



A Dynamic Weather-Driven Multi-crop Framework for Crop Water Demand Assessment Using GDD-Based Phenology and Climatic Crop Coefficient Adjustment in Semi-Arid Agriculture

Dhanali Khandagale¹, Maya Kurulekar¹*, Mahesh Kurulekar²*
and Karthik Kurup¹

¹ Vishwakarma University, Pune, India

² Vishwakarma Institute of Technology, Pune, India

maya.kurulekar@vupune.ac.in

mahesh.kurulekar@vit.edu

Abstract. Accurate evaluation of crop evapotranspiration (ET_c) is imperative for climate-based irrigation scheduling management within semi-arid zones. Traditional methods often employ predetermined crop calendars along with general crop coefficient values, thereby not adapting themselves to climate-based variability and dynamic crop growth conditions. In this paper, the application of a dynamic weather-based multi-crop evapotranspiration assessment scheme employing FAO-56 Penman-Monteith reference evapotranspiration (ET₀), GDD-based crop phenology modeling, and locally specific climatically adjusted crop-coefficients will be investigated. The daily climatic data set was collected through the NASA POWER database for the period 2023–2025 to evaluate seasonal behavior of crop water demand for crops such as wheat, rice, onion, tomato, and sugarcane under semi-arid condition. It has been found from the comparative analysis that wheat, rice, onion, and tomato crops had relatively low values of ET_c under dynamic climate adaptation; however, sugarcane had high evapotranspiration values due to its long growth period and sensitivity to atmospheric demand. Further investigations on the predictive coherence led to another XGBoost analysis that resulted in an RMSE of 0.217 mm/day and an R² of 0.977, illustrating high correlations between climatic variables, heat sums, and dynamically computed ET_c trajectories. Although field-based validations were not within the research agenda, the suggested model provides an adaptive solution for irrigation evaluation and water management in semiarid conditions, thus aligning with SDG 2, 6, and 13.

Keywords: Evapotranspiration, FAO-56 Penman–Monteith, Growing Degree Days, Climate-responsive irrigation, Crop coefficient adjustment

1 Introduction

Agricultural activities consume close to 70% of global water withdrawals, emphasizing the role of irrigation management in sustainable food production,

especially in semi-arid areas prone to climatic fluctuations [1], [14]. The increasing trend of warming, erratic precipitation regimes, and rising demands for atmospheric evaporation has escalated the strain on agricultural water sources, necessitating the implementation of climatically informed irrigation assessment methodologies in line with sustainable food security, water management, and climate-resilient agriculture [18].

The FAO-56 Penman-Monteith model is among the most popular methods of determining reference evapotranspiration (ET_0) owing to its physical coherence and suitability for varied climatic settings [13], [15]. Nevertheless, traditional ET_c determination methodologies often use predetermined crop calendars and universal crop coefficients, potentially limiting their responsiveness to climatic variations and the dynamism of crop development within semi-arid zones [5], [7]. Emerging literature has continued to emphasize that universal crop coefficients could be inadequate in capturing seasonal atmospheric variations and specific thermic reactions of crops [7], [10]. GDD-based phenological models have attracted increasing attention in their use as a thermal-time model that is able to define crop stage development in terms of accumulating temperature sums as opposed to defined calendar intervals [4], [9]. While the application of machine learning algorithms in evapotranspiration estimation and irrigation decision-making systems has proven their usefulness in identifying non-linear relationships between climate data and agriculture [2], [3], some of the irrigation assessment techniques still rely on fixed crop stage definitions, crop coefficient estimates based on generalized values, and bench-marking of different crops for comparisons [6], [18]. Furthermore, field-scale validations of evapotranspiration measurements using lysimeters or local irrigation management systems pose serious difficulties.

With these shortcomings in mind, the present work outlines a dynamic multi-crop evapotranspiration assessment approach combining ET_0 estimation using the FAO-56 model, crop phenology modeling using GDD threshold approach, and localization of climatic crop coefficients using multi-year climatic data from the NASA POWER database [16]. Benchmarking of static and dynamic ET_c estimation approaches was carried out for crops including wheat, rice, onion, tomato, and sugarcane in semi-arid climatic conditions. In addition, an auxiliary XGBoost predictive consistency analysis was introduced to test internal consistency of the generated climatic and phenological response behavior within the model dataset.

Key points of the research are outlined as follows: (1) Development of a dynamic GDD threshold-based evapotranspiration assessment approach for semi-arid agricultural ecosystems. (2) Localization of climatic crop coefficient considering wind speed, relative humidity and variable crop height. (3) Comparative benchmarking of static and dynamic approaches of evapotranspiration estimation for multiple crops. (4) Auxiliary machine learning-based predictive consistency analysis for testing climatic and phenological response within the modelled dataset. (5) Discussion of field scale evapotranspiration validation challenges and limitations of localized agriculture monitoring.

2 Literature Review

Estimating the evapotranspiration requirement of crops is still an essential research topic in the field of irrigation water management due to the direct implication of its measurement in irrigation scheduling, crop yields, and water-use efficiency [1] [18]. In the past few years, there has been a shift in estimating evapotranspiration by adopting models that use physical, satellite remote sensing, and artificial intelligence-based methods [2][5]. However, some challenges related to climate adaptability, stages of growth, and regional assessment still remain in the recent literature.

The FAO-56 Penman-Monteith method has been well established as an accepted procedure for calculating reference ET_0 due to its physical consistency and climatic universality [13], [15]. Nonetheless, traditional FAO-56 irrigation scheduling systems have been found to adopt generalized crop coefficients and pre-designed crop calendars, which might fail to capture the variations in agroclimatic conditions prevailing in semi-arid regions [7], [10]. Recent researches also indicate high variations in crop coefficients in arid and semiarid conditions, which suggests that static values of K_c may create errors when used under variable climatic conditions [5], [7]. In order to enhance the climatic variability aspect, several researchers have investigated the use of dynamic estimation techniques for crop coefficients through climatically adjustable methods, canopy characteristics, and remote sensing data [5], [10].

In addition to improvement in the climatic coefficient approach, crop phenology modeling using thermal time has also received considerable interest in precision irrigation studies. The Growing Degree Day (GDD) approach models plant growth based on thermal accumulation instead of set periods of time [4], [9]. This allows for better consideration of seasonality and climate change effects on different crops [8], [17]. However, certain irrigation systems still use simplistic crop stage-transition rules that may not be effective at modeling crop response to climate change [6], [18].

The development of machine learning in recent times has also resulted in an increase in evapotranspiration prediction capabilities as well as the application of irrigation decision-support systems [2], [3]. It has been seen that hybrid systems using a physically based approach towards evapotranspiration along with machine learning for climate analysis can capture the non-linear climatic patterns within agriculture data [2], [11]. Nevertheless, some researchers have highlighted the issues of lesser interpretability associated with data-driven methods due to the lack of explicit crop growth mechanisms within the modeling system [1], [3].

Another critical issue in irrigation modeling concerns field-scale validation and evapotranspiration measurements. While lysimeter experiments are generally accepted to be reliable in the measurement of evapotranspiration and the estimation of crop coefficients, they may necessitate considerable investment and operational support [12]. However, practical issues that have arisen from the cost involved, spatial variations, and regional applicability have been recognized in recent studies on agriculture [12]. Thus, current studies on irrigation systems have depended on process-based comparisons and climatic modeling, particularly when extensive validation data is lacking [6], [10].

Four key areas of research gaps that can be observed from the review of literature are as follows. First, most of the existing models for irrigation calculations still use fixed crop calendars and crop coefficients that have limited ability to respond to climatic variations. Second, relatively few studies combine the approach of using GDD-based crop phenology calculation and local climatic adjustments for the crop coefficient into one irrigation model. Third, there has been little work done regarding the comparison of static and climate responsive irrigation assessment. Fourth, machine learning models are mostly viewed as standalone tools for prediction and not as supplemental tools for physical models' validation.

In order to overcome such weaknesses, the current paper presents a dynamic model for evaluating multi crop ET_c using a weather-driven system combining FAO-56-based ET_0 calculations, adaptation based on threshold GDD values corresponding to different stages of crop development, and adjustments of climatic response coefficients specific to individual crops in semi-arid agricultural settings. Unlike approaches used to estimate irrigation requirements that utilize static methods of calculations, the suggested framework provides a dynamic representation of stages of crop growth based on accumulated degree days and an evaluation of seasonal ET_c dynamics.

3 Methodology

The proposed framework is designed to overcome the problems associated with static crop stages and crop coefficients. This framework incorporates several aspects, including climate-based evapotranspiration estimation, GDD-based adaptation of phenology, climate-based adjustment of crop coefficient, and benchmarking of irrigation demand. The overall process involved in the proposed approach is presented in Fig. 1. The approach entails estimation of reference evapotranspiration using the FAO-56 method, crop phenological modeling using the thermal-time concept, calibration of climatic crop coefficients, and seasonal irrigation assessment.

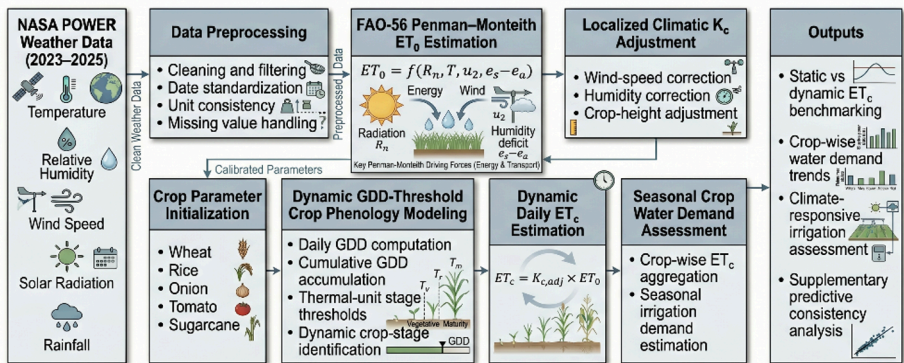


Fig. 1. Workflow of the proposed dynamic multi crop evaporation assessment framework.

Daily climatic data for the years 2023–2025 were extracted from the NASA POWER database [16]. The extracted climatic data comprised variables such as

temperature, relative humidity, wind speed, solar radiation, and precipitation, which were used in evapotranspiration calculations and the determination of climatic coefficients for crops. NASA POWER was chosen since its data is consistent over time, easily accessible, and can be utilized for agroclimatic studies in areas without well-established climate observation systems. Before calculating the value of evapotranspiration, the datasets obtained were processed by performing date normalization, checking consistency of units of measurement, removing duplicates, and replacing missing values. In addition, numerical analysis was conducted to minimize the effect of inconsistent climatic data during the calculation of evapotranspiration and crop water requirements. Reference evapotranspiration (ET_0) was estimated using the FAO-56 Penman–Monteith approach [15]:

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

where R_n represents net radiation at the crop surface, G denotes soil heat flux density, T corresponds to mean daily air temperature, u_2 denotes wind speed at 2 m height, and $e_s - e_a$ represents vapor-pressure deficit. The parameters Δ and γ denote the slope of the vapor-pressure curve and psychrometric constant, respectively. The FAO-56 framework was adopted because of its strong physical basis and widespread applicability across varying agro-climatic conditions [13], [14]. To improve climatic responsiveness during crop-stage progression, a Growing Degree Day (GDD)-based thermal accumulation approach was incorporated within the proposed framework. Daily GDD values were computed as:

$$GDD = \left(\frac{T_{max} + T_{min}}{2} - T_{base}, 0 \right) \tag{2}$$

where T_{max} and T_{min} represent daily maximum and minimum temperatures, respectively, while T_{base} denotes crop-specific base temperature. Thermal accumulation was then employed to detect dynamic crop stage changes based on GDD thresholds rather than fixed time periods. This method is more accurate in modelling seasonal climate variation and crop development behaviour in semi-arid climates [4], [9]. This research analysed five major crops grown in semi-arid agricultural climates. The crops include wheat, rice, onions, tomatoes, and sugarcane. The specific parameters required for the calculation of dynamic ET_c are shown in Table 1.

Table 1. Crop-specific parameters used in dynamic ET_c estimation

Crop	Base Temp. (°C)	Crop Duration (Days)	Initial Kc	Mid Kc	Late Kc	Crop Height (m)
Wheat	5	140	0.40	1.15	0.25	0.8
Rice	10	120	1.10	1.20	0.90	1.0
Onion	7	150	0.70	1.05	0.75	0.4
Tomato	10	140	0.60	1.15	0.80	0.6
Sugarcane	12	365	0.40	1.25	0.75	3.0

To improve the ability of crops to adapt climatically, crop coefficients were modified according to atmospheric correction factors due to wind velocity, humidity, and crop height. Adjustment of climatic effect on crop coefficient was done by FAO-56 correction factor [15]:

$$K_{c,adj} = K_c + [0.04(u_2 - 2) - 0.004(RH_{min} - 45)]\left(\frac{h}{3}\right)^{0.3} \quad (3)$$

where $K_{c,adj}$ represents the adjusted crop coefficient, K_c denotes the baseline crop coefficient, u_2 corresponds to wind speed at 2 m height, RH_{min} represents minimum relative humidity, and h denotes crop height. The effect of climatic adjustment provides better understanding of local-atmospheric variations as opposed to generalized climatic adjustment in crop coefficients [5], [7]. Daily ET_c was determined by the following equation:

$$ET_c = K_{c,adj} \times ET_0 \quad (4)$$

Here, dynamically adjusted crop coefficients and accumulated thermal units control stage development and ET_c of the crop. Seasonal water requirement was calculated from aggregation of daily ET_c values for each crop. In order to determine the effect of climate adaptation and thermal-time crop development, the proposed framework was compared to the standard approach of estimating ET_c through fixed crop development stages and unaltered crop coefficients. The comparison was made based on seasonal aggregations of ET_c values across all selected crops.

An additional predictive consistency check utilizing an XG Boost model was undertaken to gauge the consistency of the predicted climate and phenology reaction functions created by the modelling process. Climate-related factors, accumulated thermal time, and crop-related characteristics served as inputs to the model, whereas dynamically calculated ET_c values were used as target predictions. This analysis was carried out as a supplementary computational evaluation tool and not as a replacement for field-level evapotranspiration verification. The performance of the models was assessed based on RMSE and R² criteria.

4 Results and Discussion

The suggested model was tested through comparative seasonal evapotranspiration assessment in five major crop systems under semi-arid climate conditions. The findings show the impact of crop stage thermal time adjustment and localized climate adjustment in crop coefficient estimation on seasonal irrigation requirements calculation. Seasonal crop evapotranspiration estimates based on the traditional static model and the suggested dynamic model are presented in Table 2, whereas the comparative seasonal behavior for all crop systems is shown in Fig. 2. As can be seen from the comparative results, there appear to be some notable differences in the seasonal crop water demand estimates using static and dynamic approaches. There are relatively lower values of ET_c for crops such as wheat, onion, rice, and tomato due to

the dynamics of climatic conditions, while sugarcane appears to have relatively higher seasonal evapotranspiration patterns.

Table 2. Comparative seasonal ETC assessment between static and dynamic frameworks

Crop	Static ETC (mm)	Dynamic ETC (mm)	Difference (mm)	Percentage Difference (%)
Onion	467.30	445.85	-21.46	-4.59
Rice	378.93	360.71	-18.22	-4.81
Sugarcane	1224.90	1337.77	112.87	9.21
Tomato	385.21	367.68	-17.53	-4.55
Wheat	412.36	360.10	-52.26	-12.67

On the contrary, since the dynamic framework considered thermal accumulation and variability within the atmosphere in the adjustments in the transitions in crop stages and crop coefficients used, the observed variations in the ETC values were due to variations in climate-responsive irrigation performance rather than proof of better irrigation performance. It is critical to note that the main objective of this research was to assess irrigation demands using a dynamic climate model rather than validate actual irrigation performance.

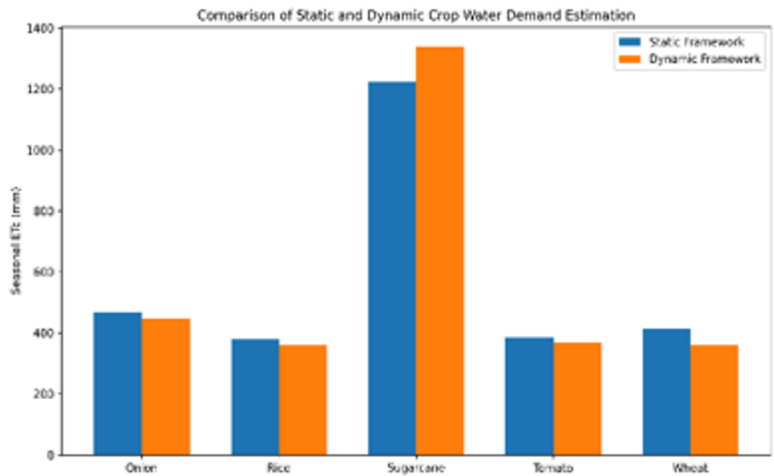


Fig. 2. Comparative seasonal ETC behavior under static and dynamic irrigation assessment frameworks

Furthermore, the crop-wise variations also confirm that the impact of thermal accumulation and climatic adjustment processes is not uniform for all types of crops when it comes to seasonal variations in the ETC. The high values in the sugarcane plantations could be attributed to the long crop duration as well as greater exposure to cumulative climatic demand. On the other hand, the low values in wheat and tomato crops were due to climatic adjustments and thermal stages. Thus, based on the findings, it can be suggested that dynamic climatic adaptations offer a more

responsive seasonal assessment of crop water demand behavior in semi-arid environments.

Temporal variation of estimated ETc under crop development was also studied using representative crops. Fig 3 shows an example of the temporal variation of estimated ETc for wheat under both static and dynamic estimation approaches. From the temporal analysis above, it can be seen that the dynamic approach changes the evapotranspiration pattern depending on the cumulative thermal accumulation and local climatic condition. The differences in static and dynamic ETc estimation were more significant for intermediate and late crop growing phases where the atmospheric demand and climatic variability played a more important role. This dynamic approach also showed a smooth transition pattern during the progression of crop stage as the crop coefficient was updated using GDD thresholds and local climatic data. This suggests that thermal-time-based crop adaption would provide better representation of irrigation demand variation influenced by climatic changes under semi-arid agriculture systems. These temporal variations were in line with the recent studies on the impact of thermal accumulation, climatic sensitivity, and evapotranspiration pattern depending on crop stages [7], [17].

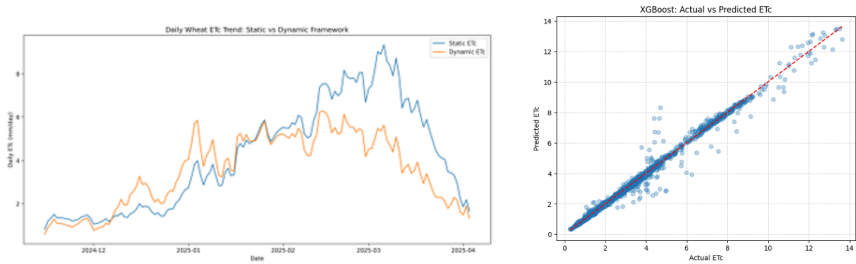


Fig. 3. Temporal variation of static and dynamic ETc estimation during wheat crop progression and comparison between actual and XGBoost predicted ETc values obtained from supplementary predictive consistency analysis

A further XGBoost-based predictive consistency analysis was performed to verify the internal consistency among the derived climatic and phenological responses within the simulated data. The final prediction model resulted in an RMSE score of 0.217 mm/day and an R^2 score of 0.977. As evident from Fig. 3, the high accuracy of predicting ETc values shows consistent predictive models among climatic factors, cumulative thermal accumulation, and estimated ETc dynamics within the simulated data. The consistency of the resulting predictions implies the consistent contribution of integrated climatic and phenological factors for ETc prediction in the given crop systems. Nonetheless, it is pertinent to note that the results from the analysis of the machine learning techniques used should be treated as a supplement for computational consistency testing as opposed to the direct field-scale validation of evapotranspiration behavior. It should also be noted that this study has not considered data from lysimeter observations, soil moisture levels, and local irrigation monitoring due to constraints in observation infrastructure, sustained maintenance requirements, and regional data availabilities [12]. Similar challenges have been identified in recent irrigation assessment comparison studies as well [6], [10].

Analysis of feature importance using the supplementary XGBoost model revealed that ET_0 , cumulative GDD, wind speed, and specific crop features exerted significant impacts on the estimation of ET_c values. The higher significance of ET_0 and the total heat units indicated the importance of evaporation demands in the atmosphere and crop development stage in the developed method. Conversely, features such as humidity and specific crops were observed to have lower impacts on the generated data set.

5 Conclusion

The proposed study introduced an adaptive climate-driven multiple-crops evaporation transpiration framework through a combination of FAO-56 Penman-Monteith ET_0 estimate, GDD threshold-based crop phenological model, and locally adjusted climatically dependent crop coefficient. As opposed to conventional static irrigation estimates, the proposed approach utilized a more adaptive consideration of thermal accumulation and climate variability in order to represent seasonal irrigation requirements. The comparative benchmarking between static and dynamic ET_c estimates revealed differences in seasonal evapotranspiration behavior in terms of wheat, rice, onion, tomato, and sugarcane farming systems. The findings suggested a different effect of climatic adjustments and crop stage development through thermal accumulation in seasonal water demands in the investigated semiarid climatic conditions. Moreover, the temporal ET_c analysis emphasized the importance of crop adaptation throughout the growing season. In addition, the additional analysis of predictive consistency using the XGBoost algorithm confirmed reliable relationships between climatic factors and dynamically estimated ET_c trends in the generated dataset. Although the above-noted factors can be considered, this paper cannot be viewed as a replacement for the validation of irrigation at the field scale. In particular, the suggested framework used climatic data obtained from the NASA POWER database without utilizing any information related to lysimeters, soil moisture, irrigation records, or local field observations. Also, soil heterogeneity, groundwater interaction, and regional-specific agricultural practices were not incorporated in this study framework. Such considerations may affect the direct applicability of estimated evapotranspiration values in different farming areas. In conclusion, further research efforts may involve implementing field scale observing systems, remote sensing crop monitoring, and irrigation scheduling. Overall, the suggested framework can be considered as a relatively flexible tool for assessing irrigation with respect to climatic conditions and multiple crops under conditions of limited observations.

Acknowledgments. We, the authors would like to thank Prof. Maya Kurulekar and Prof. Mahesh Kurulekar for their valuable guidance and support. The authors also acknowledge Vishwakarma University, Pune, and Vishwakarma Institute of Technology, Pune for providing all necessary academic support. This research was done without any financial support from any agency.

Disclosure of Interest. We, the authors declare that there are no conflict of interests.

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