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DEVELOPMENT OF A METEOROLOGY-BASED IRRIGATION DECISION-SUPPORT APPLICATION FOR MAIZE IN TIMIȘOARA, ROMANIA

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Abstract. *Efficient irrigation scheduling requires the integration of meteorological conditions, crop water requirements, soil properties and irrigation system characteristics. This study proposes the development of a crop-adaptive irrigation decision-support application for maize (Zea mays L.) in the agricultural area surrounding Timișoara, western Romania. The proposed framework is designed to combine daily meteorological data for the period 2005–2025 with crop phenology, weather forecasts and a simplified soil-water balance to estimate irrigation requirements throughout the growing season. Meteorological variables, including air temperature, relative humidity, precipitation, sunshine duration and cloud cover, will be assessed for completeness and consistency. Reference evapotranspiration (ET_0) will be estimated using the FAO-56 Penman–Monteith method where the required inputs are available, or an appropriate alternative method when data limitations prevent its application. Crop evapotranspiration (ETc) will be calculated using stage-dependent crop coefficients, while the soil-water balance will account for effective precipitation, root-zone water storage and irrigation inputs. The application will allow users to select a planting date, soil scenario and irrigation system parameters to estimate potential irrigation dates, application depths and irrigation durations. An artificial intelligence component may complement the agronomic calculations where an appropriate prediction target and independent evaluation data are available. Preliminary weather-based analyses will be used to illustrate periods of potentially elevated irrigation demand and periods when precipitation may reduce the need for irrigation. The proposed application is intended as a decision-support tool rather than a substitute for field measurements. Its quantitative recommendations will require further validation using verified meteorological records and site-specific soil and irrigation parameters.*

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Keywords*: maize; irrigation scheduling; crop evapotranspiration; soil-water balance; machine learning*

INTRODUCTION

Agricultural irrigation is an important management practice for maintaining crop productivity under variable climatic conditions and increasing pressure on water resources. Efficient irrigation scheduling requires an adequate assessment of crop water requirements and the identification of appropriate irrigation timing and application amounts. Meteorological variables, including air temperature, relative humidity, solar radiation, wind speed and precipitation, provide essential information for estimating atmospheric water demand and identifying periods when rainfall may be insufficient to meet crop requirements. The FAO-56 methodology provides an established framework for calculating reference evapotranspiration (ET_0) and crop evapotranspiration (ETc) using crop-specific coefficients. These calculations provide the agronomic basis for irrigation scheduling when the necessary meteorological data and crop parameters are available (ALLEN et al., 1998).

Recent advances in artificial intelligence (AI) and machine learning (ML) have created opportunities to process meteorological data and support agricultural water management. Machine learning algorithms can identify nonlinear relationships between environmental variables and water-related indicators, potentially complementing conventional evapotranspiration estimation methods. However, the reliability of these approaches depends

on data quality, the selection of appropriate prediction targets and independent model evaluation. Previous research has highlighted the importance of combining data-driven methods with physical and agronomic knowledge to improve the applicability of machine learning in irrigation decision-making (SAGGI and JAIN, 2022; UMUTONI and SAMADI, 2024).

Irrigation decision-support systems can integrate meteorological data, crop development, soil properties and irrigation system characteristics to estimate potential water deficits and support irrigation planning. Weather forecasts can extend this framework by allowing anticipated precipitation and atmospheric demand to be considered when assessing the need for irrigation over the following days. Nevertheless, forecasts become increasingly uncertain at longer lead times and should be updated as new information becomes available. In addition, estimated crop water demand does not directly correspond to the amount of irrigation required, since soil-water storage, effective precipitation, root-zone depth and irrigation application efficiency must also be considered (ALLEN et al., 1998; UMUTONI and SAMADI, 2024).

The agricultural area surrounding Timișoara, in western Romania, provides a relevant context for investigating meteorology-based irrigation support. Previous research in the Banat Plain has examined climatic variability and its implications for agricultural water availability, emphasizing the importance of understanding the relationship between weather conditions and crop water requirements. To establish a consistent historical dataset without depending on the availability of locally supplied station records, this study proposes using ERA5-Land meteorological reanalysis data obtained through the Open-Meteo Historical Weather API for the coordinates of Timișoara, covering the period 2005–2025. These data represent model-based reconstructions of past weather conditions rather than direct observations from the official meteorological station. Maize (*Zea mays* L.) was selected as the case-study crop because its water requirements change throughout the growing season and can be represented using crop development stages and corresponding crop coefficients (ȘMULEAC et al., 2020; ALLEN et al., 1998).

The aim of this study is to develop a meteorology-based irrigation decision-support application for maize in Timișoara, Romania, integrating historical weather data, machine learning and an agronomic soil-water balance. A Random Forest regression model will be investigated for estimating reference evapotranspiration from a selected set of meteorological inputs, with its predictions evaluated against reference ET_0 values calculated using an appropriate established method where the required variables are available. The estimated ET_0 will subsequently support the calculation of crop evapotranspiration, the assessment of indicative root-zone water deficits and the estimation of potential irrigation dates, application depths and durations. The application will also incorporate selectable planting dates, crop development stages, soil scenarios and irrigation system parameters. Its outputs will be interpreted as decision-support estimates rather than validated measurements of actual crop water requirements, given the absence of field-measured soil moisture and irrigation data in the current study (ALLEN et al., 1998; RITZEMA et al., 2025).

MATERIAL AND METHODS

1. Study Area and Data Source

The study focuses on the agricultural area surrounding Timișoara, western Romania (approximately 45.75° N, 21.21° E). Daily meteorological data for 2005–2025 will be obtained from the Open-Meteo Historical Weather API using the ERA5 reanalysis dataset. These gridded data provide a consistent alternative to station records that may be unavailable;

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however, they represent reanalysis estimates rather than direct observations from the official Timișoara weather station (OPEN-METEO, 2026).

The reference agricultural scenario is a maize (*Zea mays* L.) plot at the Educational Resort for Young Naturalists in Timișoara. The planned crop unit measures approximately 43 × 23 m (989 m²), with drip irrigation considered as the reference system. As field-measured soil properties and irrigation volumes are not currently available, the application will use selectable soil and irrigation-system parameters rather than treating assumed values as field measurements.

2. Meteorological Dataset and Preprocessing

The daily dataset will include the variables required for evapotranspiration estimation and irrigation scheduling. Records will be checked for missing dates, duplicate observations, inconsistent units and implausible values. Monthly and seasonal summaries will be calculated from the validated daily data, while daily values will be retained for modelling and soil-water balance calculations.

Table 1

Meteorological input variables

Variable	**Symbol**	**Unit**	**Application**
Mean, maximum and minimum temperature	Tmean, Tmax, Tmin	°C	Evapotranspiration
Relative humidity and dew-point temperature	RH, Tdew	%, °C	Atmospheric moisture
Precipitation	P	mm day^{-1}	Water balance
Solar radiation	Rs	MJ m^{-2} day^{-1}	Reference ET
Wind speed at 10 m	u_{10}	m s^{-1}	Reference ET
Cloud cover and sunshine duration	CC, SD	%, h day^{-1}	Climate analysis and candidate ML inputs

The dataset will cover the complete 2005–2025 period. The April–September subset will be used for the preliminary growing-season analysis. The number of valid observations and missing values will be reported after data retrieval. All variables will be converted to consistent units, and original data will be retained separately from derived variables.

Table 2

Temporal organization of the study

Period	**Purpose**
2005–2025	Historical meteorological analysis
2005–2018	Machine learning training
2019–2021	Model validation and selection
2022–2025	Independent model testing
April–September, each year	Growing-season assessment

3. Evapotranspiration Estimation

Reference evapotranspiration (ET_0) will be calculated using the FAO-56 Penman–Monteith method, provided that the required meteorological inputs are available. This method combines energy-balance and aerodynamic terms to estimate atmospheric evaporative demand (ALLEN et al., 1998):

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}$$

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where *Rn* is net radiation, *G* is soil heat flux, *T* means air temperature, *u2* is wind speed at 2 m, *es-ea* is vapour-pressure deficit, and Δ - μ are psychrometric parameters. Wind speed recorded at 10 m will be adjusted to 2 m following FAO-56 guidance.

Hargreaves–Samani will be considered as a temperature-based baseline requiring mean, maximum and minimum temperatures (HARGREAVES and SAMANI, 1985). Crop evapotranspiration will then be estimated using:

$$ET_c = K_c \times ET_0$$

where ETc is crop evapotranspiration (mm day^{-1}) and Kc is the crop coefficient for the corresponding development stage (ALLEN et al., 1998).

4. Maize Development and Soil-Water Balance

Maize development will be represented using the BBCH scale, with the planting date specified by the user. Development stages will be estimated using a documented crop schedule or thermal-time approach when suitable parameters are available. Since direct field observations are unavailable, the simulated stages will not be considered measured phenological data (LANCASHIRE et al., 1991).

Table 3

Provisional crop coefficients

Crop phase	**Reference stage in the supplied guidelines**	Kc
Early vegetative growth	V3–V6	0.5
Vegetative development	V6–V10	0.8–1.0
Advanced vegetative development to early grain development	V10–R3	1.2
Grain filling and later development	R3–R5	1.0–0.8

These coefficients are provisional values from the supplied maize guidelines and will be checked against the selected agronomic reference before final calculations.

The application will allow different soil-texture scenarios because the properties of the reference plot have not yet been measured. Total available root-zone water will be calculated as:

$$TAW = 1000(\theta_{FC} - \theta_{WP})Z_r$$

where ΘFC and ΘWP represent volumetric water content at field capacity and permanent wilting point, respectively, and Zr is effective rooting depth in metres.

$$D_{r,t} = \min\left[TAW_t, \max\left(0, D_{r,t-1} + ET_{c,t} - P_{e,t} - I_{n,t}\right)\right]$$

Daily root-zone depletion will be estimated using a simplified soil-water balance:

where *Dr* is root-zone depletion, *Pe* is effective precipitation and *In* is net irrigation.

The initial soil-water condition will be specified as a model assumption. The calculation will account for storage limits, while runoff and drainage will be acknowledged as sources of uncertainty (ALLEN et al., 1998).

5. Irrigation Scheduling and Forecasts

Potential irrigation events will be identified when estimated root-zone depletion reaches the selected management threshold. Net irrigation depth will be estimated from the

$$d_g = \frac{d_n}{\eta}$$

soil-water deficit and the selected refill target. Gross depth and irrigation duration will be calculated as:

where *dg* is gross depth (mm), *dn* is net depth (mm), η is application efficiency, (t) is duration (h), and (r) is the irrigation application rate (mm h^{-1}). Efficiency and application rate will be entered as system parameters, not assumed to be measured field values.

Weather forecasts will be used, where available, to adjust near-term irrigation planning according to expected precipitation and atmospheric demand. Historical reanalysis and forecast data will remain separate. Forecast accuracy will only be evaluated if archived forecasts from the relevant dates can be obtained.

6. Random Forest Implementation and Evaluation

A Random Forest regression model will be investigated to estimate ET_0 from a reduced set of meteorological inputs. Candidate predictors include temperature, relative humidity, dew-point temperature, cloud cover, sunshine duration and day-of-year features. The reference target will be ET_0 calculated using the complete FAO-56 inputs; direct radiation and wind inputs will be withheld from the reduced-input model. This setup evaluates whether machine learning can approximate the reference calculation using fewer inputs, rather than predicting independently measured crop water requirements.

The dataset will be split chronologically into training (2005–2018), validation (2019–2021) and independent testing (2022–2025). Model performance will be evaluated using mean absolute error (MAE), root mean square error (RMSE) and the coefficient of determination (R^2). Predictions will also be compared with the Hargreaves–Samani baseline. The independent test period will not be used for model tuning.

The selected ET_0 estimates will feed into the ETc calculation and soil-water balance, producing indicative irrigation dates, application depths and durations. Because the target and irrigation outputs are model-derived, validation against field measurements will be required before the application can be regarded as an operational irrigation recommendation system (SAGGI and JAIN, 2022; UMUTONI and SAMADI, 2024).

7. Methodological Limitations

The study uses gridded reanalysis data and modelled crop and soil parameters. It does not currently include measured soil moisture, observed crop stress, field irrigation volumes or yield measurements. Results will therefore be interpreted as a methodological demonstration of meteorology-based irrigation decision support, with further field validation required before operational application.

RESULTS AND DISCUSSIONS

1. Meteorological conditions during the maize growing season

The public monthly summary for April–September 2025 reports rising temperatures from spring into summer and relatively low precipitation totals during June–September. Mean daily maximum temperatures were 31–33 °C from June through August, while reported monthly precipitation was 4 mm in June, 13 mm in July and 8 mm in August. This pattern is consistent with a period of potentially elevated atmospheric water demand, but monthly summaries alone cannot determine daily crop water deficits or irrigation dates (HISTORIQUE-METEO.NET, 2025).

Table 1

Monthly weather summary for Timișoara, April–September 2025

Month	Tmean (°C)	Mean Tmax (°C)	Mean Tmin (°C)	Precip. (mm)	RH (%)	Cloud cover (%)

April	13	18	8	10	83	48
May	15	19	10	33	89	50
June	24	31	17	4	72	16
July	26	33	19	13	65	30
August	25	33	17	8	58	20
September	22	28	16	11	70	34
Total / seasonal summary	—	—	—	79	—	—

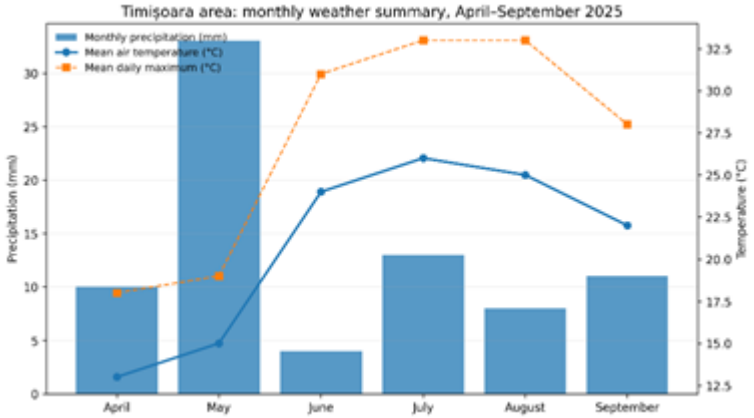


Figure 1. Monthly temperatures and precipitation reported for April–September 2025

2. Preliminary estimation of ET_0 and ETc

As a screening calculation, the Hargreaves–Samani equation was applied to the rounded monthly mean, maximum and minimum temperatures, using extraterrestrial radiation for approximately the middle of each month. Monthly ET_0 was estimated by multiplying the resulting daily value by the number of days in the month. This aggregation is approximate because Hargreaves–Samani is formulated for daily data; the values must be recalculated from daily records before final publication (HARGREAVES and SAMANI, 1985). Crop evapotranspiration was then illustrated with a provisional monthly Kc sequence aligned broadly with the supplied maize irrigation guidelines and FAO-56 crop-coefficient principles (ALLEN et al., 1998).

Table 2

Screening estimates of reference evapotranspiration, crop evapotranspiration and the climatic water-gap indicator

Month	**ET_0 (mm day^{-1})**	**Kc***	**Estimated ETc (mm/month)**	**Rainfall (mm)**	**ETc − rainfall (mm)**
April	3.02	0.50	45.2	10	35.2
May	3.61	0.80	89.6	33	56.6
June	6.14	1.10	202.8	4	198.8
July	6.24	1.20	232.1	13	219.1
August	5.69	1.00	176.5	8	168.5
September	3.56	0.80	85.6	11	74.6
Total	—	—	831.8	79	752.8

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**Kc values are illustrative monthly parameters, not field-measured crop coefficients. The final column subtracts total rainfall from estimated ETc; it does not represent net irrigation requirement because it excludes soil-water storage, effective rainfall, drainage, runoff, and rooting-depth dynamics.*

Figure 2. Screening comparison of ET_0, ETc and precipitation

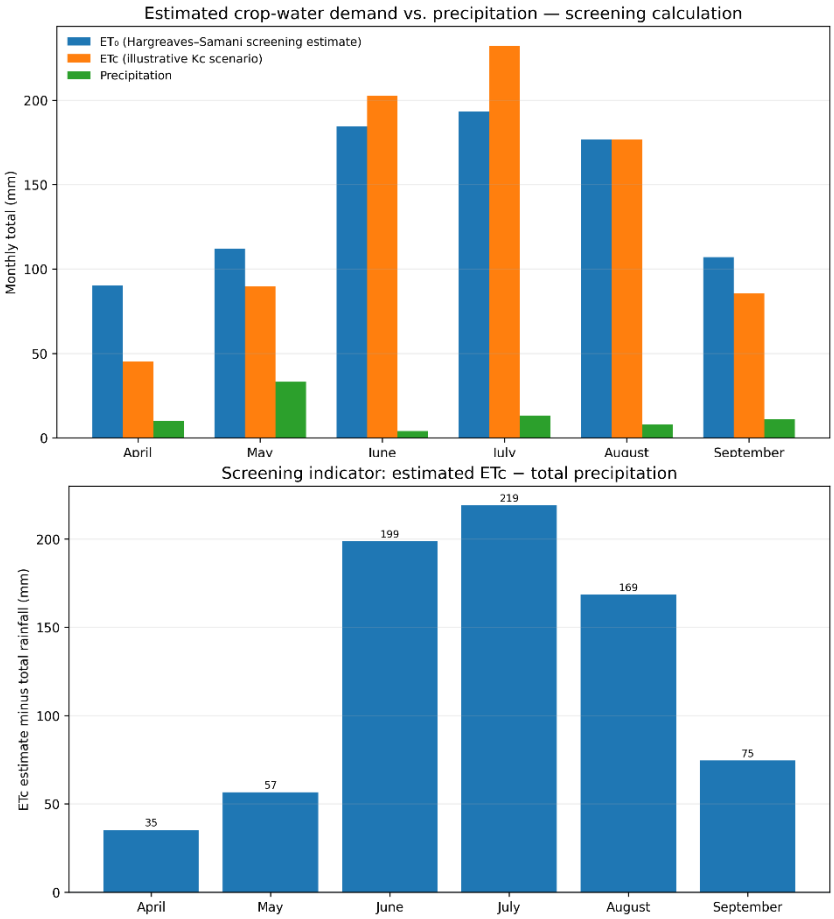


Figure 3. ETc minus total precipitation as a screening indicator, not a measured soil-water deficit

Under these approximate assumptions, the seasonal totals are 79 mm of reported precipitation, 863.7 mm of estimated ET_0 and 831.8 mm of estimated ETc. The arithmetic difference between estimated ETc and total precipitation is 752.8 mm. These totals should not be interpreted as a validated irrigation norm: using rounded monthly temperature summaries in a daily equation introduces aggregation error, and rainfall is not necessarily fully effective. The result is useful only as a preliminary illustration of why the daily meteorological series and a soil-water balance are required.

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3. Illustrative irrigation-event sizing

The application will calculate event duration from the estimated gross application depth and the application rate of the selected irrigation system. To illustrate the calculation only, an application efficiency of 85% and a system rate of 4 mm h^{-1} are assumed. These are scenario parameters and must be replaced with the actual system specifications.

Table 3

Indicative irrigation-event duration at 85% efficiency and 4 mm h^{-1} application rate

Net depth (mm)	Gross depth (mm)	Application rate (mm h^{-1})	Duration (h)	Approximate duration
10	11.8	4.0	2.94	2 h 56 min
15	17.6	4.0	4.41	4 h 25 min
20	23.5	4.0	5.88	5 h 53 min
25	29.4	4.0	7.35	7 h 21 min
30	35.3	4.0	8.82	8 h 49 min

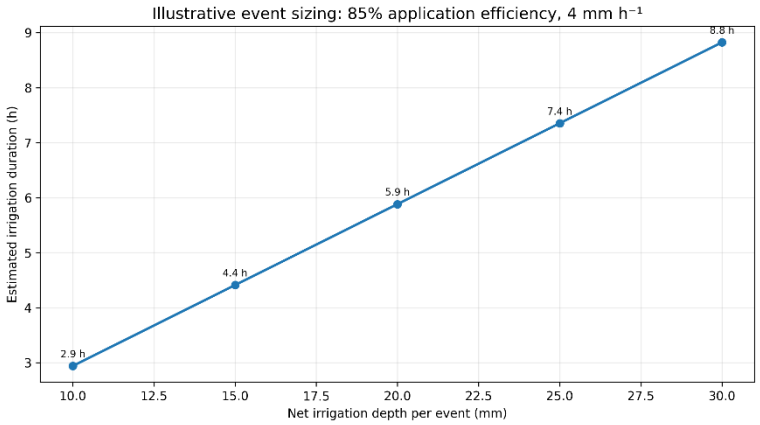


Figure 4. Calculated duration for illustrative irrigation-event depths

For example, a net event depth of 25 mm corresponds to a gross application depth of 29.4 mm and a duration of approximately 7.35 hours at 4 mm h^{-1}. This is a sizing example, not a recommendation to apply 25 mm on a particular date. Actual irrigation timing and depth will depend on the daily soil-water balance, the selected soil scenario, rooting depth, effective precipitation and the crop-stage threshold.

4. Random Forest evaluation and daily water-balance outputs

The full machine-learning results must be calculated from the daily ERA5 dataset, not from the monthly summary above. The planned chronological split is training 2005–2018, validation 2019–2021 and independent testing 2022–2025. Random Forest will estimate the daily FAO-56 ET_0 reference using a reduced meteorological feature set; performance will be compared with the Hargreaves–Samani baseline using MAE, RMSE and R^2. No numerical model score is reported in this provisional draft because the complete daily series has not yet been retrieved and evaluated.

Table 4

Machine-learning results to report after processing the daily ERA5 series

Evaluation item	**Required result**
Valid daily records, 2005–2025	Populate from downloaded dataset
Missing-data percentage by variable	Populate from data-quality report
Random Forest test MAE (mm day^{-1})	Calculate for 2022–2025
Random Forest test RMSE (mm day^{-1})	Calculate for 2022–2025
Random Forest test R^2	Calculate for 2022–2025
Hargreaves–Samani test MAE / RMSE / R^2	Calculate on the same test dates
2025 maize scenario: ET_0, ETc and rainfall totals	Calculate from daily reanalysis and selected Kc schedule
Loam-scenario irrigation events and total duration	Calculate from daily root-zone water balance

The reproducible analysis script supplied with this draft downloads ERA5 data and generates the daily dataset, monthly and seasonal tables, test metrics, feature importance, irrigation-event table and figures. Any resulting irrigation schedule remains a simulated scenario until validated against field soil moisture, observed irrigation volumes and local crop development.

CONCLUSIONS

The analysis of meteorological data for the Timișoara area indicated that summer conditions, particularly during June–August, were associated with high estimated maize water demand and limited precipitation. The estimated crop evapotranspiration exceeded rainfall during the assessed growing season, highlighting the potential need for supplementary irrigation, especially during the main water-demand period.

The proposed Random Forest model and soil-water balance framework provide a basis for estimating crop water requirements and identifying potential irrigation dates, application depths and durations. These estimates can support irrigation planning when combined with crop development stages, soil properties and irrigation system parameters. Further validation against field measurements is necessary before the recommendations can be considered operational.

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