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Advancing Precision Agriculture in Southern California, Number 4

DeepET—An AI-Driven Tool for Temperature-Based ET_o Estimation

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Introduction

Reliable estimation of reference evapotranspiration (ET_o) is fundamental for effective irrigation management. ET_o represents the evaporative demand of the atmosphere over a well-watered reference crop and serves as the foundation for calculating crop-water requirements following standard Food and Agriculture Organization (FAO) guidelines (Allen et al. 1998). The accuracy of irrigation scheduling based on the crop coefficient approach, as well as most smart irrigation technologies, depends on having trustworthy ET_o values.

The standard method for calculating ET_o is the FAO irrigation and drainage paper 56 (FAO-56) (Allen et al. 1998) Penman–Monteith equation, which requires multiple weather variables, including air temperature, humidity, solar radiation, and wind speed (Allen et al. 1998). While this method produces high-quality estimates, it requires a fully instrumented weather station with properly maintained sensors. Many growers, landscape managers, and even some agricultural regions lack access to the full suite of meteorological measurements needed to run the Penman–Monteith equation. In California, the California Irrigation Management Information System (CIMIS) network provides high-quality ET_o information, but the spatial coverage of its ground weather stations is limited, and many farms or landscapes may not have a station close enough to accurately represent local microclimate conditions.

Because air temperature is the most widely available and reliably measured climate variable, simple temperature-based ET_o equations, such as Hargreaves–Samani, have been widely used as alternatives (Singh et al. 2020). These models are easy to apply and require minimal input data; however, their performance varies across climates, seasons, and geographic regions (Kukal et al. 2020).

DeepET is a free, web-based tool developed to use modern artificial intelligence (AI) models to estimate ET_o across California using air-temperature data (Singh and Haghverdi 2023). The performance of the tool was evaluated against traditional temperature-based ET_o models and showed improved accuracy based on long-term ET_o records from CIMIS stations from 1985 to 2019.

This publication is the fourth in a series on *Advancing Precision Agriculture in Southern California*. It provides guidance on how to use DeepET and presents example ET_o estimates for three distinct weather conditions from inland, coastal, and desert regions of Southern California.

Common terms and definitions

ET_o: ET_o is the reference evapotranspiration, defined as the amount of water used from a standardized, well-watered cool season grass surface representing the evaporative demand of the atmosphere.

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CIMIS: CIMIS is a program established by the California Department of Water Resources in the early 1980s that manages close to 150 automated full weather stations across the state. The CIMIS dashboard provides ET_o estimates for each station using weather data collected over the standardized surface at that location.

AI: AI methods are advanced statistical modeling techniques that are typically trained using large amounts of data for specific tasks. DeepET uses three AI models (artificial neural networks (ANNs), long short-term memory networks (LSTMs), and convolutional neural networks (CNNs)) to estimate daily ET_o using air-temperature data.

FAO-56: FAO-56 is a widely used publication that provides guidelines for calculating crop-water requirements using the standard FAO Penman–Monteith ET_o equation and the crop coefficient method (Allen et al. 1998).

Approach and elements of DeepET

In a recently published study (Singh and Haghverdi 2023), we conducted a comprehensive evaluation of the performance of traditional temperature-based ET_o models for all climate regions in California using long-term CIMIS data. In addition, we used more than 725,000 CIMIS ET_o records from over one hundred stations from 1985 to 2019 to develop and test the performance of several AI temperature-based ET_o models. Our AI models performed 15 to 20 percent better (lower error) than the best traditional model (Hargreaves–Samani) across different seasons, climate divisions, and years, indicating that they can accurately predict ET_o in situations where only air-temperature data are available.

To make these models available for widespread use, the temperature-based AI models were incorporated into a free web tool called DeepET. DeepET allows growers, consultants, and landscape managers to generate daily ET_o estimates using only air-temperature data. Because temperature is widely available from on-site sensors, low-cost commercial weather networks, and existing weather apps, DeepET can be used in many locations where complete weather data are unavailable.

Traditional temperature-based equations such as Hargreaves–Samani are simple empirical equations and may not fully reflect the range of weather conditions, seasonal patterns, and regional climate variability captured by long-term California CIMIS records. DeepET addresses this limitation by using modern AI models trained with long-term CIMIS data, allowing the tool to identify more complex relationships between air temperature and ET_o than traditional temperature-based equations.

This tool is designed to support irrigation management in locations where full weather stations are not available, where CIMIS stations are too distant to capture local conditions, or where microclimates vary significantly within short distances, for example, in urban environments. Temperature-based deep-learning models are particularly suitable for smart ET-based irrigation controllers that currently rely on simplified empirical temperature-based equations.

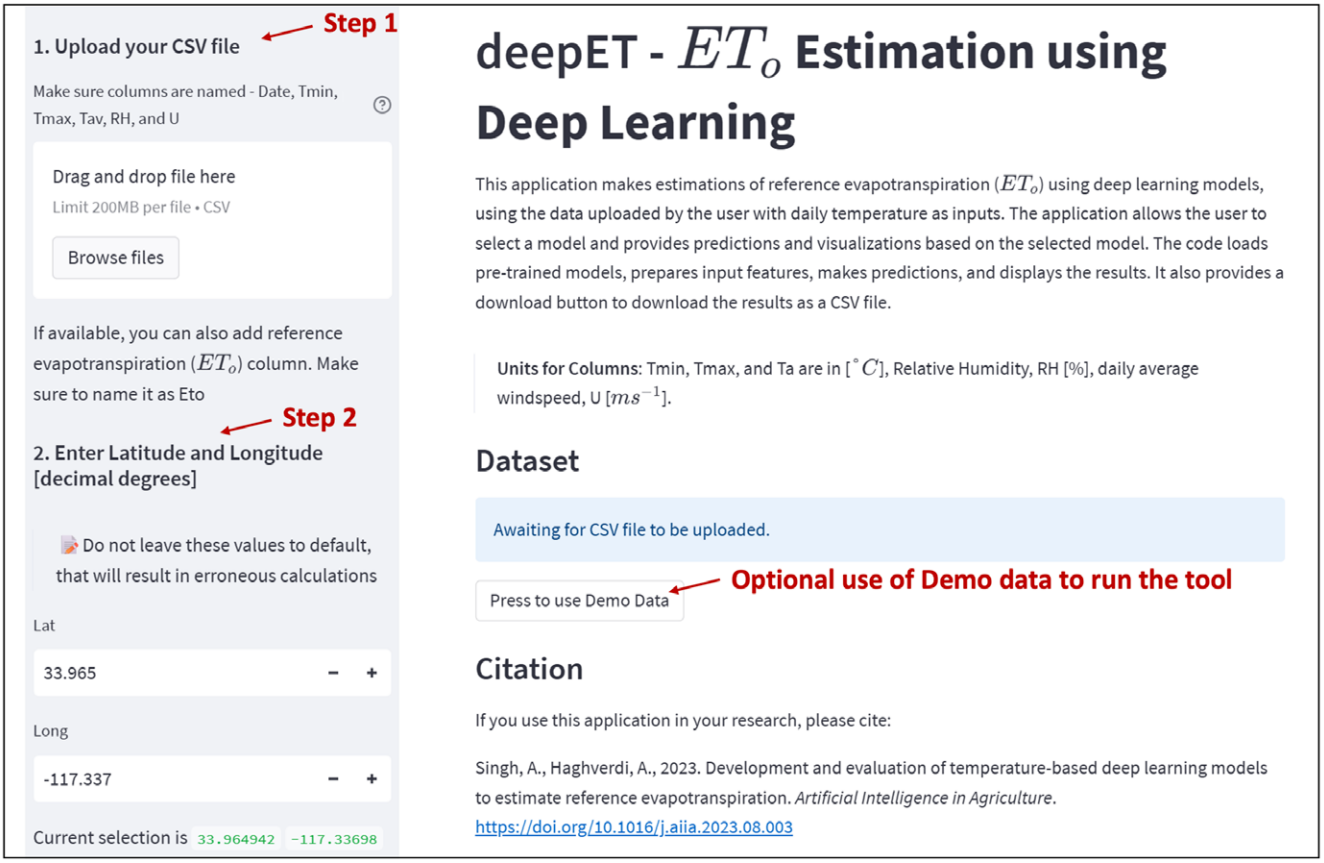
The DeepET application is accessed through a standard internet browser (fig. 1). Once opened, the interface guides users through a simple workflow. The first step is to upload the input data. At a minimum, air-temperature data should be uploaded. The tool requires daily minimum and maximum temperatures, as well as mean temperature. These values may come from on-site temperature sensors, local weather apps, or nearby weather stations. If additional weather data, including relative humidity and wind speed, are available, the user can select more sophisticated models that use these inputs to estimate ET_o.

The second step is to enter the location of interest. This allows the tool to compute extraterrestrial radiation based on latitude and time of year, following the FAO-56 approach (Allen et al. 1998). After the input data are provided, the tool checks the uploaded file to ensure that all necessary data are available, and then the user can choose an AI model to estimate ET_o.

There are six models available. ANN_T, LSTM_T, and CNN_T are models that require only temperature data, and when additional data are available, users can run ANN_all, LSTM_all, and CNN_all. Once the model is selected, the tool will generate results that can be viewed and downloaded as CSV files.

Once daily ET_o values are obtained, they can be combined with appropriate crop or landscape coefficients to estimate water requirements for irrigation scheduling. The ET_o estimates can also be exported for use in spreadsheets, irrigation scheduling tools, water-budget calculations, or smart irrigation controllers.

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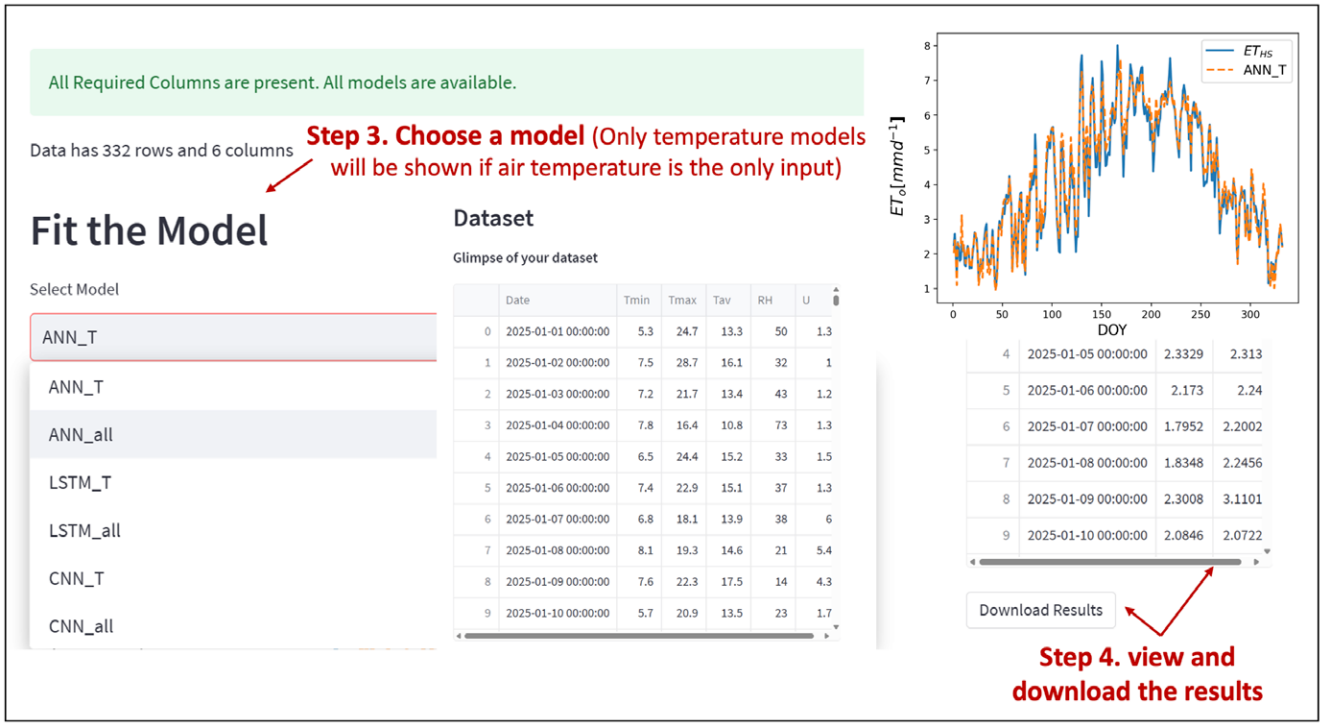


Figure 1. Snapshot of DeepET showing its various panels. DeepET can be accessed from the Verdi Water Management Group website.

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Example of ET_o estimations using DeepET in Southern California

Examples of daily ET_o estimation for 2025 for three CIMIS stations are provided here (fig. 2). The CIMIS stations are all located in Southern California and were selected to represent inland (UC Riverside, station #44), desert (Meloland, station #87), and coastal (UC ANR South Coast Research and Extension Center, Irvine, station #75) climate conditions. CIMIS ET_o data are also provided for comparison.

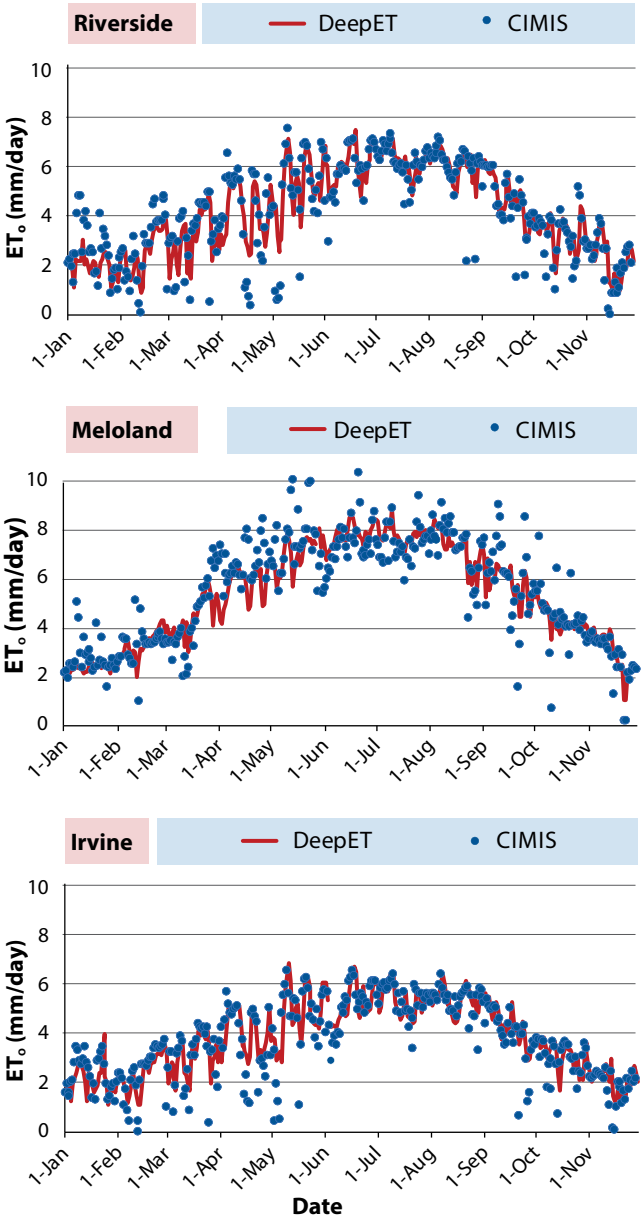


Figure 2. DeepET estimations of ET_o in 2025 compared against CIMIS ET_o at three CIMIS stations located in inland (Riverside), desert (Meloland), and coastal (Irvine) climate regions in Southern California.

As expected, ET_o peaks in summer, which is well captured by DeepET for all locations, and peak ET_o values are higher for desert and inland regions compared to the coastal region. Overall, DeepET ET_o estimates follow the CIMIS ET_o data well. However, the model did not always capture very high or very low ET_o values. DeepET sometimes overestimated low winter, spring, and fall ET_o values and underestimated some high values in late spring and summer at Meloland. These differences likely occurred on cloudy, rainy, or windy days because factors such as sunlight, humidity, and wind also affect ET_o, while DeepET relies only on air temperature to estimate ET_o. Lower performance of temperature-based models is expected due to the limited information they rely on to estimate ET_o. However, the fact that they require only temperature data also makes them suitable for areas where full weather stations are not available.

Summary and concluding remarks

Accurate ET_o estimation is essential for irrigation scheduling, yet many locations lack the full weather data needed for Penman–Monteith calculations. DeepET, developed from long-term CIMIS station data, offers accurate ET_o estimations. The DeepET tool allows users to compute ET_o using only air-temperature inputs, making reliable daily ET_o estimation accessible even in data sparse environments. This approach supports agricultural and landscape irrigation across California, particularly where complete weather data are unavailable.

Although DeepET performs better than empirical equations, it is still dependent on the quality of input temperature data. Users should ensure that the temperature data come from a location representative of the crop or landscape being irrigated. Temperature sensors placed near buildings, pavement, or other unrepresentative surfaces may influence results. In addition, microclimates in complex agricultural systems may require multiple temperature sensors to represent field conditions accurately. Even AI-based ET_o models such as DeepET may underperform in areas where temperature alone does not sufficiently capture daily atmospheric demand or in extreme situations that fall outside the dataset used to train them.

DeepET estimations should be applied in the context of local soil conditions, crop response, irrigation system uniformity, and management constraints. Like

all decision-support tools, DeepET is most effective when used alongside field observations and a clear understanding of crop-water needs.

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