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Machine learning for supporting irrigation decisions based on climatic water balance

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Abstract: A machine learning model was developed to support irrigation decisions. The field research was conducted on 'Gala' apple trees. For each week during the growing seasons (2009–2013), the following parameters were determined: precipitation, evapotranspiration (Penman–Monteith formula), crop (apple) evapotranspiration, climatic water balance, crop (apple) water balance (AWB), cumulative climatic water balance (determined weekly, $\sum CWB$), cumulative apple water balance ($\sum AWB$), week number from full bloom, and nominal classification variable: irrigation, no irrigation. Statistical analyses were performed with the use of the WEKA 3.9 application software. The attribute evaluator was performed using Correlation Attribute Eval with the Ranker Search Method. Due to its highest accuracy, the final analyses were performed using the WEKA classifier package with the J48graft algorithm. For each of the analysed growing seasons, different correlations were found between the water balance determined for apple trees and the actual water balance of the soil layer (10–30 cm). The model made correct decisions in 76.7% of the instances when watering was needed and in 87.7% of the instances when watering was not needed. The root of the classification tree was the AWB determined for individual weeks of the growing season. The high places in the tree hierarchy were occupied by the nodes defining the elapsed time of the growing season, the values of $\sum CWB$ and $\sum AWB$.

Keywords: apple trees, evapotranspiration, irrigation scheduling, machine learning, precipitation, WEKA software

INTRODUCTION

Humanity faces the challenge of feeding a dynamically growing population. Globally, acute food insecurity is increasing. In 2020, approximately 42% of the world's people did not have access to good quality food (GRFC, 2022). The only way to increase food production is to further intensify agriculture. The availability of water is a factor that significantly affects the efficiency of plant production. Currently irrigated crops covers 20% of all cultivated land and about 40% of the global yields are harvested on irrigated fields (Meier *et al.*, 2018). Higher yields of plants are obtained thanks to irrigation, which results in a high demand for water. Amarasinghe and Smakhtin (2014) estimate that agriculture uses as much as 55% of fresh water drawn.

Climatic and soil conditions and the availability of good quality water are factors determining the possibility of agricultural development, as well as the type of cultivated plants and the cultivation technologies used (Iglesias *et al.*, 2012). Since the dawn of humanity, the availability of water has determined the development opportunities of regions of the human population. The main climatic factors limiting the possibility of growing plants are the level of solar radiation, air temperature and rainfall.

The European Commission's communication points out that over 24% of abstracted water is wasted, which indicates the need to counteract this phenomenon. Therefore, it is recommended to develop and implement water resource management systems for agricultural purposes (Farmer *et al.*, 2008). The assumed goal can be achieved through the use of the most effective irrigation systems and the implementation of reliable irrigation criteria into practice.

According to Gu *et al.* (2020) the best known irrigation scheduling methods are: plant water status, soil moisture status, evapotranspiration, and water balance. Conventional methods for irrigation scheduling rely on the direct measurement of soil matric potential (ψm) or soil water content (Θ) (Mittelbach, Lehner and Seneviratne, 2012; Treder *et al.*, 2022; Yu *et al.*, 2021).

Sensors are very helpful, but due to the price, their common use is not always possible. Therefore, a cost reduction could be obtained by the use of a limited number of soil moisture sensors supported by artificial intelligence.

Farmers can make decisions on irrigation on the basis of weather conditions. Determining the water needs of a specific crop (ET_c) can be estimated by multiplying the crop coefficient (K) by reference evapotranspiration (ET_o). Evapotranspiration is determined using evaporometers or estimated using mathematical models (Allen *et al.*, 1998; Yuan, Nishiyama and Kang, 2003). Machine learning methods can also be used to determine evapotranspiration. Cobaner (2011) developed an evapotranspiration estimation method based on a fuzzy system which is trained by a learning algorithm derived from the neural network theory. The neuro-fuzzy model is also based on solar radiation, air temperature and humidity. Also Adnan, Latif and Nazir (2017) demonstrated the usefulness of the machine learning method for determining evapotranspiration with limited availability of measurement data. For proper irrigation, a precise method of estimating evapotranspiration and knowledge of the values of the K coefficient changing during the growing season are necessary. The Food and Agriculture Organization (FAO) has introduced an indirect method for ET_o estimation. This method involves incorporating the Penman–Monteith equation, which was modified by Allen *et al.* (1998), as a reference equation (FAO-56 PM). According to Davis and Dukes (2010), ET-based frameworks can save up to 42% of water over time-based irrigation scheduling.

Evapotranspiration can also be determined using computer applications, e.g. CropWat 8.0 (Gabr, 2022) and ET_o calculator (Lykhovyd, 2022). Treder *et al.* (2013) have developed an Internet platform (www.nawadnianie.inhort.pl/eto) on which evapotranspiration can be determined using the Penman–Monteith, Hargreaves, and Grabarczyk models, and a simple algorithm where the only input parameter is air temperature. The calculated ET_c values can be used to manually or automatically control the irrigation valves.

According to Martin, Stegman and Fereres (1990) irrigation scheduling can be based on water balance calculations or measurements of soil or plant hydration status. The amount of water stored in the soil is calculated on the basis of daily evapotranspiration (ET_o), precipitation, percolation, runoff and irrigation applied. The method of balancing the water content in soil is subject to a high probability of an error resulting from the difficulty of accurately estimating the inflows of water from infiltration and the correct assessment of the effectiveness of rainfall.

Soil moisture depends on the amount and intensity of rainfall. In the event of high and intense rainfall, part of the water percolates below the level of the root system or flows over the ground surface (surface runoff). Also, the initial soil moisture has a significant impact on the effectiveness of precipitation. The efficiency decreases along with the increase in soil moisture (Treder and Konopacki, 1999; Xiaoyan *et al.*, 2000; Treder *et al.*, 2022). The water balance method lacks high accuracy, but it has proved to be reliable in many conditions (Jones, 2004). Unfortunately, in the climatic conditions of Poland, where there is usually a high level of groundwater in the spring, using it causes the application of too high doses of water to plants.

Irrigation decision making can also be supported through the use of the Internet of Things (IoT) and weather forecasting. With the advancement in technologies, the weather forecasting accuracy has improved significantly and the data obtained from forecasting can be used for predicting changes in soil moisture (Goap *et al.*, 2018). IoT-based solutions have proved to be very helpful in smart irrigation with the optimal utilisation of water (Sharma *et al.*, 2016). Gill *et al.* (2006) developed a method for soil moisture prediction using support vector machines based on air and soil temperature as well as relative air humidity. Hedley *et al.* (2013) used machine learning to predict soil water status and water table depth on the basis of electromagnetic mapping. A layered neural network was used by Murase, Honami and Nishiura (1995) to identify plant water status based on the textural features of the pictorial information of the plant canopy.

The aim of the presented study was to develop a machine learning model to support irrigation decisions based on the climatic water balance.

MATERIAL AND METHODS

The field research was conducted in the years 2009–2013 in the Experimental Orchard of the National Institute of Horticultural Research, Skierniewice, Poland, on 'Gala'/M.9 apple trees planted (in 2002) at a distance 4.0 × 1.2 m. The soil was a sandy loam in texture, low in organic matter (1.5%). The trees were trained as spindles. Insects and diseases were controlled according to standard production practices. Irrigation was applied using a drip system on the basis of soil water potential measured with tensiometers (Jet-Fill, Soilmoisture Equipment Corp., USA) installed at a depth of 20 cm at half the distance between the trees (3 tensiometers per plot were installed between the drippers). Microirrigation (small doses of water: 0.5–2.0 mm) was applied during the vegetation period to keep the soil water potential at a level of –40 to –20 kPa. Soil moisture was measured every week with a (calibrated) profile probe (Diviner 2000, Australia). One PVC tube (50 mm in diameter) was installed on each plot as an access tube for the moisture meter probe. Weather conditions were recorded using an automated meteorological station (Metos, Austria). Based on the meteorological data for each week during the experiment, the following parameters were determined:

- precipitation (P) (mm);
- evapotranspiration (ET_o) (mm) determined by the automatic weather station according to the Penman–Monteith formula:

$$ET_o = \frac{0.408\,\Delta\,(R_n - G) + \gamma \frac{900}{T+273}\,u_2\,(e_s - e_a)}{\Delta\ +\ \gamma(1 + 0.34u_2)} \tag{1}$$

where: ET_o = reference evapotranspiration (mm·day^{-1}), Δ = slope vapour pressure curve (kPa·°C^{-1}), R_n = net radiation at the crop surface (MJ·m^{-2}·day^{-1}), G = soil heat flux density (MJ·m^{-2}·day^{-1}), T = mean daily air temperature at 2 m height (°C), u_2 = mean daily wind speed at 2 m height (m·s^{-1}), e_s = saturation vapour pressure (kPa), e_a = actual vapour pressure (kPa), e_s – e_a = vapour pressure deficit (kPa), γ = psychrometric constant (kPa·°C^{-1});

- apple evapotranspiration (ET_{apple}) = K_c·ET_o where: K_c = crop coefficient according to Allen *et al.* (1998);
- climatic water balance (CWB) = P – ET_o;

– apple water balance (AWB) = P – ET_{apple};
– cumulative climatic water balance (ΣCWB) = sum of consecutive weekly CWB values;
– cumulative apple water balance (ΣAWB) = sum of consecutive weekly AWB values;
– week number from full bloom (No.W);
– nominal classification variable: Irrigation (Yes), No irrigation (No).

Statistical analyses were performed with the use of the WEKA 3.9 application – Machine Learning Group, University of Waikato (Bouckeart *et al.*, 2016). The WEKA workbench contains a collection of algorithms for data analysis and predictive modelling, together with visualisation tools and user graphical interface.

The attribute evaluator was performed using Correlation Attribute Eval with the Ranker search method. The value of an attribute was assessed by measuring the correlation (Pearson) between it and the class. Attributes with the highest ranker were chosen (Fig. 1).

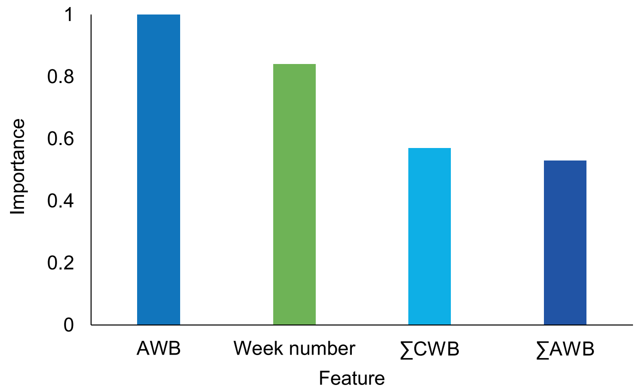

Fig. 1. Feature importance; AWB = apple water balance, ΣCWB = cumulative climatic water balance, ΣAWB = cumulative apple water balance; source: own elaboration

After the initial comparative tests of the various classification algorithms (unpublished own data), the final analyses were performed using the WEKA classifier package with the J48graft algorithm due to its highest accuracy. It is the most popular tree classifier (C4.5) developed by Quinlan (1993). A decision tree is a classifier expressed as a recursive partition of the instance space. Decision tree grafting is the process of adding nodes to an existing decision tree to reduce prediction error (Webb, 1999). Decision trees are tree-based algorithms in which each path begins in a root node representing a sequence of data divisions until reaching an outcome at a leaf node. Each leaf is assigned to one class that represents the optimal target value. The final objective is to obtain a model that can predict the search value for the specific scenario by learning simple decision rules inferred from prior data (Yang, 2019). This method was used to classify the weeks when irrigation was needed based on the CWB, AWB, ΣCWB and ΣAWB parameters. The analyses were conducted using the tenfold cross-validation mode. The obtained results were used to determine the percentage of correctly classified instances (CCI %, was calculated as the percentage of the true positive and true negative predictions). $CCI = (a + b)/N$; a = true positive (Yes), b = true negative (No).

RESULTS AND DISCUSSION

A characteristic feature of the climate in Poland is its variability, which is confirmed by the data in Table 1. Significant differences between the growing seasons of individual years occurred not only in the amounts of precipitation and evapotranspiration, but also in the average air temperature. The warmest and driest season was the growing season of 2012, when, due to very low rainfall, the climatic water balance (CWB) was as low as 241 mm. In the previous year (2011), the average temperature of the growing season was only 0.1°C lower with a 70% higher rainfall, which resulted in a positive CWB (7 mm) at the end of the growing season. Due to the different patterns of the weather in the winter and, above all, considerable differences between the amounts of rainfall in April (Tab. 1), the soil moisture levels at the beginning of the growing seasons in the individual years of the study were different.

Table 1. Meteorological data during the growing season (April–October) in 2009–2013

Year	Average temperature (°C)	Soil moisture measured at the end of April (%)	Total precipitation (mm)	ET_o (mm)	CWB (mm)
2009	14.4	18.8	389	571	–182
2010	14.1	19.9	429	508	–79
2011	14.9	24.1	505	498	7
2012	15.0	21.7	297	538	–241
2013	14.6	21.2	431	483	–52

Explanations: ET_o = reference evapotranspiration, CWB = climatic water balance.
Source: own study.

Traditionally used rain gauges provide total rainfall without information on the intensity, which has a significant impact on efficiency. The high variability of precipitation during the growing season and also between individual years significantly limits the possibility of using the balance method to determine the dates of irrigation.

For each of the growing seasons, different correlations were found between the water balance determined for apple trees and the actual water balance of the 10–30 cm soil layer. In years 2009–2013, these parameters were relatively highly correlated (r^2 = 0.60–0.72). However, the parameters of their linear regression models were different. In 2013, such a relationship was found to be insignificant (r^2 = 0.11) – Figure 2. This means that entering indiscriminately the measured precipitation value into the water inflow balance does not allow precise estimation of changes in soil moisture and thus determination of the date of the need for irrigation.

Effective rainfall depends on many factors, for example: soil and crop characteristics, climate parameters, land slope, rainfall amount and intensity, covering the soil with mulches (Ali and Mubarak, 2017; Treder *et al.*, 2022). This means that in practice, in many cases, estimates of balancing water inflows from precipitation are burdened with a large error. Also, as reported by Muzylo *et al.* (2009), the level of rainfall interception is very important and should not be neglected during the determination

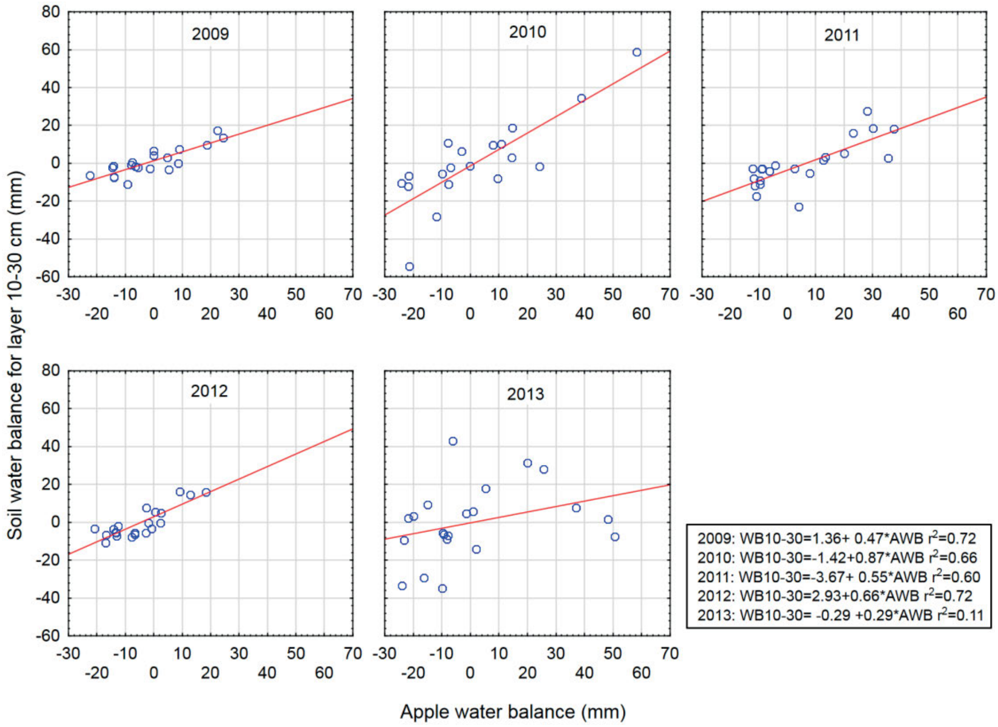

Fig. 2. Correlation between the water balance determined for apple trees and the actual water balance of the 10–30 cm soil layer in 2009–2013; source: own study

of water balances of orchards. According to Miranda de and Butler (1986), rainfall interception by plant canopies may account for 15% of total precipitation. This means that entering the actual amount of measured rainfall into the balance does not allow precise estimation of changes in soil moisture, which are the basic criterion for the irrigation of plants. An additional, almost impossible to determine, water inflow is the capillary rise of water in the soil profile. Capillary rise is a phenomenon that describes the movement of water in pores from lower to higher elevation. The maximum capillary rise height of soil is a complex phenomenon which is mainly determined by the distribution characteristics of the pores. Beltrão, Antunes da Silva and Asher (1996), who conducted research on corn, said that the upward flow from shallow water is a significant component in the water balance. Unfortunately, models estimating the amount and height of capillary rise of water, due to their specificity and lack of input data, are not available for practical use by farmers. For the same reason, many scientific publications on the climatic water balance ignore capillary rise. This is one of the reasons why the results of our own research and literature data show that the water balance method may be unreliable in practice.

Based on our research, it seems that this method can be supported by relatively simple machine learning models. The accuracy of our forecasts of irrigation needs based on climate data and the model developed with the decision tree classifier with the J48 algorithm were promising (*CCI* = 83.3%). The detailed classification outcome is shown in the confusion matrix in Table 2. The model made correct decisions in 76.7% of the instances when irrigation was needed and in 87.7% of the instances when irrigation was not needed. The prediction errors were presumably the result of imperfections in the current data entered into the learning model. During the research there was, in several cases, a situation when, after conducting irrigation because of the low soil moisture potential, heavy rainfall occurred, consequently affecting the balance data.

Table 2. Confusion matrix of the developed model

Predicted values	**Actual values**	
	yes	**no**
Yes	33	10
No	8	57

Source: own study.

Our research confirmed the previous work by many authors (Farooq *et al.*, 2020; Benos *et al.*, 2021; Meshram *et al.*, 2021), who pointed out that machine learning methods were widely used in agriculture. Increasingly, machine learning algorithms are also used in the application of precise irrigation of plants (Viani *et al.*, 2017; Megalingam *et al.*, 2020; Ramachandran *et al.*, 2022; Veerachamy and Ramar, 2022). Our results indicate that decision trees have been a powerful tool for use in making watering decisions. These results confirm the findings of Andriyas and McKee (2013), and Perea *et al.* (2019), who also used tree-based models suitable for predicting farmers' decisions whether to irrigate or not. The classifier described in our work makes a decision based on the *CWB*, *AWB*, $\sum CWB$ and $\sum AWB$, with the use the Penman–Monteih formula. Gill *et al.* (2006) and Cai *et al.* (2019) proposed the use of machine learning methods to predict variations in soil moisture as a criterion for the use of irrigation. Many authors emphasise the importance of and prospects for the development of practical applications that combine machine learning algorithms with modern IoT technologies for automatic irrigation control (Viani *et al.*, 2017; Farooq *et al.*, 2020; Veerachamy and Ramar, 2022).

The model of the classification tree developed by us is so simple that in the next stage of work we plan to use it to automatically control irrigation in the apple orchard. On the basis of meteorological measurements, climatic water balances and climatic water balances of apple trees (irrigation needs) will be automatically determined. The planned solution will cooperate with a new wireless smart farming system (utilising the IoT technologies) for controlling irrigation (described in Treder *et al.*, 2023). This system enables such implementation thanks to its open structure and the portal operating in the "cloud". Measuring probes that are a part of the system will be used for continuous learning of the decision model.

The final image of the classification tree is shown in Figure 3. The structure of the tree is relatively simple; apart from the root, it consists of 10 nodes and 12 leaves, and the classification rules of the tree are easy to interpret. According to the previously established ranking of the importance of attributes, the root of the tree is the water balance of apple trees determined for each week of the growing season. The high places in the hierarchy of the tree are occupied by the nodes defining the elapsed time of the growing season (i.e. the week number). The classifiers following them are the values of $\sum CWB$ and $\sum AWB$.

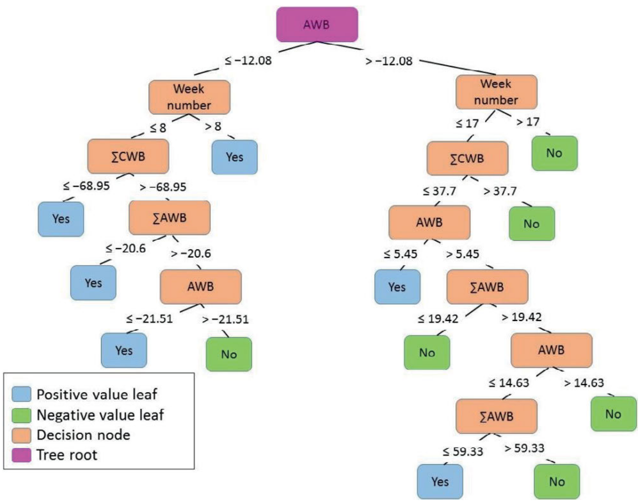

Fig. 3. Classical structure of a decision tree; AWB = apple water balance, CWB = climatic water balance, $\sum AWB/CWB$ = cumulative apple/climatic water balance; source: own study

CONCLUSIONS

The obtained results indicate that in the changeable weather conditions of the temperate climate zone, planning of irrigation schedule using only the climatic water balance approach may be burdened with a large error due to difficulty of accurately estimating the soil infiltration rates and the correct assessment of the effectiveness of rainfall. It was showed that in such conditions, machine learning can support the balancing water content in soil and thus the estimation the needs for plant irrigation. Thanks to the easy-to-determine classification rules, the presented model can be directly used in practice. With the current development of measurement equipment and computational applications, it is easy to obtain data on the amounts of evapotranspiration and precipitation, as well as the values of crop coefficients for various plant species. The prediction model presented by us using the classification tree contains only the meteorological parameters used in the traditional balance method; thanks to this, it does not require additional measurement data from the user.

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