

Forecasting Irrigation Shifts in Fruit Cultivation Under Climate Change Scenarios in Tropical Thailand

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ABSTRACT

Irrigation management in tropical fruit orchards is most difficult during the transition from the dry to the wet season, when atmospheric demand is high and rainfall is erratic. This study presents a web-based decision-support framework that converts hourly meteorological records into irrigation requirements and evaluates how they shift under climate perturbation. Vapor pressure deficit (VPD) and hourly reference evapotranspiration (ET_o) are computed with the FAO-56 Penman-Monteith equation, scaled by stage-specific crop coefficients and converted to a per-tree volume using canopy radius. The implementation reproduces the worked hourly values of FAO-56 Example 19 exactly. For a representative day in Chanthaburi, Thailand, the net requirement for durian rose from 3.53 to 7.05 liters per day for a tree of 1.0 m canopy radius under a perturbation of +2 °C and -20% relative humidity. Because this result depends on how humidity is assumed to respond to warming, the calculation was repeated under three assumptions which gave increases in mean VPD of between 12.1 and 69.9 percent and in ET_o of between 4.8 and 20.4 percent. The direction of the shift is therefore robust while its magnitude is assumption-dependent and irrigation requirements are reported as a range rather than a single value.

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1. INTRODUCTION

Irrigation is hardest to judge in eastern Thailand during the weeks when the dry season gives way to the wet one. Rain returns in short and uneven bursts and temperature and humidity swing widely within a single day [1]. Durian, mangosteen and papaya pass through sensitive growth stages in the same period, and their water requirement is highest at the stages that set fruit yield and quality. Scheduling still rests largely on experience and on monthly averages, neither of which resolves what happens between the early morning and the middle of the afternoon. Warming widens that gap because it raises atmospheric demand at the hours when the canopy is least able to respond.

Vapor pressure deficit (VPD) is the quantity that carries both atmospheric drivers at once. It is the difference between the water the air could hold and the water it does hold, rising with temperature and falling with humidity, which makes it a closer proxy for transpiration than either variable on its own [2]. On the rainfall side the change is in timing rather than in total. Storms are becoming fewer and heavier, and a day that looks wet in the daily figure can still leave the canopy short during the hours when demand peaks [3]. Both changes push the irrigation decision in the same direction and neither is visible in the records that most growers work from [4].

For Thailand the observed record already shows the direction of travel. Extreme temperature indices have risen steadily since the 1950s [5] and analyses of drought and heavy-rainfall events point to a drier and more variable dry-season transition by mid-century [6]. The temperature change itself is modest which is what makes it easy to underestimate. Evapotranspiration does not respond in proportion because saturation vapor pressure rises faster than linearly with temperature while the water actually in the air does not keep pace [7]. A warming of one or two degrees therefore shifts the irrigation requirement by more than the temperature figure alone conveys and the size of that shift depends on how humidity changes alongside it [8].

Rising VPD is not only a driver of demand. It reduces stomatal conductance and productivity directly and the effect shows up in yield and in water use efficiency as well as in the water balance [9, 10]. Heat and moisture extremes are also arriving together more often, and crops are affected more by the combination than by either extreme on its own [11]. Irrigation management built around seasonal water allocation was not designed for that combination and the instruments now available for measuring atmospheric demand in the field have outpaced the scheduling rules that use them [12, 13].

Web-based systems already carry this kind of calculation to growers. IrrigaSys provides irrigation decision support built on open-source data and technology [14], WaterSmart-GIS delivers a data assimilation model through a browser to support irrigation research and decision making [15] and reference architectures have been proposed for decision support in Agriculture 4.0 [16]. All of them are built for current conditions, and scenario analysis is not part of what they offer.

Research on tropical orchard hydrology provides the crop-coefficient basis for such estimates. Paredes *et al.* [17] systematized single and basal crop coefficients for more than thirty subtropical and tropical orchard species, and showed that reliable values for perennial canopies depend on the fraction of ground cover, canopy height and training system rather than on species alone. For durian, Ilahi *et al.* [18] related growth performance to crop water requirement under irrigation, while field studies in Chanthaburi have derived crop coefficients for the Monthong cultivar from paired reference evapotranspiration and sap flow measurements [19] and from evaporation-pan control [20]. The physiological basis of these coefficients is the stomatal response of perennial tree crops to atmospheric demand. Conductance declines once vapor pressure deficit exceeds species-specific thresholds [21]. Work by the present authors on the same orchard system established the hourly monitoring platform [22], the forecasting of vapor pressure deficit from that record [23] and the estimation of hourly crop evapotranspiration [24].

A change in irrigation requirement is also a change in cost. Growers need to know how much more water a tree will need and at which hours before they can judge whether to invest in storage or in a more efficient delivery system [25]. The same figures feed the scheme-level planning that allocates water between users [26].

What is already established is that VPD and reference evapotranspiration (ET_o) work well as the basis for scheduling under present conditions [27, 28]. Climate-informed management strategies and data-driven adaptation tools have developed quickly alongside them [29, 30] and adaptation planning has been formalized at the scheme level for large irrigation systems [31]. What is missing is the step between the two. The same scheduling calculation has rarely been carried through to a projected climate for tropical fruit and it has rarely been delivered at the scale of a single tree in a single orchard which is the scale at which the decision is taken.

This paper takes that step. It applies the hourly VPD and ET_o calculation to a perturbed climate for tropical fruit in eastern Thailand, reports the result as a per-tree volume and delivers it through an interface a grower can operate. The specific objectives are the following.

1. To apply the existing hourly VPD and ET_o calculation to a perturbed climate of +2 °C warming and a 20% reduction in relative humidity.
2. To quantify how far the per-tree irrigation requirement changes during the dry-to-wet transition, and how far that change depends on the humidity assumption.
3. To deliver the comparison through a web interface that a grower can operate, with an export path for further analysis.
4. To assess what the projected shifts imply for irrigation planning in tropical fruit production.

Therefore, this research contributes to climate-informed precision agriculture in three specific ways. The perturbation procedure applied here is the standard delta-change approach, and the contribution lies in the

resolution of the analysis and in the way the results are delivered. First, the assessment is carried out on hourly rather than daily data, which resolves the within-day course of atmospheric demand and therefore the time scale at which irrigation decisions are made. Second, the calculation is closed to a per-tree volume for a given province, district, growth stage and canopy radius, rather than being reported as a depth over an undefined area. Third, the results are delivered through a web tool that growers can operate directly, together with an export path that allows the underlying record to be analyzed further.

2. METHOD

2.1. Study Area and Data Sources

This study focuses on tropical fruit-producing provinces in Thailand and targets the high-variance transition from dry to wet season. The design extends a previously implemented VPD–ET_o–ET_c irrigation decision framework and web application for location-specific scheduling to climate-change scenario simulations.

Hourly to daily meteorological variables, including air temperature (°C), relative humidity (%), wind speed (m s⁻¹), solar radiation (MJ m⁻² h⁻¹) and rainfall (mm), were obtained for the selected province and district from the Visual Crossing weather data service through the operational pipeline used in the baseline system. The system supports three tropical fruit crops, namely durian, mangosteen (local variety) and papaya (Holland variety). Each crop follows species-specific growth stages and associated crop coefficients (K_c) implemented in the prior system interface. For example, durian growth stages and associated crop coefficients denoted as K_c , follow the stage-wise configuration implemented in the prior system interface. The durian phenological cycle comprises seven distinct stages including vegetative growth, floral initiation, fruit set, early growth, late growth and maturity. Canopy radius (m) is provided by users and field records to convert depths (mm) to per-tree volumes (L tree⁻¹ day⁻¹).

2.2. Climate Scenarios and Downscaling

This study evaluates two representative perturbation scenarios consistent with projected mid-century conditions. The scenarios include a uniform air-temperature anomaly of +2 °C and a reduction in relative humidity of –20%. To ensure local applicability, this study adopts a bias-corrected delta approach.

1. Compute a historical daily climatology for temperature (T), relative humidity (RH), wind speed, solar radiation and rainfall to establish the baseline.
2. Apply additive adjustments to T (+2 °C) and multiplicative scaling to relative humidity (0.8×) preserving the day-of-year structure.
3. Recompute saturation vapor pressure, actual vapor pressure and vapor pressure deficit from the perturbed temperature and relative humidity while leaving rainfall and solar radiation at their observed values. The scenario therefore isolates the effect of atmospheric demand.

Outputs are daily series for each site under Baseline, +2 °C and –20% relative humidity conditions.

2.3. Irrigation Modeling

Vapor Pressure Deficit (VPD)

Saturation vapor pressure (e_s) and actual vapor pressure (e_a) are computed from air temperature T and relative humidity RH :

$$e_s = 0.6108 \times \exp\left(\frac{17.27 T}{T + 237.3}\right), \quad e_a = e_s \times \frac{RH}{100}, \quad \text{VPD} = e_s - e_a. \quad (1)$$

These equations are consistent with the baseline implementation used in our earlier monitoring and forecasting work on the same orchard system [22–24].

Reference Evapotranspiration (ET_o)

Hourly reference evapotranspiration follows the FAO-56 Penman–Monteith equation [32]:

$$\text{ET}_o = \frac{0.408 \Delta (R_n - G) + \gamma \frac{37}{T_{hr} + 273} u_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34 u_2)}, \quad (2)$$

where Δ is the slope of $e_s(T)$, R_n net radiation, G soil heat flux, γ psychrometric constant, u_2 wind at 2 m, and $(e_s - e_a)$ the VPD term. Here T_{hr} denotes the mean hourly air temperature, and R_n and G are expressed in $\text{MJ m}^{-2} \text{h}^{-1}$, which gives ETo in mm h^{-1} . The hourly form of the equation uses the coefficient 37 in place of the value 900 that applies at a daily time step. In this implementation the soil heat flux is set to $G = 0$ at every hour, rather than the $G = 0.1 R_n$ by day and $G = 0.5 R_n$ by night suggested in FAO-56, because sub-canopy heat flux is not measured at the study orchards. The effect of this assumption is considered among the limitations discussed in Section 3.8. The twenty-four hourly values of ETo are then summed to give the daily reference evapotranspiration that enters the crop evapotranspiration calculation below.

Crop Evapotranspiration (ETc) and Net Irrigation

Stage-specific crop evapotranspiration is obtained from stage-dependent crop coefficients for tropical perennial canopies [17–20]:

$$\text{ETc} = K_c \times \text{ETo}. \quad (3)$$

Per-tree irrigation requirement (liters per day) accounts for rainfall and canopy area:

$$\text{Area} = \pi r^2, \quad \text{Irrig. Volume} = \max(0, \text{ETc} - \text{Rainfall}) \times \text{Area}, \quad (4)$$

with canopy radius r in meters following the baseline conversion used in the prior web tool.

2.4. Web-Based Platform Development

The decision-support system was developed as a web-based application using JavaScript for front-end interactivity and dynamic visualization. The platform retrieves meteorological data such as temperature, humidity, solar radiation, wind speed and rainfall from the backend database through Application Programming Interfaces (APIs). These APIs allow real-time communication between the web interface and the climate data repository ensuring that users can access up-to-date information without manual data handling.

The system architecture integrates three core components:

1. **Data Access Layer:** APIs connect to the meteorological database and deliver hourly records in structured JSON format.
2. **Computation Layer:** Algorithms implemented in the server-side scripts calculate reference evapotranspiration (ETo), crop evapotranspiration (ETc) and irrigation volume based on retrieved data and user-defined parameters.
3. **Presentation Layer:** A responsive web interface built in JavaScript enables users to select province, district, crop type, canopy radius and K_c stage. Results are visualized through interactive charts and can be exported as Excel files for further analysis.

This architecture ensures scalability, enabling the system to support multiple crop types and climate scenarios while maintaining accessibility for farmers and researchers through a standard web browser.

2.5. System Implementation

The application runs in the browser and is written in JavaScript. A backend service retrieves the meteorological records from an external weather data provider and returns them as hourly values of temperature, relative humidity, solar radiation, wind speed and rainfall. A request is defined by a province, a district and a date range. VPD, ETo, ETc and the per-tree irrigation volume are all derived from the returned record set, and the charts, the summary tables and the Excel export are built from that same set which keeps the displayed values and the exported file in agreement. The layout uses a fluid grid and charts and tables reflow on narrow screens.

The scope of the implementation should be stated plainly. The system is a research tool rather than a production service, and four settings that a production deployment would need to pin down are still open, namely the request interval, the caching policy, the retry and timeout behavior and the responsive breakpoints. Requests that fail or return no data are not yet handled explicitly, and the application has not been tuned for sustained multi-user operation. Section 4 identifies these as the next stage of the work.

2.6. Analysis Framework

The framework performs one-at-a-time perturbations around the baseline to quantify drivers of irrigation shifts:

1. Temperature: $T \in \{+1, +2, +3\}^{\circ}\text{C}$ (applied to the observed hourly record).
2. Relative humidity reduction: $\{-10\%, -20\%, -30\%\}$.

The interface provides a Scenario control panel where users can select between Baseline conditions and climate change scenarios ($+2^{\circ}\text{C}$, -20% relative humidity). Comparative visualizations include daily and cumulative irrigation requirements, alongside VPD and ETo time series. The system preserves the standard farmer workflow including province, district, canopy radius, K_c stage and date range selection while adding dual-axis charts and summary tables that display the differences between baseline and scenario conditions.

Users can interactively compare irrigation demands across scenarios to assess potential impacts of climate change on water management strategies for durian cultivation.

3. RESULTS AND DISCUSSION

3.1. System Interface and Study Configuration

Figure 1 shows the Home interface of the web-based Predictive Plant Water Consumption Model used in this study. Users select province, district, canopy radius, crop type and durian growth stage (K_c). The interface and calculation pipeline are consistent with the previously implemented VPD–ETo–ETc framework and web application while this paper focuses on the transition period and its climate-informed analyses.

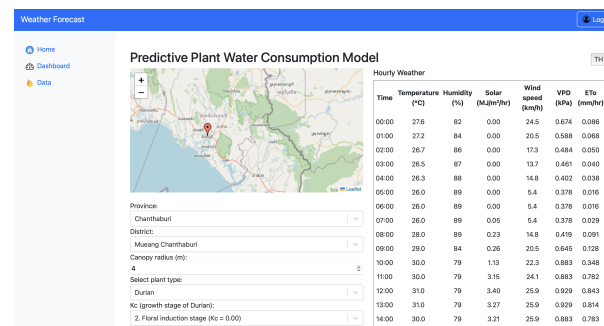


Figure 1. Home interface of the decision-support system showing map-based location selection and the hourly weather table (Temperature, RH, Solar, Wind, VPD and ETo).

3.2. Hourly Weather Patterns and Atmospheric Demand

The system ingests hourly meteorological data and derives VPD and ETo in real time. Table 1 summarizes representative hours for an example configuration at Mueang Chanthaburi District, Chanthaburi Province (canopy radius 4 m; floral induction stage, $K_c=0.00$). Night and early morning hours (00:00–06:00) exhibit low ETo due to negligible solar input and elevated humidity, whereas late morning to early afternoon (10:00–14:00) shows pronounced increases in VPD and ETo indicating peak atmospheric water demand.

Table 1. Representative hourly weather and derived variables from the system (example day).

Time	Temp ($^{\circ}\text{C}$)	RH (%)	Solar ($\text{MJ}/\text{m}^2/\text{hr}$)	Wind (km/h)	VPD (kPa)	ETo (mm/hr)
00:00	27.6	82	0.00	24.5	0.674	0.086
06:00	26.0	89	0.00	5.4	0.378	0.016
10:00	30.0	79	1.13	22.3	0.883	0.348
12:00	31.0	79	3.40	25.9	0.929	0.843
14:00	30.0	79	3.21	25.9	0.883	0.783

3.3. Diurnal Variation of VPD and ETo

These diurnal patterns confirm that ETo (and thus ETc when $K_c > 0$) peaks near midday when temperature, solar radiation and VPD align. Operationally, this enables scheduling irrigation to avoid low-efficiency hours and to prioritize windows that best replenish plant water deficits.

Figure 2 illustrates the example of hourly variation of vapor pressure deficit (VPD) on 20 September 2025 for Mueang Chanthaburi District. The curve shows low VPD values during the early morning hours (approximately 0.35–0.40 kPa between 04:00–07:00) reflecting cooler air temperatures combined with high relative humidity. As solar radiation and temperature increased after 09:00, VPD rose sharply reaching its peak around 15:00 with a maximum value close to 1.1 kPa. This indicates the period of highest atmospheric water demand and potential crop stress if irrigation is insufficient.

After 17:00, VPD decreased gradually in response to declining solar input and cooling temperatures stabilizing near 0.5–0.6 kPa in the late evening. These diurnal dynamics confirm that the system accurately captures temporal fluctuations in atmospheric evaporative demand, highlighting the importance of aligning irrigation schedules with peak VPD windows.

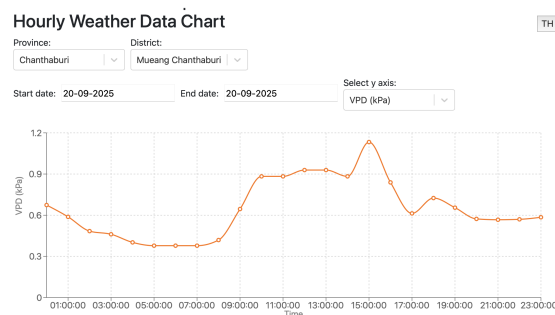


Figure 2. Hourly variation of vapor pressure deficit (VPD) on 20 September 2025 in Mueang Chanthaburi District. The midday peak illustrates maximum atmospheric water demand.

Complementary to VPD, Figure 3 shows the diurnal course of reference evapotranspiration (ET_o). ET_o values were close to zero during the night (00:00–06:00), began increasing after sunrise and rose sharply after 09:00 as solar radiation intensified. Maximum hourly ET_o was observed around 12:00–13:00, at approximately 0.85–0.90 mm/hr. Values then decreased gradually and returned to near zero after 19:00.

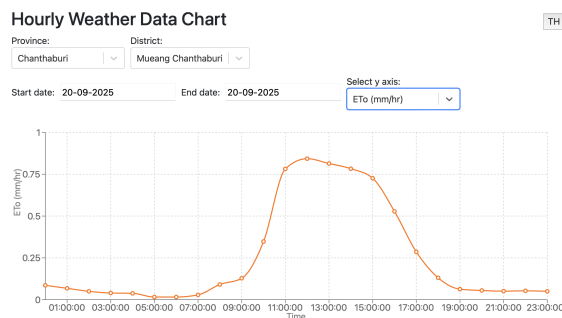


Figure 3. Hourly variation of reference evapotranspiration (ET_o) on 20 September 2025 in Mueang Chanthaburi District. The curve highlights the strong diurnal cycle with peak midday atmospheric demand.

Together, Figures 2 and 3 confirm that atmospheric drivers of crop water use exhibit strong diurnal cycles: low values overnight, rapid increases after sunrise and maxima around midday to early afternoon. This reinforces the need for irrigation scheduling that accounts for both VPD and ET_o, ensuring water application is aligned with the peak evaporative demand of durian trees.

In addition to fixed weather tables, the system provides an interactive charting interface (Figure 4), enabling users to select different meteorological and derived parameters for hourly visualization. The available options include VPD (kPa), ET_o (mm/hr), temperature (°C), relative humidity (%), solar radiation (MJ/m²/hr) and wind speed (km/hr).

This flexibility allows farmers to examine the direct drivers of irrigation demand (VPD and ETo) and the underlying meteorological conditions that contribute to these calculations. For instance, users can analyze how solar radiation and wind speed jointly influence midday peaks in ETo and how relative humidity fluctuations shape VPD dynamics. Such customizable displays enhance the decision-support capacity of the platform by allowing tailored insights according to specific research or field management objectives.

Figure 4. Interactive selection menu for y-axis variables. Users can toggle between VPD, ETo, temperature, humidity, solar radiation and wind speed to explore hourly dynamics.

3.4. Climate Scenario Impact on Irrigation Requirement

The system further allows scenario-based simulations by perturbing temperature and humidity representing plausible mid-century climate change conditions. Figure 5 summarizes an example calculation.

For the baseline day, the total daily reference evapotranspiration (ETo) was 5.872 mm, daily rainfall 2.4 mm, and the corresponding crop evapotranspiration (ETc) was 3.523 mm/day. After subtracting effective rainfall, the calculated net irrigation requirement was 3.53 liters per tree per day for a canopy radius of 1.0 m. This value follows directly from Equation (4): $(3.523 - 2.40) \times \pi \times 1.0^2 = 3.53$ liters per tree per day. The canopy radius of 1.0 m is the default setting of the interface and is used here to illustrate the calculation rather than to represent a producing tree. For a mature tree with a canopy radius of 3.5 m, the same crop evapotranspiration corresponds to about 136 liters per tree per day, which is consistent with the sap flow measurements reported for trees of that age in the same province [19].

When applying a climate change perturbation of +2 °C and –20% relative humidity, the atmospheric demand increased substantially, doubling the irrigation requirement to 7.05 liters per tree per day. Applying Equation (4) in the same way, this figure corresponds to a crop evapotranspiration of 4.644 mm day⁻¹ under unchanged rainfall, since $(4.644 - 2.40) \times \pi \times 1.0^2 = 7.05$ liters per tree per day. The two reported values are therefore internally consistent and can be checked by hand. This sharp rise highlights the nonlinear sensitivity of durian water demand to combined changes in temperature and humidity, consistent with the literature on VPD-driven evapotranspiration amplification under warming scenarios.

Total daily ETo: 5.872 mm
Daily rainfall: 2.4 mm
ETc (crop water use): 3.523 mm/day
Net irrigation required (after rainfall) = (3.523 - 2.40) × 3.1416 = 3.53 liters/tree/day
Climate Scenario causes changes in
Temperature 2 °C and Humidity -20 % Net
irrigation required = 7.05 liters/tree/day

Figure 5. Illustrative output of the decision-support system showing baseline and climate scenario (+2 °C, –20% RH) impacts on net irrigation requirement.

This example demonstrates that even modest increases in temperature and decreases in humidity can more than double the net irrigation requirement, underscoring the vulnerability of durian cultivation to pro-

jected climate shifts. Such insights enable proactive adaptation planning, including investment in more efficient irrigation systems, water storage and scheduling adjustments during high-risk transitional months.

This scenario analysis highlights that modest perturbations in temperature and humidity can more than triple peak VPD, thereby increasing crop evapotranspiration demand and irrigation requirements (see Figure 5). Such outputs emphasize the importance of integrating climate scenario modeling into irrigation planning frameworks for durian cultivation in tropical regions.

Figure 6 presents the climate scenario VPD curve (+2 °C, −20% RH) for 20 September 2025. In this scenario, baseline nighttime and early-morning VPD values that previously ranged from 0.35–0.40 kPa (Figure 2) increased to approximately 1.8 kPa. By 10:00, VPD exceeded 2.0 kPa, and a midday peak above 3.5 kPa was recorded between 13:00–15:00.

Compared with the baseline peak of 1.1 kPa, this represents more than a threefold increase in maximum hourly VPD. These elevated VPD values reflect substantially higher atmospheric water demand that can induce acute water stress in durian trees during the critical flowering induction stage when irrigation fails to meet evaporative requirements.

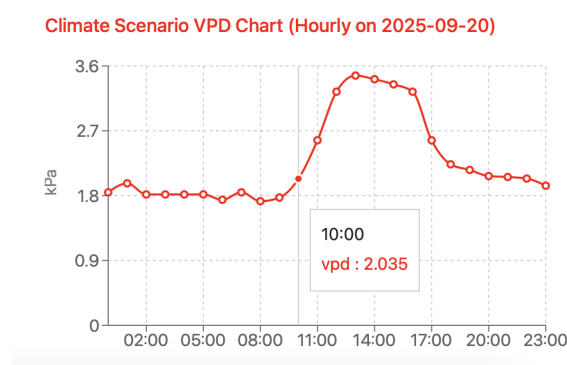


Figure 6. Climate scenario VPD profile (+2 °C, −20% RH) on 20 September 2025 in Mueang Chanthaburi District. Results show a threefold increase in peak VPD compared with baseline conditions.

This finding underscores the nonlinear amplification effect of simultaneous warming and humidity decline. The system output demonstrates that even moderate climate perturbations can dramatically intensify diurnal evaporative demand, more than doubling the net irrigation requirement calculated for baseline weather. This ratio applies to the net requirement, which is the difference between crop evapotranspiration and rainfall (Figure 5). Rainfall is unchanged between the two cases and offsets a large part of the baseline crop evapotranspiration, and the ratio is therefore driven mainly by that subtraction rather than by the change in reference evapotranspiration alone. As Table 3 shows, reference evapotranspiration itself changes by a much smaller proportion.

3.5. Verification of the Calculation Engine

The hourly Penman–Monteith procedure used by the system was re-implemented independently in Python and tested against Example 19 of FAO-56 [32], which works ETo out by hand for two single hours at N'Diaye, Senegal. Table 2 compares the published values with those produced by the independent implementation. Both hours are reproduced exactly, together with the intermediate quantities reported in FAO-56 for the afternoon hour, namely $e_s = 6.625$ kPa, $e_a = 3.445$ kPa and $\Delta = 0.358$ kPa °C^{−1}.

Table 2. Verification of the hourly reference evapotranspiration routine against Example 19 of FAO-56 (N'Diaye, Senegal, 1 October).

Period	T (°C)	RH (%)	u_2 (m s ^{−1})	R_n (MJ m ^{−2} h ^{−1})	G (MJ m ^{−2} h ^{−1})	ETo, FAO-56 (mm h ^{−1})	ETo, this study (mm h ^{−1})
14:00–15:00	38.0	52	3.3	1.749	0.175	0.63	0.63
02:00–03:00	28.0	90	1.9	−0.100	−0.050	0.00	0.00

The same implementation was then applied to the twenty-four hourly records of the study day and

compared with the values returned by the deployed system. Vapor pressure deficit agrees to three decimal places for every hour, and reference evapotranspiration differs by no more than 0.002 mm h^{-1} , giving daily totals of 5.231 and 5.241 mm, a difference of 0.2 percent. The calculation engine therefore follows the documented equations and is free from arithmetic error.

3.6. Sensitivity to the Humidity Assumption

The scenario procedure in Section 2.2 holds absolute humidity constant while air temperature is raised. This places the vapor pressure deficit at the upper limit of what is physically plausible because saturation vapor pressure rises with temperature while actual vapor pressure is held fixed. To show how far the results depend on that choice, the whole calculation was repeated under three humidity assumptions. Assumption A holds absolute humidity constant, as in the published scenario. Assumption B holds relative humidity constant which gives the lower limit of the plausible range. Assumption C reduces relative humidity by one point for each degree of warming which is closer to what climate projections indicate for land surfaces. Radiation and wind speed were left unchanged in all three cases.

Table 3. Effect of the humidity assumption on vapor pressure deficit and reference evapotranspiration under $+2^\circ\text{C}$ warming.

Assumption	Mean VPD (kPa)	Change (%)	ETo (mm day^{-1})	Change (%)
Baseline	0.684	–	5.231	–
A. Constant absolute humidity	1.162	+69.9	6.296	+20.4
B. Constant relative humidity	0.767	+12.1	5.482	+4.8
C. RH reduced by 1 point per $^\circ\text{C}$	0.855	+25.0	5.665	+8.3

Table 3 shows that the vapor pressure deficit is highly sensitive to this choice. It rises by 69.9 percent under assumption A but by only 12.1 percent under assumption B, a difference of almost sixfold. Reference evapotranspiration is much less sensitive, rising by 20.4 percent and 4.8 percent respectively, because the radiation term dominates the Penman–Monteith equation at this site and that term does not change with the humidity assumption. The direction of the result is therefore the same in every case. Warming raises atmospheric water demand and shifts the irrigation requirement upward, and only the magnitude depends on the assumption. Irrigation requirements are accordingly reported as a range spanning assumptions A and B, with assumption C as the central estimate, rather than as a single value.

3.7. Data Retrieval and Export Functionality

In addition to visualization dashboards, the system includes a data retrieval page (Figure 7) that enables users to query 24-hour weather records for a selected province and district. After specifying custom start and end dates, users receive tabular hourly weather data including temperature, humidity, solar radiation, wind speed, VPD and ETo.

The retrieved dataset can be directly exported in Excel format, thereby facilitating further statistical and machine learning analyses outside the platform. This functionality bridges the gap between real-time monitoring and offline research workflows, allowing researchers and practitioners to conduct advanced modeling such as missing data imputation, sensitivity testing and irrigation forecasting.

Date	Time	Temperature ($^\circ\text{C}$)	Humidity (%)	Solar ($\text{MJ/m}^2/\text{hr}$)	Wind speed (km/h)	VPD (kPa)	ETo (mm/hr)
04-09-2025	00:00	27.3	88	0.00	12.6	0.443	0.035
04-09-2025	01:00	27.0	90	0.00	10.4	0.360	0.025
04-09-2025	02:00	26.3	91	0.00	11.5	0.310	0.024
04-09-2025	03:00	26.3	92	0.00	13.0	0.273	0.023
04-09-2025	04:00	26.8	90	0.00	10.4	0.338	0.024
04-09-2025	05:00	26.0	94	0.00	0.0	0.194	0.000
04-09-2025	06:00	26.0	94	0.00	0.0	0.194	0.000
04-09-2025	07:00	25.0	94	0.10	0.0	0.184	0.032
04-09-2025	08:00	26.0	94	0.53	0.0	0.194	0.161
04-09-2025	09:00	27.0	89	1.11	5.4	0.398	0.320
04-09-2025	10:00	28.0	89	1.16	7.6	0.419	0.332

Figure 7. Data retrieval page of the system, allowing users to select date ranges and export hourly weather records in Excel format for downstream analysis.

Beyond durian, the system supports additional crop types, namely mangosteen (local variety) and papaya (Holland variety), as illustrated in Figure 8. This flexibility broadens the platform's application beyond a single-fruit system, enabling comparative water demand assessments across multiple tropical crops.

By allowing users to toggle between different plant types, the platform automatically adjusts crop coefficients (K_c) and growth-stage parameters to compute crop evapotranspiration (ET_c) and irrigation requirements specific to each crop. This feature provides a unified decision-support tool for diverse orchard systems common in Southeast Asia where farmers often manage more than one fruit crop within the same production area.

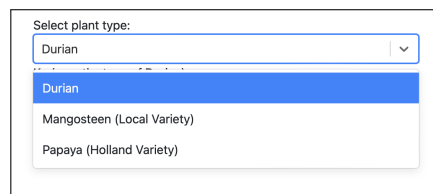


Figure 8. Plant-type selection menu showing durian, mangosteen (local variety), and papaya (Holland variety). The system adapts crop coefficients and growth stages accordingly.

3.8. Physiological Interpretation of the Diurnal Pattern

The diurnal curves in Figures 2 and 3 become useful for irrigation management once they are read against a physiological threshold. Stomatal conductance in perennial tree crops falls as atmospheric demand rises and conductance is strongly reduced once vapor pressure deficit passes a species-specific limit which for tree crops of this type is commonly placed near 2 kPa [21]. Above that limit the canopy restricts transpiration and additional atmospheric demand is therefore no longer matched by additional water uptake.

On the day shown in Figure 3 the baseline record reaches a maximum vapor pressure deficit of 1.13 kPa at 15:00 and therefore stays below the threshold for the whole day. Under the climate scenario in Figure 6 the deficit rises above the threshold during the middle of the day and part of the afternoon therefore falls within the range in which conductance is reduced. The important quantity for management is therefore not only the daily total of crop evapotranspiration but also the number of hours during which the canopy is unable to use the water that is supplied.

This changes the practical recommendation. Water applied during the hours above the threshold is taken up less efficiently than water applied earlier in the day because the canopy has already reduced its conductance. As the number of hours above the threshold increases under warming, the effective irrigation window narrows towards the early morning. The response is therefore to shift the timing of irrigation and not only to increase the volume applied. The platform supports this because it reports the hourly profile rather than a daily total alone.

Four limitations of the present formulation should be noted alongside this interpretation. The calculation does not represent boundary-layer feedback. A drying canopy modifies the humidity of the air above it and thereby moderates the vapor pressure deficit that the canopy itself experiences. It does not adjust canopy resistance in response to atmospheric demand because the crop coefficient is held fixed within each growth stage. It also does not carry a soil water balance and soil moisture depletion between irrigation events is therefore not represented. Finally, the soil heat flux is set to zero at every hour, as stated in Section 2.3 which leaves a larger share of net radiation available for evaporation during the daylight hours. Each of these omissions acts in the same direction, raising the calculated demand relative to what a tree would actually transpire which is the basis for treating the values reported here as an upper bound on the irrigation requirement.

Field measurements from the same province support this interpretation. A study of seven-year-old Monthong durian in Makham District, Chanthaburi, measured water use by sap flow and reported that uptake was highest when vapor pressure deficit was low and soil moisture was high [19]. Measured transpiration therefore does not rise in proportion to atmospheric demand once the canopy is under stress. This is consistent with the threshold behavior described above and it supports our statement that the values calculated here represent an upper bound on the irrigation requirement.

3.9. Implications for Climate Change Adaptation

The results demonstrate that the proposed decision-support framework quantifies irrigation shifts under baseline and perturbed climate conditions and highlights critical adaptation needs for tropical fruit cultivation in Thailand. The system integrates hourly weather variables such as temperature, humidity, solar radiation, wind speed, VPD and ETo with scenario analysis. Farmers and planners therefore gain a transparent view of how modest temperature increases (+2 °C) and reduced humidity (−20%) raise the net irrigation requirement. Such quantitative evidence underscores the vulnerability of traditional water management strategies that rely on historical averages and reinforces the urgency of adopting climate-informed irrigation scheduling.

The ability to export multi-day weather and crop water demand records for downstream analysis further enables stakeholders to design irrigation protocols that anticipate rather than react to climate extremes. This functionality is particularly valuable for policy makers and water resource managers, as it provides the empirical basis for long-term planning including investment in water-efficient technologies, reservoir management and regional allocation strategies.

From an agronomic perspective, the findings indicate that VPD is a sensitive driver of irrigation shifts and future adaptation strategies must prioritize real-time monitoring of atmospheric demand alongside rainfall deficits. The system thus serves as an early-warning platform allowing farmers to recognize periods of elevated risk and to allocate limited water resources accordingly. In the broader context of climate change adaptation, this research bridges the gap between climate projections and field-level decision making, equipping stakeholders with actionable insights to enhance resilience and sustainability of tropical fruit production systems under increasingly volatile climatic conditions.

4. CONCLUSION

This study developed a climate-informed irrigation decision-support framework tailored for tropical fruit cultivation in Thailand, focusing on the transition from the dry to the wet season. By integrating real-time meteorological data with VPD- and ETo-based modeling, the system quantified baseline water requirements and simulated shifts under projected climate perturbations (+2 °C warming, −20% relative humidity). The results revealed strong diurnal cycles in atmospheric demand and showed that a modest perturbation raised the net irrigation requirement for durian from 3.53 to 7.05 liters per day for a tree of 1.0 m canopy radius. Repeating the calculation under three humidity assumptions gave an increase in mean vapor pressure deficit of between 12.1 and 69.9 percent. The direction of the shift is therefore robust, while its magnitude depends on the assumption adopted. Beyond tropical fruit, the framework was extended to mangosteen and papaya, highlighting its flexibility for diverse tropical fruit systems. The interactive web-based interface allows farmers and researchers to visualize hourly dynamics, compare baseline and climate scenarios and export weather datasets for further analysis. The scenario output is therefore returned as figures that can be used directly for irrigation scheduling for investment in water infrastructure and for longer-term resource planning. The study therefore links a climate scenario to a decision that a grower takes on a given day and it reports that link as a volume per tree rather than as a depth over an area. The same procedure can be applied to other perennial crops and other locations wherever an hourly weather record and a stage-wise crop coefficient are available.

Future work will focus on field validation and user acceptance studies to evaluate the practical utility of this web-based platform in real farming contexts. Planned farmer surveys and participatory trials will assess user satisfaction with the interface design, ease of interpretation of climate scenario outputs and perceived usefulness for irrigation decision-making. Preliminary feedback sessions with durian growers in Chanthaburi and Rayong provinces will help identify barriers to adoption, refine visualization features and determine whether the climate scenario information effectively influences irrigation practices. Additionally, longitudinal monitoring of water use efficiency and yield outcomes among farmers utilizing the platform compared to traditional approaches will provide empirical evidence of the system's impact on both resource conservation and economic viability. These trials are needed before the platform can be recommended for routine use by growers in the region.

Several directions remain for future work. On the hydrological side, the delta-change procedure used here could be replaced by dynamically downscaled climate projections and the water balance could be closed by coupling the tool to a process-based soil-water model such as AquaCrop or the Soil-Water-Atmosphere-Plant model. Both steps would allow the assessment to represent canopy resistance and soil moisture depletion which the present formulation does not include. Extending the comparison with field measurements, in particular sap

flow records for trees of known canopy size, would also strengthen the validation.

On the software side, the system is at present a research tool for retrieving and organizing hourly weather data rather than a production service. The request interval, the caching policy, the retry and timeout behavior and the responsive breakpoints have not been fixed and they will be specified and reported once the underlying model is stable. Systematic performance testing, including load testing under concurrent use and measurement of the user experience with growers in the field, is planned for the same stage.

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