



# A mathematical model for estimation of leaf wetness for use in European agricultural decision support systems

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## ABSTRACT

Web-based decision support systems (DSSs) are essential tools for precision crop protection, guiding farmers and advisors in implementing need-based control measures against pests, diseases, and weeds. These systems rely heavily on weather-driven models, where data accuracy and availability are critical. Leaf wetness is a key factor for infection and reproduction of many fungal plant pathogens, making it an important input in DSSs. However, the availability of leaf wetness data from weather services is variable, leading to the development of numerous estimation models without a universally accepted standard model. This study aimed to develop a robust mathematical model for estimating leaf wetness across diverse European climate zones and to integrate the model for enabling real-time leaf wetness estimates as inputs to web based DSSs. Hourly weather data, including leaf wetness, temperature, precipitation, relative humidity and wind speed were collected from automatic weather stations. Training data came from five Norwegian sites, while testing data covered 17 locations across Europe. Five machine learning based models (decision tree (DT), random forest, K-Nearest neighbour, multi-layer perception, long short-term memory (LSTM)) were trained and their performance compared with five existing empirical models (RH87, RH90, extrRH, DPD, CART/SLD) from the literature. LSTM and DT achieved best performance, demonstrating strong robustness across climate zones. The LSTM model, required fewer data inputs and well suited for time-series data, was integrated into a Flask-based service for automatic use in forecasting models within the web-based IPM Decisions DSS platform, thereby enhancing the precision of this DSS.

## 1. Introduction

Integrated pest management (IPM) has been mandatory for all professional farmers in the EU since 2014, as part of the sustainable use of pesticides directive 2009/128/EC [1]. In IPM, web-based decision support systems (DSSs) are central tools, helping farmers and advisory services with careful considerations of need-based control measures to achieve precision in management for optimized crop protection of a wide range of pests, diseases, and weeds. These systems rely on computer models primarily driven by weather data, and their effectiveness depends on the accuracy and availability of both weather records and forecasts.

Leaf wetness, the presence of free water on the surface of plant leaves, is often used as a variable in disease forecasting models, as it influences the infection and reproduction of various fungal pathogens [2]. Accuracy in leaf wetness data may significantly enhance the ability to anticipate disease outbreaks, thereby improving plant health

management practices.

However, leaf wetness is difficult to measure due to its dependence on atmospheric conditions and vegetation characteristics. Various sensors for the measurement of leaf wetness exist, and there is no international standardization for this equipment. Hornero et al. [3] developed a compact and low-cost electronic interface circuit (EIC) using changes in capacitance, while Sentelhas et al. [4] showed that painting of the electronic sensors, designed with typical electrode spacing, could improve measurement precision. Indirect estimation methods, such as estimating leaf wetness using climate reanalysis data (ERA5 and MERRA2) [5] have also been explored, although direct comparisons with sensor data were lacking in the study. Due to the lack of standardized sensors, records of leaf wetness are rarely provided from generalized weather data networks, while agricultural weather services usually provide leaf wetness measurements. Rowlandson et al. [2] therefore recommended to estimate leaf wetness from standard meteorological variables available from most automated weather stations.

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Although no international/common method exists, numerous mathematical models have been developed to estimate leaf wetness and to replace missing records, for use in web-based DSSs for improved crop protection.

Both process-based and empirical approaches are used to estimate leaf wetness. Process-based models rely on physical principles and are usually highly accurate and valid across locations, but their complexity and need for inputs like net radiation limit their practical use. Empirical models including machine learning approaches, are based solely on observed data and are more adaptable to standard weather station inputs, though they are only able to detect dependencies present in the training data. Montone et al. [6] compared the performance of the process-based Penman-Monteith model with four empirical models (RH90, DPD, CART/SLD) across four US states. While the process-based Penman-Monteith model performed best when input data from a weather station with high precision sensors were used, the empirical CART/SLD [7] model was more robust when using input data from a weather station with lower precision sensors.

Performance of leaf wetness estimation models varies widely across studies. The empirical CART/SLD model has shown strong accuracy in the US, outperforming other empirical models, including machine learning approaches [7,8]. In recent years, machine learning algorithms have gained increasing attention and Gillespie et al. [9] demonstrated that models based on algorithms such as decision tree (DT), random forest (RF), multi-layer perceptron (MLP) and logistic regression outperformed traditional threshold-based models (e.g. the constant relative humidity threshold model RHX and the extended relative humidity threshold model extRH), when applied to UK weather data. Likewise, Park et al. [10] reported that machine learning models, including extreme learning machine, random forest and deep neural networks outperformed both empirical models (RHX and CART/SLD) and the process-based Penman-Monteith model when tested on data from cultivated areas such as rice fields and orchards of grapes.

The simple empirical RHX model, which predicts presence of leaf wetness for hours when relative humidity exceeds a threshold value, has been widely tested with adequate performance. Rowlandson et al. [2] recommended its use for replacing missing sensor data, suggesting threshold values within the range of 80 to 95 %. Studies have shown satisfactory performance with thresholds ranging from 71 % for agricultural grassland in Netherland [11] to 92 % for weather stations across the United Kingdom [9], with 90 % used with satisfactory accuracy across locations in US, Canada, Brazil and Italy [6,7,12,13]. A local optimization of the threshold value, giving site-specific threshold values, was shown as necessary to achieve sufficient performance for the empirical model in Sentelhas et al. [13].

Although numerous models to estimate leaf wetness already exist in the peer-review literature, none have demonstrated consistent performance across Europe's diverse climatic zones. Models are generally developed and tested using data received from limited geographical areas covered with a specific crop, making them difficult to generalize to other geographical regions, climatic zones or areas covered with other crops. To be suitable for a broad application across Europe, a model must prove to predict accurately under varying environmental conditions and cropping systems.

The objective of this study was twofold: first, to identify a mathematical model capable of estimating leaf wetness accurately across European climate zones, and secondly, to integrate this model into an operational, web-based DSS. This integration is essential for enabling real-time estimation of missing leaf wetness values, which are critical inputs for decision support models targeting a wide range of pests, diseases and weeds. To achieve this, we applied machine learning techniques to develop classification models and evaluated their performance against a selection of established empirical models from the literature.

## 2. Material and methods

The study followed the workflow illustrated in Fig. 1. In brief, weather data were collected, cleaned, and divided into separate sets for model training and testing. The training set was then used to develop five machine learning models. Subsequently, these newly trained models, together with five established models from the literature, were tested and their performance evaluated. A detailed description of each step is provided in the following sections.

### 2.1. Data sampling - locations and time periods

Weather data used in model development included five locations in Norway: Apelsvoll, Holt, Kvithamar, Landvik and Ullensvang (Fig. 2), covering a time-period from April to end of September for fourteen years (year 2005 to 2017). For model testing, weather data from a total of 17 locations across Europe from the year 2019 to 2021, were included. These locations include the Norwegian sites as listed above in addition to Macedonia (Otovisva, Lepovo and Barovov), Bulgaria (Pripek, Trud and Polikraishte), Italy (Ravenna and CastellArguato), Germany (Seegebiet Mansfelder Land and Zarpener Hof) and Hungary (Zsombó and Mohács) (Fig. 2). A detailed overview of the data is given in Supporting Information (Table S1).

Each location was classified within a climate zone according to the Köppen-Geiger system as described by Peel et al. [15]. The system classifies five broad climate zones: tropical, arid, temperate, cold and polar. In our study, four zones were represented: polar, cold, temperate, and arid (Table S2). Polar climate, defined as areas with mean air temperature below 10 °C in the warmest month was represented by one location in Norway (Holt). Eight locations (Kvithamar, Apelsvoll, Ullensvang and Landvik in Norway, Polikraishte in Bulgaria, Seegebiet Mansfelder Land in Germany and Zsombó and Mohács in Hungary) were categorized as cold climates with the mean air temperature of the warmest month above 10 °C and the temperature of the coldest month below 0 °C. Pripek and Trud in Bulgaria, Zarpener Hof in Germany and Ravenna and CastellArguato in Italy represent temperate climates where the mean air temperature of the warmest month is above 10 °C and temperature of the coldest month is in the range of 0 to 18 °C. Finally, arid climate, defined as areas with little precipitation was represented by the three locations in Macedonia: Otovisva, Lepovo and Barovov.

### 2.2. Weather data

Measurements with an hourly resolution of number of minutes with leaf wetness (min), mean air temperature (°C), sum of precipitation (mm), mean of relative humidity (%) and mean of wind speed (m/s) were collected from automatic weather stations at each of the 17 locations included in this study. The recorded number of minutes per hour with leaf wetness was transformed to a binomial value (presence/absence of leaf wetness), where hours with  $\geq 30$  min of leaf wetness were defined as presence.

The weather data from Norway was provided by Agrometeorology Norway [16], which have weather stations placed on mowed turfgrass in open landscapes. All data were recorded 2 m above ground and leaf wetness was monitored by flat-plate electronic impedance grids (Model 237 from Campbell Scientific), recording presence of free water on the surface of plant foliar each minute when  $> 50$  % of the sensor surface is wet. The weather data from Germany, Italy, Macedonia, Bulgaria and Hungary were provided by Meteobot [17] automatic weather stations installed on mowed turfgrass, arable land or in orchards (Table S1). In line with the user manual, sensors for temperature and relative humidity were installed 1.25 - 2 m above ground, wind speed 2 m above ground and precipitation 1.1 - 1.9 m above ground. The leaf wetness was measured by a dielectric leaf wetness sensor from Decagon Devices [18] defining presence of leaf wetness each minute when  $> 4$  % of the sensor surface is wet (MeteoBot, pers med). Different weather data services use

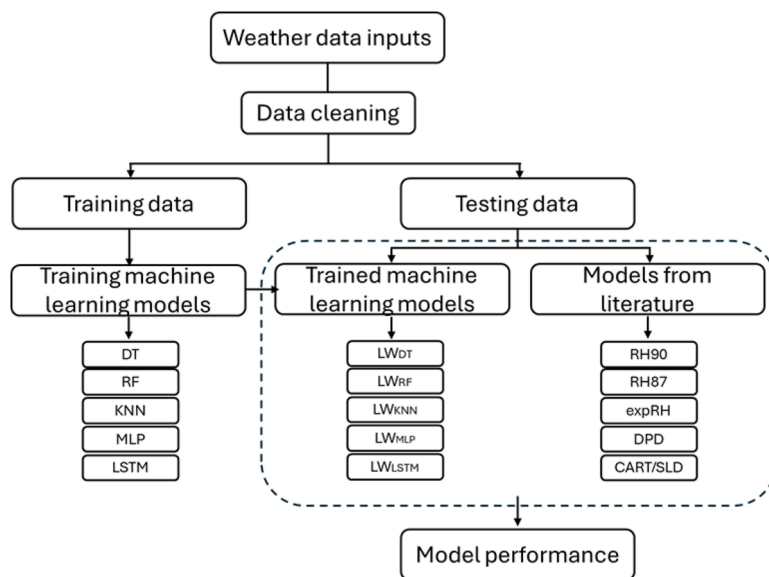


Fig. 1. A diagram of the overall workflow in the study.

Köppen–Geiger climate classification map for Europe (1980–2016)

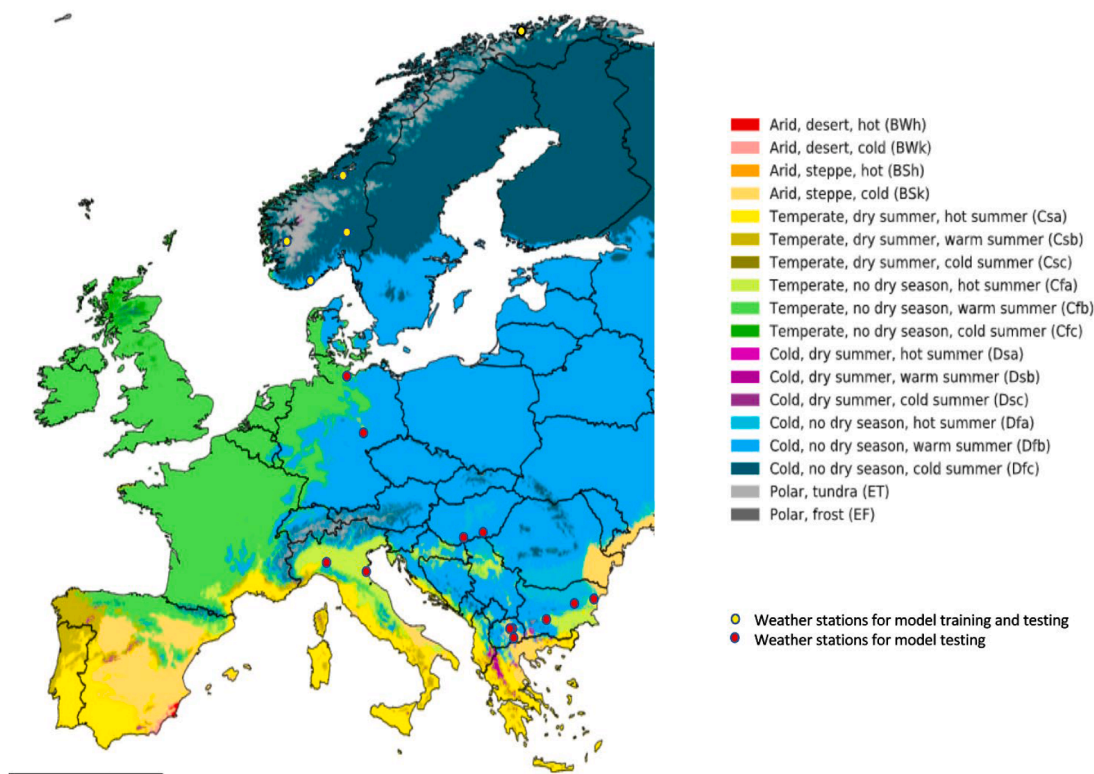


Fig. 2. Köppen–Geiger climate classification map for Europe (1980–2016) (Beck et al. [14], cropped to highlight areas of interest for this study). Yellow dots indicate locations of weather stations providing data for building models, both red and yellow dots indicate locations of weather stations providing data for testing and validation of models.

numerous different types of sensors for weather data recording, e.g. as described here for Agrometeorology Norway and Meteobot.

Linear interpolation was used for missing values for all weather variables, except precipitation, when the consecutive missing values were fewer or equal to three. Other missing values were replaced with weather records from other weather stations of geographic relevance (accounting for < 0.03 % of data). For some of the time series, longer

periods of missing values were detected at the beginning or end of the period, and for these cases, the time series were shortened and data before or after deleted (Table S1). Humidity sensors are known to be sensitive to calibration erosion, and a drift in measurements is commonly observed over time [19,20]. In our study, such drift was evident in RH measurements from a selection of the weather stations, particularly when evaluating the maximum hourly value for each month

through the season. In contrast, no drift was observed when the minimum RH values were considered. Previously Hjelkrem et al., [20] detected ranges of RH especially prone to drift by comparing data from two sensors, one exhibiting drift and one stable, placed at the same location. In accordance with Eccel, [19], an algorithm was developed for linear correction of RH readings above 70 %, ranging from 0 % correction at 70 % RH to the value required to reach 100 % at the highest RH-value recorded by the instrument when the air was actually fully saturated with water vapor [20].

Based on a literature study of mathematical models for calculation of leaf wetness, a total of 12 weather/environmental variables were included in the model development (only the first six of these were used for the time-series based LSTM model), using an hourly time resolution. These were: (1) air temperature, (2) precipitation, (3) relative humidity, (4) wind speed, (5) dew point temperature, (6) vapor pressure deficit, (7) precipitation the previous hour, (8) the difference in relative humidity the present and the previous hour, (9 and 10) hour of the day (represented by a sinus and a cosines curve), (11) the difference in air temperature the present and the previous hour and (12) a categorical value for wetness (one if  $> 0.2$  mm per hour precipitation or a relative humidity  $> 87$  %). The dew point temperature ( $^{\circ}\text{C}$ ) was estimated according to the Clausius-Clapeyron equation [21], depending on both air temperature and relative humidity, while the vapor pressure deficit (vpd; kPa) was estimated based on Perry and Green [22], depending on the estimated saturated vapor pressure [23].

### 2.3. Comparison of sensor types

To compare the sensors used by Agrometeorology Norway and Meteobot, weather data of leaf wetness, air temperature, precipitation, relative humidity and wind speed, from both weather station providers were collected in parallel at Ås, Norway. The data consisted of measurements from 2019 to 2021. To account for technical errors, only data from periods when both weather stations were operational were compared. For comparison of the two sensor types, Pearsons correlation coefficient was used in addition to root mean square error (RMSE). RMSE was further decomposed into squared bias and variance error [24].

### 2.4. Mathematical models for testing and comparison

Five empirical models for the prediction of leaf wetness were selected from the peer-review literature and included in this study. These models served as a line of comparison according to performance of the five mathematical models developed in this study.

#### 2.4.1. Existing models to predict leaf wetness

Five existing models to estimate presence or absence of leaf wetness were selected based on both their performance according to literature and their simplicity according to required input data. These models were: The constant relative humidity threshold model with a threshold value of 90 % (RH90), the constant relative humidity threshold model with a threshold value of 87 % (RH87), the extended relative humidity threshold model (extRH), the dewpoint depression model (DPD) and the classification tree algorithm (CART/SLD). A brief description of each model is given in Table 1.

#### 2.4.2. Model development

To develop a mathematical model for the prediction of leaf wetness, five different algorithms within the area of supervised machine learning were selected. These were: the simple supervised learning algorithms decision tree (DT), random forest (RF) and K-nearest neighbor (KNN), in addition to the more complex deep-learning algorithms multi-layer perceptron (MLP) and long short memory (LSTM). While DT, RF, KNN and MLP are not designed to handle time series data, their simplicity and successful application in leaf wetness estimation using UK weather data

**Table 1**

A brief description of the five peer-reviewed empirical models for prediction of leaf wetness that were included in this study.

Model	Description
RH90	The constant relative humidity threshold model [13]. The model estimates presence of leaf wetness for hours when relative humidity exceeds 90 %.
RH87	The constant relative humidity threshold model. The model estimates presence of leaf wetness for hours when relative humidity exceeds 87 % [25].
extRH	The extended relative humidity threshold model [25]. The model estimates presence of leaf wetness for hours when relative humidity exceeds 87 % and it predicts absence for hours when relative humidity is below 70 %. In between these threshold values, the model assume that leaves are becoming wet and predicts presence of leaf wetness for hours when relative humidity increases $>3$ % in 30 min, and it assumes that the leaves are drying up when relative humidity decreases $>2$ % in 30 min. In line with Bregaglio et al. [26], the 30 min values were replaced by hourly values for the presence of leaf wetness, for the hours with a relative humidity between 70 and 87 %.
DPD	The dew point depression model [27]. The model estimates onset of a period with presence of leaf wetness when the dew point depression is below or equal to $1.8^{\circ}\text{C}$ and it defines dry-off and predicts absence when the dew point depression is above or equal to $2.2^{\circ}\text{C}$ .
CART/SLD	The classification and regression tree/stepwise linear discriminant model Gleason et al. [7]. The model predicts absence of leaf wetness for all hours between 8 a.m. and 7 pm., and all hours with precipitation are assigned with presence of leaf wetness. Between 7 pm. and 8 a.m., presence of leaf wetness is estimated using a hierarchical decision tree using dew point depression, wind speed and relative humidity as input variables. Hours with no precipitation within this time interval were firstly assigned a number between one and four as follows: 1: when dew point depression is above or equal to $3.7^{\circ}\text{C}$ ; 2: when dewpoint depression is below $3.7^{\circ}\text{C}$ , wind speed is above or equal to 2.5 m/s and relative humidity is below 87.8 %; 3: when dewpoint depression is below $3.7^{\circ}\text{C}$ and wind speed is below 2.5 m/s; and 4: when dewpoint depression is below $3.7^{\circ}\text{C}$ and wind speed is above or equal to 2.5 m/s and relative humidity is above or equal to 87.8 %. Hours categorized as 1 or 2 predicted absence of leaf wetness. Hours categorized as 3 predicted presence of leaf wetness if $(1.6064 \cdot \sqrt{T} + 0.0036 \cdot T^2 + 0.1531 \cdot RH - 0.4599 \cdot W \cdot D - 0.0035 \cdot T \cdot RH) > 14.4674$ while hours categorized as 4 predicted presence of leaf wetness if $(0.7921 \cdot \sqrt{T} + 0.0046 \cdot RH^2 - 2.3889 \cdot W - 0.0390 \cdot T \cdot W + 1.0613 \cdot W \cdot D) > 37.0$ Here, T refers to air temperature, RH to relative humidity, W to wind speed and D to dew point depression.

[9] motivated for a further evaluation across diverse European conditions. The LSTM model was included for its ability to capture temporal dependencies, making it well suited for time-series analysis. The five algorithms were trained on Norwegian weather data collected between 2005 and 2017. For model evaluation, a 5-fold cross-validation technique was applied to the DT, RF and KNN methods. Due to the temporal dependencies of the data incorporated in the LSTM model, cross-validation was not used for this model. The same approach was followed for the MLP model, as it was developed within the same modeling environment.

DT is a simple supervised learning algorithm [28] that constructs binary classification tree models. The model has a tree-like structure with its root node at the top, and with a set of if-else statements used to classify. The Gini diversity index was used as a cost function to evaluate the splits in the data and a maximum of five splits were selected. The undersampling technique was used to balance the data. The resulting model for prediction of leaf wetness, based on the DT algorithm, will further be referred to as  $LW_{DT}$ .

RF is an ensemble machine learning algorithm that combines the predictions from multiple decision tree algorithms together to make more accurate predictions [29]. The sub-trees are learned so that the resulting predictions from all the sub-trees have less correlation. The Gini diversity index was used as a cost function to evaluate the splits in the data, in line with the DT model. Specifically, the bagging method

was used with a maximum of ten splits and 500 number of learning cycles. The undersampling technique was used to balance the data. The resulting model for prediction of leaf wetness, based on the RF algorithm, will further be referred to as  $LW_{RF}$ .

KNN is a nonparametric memory-based algorithm that requires data at run time [30]. The algorithm classifies each data point based on its “similarity” to the other observations. The model prediction totally relies on the training data during run time and classifies to the class most common among the ten number of closest neighbors according to Euclidean distance. All variables were regarded with equal importance in this study. The undersampling technique was used to balance the data. The resulting model for prediction of leaf wetness, based on the KNN algorithm, will further be referred to as  $LW_{KNN}$ .

MLP is an artificial neural network algorithm, usually useful for time series modelling [31]. It consists of an input layer, one or more hidden layers and an output layer, with non-linear mapping in between. MLP is a feedforward artificial neural network algorithm with no feedback connections. Each layer in the model feeds the next one with the result of its computation. The resulting model for prediction of leaf wetness, based on the MLP algorithm, will further be referred to as  $LW_{MLP}$ .

LSTM is a special type of artificial recurrent neural network (RNN), usually used for time series modelling [32]. The algorithm capture and retain long-term dependencies effectively through its unique architecture where it divides input data into sequences and produces corresponding output data sequences. Here, each input data sequence consisted of 12 features and the model processes sequences of 24 hourly time steps. The sequential architecture of the model begins with a layer comprising 50 units. This layer employs a sigmoid activation function configured to return sequences while ensuring that temporal information is preserved across time steps. Then, a second layer is incorporated, also with 50 units. This layer utilizes a tanh activation function, which helps in capturing the temporal dependencies in the data more effectively. The output of this layer is further fed into a dense (fully connected) layer with 24 units, each corresponding to a time step in the output sequence, using a sigmoid activation function to produce the final output. In this study, the model is optimized using the Adam optimizer, which is known for its efficiency and adaptive learning rate capabilities. Further, the performance of the model is measured using binary cross-entropy loss, which is suitable for binary classification tasks. The training process involves iterating over the provided data for 100 epochs with a batch size of 24, allowing the model to learn and generalize from the training data. The resulting model for prediction of leaf wetness, based on the LSTM algorithm, will further be referred to as  $LW_{LSTM}$ .

### 2.5. Model testing and comparison

The output of all models evaluated were binary hourly values, represented by one for presence of leaf wetness and zero for absence. To visualize/compare the performance of the different models, two times two confusion matrixes were created (Table 2), and summary statistics calculated [33].

Accuracy is the proportion of data correctly classified as presence or absence of leaf wetness (Eq. (1)). It ranges between zero and one, where one determines a perfect forecasting system and zero determines a total

**Table 2**  
Example of a 2 times 2 confusion matrix, used to describe model performance for binary classification models.

		Predicted	
		Presence of leaf wetness	Absence of leaf wetness
Observed	Presence of leaf wetness	A	B
	Absence of leaf wetness	C	D

failure. Among the data observed with presence of leaf wetness, sensitivity (hit rate) is defined as the proportion of data correctly predicted with presence of leaf wetness (Eq. (2)). Among the data observed with absence of leaf wetness, specificity is the proportion of data correctly predicted with absence of leaf wetness (Eq. (3)). Finally, the F1 score provides a single, balanced measure of performance, particularly useful for imbalanced datasets (Eq. (4)).

$$Accuracy = (A + D)/(A + B + C + D) \tag{1}$$

$$Sensitivity = A/(A + B) \tag{2}$$

$$Specificity = D/(C + D) \tag{3}$$

$$F1 = (2A)/(2A + C + B) \tag{4}$$

Plots were derived to show the distribution of the accuracy, sensitivity, specificity and F1 throughout the day. Additionally, the hourly results were aggregated to a daily resolution consisting of daily number of hours with presence of leaf wetness. Performance was further visualized in heat plots, showing the density of observed versus predicted. Most results were derived for each climate zone separately additionally to the combined results. All calculations were performed using Matlab R2021a.

### 2.6. Implementation and adaptation of model for integration into web-based DSS platform

The model that demonstrated the best performance for estimating leaf wetness was selected and integrated into the operational, web-based IPM Decision DSS platform. The model was reimplemented in Python using Keras and incorporated into a weather application programming interface (API). Flask was employed as the web framework to host the model, serving as the intermediary server between the model and external services. To ensure a consistent and easily deployable environment, the Flask application was containerized using Docker Compose and communication between the Java-based weather service and the Flask server was handled via HTTP requests.

## 3. Results

### 3.1. Overview of weather data

The models were developed based on weather data from five locations in Norway, covering the two climate zones “polar” and “cold” (Fig. 2). Summary statistics of the weather conditions within both zones are given in Table 3, while Figure S1 (Supporting Information) shows the summary statistics for each weather station separately. Generally, a colder and dryer climate was found in the polar compared to the cold zone. Although a lower level of precipitation was detected in the polar zone, both the percentage of hours detected with presence of leaf wetness and the percentage of hours with relative humidity above 90 % was at the same level within the two zones.

The model was tested on data from 17 locations geographically spread across Europe, covering four different climate zones (Fig. 2). One or two years of data were included from each location, and summary statistics of the weather conditions in the period from April to September, within each of the four climate zones are given in Table 3, while Figure S2 shows the summary statistics for weather data collected in the period from April to September, for each weather station separately. Generally, cold and wet conditions were detected in the northernmost zone (polar), followed by slightly warmer and dryer conditions in the cold and temperate zones, while the warmest and driest conditions were detected in the southern zone (arid). Specifically, the mean daily air temperature in the period from April to September ranged from only 8.2 °C in the polar zone to 20.8 °C in the arid zone. Also, the proportion of hours with presence of leaf wetness per day varied highly

**Table 3**

Weather summarizations within each climate zone for weather data in the period from April to September, used in model development and testing.

Climate zone	Number of weather stations	Percentage of hours per day with presence of leaf wetness	Mean daily air temperature (°C)	Daily sum of precipitation (mm)	Percentage of hours per day with relative humidity > 90 %
<i>Model development</i>					
Polar	1	24	8.3	394	11
Cold	4	23	12.2	523	13
<i>Model testing</i>					
Polar	1	37	8.2	471	13
Cold	8	21	14.8	429	19
Temperate	5	21	18.7	350	35
Arid	3	10	20.8	275	21

between these two regions, from 10 % of the hours within the arid zone to as much as 35 % in the polar zone. Despite the highest level of precipitation and the highest percentage of hours per day with presence of leaf wetness, the polar zone had the lowest percentage of hours per day with relative humidity above 90 %. The temperate climate zone had the overall highest percentage of hours per day with relative humidity above 90 %, followed by the dry arid zone.

### 3.2. Comparison of sensor types

The weather data used for comparison of two different sensors located at Ås in Norway, resulted in a total of 6 870 lines of data measured in 2019 and 2021. Due to measurement errors, precipitation was only included from 2019 with a total of 2 693 measurements, while relative humidity was only retrieved from 2021 with a total of 2 634 measurements.

During evaluation, the outputs from both sensor types were generally consistent with another. From a Pearson correlation study, significantly high correlations were found for air temperature ( $r = 0.99$ ,  $p < 0.01$ ), relative humidity ( $r = 0.99$ ,  $p < 0.01$ ), wind speed ( $r = 0.90$ ,  $p < 0.01$ ) and for precipitation ( $r = 0.90$ ,  $p < 0.01$ ). For the binomial variable leaf wetness, an accuracy of 0.92 was found. Also RMSE was calculated and decomposed into bias and variance error (Figure S3). Air temperature, precipitation and wind speed showed RMSE of respectively 1.0 °C, 0.7 mm and 1.9 m s<sup>-2</sup>, all consisting of variance error only. For relative humidity, a RMSE of 7.0 % was found, consisting of 38 % bias and 62 % variance error, while leaf wetness showed a RMSE of 13.8 min, consisting of 6 % bias and 94 % variance error.

### 3.3. Model development

In this study, five binary models were developed to classify hourly presence or absence of leaf wetness. The models were developed based on five different machine learning algorithms, using 12 different input variables calculated from air temperature, precipitation, relative humidity, wind speed and hour of the day. As the LSTM model is well suited for time-series analysis and captures temporal dependencies, only six of the input variables were included in this model. Variables specifically created to represent time series related information, as previous-hour conditions were excluded. The developed models are further described in Table 4.

### 3.4. Model testing and comparison

Both the existing models and those developed in this study were evaluated using the test dataset containing weather data from four different climate zones in Europe (Fig. 2). The existing models achieved overall accuracies between 0.70 and 0.79 across models, while the newly developed models performed better, with accuracies between 0.79 and 0.83 (Fig. 3). The three newly developed machine learning models, LW<sub>KNN</sub>, LW<sub>MLP</sub> and LW<sub>LSTM</sub>, had the highest accuracy overall (all with an accuracy of 0.83). Among the existing models, CART/SLD

**Table 4**

A brief description of the five models developed for prediction of leaf wetness.

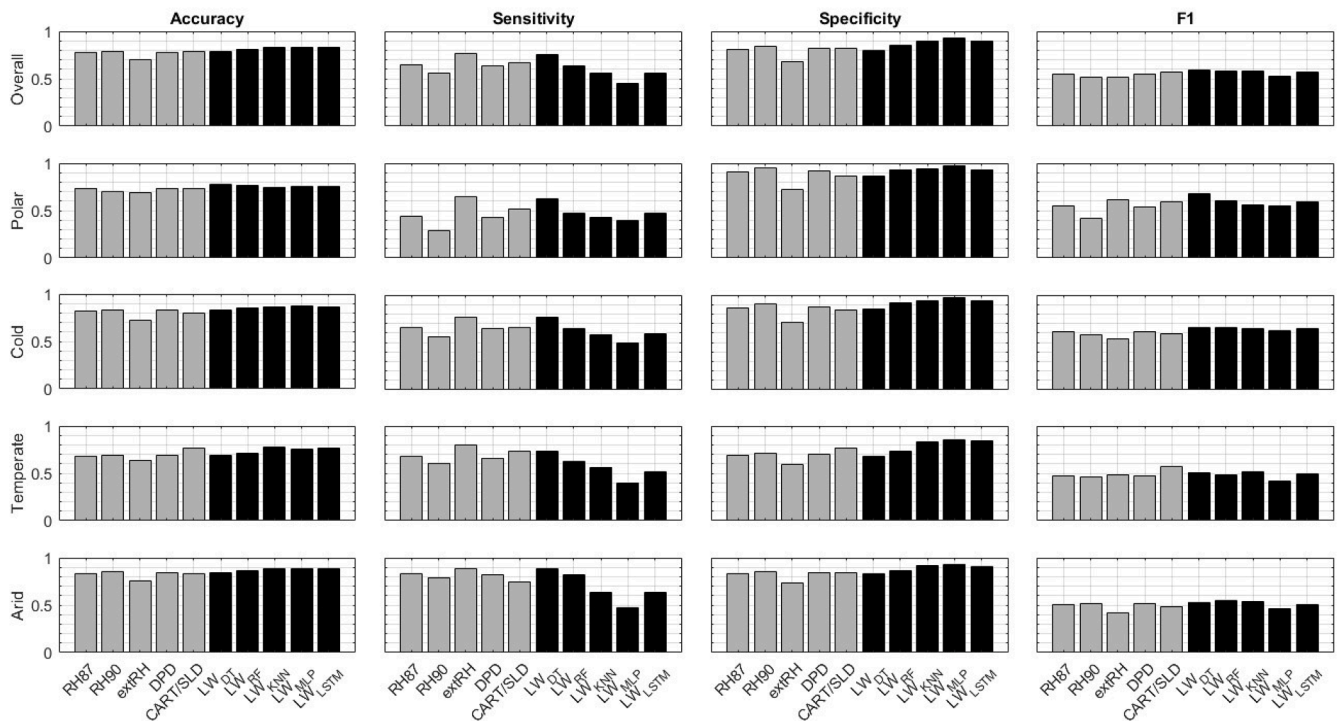
Model	Description
LW <sub>DT</sub>	The model is based on the <i>decision tree</i> algorithm and predicts presence of leaf wetness during hours when moisture conditions are met ( $P > 0.2$ mm and/or $RH \geq 87$ %). For hours that do not meet these criteria, leaf wetness is still predicted if the dewpoint depression is below 4.1 °C and there was precipitation in the previous hour ( $P_{\text{prev day}} \geq 0.2$ mm).
LW <sub>RF</sub>	The model is based on the <i>random forest</i> algorithm and consists of 500 decision tree models. Among the weather variables included in the resulting ensemble model, presence of wetness/moisture ( $P > 0.2$ mm and/or $RH \geq 87$ %) was the most frequently used variable with a relative importance of 32 %, followed by the dew-point depression (24 %), relative humidity (19 %), vpd (10 %), precipitation the previous hour (8 %) and precipitation the present hour (6 %).
LW <sub>KNN</sub>	The model is based on the <i>KNN</i> <sup>1</sup> algorithm and does not create any model but totally relies on the training data during run time. The model classifies presence or absence of leaf wetness to the class most common among the ten number of closest neighbors according to Euclidean distance.
LW <sub>MLP</sub>	The model is based on the <i>MLP</i> <sup>2</sup> algorithm, and is considered as a black box model, as the behavior of the model cannot be comprehended. The resulting model contained one input layer, 25 hidden layers and one output layer, with nonlinear mapping functions in between.
LW <sub>LSTM</sub>	The model is based on the <i>LSTM</i> <sup>3</sup> algorithm and is considered as a black box model, as the behavior of the model cannot be comprehended. The resulting model processes sequences of 24 h, iterating over the provided data for 100 epochs. Further, each data point consisted of 7 features and two layers with 50 units.

<sup>1</sup> K-nearest neighbor algorithm.<sup>2</sup> Multi-layer perceptron algorithm.<sup>3</sup> Long short term memory algorithm.

had the highest accuracy (0.79) followed by RH87, RH90 and DPD (all with an accuracy of 0.78). Lowest accuracy was revealed for the existing extrRH model. When considering each climate zone separately a more diverse pattern was revealed. The LW<sub>DT</sub> model achieved the highest accuracy in the polar zone, LW<sub>MLP</sub> in the cold zone, LW<sub>KNN</sub> and LW<sub>LSTM</sub> in the temperate zone and LW<sub>KNN</sub> in the arid zone. In the arid zone, all individual models reached their peak in accuracy.

Sensitivity, which is the proportion leaf wetness events correctly predicted, varied between 0.56 and 0.77 for the existing models and between 0.45 and 0.75 for the newly developed models (Table S3), when considering all locations overall. The highest sensitivity was achieved for the existing extrRH model (0.77), closely followed by the LW<sub>DT</sub> model (0.75). The lowest sensitivity was detected for the LW<sub>MLP</sub> model (0.45). When considering each climate zone separately, the existing extrRH model had the highest sensitivity in the polar and temperate zones, while the LW<sub>DT</sub> model had the highest sensitivity in the cold zone. In the arid zone, both models performed at similar levels. The LW<sub>MLP</sub> model was the model with lowest sensitivity, both overall and within each climatic zone separately.

Specificity, which is the proportion of observed hours with absence of leaf wetness that is correctly predicted, varied between 0.68 and 0.84 among the existing models and between 0.80 and 0.93 among the newly developed models. The LW<sub>MLP</sub> model (0.93) had the highest specificity



**Fig. 3.** Model performance of the existing models (gray) and of the newly developed models (black) given as accuracy (left column), sensitivity (middle-left column) specificity (middle-right column) and F1-score (right), for all locations overall and for the polar, cold, temperate and arid zone separately.

overall, followed by LW<sub>KNN</sub> and LW<sub>LSTM</sub> (both with 0.90). Among the existing models, RH90 had the highest specificity of 0.84. When considering each climate zone separately, the LW<sub>MLP</sub> model had highest specificity within each zone separately.

F1, which is a balanced measure of performance, particularly useful for imbalanced datasets, varied between 0.52 and 0.57 among the existing models and between 0.53 and 0.59 among the newly developed models. The LW<sub>DT</sub> model (0.59) had the highest F1 score overall, followed by LW<sub>RF</sub>, and LW<sub>KNN</sub> model which both had a score of 0.58. Among the existing models, CART/SLD had the highest F1 score of 0.57. When considering each climate zone separately, the LW<sub>DT</sub> model had highest score within the polar, cold and temperate zones, while LW<sub>RF</sub> performed best within the arid zone.

Model performance was assessed hourly and shown as a function of time of day in Fig. 4. The models showed relatively similar patterns of accuracy throughout the day, with somewhat higher accuracy during the day compared to the night. The newly developed LW<sub>LSTM</sub> model and the existing CART/SLD achieved the highest accuracy during the day. At night, the LW<sub>LSTM</sub> model was highest before midnight, closely followed by LW<sub>KNN</sub> and LW<sub>MLP</sub> in the early morning hours. In contrast, the existing extRH model stood out with the lowest accuracy, particularly overnight. Similar patterns were found within the cold and arid zones separately (Figure S5 and S7), while less variation between day and night was detected for the accuracy of the models within the polar and temperate zone (Figure S4 and S6).

When evaluating model sensitivity as a function of time of the day, notable differences emerged between the models (Fig. 4). In general, all models demonstrated lower sensitivity during the day compared to nighttime. During daytime, the LW<sub>DT</sub> model exhibited the highest sensitivity, whereas the existing CART/SLD model, closely followed by the LW<sub>KNN</sub>, LW<sub>MLP</sub> and LW<sub>LSTM</sub> models achieved the highest specificity. At night, the existing extRH and CART/SLD models showed the highest sensitivity closely followed by the newly developed LW<sub>DT</sub> model. The LW<sub>KNN</sub>, LW<sub>MLP</sub> and LW<sub>LSTM</sub> models had the lowest. In terms of specificity during nighttime, the LW<sub>KNN</sub>, LW<sub>MLP</sub> and LW<sub>LSTM</sub> models outperformed the others, whereas the existing extRH model had the lowest specificity.

Based on the F1 score, performance patterns appeared more consistent across time of the day (Fig. 4). During daytime, all newly developed models outperformed the existing ones. In the early morning, the LW<sub>MLP</sub> and extRH model exhibited lower performance compared to the other models, while RH90 and extRH showed reduced score during the late hours.

The model outputs were also aggregated to a daily resolution, and the predictive performance visualized using heat plots (Fig. 4). Across all models, presence of leaf wetness was sometimes predicted on days with zero hours of leaf wetness observed. Conversely, the existing RH87, RH90 and DPD models, as well as the newly developed LW<sub>MLP</sub> and LW<sub>LSTM</sub> models, occasionally predicted zero hours with presence of leaf wetness on days when leaf wetness had been observed. A clear diagonal pattern, indicating correct daily predictions of hours with presence of leaf wetness, was observed for the existing RH90 and DPD models, as well as for the newly developed LW<sub>DT</sub>, LW<sub>RF</sub>, LW<sub>KNN</sub> and LW<sub>LSTM</sub> models. In contrast, the existing extRH and CART/SLD models generally overestimated the number of hours with presence of leaf wetness while the LW<sub>MLP</sub> model tended to underestimate the number of hours with presence of leaf wetness. Fig. 5

To assess whether the models performed better on site-specific data, they were re-evaluated using test datasets drawn exclusively from the same regions as their respective training data (Table 5). In this case, all data originated from Norway. This country-specific evaluation resulted in significant improvement across all performance metrics.

### 3.5. Implementation and adaptation of model for integration into a web-based DSS platform

The LW<sub>LSTM</sub> model was identified as one of the best-performing models evaluated in this study, for the RH90 model, only depending on humidity data, is automatically applied instead of the LW<sub>LSTM</sub> model. Estimating leaf wetness, based on its high overall accuracy, specificity and F1 score across climate zones. In addition to its strong performance, the LW<sub>LSTM</sub> model is relatively simple, requiring fewer input weather variables because it automatically captures time series pattern. Based on

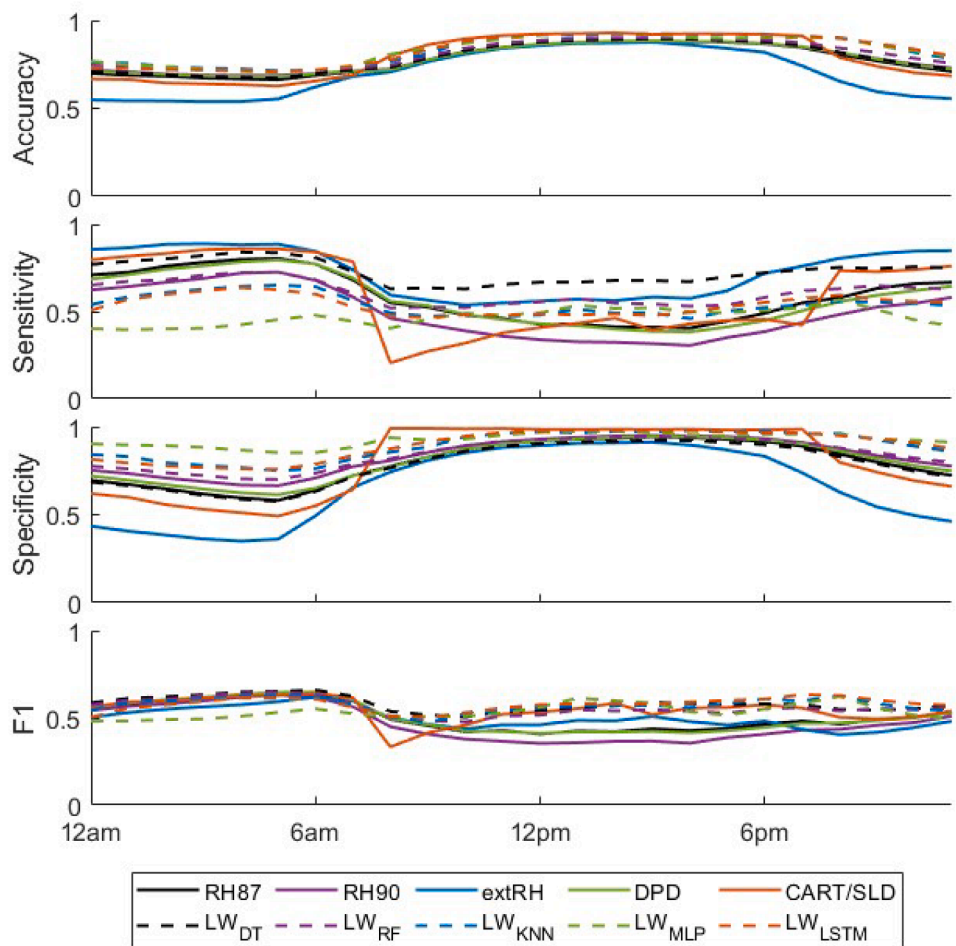


Fig. 4. Model performance of the existing models (continuous lines) and of the newly developed models (dotted lines) given as accuracy, sensitivity and specificity on an hourly time resolution.

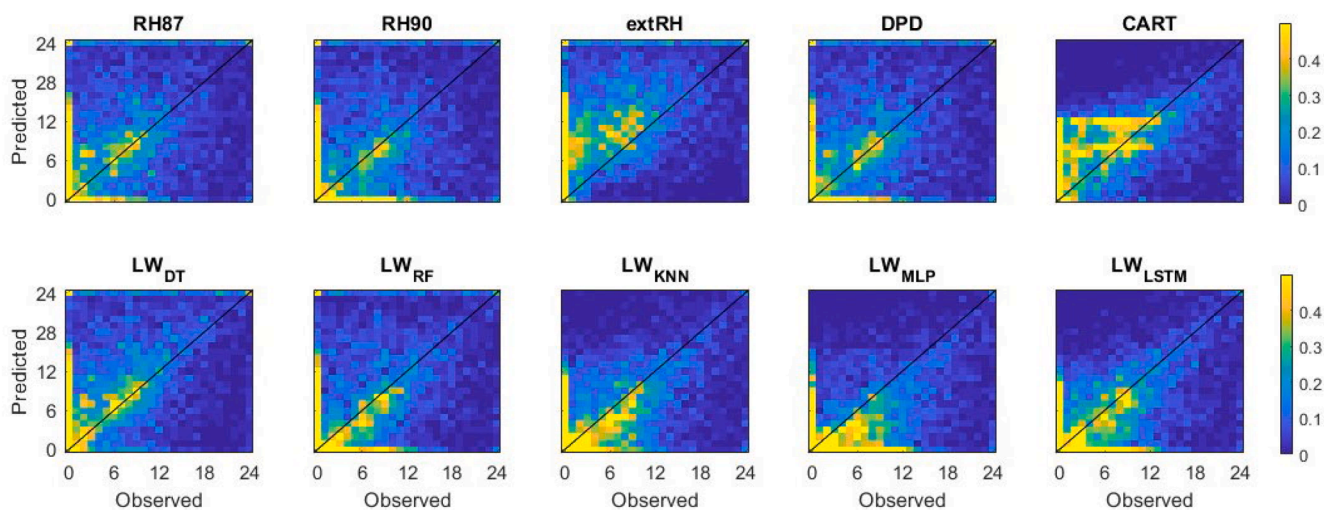


Fig. 5. Predicted versus observed daily hours with presence of leaf wetness given as a heat plot for each of ten different leaf wetness models.

these advantages, the model was selected and integrated into the weather API developed for the IPM Decisions platform (GitHub repository). It is published as an open-source web service at <https://github.com/H2020-IPM-Decisions/LWDLSTMModel>. Currently, the model is successfully applied to fill missing leaf wetness values in weather datasets that serve as inputs to DSSs for pest, disease and weed

management in agriculture. These services are delivered through the user-friendly, web-based IPM Decisions platform (platform.ipmdecisions.net). When access to weather variables is limited,

**Table 5**

The newly developed models were tested according to accuracy, sensitivity, specificity and F1, on the test data from across Europe overall, and on test data solely from the same stations as included in the training data.

Model	Test dataset	Accuracy	Sensitivity	Specificity	F1
LW <sub>DT</sub>	Across Europe	0.79	0.75	0.80	0.59
LW <sub>DT</sub>	Norwegian only	0.83	0.78	0.85	0.70
LW <sub>RF</sub>	Across Europe	0.81	0.63	0.85	0.58
LW <sub>RF</sub>	Norwegian only	0.86	0.65	0.93	0.70
LW <sub>KNN</sub>	Across Europe	0.83	0.56	0.90	0.58
LW <sub>KNN</sub>	Norwegian only	0.85	0.61	0.94	0.68
LW <sub>MLP</sub>	Across Europe	0.83	0.45	0.93	0.53
LW <sub>MLP</sub>	Norwegian only	0.87	0.57	0.97	0.69
LW <sub>LSTM</sub>	Across Europe	0.83	0.56	0.90	0.58
LW <sub>LSTM</sub>	Norwegian only	0.86	0.63	0.93	0.69

#### 4. Discussion

This study aimed to establish reliable mathematical models for estimating leaf wetness across diverse European climate zones using standard meteorological data as input variables. Five models (decision tree, random forest, K-nearest neighbor, multi-layer perceptron and long short-term memory) were developed within this study and compared with five empirical models published between 1993 and 2011. All ten models were subsequently evaluated. Among these, the LW<sub>DT</sub> model achieved the highest F1 score both overall and within individual zones (except the arid zone) and demonstrated the second-highest hit rate (sensitivity), surpassed only by the existing extRH model. The LSTM-based model (LW<sub>LSTM</sub>) exhibited high overall accuracy, specificity and F1 scores across climate zones. Furthermore, this model required fewer input variables, as its time-series architecture effectively capture temporal patterns, making it well-suited for real-time integration into DSSs.

Both the LW<sub>KNN</sub> and LW<sub>LSTM</sub> models achieved comparable performance, with the highest overall accuracy, second-highest specificity, and mid-range F1 score among the tested models. However, they also exhibited some of the lowest sensitivities, indicating strong general classification performance but limited ability to detect leaf wetness presence. The LW<sub>MLP</sub> model showed even higher specificity but at the cost of even lower sensitivity. In contrast, the existing extRH model, despite having the lowest accuracy, specificity and F1 score, demonstrated the highest sensitivity, making it the most effective at identifying leaf wetness events. The simpler machine learning models such as LW<sub>DT</sub>, offered a more balanced trade-off between sensitivity and specificity, ranking highest overall in terms of F1 score, a recommended metric for evaluation performance on imbalanced datasets. These metrics, although rarely reported in leaf wetness model evaluations, are critical for practical applications. Gillespie et al. [9] included both sensitivity and specificity in their evaluation and similarly found that models with high sensitivity often had low specificity and vice versa. A low specificity can lead to overestimation of leaf wetness, potentially triggering unnecessary control measures in DSSs for diseases like potato late blight [34] and downy mildew [35,36]. Conversely, low sensitivity may result in underestimating infection risk, leading to missed alerts and potential yield or quality losses. Ideally, both errors should be minimized to balance environmental and economic outcomes.

Our study demonstrated that machine learning algorithms are well-suited for predicting leaf wetness. All five machine learning classification algorithms tested, consistently outperformed, or matched, the accuracy of the five existing empirical models evaluated. This aligns with findings from Park et al. [10] and Gillespie et al. [9], who also reported superior performance of newly developed machine learning models over traditional empirical approaches in leaf wetness predictions. Although the LSTM algorithm is widely used for modeling temporal weather data (e.g. [37]), we did not identify any peer-reviewed publication where this algorithm had been used to predict leaf wetness. The second-best performing model, according to accuracy, across all locations in this study

was the MLP based model (LW<sub>MLP</sub>), which is consistent with Gillespie et al. [9], who identified MLP as the top-performing model approach compared to DT, RF and KNN. Although having a high accuracy, its sensitivity was the lowest among all models tested, resulting in corresponding low F1 scores.

Among the existing models evaluated in this study, the CART/SLD model demonstrated the highest overall accuracy across Europe, closely followed by the RH87, RH90 and DPD models. Compared to other simple empirical approaches, the CART/SLD has also been identified as the most effective model for estimating leaf wetness in multiple regions, ranking highest in studies conducted across four U.S. states [7], five U.S. states [6], and in Brazil [12]. Empirical models, including those based on machine learning, rely solely on observed data and are therefore limited to accurately predicting system behavior only under the weather conditions represented in the training data. The empirical models evaluated in this study have been widely tested in peer-review literature, and their portability has shown mixed results across studies [13,38]. Our findings confirm that the performance of empirical models for leaf wetness predictions varies considerably across different climate zones. In the polar climate zone, the existing RH87 model demonstrated the highest accuracy among the empirical models tested, whereas the existing RH90 emerged as the best performing model in cold climates. Our results align with previous studies, exemplified by Sentelhaas et al. [13] who reported strong performance for both RH90 and DPD in cold regions, while Gleason et al. [7] found CART/SLD to outperform RH90 in U.S. locations within the cold zone, as defined by the Köppen-Geiger classification. In the temperate climate zone, the CART/SLD model stood out, achieving the highest accuracy among the empirical models and ranking second overall when compared to all ten models evaluated in this study. This is consistent with findings from multiple studies: Gleason et al. [7] identified CART/SLD as the best model across four U.S. states; Montone et al. [6] confirmed its superiority across five U.S. states; and Lulu et al. [12] found CART/SLD to be the top performer in Brazil, followed by DPD and RH90, all within the temperate zone. Additionally, Gillespie et al. [9] reported better performance for RH90, followed by CART/SLD in the UK, which also falls within the temperate zone. In our study, CART/SLD was the second-best model overall in the temperate zone, while RH90 and DPD tied the second best among the existing empirical models. In the arid climate zone, RH90 again proved to be the most accurate among the existing empirical models, reinforcing its robustness across diverse climatic conditions.

Model performance varied across climate zones, reflecting differences in environmental conditions and data characteristics. All models achieved their highest accuracy in the arid zone, characterized by warm and dry conditions. Previous studies have shown that empirical models tend to perform better when trained on site-specific data that closely reflect local conditions [13]. To enhance performance, the newly developed models were additionally tested on data from the same locations as included in the training data, in this case, the Norwegian data only. In line with the literature, significant improvements in performance were found for all metrics. While the models already performed well on the European scale, their accuracy and robustness increased when tested within the same locations for which they were trained.

Daytime is typically the driest part of the day, as dew formation, driven by condensation, usually occurs during the early morning and evening hours. Across models, classification of the absence of leaf wetness was generally more accurate during these daytime periods, while performance declined during the more humid periods when dew was present. The LW<sub>LSTM</sub> and LW<sub>MLP</sub> models developed in this study showed the most consistent specificity throughout the day, whereas the existing extRH model exhibited the greatest variability and performed particularly poorly at identifying dry conditions during dew-prone nighttime hours. Conversely, the models generally performed better in detecting leaf wetness during the humid morning and evening periods compared to the daytime. Notably, the LW<sub>MLP</sub> and LW<sub>LSTM</sub> models maintained consistent performance throughout the day. The existing

extRH model was the most effective at correctly classifying leaf wetness during the night, while the  $LW_{MLP}$  and  $LW_{LSTM}$  models were the least effective. During daytime, the  $LW_{KNN}$  and  $LW_{RF}$  models had the highest sensitivity. Throughout the daytime, accuracy—similar to specificity—reached its peak levels for all the models, indicating that performance was most reliable during this period. Our results align with findings by Gillespie et al. [9], who observed higher accuracy during daytime compared to nighttime across 13 evaluated models.

When estimating leaf wetness as the number of hours with presence of leaf wetness per day, the  $LW_{LSTM}$  model showed a slight tendency to underestimate, while the  $LW_{MLP}$  model exhibited a more pronounced underestimation. In contrast, both the existing CART/SLD and extRH models consistently overestimated the presence of leaf wetness, a pattern also observed in previous studies. For example, Park et al. [10] and Kim et al. [39] reported an overestimation of the presence of leaf wetness by the CART/SLD model during wet seasons in northwestern Costa Rica and in South Korea, respectively, while Sentelhas et al. [13] found similar results for the extRH model across diverse locations in U. S., Canada, Italy and Brazil. The  $LW_{DT}$ ,  $LW_{RF}$  and  $LW_{KNN}$  models tended to overestimate the presence of leaf wetness during dry days, although their predictions of hours with leaf wetness were more linearly aligned with observed values. This pattern of linearity was also noted for the RF based model in Park et al. [10]. Measurement errors in specific weather variables can substantially affect the performance of disease forecasting models that rely on weather data as input. The extent of this impact depends on both the importance of the affected variable within the disease forecasting model and the timing of the error. For instance, inaccuracies in leaf wetness measurements during critical periods, such as early morning hours when many plant-pathogenic fungi release spores, can substantially reduce the reliability of disease forecasting models [40]. To assess the precision of the two weather data services included in this study, weather stations representing each service, were placed just a few meters apart in Ås, Norway. Although the measured weather data from the two services were generally consistent, the observed differences revealed typical weather data errors, which can be classified as either random (naturally occurring and reflected in variance) or systematic (caused by factors such as sensor miscalibration, wear and tear, poor maintenance, or suboptimal placement). A substantial systematic component was observed for relative humidity, accounting for 39 % of the RMSE, likely due to the documented tendency of sensor drift over time [41], which highlights the need for regular recalibration of weather data sensors. In comparison, leaf wetness, air temperature, precipitation and wind speed were primarily affected by random errors. Overall, the highest differences were detected for leaf wetness, which may be compromised by the absence of standardized measurement protocols and the differing response times of various sensor models [42].

The successful integration of the  $LW_{LSTM}$  and the RH90 models into the operational web-based IPM Decisions DSS platform, enable the real time estimation of missing leaf wetness values as inputs for disease forecasting models. The  $LW_{LSTM}$  model was implemented as the primary model, while the RH90 model is automatically applied when weather data variables are missing, as it relies solely on humidity. This study highlights the importance of combining robust model performance with scalable and interoperable software architecture. By reimplementing the model in Python and deploying it via containerized web services, the system ensures both technical flexibility and ease of maintenance and upgrade if the models are being trained on expanded or other data sets, which are critical for long-term sustainability and cross-platform compatibility in agricultural decision support.

## 5. Conclusion

Our study demonstrated the effectiveness of machine learning approaches for estimating leaf wetness across European climate zones using standard meteorological data. Among the ten models evaluated,

the decision tree model ( $LW_{DT}$ ) developed in this study achieved the highest F1 score. Overall, the LSTM-based model ( $LW_{LSTM}$ ), also developed within this study, performed well across climate zones. Leveraging its time-series architecture,  $LW_{LSTM}$  required fewer input variables, highlighting its suitability for integration into real-time decision support systems (DSSs). The model also exhibited high specificity, although its sensitivity was comparatively lower than that of other models evaluated in this study.

The simpler machine learning model  $LW_{DT}$ , developed in our study, offered a more well-balanced performance across sensitivity and specificity, leading to an overall high F1 score, providing alternative methods for the estimation of leaf wetness depending on application needs. Our study also confirmed the continued relevance of empirical models like CART/SLD and RH90, which performed well in specific climate zones.

All models showed variation in performance depending on environmental conditions, and the highest accuracy was observed in the arid zone and during dry daytime periods. These insights highlight the importance of accounting for both spatial and temporal factors when evaluating mathematical models for the estimation of leaf wetness. All models developed within this study improved their performance while tested on data from the same weather stations as included in the training data.

Finally, the successful deployment of the  $LW_{LSTM}$  and the RH models into an operational DSS platform illustrates the potential of combining advanced machine learning techniques with scalable software architecture. This integration supports a more accurate and timely disease forecasting, contributing to improved crop protection and sustainable agricultural decision-making across Europe.

## Ethical statement

The authors declare that they have no competing interests.

Ethical approval This study does not contain any studies with human participants or animals performed by any of the authors.

Consent for publication All authors consent to this submission.

## CRediT authorship contribution statement

**Anne-Grete Roer Hjelkrem:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis. **Brita Linnestad:** Writing – review & editing, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Ingerd Skow Hofgaard:** Writing – review & editing, Visualization, Supervision, Investigation. **Berit Nordskog:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.atech.2025.101723](https://doi.org/10.1016/j.atech.2025.101723).

## Data availability

The authors do not have permission to share data.

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