FRM Foods and Raw Materials. 2027;15(1) ISSN 2308-4057 (Print)
ISSN 2310-9599 (Online)

Research Article
Open Access

Available online at http://jfrm.ru/en
https://doi.org/10.21603/2308-4057-2027-1-690
https://elibrary.ru/CWMDAW

Optimizing irrigation for Dutch roses in Beni Mellal, Morocco: Predictive modeling based on reference evapotranspiration

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Received 07.08.2024; Revised 26.12.2024; Accepted 11.11.2025; Published online 22.12.2025

Abstract:
Efficient water management in agriculture is crucial for sustainable crop production, particularly in regions facing water scarcity. This article introduces a comprehensive predictive model for optimizing the current irrigation of Dutch roses in the Beni Mellal region of Morocco. The model addressed the need for precise water management across four distinct plant growth stages. The integrated system proved able to estimate the daily irrigation requirements based on historical weather data and crop-specific factors. The model incorporated four main components: weather prediction for temperature, net radiation, wind speed, and dew point; calculating the reference evapotranspiration using the Penman-Monteith equation; applying the crop coefficients specific to each growth stage; as well as estimating the crop evapotranspiration and determining daily water needs. The system offered a systematic approach to predicting the daily water requirements for Dutch roses across the entire growth cycle. By leveraging historical weather patterns and growth stage-specific crop coefficients, the system provided a predictive tool for proactive irrigation management. The model proved highly adaptable as it was able to generate forecasts based on weather trends and plant growth stages, potentially leading to a more efficient water use than conventional irrigation methods. This integrated approach is expected to allow the rose farmers of Beni Mellal to optimize their irrigation practices. While field validation is needed to quantify its impact, the model's framework already shows potential for enhancing water use efficiency in cultivating roses and other crops in arid environment.

Keywords: Precision agriculture, irrigation, evapotranspiration, crop coefficient, Dutch roses, weather prediction, rose cultivation

Please cite this article in press as: Jdi H, Falih N. Optimizing irrigation for Dutch roses in Beni Mellal, Morocco: Predictive modeling based on reference evapotranspiration. Foods and Raw Materials. 2027;15(1):17–26. https://doi.org/10.21603/2308-4057-2027-1-690

INTRODUCTION

Water scarcity is an escalating global challenge, with agriculture consuming a significant portion of freshwater resources. In semi-arid regions like Beni Mellal, Morocco, efficient water management is crucial, particularly for such high-value crops as Dutch roses. These flowers require precise irrigation throughout their entire growth cycle to maintain high quality and yield, making them an ideal candidate for advanced water management techniques. Traditional irrigation methods are often based on fixed schedules or subjective assessments. As a result, they fail to account for the dynamic nature of plant water requirements. This limitation is particularly evident in Dutch rose cultivation, where water needs fluctuate significantly across four distinct growth stages: Initial (October), Development (November–January), Middle (February–July), and Late (August–September). The inability to adapt to these changing needs may lead to either water stress or wasteful overwatering, both of which can negatively impact crop quality and resource efficiency.

The recent advancements in agricultural technology have opened new avenues for precision irrigation. By incorporating historical weather data, crop-specific factors, and predictive modeling, agricultural scientists develop more sophisticated approaches to water management. Our proposed system leverages these advancements to create a comprehensive, predictive irrigation model for Dutch roses grown in Beni Mellal, Morocco. The system consists of four interconnected modules:

1. Weather Prediction. This module uses Recurrent Neural Networks (RNN) to analyze historical time se-

ries data of temperature, net radiation, wind speed, and dew point temperature. By recognizing patterns in past weather data, the model generates forecasts for these parameters, providing essential predictions that underpin our irrigation planning strategy.

2. Reference Evapotranspiration (ET_o) Calculation. Using the predicted weather parameters, this component implements the Penman–Monteith equation to calculate the ET_o. This calculation provides a standardized estimate of atmospheric evaporative demand, crucial for determining plant water requirements.

3. Crop Coefficient (K_c). This component incorporates stage-specific crop coefficients for Dutch roses. The K_c values vary monthly, reflecting the changing water needs of the roses throughout their growth cycle: Initial Stage (October), Development Stage (November–January), Middle Stage (February–July), and Late Stage (August–September).

4. Water Need (ET_c) Prediction. This module synthesizes the ET_o calculations and the crop-specific K_c values to derive the daily ET_c, i. e., estimated crop water requirement. The resulting ET_c precisely quantifies the water requirements, indicating the water loss per area unit through evaporation and transpiration.

At the heart of our predictive system lies the Penman-Monteith method used by the Food and Agriculture Organization (FAO-PM method) as the gold standard for estimating ET_o. This method synthesizes key meteorological factors, i. e., temperature, dewpoint temperature, wind speed, and net radiation, to calculate a standardized evapotranspiration rate. After calculating the ET_o, we introduce crop-specific coefficients for Dutch roses, which adjust the ET_o to reflect the unique water requirements of roses across their growth stages. The application of the FAO-PM method to the predicted weather data, combined with stage-specific crop coefficients, enables us to forecast daily ET_c values. This stage forms the cornerstone of our water need prediction module, generating data-driven irrigation forecasts for Dutch roses in the Beni Mellal region. The power of this approach lies in its predictive capability. Farmers receive comprehensive irrigation schedules that span all four growth stages well in advance. These schedules offer valuable insights, including seasonal water requirement projections for each growth stage, enabling strategic resource allocation and planning. Additionally, the system provides daily data-driven irrigation recommendations throughout the entire growth cycle, thus ensuring potentially optimal water management for crops.

By leveraging both anticipated physiological changes in the crop and the predicted weather patterns, our system empowers farmers to proactively optimize their irrigation strategies. This foresight enables a more efficient water use, potentially reducing costs and environmental impact while maintaining or improving crop yield and quality. The proposed system leverages historical weather data, including temperature, net radiation, wind speed, and dew point, to predict future weather patterns. These predictions, combined with the reference evapotranspiration calculations and the growth stage-specific crop coefficients, enable the forecasting of daily water requirements for Dutch roses. By doing so, the model provides rose cultivators with a proactive tool for efficient irrigation management.

The study had two primary objectives: using the available weather data, to develop a predictive model that estimates daily irrigation requirements for Dutch roses across their four growth stages in Beni Mellal; to integrate the historical weather data analysis, FAO Penman-Monteith ET_o calculations, and stage-specific crop coefficients into a cohesive predictive system. By achieving these objectives, we aimed at contributing to the field of precision agriculture and water resource management. While focused on Dutch roses in Beni Mellal, our model has the potential to be adapted for diverse agricultural contexts, offering a scalable solution to the pressing challenge of agricultural water management in water-scarce regions.

The literature review below explores how reference evapotranspiration (ET_o) has emerged as a powerful tool for precision irrigation management. Numerous studies demonstrate the efficacy and potential of ET_o-based irrigation strategies, from small-scale experiments to industrial applications. These research findings provide compelling evidence for the adoption of more sophisticated irrigation techniques in modern agriculture, offering promising solutions to the complex challenge of water management in a changing world.

Weather prediction plays a crucial role in various sectors, with significant implications for agricultural production. The importance of accurate meteorological forecasts is underscored by research findings that reveal a direct correlation between the level of engagement by agricultural entities with weather predictions and the subsequent increase in income [1, 2]. Access to meteorological information is a critical determinant for the adoption of climate-smart agriculture practices [3, 4]. In the realm of climate-smart agriculture [5, 6], where agricultural strategies are tailored to mitigate the impacts of climate change while maintaining productivity, the role of weather data is paramount. Farmers with access to timely weather forecasts are more likely to optimize water usage, improve soil health, diversify crops, and make informed decisions about their farming activities. This integration of weather information empowers farmers to adapt proactively to changing environmental conditions, underscoring the pivotal role of meteorological data in fostering sustainable agricultural practices. In weather forecasting, machine learning and deep learning technologies have emerged as indispensable tools. Their significance lies in their ability to process vast amounts of data, recognize complex patterns, and generate more accurate predictions [7, 8].

Evapotranspiration (ET) comprises both evaporation from soil and plant surfaces, as well as transpiration from crops into the atmosphere. Understanding ET is crucial for estimating irrigation needs [9, 10]. The most commonly used equation to estimate ET_o is the

FAO-PM method. It takes into account various meteorological parameters such as temperature, humidity, wind speed, and solar radiation. The FAO-PM method is widely recognized as the standard approach for estimating ET_o. In fact, it is backed by the Food and Agriculture Organization of the United Nations as the sole method for determining ET_o.

ET_o data are fundamental for enhancing irrigation efficiency [11, 12]. As an important component of hydrological cycles in agricultural ecosystems [13], direct ET measurement is complex meteorological observations that provide crucial input for estimating water loss rates. The UN Food and Agriculture Organization endorses the Penman-Monteith equation, which integrates radiometric and aerodynamic parameters, as the preferred method for calculating reference evapotranspiration across diverse global climates.

Quantifying water loss through soil evaporation and plant transpiration allows farmers to adjust irrigation schedules to match crop water needs precisely [14]. This precise approach prevents yield reduction from water deficit while minimizing excess application, thus conserving this critical resource. Proper water management is vital for promoting sustainable agricultural development worldwide. In some regions, water scarcity results from poor and inappropriate water management practices [15]. ET-based irrigation scheduling [16] ensures timely water application, enhancing crop growth, yield, and quality. Additionally, irrigation management informed by ET data reduces such environmental risks as waterlogging [17, 18], soil salinization [19–21], and nutrient leaching [22], thus contributing to agricultural sustainability.

As a crucial tool for optimizing irrigation practices across various agricultural settings, ET_o is underscored by numerous studies that demonstrate its accuracy and versatility. Despite requiring fewer input parameters, ET_o-based methods were more accurate in estimating water use in mango orchards than more complex models [23]. The development of reliable frameworks for forecasting ET_o is considered essential for agricultural operations, particularly irrigation management [24]. ET_o's accuracy in estimating plant water use was validated through close correlations with actual plant transpiration measurements, as demonstrated in maize crops [25]. Furthermore, ET_o-based irrigation levels made it possible to determine the optimal water and nitrogen amounts for cultivating salt-tolerant plants in saline wastelands, highlighting its adaptability to diverse agricultural challenges [26]. The pivotal role of ET_o extends beyond field-level applications to broader water resource management, including urban and rural water allocation [27]. Researchers focus on refining the Hargreaves-Samani and FAO Penman-Monteith methods to enhance their accuracy in determining precise irrigation doses [28]. The development of machine learning approaches for ET_o prediction in challenging climates further demonstrates its global applicability and the ongoing efforts to improve its accessibility [29]. ET_o's utility in optimizing water use efficiency was demonstrated across various crops, including banana, lemon, and mango, by integrating satellite imagery and meteorological data [30]. Such flexible and customizable tools as *pyfao*56 for ET_o-based water balance modeling exemplify the practical implementation of ET_o in irrigation management research and practice [31]. Lastly, the application of ET_o in estimating crop water requirements across different agroclimatic zones reinforces its significance in tailoring irrigation strategies to specific regional conditions [32]. Collectively, these studies validate ET_o as a valid method for optimizing irrigation, offering a robust foundation for efficient water management in agriculture.

STUDY OBJECTS AND METHODS

This article introduces a predictive irrigation system for Dutch roses in the Beni Mellal region of Morocco. We integrated weather forecasting, evapotranspiration calculations, and crop-specific coefficients to estimate the daily water requirements. The following sections detail our methodology and assumptions, as well as the equations underpinning our model.

System description. Our predictive irrigation system followed the workflow process illustrated in Fig. 1. We started by predicting the key weather parameters (temperature, net radiation, wind speed, and dew point) based on historical data. The predicted weather parameters were then used to calculate the reference evapotranspiration (ET_o) using the Penman–Monteith method accepted by the Food and Agriculture Organization (FAO-PM). Then, we combined the predicted ET_o and the crop coefficients (K_c) to estimate the estimated crop water requirement (ET_c) for Dutch roses. As the final step, the ET_c was converted to daily water volume requirements.

The system operated based on daily inputs for weather parameters, highlighted in pink in the diagram. These daily inputs included temperature, dew point, net radiation, and wind speed. The optimal K_c for Dutch Roses, also shown in pink, varied monthly according to the growing stage. In this study, we worked with a monthly K_c value that naturally changed based on the development phase. The output of the system, i. e., the daily water amount needed, is shown in yellow. This approach allowed us to provide forecasts for the entire growing season divided into four stages: Initial (October), Development (November–January), Middle (February–July), and Late (August–September). Our forecasts took into account both daily weather variations and monthly changes in the crop water needs.

Weather forecast. Our weather forecasting module employed a time series analysis approach to predict the daily values for temperature, net radiation, wind speed, and dew point in Beni Mellal, Morocco. We utilized a gated recurrent unit (GRU) model, which had already proved effective for capturing trends in weather data [33]. We used the architecture indicated in Table 1, with its promising results for the four weather parameters mentioned above.

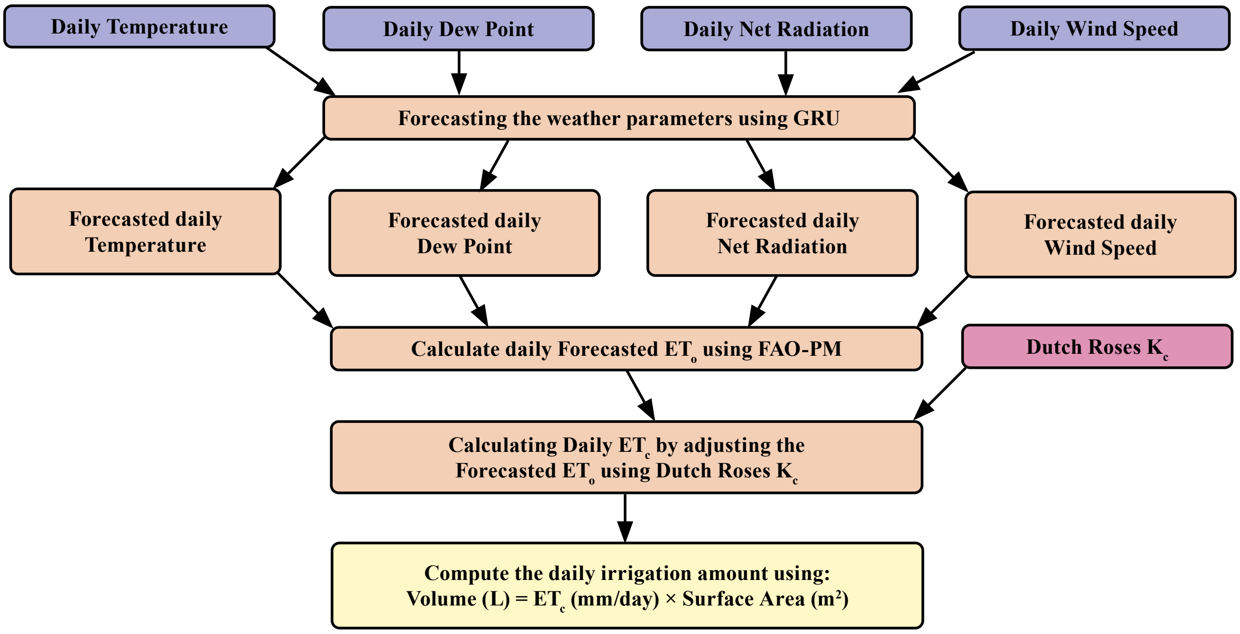

Figure 1 Workflow for forecasting daily irrigation amount: GRU – gated recurrent unit networks; ET$_o$ – reference evapotranspiration, FAO PM – Penman–Monteith method; K$_c$ – crop coefficient; and ET$_c$ – estimated crop water requirement

Table 1 Gated recurrent unit architectures

Layer (Type)	Units	Parameters
gru (GRU)	(None, 256)	198,912
dense (Dense)	(None, 64)	16,448
dense_1 (Dense)	(None, 1)	65

Model Configuration:

- Input Shape: (8, 1);
- Optimizer: Adam (lr = 0.001);
- Loss Function: Mean Squared Error (MSE);
- Metrics: Mean squared error (MSE), Mean Absolute Error (MAE), Mean absolute percentage error (MAPE).

Training Setup:

- Data Preprocessing: MinMaxScaler;
- Train-Test Split: 90–10%;
- Look-back Window: 8 time steps;
- Callback: ModelCheckpoint (save all epochs).

Calculating the daily forecasted ET$_o$ using FAO-PM. The methodology for calculating the forecasted ET$_o$ began with obtaining and processing four key weather parameters from the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) dataset. Three of these parameters, i. e., temperature, wind speed, and dew point temperature, were obtained directly from MERRA-2 as time series data. The fourth parameter, net radiation, which is a vital component of the FAO-PM equation, was derived from two MERRA-2 components. To calculate net radiation at the daily level, we subtracted the upward shortwave radiation (ALLSKY_SFC_SW_UP) from the downward shortwave radiation (ALLSKY_SFC_SW_DWN), expressed as: Net Radiation = ALLSKY_SFC_SW_DWN – ALLSKY_SFC_SW_UP. Using these 4 time series, we separately forecasted each weather parameter, resulting in predicted values for temperature, wind speed, dew point temperature, and net radiation.

These forecasted weather parameters then served as inputs for the FAO PM Eq. (1) to calculate the ET$_o$ values:

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

where ET$_o$ is the reference evapotranspiration, mm/day; R$_n$ is the net radiation at the crop surface, MJ/m^2/day; G is the soil heat flux density, MJ/m^2/day; T is the mean daily air temperature measured at 2 m above ground level, °C; u$_2$ is the wind speed measured at 2 m above ground level, m/s; e$_s$ was the saturation vapor pressure, kPa; e$_a$ is the actual vapor pressure, kPa; (e$_s$ – e$_a$) is the saturation vapor pressure deficit, kPa; Δ is the slope of the saturation vapor pressure curve, kPa/°C; and γ is the psychrometric constant, kPa/°C, rounded to 0.067 kPa/°C.

The additional components were calculated using the forecasted weather parameters:

- actual vapor pressure (e$_a$):

$$e_a = 0.6108\times\exp\left(\frac{17.27\times T_{dew}}{T_{dew}+237.3}\right) \qquad (2)$$

- saturation vapor pressure (e$_s$):

$$e_s = 0.6108\times\exp\left(\frac{17.27\times T}{T+237.3}\right) \qquad (3)$$

- slope of saturation vapor pressure curve (Δ):

$$\Delta = \frac{4{,}098\left[0.6108\times\exp\left(\frac{17.27\times T}{T+237.3}\right)\right]}{(T+237.3)^2} \qquad (4)$$

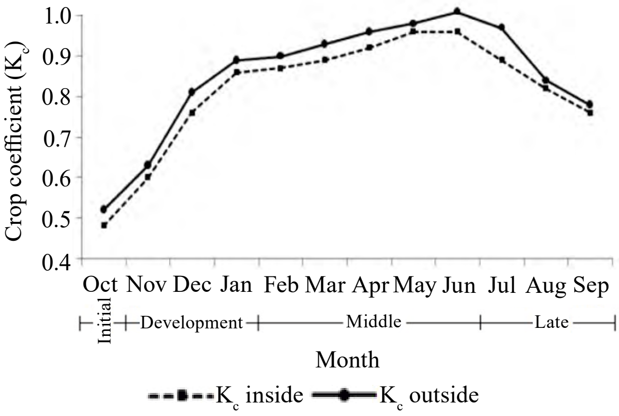

Figure 2 Monthly variations in crop coefficients for Dutch roses [34]

For daily calculations, the soil heat flux (G) was assumed to be 0 because the heating and cooling of the soil tend to balance out over a 24-hour period. The psychrometric constant (γ) was approximated as 0.067 kPa/°C. By incorporating these forecasted parameters and derived components into the FAO-PM equation, we obtained a forecasted ET_o value, which reflected the anticipated atmospheric demand for water transfer from vegetation and soil surfaces to the atmosphere.

Calculating the crop evapotranspiration. After obtaining the forecasted daily ET_o, we proceeded to calculate the ET_c, i. e., the estimated crop water requirement, using the following Eq. (5):

$$ET_c = ET_o \times K_c \tag{5}$$

where ET_o is the predicted daily reference evapotranspiration; K_c is the crop coefficient. For Dutch roses, the K_c value exhibited significant variability throughout the growth cycle, reflecting the changing water requirements. In the early growth phase, when the rose plants were small and their water needs were modest, the K_c values hovered around 0.3. As the plants matured and developed a fuller canopy, their water demands increased substantially. During the mid-season stage, characterized by vigorous growth and abundant flowering, the K_c values surged to approximately 1.2, indicating a period of peak water consumption. This dynamic nature of the K_c value is visually represented in Fig. 2, which delineates the fluctuations in crop coefficients across the various developmental stages of Dutch roses. The graph provides a comprehensive view of how water requirements evolve from the initial growth phase through to the final harvest stage, accounting for the intricate balance between the plant development and the environmental factors.

Determining the water needs. Having calculated the ET_c, we could quantify the actual water requirements for the Dutch rose by applying the following Eq. (6):

$$V = ET_c \times \text{Surface area} \tag{6}$$

where V is the total water volume required, L; ETc is the estimated daily water requirement of the crop, mm/day; and Surface area is the surface area of the rose plantation, m^2.

This equation translated the crop evapotranspiration, expressed in millimeters per day, into a volumetric measurement of water needed for a specific cultivation area. This calculation could provide farmers with a precise estimate of the daily irrigation needs, enabling them to tailor their water management strategies to the specific demands of their Dutch rose crops. The amount of water to apply not only potentially ensures optimal plant growth and flower production but also promotes water conservation by avoiding over-irrigation, thereby contributing to more sustainable agricultural practices.

RESULTS AND DISCUSSION

Weather forecast. The weather prediction system, based on a gated recurrent unit (GRU) architecture, demonstrated varying degrees of success across the 4 key parameters (Table 2). The model's performance for temperature, net radiation, and dew point temperature was particularly noteworthy, with the *R*-squared values ranging from 0.7610 to 0.9533 on the testing sets. This result indicated a robust ability to capture the underlying patterns in these parameters, which were crucial for accurate irrigation predictions.

Regarding the wind speed, while the R^2 value of 0.3594 on the testing set was low compared to other parameters, it was important to consider this result in context. Wind speed is notoriously difficult to predict due to its highly variable nature and sensitivity to local topography and microclimate conditions. Despite these challenges, our model showed some predictive capability, which was a positive outcome. Notably, the model's

Table 2 Performance evaluation of GRU for weather parameter prediction, 2021–2022

Weather parameter	Number of epochs	Mean absolute error (MAE)		Root mean square error (RMSE)		R^2	
		Training	Testing	Training	Testing	Training	Testing
Net radiation	29	0.4948	0.4710	0.7547	0.7134	0.7469	0.7625
Temperature	70	1.2296	1.2639	1.6065	1.6440	0.9559	0.9533
Wind speed	61	0.2648	0.2511	0.3919	0.3533	0.3426	0.3594
Dew point temperature	81	1.6368	1.5913	2.1243	2.1097	0.7362	0.7610

Table 3 Feature importance

Feature	Importance
Net radiation	0.999890
Temperature	0.000094
Wind speed	0.000008
Dew point temperature	0.000008

performance on the testing set (R^2 = 0.3594) slightly outperformed the training set (R^2 = 0.3426), suggesting a good generalization for this complex parameter. Furthermore, the wind speed prediction showed the lowest mean absolute error (MAE) across all parameters at 0.2511 for the testing set. While the model could not capture all the variability in wind speed, its average predictions were relatively close to the actual values. This level of accuracy could still provide a valuable input for irrigation planning, especially when combined with the highly accurate predictions for other parameters. The consistent performance across the training and testing sets for all parameters, including wind speed, suggested that the GRU model learned meaningful representations without overfitting. This fact indicates a major advantage of our model: it is likely to perform reliably on new, unseen data, which is a crucial factor for practical applications in irrigation management.

Assessing the dominance of net radiation in evapotranspiration modeling. The feature importance analysis done with Random Forest revealed a striking dominance of the net radiation in the model's decision-making process (Table 3). With an importance score of 0.999890, the net radiation overwhelmingly outweighed all other features. The temperature showed a very minor contribution with an importance of 0.000094, while the wind speed and the dew point temperature had negligible importance scores of 0.000008 each. This distribution of feature importances suggests that the model primarily relied on the net radiation for making predictions. Such a strong reliance on a single feature could indicate that the net radiation was indeed the most crucial factor in determining the irrigation needs for Dutch roses in this particular system. However, it also raised questions about the model's ability to capture the nuanced interplay between different weather parameters. The minimal importance assigned to temperature, wind speed, and dew point temperature was unexpected, given their known roles in evapotranspiration processes.

The model performance metrics in Table 4 presents an intriguing picture of the model's robustness and sensitivity to perturbations in different input features. The baseline model showed excellent performance with very low MAE (0.006702) and RMSE (0.009233) values, as well as a near-to-perfect R^2 score of 0.999983. The perturbing dew point temperature and wind speed had minimal impacts on the model's performance, with metrics remaining virtually unchanged. This result aligned with the low importance scores that these features received in the previous analysis. A slight decrease in performance was observed when the temperature was perturbed, with the MAE increasing to 0.007136 and the RMSE reaching 0.009582, though the R^2 score remained extremely high at 0.999982. While the temperature factor had a minor effect, the model remained highly robust to its changes. The most significant impact occurred when the net radiation was perturbed. The MAE increased dramatically to 0.183326, and the RMSE reached 0.229847. The R^2 score, while still high at 0.989474, showed a noticeable decrease compared to other scenarios. This substantial change in performance metrics when the net radiation was perturbed validated its dominant importance in the model's predictions.

The resulting model proved highly accurate and stable, but heavily dependent on the factor of net radiation. While this outcome suggests excellent predictive power under normal conditions, it also highlights a potential vulnerability if the net radiation measurements or predictions are inaccurate. The model's relative insensitivity to other parameters, while contributing to its stability, may limit its adaptability to scenarios where other factors play a more significant role in irrigation needs.

Calculating the daily forecasted ET_o using FAO-PM. ET_o plays a crucial role in determining the irrigation needs for crops. Our model demonstrated the capability to predict long-term weather parameters; in this study, however, we focused on the growing season of Dutch roses, which spans from October to September. This growing season can be divided into four distinct stages, each with its unique water requirements and evapotranspiration rates.

The Initial Stage (October) lasts for about 3–4 weeks, with low water needs and a K_c value of around 0.51. The Development Stage (November–January) requires more water as the plants grow, with the K_c values rising from 0.63 to 0.89. The Middle Stage (February–July) represents the peak water requirement period with the K_c values of 0.90–1.05. Finally, the Late

Table 4 Model performance metrics

Metrics	Baseline	Perturbed dew point temperature	Perturbed wind speed	Perturbed temperature	Perturbed net radiation
Test MAE	0.006702	0.006708	0.006710	0.007136	0.183326
Test RMSE	0.009233	0.009234	0.009236	0.009582	0.229847
Test R^2	0.999983	0.999983	0.999983	0.999982	0.989474

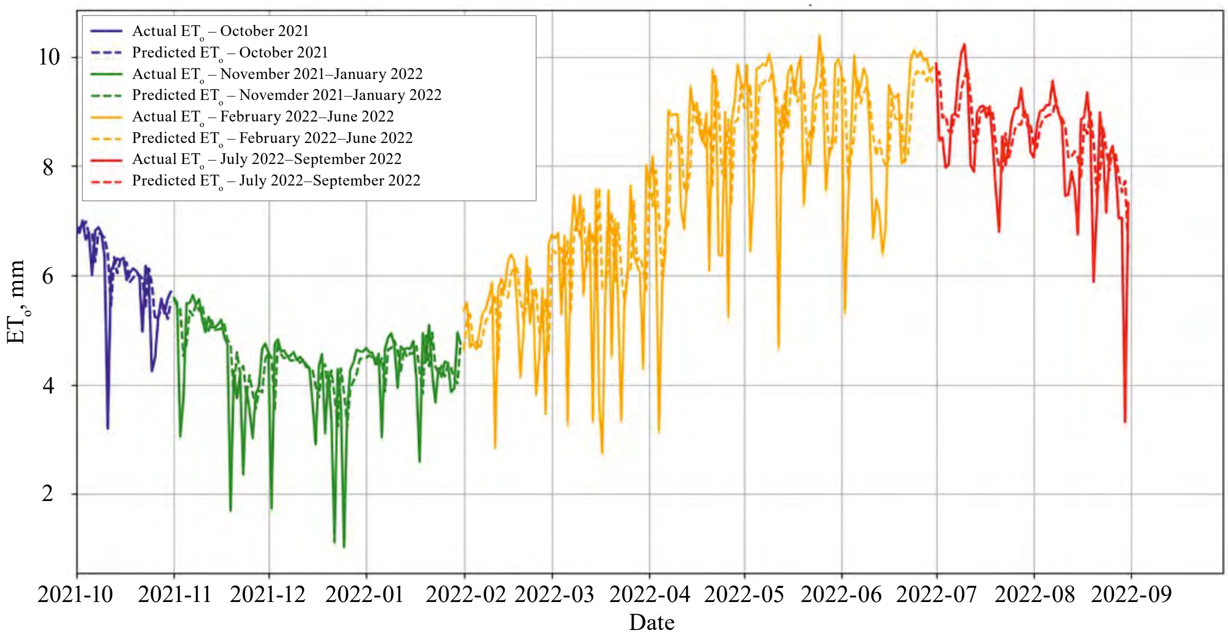

Figure 3 Actual vs. predicted reference evapotranspiration (ET$_o$), October 2021–September 2022

Stage (August–September) sees a gradual decrease in water needs, with the K$_c$ values declining from 0.84 to 0.79. Understanding these stages and their corresponding evapotranspiration rates is crucial for optimizing irrigation strategies throughout the Dutch rose growing season. Table 5 presents the MAE, RMSE, and R^2 for our evapotranspiration model. These metrics provide insight into the model's accuracy.

Figure 3 illustrates the predicted and actual ET$_o$ values throughout the October–September growing season of Dutch roses, encompassing four distinct growth stages. The graph displays the daily ET$_o$ values, with the actual data represented by a continuous line and the model predictions shown as a dashed line. Each growth stage is color-coded: blue is for the Initial Stage (October), green is for the Development Stage (November–January), orange is for the Middle Stage (February–July), and red is for the Late Stage (August–September).

Irrigation requirements for Dutch roses. To demonstrate the practical application of our ET$_o$ predictions, we examined the irrigation needs for 1 ha of Dutch roses across the complete growing season. The K$_c$ for Dutch roses varies monthly, reflecting the different growth stages (Table 6). These K$_c$ values are crucial for calculating the ET$_c$ using the ET$_c$ formula. The growing season for Dutch roses spans from October to September, encompassing four distinct stages. By applying the ET$_c$ formula with our ET$_o$ predictions and the appropriate K$_c$ values, we could determine the daily crop evapotranspiration. From this, we calculated the required irrigation volume using the equation provided in the methodology section for the surface area of our 1-hectare plot (10,000 m²).

Table 5 Evapotranspiration prediction performance metrics, 2020–2022

	Model	MAE	RMSE	R^2
ET$_o$, mm	GRU-FAO-PM	0.6873	1.0422	0.7640

Table 6 Crop coefficients (K$_c$) for Dutch roses [34]

Month	K$_c$ outside	Stage
October	0.51	Initial
November	0.63	Development
December	0.88	Development
January	0.89	Development
February	0.90	Middle
March	0.94	Middle
April	0.95	Middle
May	0.99	Middle
June	1.05	Middle
July	0.98	Middle
August	0.84	Late
September	0.79	Late

Figure 4 presents a line chart illustrating the forecasted daily irrigation requirements throughout the growing season, color-coded by growth stage. This data-driven model, based on daily meteorological observations collected in Beni Mellal, illustrates how irrigation needs are likely to fluctuate over time, with potential peaks during the middle stage when the plant water consumption is expected to be highest.

CONCLUSION

The new data-driven model for predicting irrigation requirements for Dutch roses grown in the Beni Mellal region relied on daily meteorological observations. It demonstrated high accuracy and stability under normal conditions,

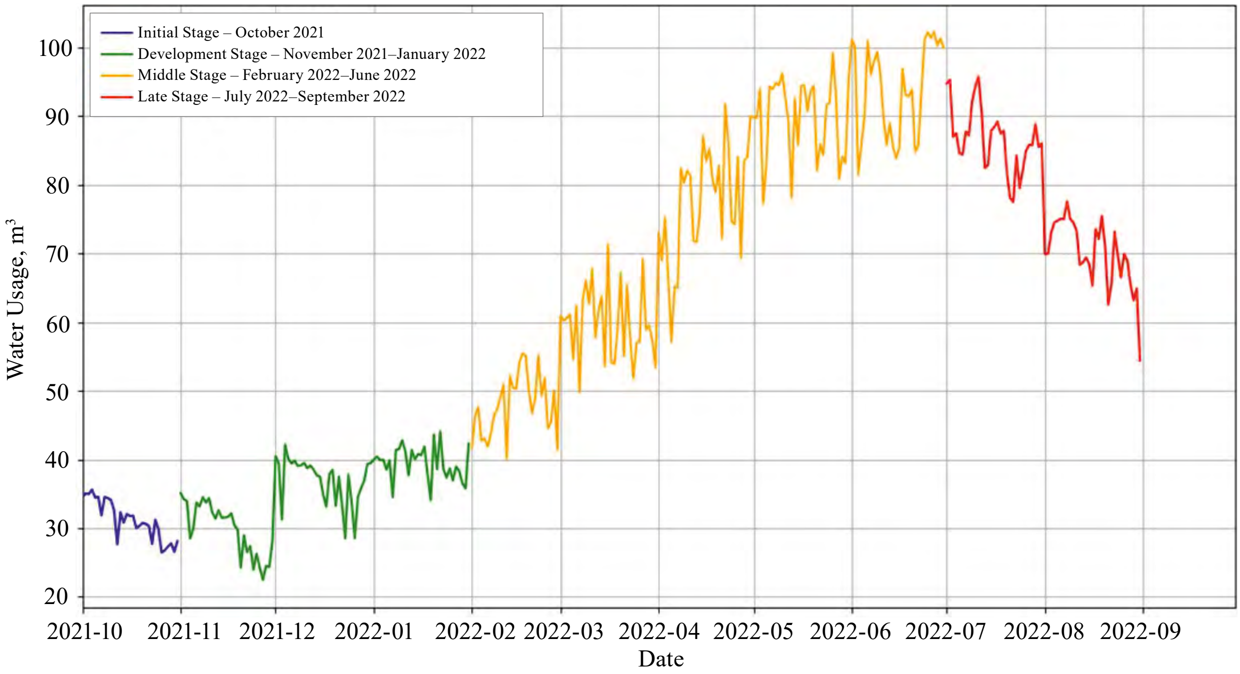

Figure 4 Irrigation requirements for Dutch roses: Water use across growth cycle (October 2021–September 2022)

primarily due to its strong reliance on net radiation. With consistently high R^2 scores and low error rates, the model provided reliable predictions for routine irrigation planning. Its simplicity proved to be its key advantage, requiring only 5 inputs to forecast irrigation needs up to 3 years in advance, making it accessible for standard personal computers. However, our attempt to validate the model through farmer surveys revealed that the current irrigation practices in the region are often based on soil saturation levels and tend towards over-irrigation. This finding underscores the need for a shift in the local irrigation strategies towards more precise, data-driven approaches.

Building on this foundational work, we intend to focus on practical implementation broaden its applicability. We plan to conduct field tests, comparing the model's irrigation schedules with traditional methods to validate its actual effectiveness. Crucially, we are going to collaborate with local farmers to refine the model, ensuring that it addresses practical needs while promoting water efficiency. To enhance the model's robustness, we plan to improve its sensitivity to extreme weather conditions without compromising its current strengths. The system's adaptability suggests a significant potential beyond its current application. By adjusting the five input crop coefficients and weather data, this model could be tailored for various crops and regions, offering a versatile solution for precision irrigation across diverse agricultural landscapes. Through these efforts, we seek to bridge the gap between theoretical modeling and practical application, potentially transforming irrigation strategies in water-sensitive regions worldwide and contributing to more sustainable agricultural practices.

CONTRIBUTION

The authors contributed equally to the study and bear equal responsibility for the information published in this article.

CONFLICT OF INTEREST

The authors declared no conflict of interest regarding the publication of this article.

ACKNOWLEDGEMENTS

This research was part of a Digital Agriculture Doctorate Project that involved a research team from the LIMATI Laboratory at Sultan Moulay Slimane University, Morocco.

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