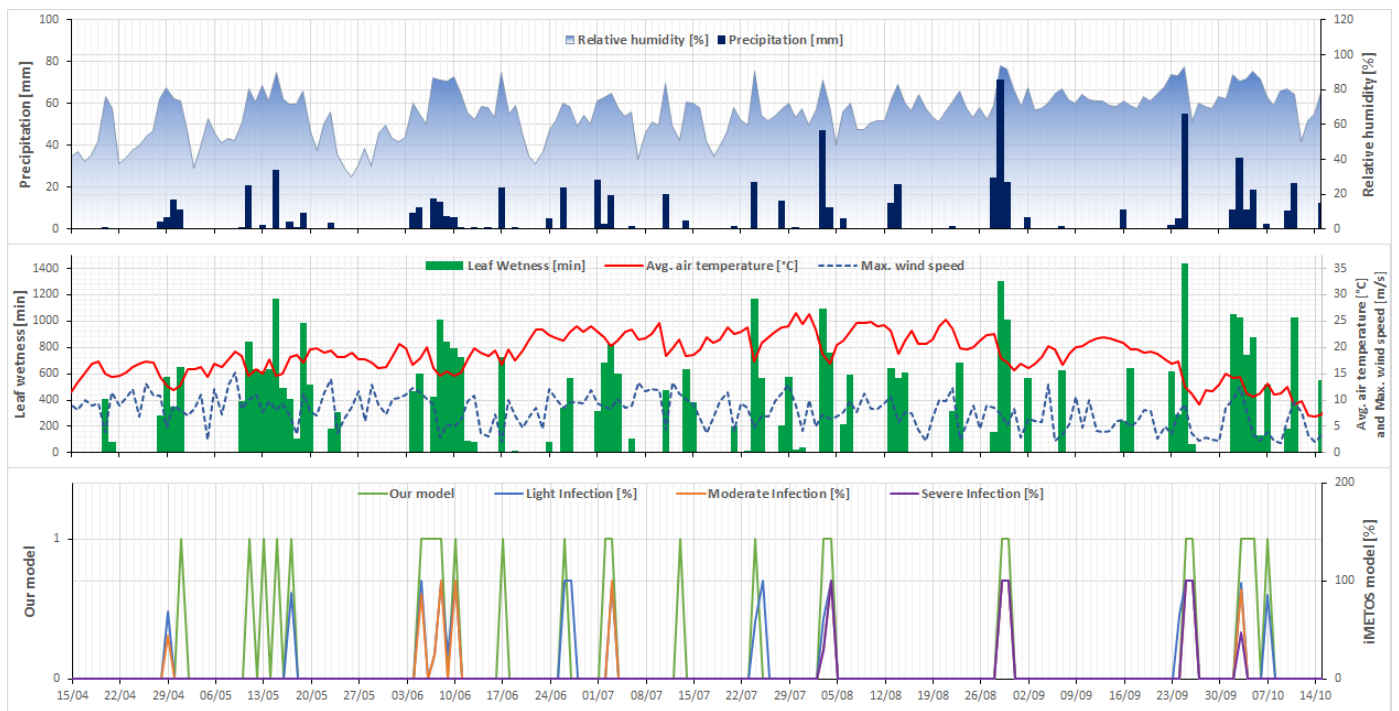


Figure 15. Primary infection alarms for the location 'Trient'.

The results for secondary infection warning alarms for the locations 'Rimski Šančevi', 'Vršački Vinogradi', and 'Trient' are presented in Figures 16–18, respectively. The results given in the figures are summarized in Table 3.

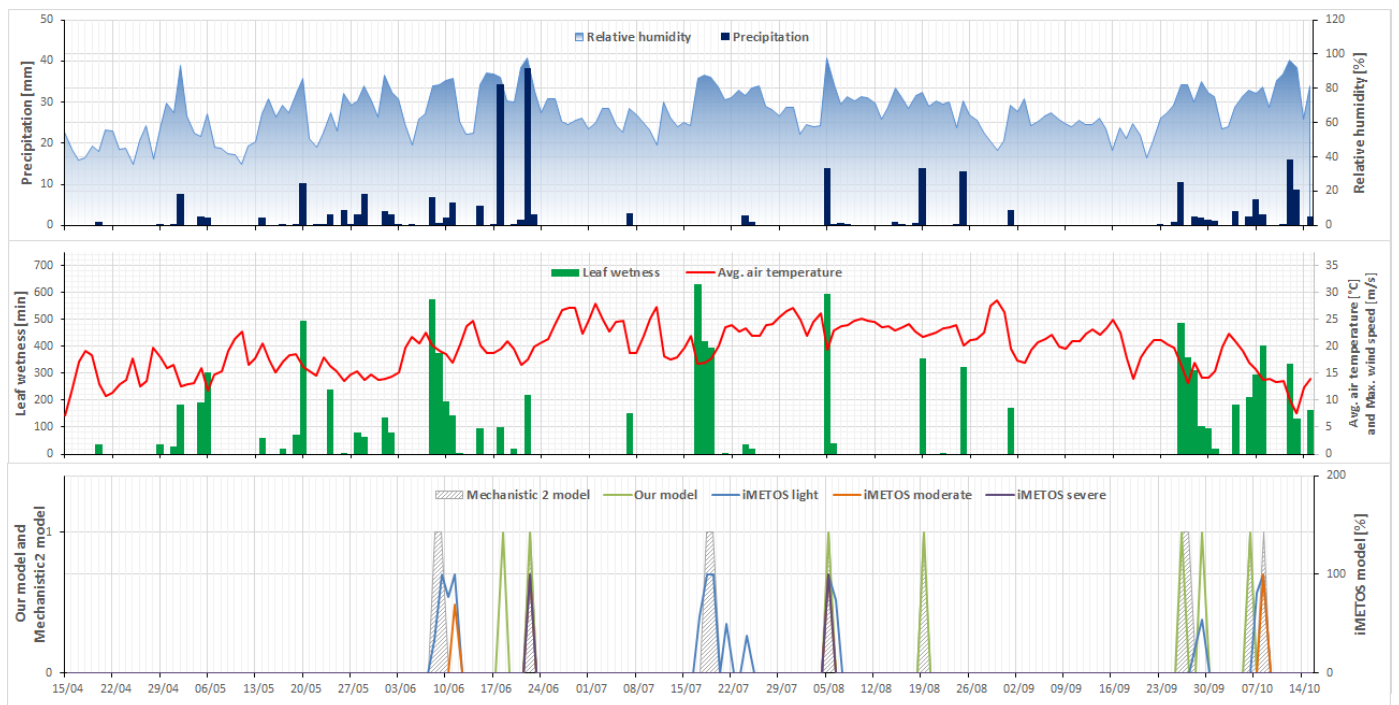


Figure 16. Secondary infection alarms for the location 'Rimski Šančevi'.

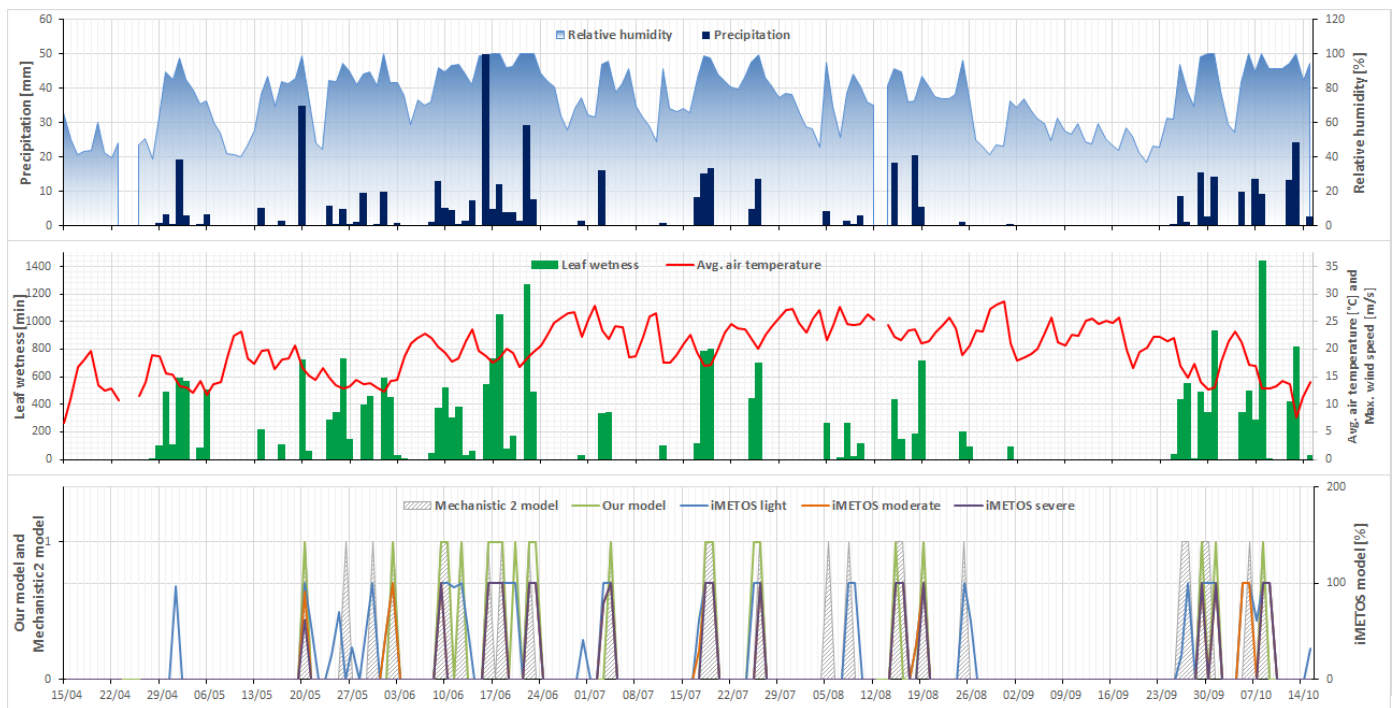


Figure 17. Secondary infection alarms for the location 'Vršački vinogradi'.

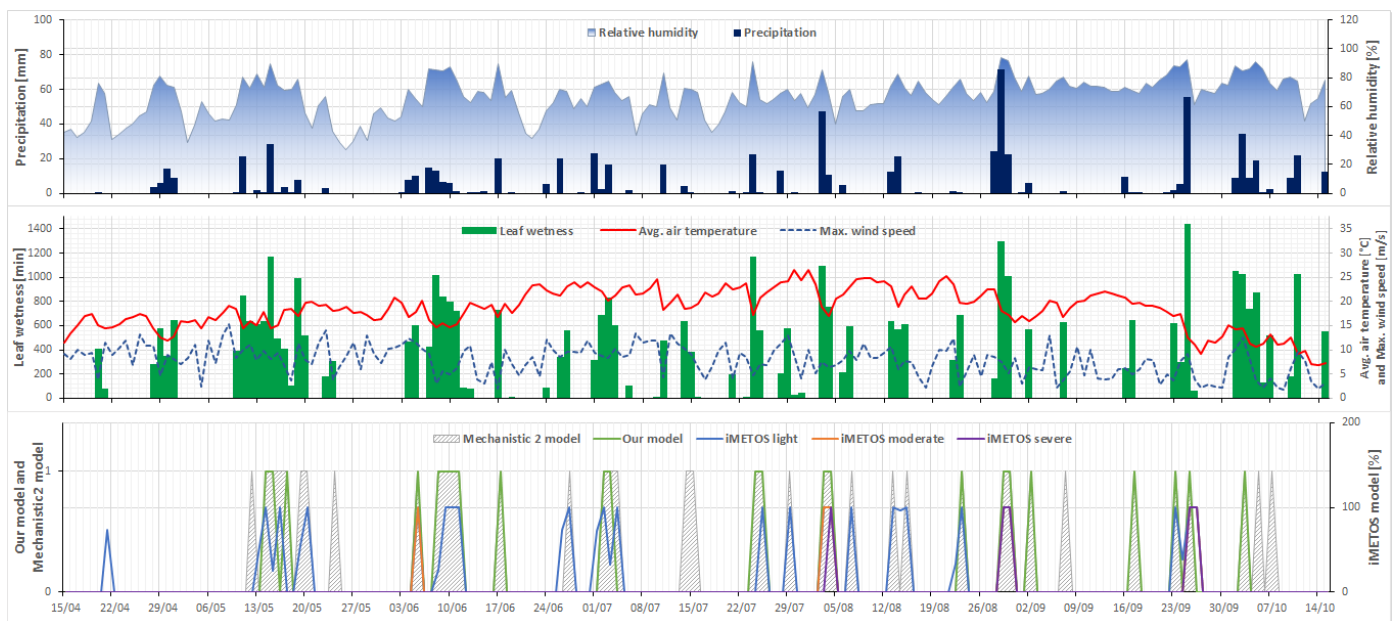


Figure 18. Secondary infection alarms for the location 'Trient'.

Table 3. Winet vs. iMetos[®] and mechanistic 2 alarm comparisons.

	RS		VV		T	
	P	S	P	S	P	S
W/iMl	4/8	4/8	10/11	14/23	13/13	12/18
W/iMm	2/5	3/4	9/10	13/14	9/9	4/4
W/iMs	2/2	2/2	8/8	12/12	4/4	3/3
W+	4	3	2	0	5	4
Cl	0.5	0.5	0.91	0.61	1	0.67
Cm	0.4	0.75	0.9	0.93	1	1
Cs	1	1	1	1	1	1
W/M2	-	5/7	-	15/21	-	15/27
W+	-	2	-	1	-	0
CM2	-	0.71	-	0.71	-	0.55

Legend: RS—'Rimski Šančevi'; VV—'Vršački Vinogradi'; T—'Trient'; P—primary infection; S—secondary infection; W—Winet; iMl—iMetos[®] light; iMm—iMetos[®] moderate; iMs—iMetos[®] severe; W+—additional Winet alarms; Cl/Cm/Cs—correlation of W and iMl/iMm/iMs; M2—mechanistic model 2 [20]; CM2—correlation of W and M2.

4. Discussion

The majority of models used for the downy mildew early warning part of the system are based on incubation methods. The purpose of incubation methods is to determine the duration of the incubation period in days (usually between 4 and 15 days). These methods usually use some common rule for the start of the incubation period (e.g., 3–10 s rule). Most of the used methods are based on temperature as the only parameter used to forecast the duration of the incubation period. An overview of these methods is given in the related work subsection (e.g., [14,34,35]).

The first improvement over the temperature-based incubation methods is the introduction of humidity as a parameter to the model. One such example is the Goidanich index (GI) [16] which introduced two categories of humidity—low and high. The GI combined with aerobiological data was recently assessed [36]. Another example of adding humidity is given in mechanistic model 1 [18] where the duration of primary inoculum season is measured based on so-called hydro-thermal time. The iMetos[®] system [13] offers a widespread, commercial monitoring solution with hourly data sampling [37].

Sporangia development is based on the germination of overwintered oospores in leaf litter on the ground. Appropriate weather conditions are necessary for germination to start. Rainfall on current and previous days has the most effect on spore concentration [36]. The most important weather parameter is the total amount of rainfall during the month of May [28]. In addition, the wind intensity is also important for sporangia dispersion [20]. Although the statistical analyses [36] demonstrated that the wind is not one of the main parameters influencing infection risk, we strongly believe that this claim needs to be more thoroughly investigated.

Our Winet model is an equation and algorithm-based model. It includes both primary and secondary alarms, has hourly monitoring and average daily data, uses air temperature, humidity, rainfall, leaf wetness (LW), day/night time, and wind speed data from sensors. As demonstrated in the Related Work section, the majority of available models from the literature are missing some parameters (e.g., all incubation methods). Mechanistic model 2 (for secondary alarms only and without the wind parameter) and iMetos[®] system are the only ones closely related to the Winet model. The cross-comparison of features among Winet and other models from the literature is presented in Table 4.

Table 4. Features comparison of different models.

Model	P/S	h/avg Data	Air Temperature	Humidity	Rainfall	LW	Light (Day/Night)	Wind Speed	E/A
Miller [14]	P	avg	✓	-	-	-	-	-	E
Shatsky [34]	P	avg	✓	-	-	-	-	-	E
Mersanin- Lipitskaya [35]	P	avg	✓	-	-	-	-	-	E
Goidanich [16]	P	avg	✓	✓	-	-	-	-	E
Mechanistic 1 [18]	P	h/avg	✓	✓	-	-	-	-	E
Mechanistic 2 [20]	S	h/avg	✓	✓	✓	✓	✓	-	E+A
iMetos [®] [13]	P+S	h+avg	✓	✓	✓	✓	✓	?	E+A
Our model	P+S	h+avg	✓	✓	✓	✓	✓	✓	E+A

Legend: P—primary infection; S—secondary infection; h—hourly data; avg—averaged daily data; LW—leaf wetness; E—equation based; A—algorithm based.

Primary infection alarm comparisons between Winet and iMetos[®] [13] from Figures 13–15, show that Winet fired 4 out of 8, 10 out of 11, and 13 out of 13 iMetos[®] light alarms for the RS, VV, and T locations, respectively. These correspond to correlations of 50%, 91%, and 100%, respectively. Moderate alarms show similar results: 2 out of 5, 9 out of 10, and 9 out of 9 with corresponding correlations of 40%, 90%, and 100%, respectively. The best results are for severe alarms: 2 out of 2, 8 out of 8, and, 4 out of 4 showing perfect 100% alignment for all locations.

Secondary infection alarms are compared to iMetos[®] [13] and mechanistic model 2 [20] (M2). The analysis of Figures 16–18 shows that Winet fired 4 out of 8, 14 out of 23, and 12 out of 18 iMetos[®] light alarms for the RS, VV, and T locations, respectively. These correspond to correlations of 50%, 61%, and 67%, respectively. Moderate alarms showed similar results: 3 out of 4, 13 out of 14, and 4 out of 4 with corresponding correlations of 75%, 93%, and 100%, respectively. The best results were again obtained for severe alarms: 2 out of 2, 12 out of 12, and 3 out of 3 showing perfect 100% alignment for all locations. Comparisons between Winet and M2 show that Winet fired 5 out of 7, 15 out of 21, and 15 out of 27 M2 alarms for the RS, VV, and T locations, respectively. The corresponding correlations are 71%, 71%, and 55%.

It can be concluded that Winet alarms are highly correlated with iMetos[®] for all severe alarms for primary and secondary infections. In the case of iMetos[®] moderate alarms, the correlation is also high (>90%) except for the location Rimski Šančevi. The correlation of Winet and iMetos[®] light infection alarms are highly correlated for the locations Vršački Vinogradi and Trient for primary infection alarms, whereas for the secondary infection, it is between 60% and 70% for both locations. In the case of Rimski Šančevi, both the primary and the secondary light infection correlations are approximately 50%. From comparisons with mechanistic model 2 for the secondary infection alarms, it can be concluded that the correlation is between 55% and 71%. The main limitation to our research is that we did not have access to any dataset with labeled primary/secondary infections from in vivo experiments. It could prove the exact effectiveness of the alarms of Winet (and other models). However, to the best of our knowledge, there is no such open access dataset.

The obtained results demonstrate that our model could be used as a grapevine downy mildew early warning system for severe and moderate infections. On the other hand, the light infection alarms do not seem to be sensitive enough in some cases and will be investigated as part of future work. The occurrences of additional alarms (W+) also need more thorough investigation.

The main drawback of the proposed system is the cost of implementation. However, since the maintenance is almost not needed due to energy harvesting, an initial, relatively high investment would be compensated in the long run.

5. Conclusions

A grapevine downy mildew early warning system for both primary and secondary infections was presented in this paper. The proposed model was compared to the models

described in literature, with certain applied modifications (e.g., favorable conditions at night for disease development) and additions (e.g., wind measurements) considered useful. The comparison of the results obtained in the proposed Winet early warning system for three vineyard locations (two in Serbia and one in Switzerland) and in commercially available iMetos[®] system indicates high correlation between the alarms (especially with alarms for moderate and severe infections). Comparisons between Winet and mechanistic model 2 [20] indicate a solid correlation. The proposed system features the new low-power NB-IoT communication and modules for energy harvesting based on photovoltaics. The system is designed to operate battery-free since the solar panel can fully compensate the daily power consumption. Winet system features both Web and mobile applications for user interactions, visualization, and alarms. The proposed system can provide a solid platform to help grape growers make decisions on the disease control strategies in order to optimize the schedule of the treatments, resulting in positive health, environmental, and economic effects.

The first step in future work will be to validate the present findings with a large set of data (including data from a number of years). The proposed model can also be compared to some “simpler” models (e.g., Miller’s). Then, a larger dataset will be used to feed an appropriate machine learning algorithm that calculates the risk of disease outbreak. It would be interesting to experiment with the proposed model in vivo to see whether any additional alerts, such as the one in Table 3 (W+), that are not provided by iMetos[®], can be valid in the next season. In addition, a more thorough investigation of the wind factor would be useful. At present, the proposed model can only forecast grapevine downy mildew. In the future, the Winet system may incorporate other disease models in order to enable the control of various diseases, not only in viticulture, but also in other areas of agriculture.

Author Contributions: System conceptualization, implementation, and tests, M.L., L.B., B.P. and I.M.; model and methodology conceptualization, I.M.; model implementation, I.M. and B.R.; dataset analysis and model simulations, B.R.; writing—original draft preparation, all authors; writing—review and editing, all authors; funding acquisition, I.M. All authors have read and agreed to the published version of the manuscript.

Funding: The work of the first and second authors is partially supported by the H2020 INCOMING grant under number 856967.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data could be provided upon request.

Acknowledgments: The authors appreciate the support from: Dragana Budakov (Faculty of Agriculture, Novi Sad) for providing the materials for the early literature review; Dragan Danilovic and A1 Serbia for providing access to A1 NB-IoT service; Kristina Males (Metos by Pessl Instruments) and Ivan Koci (PIS Vojvodina) for providing the weather, environmental, and Plasmopara viticola alarm warning data from the Metos stations.

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

Abbreviations

The following abbreviations are used in this manuscript:

WSN	Wireless Sensor Network
M2M	Machine to Machine
NB-IoT	Narrow-Band Internet of Things
LTE	Long-Term Evolution
IP	Internet Protocol
EWS	Early Warning System
SMS	Short Message Service

GPRS	General Packet Radio Service
UDP	User Datagram Protocol
HTTP	Hyper Text Transfer Protocol
API	Application Programming Interface

References

- Pearson, R.C.; Goheen, A.C. *Compendium of Grape Diseases*; APS Press: St. Paul, MN, USA, 1988; ISBN 0-89054-088-8.
- Gessler, C.; Pertot, I.; Perazzolli, M. *Plasmopara viticola* a review of knowledge on downy mildew of grapevine and effective disease management. *Phytopathol. Mediterr.* **2011**, *50*, 3–44.
- Baldacci, E. Epifitite di *Plasmopara viticola* (1941–46) nell’Oltrepó Pavese ed adozione del calendario di incubazione come strumento di lotta. *Atti Ist. Bot. Lab. Crittogam.* **1947**, *8*, 45–85.
- Kennelly, M.M.; Gadoury, D.M.; Wilcox, W.F.; Magarey, P.A.; Seem, R.C. Primary Infection, Lesion Productivity, and Survival of Sporangia in the Grapevine Downy Mildew Pathogen *Plasmopara viticola*. *Phytopathology* **2007**, *97*, 512–522. [[CrossRef](#)]
- Stojmenović, I. Machine-to-machine communications with in network data aggregation, processing, and actuation for large scale cyber physical systems. *IEEE Internet Things J.* **2014**, *1*, 122–128. [[CrossRef](#)]
- LoRa Alliance. Technical Overview of LoRa and LoRaWAN. Available online: https://lora-alliance.org/resource_hub/what-is-lorawan/ (accessed on 15 November 2021).
- Xu, J.; Yao, J.; Wang, L.; Ming, Z.; Wu, K.; Chen, L. Narrowband Internet of Things: Evolutions, Technologies, and Open Issues. *IEEE Internet Things J.* **2018**, *5*, 1449–1462. [[CrossRef](#)]
- Wang, Y.P.E.; Lin, X.; Adhikary, A.; Grovlen, A.; Sui, Y.; Blankenship, Y.; Bergman, J.; Razaghi, H.S. A Primer on 3GPP Narrowband Internet of Things. *IEEE Commun. Mag.* **2017**, *55*, 117–123. [[CrossRef](#)]
- 3GPP Technical Report 45.820 V13.1.0. *Cellular System Support for Ultra-Low Complexity and Low Throughput Internet of Things (CIoT)*; 3GPP: Nice, France, 2015.
- Wang, H.; Fapojuwo, A.O. A Survey of Enabling Technologies of Low Power and Long Range Machine-to-Machine Communications. *IEEE Commun. Surv. Tutor.* **2017**, *19*, 2621–2639. [[CrossRef](#)]
- Feltrin, L.; Tsoukaneri, G.; Condoluci, M.; Buratti, C.; Mahmoodi, T.; Dohler, M.; Verdone, R. Narrowband IoT: A Survey on Downlink and Uplink Perspectives. *IEEE Wirel. Commun.* **2019**, *26*, 78–86. [[CrossRef](#)]
- Lukić, M.; Mihajlović, Ž.; Mezei, I. Data flow in low-power wide-area iot applications. In Proceedings of the 2018 26th Telecommunications Forum (TELFOR), Belgrade, Serbia, 20–21 November 2018; pp. 1–4. [[CrossRef](#)]
- iMetos@3.3. A Complete Environmental Monitoring System. Available online: <http://metos.at/imetos33/> (accessed on 16 December 2021).
- Müller, K. Die biologischen Grundlagen für die Peronosporabekämpfung nach der Inkubationskalender-Methode. *Z. Pflanzenkrankh. (Pflanzenpathol.) Pflanzenschutz* **1936**, *46*, 104–108.
- Ostojić, Z.; Šarić, T.; Čuturilo, S. *Priručnik Izveštajne i Prognozne Službe Zaštite Poljoprivrednih Kultura*; Association of Yugoslav Societies for Plant Protection: Belgrade, Yugoslavia, 1983.
- Goidanich, G. *Manuale di Patologia Vegetale*; Edizioni Agricole: Bologna, Italy, 1964; Volume 2.
- Rossi, V.; Giosuè, S.; Girometta, B.; Bugiani, R. Influence of climatic conditions on primary infections caused by *Plasmopara viticola* in Emilia-Romagna. In Proceedings of the Atti, Giornate Fitopatologiche, Baselga di Piné, Trento, Italy, 7–11 April 2002; Volume 2, pp. 263–270.
- Rossi, V.; Caffi, T.; Giosuè, S.; Bugiani, R. A mechanistic model simulating primary infections of downy mildew in grapevine. *Ecol. Model.* **2008**, *212*, 480–491. [[CrossRef](#)]
- Bove, F.; Savary, S.; Willocquet, L.; Rossi, V. Simulation of potential epidemics of downy mildew of grapevine in different scenarios of disease conduciveness. *Eur. J. Plant Pathol.* **2020**, *158*, 599–614. [[CrossRef](#)]
- Brischetto, C.; Bove, F.; Fedele, G.; Rossi, V. A Weather-Driven Model for Predicting Infections of Grapevines by Sporangia of *Plasmopara viticola*. *Front. Plant Sci.* **2021**, *12*, 317. [[CrossRef](#)] [[PubMed](#)]
- Rosa, M.; Genesio, R.; Gozzini, B.; Maracchi, G.; Orlandini, S. PLASMO: A computer program for grapevine downy mildew development forecasting. *Comput. Electron. Agric.* **1993**, *9*, 205–215. [[CrossRef](#)]
- Mihailović, D.T.; Koči, I.; Lalić, B.; Arsenić, I.; Radlović, D.; Balaž, J. The main features of BAHUS—Biometeorological system for messages on the occurrence of diseases in fruits and vines. *Environ. Model. Softw.* **2001**, *16*, 691–696. [[CrossRef](#)]
- Caffi, T.; Rossi, V.; Bugiani, R. Evaluation of a Warning System for Controlling Primary Infections of Grapevine Downy Mildew. *Plant Dis.* **2010**, *94*, 709–716. [[CrossRef](#)]
- Karimi, N.; Arabhosseini, A.; Karimi, M.; Kianmehr, M.H. Web-based monitoring system using Wireless Sensor Networks for traditional vineyards and grape drying buildings. *Comput. Electron. Agric.* **2018**, *144*, 269–283. [[CrossRef](#)]
- Trilles Oliver, S.; González-Pérez, A.; Huerta Guijarro, J. Adapting Models to Warn Fungal Diseases in Vineyards Using In-Field Internet of Things (IoT) Nodes. *Sustainability* **2019**, *11*, 416. [[CrossRef](#)]
- Pérez-Expósito, J.P.; Fernández-Caramés, T.M.; Fraga-Lamas, P.; Castedo, L. VineSens: An Eco-Smart Decision-Support Viticulture System. *Sensors* **2017**, *17*, 465. [[CrossRef](#)]
- Dubuis, P.H.; Bleyer, G.; Krause, R.; Viret, O.; Fabre, A.-L.; Werder, M.; Naef, A.; Breuer, M.; Gindro, K. VitiMeteo and Agrometeo: Two platforms for plant protection management based on an international collaboration. *BIO Web Conf.* **2019**, *15*, 01036. [[CrossRef](#)]

28. Chen, M.; Brun, F.; Raynal, M.; Makowski, D. Forecasting severe grape downy mildew attacks using machine learning. *PLoS ONE* **2020**, *15*, e0230254. [[CrossRef](#)]
29. Pessl Instruments, FieldClimate: Agro-Meteorological Data Management System. Available online: <https://metos.at/fieldclimate/> (accessed on 16 December 2021).
30. Maddalena, G.; Russo, G.; Toffolatti, S.L. The Study of the Germination Dynamics of *Plasmopara viticola* Oospores Highlights the Presence of Phenotypic Synchrony with the Host. *Front. Microbiol.* **2021**, *12*, 698586. [[CrossRef](#)] [[PubMed](#)]
31. Caffi, T.; Legler, S.E.; González-Domínguez, E.; Rossi, V. Effect of temperature and wetness duration on infection by *Plasmopara viticola* and on post-inoculation efficacy of copper. *Eur. J. Plant Pathol.* **2016**, *144*, 737–750. [[CrossRef](#)]
32. SODAQ SARA AFF (Arduino Form Factor). Available online: https://support.sodaq.com/Boards/Sara_AFF/ (accessed on 16 December 2021).
33. Average Solar Radiation by Geographical Location. Available online: <https://www.pveducation.org/pvcdrom/properties-of-sunlight/average-solar-radiation/> (accessed on 16 December 2021).
34. Shatsky, A. *Treatment of Downy Mildew of the Vine on the Basis of Incubation Periods*; Bull. Plant Prot.: Leningrad, Soviet Union, 1935; Volume 6, pp. 75–85.
35. Merjanian, A.; Lipetzkaya, M.A. Effect of constant and fluctuating temperatures on the length of the incubation period of downy mildew of the Vine. *Sov. Bot.* **1936**, *3*, 68–77.
36. Fernández-González, M.; Piña-Rey, A.; González-Fernández, E.; Aira, M.J.; Rodríguez-Rajo, F.J. First assessment of Goidanich Index and aerobiological data for *Plasmopara viticola* infection risk management in north-west Spain. *J. Agric. Sci.* **2019**, *157*, 129–139. [[CrossRef](#)]
37. Walker, S.; Haasbroek, P. Use of mathematical model with hourly weather data for early warning of downy mildew in vineyards. In *Proceedings of the Farming Systems Design 2007—International Symposium on Methodologies for Integrated Analysis of Farm Production Systems*, Catania, Italy, 10–12 September 2007; pp. 104–105.