



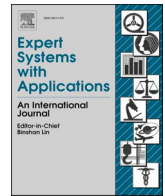
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# Can machine learning classification methods improve the prediction of leaf wetness in North-Western Europe compared to established empirical methods?

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## ABSTRACT

Leaf wetness is an important input parameter into disease prediction models. The use of machine learning algorithms for the classification of leaf wetness measurements from 30 meteorological stations in North Western Europe during the period of January 2014 to October 2018 was assessed in this study. The accuracy of the empirical models utilised within in this study was enhanced by increasing the relative humidity threshold from 90% to 92%. Increasing the relative humidity threshold led to an average increase in the classification accuracy of 1.12%. The use of machine learning classification algorithms consistently provided more accurate results for the prediction of leaf wetness when compared to the empirical models that were studied with an average increase in the classification accuracy of 4.85%. The sub-division of the data into regional subsets had a greater effect on the accuracy of the models than the temporal sub-division of the data. Machine learning classification techniques performed well compared with previously established empirical models for the prediction of leaf wetness. Further improvements in the algorithms are possible, making the techniques studied here a viable research tool.

## 1. Introduction

The development of a number of plant fungal and bacterial diseases are dependent upon the presence of water on plant surfaces, commonly referred to as leaf wetness (Rowlandson et al., 2015; Sentelhas et al., 2008) examples include bacterial spot disease of stone fruits and almond (Morales et al., 2018), Gibberella ear rot in Maize (Rao et al., 1998), apple scab in apples (Stella et al., 2017) and yellow rust and septoria blotch in wheat (Matzen et al., 2019). Typically water may accumulate on the canopy as a result of either rainfall events, irrigation, guttation (the secretion of droplets of water from the pores of a plant), dewfall from the atmosphere or distillation from the soil (Amir, 2016; Rowlandson et al., 2015; Sentelhas et al., 2008). As this paper is focussed on cultivation regions in north-western Europe, irrigation is not considered as a significant contributor to leaf wetness as it is not common to irrigate cereal crops or other broadacre crops. Guttation is an internal leaf process which exudes free water onto the leaf surface, little is known about guttation except that it primarily occurs on injured leaves and during periods of intense root growth activity (Jacobs et al., 1994). The

occurrence of leaf wetness is an important parameter as an input variable into a disease prediction model along with temperature. Temperature is an important parameter for all phases of plant disease development while moisture is important for the infection process and the release of bacterial spores (Gillespie & Sentelhas, 2008). The development of accurate disease warning systems has the potential to allow farmers to reduce the amount of chemical fungicides they apply without affecting the yield of their crops (Gleason et al., 2008). In the United Kingdom in 2016 alone, over 5,684.4 tonnes (active substance) of fungicides were applied to broadacre crops (Garthwaite et al., 2016), a reduction in this usage would have substantial impacts from both an environmental standpoint and on the economics of crop production. Environmental impacts of fungicides and other chemical products applied to crops present as residues in crop products, side effects on ground water contamination, impacts on local wildlife and eco-systems, and so on.

Current methods to determine the occurrence of leaf wetness include visual observation, threshold or empirical models and physical models (Kim et al., 2002; Pedro and Gillespie, 1982; Sentelhas et al., 2008;

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Wichink Kruit et al., 2004). The visual observation method is not a feasible method for implementation as it is time consuming, labour intensive and is subject to observer interpretation (i.e. at what level of observed moisture is the leaf considered wet?). The more common method of measuring leaf wetness is through the use of plate sensors which measure electrical resistance, as the surface of the sensor becomes wet the resistance decreases. These sensors have been developed and deployed since the late 1970's when Gillespie and Kidd (1978) used a grid of solder-coated copper fingers mounted on a 1 mm thick, epoxy fibreglass board to compare the drying times of various colours of the sensors within an onion crop.

The use of leaf wetness sensors on agricultural meteorological stations is limited, as a consequence many models for the prediction of leaf wetness have been developed including, but not limited to, (Gleason et al., 2008; Pedro and Gillespie, 1982; Rao et al., 1998). These models include both physical and empirical models. Empirical models are based on readily available meteorological data such as rainfall, relative humidity and windspeed (Francl & Panigrahi, 1997). Francl and Panigrahi (1997) reported that surface wetness obviously coincides with rainfall events, however, the time surfaces remain wet after rainfall is a more complex issue and depends on post-precipitation environmental conditions that influence drying times. An advantage of empirical based models over physical based models is that they require fewer input variables that are more readily available for most regions where crops are cultivated (Montone et al., 2016). Physical models for the prediction of leaf wetness may provide a more accurate prediction, however, the need for complex environmental conditions related to cloud cover, solar radiation, energy fluxes, crop growth parameters and soil parameters make the models complicated and less suitable as general models for the prediction of leaf wetness over larger areas (Allen et al., 1998; Bregaglio et al., 2011; Montone et al., 2016; Stella et al., 2017).

Remote sensing of agricultural crops from both satellite and drone images has become increasingly common in recent years (Huang et al., 2018; Maes & Steppe, 2019). Leaf wetness may play an important role in the accuracy of the models produced from these images. Hornbuckle et al. (2006) and Hornbuckle et al. (2010), have demonstrated that free water, in the form of dew, on the canopy of a maize crop had the effect of decreasing the brightness temperature of that crop while free water on the canopy of a wheat and grass crop had the effect of increasing the brightness temperature of the crop at the 1.4 GHz frequency of the European Space Agency's Soil Moisture and Ocean Salinity satellite. If the effect of free water upon canopies is not taken into account during image acquisition estimations of soil moisture could be biased which may have an effect on drought stress, yield prediction and disease monitoring models of crops.

Machine Learning (ML) has been defined by Liakos et al. (2018) as the scientific field that gives machines the ability to learn without being strictly programmed allowing for large non-linear problems to be solved autonomously (Chlingaryan et al., 2018). ML techniques have been adopted in a range of agricultural problems in order to help with the prediction and classification of a diverse range of parameters. Piedad et al. (2018) utilised tier-based ML combined with machine vision for the postharvest classification of banana with an accuracy of 94.2% achieved using the Random Forest (RF) classifier. A number of ML algorithms combined with spectral reflectance values have been implemented by Karadağ et al. (2020) to detect fusarium disease in peppers. The average success rate for the classification of peppers into diseased and healthy peppers was found to be 100% for the K-nearest neighbours (KNN) algorithm, 97.5% for an artificial neural network algorithm and 90% for the Naïve Bayes algorithm (Karadağ et al., 2020). Mehra et al. (2016) used ML techniques, mainly artificial neural networks and RF to predict the risk of *Stagonospora nodorum* blotch in winter wheat using pre-planting factors.

This paper specifically seeks to investigate the efficacy of ML techniques for the prediction of leaf wetness in North-Western Europe. It compares five popular ML classification algorithms with six pre-existing

empirical models for the prediction of leaf wetness in a temperate maritime climate. This paper is novel as it constitutes the first comprehensive methodological study which compares a range of ML techniques with established 'blue ribbon' benchmarks for the prediction of leaf wetness. To date limited work has been undertaken in considering ML techniques for the prediction of leaf wetness.

## 2. Machine learning classification background

The classification methods used in this paper are each briefly described in the subsections below (Sections 2.1 to 2.7), the aim of this paper is not to provide an exhaustive explanation of each classification method, but to give an understanding of how each method operates. Further detail on all of the classification methods used in this paper and the underlying mathematical processes of each can be found in the Scikit-learn documentation (<https://scikit-learn.org/stable/supervised-learning.html#supervised-learning>). The described classification methods were chosen as a review of scientific literature shows them to be the most commonly used algorithms for classification purposes of agricultural and meteorological data.

### 2.1. Support Vector classification (SVC)

Support Vector Machines (SVMs) are a group of supervised learning algorithms, which can be used for both classification and regression purposes (Binkhonain & Zhao, 2019). The objective of SVM algorithms is to find a hyperplane in N-dimensional space (with N being the number of features used to develop the model) which distinctly classifies the data points. SVMs attempt to maximise the distance between data points of the classes used in the classification, in the case of this paper the 'wet' and 'dry' time periods (Binkhonain & Zhao, 2019; Leena & Saju, 2019). These algorithms look for all data points that are close to the opposing class. These data points, which are known as support vectors, are important in the classification task, while the rest of the training data points are ignorable. Thereafter, the best separation line, known as the decision boundary, is defined (Leena & Saju, 2019). Due to the long training time required for SVC algorithms on large datasets with non-linear kernels, LinearSVC was used in this study. According to Pedregosa et al. (2011) LinearSVC is appropriate for large datasets (where the number of samples is  $> \sim 50,000$ ) as the fit time complexity is more than quadratic with the number of samples making it difficult to scale to larger datasets.

### 2.2. Gaussian Naïve Bayes (GNB):

GNB is a statistical method based on Bayes' theorem, with a strong 'assumption of independence between features' (Karadağ et al., 2020). GNB computes the probability of an input that is relevant to a specific pre-defined class, with the help of certain statistical functions (Binkhonain & Zhao, 2019; Kamilaris and Prenafeta-Boldú, 2018). The output of this algorithm is the category with the highest probability (Binkhonain & Zhao, 2019; Kamilaris and Prenafeta-Boldú, 2018; Karadağ et al., 2020). The Bayesian approach for classification consists in finding the most probable class for a new example within a finite set of classes given the attributes that describe this example (Casamayor et al., 2010; Rehman et al., 2019).

### 2.3. Decision tree (DT)

DTs are logic based algorithms where datasets are modelled in hierarchical structures using a series of comparisons of if/else statements to arrive at a homogenous classification of a target variable (Alpaydin, 2010; Moller et al., 2019). Each node in the tree consists of either decision nodes containing terms or 'leaves' (Alpaydin, 2010), which consist of class label predictions. The branches are labelled by the weight of each term in the document (Binkhonain & Zhao, 2019;

Chlingaryan et al., 2018).

#### 2.4. Random forest (RF):

A RF is a collection of DT classifiers grouped together to form a forest (Breiman, 2001; Chaudhary et al., 2016). RFs are popular machine learning algorithms used for several types of classification tasks for noisy and unbalanced data and can identify non-linear patterns in the data (Chaudhary et al., 2016; Hart et al., 2019). A RF algorithm builds a collection of independent DTs whose results are combined to make a prediction for a given data record. Every tree of the forest gives a unit vote, assigning each input to the most probable class label (Hart et al., 2019; Saggi & Jain, 2019). Some of the major advantages of the RF classifier is that they are fast to train and do not suffer from over fitting, even if more trees are appended to the forest (Chaudhary et al., 2016; Hart et al., 2019).

#### 2.5. K Nearest neighbours (KNN)

KNN is a statistical method used to predict the new input by computing the similarity between the test data and the new instance through finding the nearest K data points in the training dataset based on certain distance functions (Karadağ et al., 2020). K represents the number of nearest data points (i.e. neighbours) (Alpaydin, 2010; Chlingaryan et al., 2018; Khan et al., 2010).

#### 2.6. Logistic regression (LR):

LR estimates the probability of a binary response variable based on a set of predictor inputs (Hart et al., 2019; Sirsat et al., 2017). Unlike linear regression which outputs continuous number values, LR transforms its output using the logistic sigmoid function to return a probability value which can then be mapped to two or more discrete output classes (Hart et al., 2019; Piccini et al., 2019).

#### 2.7. Multi-Layer Perceptron (MLP)

An MLP is a type of feed forward artificial neural network (Piedad et al., 2018). For classification problems, the aim of an MLP is to approximate a nonlinear function to map covariates to a class label from a set of K possible class labels using model parameters (Augusta et al., 2019; Goodfellow et al., 2016). These model parameters are in effect the values of the weights on the connections between nodes (Goodfellow et al., 2016). Modelling begins with the input layer, proceeds to (at least) one hidden layer, and ends at the output layer (Ferentinos, 2018; Kamilaris and Prenafeta-Boldú, 2018). There are no feedback connections in which outputs of the model are fed back into itself (Saggi & Jain, 2019).

### 3. Materials and methods

#### 3.1. Meteorological data

Meteorological data for this study was collected from 31 weather stations from across the United Kingdom (Fig. 1.) These weather stations were also grouped into smaller regions to determine if better predictions could be made from similar regions as opposed to a general model for the entire of the United Kingdom. The regional subsets of the data were determined following a visual assessment of the spatial distribution of the meteorological stations that were used in this study. All of the weather stations recorded rainfall (mm), air temperature (°C), relative humidity (%), windspeed ( $\text{m s}^{-1}$ ), wind direction (°) and solar radiation ( $\text{W m}^{-2}$ ) in 15 min intervals between January 1st 2014 and October 22nd 2018 totalling 3.23 million weather records.

All of the sensors used in this study were supplied by ADCON (<http://www.adcon.com/products/sensors-284/>), OTT HydroMet GmbH,

Klosterneuburg, Austria). Rainfall was measured with a resolution of 0.2 mm ( $\pm 1\% < 50 \text{ mm h}^{-1}$ ;  $\pm 3\% 50 - 100 \text{ mm h}^{-1}$ ;  $\pm 5\% > 100 \text{ mm h}^{-1}$ ) using the RG1-200 tipping bucket rain gauge. Air temperature ( $\pm 0.1 \text{ }^\circ\text{C}$ ) and relative humidity ( $\pm 1\% 0 - 90\%$  and  $\pm 2\% 90 - 100\%$ ) were measured using the TR1 combi-sensor. Wind speed was measured with the 3 cup anemometer ( $\pm 0.3 \text{ m s}^{-1}$ ) and wind direction was measured with the wind vane ( $\pm 2^\circ$ ) of the Vento1 wind sensor set. Solar radiation was measured using the SP-Lite pyranometer. The pyranometer has a temperature dependence of  $+ 0.15\% \text{ }^\circ\text{C}^{-1}$  and a directional error of  $\pm 5\%$  at  $80^\circ$ . Soil temperature ( $^\circ\text{C}$ ,  $\pm 0.3 \text{ }^\circ\text{C}$ ) was recorded at a depth of 10 cm using the ST2 sensor (Fig. 1.). Leaf wetness was measured using the WET leaf wetness sensor. The leaf wetness sensor has an output that is between 0 and 10, this was converted to a dichotomous signal (0; dry and 1; wet) for comparison with other relevant studies. Readings from this sensor between 0 and 3 were deemed dry whilst readings from 4 to 10 were deemed wet in accordance with the sensors technical data. All of the meteorological stations used in this study followed a rigorous installation process and undergo routine monitoring and maintenance to ensure no issues with biofouling and leaf build up affect the measurements for prolonged periods of time.

#### 3.2. Leaf wetness models

The ML models were compared against previously published empirical models for the prediction in leaf wetness. The empirical models that were chosen for comparison included models that were developed solely using meteorological data as input parameters as no information on the soil characteristics, canopy height measurements or Leaf Area Index (LAI) measurements were available for inclusion from other physical based models. *Threshold models* are a subset of empirical models that define a time period as wet if a meteorological variable, typically relative humidity (RH), is greater than a specified value. The current threshold value that is widely used is when  $\text{RH} > 90\%$ . The authors also increased the threshold values of RH to 92% and 95% to determine if these higher values would lead to more accurate predictions. van Jaarsveld (2004) outlined a threshold value of  $\text{RH} > 87\%$  which is used in the atmospheric transport model (OPS) of RIVM. Kim et al. (2002) expanded on a model that was previously published by Gleason et al. (1994) which used a classification and regression tree (CART) approach (Fig. 2) combined with a stepwise linear discriminant regression and a corrected windspeed factor to estimate the leaf wetness duration (LWD) of 15 sites in the United States. The DPD parameter illustrated in Fig. 2 is the Dew Point Depression which is defined as the difference between the air temperature and the dew point. Hours are classified as wet if either Inequality 1 or Inequality 2 are met. The model developed by Kim et al. (2002) predicted the LWD more accurately than a proprietary model for both the dew eligible and dew ineligible time periods.

$$\text{Inequality 1} = (1.6064\sqrt{T_{\text{air}}} + 0.0036T_{\text{air}}^2 + 0.1531\text{RH} - 0.4599 \text{Wind} * \text{DPD} - 0.0035T_{\text{air}} * \text{RH}) > 14.4674$$

$$\text{Inequality 2} = (0.7921\sqrt{T_{\text{air}}} + 0.0046\text{RH} - 2.3889\text{Wind} - 0.039T_{\text{air}} * \text{Wind} + 1.0613\text{Wind} * \text{DPD}) > 37.0$$

The final two empirical models used for the prediction of leaf wetness are extended from threshold models outlined by (Wichink Kruit et al., 2004). These models account for changes in the RH over a defined time period. In this study two time periods were used, 15 min and 30 min. The models define a time period as wet if the RH is above 87%, and dry if it is below 70%. For RH values between these values leaves are assumed to be wet if the RH increases by  $> 3\%$  in the time period and dry if it decreases by  $> 2\%$  (Wichink Kruit et al., 2004).

#### 3.3. Machine learning classification algorithms

The Scikit-learn module (Pedregosa et al., 2011) in the Python programming language compiled into a script was used to test whether or

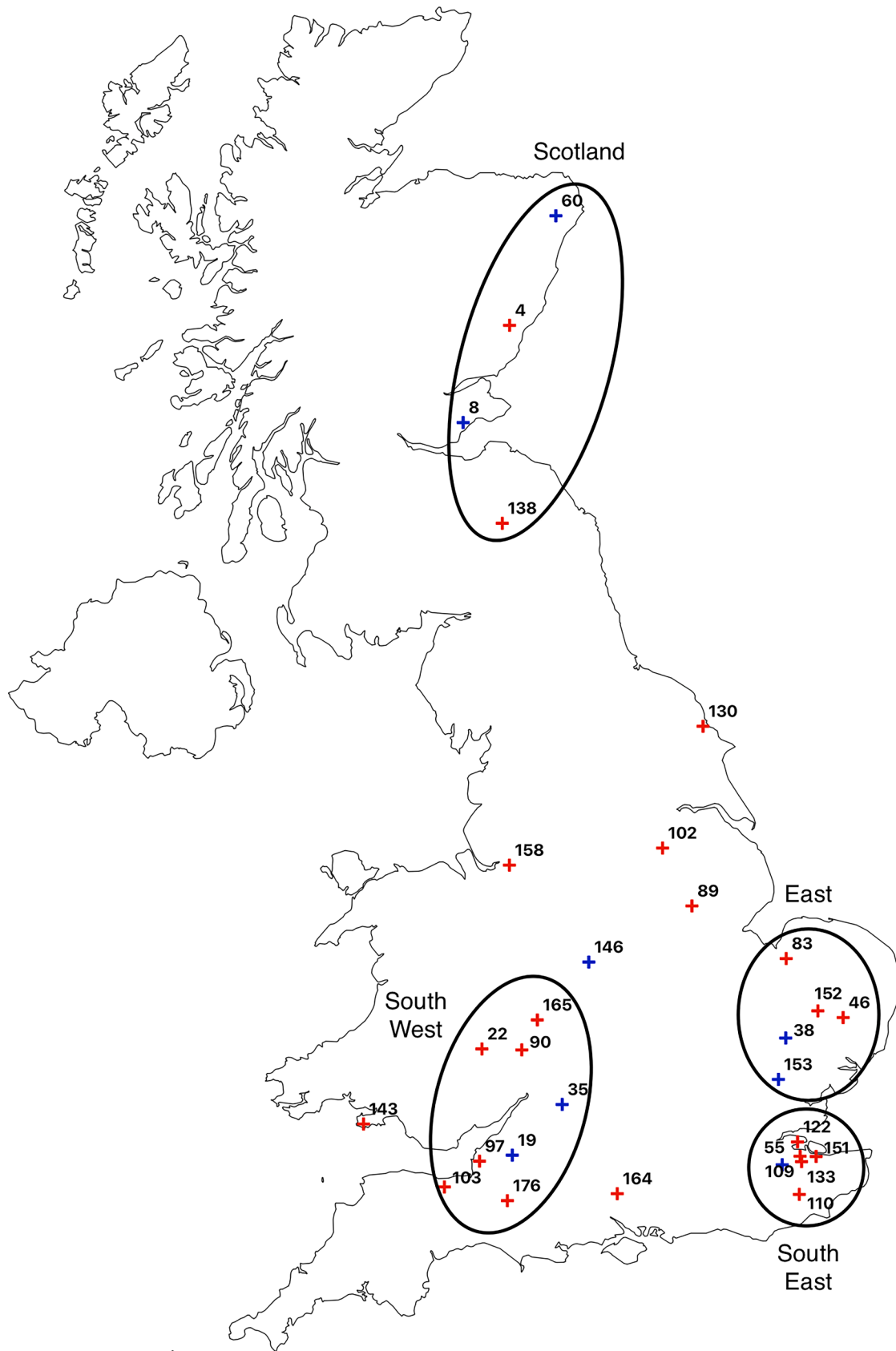


Fig. 1. Map of the locations of the weather stations used in this study and sub-regions for localised determination of leaf wetness. Blue +; stations with soil temperature measurements, Red +; stations without soil temperature measurements, numbers indicate the station ID.

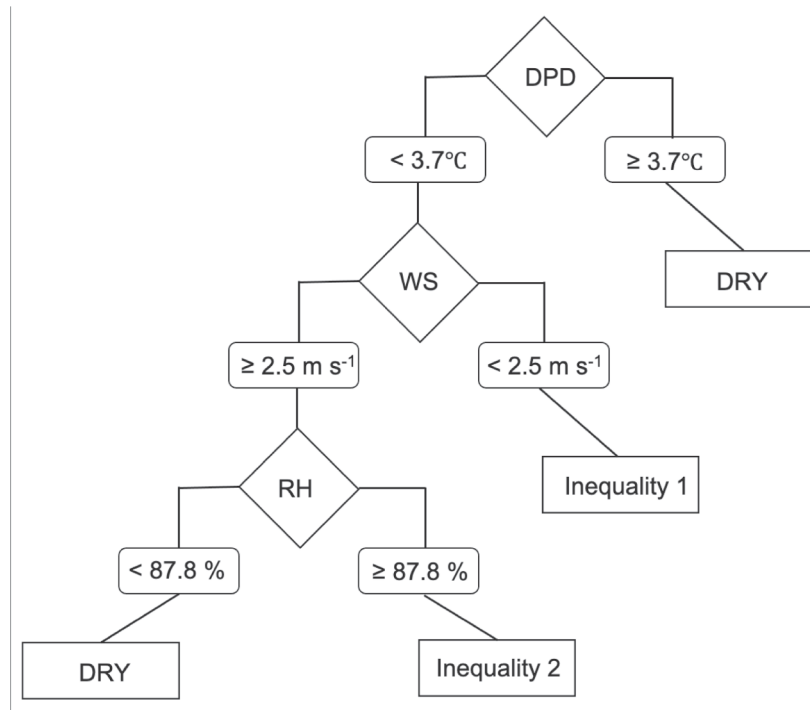


Fig. 2. Classification and Regression tree for the prediction of leaf wetness duration used by Kim et al., 2002.

not the described ML classification methods could correctly differentiate the time periods of weather data into two classes of leaf wetness: ‘wet’ and ‘dry’. The Scikit-learn module was selected as Python is considered globally to be one of the most popular programming languages for scientific computing and has extensive scientific libraries available. In this study the data was split into training and test sets with the test set size being 20% of the initial dataset. All of the classification methods were set to default parameters unless specified otherwise. The air temperature, rainfall, relative humidity, solar radiation and windspeed parameters were used as input variables in all of the models that were developed in this paper. The soil temperature variable was only used as an input variable in the subset of data that looked at the meteorological stations that had this sensor installed. Data points were only considered as outliers if they exceeded possible ranges (e.g. a relative humidity value of >100%) otherwise all data points were included in the datasets. The data was not normalised prior to classification. 3-fold cross validation was used to validate model robustness. 3-fold was used as Feng et al. (2008) found no statistical difference between this and 5-fold cross validation techniques. Also Romeiko et al. (2020) found 3-fold cross validation useful for implementation on agricultural data such as that utilised in this study.

### 3.4. Model metrics

In this section we describe the measures that were used to evaluate the performance of the models developed. This paper presents results of the performance of the models on the test set data. The confusion matrix of each model was obtained which allowed for the classification accuracy and a number of performance metrics to be calculated. These metrics included the *precision*, *recall*, *specificity* and *F-score*. The log loss and AUC-ROC score for each model were also obtained. The classification accuracy is defined as the number of correct predictions / total number of predictions  $((TP + TN) / (TP + TN + FP + FN))$ , where TP is true positives, TN is true negatives, FP is false positives and FN is false negatives. Precision is defined (Binkhonain & Zhao, 2019) as  $TP / (TP + FP)$ . It measures the total number of correctly classified observations with respect to the total number of observations retrieved. Recall (also

called the true positive rate) measures the fraction of observations that were correctly classified by the model and is expressed as  $TP / (TP + FN)$  (Kamilaris and Prenafeta-Boldú, 2018). Specificity (also referred to as the true negative rate) is the opposite of Recall and is defined as  $TN / (TN + FP)$ . The *F-Score* corresponds to the trade-off value of precision and recall is the harmonic mean of the two (Kamilaris and Prenafeta-Boldú, 2018). It is expressed as  $2 * (precision \times recall) / (precision + recall)$ . The *F-Score*, which is also commonly referred to as the *F1 score*, can also be considered as a measure of a models robustness, with higher *F-Scores* allowing for greater confidence in the predictions made by the classifier. The ROC score outlines the diagnostic ability of a binary classification system. Hindle et al. (2013) argue that the ROC score is less biased when compared to measures such as the *F-Score* which tends to skew towards the positive class in the case of unbalanced class distribution (Binkhonain & Zhao, 2019). ROC curves describe how good the models are at predicting the positive class when the actual outcome is positive and for this reason were chosen to display the results of the models evaluated in this work. The area under the ROC curve (AUC) is a measure of how well a parameter can distinguish between two classes (wet/dry). For the ROC curves displayed in this work (for the ML models) the predicted probabilities of achieving a classification result are presented in an effort to smooth the curves, this was achieved by employing the predict\_proba function of the sklearn module that was utilised to develop the models. As there is no inherent probability of an outcome associated with the empirical models the ROC curves for these models have not been smoothed. The log loss metric measures the uncertainty of the probabilities of a model by comparing them to the actual labels. The lower the uncertainty of the prediction the better the model is at predicting the correct classification class.

## 4. Results and discussion

The accuracy results from the K-means models ranged from 44.23% to 67.12% with an average accuracy of 51.77% and were therefore not presented in this study.

Table 1 shows the results of the models produced using the entire dataset and the subset produced using the soil temperature parameter as

**Table 1**  
Performance metrics with standard deviation in parentheses for the unfiltered and soil temperature dataset models<sup>a</sup>.

Data Subset	Model	A	P	R	S	F	L	Model <sup>b</sup>	A <sup>f</sup>	P	R	S	F	L
All Records <sup>c</sup> [3,229,242]	<b>RH &gt; 87</b>	73.43 (0.91) <sup>e</sup>	0.91 (0.01)	0.66 (0.01)	0.88 (0.02)	0.76 (0.01)	9.18 (0.31)	<b>GNB</b>	68.63 <sup>ns</sup> (0.13)	<b>0.91</b> ( <b>0.01</b> )	0.58 (0.01)	<b>0.89</b> ( <b>0.01</b> )	0.70 (0.01)	8.48 (1.37)
	<b>RH &gt; 90</b>	76.69 (1.01)	0.87 (0.01)	0.75 (0.01)	0.80 (0.03)	0.81 (0.01)	8.05 (0.35)	<b>DT</b>	74.02 <sup>ns</sup> (0.10)	0.80 (0.01)	0.80 (0.01)	0.62 (0.01)	0.80 (0.01)	9.01 (0.05)
	<b>RH &gt; 92</b>	<b>77.85</b> (1.08)	0.85 (0.01)	0.81 (0.01)	0.73 (0.03)	<b>0.83</b> (0.01)	<b>7.65</b> (0.37)	<b>RF</b>	78.24* (0.43)	0.81 (0.01)	0.86 (0.01)	0.63 (0.02)	0.84 (0.01)	7.54 (0.17)
	<b>CART</b>	69.70 (0.61)	0.70 (0.01)	<b>0.95</b> (0.01)	0.23 (0.02)	0.80 (0.01)	10.46 (0.21)	<b>KNN</b>	77.28 <sup>ns</sup> (0.02)	0.82 (0.01)	0.84 (0.01)	0.65 (0.01)	0.83 (0.01)	7.92 (0.03)
	<b>RH_ext15</b>	66.48 (1.01)	0.94 (0.01)	0.51 (0.01)	0.94 (0.01)	0.67 (0.01)	11.58 (0.35)	<b>MLP</b>	<b>80.03</b> <sup>***</sup> ( <b>0.05</b> )	0.82 (0.01)	<b>0.89</b> ( <b>0.02</b> )	0.64 (0.03)	<b>0.85</b> ( <b>0.01</b> )	<b>6.90</b> ( <b>0.02</b> )
	<b>RH_ext30</b>	63.78 (0.97)	<b>0.95</b> (0.01)	0.47 (0.01)	<b>0.95</b> (0.01)	0.63 (0.01)	12.50 (0.34)	<b>LR</b>	78.72 <sup>***</sup> (0.04)	0.84 (0.01)	0.83 (0.01)	0.71 (0.01)	0.84 (0.01)	7.32 (0.03)
								<b>LSVC</b>	39.97 <sup>ns</sup> (7.89)	0.98 (0.04)	0.08 (0.13)	1.00 (0.03)	0.41 (0.19)	20.74 (2.73)
Soil Temperature <sup>d</sup> [817,082]	<b>Model</b>	<b>A</b>	<b>P</b>	<b>R</b>	<b>S</b>	<b>F</b>	<b>L</b>	<b>Model</b>	<b>A</b>	<b>P</b>	<b>R</b>	<b>S</b>	<b>F</b>	<b>L</b>
	<b>RH &gt; 87</b>	71.59 (0.84)	0.90 (0.01)	0.64 (0.01)	0.87 (0.01)	0.75 (0.01)	9.94 (0.38)	<b>GNB</b>	65.04 <sup>ns</sup> (4.71)	<b>0.91</b> ( <b>0.02</b> )	0.52 (0.10)	<b>0.90</b> ( <b>0.06</b> )	0.66 (0.07)	12.08 (1.63)
	<b>RH &gt; 90</b>	74.70 (0.78)	0.86 (0.01)	0.73 (0.02)	0.77 (0.01)	0.79 (0.01)	8.78 (0.30)	<b>DT</b>	79.37 <sup>***</sup> (0.16)	0.84 (0.01)	0.84 (0.01)	0.70 (0.01)	0.84 (0.01)	7.13 (0.06)
	<b>RH &gt; 92</b>	<b>75.81</b> (0.79)	0.83 (0.01)	0.79 (0.01)	0.69 (0.01)	<b>0.81</b> (0.01)	<b>8.31</b> (0.24)	<b>RF</b>	<b>83.16</b> <sup>**</sup> (1.05)	0.85 (0.01)	<b>0.91</b> (0.01)	0.69 (0.03)	<b>0.88</b> (0.01)	<b>5.82</b> (0.37)
	<b>CART</b>	68.42 (0.25)	0.68 (0.01)	<b>0.96</b> (0.01)	0.16 (0.01)	0.80 (0.01)	10.85 (0.13)	<b>KNN</b>	78.42 <sup>***</sup> (0.04)	0.83 (0.01)	0.85 (0.01)	0.65 (0.01)	0.84 (0.11)	7.46 (0.01)
	<b>RH_ext15</b>	64.45 (1.18)	<b>0.94</b> (0.01)	0.49 (0.02)	0.94 (0.01)	0.64 (0.02)	12.41 (0.49)	<b>MLP</b>	78.43 <sup>**</sup> (0.31)	0.85 (0.01)	0.81 (0.02)	0.73 (0.02)	0.83 (0.01)	7.45 (0.10)
	<b>RH_ext30</b>	62.02 (1.25)	0.94 (0.01)	0.45 (0.02)	<b>0.95</b> (0.01)	0.61 (0.01)	13.24 (0.52)	<b>LR</b>	77.50 <sup>**</sup> (0.26)	0.83 (0.01)	0.83 (0.01)	0.67 (0.01)	0.83 (0.01)	7.77 (0.09)
							<b>LSVC</b>	65.49 <sup>ns</sup> (2.01)	0.65 (0.02)	1.00 (0.01)	0.01 (0.08)	0.79 (0.01)	11.92 (0.83)	

<sup>a</sup> Key for parameters: A; Accuracy, P; Precision, R; Recall, S; Specificity, F; F-Score, L; Log loss metric

<sup>b</sup> GNB, Gaussian Naïve Bayes; DT, Decision Tree; RF, Random Forest; KNN, K-Nearest Neighbours; MLP, Multi-Layer Perceptron; LR, Logistic Regression; LSVC, Linear Support Vector Classification

<sup>c</sup> Numbers in square parentheses refer to the number of records in the dataset

<sup>d</sup> cf. Fig. 1 for the stations that recorded soil temperature at 10 cm depth

<sup>e</sup> Numbers in parentheses refers to the standard deviation from the average following 1 iteration of 3-fold cross validation

<sup>f</sup> Denotes whether the machine learning model accuracy is significantly greater than the preferred empirical model for that data subset based on the results of a one sample *t*-test. (ns, not significant; \*\*\*, p-value < 0.001; \*\*, p-value < 0.01; \*, p-value < 0.05.)

an independent variable. Soil temperature was chosen as an independent variable to determine if soil heat fluxes and evapotranspiration rates could be accounted for with this variable. From Fig. 3 the variable with the strongest correlation to leaf wetness is the relative humidity (Pearson's  $R = 0.52$ ) parameter followed by the solar radiation (SPLite) parameter (Pearson's  $R = -0.31$ ). The leaf wetness is negatively correlated with solar radiation as higher readings of solar radiation are related to bright, clear days which would increase the evaporation of water from the surface of leaves. This can also be seen as the RH is correlated with solar radiation with a Pearson's  $R$  value of  $-0.58$ . The low correlation of LW Binary (Fig. 3) to a single input variable illustrates the complex nature of predicting leaf wetness. The stations that recorded soil temperature are highlighted in Fig. 1. From Table 1 it appears that the addition of soil temperature as an independent variable to the models has a limited positive effect on the accuracy of the models. The preferred models (Table 1 and Fig. 4) with and without soil temperature had classification accuracies of 83.16% and 80.03%, respectively.

The 10 cm soil temperature is correlated with the air temperature with a Pearson's  $R$  value of 0.77 for the meteorological stations used in this study. Onwuka and Mang (2018) reported that increased soil temperature influences the interspheric process of gas exchange between the atmosphere and the lithosphere. This may have an effect on leaf wetness as it would result in greater amounts of atmospheric moisture present at crop height. Soil temperature also increases the rate of plant growth (Onwuka & Mang, 2018), and as a consequence this may increase the amount of guttation from plants which would keep the leaves of plants wet for longer periods. Kim et al. (2010) reports that a RH threshold of  $> 90\%$  has long been used as the standard to estimate LWD. The results from the empirical models for the full dataset and the soil temperature dataset in this study show that increasing the RH threshold from 90% to 92% increases the classification accuracy by 1.1% in both datasets. The increase in the RH threshold also increases the  $F$ -Score metric from 0.81 to 0.83 and reduces the log loss metric from 8.05 to 7.65 for the full dataset, indicating that the model is more robust in predicting the presence of water on the surface of a leaf. This increase in model capabilities can also be seen in the ROC curves shown in Fig. 4 and the AUC values of these curves presented in Table 4 with the  $RH > 92\%$  model having a similar or greater area under the curve to the other models. The area under an ROC curve indicates how well a model can distinguish between the classes. The results for the threshold model of  $RH > 95\%$  did not improve on the  $RH > 90\%$  model and thus were not shown in this work. The empirical models that expanded on the RH threshold value, (RH\_ext15 and RH\_ext30), and the CART model performed considerably worse than the  $RH > 92$  model with accuracies ranging from 63.78% to

69.7% for the full dataset.

For the full dataset the most accurate ML model in predicting the leaf wetness was that of the MLP model with an accuracy of 80.03%. The second best model was the LR model which had an accuracy of 78.72%. Using soil temperature at 10 cm depth as an independent variable in ML classification algorithms results in a 7.35% increase in the classification accuracy when compared with an empirical approach using the  $RH > 92\%$  threshold, this increases to 8.46% when the standard threshold of  $RH > 90\%$  is used. This may be due to the increased rate of evapotranspiration from warm soils as reported by Onwuka and Mang (2018).

#### 4.1. Effect of temporal subsets

Table 2 shows the results of the models that were split on a temporal basis. The time periods for the day-time subset contained records from 07:00 to 19:45, inclusive, while the night-time subset contained records from 20:00 to 06:45, inclusive. These datasets were not adjusted to account for any seasonal variation in day length that may occur during the growing season at the latitudes at which this study was conducted. The accuracies of the temporal models (Table 2, Table 4 and Fig. 5) were highest for the models that were developed using the MLP classification algorithm for both the day-time and the night-time subsets (84.05% and 75.63%, respectively). These models also had the lowest log loss parameters of 5.51 and 8.42, respectively. The models with the highest accuracies produced using the empirical approaches were developed when the  $RH > 92$  threshold was used (81.48% and 73.47% for the day-time and night-time subsets, respectively). The CART and extended threshold models were again the worst performing empirical models for the stations used in this study (Table 2, Table 4 and Fig. 4). As the CART model developed by Kim et al. (2002) used meteorological data for the states of Iowa, Nebraska and Illinois in the USA it may not be a suitable model for use in the humid maritime regions of North-Western Europe. Although the classification accuracy of the day-time model (84.05%) was higher than the classification accuracy of the full dataset model (80.03%), the average accuracy of the temporal models (79.84%) was comparable with the results of the full dataset model. This result would indicate that models produced using the full dataset would be more useful for farmers and decision makers as there would be less confusion between when/if the day-time model should be used. Henze et al. (2007) suggest that increasing day length at higher latitudes may affect the inoculation of some plant diseases. Conversely, night-time periods may not affect the growth of fungal spores on plants, however, more research would be needed to support or reject this hypothesis. As a full understanding of fungi that cause diseases such as *Septoria tritici* is not available, the details of their interactions with cereal crops remains elusive (Fones & Gurr, 2015). If this hypothesis held true then only leaf wetness periods during the day-time hours would be needed for disease prediction models allowing for the accuracy of 84.05% to be used. Further research on this topic would be required before any assessment could be made.

#### 4.2. Effect of regional subsets

Kim et al. (2010) reported that empirical based models may have issues with their spatial portability as climatic conditions associated with leaf wetness may differ by geographical location and the topography of the surrounding region (Duttweiler et al., 2008). The data in this study was sub-divided into 4 regions (Fig. 1) to determine if this had an effect on the accuracy of the models produced. The results of the regional models are presented in Table 3 and the ROC curves for the empirical and ML models are illustrated in Fig. 6 with the AUC values presented in Table 4. The accuracies of these models ranged from 78.88% to 81.80% for the empirical models and from 83.77% to 88.52% for the ML models. The average accuracy across the four regions used in this study for the empirical models and the ML models was 80.07% and 86.19%, respectively (Table 3). This compares to the accuracies of the

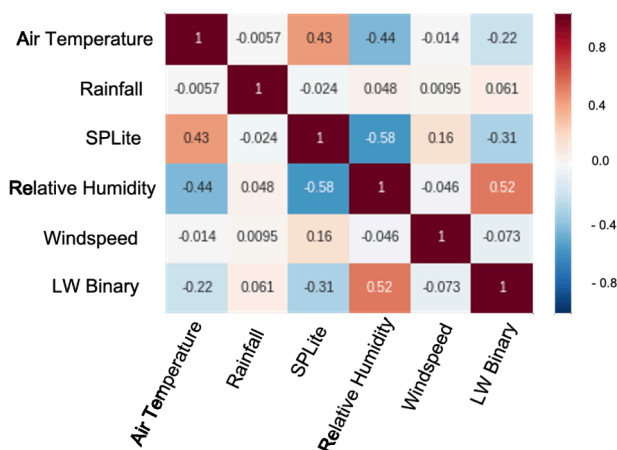


Fig. 3. Heatmap of the correlations between the input parameters. LW Binary refers to the leaf wetness readings from the sensor converted to a dichotomous signal.

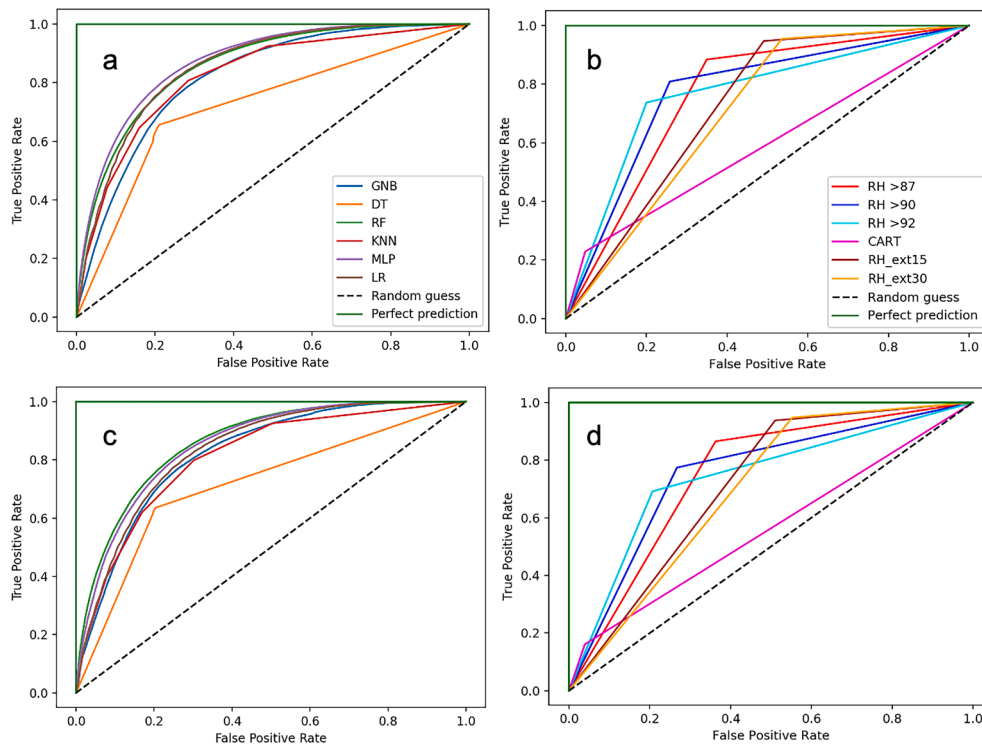


Fig. 4. ROC curves for (a) machine learning models of the full data set, (b) empirical models of the full dataset, (c) machine learning models of the soil temperature subset, and empirical models of the soil temperature subset (d).

Table 2

Performance metrics and standard deviations in parentheses for the models of the datasets filtered by time period<sup>a</sup>.

Data Subset	Model	A	P	R	S	F	L	Model	A	P	R	S	F	L	
Day-time <sup>b</sup> [1,749,201]	RH > 87	76.83 (0.89)	0.94 (0.01)	0.75 (0.01)	0.83 (0.01)	0.83 (0.01)	8.00 (0.31)	GNB	73.41 <sup>ns</sup> (0.20)	<b>0.94</b> (0.01)	0.70 (0.01)	<b>0.85</b> (0.01)	0.80 (0.01)	9.18 (0.07)	
	RH > 90	80.07 (0.80)	0.91 (0.01)	0.82 (0.01)	0.75 (0.02)	0.86 (0.01)	6.88 (0.28)	DT	78.84 <sup>ns</sup> (0.05)	0.86 (0.01)	0.86 (0.01)	0.56 (0.01)	0.86 (0.01)	7.31 (0.02)	
	RH > 92	<b>81.48</b> (0.75)	0.90 (0.01)	0.86 (0.01)	0.68 (0.03)	<b>0.88</b> (0.01)	<b>6.40</b> (0.26)	RF	83.21 <sup>**</sup> (0.44)	0.86 (0.01)	0.92 (0.01)	0.53 (0.03)	0.89 (0.01)	5.80 (0.15)	
	CART	77.85 (0.33)	0.79 (0.01)	<b>0.97</b> (0.01)	0.14 (0.01)	0.87 (0.01)	7.65 (0.12)	KNN	81.21 <sup>ns</sup> (0.05)	0.86 (0.01)	0.90 (0.01)	0.53 (0.01)	0.88 (0.01)	6.49 (0.02)	
	RH_ext15	69.09 (1.13)	<b>0.96</b> (0.01)	0.62 (0.01)	<b>0.92</b> (0.01)	0.75 (0.01)	10.68 (0.39)	MLP	<b>84.05</b> <sup>***</sup> (0.11)	0.86 (0.01)	<b>0.94</b> (0.02)	0.52 (0.05)	<b>0.90</b> (0.01)	<b>5.51</b> (0.04)	
	RH_ext30	67.24 (1.07)	0.96 (0.01)	0.60 (0.01)	0.92 (0.01)	0.74 (0.01)	11.32 (0.37)	LR	83.19 <sup>**</sup> (0.10)	0.87 (0.01)	0.91 (0.01)	0.57 (0.01)	0.89 (0.01)	5.81 (0.03)	
								LSVC	76.08 <sup>ns</sup> (23.5)	0.93 (0.02)	0.74 (0.33)	0.82 (0.08)	0.83 (0.33)	8.26 (8.21)	
		Model	A	P	R	S	F	L	Model	A	P	R	S	F	L
	Night-time [1,480,041]	RH > 87	68.96 (0.88)	0.85 (0.02)	0.48 (0.01)	0.91 (0.02)	0.62 (0.01)	10.72 (0.31)	GNB	71.93 <sup>ns</sup> (0.07)	<b>0.81</b> (0.01)	0.60 (0.01)	<b>0.85</b> (0.01)	0.69 (0.01)	9.70 (0.03)
		RH > 90	72.39 (1.20)	0.80 (0.02)	0.61 (0.01)	0.84 (0.03)	0.70 (0.01)	9.54 (0.41)	DT	69.40 <sup>ns</sup> (0.08)	0.70 (0.01)	0.71 (0.01)	0.67 (0.01)	0.71 (0.01)	10.57 (0.03)
RH > 92		<b>73.47</b> (1.47)	0.76 (0.02)	0.70 (0.01)	0.77 (0.04)	<b>0.73</b> (0.01)	<b>9.16</b> (0.51)	RF	73.43 <sup>ns</sup> (0.37)	0.73 (0.01)	0.77 (0.01)	0.70 (0.01)	0.75 (0.01)	9.18 (0.13)	
CART		60.53 (0.94)	0.57 (0.01)	<b>0.91</b> (0.01)	0.28 (0.03)	0.70 (0.01)	13.63 (0.32)	KNN	73.09 <sup>ns</sup> (0.05)	0.74 (0.01)	0.74 (0.01)	0.72 (0.01)	0.74 (0.01)	9.30 (0.02)	
RH_ext15		59.96 (0.69)	<b>0.90</b> (0.02)	0.25 (0.01)	0.97 (0.01)	0.40 (0.01)	13.83 (0.24)	MLP	<b>75.63</b> <sup>***</sup> (0.08)	0.76 (0.01)	<b>0.78</b> (0.02)	0.73 (0.03)	<b>0.77</b> (0.01)	<b>8.42</b> (0.03)	
RH_ext30		58.08 (0.77)	0.90 (0.01)	0.21 (0.01)	<b>0.98</b> (0.01)	0.34 (0.01)	14.48 (0.26)	LR	73.91 <sup>*</sup> (0.11)	0.77 (0.01)	0.71 (0.01)	0.78 (0.01)	0.74 (0.01)	9.01 (0.04)	
								LSVC	51.78 <sup>ns</sup> (0.11)	0.52 (0.01)	1.00 (0.01)	0.00 (0.01)	0.68 (0.01)	16.65 (0.04)	

<sup>a</sup> cf. Table 1f or parameters

<sup>b</sup> Day-time refers to the time period between 07:00 and 19:45 inclusive while night-time refers to the time period between 20:00 and 06:45

full dataset of 77.85% and 80.03% for the empirical and ML models, respectively (Table 1). This would suggest that regional sub-division of the data has a greater effect on the classification accuracy of models when compared to temporal subdivision of the data (Table 2 and

Table 3). The highest accuracy in this study (88.52%) was found for the East region using the RF algorithm. The data used in this study was not further sub-divided into temporal subsets for each of the regions studied as there may be an increased risk of overfitting the data resulting in less

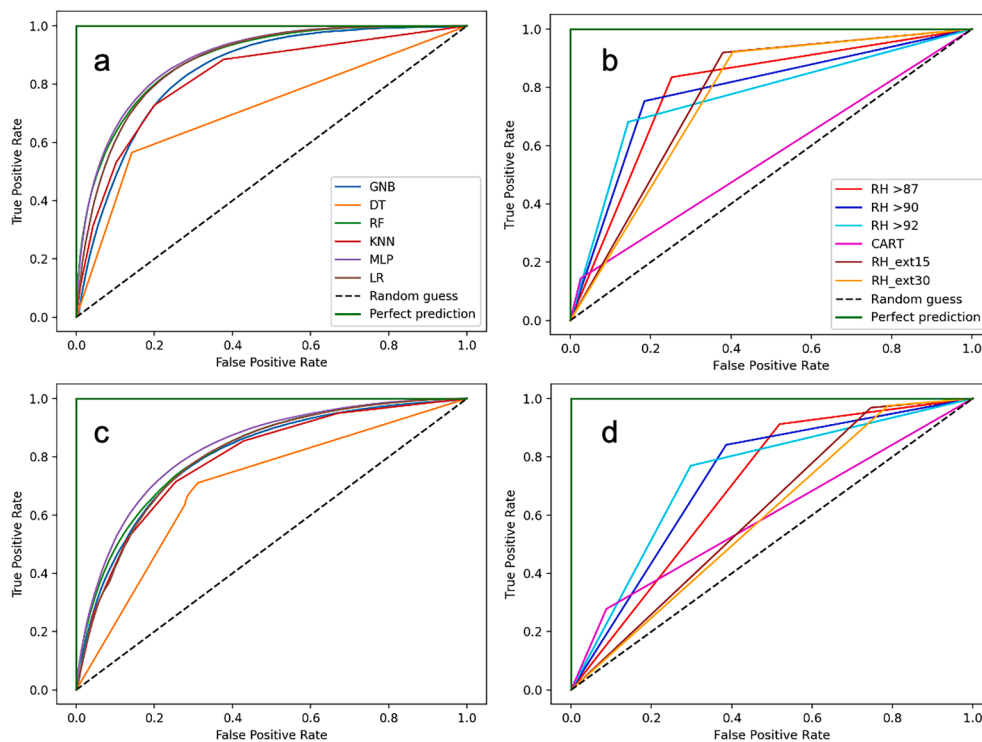


Fig. 5. ROC curves for (a) machine learning models of the day-time data subset, (b) empirical models of the day-time subset, (c) machine learning models of the night-time subset, and empirical models of the night-time subset (d).

robust models being produced. Interestingly, the East region is also the only data subset where, for the empirical models, the  $RH > 90$  model (81.80% accurate) outperformed the  $RH > 92$  model (80.22% accurate). The  $F$ -Scores and the log loss metrics were similar for both the  $RH > 90$  and the  $RH > 92$  models for this region (Table 3). Using ML models to predict regional leaf wetness led to an average increase in the classification accuracies of 6.13% (with range of 4.18% to 8.78%) over the best performing empirical models. The RF classification algorithm provided the best models for all of the regional subsets used, this is in contrast to the temporal subsets where the MLP model provided the most accurate results. The next best model for the regional subsets was the KNN algorithm which was on average 2.64% less accurate than the RF algorithm. Francil and Panigrahi (1997) reported predictions of leaf wetness in a 5,000 m<sup>2</sup> wheat field for the years 1992 – 1994, inclusive, using an artificial neural network with an accuracy of 93%.

The input parameters used in this study were similar to those used in the model developed by Francil and Panigrahi (1997). The results of Francil and Panigrahi (1997) and the results of this study (Fig. 1, Table 1 and Table 3) show that the smaller the region used to develop the model the more accurate the results. However, it may not be feasible to determine the leaf wetness on a field level scale for every field due to the amount of weather stations that would be required and the data handling and processing techniques necessary.

#### 4.3. Discussion

RFs are powerful algorithms particularly suited to handling prediction and classification problems that include nonlinear relationships and complex interactions between variables (Breiman, 2001; Chaudhary et al., 2016) making them suitable for the prediction of leaf wetness. The MLP algorithm yielded the preferred models when the number of records used for development of the model was relatively large. This occurred for the temporal subsets and for the full dataset (Table 1 and Table 2). In these cases the RF models were the second best performing models (Fig. 4 and Fig. 5) with an average accuracy 1.61% lower than

the MLP models (Table 1 and Table 2).

As the use of satellites for crop and agricultural monitoring grows (Liu et al., 2019; Maes & Steppe, 2019; Nayak et al., 2019; Urban et al., 2018) leaf wetness may become an important variable for crop models that predict a number of crop health and agricultural practices. Ben-Asher et al. (2010) reported that the presence of dew on leaves (leaf wetness) plays an important role in the production of plant biomass at a low water cost. This would mean that the presence of water on the leaves of plants has an important role in the water use efficiency of plants. Models that determine plant growth and crop yields in changing climatic scenarios may need to include leaf wetness as a factor within their analysis in order to better determine the effect of climate change on the growth of crops. Hornbuckle et al. (2006) and Hornbuckle et al. (2010) found that the presence of free water on the leaves of maize plants has an effect on the brightness values of the horizontally and vertically polarised L-bands. It was also reported that the majority of microwave emission models for the determination of soil moisture content do not account for the presence of dew on leaves which may represent a significant source of error for the models (Hornbuckle et al., 2006). Consequently, the evaporation of moisture from the soil decreases with the presence of dew (Ye & Peng, 2011). Inclusion of dew events or indeed the presence of leaf wetness would facilitate more accurate measurements of evapotranspiration and soil moisture content. This would for example allow for irrigation schedules of high value crops to be adjusted to a more suitable frequency.

The main use of leaf wetness measurements is as an input into disease prediction models (Bregaglio et al., 2011; Chungu et al., 2001; Montone et al., 2016; Morales et al., 2018; Rowlandson et al., 2015). The pathogens of fungi and bacteria release spores and infect the host plants under the presence of moisture, inducing plant disease easily, thus dew supplies opportunities for growth of pathogens (Ye & Peng, 2011). Accurate measurements of this phenomenon would allow for timely interventions on the part of farmers reducing the risk of yield loss and the need for increased levels of pesticides to deal with more major epidemics of specific diseases. The  $F$ -Scores of the ML models were also consistently

**Table 3**  
Performance metrics and standard deviations in parentheses for the models produced using regional data subsets<sup>a</sup>.

Data Subset	Model	A	P	R	S	F	L	Model	A	P	R	S	F	L	
Scotland [379,270]	RH > 87	75.16 (4.02)	0.89 (0.02)	0.70 (0.08)	0.85 (0.03)	0.78 (0.05)	8.58 (1.38)	GNB	79.72 <sup>ns</sup> (4.43)	<b>0.89</b> (0.01)	0.78 (0.06)	<b>0.83</b> (0.01)	0.83 (0.04)	7.01 (1.52)	
	RH > 90	77.70 (3.04)	0.86 (0.02)	0.78 (0.06)	0.78 (0.04)	0.82 (0.03)	7.70 (1.05)	DT	84.34 <sup>ns</sup> (5.84)	0.88 (0.04)	0.88 (0.04)	0.78 (0.09)	0.88 (0.04)	5.39 (2.03)	
	RH > 92	<b>78.88</b> (2.60)	0.84 (0.02)	0.83 (0.05)	0.72 (0.04)	<b>0.83</b> (0.02)	<b>7.30</b> (0.89)	RF	<b>87.66*</b> (4.81)	0.88 (0.03)	0.93 (0.04)	0.78 (0.07)	<b>0.91</b> (0.04)	<b>4.37</b> (1.60)	
	CART	69.57 (1.37)	0.69 (0.01)	<b>0.94</b> (0.02)	0.26 (0.10)	0.80 (0.01)	10.51 (0.47)	KNN	84.83 <sup>ns</sup> (5.44)	0.87 (0.04)	0.89 (0.04)	0.77 (0.09)	0.88 (0.04)	5.24 (1.88)	
	RH_ext15	61.99 (2.31)	<b>0.94</b> (0.01)	0.44 (0.04)	<b>0.95</b> (0.01)	0.60 (0.04)	13.13 (0.80)	MLP	76.68 <sup>ns</sup> (0.36)	0.78 (0.04)	0.91 (0.06)	0.50 (0.12)	0.84 (0.01)	8.05 (0.12)	
	RH_ext30	62.19 (3.01)	0.93 (0.01)	0.44 (0.05)	0.94 (0.01)	0.60 (0.04)	13.06 (1.04)	LR	82.41 <sup>ns</sup> (3.78)	0.87 (0.03)	0.86 (0.02)	0.76 (0.07)	0.86 (0.03)	6.08 (1.31)	
								LSVC	65.58 <sup>ns</sup> (9.54)	0.66 (0.18)	0.71 (0.26)	0.38 (0.49)	0.79 (0.09)	13.23 (2.93)	
		<b>Model</b>	<b>A</b>	<b>P</b>	<b>R</b>	<b>S</b>	<b>F</b>	<b>L</b>	<b>Model</b>	<b>A</b>	<b>P</b>	<b>R</b>	<b>S</b>	<b>F</b>	<b>L</b>
	South East [152,971]	RH > 87	77.56 (0.01)	0.91 (0.01)	0.69 (0.01)	0.90 (0.01)	0.79 (0.01)	7.75 (0.01)	GNB	79.15 <sup>ns</sup> (0.57)	0.88 (0.01)	0.75 (0.01)	0.85 (0.01)	0.81 (0.01)	7.20 (0.20)
		RH > 90	80.12 (0.01)	0.88 (0.01)	0.78 (0.01)	0.83 (0.01)	0.83 (0.01)	6.87 (0.01)	DT	81.44 <sup>*</sup> (0.32)	0.84 (0.01)	0.85 (0.01)	0.77 (0.01)	0.84 (0.01)	6.39 (0.10)
RH > 92		<b>80.63</b> (0.01)	0.84 (0.01)	0.83 (0.01)	0.77 (0.01)	<b>0.84</b> (0.01)	<b>6.69</b> (0.01)	RF	<b>84.81**</b> (0.61)	0.85 (0.01)	0.90 (0.01)	0.77 (0.02)	0.88 (0.01)	5.22 (0.20)	
CART		67.94 (0.01)	0.66 (0.01)	<b>0.95</b> (0.01)	0.26 (0.01)	0.78 (0.01)	11.07 (0.01)	KNN	82.00 <sup>**</sup> (0.11)	0.84 (0.01)	0.86 (0.01)	0.77 (0.01)	0.85 (0.01)	6.22 (0.04)	
RH_ext15		71.46 (0.01)	<b>0.95</b> (0.01)	0.56 (0.01)	<b>0.96</b> (0.01)	0.70 (0.01)	9.86 (0.01)	MLP	82.93 <sup>*</sup> (0.83)	0.86 (0.04)	0.85 (0.05)	0.80 (0.09)	0.86 (0.01)	5.90 (0.88)	
RH_ext30		68.63 (0.01)	0.95 (0.01)	0.51 (0.01)	0.96 (0.01)	0.66 (0.01)	10.84 (0.01)	LR	81.24 <sup>+</sup> (0.09)	0.86 (0.01)	0.82 (0.01)	0.80 (0.01)	0.84 (0.01)	6.48 (0.03)	
							LSVC	59.42 <sup>ns</sup> (9.78)	0.60 (0.09)	0.98 (0.04)	0.01 (0.30)	0.74 (0.05)	15.13 (4.02)		
East [397,220]	RH > 87	80.63 (3.01)	0.89 (0.02)	0.74 (0.04)	0.89 (0.03)	0.81 (0.02)	6.69 (1.04)	GNB	81.18 <sup>ns</sup> (2.34)	0.79 (0.05)	0.89 (0.09)	0.72 (0.07)	0.84 (0.02)	6.50 (0.81)	
	RH > 90	<b>81.80</b> (2.09)	0.84 (0.02)	0.83 (0.04)	0.80 (0.04)	<b>0.84</b> (0.01)	<b>6.29</b> (0.72)	DT	85.59 <sup>ns</sup> (3.63)	<b>0.87</b> (0.02)	0.86 (0.02)	0.85 (0.07)	0.87 (0.02)	4.98 (1.25)	
	RH > 92	80.22 (0.83)	0.79 (0.03)	0.88 (0.04)	0.70 (0.05)	0.83 (0.01)	6.83 (0.29)	RF	<b>88.52<sup>ns</sup></b> (2.75)	0.88 (0.01)	<b>0.92</b> (0.02)	<b>0.85</b> (0.04)	<b>0.90</b> (0.02)	<b>4.28</b> (0.77)	
	CART	75.18 (4.33)	0.71 (0.03)	<b>0.95</b> (0.02)	0.51 (0.21)	0.81 (0.01)	8.57 (1.50)	KNN	85.77 <sup>ns</sup> (2.99)	0.86 (0.01)	0.88 (0.02)	0.83 (0.05)	0.87 (0.02)	4.91 (1.04)	
	RH_ext15	68.54 (1.34)	0.95 (0.02)	0.45 (0.05)	0.97 (0.03)	0.62 (0.04)	10.87 (0.46)	MLP	82.43 <sup>*</sup> (0.21)	0.86 (0.01)	0.85 (0.01)	0.78 (0.01)	0.86 (0.01)	6.07 (0.06)	
	RH_ext30	69.41 (1.50)	<b>0.96</b> (0.01)	0.47 (0.02)	<b>0.98</b> (0.02)	0.63 (0.02)	10.56 (0.52)	LR	83.70 <sup>ns</sup> (1.95)	0.87 (0.01)	0.83 (0.01)	0.85 (0.04)	0.85 (0.01)	5.63 (0.68)	
							LSVC	75.99 <sup>ns</sup> (4.09)	0.84 (0.09)	0.76 (0.11)	0.77 (0.28)	0.80 (0.01)	13.37 (1.68)		
South West [1,273,410]	RH > 87	73.85 (0.88)	0.93 (0.01)	0.63 (0.04)	0.92 (0.04)	0.75 (0.02)	9.03 (0.30)	GNB	74.79 <sup>ns</sup> (4.02)	<b>0.90</b> (0.01)	0.67 (0.06)	<b>0.88</b> (0.02)	0.77 (0.04)	8.71 (1.39)	
	RH > 90	77.56 (0.37)	0.90 (0.02)	0.72 (0.04)	0.86 (0.06)	0.80 (0.02)	7.75 (0.12)	DT	80.26 <sup>ns</sup> (2.55)	0.84 (0.01)	0.84 (0.01)	0.73 (0.05)	0.84 (0.01)	6.82 (0.88)	
	RH > 92	<b>78.95</b> (0.22)	0.87 (0.02)	0.78 (0.04)	0.80 (0.08)	<b>0.82</b> (0.01)	<b>7.27</b> (0.08)	RF	<b>83.77*</b> (1.74)	0.85 (0.01)	<b>0.90</b> (0.02)	0.74 (0.03)	<b>0.87</b> (0.01)	<b>5.59</b> (0.61)	
	CART	74.11 (1.66)	0.73 (0.02)	<b>0.94</b> (0.02)	0.41 (0.08)	0.82 (0.01)	8.94 (0.57)	KNN	81.60 <sup>ns</sup> (1.79)	0.84 (0.01)	0.86 (0.01)	0.74 (0.05)	0.85 (0.01)	6.36 (0.62)	
	RH_ext15	59.61 (4.80)	<b>0.97</b> (0.01)	0.37 (0.10)	<b>0.98</b> (0.03)	0.53 (0.09)	13.95 (1.66)	MLP	81.14 <sup>***</sup> (0.05)	0.84 (0.01)	0.87 (0.01)	0.69 (0.02)	0.86 (0.01)	6.51 (0.02)	
	RH_ext30	59.97 (2.92)	0.97 (0.01)	0.37 (0.07)	0.98 (0.02)	0.54 (0.07)	13.82 (1.01)	LR	79.71 <sup>ns</sup> (0.32)	0.85 (0.01)	0.82 (0.01)	0.76 (0.04)	0.83 (0.01)	7.01 (0.11)	
							LSVC	65.57 <sup>ns</sup> (8.55)	0.66 (0.14)	0.82 (0.17)	0.31 (0.46)	0.79 (0.04)	18.18 (4.45)		

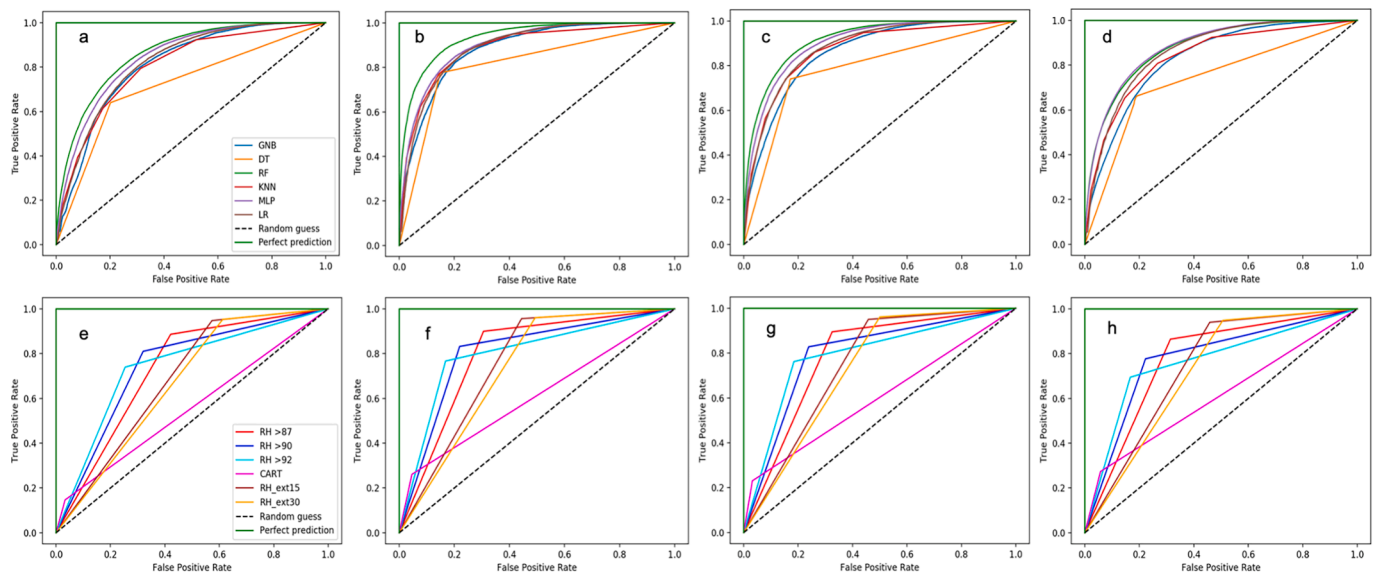
<sup>a</sup> cf. Table 1 for model parameters and Fig. 1 for regional subsets

higher than the F-Scores of the compared empirical models. This means that although the increased accuracy of the ML models may be comparatively small the confidence in the accuracy of the predictions is increased, which would make the predictions from ML techniques more suitable for inclusion in disease prediction models where accurate predictions are required to effectively time the applications of crop protection products.

The presence of moisture on the leaves of crops also has an effect on the efficacy of crop protection due to the dilution of the active ingredients and the possibility of subsequent run-off (Abi Saab et al., 2017) resulting in increased levels of pesticides in aquatic environments

(Casado et al., 2019). Application of pesticides when this is less likely to occur would reduce the amount of run-off from an environmental aspect and would reduce the amount required by the farmers from an economical aspect.

From an assessment of the influence of each meteorological variable for each classification algorithm used in this paper it was found that the RH values were the most important for the classification of LW in all cases with coefficient weights ranging from 0.107 to 0.190. The other meteorological variables used as input variables into the classification algorithms (Air temperature, Rainfall, Solar Radiation, and Windspeed) all had similar influences on the classification results according to their



**Fig. 6.** ROC curves of the machine learning models for the regions (a) Scotland, (b) South East, (c) East, (d) South West and for the empirical models of the regions (e) Scotland, (f) South East, (g) East, (h) South West.

**Table 4**

Area under the curve (AUC) scores for each of the models and subsets used in this study.

Region <sup>a</sup>	All Records	Soil Temperature	Scotland	East	South East	South West	Daytime	Night-time
GNB <sup>b</sup>	0.819	0.823	0.810	0.859	0.881	0.829	0.842	0.804
DT	0.722	0.716	0.719	0.784	0.814	0.736	0.712	0.700
RF	0.859	0.862	0.862	0.915	0.934	0.878	0.884	0.817
KNN	0.824	0.810	0.803	0.869	0.887	0.837	0.824	0.792
MLP	0.873	0.854	0.847	0.899	0.908	0.882	0.890	0.832
LR	0.856	0.837	0.823	0.880	0.890	0.861	0.878	0.807
LSVC	0.741	0.512	0.500	0.733	0.512	0.599	0.499	0.558
RH > 87	0.775	0.748	0.728	0.794	0.797	0.773	0.799	0.699
RH > 90	0.786	0.749	0.748	0.806	0.807	0.782	0.794	0.735
RH > 92	0.782	0.736	0.749	0.801	0.799	0.774	0.779	0.747
CART	0.599	0.562	0.531	0.643	0.608	0.610	0.559	0.609
RH_ext15	0.734	0.686	0.675	0.751	0.756	0.735	0.778	0.609
RH_ext30	0.715	0.658	0.658	0.732	0.733	0.715	0.766	0.592

<sup>a</sup> cf. Fig. 1

<sup>b</sup> cf. Table 1

model coefficients. The coefficient weights for these variables all range between 0.0002 and 0.032. This was particularly true when only the RF and MLP models were looked at, the ranges for these algorithms reduced to between 0.008 and 0.031. In all cases these meteorological variables had a higher importance for the RF algorithm than the MLP algorithm. These results align with Fig. 2 where Kim et al. (2002) utilised the DPD, which is related to the air temperature, and the windspeed along with the RH value to classify the LWD of sites in the United States. From our assessment it would suggest that all of the meteorological variables that were assessed as part of this study would be required for the accurate classification of LW time periods.

## 5. Conclusions

This study compared machine learning algorithms with previously established empirical models for the prediction of leaf wetness in North Western Europe. Results from the empirical models show that increasing the RH threshold from 90% to 92% resulted in an average increase in classification accuracy of 1.12% (Range; 0.51% – 1.41%). Only one region studied (East) had a lower accuracy score when the RH > 92% threshold was used. In this region the accuracy was 1.58% lower. The machine learning classification algorithms used in this study consistently provided more accurate predictions of leaf wetness than best of

breed empirical models that were studied. The average increase in accuracy for the machine learning algorithms over the empirical models was 4.85% (Range; 2.16% – 8.78%). Sub-division of the meteorological stations into regions had a greater effect on the accuracy of the results obtained when compared with that of temporal sub-division of the data. The results of this study show that machine learning classification algorithms are a suitable techniques for the prediction of leaf wetness in a more accurate and robust manner than the empirical methods studied. Further sub-division of data in regional and temporal subsets may yield further increases in the accuracy of developed models if enough data to create sufficiently large datasets was available. To the authors knowledge, this is the first paper that looks at predicting leaf wetness in North Western Europe, while at the same time being one of the first papers to look at common machine learning classification algorithms for the prediction of leaf wetness.

## 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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## References

- Saab, O. J. G. A., Griesang, F., Alves, K. A., Higashibara, L. R., & Genta, W. (2017). Pesticides deposition in vineyards on different conditions of leaf wetness. *Journal of the Brazilian Association of Agricultural Engineering*, 37(2), 286–291.
- Allen, R., Pereira, L., Raes, D., & Smith, M. (1998). *Crop Evapotranspiration - Guidelines for computing crop water requirements - FAO Irrigation and Drainage paper 56*. Itlay: Retrieved from Rome.
- Alpaydin, E. (2010). *Introduction to Machine Learning (T. Dietterich Ed (2nd ed.)*. London, England: The MIT Press.
- Amir, F. (2016). *Leaf Wetness Duration Modelling using Adaptive Neuro Fuzzy Inference System (Masters)*. Auckland University of technology.
- Augusta, C., Deardon, R., & Taylor, G. (2019). Deep learning for supervised classification of spatial epidemics. *Spatial and Spatio-temporal Epidemiology*, 29, 187–198.
- J. Ben-Asher P. Alpert A. Ben-Zvi Dew is a major factor affecting vegetation water use efficiency rather than a source of water in the eastern Mediterranean area Water Resources Research 46 10 2010 W10532.
- Binkhonain, M., & Zhao, L. (2019). A Review of Machine Learning Algorithms for Identification and Classification of Non-Functional Requirements. *Expert Systems with Applications X*, 1, 100001. <https://doi.org/10.1016/j.eswax.2019.100001>
- Bregaglio, S., Donatelli, M., Confalonieri, R., Acutis, M., & Orlandini, S. (2011). Multi metric evaluation of leaf wetness models for large-area application of plant disease models. *Agricultural and Forest Meteorology*, 151(9), 1163–1172.
- Breiman, L. (2001). Random Forests. *Machine Learning*, 45(1), 5–32.
- Casado, J., Bridgen, K., Santillo, D., & Johnston, P. (2019). Screening of pesticides and veterinary drugs in small streams in the European Union by liquid chromatography high resolution mass spectrometry. *Science of the Total Environment*, 670, 1204–1225.
- Casamayor, A., Godoy, D., & Campo, M. (2010). Identification of non-functional requirements in textual specifications: A semi-supervised learning approach. *Information and Software Technology*, 52(4), 436–445.
- Chaudhary, A., Kolhe, S., & Kamal, R. (2016). An improved random forest classifier for multi-class classification. *Information Processing in Agriculture*, 3(4), 215–222.
- Chlingaryan, A., Sukkarieh, S., & Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Computers and Electronics in Agriculture*, 151, 61–69.
- Chungu, C., Gilbert, J., & Townley-Smith, F. (2001). Septoria tritici Blotch development as affected by temperature, duration of leaf wetness, inoculum concentration, and host. *Plant Disease*, 85(4), 430–435.
- Duttweiler, K., Gleason, M., Dixon, P., Sutton, T., & Monteiro, J. (2008). Adaptation of an Apple Sooty Blotch and Plespeck Warning System for the Upper Midwest United States. *Plant Disease*, 92(8), 1215–1222.
- Feng, C.-X.-J., Yu\*\*, Z.-G.- S., Emanuel, J. T., Li, P.-G., Shao, X.-Y., & Wang, Z.-H. (2008). Threefold versus fivefold cross-validation and individual versus average data in predictive regression modelling of machining experimental data. *International Journal of Computer Integrated Manufacturing*, 21(6), 702–714. <https://doi.org/10.1080/09511920701530943>
- Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, 145, 311–318.
- Fones, H., & Gurr, S. (2015). The impact of Septoria tritici Blotch disease on wheat: An EU perspective. *Fungal Genetic Biology*, 79, 3–7.
- Francl, L. J., & Panigrahi, S. (1997). Artificial neural network models of wheat leaf wetness. *Agricultural and Forest Meteorology*, 88(1-4), 57–65.
- Garthwaite, D., Barker, I., Ridley, L., Mace, A., Parrish, G., MacArthur, R., & Lu, Y. (2016). *Pesticide Usage Survey Report 271 Retrieved from York*. United Kingdom.
- GILLESPIE, T. J., & KIDD, G. E. (1978). Sensing duration of leaf moisture retention using electrical impedance grids. *Canadian Journal of Plant Science*, 58(1), 179–187.
- Gillespie, T. J., & Sentelhas, P. C. (2008). Agrometeorology and plant disease management - A happy marriage. *Scientia Agricola*, 65(spe), 71–75.
- Gleason, M. L., Duttweiler, K. B., Batzer, J. C., Taylor, S. E., Sentelhas, P. C., Monteiro, J. E. B. A., & Gillespie, T. J. (2008). Obtaining weather data for input to crop disease-warning systems: leaf wetness duration as a case study. *Scientia Agricola*, 65(spe), 76–87.
- Gleason, M., Taylor, S., Loughin, T., & Koehler, K. (1994). Development and validation of an empirical model to estimate the duration of dew periods. *Plant Disease*, 78, 1011–1016.
- Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*: MIT Press.
- Hart, E., Sim, K., Kamimura, K., Meredieu, C., Guyon, D., & Gardiner, B. (2019). Use of machine learning techniques to model wind damage to forests. *Agricultural and Forest Meteorology*, 265, 16–29.
- Henze, M., Beyer, M., Klink, H., & Verreet, J. (2007). Characterizing meteorological scenarios favorable for Septoria tritici infections. in wheat and estimation of latent periods. *Plant Disease*, 91, 1445–1449.
- Hindle, A., Ernst, N. A., Godfrey, M. W., & Mylopoulos, J. (2013). Automated topic naming. *Empirical Software Engineering*, 18(6), 1125–1155.
- Hornbuckle, B. K., England, A. W., Anderson, M. C., & Viner, B. J. (2006). The effect of free water in a maize canopy on microwave emission at 1.4 GHz. *Agricultural and Forest Meteorology*, 138(1-4), 180–191.
- B. Hornbuckle T. Rowlandson E. Russell A. Kruger T. Sauer Water residing on plants alters the L-band brightness of senescing corn 2010 Washington DC, USA.
- Huang, Y., CHEN, Z.-X., YU, T., HUANG, X.-Z., & GU, X.-f. (2018). Agricultural remote sensing big data: Management and applications. *Journal of Integrative Agriculture*, 17(9), 1915–1931.
- Jacobs, A. F. G., van Pul, A., & El-Kilani, R. M. M. (1994). Dew formation and the drying process within a maize canopy. *Boundary Layer Meteorology*, 69(4), 367–378.
- Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep Learning in Agriculture: A Survey. *Computers and Electronics in Agriculture*, 147, 70–90.
- K. Karadağ M.E. Tenekeci R. Taşaltın A. Bilgili 28 2020 100299 10.1016/j.suscom.2019.01.001.
- Khan, A., Baharudin, B., Lee, L., & Khan, K. (2010). A review of machine learning algorithms for text-document classification. *Journal of Advance in Information Technology*, 1(1), 4–20.
- Kim, K. S., Taylor, S. E., Gleason, M. L., & Koehler, K. J. (2002). Model to enhance site-specific estimation of leaf wetness duration. *Plant and Disease*, 86(2), 179–185.
- Kim, K. S., Taylor, S. E., Gleason, M. L., Nutter Jr., F. W., Coop, L. B., Pfender, W. F., ... Dalla Marta, A. (2010). Spatial portability of numerical models of leaf wetness duration based on empirical approaches. *Agricultural and Forest Meteorology*, 150(7-8), 871–880.
- Leena, N., & Sajū, K. K. (2019). Classification of macronutrient deficiencies in maize plants using optimized multi class support vector machines. *Engineering in Agriculture, Environment and Food*, 12(1), 126–139.
- Liakos, K., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). machine learning in agriculture: A review. *Sensors*, 18, 2674–2702.
- Liu, M., Wang, T., Skidmore, A. K., Liu, X., & Li, M. (2019). Identifying rice stress on a regional scale from multi-temporal satellite images using a Bayesian method. *Environmental Pollution*, 247, 488–498.
- Maes, W. H., & Steppe, K. (2019). Perspectives for remote sensing with unmanned aerial vehicles in precision agriculture. *Trends in Plant Science*, 24(2), 152–164.
- Matzen, N., Ravn Jørgensen, J., Holst, N., & Nistrup Jørgensen, L. (2019). Grain quality in wheat - Impact of disease management. *European Journal of Agronomy*, 103, 152–164.
- Mehra, L., Cowger, C., Gross, K., & Ojiambo, P. (2016). Predicting Pre-planting risk of *Stagonospora nodorum* blotch in winter wheat using machine learning models. *Frontiers in Plant Science*, 7, 390. <https://doi.org/10.3389/fpls.2016.00390>
- Moller, A., Iversen, B., Beucher, A., & Greve, M. (2019). Prediction of soil drainage classes in Denmark by means of decision tree classification. *Geoderma*, 352, 314–329. <https://doi.org/10.1016/j.geoderma.2017.10.015>
- Montone, V. O., Fraise, C. W., Peres, N. A., Sentelhas, P. C., Gleason, M., Ellis, M., & Schnabel, G. (2016). Evaluation of leaf wetness duration models for operational use in strawberry disease-warning systems in four US states. *International Journal of Biometeorology*, 60(11), 1761–1774.
- Morales, G., Moragrega, C., Montesinos, E., Llorente, I., & Hong, J. K. (2018). Effects of leaf wetness duration and temperature on infection of *Prunus* by *Xanthomonas arboricola* pv. *pruni*. *PLoS ONE*, 13(3), e0193813. <https://doi.org/10.1371/journal.pone.0193813>
- Nayak, A. K., Rahman, M. M., Naidu, R., Dhal, B., Swain, C. K., Nayak, A. D., ... Pathak, H. (2019). Current and emerging methodologies for estimating carbon sequestration in agricultural soils: A review. *Science of the Total Environment*, 665, 890–912.
- Onwuka, B., & Mang, B. (2018). Effects of soil temperature on some soil properties and plant growth. *Advances in Plants and Agriculture Research*, 8(1), 34–37.
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12(2825–2830).
- Pedro, M., Jr., & Gillespie, T. (1982). Estimating dew duration. II. Utilizing standard weather station data. *Agricultural Meteorology*, 25, 297–310.
- Piccini, C., Marchetti, A., Riveccio, R., & Napoli, R. (2019). Multinomial logistic regression with soil diagnostic features and land surface parameters for soil mapping of Latium (Central Italy). *Geoderma*, 352, 385–394. <https://doi.org/10.1016/j.geoderma.2018.09.037>
- Piedad, E. J., Larada, J. I., Pojas, G. J., & Ferrer, L. V. V. (2018). Postharvest classification of banana (*Musa acuminata*) using tier-based machine learning. *Postharvest Biology and Technology*, 145, 93–100.
- Rao, P. S., Gillespie, T. J., & Schaafsma, A. W. (1998). Estimating wetness duration on maize ears from meteorological observations. *Canadian Journal of Soil Science*, 78(1), 149–154.
- Rehman, T. U., Mahmud, M. S., Chang, Y. K., Jin, J., & Shin, J. (2019). Current and future applications of statistical machine learning algorithms for agricultural machine vision systems. *Computers and Electronics in Agriculture*, 156, 585–605.
- Romeiko, X., Guo, Z., Pang, Y., Lee, E., & Zhang, X. (2020). Comparing machine learning approaches for predicting spatially explicit life cycle global warming and eutrophication impacts from corn production. *Sustainability*, 12, 1481. <https://doi.org/10.3390/su12041481>
- Rowlandson, T., Gleason, M., Sentelhas, P., Gillespie, T., Thomas, C., & Hornbuckle, B. (2015). Reconsidering leaf wetness duration determination for plant disease management. *Plant and Disease*, 99(3), 310–319.
- Saggi, M. K., & Jain, S. (2019). Reference evapotranspiration estimation and modeling of the Punjab Northern India using deep learning. *Computers and Electronics in Agriculture*, 156, 387–398.
- Sentelhas, P. C., Dalla Marta, A., Orlandini, S., Santos, E. A., Gillespie, T. J., & Gleason, M. L. (2008). Suitability of relative humidity as an estimator of leaf wetness duration. *Agricultural and Forest Meteorology*, 148(3), 392–400.

- Sirsat, M. S., Cernadas, E., Fernández-Delgado, M., & Khan, R. (2017). Classification of agricultural soil parameters in India. *Computers and Electronics in Agriculture*, *135*, 269–279.
- Stella, A., Caliendo, G., Melgani, F., Goller, R., Barazzuol, M., & La Porta, N. (2017). leaf wetness evaluation using artificial neural network for improving apple scab fight. *Environments*, *4*(2), 42–57.
- Urban, D., Guan, K., & Jain, M. (2018). Estimating sowing dates from satellite data over the U.S. Midwest: A comparison of multiple sensors and metrics. *Remote Sensing of Environment*, *211*, 400–412. <https://doi.org/10.1016/j.rse.2018.03.039>
- J. van Jaarsveld The Operational Priority Substances model - Report No 500045001/2004 2004 Retrieved from Bilthoven, The Netherlands.
- Wichink Kruit, R., van Pul, W., Jacobs, A., & Heusinkveld, B. (2004). Comparison between four methods to estimate leaf wetness duration caused by dew on grassland. *Paper presented at the 26th Conference on Agricultural and Forest Meteorology*.
- Ye, Y., & Peng, S. (2011). Review of dew action effect on plants. *Shengtai Xuebao/Acta Ecologica Sinica*, *31*, 3190–3196.