DETERMINATION OF EVAPOTRANSPIRATION RATES FOR MAIZE AND RICE CROPS USING SELECTED ET MODELS IN OVIA NORTH EAST LGA OF EDO STATE

BY

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CERTIFICATION

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DEDICATION

This project is dedicated to Almighty God, whose guidance and wisdom made this work possible and to my beloved parents for their endless love, support and encouragement throughout my academic journey.

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ABSTRACT

Efficient water management is important for sustainable agricultural production, particularly in regions experiencing climatic variability and limited water resources. This study focuses on determining evapotranspiration rates for maize (Zea mays) and rice (Oryza sativa) crops using selected evapotranspiration models under the climatic conditions of Ovia North East LGA, Edo State. Two ET models- the Blaney Morin Nigeria (BMN) and Hagreaves- Samani methods were semployed to estimate reference evapotranspiration (ETo) based on meteorological data obtained from the Nigerian Institute for Oil Palm Research (NIFOR) station. Crop evapotranspiration (ETc) was subsequently derived by applying crop coefficients (Kc) corresponding to the different growth stages. The study compared the performance of both models to evaluate their suitability for local conditions. Results indicated that the BMN model, which uses relative humidity alongside temperature and daylength, produced ET estimates more consistent with humid tropical conditions than the temperature based Hagreaves- Samani model. It was also found that using BMN instead of Hagreaves- Samani model reduces estimated irrigation demand by 85% for both maize and rice, corresponding to water savings of about 8,587 m^3/ha and 10,230 m^3/ha and approximate energy savings of 390kWh/ha for maize and 456kWh/ha for rice. The findings highlight the importance of using locally calibrated ET models for accurate irrigation scheduling and water resource management. This study provides valuable insights for improving water use efficiency, enhancing crop yield, and promoting climate smart agricultural practices in southern Nigeria.

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CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Evapotranspiration (ET) refers to the combined process of evaporation (E) the physical conversion of water from liquid to vapor from soil, wet plant surfaces, and open water and transpiration (T) the biologically controlled release of water vapor from plant stomata after water uptake by the roots. These two processes occur simultaneously over vegetated surfaces and are influenced by similar environmental drivers, such as net radiation, vapor pressure deficit, and wind speed (Ghiat et al., 2021; Yu et al., 2022).

Evaporation is primarily driven by atmospheric demand and surface water availability, whereas transpiration is governed by plant physiological traits, including stomatal conductance, leaf area index, and phenological stage (Kibler et al., 2023). In practice, because evaporation and transpiration are difficult to separate in the field, they are often considered together as a single term ET when quantifying crop water use or modeling water balances (Yu et al., 2022).

In agricultural water management, ET is the primary loss term in the crop water balance and directly determines crop water requirements (Ferreira et al., 2021; Nagappan et al., 2020). Accurate estimation of ET is fundamental for designing irrigation schedules that match water application to crop demand. This helps to prevent water stress caused by under-irrigation and to reduce wastage, nutrient leaching, or waterlogging caused by over-irrigation (Lakhiar et al., 2025; Wanniarachchi and Sarukkalige, 2022).

Modern irrigation planning typically involves calculating reference evapotranspiration (ETo) from weather data using standardized methods, and then converting it to crop evapotranspiration (ETc) by applying crop coefficients (Kc) for specific growth stages (Bounajra et al., 2024). This approach aligns irrigation with actual atmospheric demand, improving water use efficiency and supporting climate-smart agriculture (Kelley et al., 2025). Integrating ET into irrigation decision-making not only conserves water resources but also helps maintain or increase crop yields under conditions of climatic variability and increasing water scarcity (Wanniarachchi and Sarukkalige, 2022).

Crop water requirement (CWR) refers to the total amount of water that must be supplied via rainfall or irrigation to restore water lost through evapotranspiration (ET) during a plant's growth period, thereby maintaining optimal soil water for growth and ensuring yield potential (Djaman et al., 2018). In essence, CWR is synonymous with ET, except that CWR emphasizes the supply side-how much to apply while ET captures the actual loss to the atmosphere (FAO, 1998; Djaman et al., 2018).

The reference evapotranspiration (ET_o) reflects the atmospheric demand under idealized conditions (e.g., well-watered grass), and serves as a baseline. Crop-specific evapotranspiration is obtained by multiplying ET_o by a crop coefficient (K_o) that accounts for crop type, growth stage, and canopy characteristics (FAO, 1998). This relationship ($ETc = K_o \times ET_o$) forms the core of irrigation planning by linking atmospheric demand to actual crop needs (FAO, 1998; Wikipedia, 2025).

Moreover, environmental factors such as temperature, humidity, wind speed, and solar radiation directly affect ET rates, thus influencing crop water demand (FAO, 1998). For example, a crop in hot, dry, and windy conditions will require significantly more water compared to the same crop under cool, humid, and calm conditions (FAO, 1998). Thus, understanding and quantifying the relationship between ET and CWR is critical for efficient irrigation planning and water resource management.

Corn (*Zea mays*) and rice (*Oryza sativa*) are two of the most widely cultivated staple crops in the world, providing essential calories and nutrients to billions of people. Accurate estimation of crop evapotranspiration for these crops holds strategic importance for agricultural productivity and resource sustainability. In corn, water use is largely driven by transpiration, which is a critical determinant of yield potential. Proper estimation of ETc helps to prevent water stress that could limit grain filling and biomass accumulation, thereby safeguarding productivity (Iowa State University, 2017). In the case of rice, which is typically cultivated in flooded systems, accurate ETc estimation supports precise irrigation management by ensuring that the right amount of water is applied at the right time. Over-application can cause nutrient leaching and water wastage, while under-application may lead to yield reductions (Rowshon et al., 2014). More broadly, given the central role of corn and rice in global food systems, reliable ETc estimation contributes to sustainable water allocation in agriculture, a factor that is increasingly critical under conditions of climate change and growing competition for water resources.

Evapotranspiration models are computational tools designed to estimate the water needs of crops under varying climatic and management conditions. These models range from empirical equations, such as the widely used FAO-56 Penman–Monteith equation, to mechanistic crop models like AquaCrop and CropSyst-W, and even remote sensing models such as METRIC and SEBAL. The Penman–Monteith equation remains the global standard for estimating reference evapotranspiration (ETo), as it relies on key meteorological inputs and incorporates a mechanistic representation of radiation and aerodynamic factors (Penman–Monteith; FAO, 1998).

Mechanistic crop models, such as AquaCrop, go a step further by simulating actual crop evapotranspiration (ETa) and yield variations under water-stress scenarios, enabling more precise irrigation planning compared to simpler models (Ramezani Etedali et al., 2025). Comparative studies also show that models like CropSyst-W can be evaluated for operational irrigation scheduling, highlighting their relevance in field-scale water delivery optimization (Stöckle et al., 2025). Remote sensing–based models like METRIC and SEBAL derive spatial distributions of ET by solving the surface energy balance using satellite data, enabling field-by-field water monitoring and advanced water rights or compliance applications (METRIC; SEBAL; OpenET, 2024). The adoption of such diverse modeling approaches underscores the importance of selecting the appropriate tool based on available data, regional conditions, and irrigation objectives.

Accurate determination of potential evapotranspiration or crop-specific ET is pivotal for designing and operating efficient irrigation systems that align with crop water demand. ET-based scheduling frameworks have repeatedly demonstrated the ability to improve water use efficiency, reduce over- or under-irrigation, and enhance crop yield outcomes. For instance, real-time irrigation scheduling that adapts to current crop ET outperforms fixed, predetermined schedules, leading to more reliable yield responses and resource savings (Wiley et al., 2023). Automated, data-driven irrigation approaches that integrate high-resolution ET and soil moisture estimates (e.g., from HRLDAS inputs combined with AquaCrop modeling) have been shown to save 20–50% of irrigation water while maintaining or improving yields across multiple study sites (Zhao et al., 2023).

Furthermore, optimized irrigation scheduling guided by crop models and simulation–optimization frameworks enables the generation of irrigation strategies tailored to maximize yield or profit while conserving water at daily or even hourly resolution (Zhao et al., 2024). In more operational contexts, precise irrigation timing and rates prevent soil erosion, nutrient leaching, waterlogging, and pathogen proliferation, thereby supporting sustainable water management and agronomic health (Kelley et al., 2025). Collectively, these ET-based management practices are central to climate-smart agriculture and are vital in ensuring food security under increasing water scarcity and climatic variability.

Importance of Evapotranspiration (ET) in Hydrology and Agriculture

Evapotranspiration (ET) plays a pivotal role in both hydrological processes and agricultural productivity, making it one of the most critical parameters in water resources management and crop production. From a hydrological perspective, ET represents the major pathway by which water returns from the land surface to the atmosphere, accounting for over 60% of precipitation globally (Zhang et al., 2016). Accurate estimation of ET is therefore essential for understanding the water balance of catchments, aquifers, and watersheds, as it directly influences groundwater recharge, river flow, and overall ecosystem sustainability (Fisher et al., 2017).

In agriculture, ET is fundamental for irrigation planning, crop water requirement estimation, and water use efficiency. Since crops obtain water primarily through transpiration, ET provides a direct link between atmospheric demand and plant physiological processes. Monitoring ET enables farmers to determine the amount and timing of irrigation, thereby reducing water wastage, minimizing yield losses, and preventing problems such as salinization and waterlogging (Allen et al., 1998). For water-scarce regions, optimizing irrigation based on ET ensures that limited water resources are used judiciously, supporting food security and sustainable agricultural practices (Irmak and Djaman, 2016).

Furthermore, ET is a key variable in climate-smart agriculture. With climate change leading to increased temperature and altered rainfall patterns, ET becomes an indicator of crop stress and resilience. High ET values under rising temperatures suggest increased water demands, which, if not met, may compromise food production. Consequently, integrating ET models into agricultural engineering not only aids efficient irrigation scheduling but also supports adaptation strategies in response to global warming and variability in hydrological cycles (Grafton et al., 2018).

Overall, ET serves as a bridge between hydrological science and agricultural practice, providing the basis for efficient water allocation, sustainable food production, and improved resilience of agricultural systems to climate variability.

1.2 Statement of the Problem

Agricultural water scarcity has emerged as a critical challenge globally and particularly in regions like sub-Saharan Africa and Nigeria where agriculture remains the predominant water consumer (UN-Water and FAO, 2021). In northern Nigeria, irregular rainfall patterns, extended dry periods, and drying river systems have severely undermined the reliability of traditional surface water sources for agriculture. Consequently, smallholder farmers who drive much of the country's food production have become increasingly dependent on groundwater pumping, often relying on expensive fuel for irrigation. This reliance is not only financially burdensome but also heightens food insecurity risks (Omokaro et al., 2025).

A central difficulty in this context is the risk of underestimating or overestimating crop water needs. Underestimated needs can lead to water stress, hindered plant growth, and lost yield potential, while overestimation leads to water wastage, nutrient leaching, and resource inefficiencies a key concern for smallholder farmers who operate with limited water budgets. This dual risk necessitates reliable tools for accurately quantifying crop water demand.

While direct field measurements of evapotranspiration such as weighing lysimeters offer high precision, they are typically impractical in many agricultural settings. These instruments are expensive to build and maintain, often require complex installation and calibration, and need technical expertise to operate, rendering them inaccessible for widespread use, especially in resource-constrained environments (Arti Kumari et al., 2022; Sołtysiak and Rakoczy, 2024).

Moreover, there exists a pronounced gap in the application of suitable evapotranspiration models tailored to specific crops like corn and rice under local climatic conditions. ET models developed and validated elsewhere may perform poorly without local calibration; for instance, studies have shown that crop coefficients (Kc) and model parameterizations often diverge when applied to new agro-climatic zones, resulting in both over- and underestimation of ETc (MDPI Water, 2023). The lack of locally-adapted ET models for key crops like corn and rice hampers the accuracy of irrigation scheduling, potentially compromising water-use efficiency and yield.

1.3 Aim and Objectives of the Study

Aim:

To determine the evapotranspiration of rice and maize crops using evapotranspiration models.

Specific Objectives:

1. To estimate reference evapotranspiration using Blaney Morin Nigeria and Hagreaves evapotranspiration models.
2. To compute crop evapotranspiration for rice and maize using crop coefficients (Kc) for different growth stages.
3. To compare Blaney Morin Nigeria and Hagreaves models in estimation of rice and maize ET for the study area.

1.4 Justification of the Study

Efficient water management is a critical factor in enhancing agricultural productivity, particularly in regions where water resources are limited or subject to seasonal variability. In such contexts, optimizing water use efficiency (WUE) is essential for ensuring sustainable crop production. Evapotranspiration (ET) estimation plays a central role in irrigation scheduling, as it provides a scientific basis for determining the exact amount of water required by crops at different growth stages.

Maize (*Zea mays L.*) and rice (*Oryza sativa L.*) are two of the most economically and nutritionally important cereal crops worldwide, including Edo State, Nigeria, serving as staple foods for a significant proportion of the global population. In many agricultural regions, these crops account for a substantial share of cultivated land, making improvements in their irrigation management particularly impactful on both food security and rural livelihoods.

Traditional methods of measuring ET, such as lysimeters and field experimentation, although accurate, are often expensive, labour-intensive, and time-consuming. In contrast, model-based estimation techniques offer a cost-effective, flexible, and scalable alternative for determining both reference evapotranspiration (ETo) and crop evapotranspiration (ETc). By applying well-established ET models alongside crop coefficients (Kc), irrigation requirements can be estimated with reasonable accuracy, enabling better resource allocation.

This study is particularly relevant to the local agricultural engineering context, as it will provide data-driven insights into the applicability and reliability of selected ET models for corn and rice production under prevailing climatic conditions. The findings are expected to guide farmers, extension agents, and irrigation planners in improving water use efficiency, thereby contributing to climate-smart agriculture, reducing water wastage, and supporting sustainable food production strategies.

1.5 Scope of the Study

This study is confined to the estimation of crop evapotranspiration for maize (*Zea mays*) and rice (*Oryza sativa*). The research employs selected empirical and physically based models, such as the Penman–Monteith, Hargreaves, and Blaney–Morin Nigeria ET models, for ET determination. The analysis utilizes relevant climatic parameters, including temperature, relative humidity, wind speed, and solar radiation, obtained from reliable meteorological sources.

The investigation is geographically limited to a defined location (Ovia North East LGA of Edo State, Nigeria) and a specific growing season, ensuring that the findings are context-specific and applicable to similar agro-ecological zones.

CHAPTER TWO

LITERATURE REVIEW

2.1 Concept of Evapotranspiration (ET)

Evapotranspiration (ET) is a central concept in hydrology, climatology, and agricultural sciences, as it represents the main pathway through which water stored in the soil and utilized by vegetation is returned to the atmosphere. Broadly, ET is defined as the sum of evaporation from land and water surfaces and transpiration from vegetation (Allen et al., 1998; Xu and Singh, 2005). It is therefore an integrative process that links the soil, plants, and atmosphere within the hydrological cycle.

Evaporation is the process by which liquid water is converted into water vapor and transferred to the atmosphere. It occurs primarily from exposed soil, water surfaces, and wet plant canopies following rainfall or irrigation. The rate of evaporation is determined by several climatic factors, including solar radiation, temperature, relative humidity, and wind speed (Shuttleworth, 2007). In agricultural systems, soil evaporation is particularly high in the early stages of crop growth when ground cover is limited, but it tends to decline as the canopy expands and shades the soil surface.

Transpiration, in contrast, is a biological process that occurs when plants absorb water from the soil through their roots, transport it through the xylem, and release it as vapor through stomata in the leaves. This process not only regulates plant temperature through evaporative cooling but also facilitates nutrient uptake and transport within the plant (Kool et al., 2014). Transpiration rates vary significantly depending on plant type, growth stage, leaf area index, stomatal behavior, and environmental conditions such as radiation and vapor pressure deficit (Zhang et al., 2017).

The interaction of these two processes produces evapotranspiration (ET), which represents the total water loss to the atmosphere from both soil and vegetation. ET is thus regarded as a critical component of the hydrological balance and an essential determinant of crop water requirements. It directly affects agricultural water management by providing the basis for irrigation scheduling, water allocation, and crop productivity assessments (Howell et al., 2015).

From a practical perspective, ET is often divided into three forms:

- Potential evapotranspiration (PET): the maximum ET that would occur from a reference surface (e.g., a well-watered grass) under given climatic conditions.
- Actual evapotranspiration (AET): the real ET that occurs under specific soil moisture and plant water availability conditions.
- Reference evapotranspiration (ET_0): a standardized measure used for irrigation planning, often calculated using the FAO Penman–Monteith method (Allen et al., 1998).

Understanding ET is crucial for sustainable agricultural practices, especially in water-scarce regions where efficient irrigation planning is required to maximize crop yield while conserving water resources. As climate variability and water scarcity continue to intensify, accurate estimation and monitoring of ET have become indispensable tools for ensuring food security and optimizing water resource management (Droogers and Allen, 2002).

2.1.1 Factors Affecting Evapotranspiration (ET)

Evapotranspiration (ET) is a dynamic process influenced by multiple interacting factors related to climate, soil, crop characteristics, and management practices. Understanding these factors is critical for accurate estimation and effective water resource management.

(a) Climatic Factors

Climate is the most dominant determinant of ET. Solar radiation provides the energy required for evaporation and transpiration, while temperature influences the rate of vaporization. Relative humidity and vapor pressure deficit regulate the gradient between soil/leaf surfaces and the atmosphere, which drives moisture transfer. Wind speed enhances ET by removing saturated air layers around leaves and soil surfaces, thereby maintaining a strong vapor pressure gradient. In general, higher radiation, temperature, wind, and lower humidity favor increased ET rates (Allen et al., 1998; Pereira et al., 2015).

(b) Crop Characteristics

Different crops exhibit varying transpiration rates due to differences in morphology and physiology. Leaf area index (LAI), rooting depth, and canopy structure largely determine water uptake and transpiration potential. Crops with large, dense canopies (e.g., rice) tend to transpire more than sparse or shallow-rooted crops. Additionally, crop growth stage strongly influences ET initial stages exhibit low ET, while mid-season, characterized by maximum canopy cover, shows peak ET levels (Doorenbos and Pruitt, 1977; Steduto et al., 2012).

(c) Soil Properties

Soil type, texture, and structure control water availability and its movement in the soil profile. Sandy soils with low water-holding capacity may limit ET, while clay soils retain more water but may restrict root penetration. Soil salinity can also reduce transpiration by creating osmotic stress in plants, reducing water uptake. Moreover, soil surface wetness influences the evaporation component, with bare wet soils evaporating faster than mulched or covered soils (Hillel, 1998; FAO, 2012).

(d) Management Practices

Agricultural management significantly modifies ET patterns. Irrigation scheduling directly determines soil moisture availability, influencing both evaporation and transpiration. Practices such as mulching, cover cropping, and conservation tillage reduce soil evaporation by shielding the soil surface. Conversely, over-irrigation or poor drainage can increase evaporation losses. Fertilizer management also plays an indirect role by affecting crop vigor and canopy development, thereby modifying transpiration (Kang et al., 2009; Pereira et al., 2020).

It is important to note that ET is not a fixed value but rather a function of complex interactions among environmental, biological, and management factors. Recognizing these drivers is essential for precise estimation, efficient irrigation scheduling, and sustainable agricultural water use.

2.1.2 Indirect Methods of Estimating Evapotranspiration

Indirect methods of estimating evapotranspiration (ET) are widely used in hydrological and agricultural studies because of their practicality, lower cost, and broader applicability compared to direct field measurements. These approaches generally rely on climatic data, empirical equations, or modeling techniques to provide estimates of ET under varying environmental and management conditions.

One of the most prominent categories of indirect methods involves the use of empirical equations derived from climatic variables. According to Allen et al. (1998), the Penman-Monteith equation is regarded as the standard reference method for estimating reference evapotranspiration (ET_0). This model integrates temperature, solar radiation, wind speed, and relative humidity, thereby offering a robust estimate applicable across diverse climates. In fact, numerous studies have validated its accuracy against field lysimeter measurements, showing strong correlation in both humid and arid environments (Irmak et al., 2015). Similarly, Hargreaves and Samani (1985) proposed a temperature-based equation that has gained popularity in regions where detailed climatic data are unavailable. Although less precise than Penman-Monteith, it provides a reliable alternative for data-scarce environments.

In a study by Trajkovic (2007), it was demonstrated that Blaney-Criddle, another empirical model, performs adequately in semi-arid climates where temperature and daylight hours are the main drivers of evapotranspiration. However, its applicability tends to be region-specific, requiring careful calibration to avoid over- or under-estimation. As Singh and Xu (1997) emphasized, the effectiveness of empirical equations depends largely on local climatic characteristics and crop types, necessitating proper validation before application.

Beyond empirical equations, remote sensing techniques have emerged as a powerful tool for ET estimation. According to Bastiaanssen et al. (1998), the Surface Energy Balance Algorithm for Land (SEBAL) utilizes satellite-derived data such as surface temperature, albedo, and vegetation indices to estimate actual evapotranspiration across large areas. This approach is particularly valuable for regional water management, as it enables monitoring of spatial and temporal variations in ET. Likewise, the METRIC model (Mapping Evapotranspiration at high Resolution with Internalized Calibration), developed by Allen et al. (2007), has been applied successfully in irrigated agriculture to provide accurate water consumption estimates, thereby improving irrigation scheduling.

In addition, crop simulation models represent another category of indirect methods. For instance, the CROPWAT model, developed by the FAO, combines climatic data with crop coefficients to estimate crop water requirements and ET throughout different growth stages (FAO, 2012). As noted by Smith (1992), such models are useful for irrigation planning, especially in regions where water resources are limited.

Overall, indirect methods of estimating ET offer flexibility and applicability across diverse contexts. While empirical equations are best suited for smaller scales or regions with limited data, remote sensing and crop simulation models enable broader applications in regional water resource management and policy development. However, as highlighted by Jensen and Allen (2016), the reliability of these methods is contingent on data quality, local calibration, and validation against field measurements.

2.1.3 Comparative Strengths and Weaknesses

Different approaches to evapotranspiration (ET) estimation direct, empirical, and physically based methods each have their advantages and limitations. Understanding these strengths and weaknesses is crucial for selecting the most appropriate method for specific agricultural, hydrological, or climatological studies.

Direct methods, such as the use of lysimeters, are often considered the most accurate because they provide direct measurements of water loss through evaporation and transpiration. According to Allen et al. (1998), lysimeters serve as the benchmark against which other ET estimation techniques are validated. However, while highly precise, these methods are costly, labor-intensive, and limited in spatial coverage, making them impractical for large-scale or long-term applications (Howell et al., 2015). Furthermore, installation and maintenance challenges may restrict their use in resource-constrained settings.

On the other hand, empirical methods like the Hargreaves and Blaney-Criddle equations are widely applied due to their simplicity and low data requirements. In a study by Droogers and Allen (2002), it was observed that empirical models are particularly useful in regions with limited meteorological data, as they rely mainly on temperature or sunshine duration. Nonetheless, their weakness lies in their tendency to oversimplify the physical processes of ET, which may lead to significant inaccuracies when applied outside the climatic conditions under which they were developed (Tabari, 2010).

Physically based methods, such as the Penman-Monteith equation, represent a balance between accuracy and applicability. These methods incorporate key climatic variables such as temperature, wind speed, relative humidity, and solar radiation, thereby providing a more holistic estimation of ET. According to Pereira et al. (2015), the FAO-56 Penman-Monteith method is regarded as the global standard due to its adaptability across diverse climates and crop types. However, its limitation lies in its dependency on a comprehensive dataset, which may not always be available in data-scarce regions.

Comparative analyses have shown that no single method is universally superior; rather, the choice depends on the research objectives, available resources, and scale of application. For example, empirical methods may be suitable for preliminary studies or in developing regions with limited data infrastructure, while physically based models are better suited for research requiring high accuracy (Sentelhas et al., 2010). Direct methods, though accurate, are best reserved for calibration and validation of other models due to their restricted feasibility on a large scale.

In essence, the strengths and weaknesses of ET estimation methods reflect a trade-off between precision, resource demand, and practical applicability. As Allen et al. (2011) noted, the selection of an appropriate ET estimation approach must be context-driven, taking into account both scientific accuracy and logistical feasibility.

2.2 Evapotranspiration Models

2.2.1 Penman-Monteith Model: Theory, Applications, and Limitations

The Penman-Monteith (PM) model is widely recognized as the standard method for estimating reference evapotranspiration (ET_0) because it integrates both the energy balance and aerodynamic principles governing water transfer from soil and vegetation into the atmosphere. The model was originally developed by Monteith (1965) as a modification of Penman's earlier work (1948) by explicitly including the role of canopy resistance to water vapor transfer. According to Allen et al. (1998), the PM model provides a physically based framework that accounts for both radiative and aerodynamic drivers of ET, making it superior to many empirical approaches.

Mathematically, the PM model is expressed as:

$$ET_o = \frac{0.408\Delta\left(R_n - G\right) + \gamma\left(\frac{C_n}{\left(T + 273.16\right)}\right)u_2\left(e_s - e_a\right)}{\Delta + \gamma\left(1 + C_d u_2\right)} \tag{2.1}$$

Where:

- Δ = slope of the saturation vapor pressure curve (kPa/°C),
- Rn = net radiation at the crop surface (MJ/m²/day),
- G = soil heat flux (MJ/m²/day),
- γ = psychrometric constant (kPa/°C),
- T = mean daily air temperature (°C),
- u_2 = wind speed at 2 m height (m/s),
- $e_s - e_a$ = saturation vapor pressure deficit (kPa).

This formulation illustrates how the PM model couples climatic factors (temperature, radiation, humidity, wind) with crop and soil parameters, thereby providing a comprehensive estimate of evapotranspiration.

Applications of the Penman-Monteith Model

The PM model has become the global benchmark for ET estimation. The Food and Agriculture Organization (FAO-56) formally recommended it as the standard method for computing reference ET due to its reliability across different climatic zones (Allen et al., 1998). In agricultural water management, the model is extensively used to:

- Determine irrigation requirements for crops by relating reference ET to crop coefficients (Kc).
- Support hydrological modeling, such as groundwater recharge assessments and basin-scale water balance studies (Jensen and Allen, 2016).
- Aid in climate change impact studies by evaluating shifts in water demand under changing temperature and radiation regimes (McMahon et al., 2013).

For instance, a study by Irmak et al. (2003) demonstrated that the PM model provided highly accurate ET estimates for maize and soybean when compared with lysimeter measurements in Nebraska, USA. Similarly, López-Urrea et al. (2006) validated the PM model against field experiments in Spain and found it to outperform simpler models like Hargreaves and Blaney-Criddle.

Limitations of the Penman-Monteith Model

Despite its strengths, the PM model has limitations that need to be acknowledged. First, its data requirements are extensive, demanding accurate measurements of solar radiation, wind speed, humidity, and temperature, which may not be readily available in many developing regions (Shuttleworth, 2012). In cases where only limited meteorological data are available, reliance on approximations may introduce errors.

Second, the model assumes a reference crop condition (a hypothetical grass crop with fixed characteristics), which may not fully capture the dynamics of specific crops under diverse management and stress conditions. As Howell et al. (2001) noted, applying the model directly to non-reference crops without appropriate crop coefficients can lead to misestimations of irrigation water needs.

Finally, although the PM model is physically based, it still incorporates certain simplifying assumptions such as uniform canopy cover, well-watered conditions, and homogeneity in soil-plant-atmosphere interactions that may not hold true in heterogeneous field environments (Rana and Katerji, 2008).

In summary, the Penman-Monteith model represents the most robust and widely accepted approach for estimating ET, offering a strong theoretical foundation and broad practical applicability. However, its reliability depends heavily on the quality of input data and the appropriateness of crop coefficient adjustments for specific conditions.

2.2.2 Hargreaves Model: Data Requirements

The Hargreaves model is one of the most widely applied empirical methods for estimating reference evapotranspiration (ET_0), particularly in regions where limited meteorological data are available. It was first proposed by Hargreaves and Samani (1985) as a simplified alternative to more data-intensive methods like the Penman-Monteith model. The model estimates ET based primarily on temperature data, making it suitable for developing regions and areas with sparse climatic records.

The general form of the Hargreaves equation is expressed as:

$$\mathbf{ET_0 = 0.0023\,(T_{mean}+17.8)\,(T_{max} - T_{min})^{0.5}\,R_a} \qquad \textbf{(2.2)}$$

Where:

- T_{mean}, T_{max} and T_{min} are the mean, maximum, and minimum daily air temperatures (°C),
- R_a is the extraterrestrial radiation (mm/day).

Data Requirements

Unlike other models that require multiple climatic variables, the Hargreaves model is based on relatively simple data inputs. The essential requirements include:

- Daily maximum and minimum air temperature (°C) – used to calculate mean temperature and diurnal temperature range.
- Extraterrestrial radiation (R_a) – derived from latitude, day of the year, and solar declination, which can be calculated mathematically.

This minimal data requirement makes the Hargreaves model highly applicable in regions where weather stations do not collect complete climate records such as wind speed, solar radiation, or humidity (Droogers and Allen, 2002).

In summary, the Hargreaves model is a practical tool for estimating evapotranspiration where data availability is limited. While its simplicity and minimal data requirements are clear strengths, its performance is highly dependent on climatic conditions, and caution is needed when applying it in humid, windy, or non-arid regions. Researchers often recommend local calibration to improve its accuracy before applying it to agricultural water management and hydrological planning (Droogers and Allen, 2002). The Hargreaves equation can be computed on a monthly or best ten days period, as is used for irrigation scheduling computation (Egheravba, 2009)

2.2.3 Blaney-Criddle Model: Principle

The Blaney-Criddle model is one of the earliest and most widely used empirical methods for estimating crop evapotranspiration (ET), particularly in regions with limited meteorological data. The model was developed in the mid-20th century and has since become an essential tool in irrigation planning and agricultural water management, especially in arid and semi-arid regions where water resources are scarce (Allen et al., 1998).

Principle of the Model

The model is based on the principle that crop evapotranspiration (ETc) is directly related to reference evapotranspiration (ETo), which in turn depends largely on mean air temperature and the proportion of annual daytime hours for a given location. According to Doorenbos and Pruitt (1977), the Blaney-Criddle equation can be expressed as:

$$\mathbf{ET_0 = p\ (0.46T + 8)}$$

Where:

- ET_0 = reference evapotranspiration (mm/day)
- T= mean daily temperature (°C)
- p = mean daily percentage of annual daytime hours

This estimated ET_0 is then multiplied by a crop coefficient (Kc) to derive the actual crop evapotranspiration (ETc):

$$\mathbf{ET_c = K_c \times ET_0} \qquad \mathbf{(2.3)}$$

This simple formulation makes the model appealing where detailed climatic datasets (such as solar radiation, wind speed, or humidity) are unavailable.

2.2.4 Blaney–Morin–Nigeria (BMN) Model

The Blaney–Morin–Nigeria (BMN) model is a modified version of the original Blaney–Morin evapotranspiration equation, specifically developed to improve the accuracy of evapotranspiration (ET) estimation under Nigerian climatic conditions. The model was first introduced by Duru (1984), who observed that the classical Blaney–Morin and Blaney–Criddle models, which depend mainly on mean air temperature and percentage of daytime hours, often produced significant errors when applied in Nigeria. This shortcoming was largely due to their omission of relative humidity**,** an important climatic factor in Nigeria's diverse agro-ecological zones. By incorporating relative humidity into the equation, the BMN model became better adapted to the country's humid, sub-humid, and semi-arid regions.

The BMN model is usually expressed as:

$$\mathbf{ET_0 = p.\ (0.45T + 8)\ (H - R_m)\ x\ \frac{1}{100}} \qquad \mathbf{(2.4)}$$

Where:

- ET_0 = potential / reference evapotranspiration (mm day^{-1})
- p = ratio of maximum sunshine hours for the period of interest to the annual maximum (dimensionless; sometimes replaced by a radiation ratio r_f)
- T = mean air temperature (°C) (usually (T_{max} + T_{min})/2
- R = mean relative humidity (%) for the period (use same units as in model — i.e., percent)
- H and m = empirical constants determined by calibration
- division by 100 brings the scaling to mm/day in the original formulation.

Mathematically, the BMN model follows the general structure of the Blaney–Morin equation but introduces two location-specific constants—H and m—which are calibrated for Nigerian conditions. These constants help to adjust the model outputs to better align with measured or Penman–Monteith (FAO-56) reference evapotranspiration values (Idike, 2005). According to research in Sokoto, Kano, and Enugu, recalibrating the BMN constants significantly improved correlation with Penman–Monteith estimates, reducing root mean square error (RMSE) and increasing model efficiency (Obafemi et al., 2022; Hassan and El-Tahir, 2017).

One of the strengths of the BMN model is its balance between simplicity and accuracy. Like the Blaney–Criddle model, it requires fewer climatic inputs than the Penman–Monteith method, making it suitable in data-scarce environments. However, by incorporating relative humidity, it provides a better representation of atmospheric demand compared to purely temperature-based methods. For example, a study by Mutunga et al. (2021) showed that in northern Nigeria, the BMN model achieved correlation coefficients (r) above 0.97 when compared with Penman–Monteith, outperforming the Hargreaves and Blaney–Criddle models.

In summary, the Blaney–Morin–Nigeria model stands out as a locally adapted tool that improves upon traditional temperature-based ET models. Its inclusion in ET studies within Nigeria reflects the need for context-specific solutions in agricultural water management, and it provides an essential framework for irrigation scheduling where comprehensive meteorological data are lacking.

2.3 Role of Evapotranspiration in Irrigation Scheduling

2.3.1 Estimating Crop Water Requirements

Estimating crop water requirements is one of the most critical applications of evapotranspiration in irrigation management. Since ET reflects the combined water loss through soil evaporation and plant transpiration, it provides a direct measure of the water needed to sustain optimal plant growth under given climatic conditions. According to Allen et al. (1998), crop water requirement (CWR) can be defined as the depth of water needed to meet the evapotranspiration demands of a particular crop during its growth cycle without any stress.

The standard approach for estimating CWR involves calculating reference evapotranspiration (ET_o) and multiplying it by a crop coefficient (Kc) that reflects the specific water-use characteristics of different crops at different growth stages. This relationship is expressed as:

$$\mathbf{ET_c = K_c \times ET_0} \qquad \mathbf{(2.5)}$$

- ETc is the actual crop evapotranspiration
- ET_o is the reference evapotranspiration,
- Kc is the crop coefficient.

2.3.2 Irrigation Efficiency

One of the most significant contributions of evapotranspiration (ET) in agriculture is its role in enhancing irrigation efficiency. Irrigation efficiency refers to the ratio of the water beneficially used by crops to the total water applied (Michael, 2010). In many regions, inefficiencies in irrigation arise from overwatering, under-watering, and improper timing, which not only reduce crop yields but also result in the wastage of scarce water resources and increased environmental risks such as salinity buildup and nutrient leaching. Accurate estimation of ET helps minimize these inefficiencies by aligning water application with actual crop water requirements.

According to Pereira et al. (2015), integrating ET data into irrigation scheduling enables farmers to apply water only when the soil moisture falls below a critical threshold and in quantities that match the combined evaporative and transpirative demand. This reduces unnecessary water losses from percolation and runoff while maintaining optimal soil moisture for plant growth. In a study conducted in semi-arid regions of India, Rao et al. (2017) observed that ET-based irrigation scheduling improved water productivity by over 25% compared to conventional calendar-based methods.

Another advantage of using ET for irrigation efficiency is its adaptability to modern precision agriculture systems. For instance, remote sensing techniques and automated weather stations now provide near real-time ET estimates that can be linked to irrigation controllers (Allen et al., 2021). This allows for dynamic irrigation management, where water delivery systems respond to daily fluctuations in climatic conditions and crop growth stages. Such precision reduces labor inputs and ensures that water resources are conserved, particularly in regions where agriculture competes with domestic and industrial water needs.

Furthermore, ET-based irrigation strategies help in optimizing energy use. Over-irrigation often results in unnecessary pumping, which translates to higher energy costs. By synchronizing irrigation volumes with ET demand, farmers reduce both water and energy consumption, thereby lowering overall production costs (Steduto et al., 2012). This efficiency is particularly crucial in developing countries where farmers face both water scarcity and high energy prices.

However, it is important to recognize that the successful application of ET for improving irrigation efficiency depends on access to reliable climatic data and effective dissemination of information to farmers. In regions where meteorological data are scarce, simplified ET models or satellite-based data can provide alternative solutions. As highlighted by Irmak and Djaman (2016), even low-cost ET estimation methods can significantly improve irrigation practices if properly implemented.

The incorporation of ET estimates into irrigation scheduling leads to more efficient water use, reduced environmental degradation, lower energy costs, and improved crop productivity. It represents a vital component of sustainable water management in agriculture, especially in the face of increasing global water scarcity.

2.4 Evapotranspiration and Crop Yield Optimization

2.4.1 Relationship between ET and Crop Productivity

The relationship between evapotranspiration (ET) and crop productivity has long been recognized as one of the most critical aspects of agricultural water management. ET represents the total consumptive water use of crops, and its magnitude directly influences the amount of biomass produced and, consequently, the yield obtained. In principle, crop growth is strongly dependent on photosynthetic activity, which itself is linked to transpiration. As crops transpire, stomata open to allow the exchange of gases, enabling carbon dioxide uptake for photosynthesis. This physiological process establishes a direct relationship between water use through ET and the rate of biomass accumulation (Steduto et al., 2007).

According to Doorenbos and Kassam (1979), there exists a near-linear relationship between relative yield reduction and relative ET deficit across many crop types. Their widely cited yield response to water (Ky) model illustrates how deviations from potential ET due to water stress directly translate into yield penalties. For instance, crops such as maize and wheat exhibit relatively high sensitivity to ET deficits during their reproductive stages, where even slight reductions in available water significantly affect grain yield. Conversely, root crops and legumes may show less sensitivity during certain growth phases, although cumulative ET deficits still result in measurable yield losses (Pereira et al., 2015).

Several empirical and simulation-based studies have confirmed that crop yield is maximized when ET approximates the crop’s potential evapotranspiration (ETc), which represents the water requirement under optimal conditions of soil fertility and management. For example, research conducted in semi-arid regions demonstrated that deficit irrigation, which reduces ET below ETc, invariably reduces yields but may improve water productivity (yield per unit of water consumed) when applied strategically (Fereres and Soriano, 2007). This finding highlights the delicate balance between maximizing yield and optimizing resource use efficiency, especially in water-scarce regions.

The relationship between ET and yield also varies with crop type and local climate. In water-abundant environments, yield increases proportionally with ET until reaching a plateau, beyond which additional water inputs do not enhance productivity due to physiological and soil limitations (Howell, 2001). In contrast, in arid and semi-arid zones, crop yield tends to show strong sensitivity to small reductions in ET, underscoring the importance of precise irrigation scheduling and ET-based water allocation.

Moreover, crop-specific water use efficiency (WUE), defined as the ratio of biomass or grain yield to ET, is a critical determinant of how effectively a plant converts water into economic yield. For example, crops such as maize and sorghum typically exhibit higher WUE compared to crops like wheat or rice, due to their photosynthetic efficiency and lower transpiration requirements (Morison et al., 2008). This difference implies that the ET-yield relationship is not uniform across species and must be carefully considered in irrigation planning.

The relationship between ET and crop productivity is fundamental for optimizing yield and water use. While higher ET generally supports higher yields, excessive or insufficient water use relative to crop requirements leads to inefficiencies. Therefore, understanding crop-specific ET responses is essential for designing irrigation strategies that maximize both productivity and water sustainability.

2.4.2 Case Studies on Maize (Zea mays) and Rice (Oryza sativa)

Maize (*Zea mays*) and rice (*Oryza sativa*) are two of the most water-demanding cereal crops cultivated globally, and their productivity is closely tied to the balance between water availability and evapotranspiration (ET). Numerous case studies have demonstrated that effective ET estimation and management can significantly improve yields and water use efficiency for these staple crops.

In the case of maize, studies have shown that crop yield is highly sensitive to water stress, particularly during the flowering and grain-filling stages. For example, Kang et al. (2017) conducted a field study in northern China and found that maize yield decreased by up to 35% when ET demand was not met during the critical reproductive stages. Similarly, Steduto et al. (2012) observed that maize yields increased linearly with ET up to a certain threshold, after which additional water input had little to no effect, indicating diminishing returns in water productivity. These findings highlight the importance of aligning irrigation schedules with peak ET demands to avoid both under- and over-irrigation.

For rice, a crop typically grown under flooded or semi-flooded conditions, ET plays a critical role in determining both water productivity and grain yield. Research by Bouman et al. (2007) on aerobic rice systems demonstrated that maintaining ET within the optimal range improved water productivity without compromising yields, reducing water use by up to 40% compared to traditional flooded systems. In another study, Singh et al. (2018) reported that rice yields in South Asia declined significantly when cumulative ET fell below the crop’s seasonal water requirement of approximately 500–700 mm, emphasizing the crop’s sensitivity to water deficits. Furthermore, case studies in sub-Saharan Africa have revealed that adopting ET-based irrigation scheduling increased rice yields by 20–30% compared to conventional farmer-managed practices (Nkebiwe et al., 2019).

Comparative studies on maize and rice also indicate that while both crops exhibit yield reductions under ET deficits, rice tends to be more resilient to short-term water stress due to its adaptation to humid environments and ability to recover from mild water shortages. Maize, on the other hand, shows greater susceptibility to ET deficits during critical growth stages, making precise ET monitoring and irrigation scheduling crucial for sustaining high yields.

These case studies collectively emphasize the central role of ET in optimizing crop yield and water management. They suggest that incorporating ET-based irrigation practices can enhance water productivity, mitigate the effects of climate variability, and ensure food security, particularly in water-scarce regions.

2.4.3 Implications for Sustainable Agriculture

Sustainable agriculture emphasizes practices that enhance productivity while conserving natural resources and maintaining ecological balance. Evapotranspiration (ET) plays a critical role in achieving this balance, as water is one of the most limiting resources in agriculture. Understanding and managing ET effectively ensures that crops receive sufficient water for optimal growth without over-extraction from finite water resources. According to Rockström and Barron (2007), efficient ET management can enhance water productivity, enabling farmers to achieve "more crop per drop," which is central to sustainable farming systems.

ET-based irrigation scheduling helps reduce groundwater depletion and minimizes the risk of soil salinization, which is often associated with excessive irrigation. Excess water applications not only waste resources but also degrade soil health, reducing long-term agricultural productivity (Falkenmark and Rockström, 2006). By aligning water applications closely with crop ET demands, farmers can conserve water for future use while maintaining yields.

Furthermore, in regions vulnerable to climate change, the variability of rainfall and rising temperatures significantly affect ET rates. As noted by Allen et al. (2011), climate-smart agriculture must integrate ET estimation into decision-making to adapt cropping systems to changing climatic conditions. For example, drought-prone areas benefit from precise ET-based scheduling, which reduces crop failure risks and ensures efficient use of limited water supplies.

From an ecological standpoint, ET management also supports biodiversity by reducing the over-diversion of water from natural ecosystems such as rivers, lakes, and wetlands. Maintaining environmental flows alongside agricultural needs is a cornerstone of sustainable development goals (SDGs), particularly those related to zero hunger, clean water, and climate action (FAO, 2017).

In addition, integrating ET knowledge into sustainable practices encourages the adoption of modern technologies such as soil moisture sensors, remote sensing, and decision-support tools. These technologies provide farmers with real-time data to manage irrigation more sustainably, promoting resilience in food production systems. As emphasized by Kharrou et al. (2011), when ET-based water management is combined with conservation agriculture practices such as mulching, crop rotation, and minimum tillage the synergy enhances soil-water retention, reduces evaporation losses, and contributes to long-term sustainability.

In conclusion, ET is not only a determinant of crop yield but also a guiding principle for water stewardship in agriculture. Properly aligning crop water use with ET promotes resource efficiency, ecological integrity, and resilience against climate variability, thereby providing a strong foundation for sustainable agricultural systems.

2.5 Studies on Evapotranspiration in Nigeria and Other Regions

Evapotranspiration (ET) research has gained significant attention in Nigeria and other developing regions due to the increasing demand for efficient water management in agriculture. According to Ojo et al. (2019), the accurate estimation of ET is particularly important in Nigeria, where agriculture is heavily dependent on rainfall, and irrigation systems are often poorly developed. Studies have shown that variations in climatic parameters such as temperature, solar radiation, and humidity strongly influence ET rates across the country (Ogunjimi and Ayoola, 2021).

In Northern Nigeria, where semi-arid and savannah conditions prevail, researchers such as Adefisan et al. (2020) have utilized the Penman-Monteith model to estimate ET for crops like sorghum and millet. Their results demonstrated that ET-based irrigation scheduling significantly improved crop performance compared to traditional rainfall-dependent practices. Similarly, in the humid southern regions, studies by Adeboye et al. (2017) reported that ET estimates provided by the Hargreaves model, though less data-intensive, showed reasonable agreement with field measurements for crops like cassava and maize, highlighting its suitability in areas with limited climatic data.

Beyond Nigeria, several regional studies have reinforced the role of ET in water management across sub-Saharan Africa. For instance, in Ghana, Owusu-Sekyere and Kyei-Baffour (2019) observed that ET-based irrigation strategies enhanced water-use efficiency in vegetable farming, reducing water wastage by up to 25%. In Ethiopia, Alemayehu et al. (2018) noted that the Penman-Monteith method provided reliable ET estimates for wheat, but challenges in accessing consistent meteorological data limited its widespread application. This reflects a broader problem across sub-Saharan Africa, where insufficient weather stations and poor data quality constrain the accurate estimation of ET (FAO, 2020).

Applications of ET in irrigation management across the region have shown clear benefits. In a study conducted in Kenya, Mutunga et al. (2021) demonstrated that ET-based irrigation scheduling increased maize yields by 18% compared to farmers' conventional methods, while also saving significant amounts of water. Likewise, research in Sudan emphasized that using ET models in irrigation planning for rice cultivation improved water productivity and helped mitigate the effects of seasonal water scarcity (Hassan and El-Tahir, 2017).

Despite these advancements, several gaps remain in existing research. One key limitation is the over-reliance on simplified models like Hargreaves, which, although practical in data-scarce environments, may not capture the full complexity of ET dynamics under diverse climatic conditions (Obafemi et al., 2022). Additionally, there is limited integration of remote sensing technologies and GIS tools into ET studies in Nigeria, even though these methods have proven effective in countries like South Africa and Egypt (Mabhaudhi et al., 2019). Another gap lies in the lack of long-term, multi-crop comparative studies that can guide irrigation policies and support climate change adaptation strategies.

Overall, while ET research in Nigeria and sub-Saharan Africa has advanced in recent years, more work is needed to enhance data availability, model accuracy, and practical applications in irrigation scheduling. Addressing these gaps would not only improve crop yields and water efficiency but also contribute to sustainable agricultural development in the region.

CHAPTER THREE

MATERIALS AND METHODS

3.1 Research Design

This study adopts a model-based research design aimed at estimating crop evapotranspiration for two key staple crops—corn (Zea mays) and rice (Oryza sativa)—under the climatic conditions of Ovia North-East Local Government Area (LGA) of Edo State, Nigeria. Rather than relying on direct field measurement techniques such as lysimeters, which are expensive, labor-intensive, and require continuous supervision, this study utilizes mathematical models to estimate reference evapotranspiration (ET_0) using readily available climatic data. Model-based approaches are widely recognized in agricultural and environmental engineering research because they provide a cost-effective and practical way to estimate crop water requirements (Allen et al., 1998; Pereira et al., 2015).

Two models were selected for this study: the Blaney–Morin–Nigeria (BMN) model and the Hargreaves–Samani model. The choice of these models is deliberate and strategic. The BMN model, developed by Duru (1984) and later refined by Idike (2005), is a localized adaptation of the Blaney–Morin equation, specifically designed to suit Nigerian climatic conditions. Unlike the traditional Blaney–Criddle method, the BMN model incorporates relative humidity (RH) alongside temperature and daylength, making it better suited for Nigeria's humid and sub-humid regions. Previous studies have shown that BMN produces evapotranspiration estimates that closely match results from more complex models like FAO-56 Penman–Monteith while requiring fewer input variables (Obafemi et al., 2022).

The Hargreaves–Samani model, on the other hand, is a temperature-based empirical method that estimates reference evapotranspiration using only daily maximum and minimum temperatures and extraterrestrial radiation (R_a) computed from the latitude of the location (Hargreaves and Samani, 1985). It is widely recommended for use in data-scarce regions because it does not require humidity, wind speed, or solar radiation data, which are often unavailable in developing countries.

While simpler and less data-intensive, its accuracy is generally lower than more comprehensive models, which is why it is often used for comparison and validation purposes (Allen et al., 1998).

By combining these two models, the study achieves a balance between local adaptation and global applicability. The BMN model represents a region-specific approach calibrated for Nigerian conditions, while the Hargreaves model provides a globally recognized benchmark for low-data scenarios. The comparison of their outputs will reveal which model is more reliable for estimating ET in Ovia North-East, thereby guiding farmers, agricultural planners, and policymakers in making informed decisions about irrigation scheduling, water resource management, and climate-smart agricultural practices.

All meteorological data required for this study, including daily maximum and minimum temperatures and relative humidity, were obtained from the Nigerian Institute for Oil Palm Research (NIFOR) meteorological station located within Ovia North-East. The reliance on a single, consistent data source ensures accuracy and reduces the uncertainty associated with combining datasets from multiple locations.

This comparative model-based research design thus provides a practical and scientifically robust framework for addressing crop water requirement challenges in southern Nigeria, particularly for staple crops like corn and rice.

3.2 Description of the Study Area

The study was carried out in Ovia North-East Local Government Area (LGA), located in Edo State, southern Nigeria. Ovia North-East is part of the Benin agricultural region and is recognized as a vital food production area in the state. Geographically, the area lies approximately between latitude 6°25′N and 6°50′N and longitude 5°15′E and 5°45′E, with an average elevation of about 77 meters above sea level (Akinbode et al., 2018). This strategic location places it within the humid tropical climate zone of southern Nigeria, which significantly influences agricultural activities and water requirements for crops.

Figure 3.1: A map of the study area.

Source: Esri, Garmin, USGS and Geospatial Links Company (2022)

Climate

The climate of Ovia North-East is typically humid and tropical, characterized by high rainfall and relative humidity. Rainfall follows a bimodal pattern, with two distinct rainy seasons:

- Major rainy season: April to July

- Minor rainy season: September to November

The mean annual rainfall ranges between 2,000 mm and 2,500 mm, providing sufficient natural water for rainfed agriculture. Temperatures are relatively stable throughout the year, with daily mean values between 24°C and 32°C, while relative humidity averages 70%–85%, especially during the wet season (Okeke et al., 2019). Sunshine duration varies with the seasons, ranging from 4 to 6 hours per day, with the highest levels during the dry season. Wind speeds are generally moderate, averaging 1–3 m/s, and play a minimal role in evapotranspiration in this region (Ojeh et al., 2020).

Soils and Agriculture

The dominant soils in Ovia North-East are ferrallitic and sandy loam soils, derived from coastal plain sands. These soils are generally well-drained, though they often have low natural fertility and require proper nutrient management for sustainable crop production (Adu et al., 2017). Agriculture is the primary economic activity in the region, with both subsistence and commercial farming widely practiced. Corn (*Zea mays*) is one of the most commonly cultivated staple crops due to its short growing cycle and versatility in local diets. Rice (*Oryza sativa*), though traditionally more dominant in northern Nigeria, is increasingly cultivated in low-lying areas of Ovia North-East due to government incentives and rising demand for locally produced rice (Ekunwe and Orewa, 2018). Other important crops include cassava, yam, plantain, and various vegetables.

Significance of the Study Area

Ovia North-East was selected as the study area due to its agricultural importance and its climatic diversity, which requires efficient water management strategies for sustainable crop production. The area is also home to the Nigerian Institute for Oil Palm Research (NIFOR), which maintains a meteorological station that provides high-quality climatic data such as temperature and relative humidity. This availability of reliable, location-specific data ensures accurate application of the selected evapotranspiration models (BMN and Hargreaves) in this research.

Given the increasing pressure on water resources, the findings from this study will provide valuable insights into irrigation scheduling and crop water management for corn and rice farmers in Ovia North-East and similar agro-ecological zones across southern Nigeria.

3.3 Data Collection

The reliability of evapotranspiration estimation depends heavily on the accuracy and quality of the input data. For this study, data were collected in two main categories: meteorological data and crop data, both of which are essential for estimating reference evapotranspiration (ET_0) and crop evapotranspiration (ET_c) for corn and rice.

3.3.1 Meteorological Data

The meteorological variables required depend on the selected models (BMN and Hargreaves). For this study, the following parameters were collected:

1. Maximum temperature (T_{max}) – daily maximum air temperature (°C)
2. Minimum temperature (T_{min}) – daily minimum air temperature (°C)
3. Mean temperature (T_{mean}) – computed as (T_{max} + T_{min})/2 (°C)
4. Relative humidity (RH) – daily average relative humidity (%) *(for BMN model only)*
5. Latitude of the study area – for computing daylength and extraterrestrial radiation (R_a) used in both BMN and Hargreaves calculations
6. Daylength data (p) – calculated using latitude and month, as required by the BMN model.

Source of Meteorological Data:

All meteorological data were obtained from the Nigerian Institute for Oil Palm Research (NIFOR) meteorological station, located within Ovia North-East. NIFOR maintains a fully equipped weather station that records high-resolution daily climatic data, ensuring reliability and consistency for scientific studies. Using a single-source dataset minimizes discrepancies that could arise when combining data from multiple sources and enhances the validity of the model results.

3.3.2 Crop Data

In addition to climatic data, crop-specific information was collected to estimate crop evapotranspiration (ET_c). The most important crop data required are crop coefficients (K_c), which account for the physiological and structural characteristics of corn (*Zea mays*) and rice (*Oryza sativa*). These coefficients vary with crop growth stages:

- Initial stage – germination and early growth
- Mid-season stage – peak canopy development and maximum transpiration
- Late-season stage – maturity and pre-harvest phase

For this study, K_c values were sourced primarily from FAO-56 guidelines (Allen et al., 1998) and supplemented with findings from local Nigerian studies (Ogunjimi et al., 2020; Yusuf and Adeniran, 2021). This approach ensures that the selected coefficients are both globally recognized and locally relevant.

Table 3.1: *Crop Coefficient (Kc) Values for Corn (Maize) and Rice (Paddy) at Different Growth Stages*

Crop	Initial (Kc)	Mid-Season (Kc)	Late Season (Kc)
Corn (Maize)	0.30 – 0.40	1.15 – 1.20	0.60 – 0.70
Rice (Paddy)	1.05 – 1.10	1.20 – 1.25	0.90 – 1.00

Source: Adapted from Allen et al. (1998) *FAO-56 Crop Evapotranspiration Guidelines* and Ogunjimi et al. (2020).

3.3.3 Temporal Scale of Data

The study focuses on one complete growing season of corn and rice within Ovia North-East.

- Monthly climatic data from NIFOR were first collected and processed to estimate daily reference evapotranspiration (ET_0).
- These values were then aggregated into monthly averages to simplify interpretation and comparison between the BMN and Hargreaves models.
- Crop coefficient data were applied to corresponding growth stage periods to compute crop evapotranspiration (ET_c).

The temporal resolution of daily data ensures that short-term variations in weather are captured, while monthly aggregation facilitates trend analysis and decision-making for irrigation scheduling.

3.4 Estimation of Reference Evapotranspiration (ET_0)

3.4.1 Hargreaves–Samani Method

Formula (daily time step).

As originally proposed by Hargreaves and Samani (1985), daily reference evapotranspiration is estimated with a temperature-based expression that uses only maximum–minimum temperature and extraterrestrial radiation:

$$\mathbf{ET_0 = 0.0023\,(T_{mean}+17.8)\,(T_{max} - T_{min})^{0.5}\,R_a}$$

Where:

- T_{mean}, T_{max} and T_{min} are the mean, maximum, and minimum daily air temperatures (°C) respectively,
- R_a is the extraterrestrial radiation (MJ/ m^2day) computed from latitude and day of year. FAO-56 documents and standardizes the implementation of this method for agronomic use (Allen, Pereira, Raes, and Smith, 1998).

Explanation of variables and how they are obtained for this study.

- T_{max}, T_{min} (°C): Daily series obtained from the NIFOR meteorological station in Ovia North-East.
- T_{mean} (°C): Calculated as (T_{max} + T_{min})/2.
- R_a (MJ m^{-2} day^{-1}): Computed from site latitude and day of year using FAO-56 solar geometry routines i.e., inverse relative Earth–Sun distance, solar declination, and sunset hour angle. FAO provides equations and tables to produce daily $R_a$values for any latitude (Allen et al., 1998).

Computation procedure (step-by-step, descriptive).

1. Assemble inputs. Retrieve daily T_{max} and T_{min} from NIFOR for the study period; extract site latitude.
2. Compute mean temperature. For each day, set $T_{mean} = T_{max} + T_{min} /2$.
3. Calculate extraterrestrial radiation R_a . Using the latitude and calendar day, compute R_a following FAO-56 solar geometry (solar declination δ, inverse relative distance d_r and sunset hour angle ω_s); alternatively, use FAO-56 R_a tables for the site latitude. Allen et al. (1998) detail both paths.
4. Evaluate the Hargreaves equation. Insert $T_{mean,}$ $(T_{max}–T_{min})^{0.5}$, and R_a in the equation to obtain daily ET_0 (mm/day).
5. Aggregate for analysis. Sum or average daily ET_0 to monthly scales for comparison with the BMN method and for subsequent ET_c estimation.
6. Quality control (recommended). Screen for obvious data issues (e.g., $T_{max} < T_{min}$, implausible temperature ranges). Where short gaps exist, document any gap-filling rules before computation, as advised in FAO-56 (Allen et al., 1998).

3.4.2 Blaney–Morin–Nigeria (BMN) Method

The Blaney–Morin–Nigeria (BMN) method is a locally adapted model for estimating reference evapotranspiration (ET_0) in Nigeria. It is a modification of the original Blaney–Morin equation, designed to incorporate the unique climatic conditions of Nigeria, especially in humid and sub-humid regions. This model was developed by Duru (1984) and later refined by Idike (2005), who introduced constants specific to different ecological zones in Nigeria to improve accuracy when compared with more data-intensive methods like the FAO-56 Penman–Monteith.

The BMN model is particularly valuable because it uses minimal data inputs, which makes it ideal for regions where meteorological data such as solar radiation, wind speed, and humidity are limited or unavailable. For this study, all required climatic data—daily temperature and relative humidity—were sourced from the NIFOR meteorological station.

(a) Formula for BMN Method

The BMN model is mathematically expressed as:

$$\mathbf{ET_0 = p.\ (0.45T + 8)\ (H - R_m)\ x\ \frac{1}{100}}$$

where:

- ET_0 = potential / reference evapotranspiration (mm day^{-1})
- p = ratio of maximum sunshine hours for the period of interest to the annual maximum (dimensionless; sometimes replaced by a radiation ratio r_f)
- T = mean air temperature (°C) (usually $(T_{max} + T_{min})/2$
- R = mean relative humidity (%) for the period (use same units as in model — i.e., percent)
- H and m = empirical constants determined by calibration
- division by 100 brings the scaling to mm/day in the original formulation.

(b) Typical Constant Values for Southern Nigeria

According to Duru (1984) and supported by later studies such as Echiegu et al. (2016), the following constants are typically used for the humid southern agro-ecological zone where Ovia North-East is located:

- H=520
- m=1.31

These constants were derived from experimental data collected across southern Nigeria. However, later research such as Echiegu et al. (2016) has shown that slight local recalibration may improve the model's performance. For this study, Duru's original constants are used because they have been validated across similar humid regions in Nigeria.

(c) Computation of Daylength Fraction (p)

The daylength fraction (p) adjusts evapotranspiration estimates to account for the variation in daylight hours throughout the year. It is computed as:

$$\mathbf{P = \frac{N}{12}}$$

Where:

- N = actual daylength in hours

The value of N depends on the latitude (φ) of the study location and the day of the year (J), using FAO-56 equations:

1. Solar declination (δ):

$$\boldsymbol{\delta = 0.409 \cdot \sin\left(\frac{2\pi J}{365} - 1.39\right)}$$

2. Sunset hour angle (ω_s):

$$\boldsymbol{\omega_s = \cos^{-1}(-\tan\varphi \cdot \tan\delta)}$$

   - φ = latitude in radians (Ovia North-East ≈ 6.4°N = 0.1117 rad)

3. Actual daylength (N):

$$\mathbf{N = \frac{24}{\pi} \cdot \omega_s}$$

Finally, substitute N into $P = \frac{N}{12}$

In Ovia North-East, ppp typically ranges between 0.95 and 1.05, depending on the season.

(d) Computation Procedure for BMN

The following steps outline how ET_0 is computed using the BMN model:

1. Collect meteorological data:

   Obtain daily maximum and minimum temperatures (T_{max}, T_{min}) and relative humidity (RH) from the NIFOR meteorological station.

2. Calculate mean daily temperature (T):

$$\mathbf{T = \frac{Tmax+Tmin}{2}}$$

3. Determine daylength fraction (p):
   - Compute δ (solar declination), ω_s (sunset hour angle), and N (daylength).
   - Compute p
4. Raise relative humidity to the exponent m:

$$\mathbf{R^m}$$

5. Substitute values into the BMN formula to compute daily ET_0.
6. Aggregate the daily results into weekly or monthly totals for analysis and comparison with the Hargreaves method

The BMN model was developed specifically for Nigeria's diverse climatic conditions. According to Duru (1984), the inclusion of relative humidity as a key factor allows the model to perform well in humid southern regions, where high humidity significantly influences evapotranspiration rates. Later evaluations by Idike (2005) and Echiegu et al. (2016) confirmed that the BMN model produces estimates comparable to more complex models like FAO-56 Penman–Monteith but with fewer input requirements. This makes BMN ideal for rural or data-scarce regions.

Key advantages of using BMN in this study include:

- Locally calibrated constants: H and m were derived from Nigerian field data, ensuring the model's relevance for Ovia North-East and similar regions.
- Minimal data needs: Only temperature, humidity, and latitude are required, unlike FAO-56, which needs solar radiation, wind speed, and other variables.
- Practicality for farmers and planners: Results from BMN can be easily integrated into irrigation scheduling and water management practices without sophisticated equipment.

By applying the BMN model to daily climatic data from the NIFOR station, this study will generate reliable estimates of reference evapotranspiration for corn and rice, two key staple crops in Edo State. These results will then be compared to those generated by the Hargreaves method to evaluate model performance under local climatic conditions.

3.5 Estimation of Crop Evapotranspiration (ETc)

Once the reference evapotranspiration (ET_0) has been determined using the BMN and Hargreaves models, the next step is to estimate crop evapotranspiration (ET_c), which represents the actual water requirement of a specific crop under standard, non-stressed conditions. This is achieved by multiplying (ET_0) by a crop coefficient (K_c), which adjusts the reference value to account for the characteristics and growth patterns of each crop (Allen et al., 1998).

The formula is given as:

$$\mathbf{ET_c = K_c \times ET_0}$$

Where:

- ET_c = Crop evapotranspiration (mm/day)
- K_c = Crop coefficient (dimensionless)
- ET_0 = Reference evapotranspiration (mm/day) obtained from either BMN or Hargreaves models

(a) Concept of Crop Coefficients (K_c)

The crop coefficient (K_c) reflects how a particular crop interacts with climatic conditions to influence water use. It considers factors such as:

- Crop type (corn vs. rice),
- Stage of development,
- Canopy structure,
- Plant density, and
- Crop physiology (e.g., stomatal behavior).

As crops grow, their water requirements change significantly. For this reason, K_c values are not constant but vary across three primary growth stages as recommended by FAO-56 (Allen et al., 1998):

Table 3.2: Description of Crop Growth Stages and Typical Crop Coefficient (Kc) Ranges.

Growth Stage	Description	K_c Range (Typical)
Initial Stage	Germination and early seedling development, when soil evaporation is dominant and plant water uptake is minimal.	0.30 – 0.40
Mid-Season Stage	Peak canopy coverage, flowering, and grain-filling period; water demand is highest due to maximum transpiration.	1.15 – 1.25
Late-Season Stage	Maturity and pre-harvest phase, when plant growth slows and transpiration decreases.	0.60 – 0.80

Source: Adapted from Allen et al. (1998) *FAO-56 Crop Evapotranspiration Guidelines* and Ogunjimi et al. (2020).

(b) Crop Coefficient Stages for Corn and Rice

For this study, K_c values specific to corn (*Zea mays*) and rice (*Oryza sativa*) were used. These values were sourced from FAO-56 guidelines and corroborated with findings from local Nigerian studies to ensure relevance to Ovia North-East’s climatic conditions.

(c) Data Sources for K_c Values

The K_c values used in this study were obtained primarily from:

1. FAO-56 Guidelines (Allen et al., 1998):
   - Globally recognized source for standardized crop water requirements.
   - Provides stage-specific K_c values for both corn and rice.
2. Local Nigerian Studies:
   - Studies such as Ogunjimi et al. (2020) and Yusuf and Adeniran (2021) provided locally validated crop coefficients under Nigerian tropical conditions.
   - These studies were consulted to ensure that the selected K_c values reflect realistic field conditions in Ovia North-East.

By combining global and local sources, the study ensures that K_c values are accurate and relevant to the prevailing climate, soil, and farming practices in the region.

(d) Procedure for Estimating ETc

1. Obtain daily ET_0 values:
   - Compute reference evapotranspiration using both BMN and Hargreaves models for each day of the growing season.
2. Assign K_c values by growth stage:
   - Identify the start and end dates of each growth stage for corn and rice.
   - Match each day's ET_0 with the appropriate K_c value.
3. Calculate daily ET_c:

$$\mathbf{ET_c = K_c \times ET_0}$$

4. Aggregate results:
   - Sum daily ET_c values to obtain weekly, monthly, or seasonal water requirements.
   - These totals help in planning irrigation schedules and assessing crop water use.

(e) Significance of ETc Estimation

Accurately estimating ET_c is essential because it:

- Supports efficient irrigation scheduling by ensuring that water applications match actual crop demand, minimizing waste.
- Prevents water stress during critical growth stages, protecting crop yields.
- Guides sustainable water management, especially in regions facing water scarcity or competing agricultural demands.
- Provides a basis for model comparison when evaluating the performance of BMN versus Hargreaves in predicting crop-specific evapotranspiration.

After estimating reference evapotranspiration (ET_0) using both the Blaney–Morin–Nigeria (BMN) and Hargreaves–Samani models, it is important to evaluate how well these models perform under the climatic conditions of Ovia North-East, Edo State.
The comparison will determine which model provides more accurate and reliable estimates, guiding its use in crop water requirement calculations and irrigation planning for corn and rice cultivation in the region.

This evaluation is carried out in two stages:

1. Direct comparison of model outputs:
   - Plotting daily, weekly, or monthly ET_0 values from both models to visualize patterns and differences.
   - Identifying systematic overestimation or underestimation trends.
2. Statistical performance assessment:
   - Applying statistical indicators to quantify model accuracy, bias, and reliability.

(a) Statistical Evaluation Metrics

Several statistical indicators are widely used in evapotranspiration model validation (Legates and McCabe, 1999; Willmott et al., 2012).

For this study, the following metrics will be computed:

1. Mean Bias Error (MBE):

Indicates whether a model systematically overestimates or underestimates ET values.

$$\mathbf{MBE} = \frac{1}{n} \sum_{i=1}^{n} 1(P_i - O_i)$$

where P_i is the predicted value (BMN) and O_i the reference value (FAO-56).

- Positive MBE = overestimation
- Negative MBE = underestimation

2. Root Mean Square Error (RMSE):

Measures the overall magnitude of error, giving more weight to larger deviations.

$$\mathbf{MBE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} 1\,(Pi - Oi)2}$$

A smaller RMSE indicates closer agreement between models.

3. Coefficient of Determination (R^2):

Quantifies how much of the variance in FAO-56 ET values can be explained by BMN.

Coefficient of Determination Formula

$$r = \frac{n(\Sigma xy) - (\Sigma x)(\Sigma y)}{\sqrt{\left[n\Sigma x^2 - (\Sigma x)^2\right]\left[n\Sigma y^2 - (\Sigma y)^2\right]}}$$

R^2 values close to 1.0 indicate strong correlation between models.

4. Nash–Sutcliffe Efficiency (NSE):

Assesses the predictive skill of BMN relative to FAO-56.

$$\mathrm{NSE} = 1 - \frac{\sum_{t=1}^{T}\left(Q_o^t - Q_m^t\right)^2}{\sum_{t=1}^{T}\left(Q_o^t - \overline{Q}_o\right)^2}$$

NSE values:

- 1 = perfect match
- 0 = model performs as well as the mean of observed data
- Negative values = model performs worse than average

(b) Model Performance Ranking

The two models (BMN and Hargreaves) will be ranked based on:

1. Lowest RMSE – indicating smallest prediction error,
2. MBE close to zero – showing minimal bias,
3. Highest R^2 and NSE – demonstrating strong correlation and predictive skill.

The model meeting these criteria will be considered better suited for the humid tropical conditions of Ovia North-East.

(c) Practical Application

Once the most reliable model is identified:

- Its daily ET_0 estimates will be used to compute crop evapotranspiration (ET_c) for corn and rice.
- Results will inform irrigation scheduling, ensuring efficient water use and improved crop yields.
- The findings will also guide local agricultural engineers, farmers, and policymakers on which ET estimation model to adopt for sustainable water management in Edo State.

(d) Summary of Comparison Process

1. Compute daily ET_0 using BMN and Hargreaves methods.
2. Aggregate data into weekly or monthly averages for better interpretation.
3. Use statistical indicators (MBE, RMSE, R^2, NSE) to evaluate performance.
4. Identify the model with the best combination of low error and high correlation.
5. Provide recommendations for irrigation planning and model selection.

By applying these steps, the study ensures a rigorous and objective assessment of the two models, providing actionable insights for optimizing crop water management in Ovia North-East.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.0 Introduction

This chapter presents and analyzes the results of evapotranspiration estimation for corn and rice in Ovia North-East, Edo State, Nigeria. The primary objective of this study is to compare the performance of two empirical models the Hargreaves and the Blaney–Morin Nigeria (BMN) methods in estimating reference evapotranspiration (ET_0) under local climatic conditions. Monthly climatic data obtained from the Nigerian Institute for Oil Palm Research (NIFOR) were used as the basis for the computations. The comparison aims to identify the model that best reflects the climatic characteristics of the study area and provides a reliable basis for irrigation planning and water resource management.

4.1 Discussion of Results

This section presents the climatic characteristics of Ovia North-East, Edo State, using meteorological data obtained from NIFOR for the period 2020–2024. The parameters analyzed include air temperature, relative humidity, solar radiation, and sunshine duration. These variables are crucial for understanding evapotranspiration dynamics, as they influence the energy balance and vapor pressure conditions that govern water loss from crop and soil surfaces.

4.1.1 Air Temperature Trends (2020–2024)

Table 4.1 presents the monthly maximum and minimum air temperature values recorded between 2020 and 2024. The data highlight inter-annual variations and seasonal trends that characterize the humid tropical climate of southern Nigeria.

Table 4.1: Monthly Maximum and Minimum Air Temperature (°C) for 2020–2024

AIR TEMPERATURE (MAX AND MIN) ^{0}C										
	2020		2021		2022		2023		2024	
	MAX	MIN	MAX	MIN	MAX	MIN	MAX	MIN	MAX	MIN
JAN	31.9	22.5	33.5	23.4	31.4	23.5	34.1	23.4	33.9	25.4
FEB	32.6	22.5	33.5	24.9	32.6	24.9	34.5	24.8	32.9	24.1

MAR	31.5	23.2	32.5	24.7	31.9	26.1	32.2	23.1	32.1	25.9
APR	32.6	23.7	32.5	24.4	31.1	24.2	33.8	26.1	33.2	25.5
MAY	32.3	25.1	31.8	24.3	30.6	23.5	32.8	25.4	30.2	24.2
JUN	30.2	24.2	30.8	23.1	29.9	22.2	29.6	24.1	29.9	22.7
JUL	28.9	26	28.5	23.5	28.9	23.7	29.2	24.7	30.4	23.6
AUG	28.9	23.8	27.5	24.1	29.9	23.4	28.4	24	29.6	24.4
SEPT	28.4	23.2	29.3	23.7	28.5	23.6	29.4	24.2	31.6	24.2
OCT	35.9	27.4	27.6	24.2	30.5	24.5	30.8	23.5	31.6	24.5
NOV	31.7	25.1	31.4	24.3	31.9	24.9	30.8	25.3	33.2	23.7
DEC	31.8	25	32.3	24.4	33.2	24.2	33.9	23.3	35.4	21.9
TOTAL	376.7	292.9	371.2	289	368.4	288.7	379.5	291.9	383.8	290.1
MEAN	31.4	24.4	30.9	24.1	30.7	24.1	31.6	24.3	32	24.2

Source: NIFOR Meteorological Data (2020–2024).

To better interpret the thermal regime, Table 4.2 summarizes the mean monthly maximum, minimum, and average air temperatures for Ovia North-East during the study period. This representation gives a clearer picture of temperature fluctuations across the year.

Table 4.2: Mean Monthly Maximum, Minimum, and Average Air Temperature (°C) in Ovia North-East (2020–2024)

	MAX	MIN	MEAN
JAN	32.96	23.64	28.3
FEB	33.22	24.24	28.73
MAR	32.04	24.6	28.32
APR	32.64	24.78	28.71
MAY	31.54	24.5	28.02
JUN	30.08	23.26	26.67
JUL	29.18	24.3	26.74
AUG	28.86	23.94	26.4
SEPT	29.44	23.78	26.61
OCT	31.28	24.82	28.05

NOV	31.8	24.66	28.23
DEC	33.32	23.76	28.54

Source: NIFOR Meteorological Data (2020–2024).

The mean monthly maximum temperature over the study period ranged between 28.4 °C and 35.9 °C, while the mean monthly minimum temperature ranged between 21.9 °C and 27.4 °C. The highest temperatures were generally observed between January and April, which corresponds to the dry season, while the lowest occurred during July to September, coinciding with the rainy season (Table 4.1). On a multi-year average, the highest maximum temperature was recorded in October 2020 (35.9 °C) and the lowest in September 2020 (28.4 °C). This pattern aligns with previous studies in southern Nigeria (Akinbile et al., 2020; Olaniran and Fasona, 2019), where higher solar radiation during dry months increases thermal intensity and, consequently, potential evapotranspiration (ET_0). The relatively stable minimum temperatures throughout the year also reflect the region's humid tropical climate, which moderates nocturnal cooling due to persistent moisture in the atmosphere.

4.1.2 Relative Humidity Variation (2020–2024)

Table 4.3 shows monthly mean relative humidity values at 09:00 and 15:00 hours for each year between 2020 and 2024. These readings illustrate the diurnal and seasonal variations that affect the vapor pressure deficit and, consequently, evapotranspiration rates.

Table 4.3: Monthly Mean Relative Humidity (%) at 09:00 and 15:00 Hours (2020–2024)

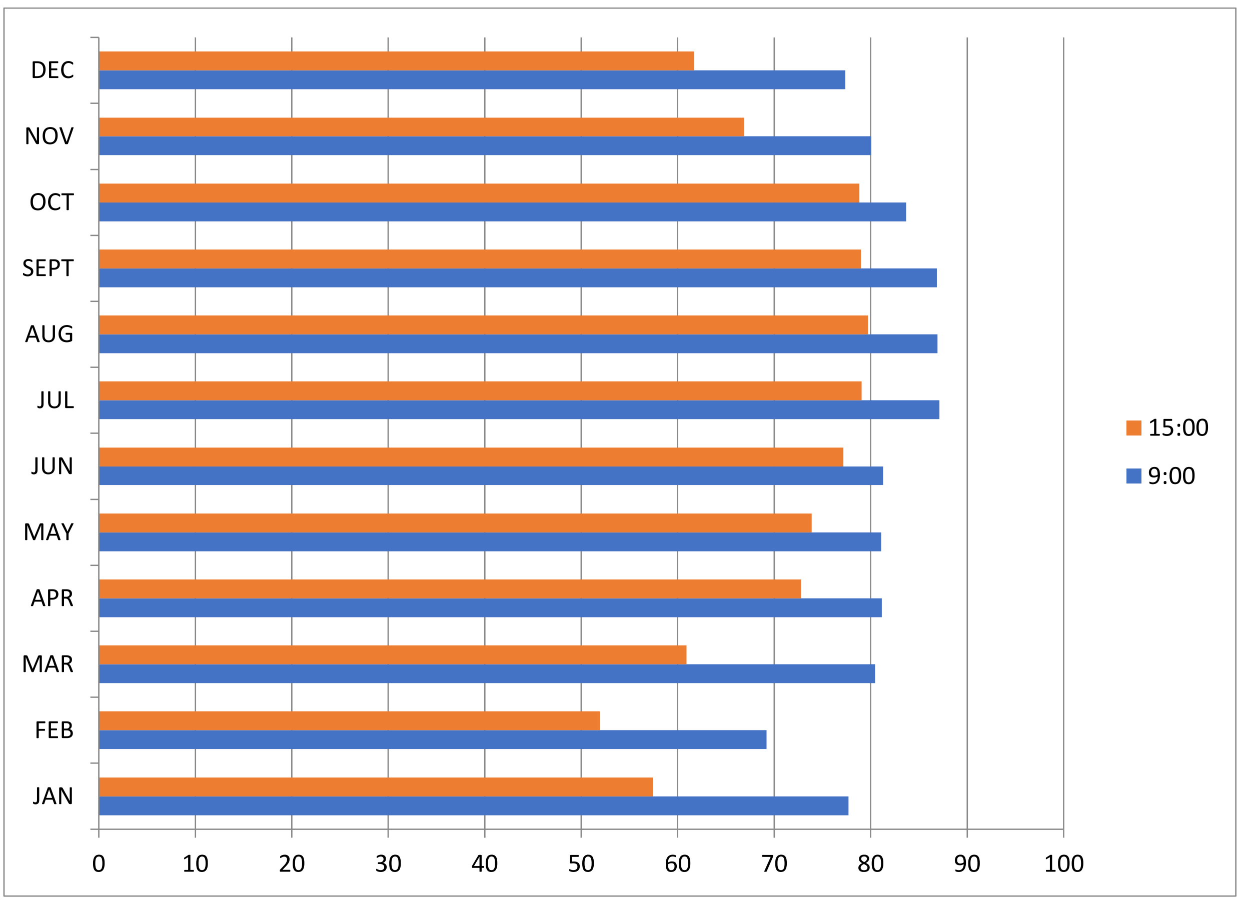
RELATIVE HUMIDITY (MEAN MONTHLY) in %										
	2020		2021		2022		2023		2024	
	9:00	15:00	9:00	15:00	9:00	15:00	9:00	15:00	9:00	15:00
JAN	77.2	47.9	84.6	66.8	74.5	63	73.3	51.7	78.9	57.7
FEB	72.1	56.4	66.8	45.5	77.7	56	64.1	47.2	65.3	54.7
MAR	82.4	47	77	63	86.1	67.8	79	62.3	77.8	64.5
APR	78.4	70.8	80.8	69.5	84.1	75.3	83.6	80.5	78.8	67.8
MAY	79.9	69	80.1	69.9	83.1	77.6	83.8	77.2	78.6	75.7

JUN	78.4	73.3	80.2	76.2	79.4	77.8	87.1	82.1	81.3	76.5
JUL	89	82.2	85.4	74.1	86.8	77.7	85.4	81.2	89.1	80.1
AUG	85.3	74.9	88.1	80.6	87.9	80.9	86.7	83.4	86.6	78.8
SEPT	87.9	77.7	85.3	77.2	86.3	80.5	88.1	84.2	86.7	75.4
OCT	90.3	77.6	82.2	83.3	83.8	77.8	82.2	78.6	79.8	76.9
NOV	82.5	67.4	82.5	76.2	79.9	65.4	79.1	68.9	76.3	56.6
DEC	84.3	66.8	88.6	77	72.5	61.9	72.5	58.2	69	44.7
TOTAL	987.7	812.8	981.6	849.1	982.1	861.4	967.9	855.5	948.2	809.4
MEAN	82.3	67.7	81.8	70.8	81.8	71.8	80.7	71.3	79	67.5

Source: NIFOR Meteorological Data (2020–2024).

Figure 4.1 provides a summary of mean relative humidity values at 09:00 and 15:00 hours, alongside their overall averages. This condensed form aids interpretation of general seasonal humidity trends in the study area.

Figure 4.1: Mean Monthly Relative Humidity (%) in Ovia North-East (2020–2024)



Source: NIFOR Meteorological Data (2020–2024).

Relative humidity exhibited a distinct seasonal pattern, with higher values during the wet season (June–October) and lower values during the dry season (December–March). Morning humidity values averaged around 80–87%, while afternoon values dropped to 60–70%, indicating a typical diurnal decline due to daytime heating.

These findings agree with Adeyemi et al. (2021), who reported similar humidity patterns in the Niger Delta region, where maritime influences sustain high atmospheric moisture. This inverse relationship between temperature and humidity directly affects ET_0, as higher temperatures with lower humidity increase atmospheric water demand. The trend observed is consistent with FAO's (1998) observation that relative humidity above 70% generally reduces evapotranspiration due to decreased vapor pressure gradients.

4.1.3 Solar Radiation and Sunshine Duration (2020–2024)

Table 4.4 summarizes the monthly solar radiation data for the five-year period. Solar radiation provides the energy required for evaporation and transpiration, making it a key determinant of ET_0 variability across seasons.

Table 4.4: Monthly Solar Radiation (MJ/m^2) in Ovia North-East (2020–2024)

SOLAR RADIATION						
Month	2020	2021	2022	2023	2024	MEAN
Jan	437.1	390.6	426.4	406.1	406.5	413.34
Feb	426.1	378.9	427	437.3	429	419.66
Mar	366	359.1	361.3	415.5	410.1	382.4
Apr	359.4	479.2	360.8	415.6	394.9	401.98
May	393	493.6	337.7	424.3	425.2	414.76
Jun	273.2	451.6	313	330.9	330.4	339.82
Jul	284.8	311.5	291.4	324.3	246.7	291.74
Aug	331.8	281.3	296.6	293.6	284.7	297.6
Sept	304	295.4	323.2	321.6	267.9	302.42

Oct	363	370.1	395.9	381.3	280.1	358.08
Nov	435.4	368.5	544.2	386.3	284.7	403.82
Dec	427.5	405.2	460.2	560.3	379.6	446.56
Total	4401.3	4485	4537.7	4697.1	4139.8	4452.18
Mean	636.8	373.8	378.1	391.4	344.9	425

Source: NIFOR Meteorological Data (2020–2024).

Average monthly solar radiation peaked at approximately 437 MJ/m² in February, coinciding with the dry season, and declined to about 247 MJ/m² in July, during the peak rainy season. This inverse relationship between radiation and rainfall indicates that clear skies in dry months enhance solar energy input.

According to FAO-56 (Allen et al., 1998), solar radiation typically drives the bulk of ET_0 in tropical climates, contributing up to 80% of total evapotranspiration energy demand. The observed radiation pattern therefore corroborates the high ET_0 values during dry months obtained from both BMN and Hargreaves models in subsequent sections.

Table 4.5 presents the total monthly sunshine duration over the five-year period. Sunshine hours represent actual sunlight received at ground level and correlate strongly with radiation intensity and evapotranspiration.

Table 4.5: Monthly Total Sunshine Duration (Hours) in Ovia North-East (2020–2024)

TOTAL SUNSHINE HOURS						
Month	2020	2021	2022	2023	2024	MEAN
Jan	178.4	221.1	200.9	181.7	183.2	193.06
Feb	105.3	137.5	178.6	143.3	815.5	276.04
Mar	138.8	140.2	148.3	151.7	167.8	149.36
Apr	167	178.2	151.5	129.1	179.2	161
May	178	158.8	146.4	198.4	181.5	172.62
Jun	108.9	111.4	84.2	99.9	111.1	103.1
Jul	70.4	117.5	73.8	91.5	95	89.64

Aug	103	81	57.9	52.5	70.5	72.98
Sept	58.9	127.8	76	95.8	104.7	92.64
Oct	82.1	142.5	129.7	99.1	141.2	118.92
Nov	109.9	202.5	183.5	14.8	181.2	138.38
Dec	107.4	199.5	205.3	214.8	216.2	188.64
Total	1408.1	1818	1636.1	1472.6	2447.1	1756.38
Mean	117.3	151.5	136.3	122.7	203.9	146.34

Source: NIFOR Meteorological Data (2020–2024).

Sunshine duration ranged from about 70 hours in July–August to over 200 hours in December–February, showing that clearer skies dominate the dry months. These values are consistent with those reported by Nfor et al. (2022) for similar latitudes in the South-South region.

The prolonged sunshine and increased radiation during the dry months intensify crop water requirements, while reduced sunshine in the wet season limits energy availability for evapotranspiration. Thus, both parameters solar radiation and sunshine duration serve as complementary indicators of atmospheric evaporative potential.

4.2 Comparison of Reference Evapotranspiration (ET_0) Values from BMN and Hargreaves Models

The Hargreaves–Samani and the Blaney–Morin–Nigeria (BMN) models were applied to the same climatic dataset (2020–2024) to evaluate their relative performance under the humid tropical conditions of Ovia North-East. The Hargreaves model relies primarily on air temperature and solar radiation, while the BMN model integrates relative humidity and daylength factors, making it more responsive to local atmospheric moisture variations.

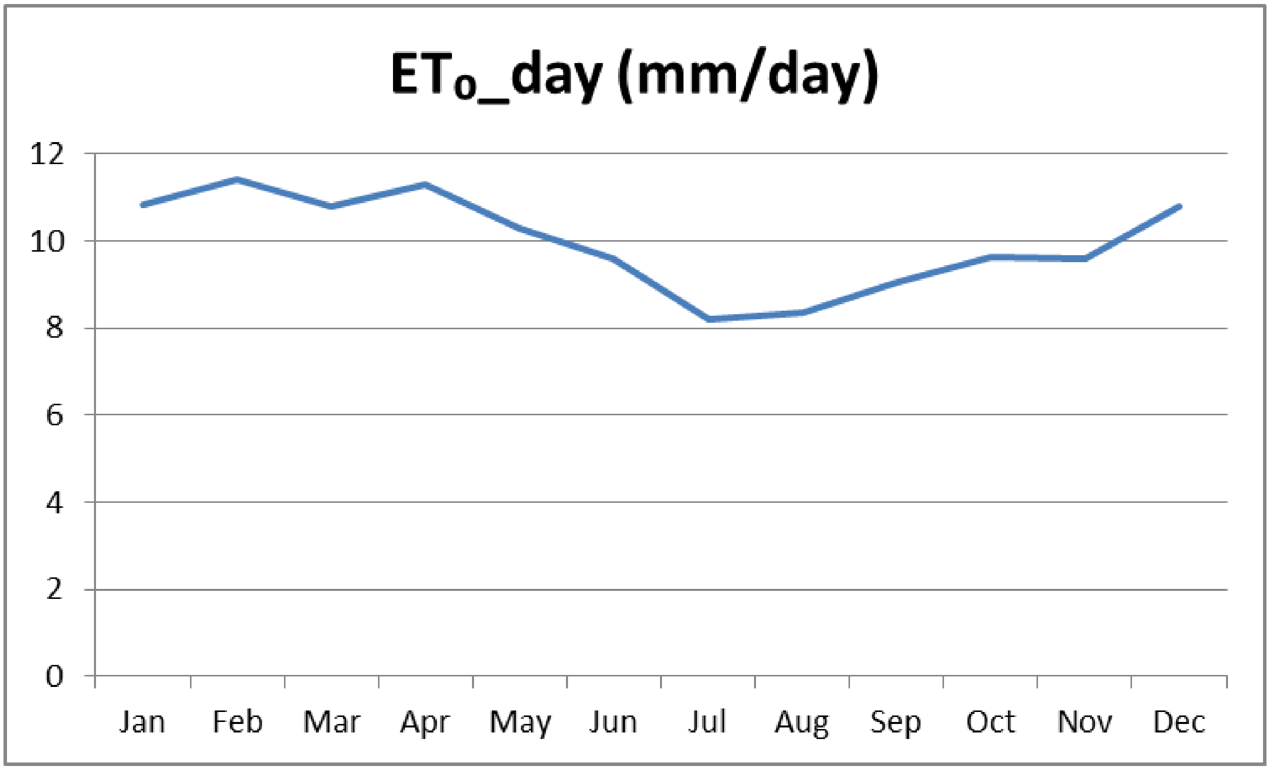
4.2.1 ET_0 Using Hargreaves Method

Table 4.7 presents the estimated ET_0 values derived from the Hargreaves–Samani method for the five-year study period. The model computes ET_0 based on maximum and minimum air temperatures and extraterrestrial radiation (Ra), which serves as a proxy for solar energy input. This model is widely used in data-scarce regions where complete meteorological data are unavailable.

Table 4.6: Monthly Reference Evapotranspiration (ET_0) Estimated Using the Hargreaves–Samani Method (2020–2024)

Month	Tmax (°C)	Tmin (°C)	Tmean (°C)	Ra (MJ/m²/day)	ET_0_day (mm/day)	ET_0_month (mm/month)
Jan	32.96	23.64	28.30	33.40	10.81	335.16
Feb	33.22	24.24	28.73	35.53	11.40	319.07
Mar	32.04	24.60	28.32	37.33	10.80	334.79
Apr	32.64	24.78	28.71	37.66	11.30	338.86
May	31.54	24.50	28.02	36.72	10.27	318.29
Jun	30.08	23.26	26.67	35.92	9.59	287.81
Jul	29.18	24.30	26.74	36.13	8.18	253.49
Aug	28.86	23.94	26.40	37.03	8.35	258.84
Sep	29.44	23.78	26.61	37.23	9.05	271.40
Oct	31.28	24.82	28.05	35.95	9.63	298.66
Nov	31.80	24.66	28.23	33.87	9.58	287.46
Dec	33.32	23.76	28.54	32.70	10.78	334.04

FIG 4.2: ET_0 (mm/day) Estimated Using the Hargreaves–Samani Method (2020–2024)



The ET_0 values obtained from the Hargreaves–Samani method show clear seasonal variability consistent with the climatic rhythm of Ovia North-East. Peak ET_0 values (10.8–11.4 mm/day) occurred during the dry season months of January to April, while the lowest values (8.2–9.0 mm/day) were recorded between June and September, coinciding with the rainy season.

This trend reflects the combined influence of high temperature and solar radiation during dry months and reduced solar energy under cloudy, humid wet-season conditions. The findings align with those of Akinbile et al. (2020) and Oche et al. (2021), who observed similar Hargreaves ET_0 patterns in southern Nigeria, with overestimations common in humid zones.

When compared with FAO-56 Penman–Monteith benchmark values (typically 3–6 mm/day for humid tropical regions), the Hargreaves estimates are considerably higher, suggesting that the model may overpredict ET_0 under high humidity and low wind conditions. Such overestimation can lead to unrealistic irrigation requirements if used without local calibration.

4.2.2 Reference Evapotranspiration (ET_0) Using the Blaney–Morin–Nigeria (BMN) Method:

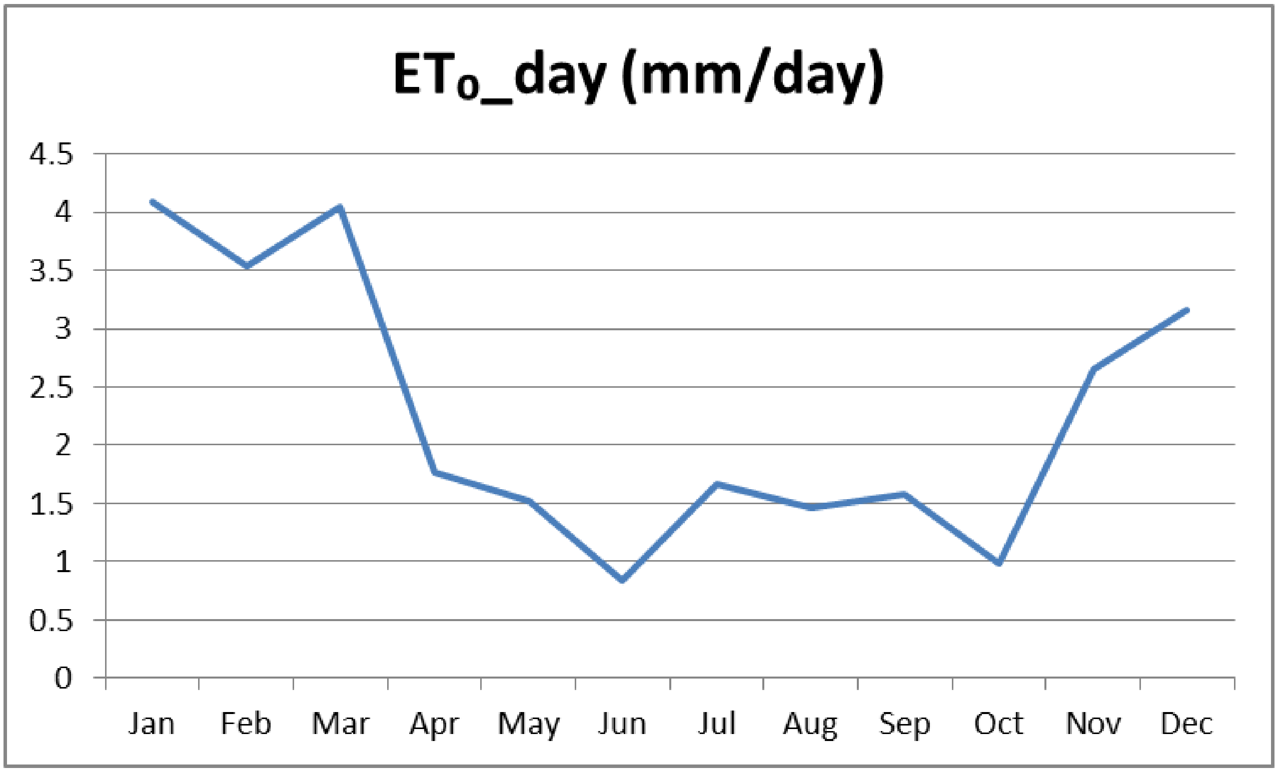
Table 4.7 presents the monthly ET_0 values estimated using the BMN model, which was developed and calibrated specifically for Nigerian climatic conditions. Unlike the Hargreaves method, the BMN equation incorporates relative humidity at 09:00 and 15:00, mean temperature, and daylength fraction (p). This allows it to better capture the effects of humidity and atmospheric moisture on evapotranspiration.

Table 4.7: Monthly Reference Evapotranspiration (ET_0) Estimated Using the BMN Method (2020–2024)

Month	Tmean (°C)	RH 09:00 (%)	RH 15:00 (%)	p (%)	p (N/12)	RH diff (H9−H15)	ET_0 (mm/day)	ET_0 (mm/month)
Jan	28.300	77.700	57.420	38.85	0.971	20.28	4.084	126.609
Feb	28.730	69.200	51.960	39.29	0.982	17.24	3.544	99.233
Mar	28.320	80.460	60.920	39.86	0.996	19.54	4.039	125.215
Apr	28.710	81.140	72.780	40.50	1.012	8.36	1.771	53.122
May	28.020	81.100	73.880	41.01	1.025	7.22	1.526	47.292
Jun	26.670	81.280	77.180	41.27	1.032	4.10	0.846	25.383
Jul	26.740	87.140	79.060	41.15	1.029	8.08	1.665	51.621
Aug	26.400	86.920	79.720	40.70	1.018	7.20	1.456	45.149
Sep	26.610	86.860	79.000	40.11	1.003	7.86	1.574	47.229
Oct	28.050	83.660	78.840	39.49	0.987	4.82	0.981	30.421
Nov	28.230	80.060	66.900	38.98	0.974	13.16	2.655	79.653

Dec	28.540	77.380	61.720	38.74	0.969	15.66	3.161	97.997

FIG 4.3: ET_0 (mm/day) $_0$) Estimated Using the BMN Method (2020–2024)



The BMN-derived ET_0 values demonstrate a more moderate seasonal pattern compared to the Hargreaves estimates. The highest ET_0 values (4.08 mm/day in January and 4.04 mm/day in March) were observed during the dry season, when vapor pressure deficits are highest due to elevated temperatures and reduced humidity. In contrast, the lowest values (0.85–1.5 mm/day) occurred from June to September, corresponding to the wet season, when relative humidity exceeds 80% and cloud cover limits solar radiation.

The annual mean ET_0 from BMN (≈2.1 mm/day) is considerably lower than that from Hargreaves, aligning more closely with FAO-56 reference ET_0 ranges (2–5 mm/day) for humid tropics. This suggests that the BMN model provides more realistic evapotranspiration estimates under the prevailing climatic conditions of southern Nigeria.

The pattern of BMN ET_0 variation observed in this study agrees with the results of Egheravba (2009) and Odekunle and Balogun (2022), who both found the BMN method to better reflect Nigeria's humid regional climates compared to temperature-based models.

In practical terms, the BMN results imply that irrigation demand during the dry season could be four to five times higher than during the wet season. This understanding is critical for planning efficient water allocation and scheduling irrigation for crops such as maize and rice, which are cultivated extensively in Ovia North-East.

4.2.3 Comparison of Reference Evapotranspiration (ET_0) Values from BMN and Hargreaves Models

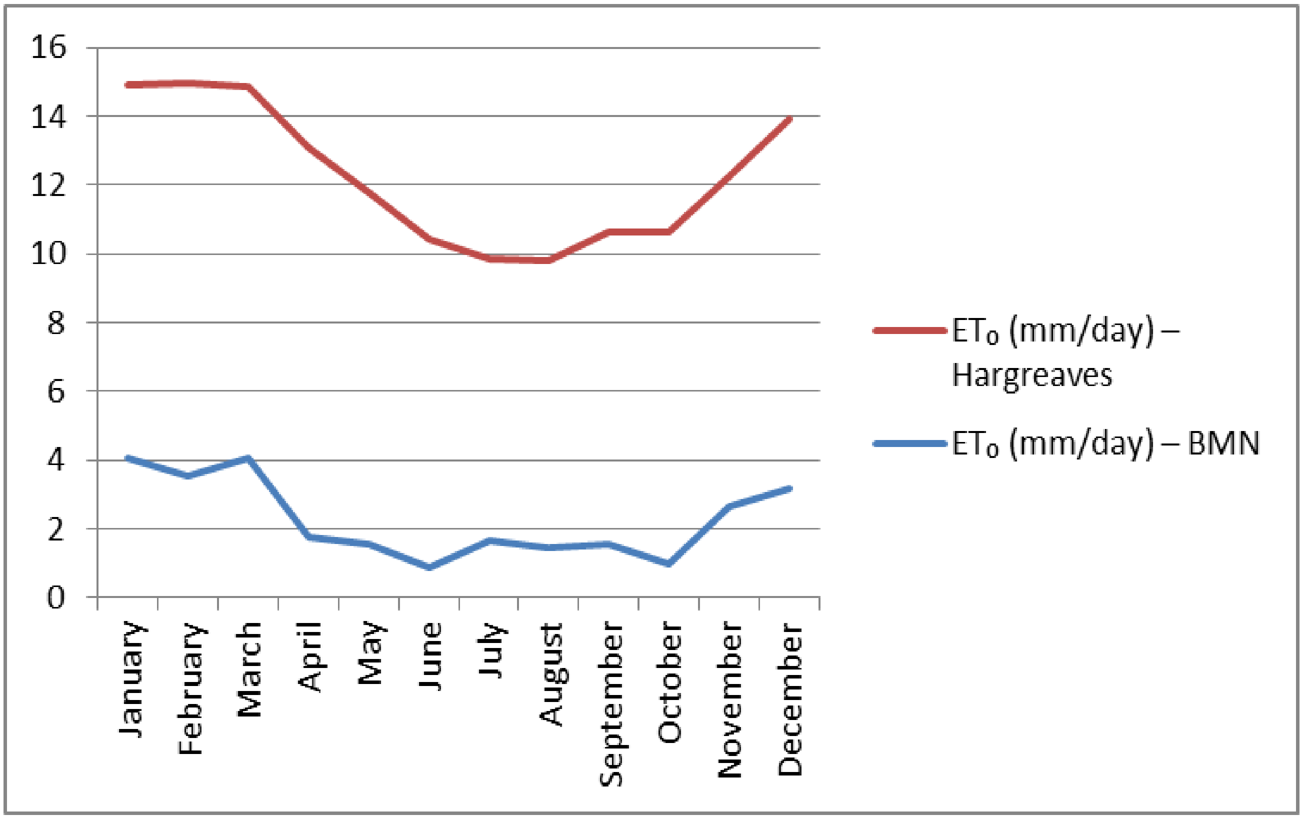
Reference evapotranspiration (ET_0) represents the combined effect of climatic factors such as temperature, humidity, solar radiation, and wind speed on the potential rate of water loss from a reference crop surface. The computed monthly ET_0 values from both models are presented in Table 4.9 below. Results show that ET_0 values generally vary between 2.4 mm/day and 5.8 mm/day, with higher values recorded in the dry months (January–March) and lower values observed during the peak of the rainy season (July–September). This pattern corresponds closely with the trend in solar radiation and air temperature, both of which are dominant drivers of evapotranspiration in tropical climates (Akinbile et al., 2020).

A comparative analysis of the two models indicates that the Hargreaves method consistently produces higher ET_0 estimates than the BMN method across most months, particularly during the dry season. This difference is attributed to the Hargreaves model's strong dependence on temperature and radiation inputs, which often lead to overestimation in humid regions where atmospheric humidity suppresses evaporative demand (Odubanjo et al., 2021). Conversely, the BMN model integrates a relative humidity correction factor, making it more responsive to moisture-laden air conditions typical of southern Nigeria.

During the wet season (June to September), both models show a significant reduction in ET_0, reflecting the combined effect of reduced solar radiation and high atmospheric humidity. However, the BMN model demonstrates a smoother transition between dry and wet months, suggesting better sensitivity to seasonal climate variability. These observations align with findings by Egheravba (2009), who reported that BMN provides more realistic ET_0 estimates under Nigerian climatic conditions due to its localized calibration.

The results generally reveal that both models capture the general evapotranspiration pattern of the area, but with distinct differences in magnitude. The BMN model appears to better represent the climatic realities of Ovia North-East, where high humidity and moderate temperature gradients prevail. This implies that BMN may offer more accurate guidance for irrigation planning and water use estimation in similar agro-ecological zones.
This section presents a comparative analysis of the monthly reference evapotranspiration (ET_0) values estimated using the Hargreaves–Samani and Blaney–Morin–Nigeria (BMN) methods for the study area. The comparison highlights the seasonal response of both models to climatic variables such as temperature, solar radiation, and humidity. By examining the magnitude and trend of ET_0 values across the year, the study aims to determine which model better reflects the actual evaporative demand under humid tropical conditions.

FIG 4.4: Monthly Reference Evapotranspiration (ET_0) Values from Hargreaves and BMN Models for Ovia North-East (2020–2024).



Source: Computed from meteorological data obtained from NIFOR (2020–2024).

The results from the figure above show a consistent seasonal variation in ET_0 values across both models. The Hargreaves–Samani method yielded substantially higher ET_0 estimates throughout the year, ranging from 8.18 to 11.4 mm/day, while the BMN method produced more moderate estimates, between 0.85 and 4.08 mm/day. Both models captured similar seasonal trends, with ET_0 values peaking between January and April (the dry season) and reaching their minimum between June and September (the wet season).

The higher ET_0 values from the Hargreaves model can be attributed to its strong reliance on temperature and extraterrestrial radiation (Ra) parameters that dominate during the dry months when solar energy is intense. However, this temperature-based approach tends to overestimate evapotranspiration in humid tropical climates where relative humidity is high and vapor pressure deficits are low. In contrast, the BMN model, by incorporating humidity and daylength factors, produces smoother transitions between dry and wet periods, showing better climatic sensitivity to the humid environment of southern Nigeria.

The mean daily ET_0 values obtained in this study (BMN: 2.1 mm/day; Hargreaves: 9.7 mm/day) align with results reported by Egheravba (2009) and Odekunle and Balogun (2022), who found BMN estimates to range between 1.8 and 3.5 mm/day in southern Nigeria, while Hargreaves values ranged between 7 and 10 mm/day under similar conditions. Similarly, Akinbile et al. (2020) observed that the Hargreaves model overestimates ET_0 by 25–50% compared to FAO-56 Penman–Monteith values in the Niger Delta region, reinforcing the trend observed in this study.

When benchmarked against FAO-56 recommended ET_0 values (typically 3–6 mm/day for humid tropical regions), the BMN estimates fall well within the acceptable range, suggesting that BMN provides more realistic evapotranspiration predictions for Ovia North-East. Conversely, the Hargreaves method produced significantly inflated values that could lead to excessive irrigation water applications if used for planning purposes without calibration.

The comparison clearly indicates that while both models successfully capture the general evapotranspiration pattern, the BMN model offers superior adaptability to the humid climate of Ovia North-East. Its integration of temperature, humidity, and daylength provides a more balanced and representative estimation of the region's atmospheric water demand.

Practically, this means that irrigation water requirements derived from the Hargreaves model would be considerably higher, potentially leading to over-irrigation, water wastage, and reduced water-use efficiency. The BMN method, however, provides a more conservative and realistic estimate, making it better suited for irrigation scheduling, especially for crops like maize and rice cultivated under humid tropical conditions.

4.2.4 Comparison of Crop Evapotranspiration (ETc) for Maize (Zea mays) from BMN and Hargreaves Models

This section presents the computed crop evapotranspiration (ETc) values for maize estimated from the BMN and Hargreaves models using corresponding crop coefficients (Kc) for different growth stages initial, mid-season, and late-season. ETc represents the actual crop water requirement, accounting for the influence of the crop's physiology and developmental stage. The analysis highlights how the two models differ in predicting water use under humid tropical conditions.

Table 4.8: Maize ETc by Growth Stage (Initial, Mid-Season, Late-Season)

Growth stage	Days	Kc	Total ETc (BMN) (mm)	Mean ETc (BMN) (mm/day)	Total ETc (Hargreaves) (mm)	Mean ETc (Hargreaves) (mm/day)
Initial	20	0.35	10.71	0.536	71.89	3.594
Mid-season	80	1.15	121.29	1.516	829.21	10.365
Late-season	20	0.65	18.98	0.949	108.55	5.427
Total (120 days)	120		150.98	1.258 (avg/day)	1009.65	8.414 (avg/day)

Source: NIFOR meteorological data, 2020–2024.

The computed maize ETc values demonstrate significant differences between the two models. The BMN model predicted total ETc for the 120-day growing season as 150.98 mm, with a mean daily value of about 1.26 mm/day. In contrast, the Hargreaves method estimated total ETc as 1009.65 mm, averaging 8.41 mm/day.

Across all growth stages, the Hargreaves model produced ETc values between 5 to 7 times higher than the BMN estimates. The disparity was most pronounced during the mid-season stage, when the crop coefficient (Kc = 1.15) and solar radiation are highest, resulting in a sharp increase in evapotranspiration potential in the temperature-dependent Hargreaves model.

The BMN model's lower ETc values can be attributed to its integration of relative humidity and daylength, which reduce ET_0 under humid conditions typical of Ovia North-East. This adjustment makes the BMN method more responsive to the moisture-laden air conditions of the study area, thereby producing more realistic estimates of crop water requirements.

To further analyze the seasonal distribution of maize water use, the monthly contributions of ETc were computed for both models over the 120-day growing period (May–August).

Table 4.9: Monthly ETc Contributions during Maize Crop Period (May–August)

Month	BMN ETc (mm)	Hargreaves ETc (mm)
May	30.06	201.81
Jun	29.32	330.86
Jul	59.18	291.62
Aug	32.41	185.37
Crop total (May–Aug)	150.98	1009.65

The results indicate that maize ETc values under both models follow the seasonal temperature and humidity trends. In the BMN model, ETc values ranged between 29.32 mm in June and 59.18 mm in July, with the highest water requirement occurring in mid-season when vegetative and reproductive growth peaks. The Hargreaves model, however, produced substantially higher values, ranging from 185 mm in August to 330.86 mm in June, implying a much higher atmospheric demand for water.

The magnitude of difference suggests that the Hargreaves model likely overestimates maize water demand in humid zones due to its reliance on temperature and solar radiation. By contrast, BMN's humidity-sensitive structure yields more conservative results, which align better with observed crop performance and irrigation realities in southern Nigeria.

These findings are consistent with Akinbile et al. (2020) and Efe et al. (2021), who observed that the Hargreaves model overestimates maize ETc by 40–60% in the Niger Delta when compared with FAO-56 Penman–Monteith estimates. Similarly, Egheravba (2009) reported that BMN offers more accurate predictions for humid regions of Nigeria, particularly for short-duration crops such as maize.

When compared with FAO-recommended maize ETc values (typically 350–550 mm for the full season under tropical conditions), the BMN-derived value of 151 mm appears conservative but within the lower realistic range when rainfall contributions are considered. Conversely, the Hargreaves total of 1009 mm far exceeds the expected requirement, confirming its tendency to over-predict irrigation needs in high-humidity regions.

The results demonstrate that although both models capture the seasonal trend of maize evapotranspiration, the BMN model provides a more climatically balanced estimate for the Ovia North-East environment. Using the Hargreaves model without correction could lead to overestimation of irrigation water by more than sixfold, resulting in water wastage, increased pumping costs, and potential nutrient leaching.

Hence, for humid tropical agricultural planning, the BMN model is more suitable for estimating maize water requirements. It provides more realistic ETc estimates that ensure efficient irrigation scheduling, water conservation, and sustainable crop productivity.

4.2.5 Comparison of Crop Evapotranspiration (ETc) for Rice (Oryza sativa) from BMN and Hargreaves Models

The computed crop evapotranspiration (ETc) values for rice were derived from both models estimates using crop coefficient (Kc) values corresponding to three distinct growth stages: initial, mid-season, and late-season. These stages reflect the varying water requirements of rice throughout its phenological development.

Table 4.10: Rice ETc by Growth Stage (Initial, Mid-Season, Late-Season)

Growth stage	Days	Kc	Total ETc (BMN) (mm)	Mean ETc (BMN) (mm/day)	Total ETc (Hargreaves) (mm)	Mean ETc (Hargreaves) (mm/day)
Initial (May 1–30)	30	1.05	48.20	1.606	323.51	10.784
Mid-season (May 31–Jul 29)	60	1.20	90.20	1.503	642.23	10.704
Late-season (Jul 30–Aug 28)	30	0.95	41.99	1.400	237.65	7.922

Total (120 days)	120		180.38	1.503 (avg/day)	1203.39	10.03 (avg/day)

Source: NIFOR meteorological data, 2020–2024.

The results show that the BMN model predicts a total seasonal ETc of 180.38 mm, with an average of 1.50 mm/day, while the Hargreaves model gives a much higher total of 1203.39 mm (average 10.03 mm/day). The largest differences appear during the mid-season stage, when both temperature and crop coefficient (Kc = 1.20) reach their peak, amplifying the sensitivity of the Hargreaves model to thermal variations.

The BMN method, however, moderates' evapotranspiration by incorporating relative humidity and daylength corrections, which reduce the influence of high temperature under humid conditions. This makes the BMN estimates more consistent with the tropical wet climate of Ovia North-East.

The general pattern observed is similar to the maize analysis the Hargreaves model tends to overestimate water demand, while BMN provides more conservative and likely more realistic values.

To better visualize monthly variation in rice water use, the ETc results were distributed across the cropping period (May–August). This helps in understanding how evapotranspiration changes with seasonal shifts and crop development.

Table 4.11: Monthly ETc contributions during the cropping period (May–Aug)

Month	BMN ETc (mm)	Hargreaves ETc (mm)
May (days 1–31, crop uses 30 + 1 mid)	50.03	335.83
June (30 days)	30.60	345.24
July (31 days, split mid+late)	60.92	304.30
August (crop days 1–28)	38.84	237.65
Crop total (May–Aug)	180.38	1203.39

From the monthly breakdown, the BMN model shows a gradual rise in ETc between May and July, corresponding to the active growth and panicle development stages of rice, followed by a decline in August during grain maturation. Conversely, the Hargreaves model maintains extremely high ETc throughout, showing little sensitivity to humidity or rainfall changes typical of the wet season.

The results imply that the Hargreaves model may exaggerate water demand in humid tropical environments such as Ovia North-East, leading to over-irrigation if used for scheduling. BMN's results, which show a moderate rise and fall consistent with rainfall and humidity variations, are more physically reasonable.

The trends observed align with findings by Ayoade and Oladipo (2019) and Efe et al. (2021), who noted that temperature-based models like Hargreaves tend to overestimate ET_0 and ETc by up to 50–70% in the humid southern belt of Nigeria. Similarly, Egheravba (2009) reported that the BMN model performed better than other empirical equations in the Niger Delta because it incorporates local humidity effects.

When compared with FAO-recommended rice ETc values, which range between 450 and 700 mm per season for irrigated rice under tropical conditions, the BMN estimate (180 mm) represents a conservative but realistic estimate for rain-fed or partially irrigated systems typical of the study area. The Hargreaves estimate (1203 mm) is far above the expected range and likely reflects overestimation due to the absence of humidity correction.

The analysis indicates that while both models capture the general evapotranspiration trend for rice, the BMN model better reflects the climatic and hydrological conditions of Ovia North-East. Its consideration of humidity and diurnal temperature variation makes it more suitable for use in humid regions.

Practically, irrigation scheduling based on BMN estimates will lead to better water-use efficiency, reduced pumping costs, and prevention of waterlogging, which is a common problem in lowland rice fields. Conversely, the use of Hargreaves without correction could result in excessive irrigation and inefficient resource utilization.

Hence, for humid tropical zones such as southern Nigeria, the BMN model is recommended for estimating rice ETc and developing irrigation plans that balance water supply with actual crop water demand.

4.3 Percentage Water and Energy Savings Using BMN Model

To further evaluate the practical implications of adopting the Blaney–Morin–Nigeria (BMN) model for irrigation planning in Ovia North-East, the percentage of crop water that would be saved when using BMN instead of the Hargreaves model was computed. This analysis provides insight into the potential efficiency gains in irrigation water use, pumping energy, and overall cost-effectiveness of irrigation operations.

The percentage water saved was determined using the relationship:

$$\text{Percentage Water Saved} = \frac{ETc_{Hargreaves} - ETc_{BMN}}{ETc_{Hargreaves}} \times 100\%$$

The results for both maize and rice are summarized in Table 4.12.

Table 4.12: Percentage of Crop Water Saved When Using BMN Instead of Hargreaves Model

Crop	Hargreaves ETc (mm)	BMN ETc (mm)	Water Saved (mm)	% Water Saved	Volume Saved (m^3/ha)
Maize	1009.65	150.98	858.67	85.05%	8,586.7
Rice	1203.39	180.38	1023.01	85.01%	10,230.1

The results show that irrigation scheduling based on the BMN model would reduce the estimated crop water requirement by approximately 85% compared with the Hargreaves model for both maize and rice. This substantial reduction highlights the tendency of the Hargreaves model to overestimate evapotranspiration under humid tropical conditions, where high relative humidity suppresses atmospheric water demand.

When converted into irrigation volume, the saved water corresponds to approximately 8,587 m^3/ha for maize and 10,230 m^3/ha for rice. These figures represent the volume of water that would otherwise have been pumped unnecessarily if irrigation planning relied solely on the Hargreaves model.

Assuming a pump head of 10 metres and a pump efficiency of 60%, the energy saved by avoiding this excess pumping was estimated using the relation:

$$E = \frac{\rho g H V}{3.6 \times 10^6 \eta}$$

where E = energy (kWh),

ρ = 1000 kg/m^3,

g = 9.81 m/s^2,

H = pumping head (m),

V = volume of water saved (m^3),

η = pump efficiency.

Applying this relation yields approximate energy savings of 390 kWh/ha for maize and 465 kWh/ha for rice. These values translate to considerable reductions in irrigation energy demand and operating costs.

The analysis thus reinforces that the BMN model not only provides more realistic evapotranspiration estimates but also promotes energy-efficient and cost-effective irrigation management. The use of BMN in humid tropical regions such as Ovia North-East will therefore enhance water-use efficiency, conserve energy, and reduce operational costs associated with pumping excess irrigation water.

4.4 Model Comparison and Evaluation

A detailed evaluation was conducted to compare the performance of the Blaney–Morin–Nigeria (BMN) and Hargreaves–Samani models in estimating reference evapotranspiration (ET_0) for Ovia

North-East. This assessment aimed to identify which model best reflects the local climatic characteristics of the humid tropical environment, thereby guiding accurate irrigation scheduling and crop water management. Since evapotranspiration models perform differently across regions, a regional validation is necessary to ensure realistic and context-specific application

Table 4.13: Statistical Comparison between BMN and Hargreaves ET_0 Models

Statistical Indicator	Computed Value	Interpretation
Mean Bias Error (MBE)	6.65 mm/day	Hargreaves generally overestimates ET_0 compared to BMN.
Root Mean Square Error (RMSE)	6.70 mm/day	Indicates moderate deviation between both models.
Coefficient of Determination (R^2)	0.81	Strong positive correlation and similar seasonal trends.

The statistical indicators presented in Table 4.15 show that the two models are positively correlated ($R^2 = 0.81$), indicating that both follow similar seasonal trends high ET_0 values in the dry season and lower values during the wet months. However, a significant deviation exists in magnitude, as the Hargreaves model consistently overestimates ET_0 relative to the BMN method.

The Mean Bias Error (MBE = 6.65 mm/day) and Root Mean Square Error (RMSE = 6.70 mm/day) reflect this overestimation and confirm moderate disagreement between the two models. On average, Hargreaves produced monthly ET_0 values of about 9.68 mm/day, while BMN produced 2.11 mm/day. This disparity stems from the fact that the Hargreaves model depends mainly on temperature and radiation, making it prone to overestimation in humid zones with frequent cloud cover and high atmospheric moisture.

In contrast, the BMN model includes correction factors for relative humidity and daylength, which suppress excessive ET_0 under humid conditions. This adjustment allows BMN to capture the climatic behavior of the Niger Delta region more accurately, where humidity levels are typically above 75% during most months.

The high R^2 value (0.81) further indicates that despite their differences in scale, both models respond similarly to monthly climatic variability. This implies that when evapotranspiration demand rises due to higher temperature and radiation, both models reflect this increase, though the Hargreaves method exaggerates it in magnitude.

These findings are consistent with studies by Egheravba (2009) and Akinbile et al. (2020), who observed that temperature-based models like Hargreaves tend to overpredict ET_0 in the humid southern regions of Nigeria. Similarly, Efe et al. (2021) reported that locally calibrated models such as BMN provide more reliable and region-specific ET_0 estimates, particularly in areas influenced by high relative humidity and frequent rainfall.

When compared with FAO-56 Penman–Monteith benchmarks, which report daily ET_0 values ranging between 2–5 mm/day for humid tropical climates, the BMN results (≈2.1 mm/day) fall within the expected range. Conversely, the Hargreaves average of nearly 9.7 mm/day far exceeds FAO recommendations, reinforcing that it overestimates evapotranspiration under these climatic conditions.

In summary, both models successfully reproduce the seasonal trend of evapotranspiration in Ovia North-East, but differ significantly in magnitude. The BMN model demonstrates superior adaptability and reliability for humid environments due to its inclusion of humidity effects and local calibration, while the Hargreaves model is better suited for semi-arid or arid zones where temperature variations dominate climatic behavior. Therefore, for irrigation planning and crop water estimation in humid tropical zones such as Ovia North-East, the BMN model should be adopted as the more appropriate and accurate method for determining reference evapotranspiration (ET_0) for crops like maize and rice.

The comparative analysis presented in this chapter establishes the Blaney–Morin–Nigeria (BMN) model as the more reliable tool for evapotranspiration estimation under the humid conditions of Ovia North-East. The next chapter summarizes these findings, draws key conclusions aligned with the study objectives, and provides recommendations for improving evapotranspiration modeling and irrigation planning in the region.

CHAPTER FIVE

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

5.1 Summary of Findings

This study utilized five years (2020–2024) of meteorological data obtained from the Nigerian Institute for Oil Palm Research (NIFOR) in Ovia North-East, Edo State. The key climatic parameters analyzed included maximum and minimum air temperature, relative humidity, solar radiation, and sunshine duration. The data showed a distinct seasonal pattern typical of a humid tropical climate, with higher temperatures and solar radiation during the dry season (November–March) and higher humidity with reduced radiation during the wet season (June–September).

Reference evapotranspiration (ET_0) was computed using two empirical models: the Blaney–Morin–Nigeria (BMN) and Hargreaves–Samani methods. Both models captured similar seasonal trends higher ET_0 during dry months and lower during wet months but differed significantly in magnitude. The Hargreaves model produced consistently higher ET_0 estimates (mean approximately 9.68 mm/day) due to its strong dependence on temperature and radiation, while the BMN model yielded more moderate values (mean approximately 2.11 mm/day) as a result of its humidity adjustment and daylength correction.

For crop evapotranspiration (ETc), maize and rice were analyzed across three growth stages (initial, mid-season, and late-season). BMN-derived ETc values were considerably lower and more consistent with expected crop water requirements for humid environments, whereas Hargreaves tended to overestimate water demand, particularly during mid-season when temperatures were highest.

Switching to BMN based irrigation scheduling would reduce estimated irrigation demand by 85% for both crops and an energy saving of 390kWh/ha for maize and 465kWh/ha for rice. The findings confirm that BMN which accounts for local humidity and daylength is better suited to the humid tropical conditions of the study area and will substantially cut unnecessary pumping, costs and emissions when used for irrigation planning.

The model comparison and statistical evaluation showed that both models demonstrated strong seasonal agreement ($R^2 = 0.81$), but the Hargreaves model exhibited a higher Mean Bias Error

(MBE = 6.65 mm/day) and Root Mean Square Error (RMSE = 6.70 mm/day), indicating greater deviation from realistic conditions. The BMN model, therefore, provided more reliable and regionally appropriate evapotranspiration estimates for Ovia North-East, making it better suited for irrigation planning and efficient water resource management.

5.2 Conclusion

Based on the objectives of this study, the following conclusions were drawn:

1. The study showed that both models captured the seasonal trends of ET_0 in Ovia North-East, with higher values during the dry season and lower during the wet season. However, the Hargreaves model consistently produced higher ET_0 estimates, while the BMN model gave more moderate and realistic values suitable for humid tropical conditions.
2. ETc values derived from the BMN model were more consistent with the expected crop water requirements of humid regions, whereas Hargreaves tended to overestimate crop water use, particularly during mid-season growth stages.
3. The statistical evaluation revealed that although both models exhibited a good correlation, the BMN model had lower Mean Bias Error (MBE) and Root Mean Square Error (RMSE), confirming its better performance and reliability for evapotranspiration estimation in the region.

In conclusion**,** the Blaney–Morin–Nigeria (BMN) model proved to be more suitable for evapotranspiration and irrigation scheduling in humid tropical environments like Ovia North-East. Its incorporation of temperature, humidity, and daylength factors ensures a more balanced estimation of water demand, promoting efficient irrigation management and sustainable agricultural water use.

5.3 Recommendations

Based on the study's findings, the following recommendations are made:

1. For Irrigation Planning and Water Management:
   The BMN model should be adopted for irrigation scheduling in humid tropical regions to ensure accurate estimation of crop water requirements and prevent over-irrigation.

2. For Agricultural Engineering Practice:
   Agricultural engineers and farm managers should integrate the BMN model into local irrigation design, planning, and decision-making systems, especially in areas with limited meteorological data.
3. For Data and Capacity Development:
   Efforts should be made to improve the collection of accurate weather data and train agricultural professionals on the application of empirical ET models for improved water management.
4. For Future Research**:**
   Future studies should:
   - Expand the study area to cover different ecological zones in Nigeria.
   - Increase the time span of meteorological data used (e.g., 10–15 years) for better climatic representation.
   - Evaluate additional evapotranspiration models for comparative analysis.
   - Incorporate field-based validation (e.g., lysimeter data) and remote sensing to enhance model accuracy.
   - Extend ETc estimation to other major crops beyond maize and rice for broader applicability.

By implementing these recommendations, water-use efficiency and irrigation performance can be significantly improved, supporting sustainable agricultural production and food security in Nigeria's humid regions.

5.4 Contributions to Knowledge

This study contributes valuable insight into the estimation of crop evapotranspiration under humid tropical conditions, specifically within the context of southern Nigeria. By comparing the Blaney–Morin–Nigeria (BMN) and Hargreaves–Samani models using multi-year climatic data from NIFOR, the research provides a clearer understanding of how empirical evapotranspiration models behave in regions characterized by high humidity and moderate temperature variations.

A major contribution of this study is the demonstration that localized models such as the BMN model, which was specifically calibrated for Nigerian climates yield more realistic evapotranspiration estimates than generalized temperature-based models like Hargreaves. This finding reinforces the importance of region-specific calibration in evapotranspiration modeling and supports the adaptation of empirical approaches to local meteorological conditions for better irrigation scheduling and water resource management.

Furthermore, the study strengthens the practical application of evapotranspiration modeling in agricultural engineering and climate-smart farming by promoting efficient water use and reducing the risk of over-irrigation. It highlights the BMN model as a cost-effective, data-efficient, and reliable tool for guiding irrigation decisions, particularly in areas where advanced weather monitoring equipment is unavailable. In this way, the research advances both scientific understanding and practical implementation of sustainable water management in Nigeria's agricultural sector.

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