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How Much Is Enough? Data Requirements for Practical Irrigation Decision-Making in Vietnamese Coffee Production

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Abstract: In making irrigation decisions, farmers typically rely on local observation and experience, such as observing crops and neighbors' actions. Research has mainly focused on understanding crop water requirements to improve farming practices, but it is important to acknowledge that farmers have unique perspectives, access to diverse local "signals", and experience. The challenge is to strike a balance between complex technical assessments of field conditions (the science) and harnessing farmers' skills to manage their irrigation in ways that maximize yield and quality. This study established a basis for specifying minimum data requirements for pragmatic, but not necessarily perfect, irrigation decision-making for small-scale Vietnamese coffee farmers. This study focuses on three areas in Dak Lak province in the Central Highlands of Vietnam. To explore the role of monitoring in irrigation management, two contrasting monitoring systems were set up to collect soil, weather, and irrigation data. We also compared a variety of water balance models with different data requirements, with a focus on processes that used "passive data collection", i.e., farmers do not manually collect data, rather data can be accessed readily from external sources. In Vietnam, traditional hosepipe irrigation is applied where it is impractical to know the volume of applied water. The proposed Low Data Model (LDM) is suited to more informed irrigation scheduling decisions, which have potential to improve the likelihood of coffee growers adopting measurement-based decision-making. While researchers may seek a detailed daily sub-millimeter understanding of soil water dynamics, farmers require practical decision support if there is to be any adoption of improved methods. This study offers a simple and practical approach for irrigation scheduling rather than a model using numerically perfect data that is unachievable in the field. The work demonstrates that on-site rainfall data is essential. However, other data can be collected passively to reduce the burden of data collection on users. This approach may enhance the likelihood of model-based irrigation scheduling being adopted by coffee farmers in Vietnam.

Keywords: coffee; Vietnam; irrigation strategy; irrigation scheduling; dss; decision

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1. Introduction

Vietnam is the world's leading Robusta coffee producer and the second-largest coffee producer in the world. Approximately 80 percent of the coffee is produced in the Central Highlands regions, with most of Vietnam's coffee produced by small land holders. Yields are among the highest in the world, with irrigation critical to Vietnam's success in maintaining a sustainable coffee industry. Without irrigation, coffee trees would struggle to survive the region's extended dry season, with most small farmers having access to

constructed wells, surface water, or groundwater for irrigation. Farmers face "agricultural droughts" when both groundwater and surface water flows are reduced and irrigation is not possible [1,2].

Irrigation from January to April is critical to achieving high yield. Approximately three-quarters of annual rainfall in the Central Highlands occurs in the monsoon season (June through September) with the remaining 8 months characterized by unreliable and small falls, insufficient to sustain a perennial crop such as coffee. While total annual rainfall (1800–3000 mm) appears sufficient for Robusta coffee [3], it does not occur at critical periods for maximum yields. Irrigation is required to offset the impacts of inter and intra-seasonal rainfall variability [4], but over-irrigation can be costly and reduce crop growth. Consequently, improved irrigation practices are necessary for the future success of the Vietnamese coffee industry, as resources become less reliable and area increases [5]. Previous studies have determined coffee crop water requirements of higher-grade Coffea arabica [6,7], with a few studies focused on the Coffea Canephora (Robusta) varieties that represent 30% of global production [8].

While irrigation is an essential part of coffee production, Amarasinghe, et al. [9] found coffee in Vietnam benefited from some induced water stress between January and April to boost flowering and pollination with higher and more uniform yields. Kath, et al. [10] provide evidence that there is a quantifiable response between irrigation and yield and that future work should investigate the relationships between irrigation, water stress, flowering, and yield. Clearly, there is a need to manage water supply to meet crop needs as well as constrain watering at critical growth stages.

Current irrigation of coffee in the Central Highlands involves hand-held hosepipes to individually bunded trees. Volumes applied vary with rainfall, antecedent moisture conditions, water availability, and farmers' opinions on crop needs. Visual performance of the crop and neighboring actions typically trigger irrigation as few farmers have on-farm water, soil, plant, or weather-sensing equipment to support data-driven decisions. Irrigation is generally based on experience and routines [11], with few other metrics used to assess benefit, making it difficult to compare alternative practices. A typical response of smallholders is to apply luxury water, estimated to be up to double crop needs [12]. While under-irrigating may carry risks of crop failure, over-irrigating is viewed by farmers as "insurance" for their high-yielding crops, yet this practice is clearly wasteful and may limit industry development when water supply becomes more limited under climate uncertainty [13].

Drip and micro-sprinkler irrigation systems are increasing in use [6] as they can apply small, measured volumes of water and are promoted as water and energy-saving with environmental and catchment-wide benefits. However, because of poor training or maintenance, irrigation systems are not always managed in a way that supports productivity and profit [14].

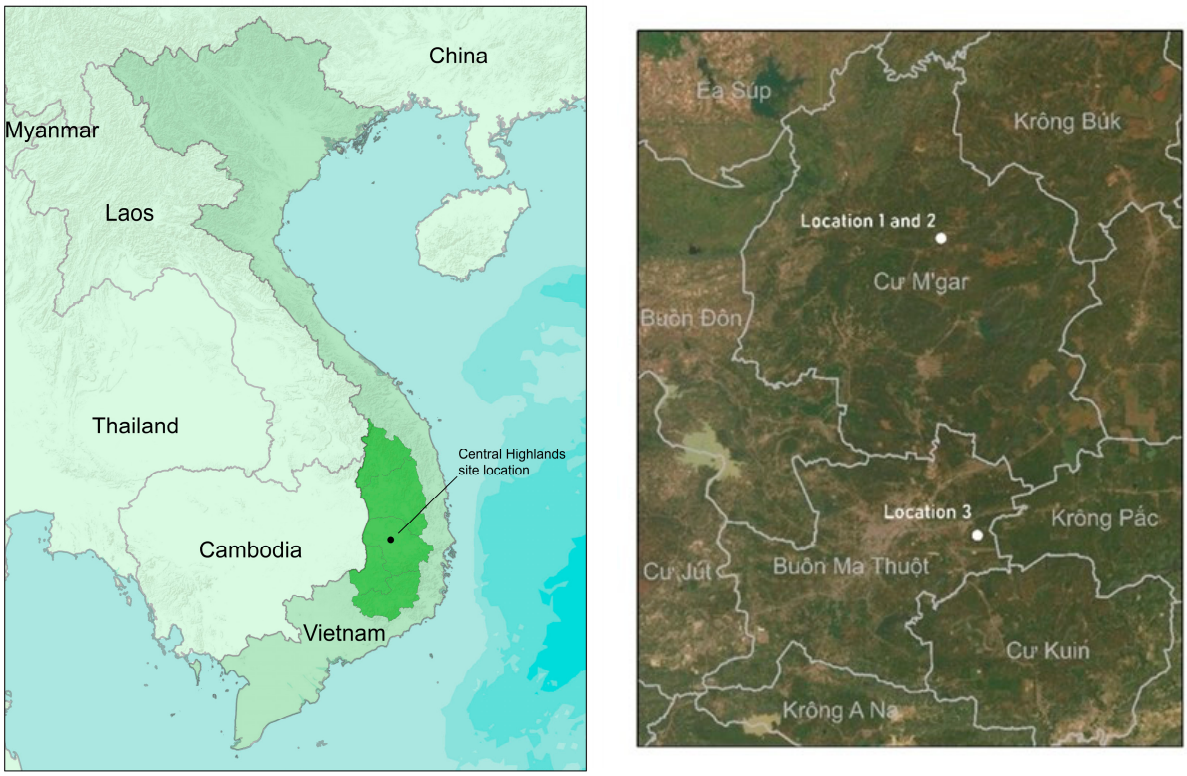
Recent unpublished data indicate that approximately 90% of coffee farmers in the Central Highlands use irrigation on their coffee farms at least once per season and 85% use irrigation twice or more each season. However, less than 2% of farmers use a quantitative method to determine volumes and timing of irrigation schedules. Farmers and their local service providers are generally making decisions based on set practices, with little attention to site-specific conditions that might improve water application volumes.

Computing power available in handheld devices now makes dependence on large computer systems redundant. Freely available remote sensing and synthetic weather data provide opportunities to develop irrigation tools for farmers that avoid some of the previous constraints to adoption. Even with the elimination of technical constraints, challenges remain on how best to present information to small-scale irrigators. For example,

can datasets be used in isolation or is local validation required? What are the minimum data requirements to make reasonable irrigation decisions, accounting for the relative inefficiency of traditional irrigation and the inherent error in volumes applied? Nguyen, et al. [15] propose a smart agriculture platform that utilizes LoRaWAN IoT, Big Data, Blockchain, and AI for improved decision-making for farmers who do not yet record any data. A commonsense beginning is needed in the design, analysis, and delivery of irrigation guidance information.

Industry Description

Coffee production in Vietnam's Central Highlands region is characterized by diverse topography, fertile soils, and favorable climatic conditions for a range of crops with potential for broad commercial agricultural development (Figure 1). The region is home to many of Vietnam's agricultural commodities and is the world's second-largest exporter of coffee and a top producer of pepper globally [16].



(**a**) (**b**)

Figure 1. (**a**) Location of Dak Lak Province in the Central Highlands of Vietnam and (**b**) the locations of the study sites in Dak Lak province in the Cu M'Gar and Buon Ma Thuot districts. Locations 1 and 2 were near Cu M'Gar, located at selected farms (farmer sites), and Location 3 was at a research station near Buon Ma Thuot.

The Central Highlands region accounts for 95 percent of Vietnam's coffee-growing area [17], with an annual production of approximately 1.68 million tonnes in an area of 683,800 ha [18]. It is estimated that more than 640,000 smallholdings are involved in coffee production (around 85% of the total coffee area) [19], most of which access irrigation for a portion of the growing season.

Coffee production in the Central Highlands has been expanding since the late 1990s. Between 1980 and 2000, the area cultivated under coffee in Vietnam increased 23-fold, with an 83-fold production increase [20] primarily due to expansion in the Central Highlands.

Soils and climate in the Central Highlands are ideal for irrigated coffee production, with most of the coffee grown in deep weathered Rhodic Ferrosols derived from basalt [21]. To achieve high yields, irrigation is required in the dry months to break bud dormancy [6,22] and to promote uniform flowering and fruit development. Due to the Asian monsoon impacting the Central Highlands (Figure 2), rainfall provides ~25% of potential crop evapotranspiration demand [9].

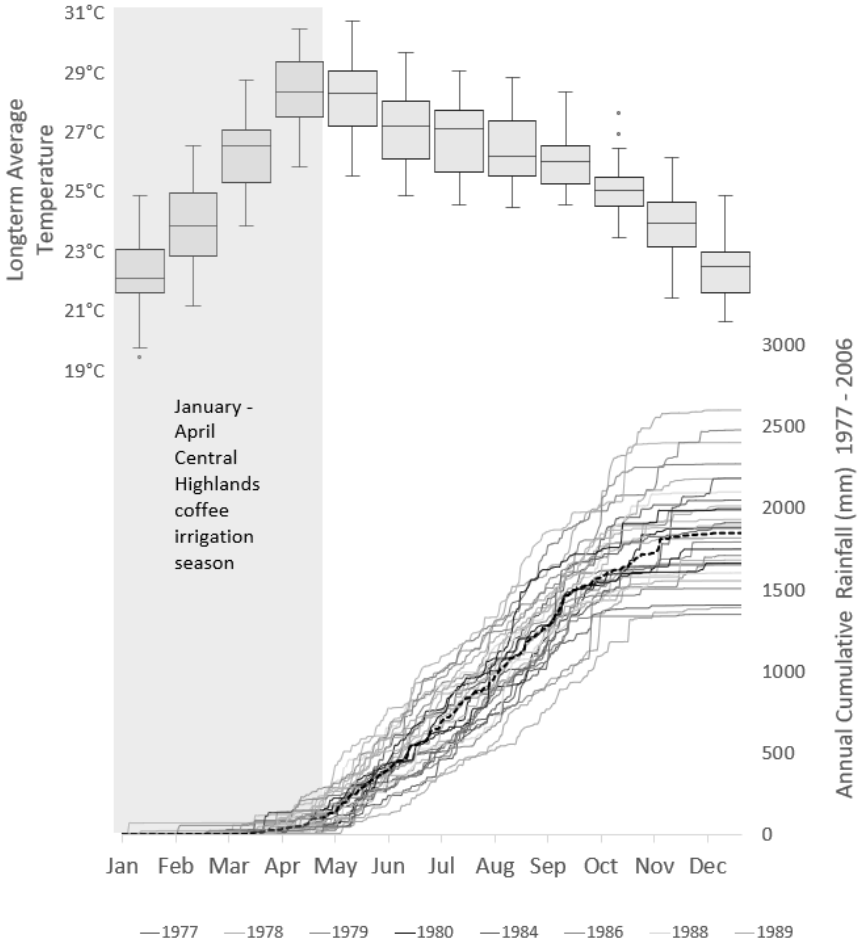


Figure 2. Long-term average monthly temperature (box and whisker) and accumulated annual rainfall (witches' hair plot) for Buon Ma Thuot (1977–2002). Each grey line indicates one year of accumulated rainfall data from January to December. The dotted line is the median accumulated rainfall. The grey section to the left is the typical irrigation season from January to April. This period is characterized by temperatures increasing to a peak in April, and by minimal accumulated rainfall (mean < 100 mm) during the period.

The extensive expansion of coffee areas and unsustainable irrigation practices threaten the Central Highlands' groundwater reserves through over-extraction [12,21]. Modelling undertaken by Truong, et al. [23] has shown that farmers' irrigation directly affects the depletion of the groundwater resources and fundamentally disrupts the regional hydrological cycle. Water supply is finite, and water use efficiency will determine the extent of future development. If irrigation can be optimized, the risk of water shortage is minimized, especially in drought years [1,24]. More efficient irrigation can conserve groundwater, reduce irrigation costs, and improve profitability of coffee farmers. Policy and regulation of the systems are key to ensuring long-term viability [25,26].

Government-funded extension of the Central Highlands coffee industry is a well-regarded source of agronomic information; however, less than 1% of farmers use the agency for irrigation scheduling advice. Using experience and data from three locations in Dak

Lak province in the Central Highlands of Vietnam and freely available climate data, we develop a physically based crop water-use model to achieve a balance between complexity of technical information, data access, and farmers' ability to action a decision. We compare complex and simpler water balance models to explore trade-offs between effort, reliability, and repeatability. We test the use of a tailored, fit-for-purpose, irrigation scheduling model, which can provide reasonable, measurement-based advice for farmers, with a minimal burden of cost, data collection, and analysis.

2. Materials and Methods

Three locations were selected in Dak Lak province of the Central Highlands for detailed monitoring in 2019 (Figure 1). The predominant soils at both the Cu M'Gar and Buon Ma Thuot sites are deep (>1000 mm), well-drained, uniformly textured ferrosols derived from basalt and are well suited to a variety of cropping systems including coffee, rubber, and cashew [27].

Datasets for atmospheric, soil, and water flow parameters were recorded for three sites over three irrigation seasons. The instrumentation supported a data-rich representation of crop water usage patterns during irrigation seasons. Data were recorded at 15-min intervals at all sites, with 2020 data sets used to calibrate models and 2021 and 2022 data applied for model validation.

2.1. Data Sets

Two on-site data collection systems were deployed: a high-end system from The Meter Group (Pullman, Washington, DC, USA); and a low-cost system from a local AgTech Start-up, MimosaTEK (Ho Chi Minh City, Vietnam). A comparison was made between the cost, quality, and reliability of the two systems.

2.1.1. Weather—Local

Both the Cu M'Gar and Buon Ma Thuot locations were equipped with two automatic weather stations. An Atmos 41 (The Meter Group) recorded air temperature, solar radiation, wind speed and direction, relative humidity, atmospheric pressure, and rainfall at 15-min time intervals. The second automatic weather station (MimosaTEK) recorded air temperature, illuminance (lux), wind speed and direction, relative humidity, and rainfall at 15-min intervals.

2.1.2. Weather—Remote Sensing

Remote-sensing platforms including NASA POWER data (https://power.larc.nasa.gov/, accessed on 15 February 2025) [28,29] are available with varying reliability across much of Southeast Asia. Satellite and model-based products provide reliable solar and meteorological data in Dak Lak Province, where historical and reliable measurements are not readily available. These data series are available on a 0.5° latitude by 0.5° longitude grid as a range of time series. Local meteorological datasets are available for Dak Lak province from 1981 (Figure 2).

2.1.3. Soil Moisture

Two independent soil moisture monitoring systems were installed at each site to ensure greater reliability and provide some redundancy capacity (Figure 3). Five Teros 12 water content sensors (The METER Group) were installed at each site at depths of −150 mm, −300 mm, −600 mm, −900 mm and −1200 mm. These sensors have a volume of influence of 1100 mL with a reported accuracy of ± 3% volumetric water content in mineral soils, an electrical conductivity of <8 dS/m, and a resolution of 0.001 m^3/m^3. (MeterGroup, 2023).

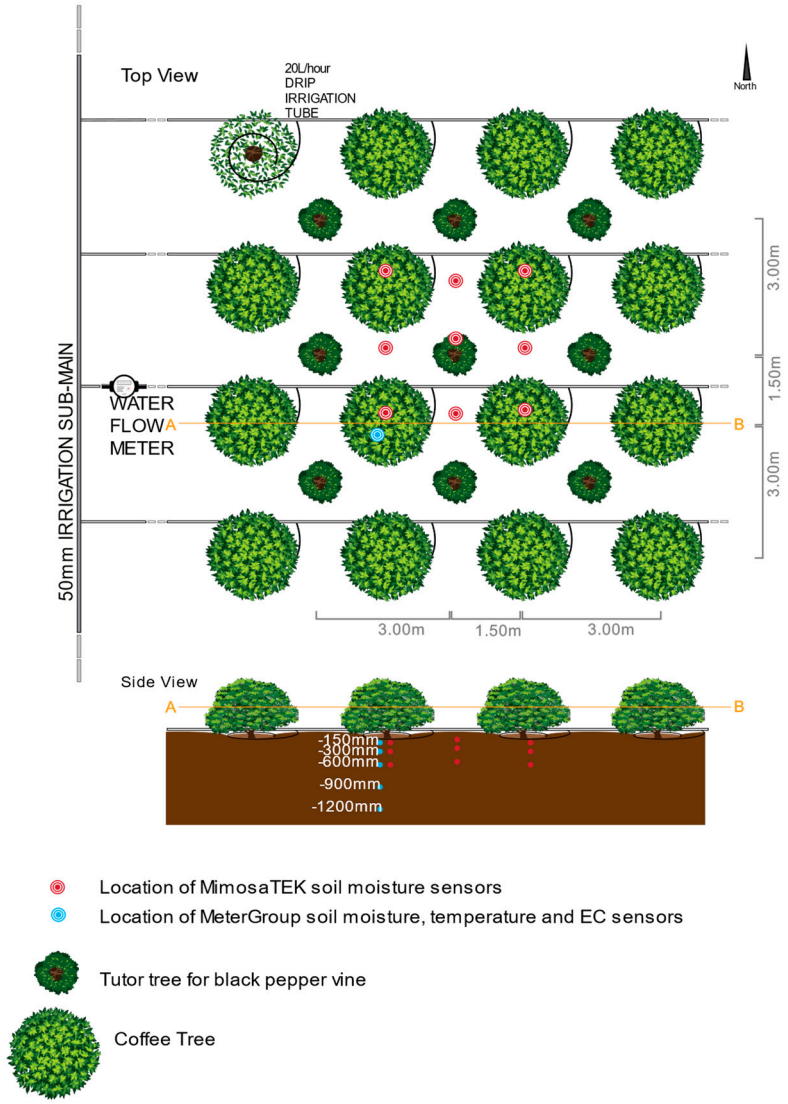


Figure 3. Systematic view of irrigation and soil water measurement instrumentation. Plant spacing between coffee trees is typically 3 m × 3 m. An opportunity or shade tree may be planted interspersed between the coffee at offset 3 m × 3 m spacing. The red targets show the location of the low-cost MimosaTEK sensors in an intensive grid pattern on the northern side of the tree line. The Meter Group sensors were installed near the southwest-most MimosaTEK sensor at the same depths to compare the sensing systems.

Lower-cost moisture sensing equipment (MimosaTEK) was also installed at the same depths. These sensors report apparent soil moisture content calculated using soil capacitance.

Soil samples were taken at each soil sensor location and depth at the time of sensor installation. Laboratory analysis of the volumetric water content [30] and the texture classification was undertaken and used to calibrate sensors and parameterize soils for modelling.

2.2. Approaches to Estimating Evapotranspiration

Crop water use estimations can be calculated using a range of methods involving measurements of one or more parameters in the soil–plant–atmosphere continuum. Allen, et al. [31] note that there have been many approaches to validation of evapotranspiration and crop water use estimates for coffee and other crops through calculation of atmospheric demand and undertaking a soil water balance. These studies aimed at defining reference evapotranspiration at daily or sub-daily scales. The ability to quantify irrigation inputs

with millimeter precision is beyond what a small-scale holder farmer can action using traditional hosepipe irrigation.

There are numerous methods for calculating reference crop evapotranspiration from meteorological data with varying input requirements and reliability. This study does not assess the relative performance of the range of methods; rather, two methods were chosen, the industry-standard FAO56 Penman–Monteith [31] and the Hargreaves method [32]. These two methods were then assessed with a range of input sources of varying accessibility and local reliability.

Penman–Monteith (P-M) (Equation (1)) was recognized as the standard by the International Commission for Irrigation and Drainage (ICID) and the World Meteorological Organization (WMO) in May 1990 [33]. The method is seen to overcome concerns with the previous Penman method and has been shown to represent crop water use reliably for a wide range of soil and environmental conditions. However, the application of P-M requires radiation, air temperature, air relative humidity, and wind speed data [31] at the local level, which is a limitation in many situations, with on-site equipment requirements.

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

ET_0 = reference evapotranspiration (mm day^{-1}),
R_n = net radiation at the crop surface (MJ m^{-2} day^{-1}),
G = soil heat flux density (MJ m^{-2} day^{-1}),
T = mean daily air temperature at 2 m height (°C),
U_2 = wind speed at 2 m height (m s^{-1}),
e_s = saturation vapor pressure (kPa),
e_a = actual vapor pressure (kPa),
$e_s - e_a$ = saturation vapor pressure deficit (kPa),
Δ = slope vapor pressure curve (kPa °C^{-1}),
γ = psychrometric constant (kPa °C^{-1})

Many empirical methods use temperature as a primary input. Allen, Pereira, Raes, and Smith [31] note that the Hargreaves and Samani [32] method (Equation (2)) shows satisfactory results globally without significant local calibration. Input data requirements of the Hargreaves method are lower and simpler to collect.

$$ET_0 = 0.0023(T_{max} - T_{min})^{0.5}(T_{mean} + 17.8)0.408R_a \quad (2)$$

ET_0 = reference evapotranspiration (mm day^{-1}),
T_{max} = maximum daily air temperature (°C),
T_{min} = minimum daily air temperature (°C),
T_{mean} = mean daily air temperature (°C),
R_a = extra-terrestrial radiation (MJ m^{-2} day^{-1}),
Empirical Hargreaves Coefficient = 0.0023

This study calculated evapotranspiration using both the FAO56 Penman–Monteith and the Hargreaves Equations from two data types: on-site weather station; and synthetic satellite-based data from NASA POWER.

2.3. Modelling Crop Water Use and Soil Moisture Change

Soil moisture sensors in the top 600 mm were interrogated at 15-min time steps to better understand the soil water dynamics within a day and crop use characteristics through irrigation seasons. Numerous investigations into soil moisture monitoring have provided insight into the behavior of soil water under different situations. For example, D'Haeze,

Deckers, Raes, Phong, and Chanh [21] indicate that the active root zone of Robusta coffee is the surface 600 mm of soil, which is supported by our intensive monitoring data.

The FAO56 Penman–Monteith model was calibrated to minimize RMSE between the model and the observed data on the 2020 irrigation data set for all sites. The parameters shown in Table 1 were adjusted to conform with four phases of the measured soil moisture detailed above.

Table 1. Model rules to mimic simplified soil moisture trace phases.

Phase	Model Rule or Parameter
Dormancy	Reducing the crop coefficient for the period up to 15 February or before the first rainfall or irrigation to 0.3.
Non-stressed crop water use	Crop coefficients were taken from Allen, Pereira, Raes, and Smith [31] and Amarasinghe, Hoanh, D'Haeze, and Hung [9]
Increasing stress condition	Method from Allen, Pereira, Raes, and Smith [31]
Drainage above field capacity	If previous 5 days' irrigation plus rainfall exceeds 20 mm or soil moisture > field capacity, drain at saturated hydraulic conductivity rate from D'Haeze, Deckers, Raes, Phong, and Chanh [21] for Central Highland ferrosols

2.4. Simplified Models

A number of reduced data models were constructed using combinations of data sources and ET estimates. (Table 2). The impact of data source and model on irrigation decisions were then compared on the basis of their ability to replicate the irrigation decisions made by the FAO56 Penman–Monteith approach.

Table 2. Limited sources and options for atmospheric and rainfall data, evapotranspiration, crop coefficients, and stress coefficients to be used in combinations for modelling.

Parameter Group	Option	Data Detail
Atmospheric Data	A1	On-site Automatic Weather Station
	A2	NASA Power (daily data)
	A3	NASA Power (long-term average [1])
Rainfall Data	R1	On-site rain gauge (daily data)
	R2	NASA Power (daily data)
Evapotranspiration	E1	FAO56 Penman–Monteith
	E2	Hargreaves
	E3	Hargreaves corrected
Crop coefficients	C1	FAO56 method
	C2	Modified to accommodate dormancy
Stress coefficients	S1	FAO56 method
	S2	No accommodation for stress

Note: [1] Atmospheric data sets were downloaded from NASA POWER for all irrigation seasons from 1981–2021.

Observations from Allen, Pereira, Raes, and Smith [31] indicate that the Hargreaves Equation will tend to over predict ET_0 in regions of high humidity, including tropical climates. Therefore, the Hargreaves equation was adjusted to meet local conditions by undertaking a regression analysis as recommended by Allen, Pereira, Raes, and Smith [31].

Figure 4 shows the daily values of ETo (mm day^{-1}) calculated using the Hargreaves equation (grey) and the corrected Hargreaves (black), overlaying the FAO56 PM (green) daily values. Figure 4 indicates that the corrected Hargreaves tends to underpredict on

days with low FAO56 PM ETo, however, these underestimates are typically outside the irrigation season (January–April).

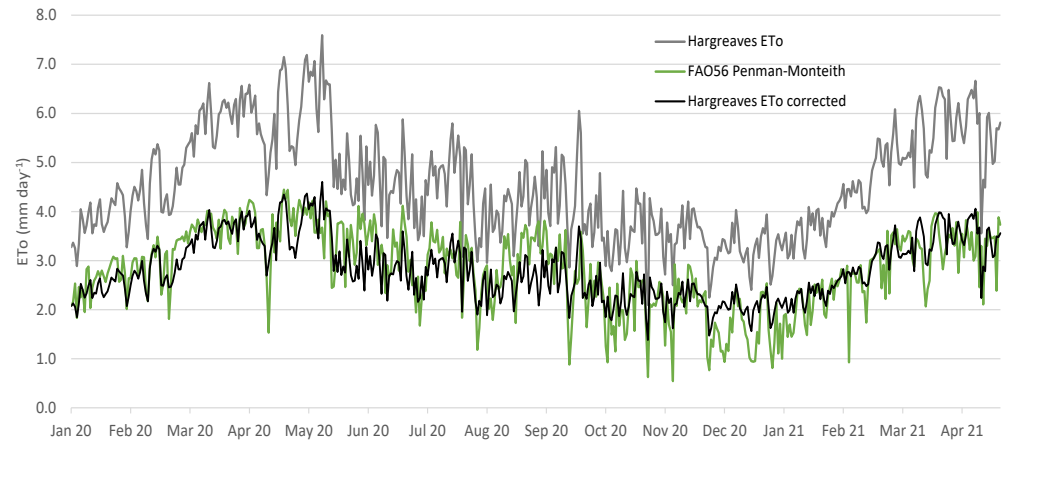


Figure 4. Estimated daily evapotranspiration rates (mm/day) showing variability in Hargreaves (grey), Hargreaves corrected (black), and FAO56 Penman–Monteith calculations (green).

Model Scenario Combinations

Seventy-two possible model/data scenarios are detailed in Table 2, but, for pragmatic purposes, these were limited to 10 practical combinations using options across 5 parameters including FAO56 Penman–Monteith.

Table 3 lists data and method combinations used for each model scenario, identified from the data sets (i) atmospheric data, (ii) rainfall data, (iii) reference evapotranspiration methods, (iv) crop coefficients, and (v) stress coefficients.

The FAO56 Penman–Monteith model (Figure 4) was calibrated against actual soil moisture at three sites and is taken as the reference water balance model. Irrigation was triggered with a refill point of 30% volumetric water content [21] and filled to field capacity with an application efficiency of 90%. Scenarios 2–10 used the same irrigation rules (Table 3).

Table 3. Model scenarios explored using a range of model and data detail (to be read in conjunction with Table 2).

Model Scenario	Atmospheric Data	Rainfall Data	Evapotrans-piration Calculation	Crop Coef-ficients	Stress Coefficients
FAO56 Penman Monteith	A1	R1	E1	C1	S1
Model Scenario 2	A1	R1	E1	C2	S1
Model Scenario 3	A1	R1	E1	C1	S2
Model Scenario 4	A2	R2	E1	C1	S1
Model Scenario 5	A2	R1	E1	C1	S1
Model Scenario 6	A2	R1	E2	C1	S1
Model Scenario 7	A2	R1	E3	C1	S1
Model Scenario 8	A3	R1	E1	C1	S1
Model Scenario 9	A3	R1	E2	C1	S1
Model Scenario 10	A3	R1	E3	C1	S2

2.5. Modelling Irrigation Decision-Making

The aim was not to compare and/or contrast a range of models and their suitability for coffee growing systems, rather to determine whether a simple model with lower input requirements could provide a robust and practical irrigation guide to support farmers'

decision-making. Assessment of model options was based on number of irrigations, date, and timing between irrigations.

Traditional irrigation practice is to fill tree bunds two to four times during each irrigation season. Due to variation in soil texture and water holding capacity, traditional practices effectively refill the soil profile (field capacity), as surface ponding is an indicator of successful irrigation, as reported by farmers.

2.6. Statistical Methods

MAE, RMSE, and MAPE were used to describe each modelling scenario's performance against the measured soil moisture data sets for each of the model calibration runs. These indicators are defined as

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|Me_t - Mo_{t,i}| \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Me_t - Mo_{t,i})^2} \quad (4)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Me_t - Mo_{t,i}}{Me_t}\right| \times 100 \quad (5)$$

where

t = daily time step
n = number of days in the irrigation season
Me = measured soil moisture
Mo = modelled soil moisture
i = model scenario

3. Results and Discussion

3.1. Features of Soil Moisture Time Series Data

Without field calibration of sensors, the values on the y-axis of soil moisture curves can be misleading. Regardless, the shape and inflection points of curves provide insights into soil water dynamics.

Figure 5 illustrates volumetric soil moisture at Site 1 in Cu M'Gar. Label 1 shows a slow daily decline in soil moisture through winter when there is lower evapotranspiration, i.e., the coffee plant is in a semi-dormant state. Dormancy is broken by either the first irrigation or rainfall of the season, with increased crop water use (label 2) following, as the crop is actively transpiring under a "no-stress" condition. There is adequate, but not excessive, moisture available in the root zone.

The increasing stress condition (labelled 3 in Figure 5) shows a reduction in the moisture extraction rate as the crop depletes stored soil moisture from the most readily available soil water with increasing crop water stress.

The rapid decline in soil moisture (after rain or irrigation) (label 4 on Figure 5) indicates drainage of water through the soil profile (water in excess of the field capacity), which would add to a drainage term in systems water balance.

"Best Practice" Model (FAO56)

Daily crop water use was derived using the FAO56 Penman–Monteith model with ETo estimated by applying crop coefficients (Kc) to various stages of the crop growth cycle using daily data from the on-site weather station. Default crop coefficients were taken from Allen, Pereira, Raes, and Smith [31] and Amarasinghe, Hoanh, D'Haeze, and Hung [9]. These were adjusted to account for crop dormancy before the first rainfall or irrigation of each season. Daily rainfall and irrigation values were inputs to the water balance. Due to

the irrigation season typically having low rainfall, run-on, run-off, and deep percolation were ignored.

Figure 6 shows the calibrated model and measured soil moisture at Site 1 between 1 January and 30 April 2020.

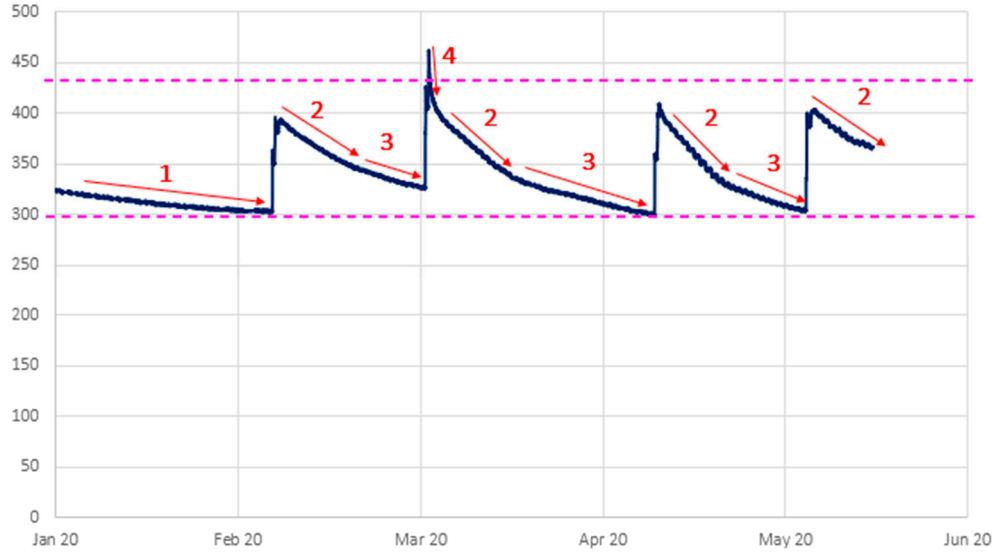


Figure 5. Fifteen-minute soil moisture trace of the surface 600 mm of soil showing phases of soil moisture depletion. The shape of the trace provides some insight into the availability and state of the water in the soil profile.

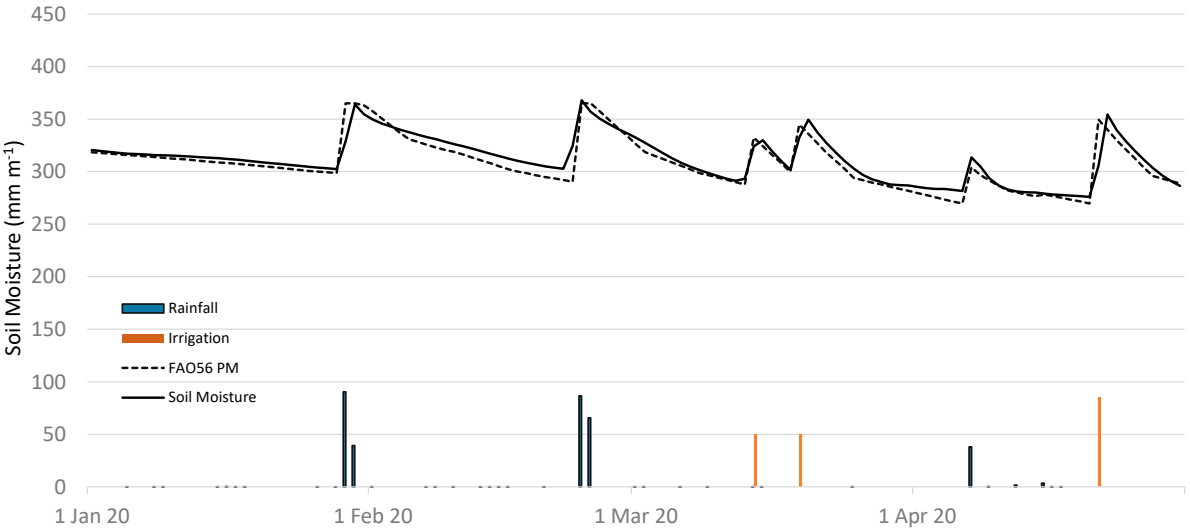


Figure 6. Measured soil water in top 600 mm of ferrosol soil at Site 1 (solid line) and FAO56 PM modelled soil moisture (dotted line). Blue vertical bars represent timing and volume of rainfall events and orange vertical bars represent timing and volume of irrigation events.

3.2. Model Scenario Selection

Each of the nine model scenarios (2–10) shown in Table 3 were calibrated against measured soil moisture at three sites through the 2020 irrigation season (January–April 2020). The objective functions to compare models were Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Errors (MAPE) for daily soil moisture.

3.3. Model Calibration

Each of the model scenarios described in Table 3 was calibrated using the irrigation season data set from 2020 through adjustment of the coefficients presented in Table 4.

Table 4. Calibration results: MAE (mm/m volumetric soil moisture), RMSE (mm/m volumetric soil moisture), and MAPE (%) of the calibration of FAO56 model and nine simpler model scenarios against actual soil moisture measurement in the top 600 mm of the soil profile for 2020.

Model Scenario	Site 1 2021			Site 2 2021			Site 3 2021		
	MAE	**RMSE**	**MAPE**	**MAE**	**RMSE**	**MAPE**	**MAE**	**RMSE**	**MAPE**
FAO56 Penman–Monteith	6.1	8.6	1.9	4.6	8.0	1.5	5.7	8.6	2.1
Model 2	10.2	13.4	3.3	7.7	10.0	2.5	5.4	8.4	1.9
Model 3	18.8	28.0	6.2	7.7	13.4	2.6	36.0	55.4	13.5
Model 4	22.6	32.0	7.0	40.4	52.4	12.3	27.1	33.3	9.8
Model 5	15.6	20.0	5.2	26.6	33.8	8.9	10.0	11.6	3.8
Model 6	81.4	117.9	27.1	64.1	96.5	21.6	91.2	127.0	34.1
Model 7	5.1	7.8	1.6	6.6	9.7	2.1	6.1	8.9	2.2
Model 8	15.2	19.7	5.0	25.9	32.9	8.6	9.9	11.5	3.8
Model 9	29.7	34.5	9.7	49.6	63.3	16.4	16.7	22.2	6.1
Model 10	10.7	14.2	3.5	6.8	10.3	2.2	10.0	14.4	3.7

The PM FAO56 model did not outperform all models at each site. Model Scenario 7 had a lower MAE, RMSE, and MAPE at Site 1. However, PM FAO56 errors were consistently lower (MAE average 4.6–6.5 mm/m, RMSE average 8.0–8.6 mm/m, MAPE average 1.5–2.1%) across the whole data set.

Three models that used on-site rainfall showed low MAE, RMSE, and MAPE:

- Model 2 (PM FAO56 with crop coefficients adjusted to allow for winter dormancy);
- Model 7 (daily NASA POWER data with adjusted Hargreaves equation, on-site rainfall);
- Model 10 (long-term average NASA POWER data with adjusted Hargreaves equation, on-site rainfall).

These three models were used in model validation.

3.4. Model Validation

Calibrated models using data from 2020 and observations from the three sites (2021) were used to test four models (Table 5) for the 2021 data set.

Table 5. Validation results: MAE (mm/m volumetric soil moisture), RMSE (mm/m volumetric soil moisture), and MAPE (%) of the validation of FAO56 model and three simpler model scenarios against actual soil moisture measurement in the top 600 mm of the soil profile.

Model Scenario	Site 1 2021			Site 2 2021			Site 3 2021		
	MAE	**RMSE**	**MAPE**	**MAE**	**RMSE**	**MAPE**	**MAE**	**RMSE**	**MAPE**
FAO56 Penman–Monteith	5.6	7.4	1.7	8.2	11.8	8.9	8.9	13.8	3.1
(Model 2) FAO56 w/dormancy	29.5	38.4	9.0	29.6	35.9	9.3	18.1	21.0	6.3
(Model 7) Hargreaves daily NASA temperature	6.5	8.9	1.9	8.0	11.4	2.4	6.9	9.5	2.4
(Model 10) Hargreaves average NASA temperature	6.9	9.0	2.0	9.6	13.3	3.0	8.5	13.0	2.9

The FAO56 reference model had lower MAE, RMSE, and MAPE indices of prediction compared to Model 7 and at Sites 1 and 2; however, results were higher than Model 10

(MAE average 6.9–9.6 mm/m, RMSE average 9.0–13.3 mm/m, MAPE average 2.0–3.0%) at Site 3 (Table 5).

The poor performance of Model 2 (PM FAO56 with crop coefficients adjusted to allow for winter dormancy) is the result of the long dormancy and the extended period between rainfall events, where the model was not reset by irrigation or rainfall refilling the soil moisture profile and errors in the evapotranspiration (Table 5).

Model 7 (daily NASA POWER data with adjusted Hargreaves equation, on-site rainfall) was the most reliable predictor across all sites in both the calibration (MAE average 5.1–6.1 mm/m, RMSE average 7.8–9.7 mm/m, MAPE average 1.6–2.2%) and validation phases (MAE average 6.5–8.0 mm, RMSE average 8.9–11.4 mm, MAPE average 1.9–2.4%). Model Scenario 7 was accepted as having similar reliability to the PM FAO56 model.

Model 7, referred to as the Low Data Model (LDM), was taken through to the next analysis to understand how it would determine irrigation schedules based on a longer-term historic data set.

3.5. Long-Term Analyses

To assess the decision-making skill of the LDM, a series of historical data sets were analyzed. These data sets were not collected on-site; instead, they were generated synthetically using data sourced from NASA POWER for the locations of the study sites. The following sections show the analysis of this data using the models described above.

Historically, irrigation volumes applied have been based on the amount of water required to fill a bund around each tree. If this deficit-controlled approach is maintained, there is little scope to control irrigation amounts [21,31]. Therefore, the measure of agreement between models was similarity in irrigation timing recommendations between FAO56 and the LDM.

Figure 7 presents an example of two seasons of scheduled irrigation using historic rainfall and a soil moisture deficit of 60 mm. Models were in close agreement in 2007 (1–4 days difference and total of four irrigations for both models). However, in 2008, the models were in lesser agreement, with greater differences between the irrigation dates of first, second, and third irrigations and the LDM scheduling an additional (fourth) irrigation.

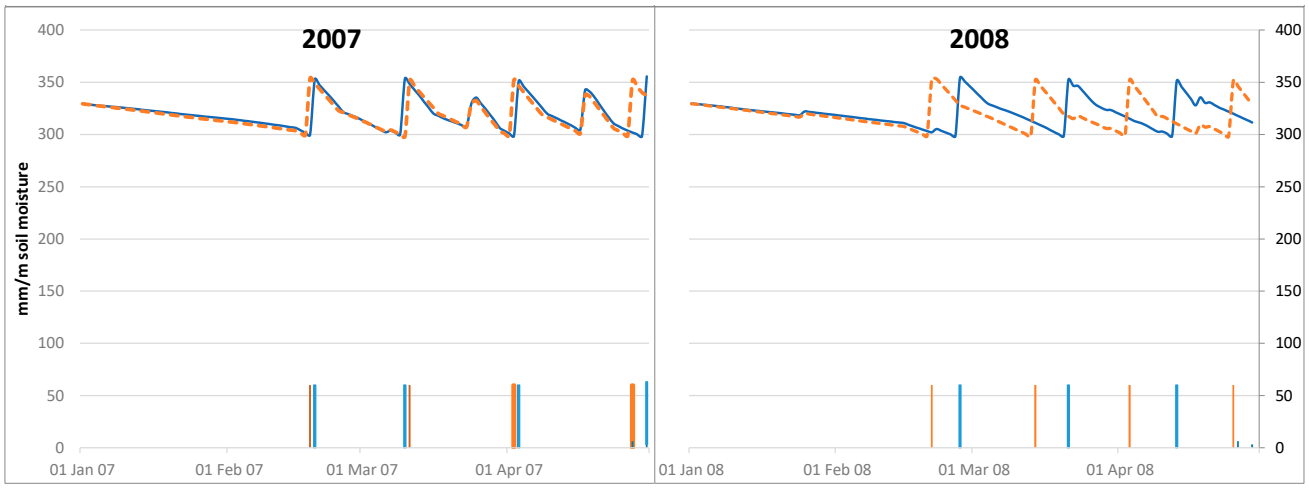


Figure 7. Soil moisture traces estimated using FAO56 P-M (blue trace and bars) and LDM (orange dotted trace and bars) for historic data sets from the 2007 and 2008 irrigation seasons. The timing and volume of rainfall events impact the performance of the LDM.

Table 6 shows the number of irrigations and volume applied recommended by the PM FAO56 and LDM between 2005 and 2018 using on-site rainfall and synthetic weather variables from NASA POWER data sets. To explore how each approach performs across

season types, each year/season was categorized into dry seasons (years with in-season rainfall in the lower quartile of years); average seasons (years with in-season rainfall within the interquartile range); and wet seasons (years with in-season rainfall in the upper quartile of the data set).

In each dry season, the LDM applied one more irrigation. The exception was 2008, which followed the trend of an average rainfall season applying less than PM FAO56. The average number of irrigations (PM FAO56 = 3.7, LDM = 3.6) and the total volumes applied (PM FAO56 = 222 mm and LDM = 214 mm) across all seasons modelled were similar.

Table 6 shows that Model Scenario 7 performs similarly to the FAO56 PM model in wet years, underpredicting by just one irrigation in one year out of four (2018), and with good agreement in the remaining three wet years.

In average rainfall irrigation seasons, the LDM underpredicts in three out of the six years, but only by one irrigation each year, with good agreement in the other three years.

In dry irrigation seasons, the LDM predicts greater irrigation requirements with respect to FAO56 PM in three out of four years and predicts less irrigation required in the remaining dry year.

Rainfall sufficient to refill the soil profile acts as a model reset, removing the accumulated differences in soil water that develop in prolonged dry conditions without irrigation.

Table 6 shows the number and depth of irrigation recommendations from both models between 2005 and 2018; however, the timing of these irrigations is equally important to the soil water balance to ensure that soil water is available to meet crop demand. The Low Data Model predicts the first irrigation of the season within 7 days of the FAO56 PM model (median = 2.2 days late, interquartile range = 2.8 days). Agreement between models diverges for subsequent irrigations; the second irrigation is 3.8 days later, the third 4.3 days later, and the fourth irrigation 3.6 days. Based on the irrigation system capacity and cycle times for coffee farmers in the Central Highlands, it is expected that a 7-day window for irrigation advice is adequate (Should I irrigate this week?). Therefore, it is expected that the LDM is adequate for at least the first two irrigations of the season. Further, a 7-day window for advice will capture 77.6% of the irrigation decisions determined over the analysis period (Figure 8).

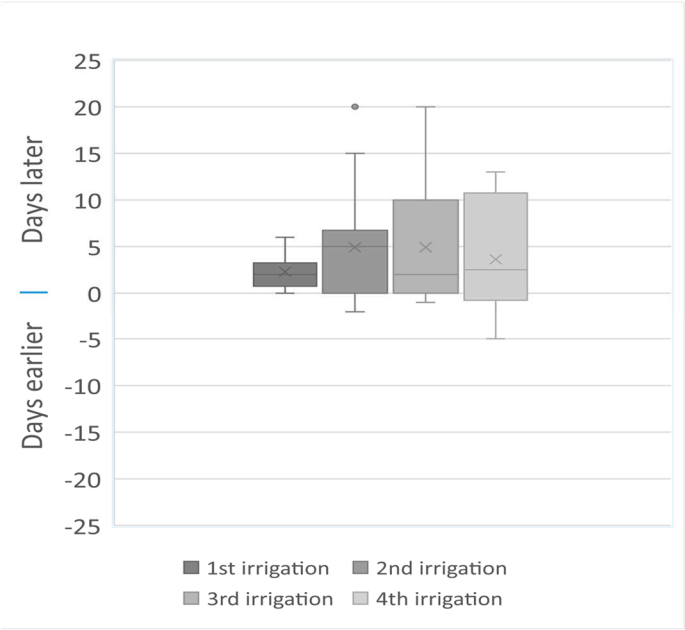


Figure 8. Differences in timing of irrigation recommendation using Low Data Model compared to FAO56 (PM model). Blue bars indicate a 7-day window before and after irrigation dates as modelled using PM FAO56. Dot above the whisker in the 2nd irrigation is an outlier.

Table 6. Comparison of FAO56 PM and the LDM annual irrigation events and water applied (mm) for a 14-year period (2005–2018).

		FAO56 Penman–Monteith			Low Data Model	
		Total Rainfall January–April (mm)	**Irrigations Applied (count)**	**Equivalent Depth of Irrigation Applied (mm)**	**Irrigations Applied (count)**	**Equivalent Depth of Irrigation Applied (mm)**
Dry seasons (lower quartile of in-season rainfall)	2015	8.2	4	240	5	300
	2005	9.4	4	240	5	300
	2006	21.1	4	240	5	300
	2008	32.0	4	240	3	180
Average seasons (interquartile range of in-season rainfall)	2011	32.5	4	240	3	180
	2017	66.0	4	240	3	180
	2006	83.4	4	240	4	240
	2007	89.6	4	240	4	240
	2010	93.9	4	240	4	240
	2009	101.3	4	240	3	180
Wet seasons (upper quartile of in-season rainfall)	2013	19.6	3	180	3	180
	2018	186.0	4	240	3	180
	2014	165.1	3	180	3	180
	2012	249.6	2	120	2	120
Average		89.8	3.7	222	3.6	214

4. Discussion

4.1. Sensitivity

Irrigation refill point (RP) is a key parameter in irrigation scheduling models. A generic refill point value is often taken as halfway between the field capacity and the permanent wilting point [31] on ferrosol soils. D'Haeze, Deckers, Raes, Phong, and Chanh [21] used a volumetric soil moisture of 30% or 300 mm/m. The calibration parameters here have RMSEs of 11.7 mm/m (wet), 13.1 mm/m (average), and 14.9 mm/m (dry seasons).

If the RP is increased to 330 mm/m, RMSE decreases to 7.4 mm/m, 7.8 mm/m, and 8.3 mm/m 1 for wet, average, and dry seasons, respectively; however, the number of irrigations increases to an average of 13.2 per season for the FAO56 PM model and 12.3 per season for the LDM, though this would be unrealistic for farmers as irrigating almost every week is inefficient [34], requires more time, and results in increased costs. Reducing the refill point by 10% (to 270 mm/m) has a lesser effect on the model agreement, increasing the RMSE to 13.3 mm/m in wet seasons, 17.9 mm/m in average rainfall seasons, and 16.0 mm/m in dry seasons. This affects the number of irrigations, which reduces to an average of 1.7 per season for the FAO56 PM model and 1.6 per season for Model Scenario 7. This is unrealistic, as the first irrigation is not recommended until the first week of March in most cases, which is very unlikely in practice.

All models are sensitive to the quality of rainfall inputs, indicating that, in the calibration phase, synthetic rainfall data from satellite observations did not reflect the actual rainfall on site and therefore created significant error in the water balance when compared with actual soil moisture.

Both models have a simplified rainfall routine and do not account for initial losses from surface run-off, but do account for drainage of excess water through the profile, which is reasonable considering the saturated hydraulic conductivity reported by D'Haeze, Deckers, Raes, Phong, and Chanh [21] and grower experience with low rainfall and low run-off during the irrigation season.

4.2. Implications for Coffee Farmers

Optimal irrigation scheduling maintains adequate water supply in the rootzone to meet daily crop demand. Excess water in the rootzone may create problems associated with water logging and does not leave capacity to take opportunity of incoming moisture from rainfall. Crops that spend time at either end of the soil moisture spectrum are likely to experience yield penalties. This study tests a model that requires little active data collection from a farmer to generate an acceptable starting point for irrigation scheduling. Such a model is well suited to translation into a mobile decision support tool that farmers could access to aid in irrigation scheduling decisions to maximize production.

Kandulu and Connor [35] note that large-scale investments in irrigation may not be as cost-effective as small-scale localized investments. A simple tool that required little effort to set up and use could be promoted by coffee traders and buyers as a discussion starter and to ensure that more objective decisions were being made with respect to irrigation scheduling. Zheng, Ma, Boansi, and Owusu [34] conclude that promotion and adoption of water management technologies reduce water use, but may also support improvements in the performance of other farming practices. Improved irrigation scheduling, including more site-specific information, can contribute to improved productivity and profitability in a more environmentally sustainable cropping system.

5. Conclusions

Local and reliable rainfall data are a prerequisite of any irrigation scheduling approach as synthetic data underrepresented actual rainfall, which has a large impact on the water balance that drives irrigation decision advice for all models.

This study has shown that, while synthetic temperature data sets are available, site-specific calibration is important when using the Low Data Model with the Hargreaves equation to generate ETo estimates based on daily temperature alone.

A calibrated Low Data Model was able predict the first two irrigations in the coffee growing season to within 7 days of the industry standard FAO56 PM model and provides an acceptable decision point for Central Highland coffee farmers that generally use the traditional method of a hosepipe filling a bund around each tree.

All models tested are sensitive to soil water holding capacity data and irrigation refill trigger values. Therefore, soil texture analysis and understanding water holding capacity must be understood at a site level.

The Low Data Model also performs better in high and average rainfall years than in low rainfall years due to the resetting of the soil moisture balance on each rainfall event that refills the soil profile. This approach can be used by farmers to optimize their water use efficiency by understanding the seasonal variability in the daily water requirement of the crop.

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