

# Towards Data-Driven Energy Planning in Higher Education: An Inventory-Based Energy Consumption Analysis at JKUAT, Kenya

James Paul Okwii<sup>1</sup>, Francis Xavier Ochieng<sup>1</sup>, David Mulati<sup>2</sup>

<sup>1</sup>Institute of Energy and Environmental Technology, Jomo Kenyatta University of Agriculture and Technology (JKUAT), Nairobi, Kenya

<sup>2</sup>College of Pure and Applied Sciences, Jomo Kenyatta University of Agriculture and Technology (JKUAT), Nairobi, Kenya  
Email: jameopaul11@gmail.com

**How to cite this paper:** Okwii, J.P., Ochieng, F.X. and Mulati, D. (2025) Towards Data-Driven Energy Planning in Higher Education: An Inventory-Based Energy Consumption Analysis at JKUAT, Kenya. *Journal of Power and Energy Engineering*, 13, 24-40.  
<https://doi.org/10.4236/jpee.2025.1310003>

**Received:** August 26, 2025

**Accepted:** October 20, 2025

**Published:** October 23, 2025

Copyright © 2025 by author(s) and Scientific Research Publishing Inc.

This work is licensed under the Creative Commons Attribution-NonCommercial International License (CC BY-NC 4.0).

<http://creativecommons.org/licenses/by-nc/4.0/>



Open Access

## Abstract

Buildings play a substantial role in global energy consumption and greenhouse gas emissions, including residential, commercial, industrial, and educational structures. They account for about 40% of total global energy use and nearly one-third of greenhouse gas emissions. In Sub-Saharan Africa, educational buildings may consume less energy than commercial or industrial sectors, but their demand is becoming increasingly important due to digital learning, longer operating hours, and diverse campus facilities. However, limited data, lack of local research, and poor monitoring have made it difficult to assess and manage energy use, particularly in East Africa. This study aimed to develop a comprehensive inventory of energy consumption and building usage for university buildings at Jomo Kenyatta University of Agriculture and Technology (JKUAT). The inventory compiles electricity consumption records from 2018-2024, alongside student enrolment data and climate variables, to capture both historical and seasonal trends. Annual energy use ranged from 2.33 GWh in 2020, during COVID-19 disruptions, to 3.28 GWh in 2018, with July emerging as the peak month of demand. Statistical analysis showed a strong positive correlation between energy consumption and institutional enrolment ( $r = 0.63$ ), while associations with climate were modest like temperature ( $r = 0.16$ ) and rainfall ( $r = -0.21$ ). This foundational inventory not only highlights the growing influence of institutional growth on energy demand but also establishes a data-driven platform for predictive modelling. The study supports the development of evidence-based energy policies and sustainable planning frameworks within higher education institutions in Sub-Saharan Africa.

## Keywords

University Energy Inventory, Campus Sustainability, Sub-Saharan Africa, Student Enrolment, Climate Influence

---

## 1. Introduction

Energy has been the backbone of human civilization since time immemorial & its desire is increasing gradually with increase in population, industrialization, economic growth all around the world [1].

All over the world, energy consumption within university campuses is continually rising as institutions expand their operations and energy facilities to accommodate increasing student enrolments and evolving technological needs [2]-[6]. In educational environments such as universities, energy is needed for lighting, operating laboratory equipment, supporting administrative functions, and, in certain instances, for heating and cooling purposes [7] [8]. This high demand makes universities significant consumers of energy, thereby contributing to operational costs and carbon emissions [6].

Globally, buildings account for approximately 40% of energy consumption and one-third of greenhouse gas emissions, with educational institutions being key contributors [9] [10]. In Sub-Saharan Africa, while educational buildings may not match the scale of energy use seen in commercial or industrial sectors, their consumption patterns are critical due to the increasing push toward digital learning, extended operating hours, and the diversity of building types within campuses [9]. Nevertheless, the scarcity of data, absence of region-specific research, and inadequate monitoring systems have hindered effective assessment and management of energy consumption, particularly in the East African region [11].

A conventional energy audit provides a one-time assessment of inefficiencies and conservation opportunities but may miss long-term trends influenced by institutional and climatic factors. In contrast, an inventory-based energy analysis collects and organizes longitudinal data on consumption, building use, and external drivers, allowing trends, correlations, and evolving demand patterns to be identified, making it especially suitable for higher education institutions with variable energy use.

In Kenya, and particularly at Jomo Kenyatta University of Agriculture and Technology (JKUAT), energy consumption continues to rise with infrastructural growth and enrollment increases. However, there is no comprehensive energy inventory for universities in East Africa, where most studies remain one-time audits or household surveys [11] [12]. In contrast, inventory-based analyses in Europe and Asia have demonstrated value for forecasting and campus sustainability [3] [4] [9], but their findings are not directly transferable to Sub-Saharan contexts with different climates, enrolment dynamics, and infrastructure [13].

To address this gap, this study focuses on developing a detailed inventory of

energy consumption university buildings at JKUAT. The inventory is intended to serve as a foundational tool for predictive modelling, energy optimization, and policy development. By analysing trends in energy use alongside factors such as occupancy levels, student intake patterns, and climate data, the study seeks to identify critical variables influencing consumption. The resulting inventory provides both a snapshot of current energy usage and a baseline for forecasting and decision-making. This inventory captures annual, and monthly, energy use, correlates these with student activity levels, and incorporates climatic variables such as temperature, humidity, rainfall, and windspeed. The resulting dataset is designed to serve as a foundation for predictive modelling and informed energy management.

Furthermore, integrating renewable energy sources such as geothermal and small hydropower can support sustainable campus energy management by reducing reliance on conventional electricity and lowering carbon emissions [14] [15]. These low-impact solutions can complement existing energy strategies and enhance long-term campus sustainability [14] [15].

## 2. Methodology

This study employed a quantitative and exploratory research design to develop an inventory of energy consumption at Jomo Kenyatta University of Agriculture and Technology (JKUAT) from 2018 to 2024. Historical energy use, student enrolment trends, and relevant climate data were collected, analyzed and interpreted with the aim of identifying the key variables influencing electricity consumption across the university's-built environment, as captured below.

### 2.1. Data Collection

Energy consumption data (in kWh) was obtained from university meter logs, covering both total annual and monthly use for each year from 2018 to 2024. Sub-metered data from ten major buildings and facilities were also collected to analyse building-level consumption patterns. The ten sub-metered buildings were selected because they represent the most energy-intensive and functionally diverse spaces on campus. These include student hostels, teaching and laboratory blocks, administrative facilities, and essential service installations such as water pumps. Together, they capture the main categories of functional space at JKUAT academic, residential, service, and research ensuring that the inventory reflects both core and support operations. This provides a reliable basis for analysing institutional consumption patterns.

Student population data included annual enrolment totals and intake statistics disaggregated by semester (January, May, September), obtained from university admission and registry records.

Climatic data (temperature, humidity, rainfall, wind speed) were sourced from the Kenya Meteorological Department, specifically for the Juja area, where JKUAT is located. Monthly averages were used to align with energy consumption trends.

## 2.2. Data Organization and Cleaning

All data were organized into Microsoft Excel, with separate sheets for Annual and monthly energy consumption, Enrolment and intake trends, Monthly average climate variables.

Missing data were interpolated using yearly averages when applicable. Outliers were examined and retained only if consistent with known events (e.g., COVID-19 disruptions in 2020).

For missing monthly entries, mean substitution based on annual averages was applied rather than linear interpolation, to maintain consistency with academic calendar cycles. While this approach reduces bias in long-term trend analysis, it may slightly smooth out short-term fluctuations, potentially underestimating true peak-load variations. This limitation was considered when interpreting results, particularly for monthly peak demand assessments.

## 2.3. Descriptive Analysis

**Table 1** represents the descriptive statistics including means, standard deviations, ranges, and coefficients of variation computed for energy consumption and all influencing variables. This provided a foundational understanding of the variability and patterns in the dataset.

**Table 1.** Descriptive statistics including means, standard deviations, ranges, and coefficients of variation.

| Variables         | mean      | Std Dev  | Min      | Max      | Cv (%) |
|-------------------|-----------|----------|----------|----------|--------|
| Energy (kwh)      | 194972.90 | 28882.28 | 119275.7 | 264486.1 | 14.8   |
| Rainfall (mm)     | 73.86     | 45.62    | 19       | 244      | 61.8   |
| Temperature (°C)  | 23.69     | 1.27     | 20.8     | 26.4     | 5.4    |
| Humidity (%)      | 72.41     | 6.43     | 60       | 84       | 8.9    |
| Enrolment         | 25112.07  | 13216.42 | 5674     | 37595    | 52.6   |
| Wind speed (km/h) | 11.34     | 1.87     | 16       | 9        | 16.5   |

## 2.4. Figural and Trend Analysis

Time series Figures were developed to visualize:

- i. Annual trends in energy use vs. enrolment,
- ii. Monthly consumption patterns aligned with academic calendars,
- iii. The relationship between energy use and each climate variable.

Trend lines were fitted using Excel's built-in regression tool. Both linear and non-linear trendlines were tested. For each, the equation and "r" value were determined to get the strength of fit.

## 2.5. Regression Analysis

To further quantify relationships between energy use and its drivers, simple linear regression models were created for each variable:

- $y_1 = 0.3718X_1 + 184570$  (Student Enrollment) (1)

- $y_2 = 3212.1X_2 + 117388$  (Temperature) (2)

- $y_3 = 1230.3X_3 + 180204$  (Wind Speed) (3)

- $y_4 = -96.97X_4 + 200876$  (Humidity) (4)

- $y_5 = -139.52X_5 + 203332$  (Rainfall) (5)

Here,  $y$  is the estimated monthly energy consumption, and each  $X$  represents one influencing variable. These regressions were not validated as predictive models but served to establish empirical links during inventory development.

The analysis was based on a sample size of  $n = 84$  monthly observations (2018-2024). To ensure model validity, multicollinearity among climate variables was checked using Variance Inflation Factor (VIF) values, all of which were below common cut-offs ( $VIF < 5$ ), indicating no severe multicollinearity.

### 2.6. Multivariable Regression Model

To capture the combined effects of enrolment and climate drivers, a multivariable ordinary least squares (OLS) regression was estimated:

$$y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \varepsilon \tag{6}$$

where,  $y$  is monthly energy consumption (kWh) and each  $X$  represents an influencing factor for example  $X_1$  is student enrolment,  $X_2$  is average temperature ( $^{\circ}\text{C}$ ),  $X_3$  is average wind speed (km/h),  $X_4$  is average humidity (%) and  $X_5$  is average rainfall (mm). Predictors were mean-centered, so that the intercept  $\beta_0$  represents the baseline monthly energy use at average conditions. This preliminary model was used not for forecasting but to showcase the inventory’s ability to support model formulation in subsequent phases.

### 2.7. Correlation Analysis

Pearson correlation coefficients were computed to determine the strength and direction of linear associations between energy consumption and independent variables. The results informed the choice of regression models and helped confirm observed trends.

### 2.8. Equations and Formulas to Be Used

The following equations were applied in the analysis:

1. Mean/average:  $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$  (7)

2. Standard deviation:  $s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2}$  (8)

3. Coefficient of variation:  $CV = \frac{S}{\bar{X}} \times 100\%$  (9)

4. Pearson correlation coefficient:  $r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$  (10)

### 3. Results and Discussion

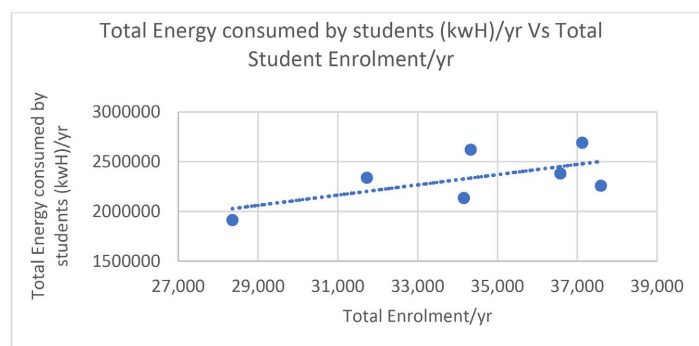
#### 3.1. Annual Energy Consumption and Enrolment Trends (2018-2024)

**Table 2** shows the historical data of: annual of energy consumption, Annual total enrolment and annual total intakes at JKUAT for the past 7 years. It shows that in the past three years the highest annual intake was in 2021 (9421 students) and lowest in 2020 (7295 students). The rise in the 2021 intake was to account for the students who failed to enroll during the COVID-19 pandemic which had affected the 2020 intake. The total enrolment was the highest in 2023 (37,595 students) and lowest in 2020 (28,359 students). It also showed that total annual energy consumption in the institution ranged from 2,330,370 KWh in 2020 to 3,279,692 KWh in 2018 which also had the second highest total enrollment.

**Figure 1** shows a positive correlation between total annual energy consumption and student enrollment between 2018 and 2024. The highest energy usage (3.28 GWh) occurred in 2018, which also saw high enrollment. The lowest energy consumption (2.33 GWh) was recorded in 2020, aligning with a drop in student presence due to COVID-19 disruptions.

**Table 2.** History of total intakes, total enrolment and total energy consumed from 2018-2024.

| year | Total Intakes/yr | Total Enrolment/yr | Total Energy (Kwh)/yr |
|------|------------------|--------------------|-----------------------|
| 2018 | 8,499            | 37,126             | 3,279,692             |
| 2019 | 9,123            | 34,333             | 3,194,542             |
| 2020 | 7295             | 28,359             | 2,330,370             |
| 2021 | 9421             | 31,728             | 2,848,918             |
| 2022 | 8512             | 36,580             | 2,900,665             |
| 2023 | 9366             | 37,595             | 2,751,544             |
| 2024 | 9254             | 34,160             | 2,601,501             |



**Figure 1.** The relationship between total annual energy consumption and total annual enrolments.

**Figure 1** revealed a direct positive correlation between student enrollment and

energy consumption, confirming that academic activity is a primary driver of energy demand hence Student presence on campus is the most dominant factor influencing energy usage. More students mean more demand for classrooms, labs, lighting, computing, and support services.

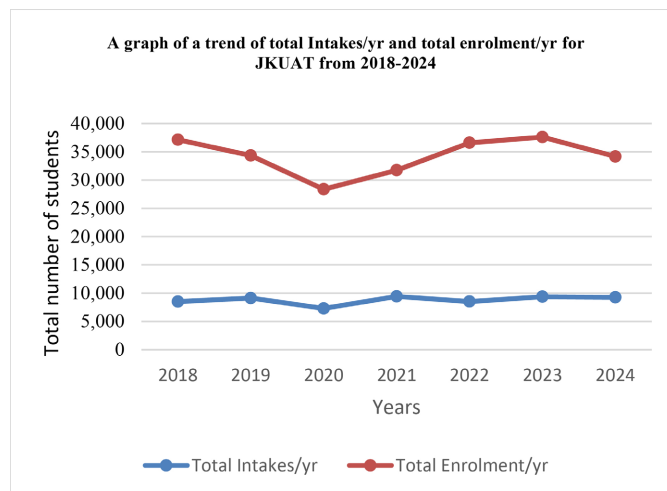
**Table 2** shows the intakes for the past years. This breaks the numbers to three annual intakes that JKUAT always receives. Both **Table 3** and **Figure 4** illustrate that September remains the dominant intake month every year, contributing over 80% of total annual admissions in most cases. For example, in 2024, 8,558 out of 9,254 new students were admitted in September alone.

**Table 3.** Number of students admitted from 2018 to 2024 according to intakes.

| Year | Jan. | May  | Sept. |
|------|------|------|-------|
| 2018 | 1442 | 0    | 7057  |
| 2019 | 743  | 1046 | 7334  |
| 2020 | 921  | 229  | 6145  |
| 2021 | 917  | 320  | 8184  |
| 2022 | 149  | 330  | 8033  |
| 2023 | 714  | 600  | 8052  |
| 2024 | 483  | 213  | 8558  |

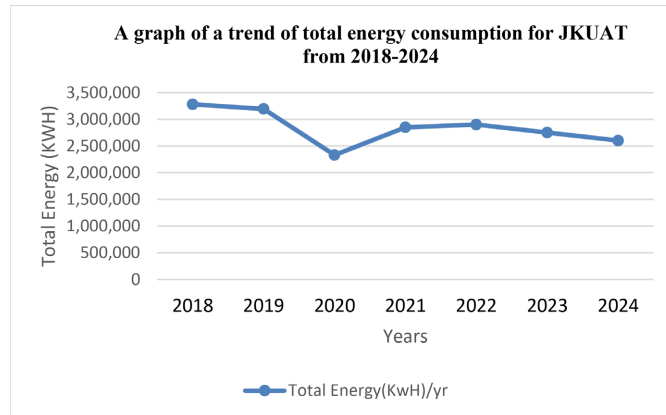
Since the majority of students are admitted in September, this month leads to higher utility loads. New admissions also increase the use of ICT labs, orientation activities, dormitories, and cafeterias hence strongly influencing the university’s energy profile.

**Figure 2** a trend in the total intakes and the total enrolment, showing that intake affects the enrolment as the drop in intakes leads to a drop in enrolment.

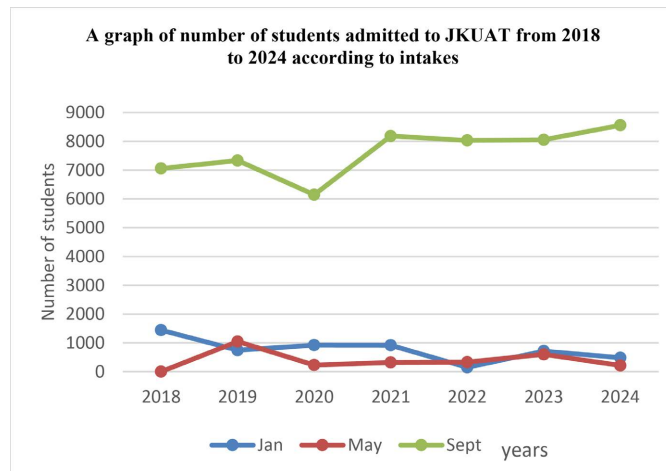


**Figure 2.** A trend of total Intakes/yr and total enrolment/yr for JKUAT from 2018-2024.

**Figure 3** shows the trend of total energy consumption for JKUAT from 2018-2024. It clearly shows a drop in 2020 due to COVID-19 pandemic before the total enrolment normalized. The average total consumption being between 2,500,000 KWh to 3,000,000 KWh.



**Figure 3.** A trend of total energy consumption for JKUAT from 2018-2024.



**Figure 4.** The showing number of students admitted to jkuat from 2018 to 2024 according to intakes.

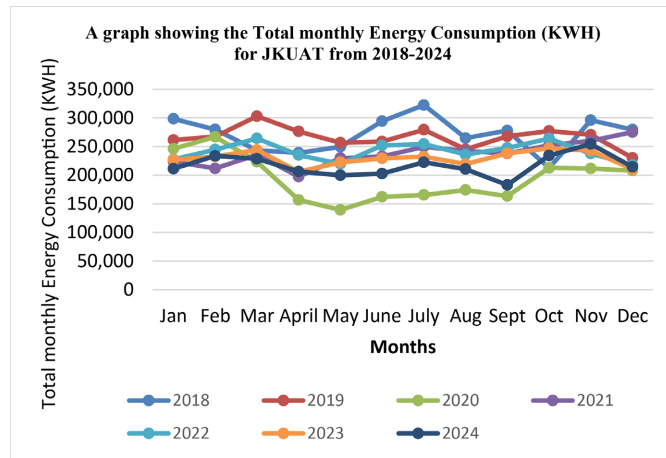
### 3.2. Monthly Consumption Patterns

**Figure 5** reveals distinct monthly energy data indicating that July consistently recorded the highest energy use, while May showed the lowest. The peak monthly consumption occurred in July 2018, while the lowest was in May 2020. **Figure 5** trends aligned more closely with academic term cycles than with environmental factors, reaffirming the role of institutional operations in driving electricity demand.

It should be noted that because missing values were treated using mean substitution, some short-term variability may have been smoothed. While this does not affect the long-term trends presented here, it could result in a slight underestimation of true peak loads.

### 3.3. Building-Level Energy Use

**Table 4** illustrates how energy consumption analysis of sub-metered data for 2024 revealed that the Main Meter alone accounted for 49% of total consumption.



**Figure 5.** The trends of the total monthly consumption (KWH) for JKUAT from 2018-2024.

**Table 4.** The categorization of meters based on association with student enrolment.

| S/N | NAME OF METER   | Ave. Monthly Cons. 2024 (KWH) | %tage Cons. 2024 (%) |
|-----|-----------------|-------------------------------|----------------------|
| 1   | Main            | 105476                        | 49                   |
| 2   | Hall 6          | 33465                         | 16                   |
| 3   | Science Complex | 24208                         | 11                   |
| 4   | Booster Pump    | 17035                         | 8                    |
| 5   | Ndarugu Pump    | 10380                         | 5                    |
| 6   | Sajorec         | 8980                          | 4                    |
| 7   | COHRED (SPA)    | 6946                          | 3                    |
| 8   | IEET            | 4534                          | 2                    |
| 9   | COHES           | 1164                          | 1                    |
| 10  | Others Combi)   | 1424                          | 1                    |

Buildings associated with student use, including main, Hall 6, the Science Complex, and COHRED, collectively consumed approximately 95% of campus electricity. This is shown in **Table 5** with a small percentage of about 5% not associated with students enrolment.

The ten sub-metered sites were intentionally selected because they capture the major functional categories of campus space: academic blocks (Science Complex, COHRED, IEET, COHES), residential facilities (Hall 6), administrative/service installations (Main, Sajorec), and essential utilities (Booster Pump, Ndarugu Pump). Together, these meters account for approximately 95% of total electricity consumption, providing a comprehensive picture of both student-driven and support operations.

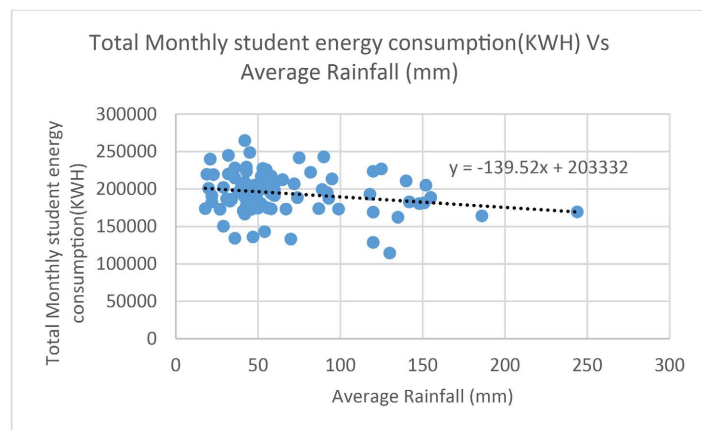
**Table 5.** The categorization of meters based on association with student enrolment.

| Meters associated with student enrolment number: |     | Meters not associated with student enrolment number: |    |
|--|-----|--|----|
| • Main   | 49% | • Others (Combi)                                     | 1% |
| • Hall 6   | 16% | • Sajorec  | 4% |
| • Science Complex                                | 11% |  |    |
| • Booster Pump                                   | 8%  |  |    |
| • Ndarugu Pump                                   | 5%  |  |    |
| • COHRED(SP)                                     | 3%  |  |    |
| • IEET   | 2%  |  |    |
| • COHES  | 1%  |  |    |
| Total:   | 95% | Total:   | 5% |

**Table 5** confirms that there is a high energy use strongly linked to student-focused buildings of about 95%, indicating the combined effect of lighting, laboratory use, ICT equipment, and increased occupancy, therefore future energy-saving interventions must focus on student-accessed spaces.

### 3.4. Climate Influence

While JKUAT has minimal reliance on HVAC systems, climate still exhibited modest effects. A negative correlation was observed between rainfall and energy consumption, particularly during April and May when heavy rains coincided with decreased campus activity. Rainfall tends to reduce physical movement and activity on campus therefore students and staff are less likely to attend classes or use facilities extensively during heavy rain leading to cancellation or postponement of the activities like lab activities due to lower attendance hence reduced overall occupancy. Moreso JKUAT with agricultural programs may rely on irrigation systems, pumps, and greenhouses, which operate less during rainy months. Since these operations are powered electrically, rainfall reduces this demand significantly.



**Figure 6.** The relationship between total monthly energy consumption and average rainfall.

Figure 6 shows the relationship between total monthly energy consumption and average rainfall and the relationship seen is slightly negative. Temperature showed a slight positive correlation with energy use, especially during warm months like March and October in Figure 7 due to cooling requirement and more irrigation need for the farms and the green houses.

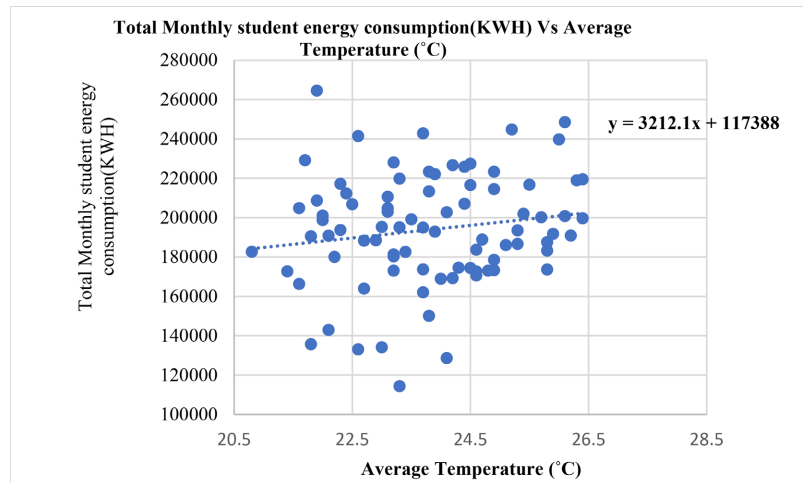


Figure 7. The relationship between total monthly student energy consumption and average Temperature.

Humidity and windspeed had minimal direct influence but appeared to align with periods of lower academic activity as shown in Figure 8 and Figure 9 respectively. The relation is negative for rainfall and humidity because an increase in rainfall and humidity reduces the need to pump water in the farms as JKUAT is an agricultural university and also reduces the Laboratory activities. It also reduces the need for the use of fans for cooling.

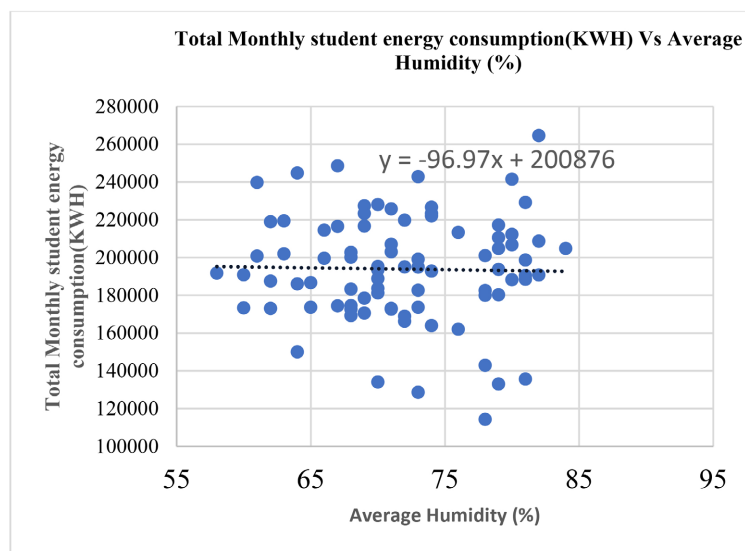
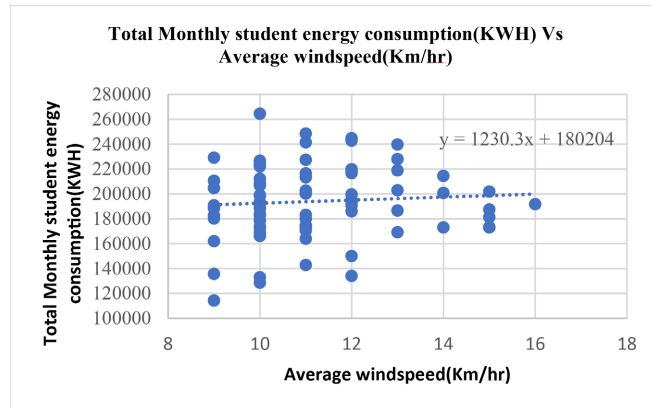


Figure 8. The average monthly variation in Humidity (%) from 2018-2024.

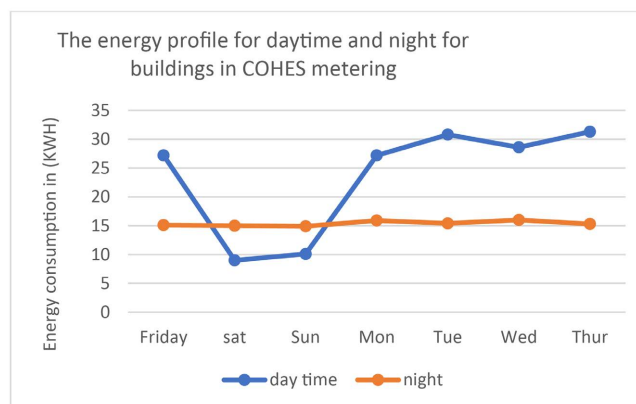


**Figure 9.** The average monthly variation in wind speed (Km/h) from 2018-2024.

### 3.5. Consumption Profiles for College of Health Science (COHES) and Institute of Energy and Environmental Technology (IEET) Metering as of the Month of June

**Figure 11** and **Figure 14** show total daily consumption of the two-building metering that is COHES and IEET respectively. The results show that more energy was consumed by the building during weekdays as compared to weekends. For example, the weekdays ranged from 42.3 kwh to 46.6 kwh and weekends between 24 kwh to 25 kwh for COHES metering and weekdays for IEET between 164.5 kwh to 171.8 kwh and weekends between 143.4 kwh to 156.1 kwh. This is because during the weekends the school activities like lecture, lab practical was not done or just a few. On Sunday even the offices were not operating.

**Figure 10** and **Figure 13** show the energy consumption at night is nearly constant daily for both building metering but varies during daytime depending on the day for example week days have a higher consumption as compared to weekends. **Figure 13** further explains that IEET metering contains greenhouses which need to be run by night just as day time hence more energy is consumed during the night compared to day time.



**Figure 10.** The energy profile for daytime and night for buildings in COHES metering.

Figure 12 and Figure 15 show an hourly trend in energy consumption during daytime and night and it clearly shows that the energy consumed every hour at night is nearly constant as compared to daytime hours where energy varies depending on time that is lunch hours energy use reduces, departure time the energy use reduces and before working hours the energy use is low.

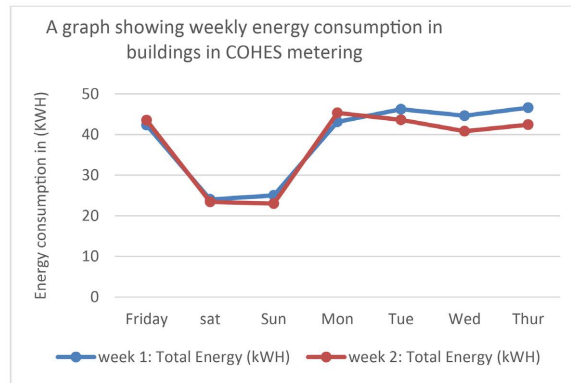


Figure 11. The profile of the total daily energy consumption in buildings in COHES metering.

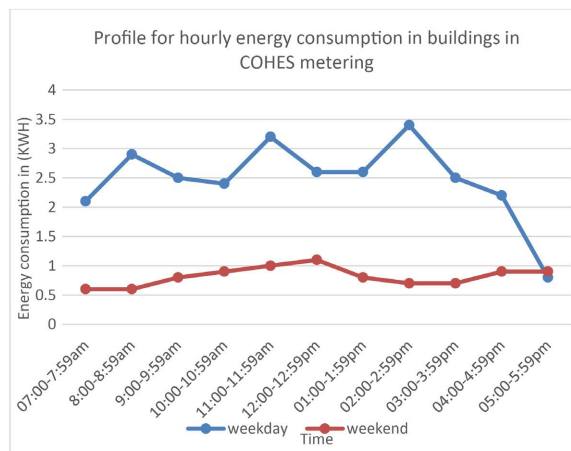


Figure 12. The hourly profile for energy consumption in buildings in COHES metering.

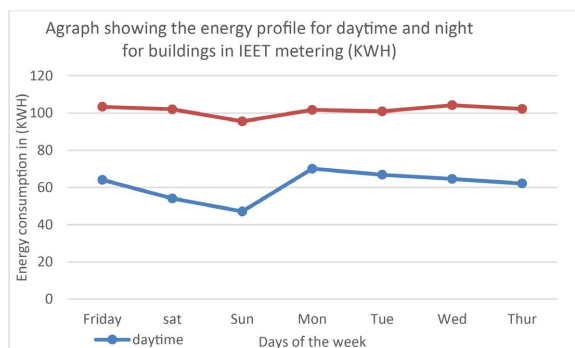


Figure 13. The energy profile for daytime and night for buildings in IEET metering.

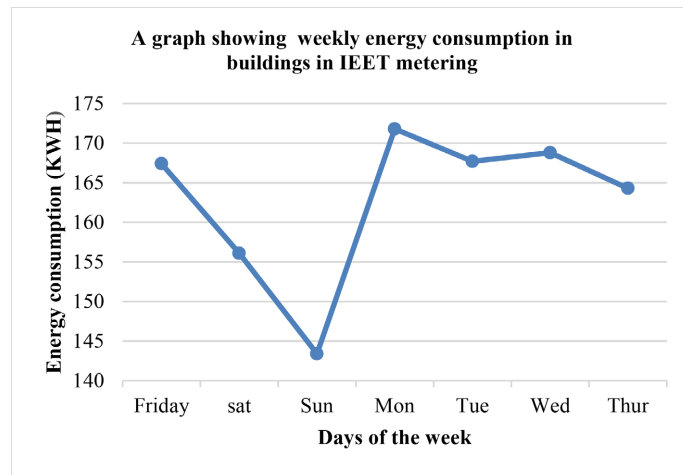


Figure 14. Daily energy consumption in buildings in IEEET metering.

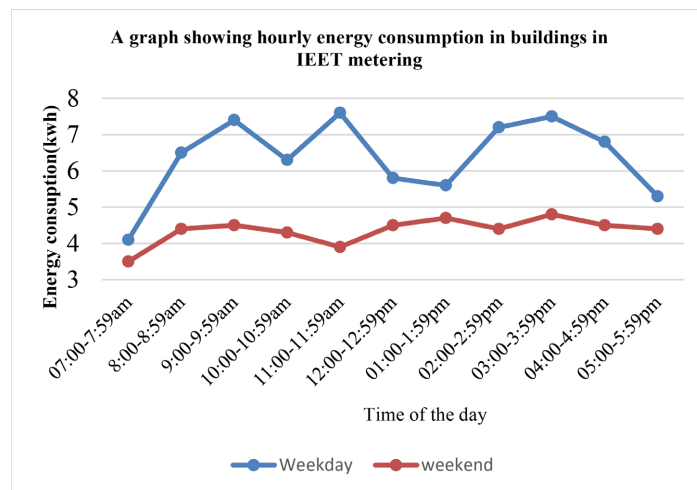


Figure 15. Hourly energy consumption in buildings in IEEET metering.

### 3.6. Predictive Energy Consumption Equation

To support predictive model development, the combined influence of enrolment and climate factors was quantified using the multivariable OLS regression model described in Section 2.6. With predictors centered on their means, the intercept  $\beta_0$  represents the baseline monthly energy consumption under average enrolment and climate conditions.

The estimated coefficients provide marginal effects of each variable while holding others constant. For instance, the enrolment coefficient reflects the additional kWh associated with each extra student, independent of climate variation. This specification avoids the omitted-variable bias inherent in univariate regressions and ensures a statistically coherent predictive equation.

Note: The intercept represents the baseline energy consumption independent of the selected predictors.

This model provides a useful foundation for forecasting monthly energy needs based on anticipated student numbers and seasonal climatic variations, paving the

way for the next phase of data-driven energy management and planning. While the model captures broad patterns, future work should validate predictive capacity using out-of-sample testing and additional performance indicators for example the Root Mean Square Error and the mean Absolute Error.

### 3.7. Correlation Analysis

**Table 7** illustrates Pearson correlation coefficient between energy consumption and five influencing variables. Energy use shows a strong positive correlation with student enrolment ( $r = 0.6337$ ) confirming that total number of students is a major driver of electricity demand. A slight positive correlation was found with average temperature and a very weak correlation with windspeed.

Conversely, rainfall showed a negative small correlation with energy use hence supporting the observed trend that heavy rain reduces campus activities and energy consumption. These results statistically confirmed the trends identified visually in Figures and seasonal patterns.

To further support model validity, multicollinearity among the climate variables was tested using Variance Inflation Factor (VIF) analysis. All VIF values were below 5, confirming that the variables could be used together in regression without posing collinearity concerns.

**Table 7.** Pearson correlation coefficients between the energy consumption and influencing variables.

| Variables  | Energy use | Enrolment | Temp.   | Rainfall | Humidity | windspeed |
|------------|------------|-----------|---------|----------|----------|-----------|
| Energy use | 1.00       | 0.6337    | 0.1589  | -0.21124 | -0.02192 | 0.0739    |
| Enrolment  | 0.6337     | 1.00      | 0.7605  | -0.1625  | -0.7769  | 0.5077    |
| Temp.      | 0.1589     | 0.7605    | 1.00    | -0.1625  | -0.8290  | 0.4654    |
| Rainfall   | -0.21124   | -0.1625   | -0.1625 | 1.00     | 0.3322   | -0.19402  |
| Humidity   | -0.02192   | -0.7769   | -0.8290 | 0.3322   | 1.00     | -0.7058   |
| windspeed  | 0.0739     | 0.5077    | 0.4654  | -0.19402 | -0.7058  | 1.00      |

### 4. Conclusions

This study successfully developed a comprehensive energy consumption inventory for JKUAT. The developed inventory reveals that student numbers and academic calendar are the most significant drivers of energy consumption at JKUAT. The influence of climate variables, while present, is secondary due to the limited use of heating and cooling systems. But they are highly applicable in other places with high heating and cooling. The identified trends justify the need for integrating student population forecasts and term schedules in future predictive energy models.

This inventory provides a data-driven foundation for the next phase of the project: the development of a predictive energy consumption model. The high correlation between student presence and energy use underscores the importance of

managing consumption around academic schedules. Future phases will build on this data to train machine learning models for energy forecasting. It also offers practical guidance for energy managers in universities seeking to align resource use with institutional planning and sustainability goals.

It should be noted that the predictive model presented here is preliminary. While diagnostic checks confirmed statistical soundness, the model has not yet undergone external validation. Future work should apply cross-validation or out-of-sample testing to strengthen predictive reliability.

## Acknowledgements

I gratefully acknowledge Jomo Kenyatta University of Agriculture and Technology (JKUAT) for data access and institutional support. Special thanks to the Directorate of Energy and ICT Department for providing energy and enrolment records, and to the Kenya Meteorological Department for providing online climate data from Juja.

I appreciate the guidance of my academic supervisors and Dr. Emmanuel Kombe Yeri for their valuable inputs that significantly contributed to this work.

Finally, I thank my family and friends for their unwavering support throughout this research.

## Data Availability Statement

The datasets generated and analyzed during this study are in the possession of the author and are not publicly available due to institutional restrictions. However, they can be provided by the author upon reasonable request and with appropriate permissions from JKUAT and the Kenya Meteorological Department.

## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

## References

- [1] Kumar, S., Rawat, M.K. and Gupta, S. (2019) An Evaluation of Current Status of Renewable Energy Sources in India. *International Journal of Innovative Technology and Exploring Engineering*, **8**, 1234-1239. <https://doi.org/10.35940/ijitee.g6004.0881019>
- [2] Oyedepo, S.O., Anifowose, E.G., Obembe, E.O. and Khanmohamadi, S. (2021) Energy-saving Strategies on University Campus Buildings: Covenant University as Case Study. In: Borge-Diez, D. and Rosales-Asensio, E., Eds., *Energy Services Fundamentals and Financing*, Academic Press, 131-154. <https://doi.org/10.1016/b978-0-12-820592-1.00006-3>
- [3] Chen, X., Peng, X., Li, Y. and He, B. (2024) Based on the Improved Fuzzy Analytic Hierarchy and the TSE-MLR Model Energy Consumption Prediction of University: A Case Study. *Heliyon*, **10**, e36979. <https://doi.org/10.1016/j.heliyon.2024.e36979>
- [4] Pradeep, B., Kulkarni, P., Ullah, F. and Lakas, A. (2025) Energy Use and Demand Prediction Using Time-Series Deep Learning Forecasting Techniques: Application for a University Campus. *IEEE Open Journal of the Computer Society*, **6**, 189-198. <https://doi.org/10.1109/ojcs.2024.3520198>

- [5] Ng, T.F., Ahmad Shabudin, A.F., Hassan, M.S., Muslim, M. and Ibrahim, K. (2016) Energy Consumption in Student Hostels of Universiti Sains Malaysia: Energy Audit and Energy Efficiency Awareness. In: Leal Filho, W., Mifsud, M., Shiel, C. and Pretorius, R., Eds., *World Sustainability Series*, Springer International Publishing, 191-207. [https://doi.org/10.1007/978-3-319-47895-1\\_12](https://doi.org/10.1007/978-3-319-47895-1_12)
- [6] Oyedepo, S.O., Anifowose, E.G., Obembe, E.O., Dirisu, J.O., Khanmohamadi, S., Kilanko, O., Babalola, P.O., Ohunakin, O.S., Leramo, R.O. and Olawole, O.C. (2020) Assessment of Economic and Environmental Impacts of Energy Conservation Strategies in a University Campus. In: Tripathi, S.L. and Padmanaban, S., Eds., *Green Energy: Solar Energy, Photovoltaics, and Smart Cities*, Scrivener Publishing LLC, 441-468.
- [7] Rucińska, J. and Trząski, A. (2020) Measurements and Simulation Study of Daylight Availability and Its Impact on the Heating, Cooling and Lighting Energy Demand in an Educational Building. *Energies*, **13**, Article 2555. <https://doi.org/10.3390/en13102555>
- [8] Sergeev, S., Barykin, S., Kalinina, O., Naumova, E., Dedyukhina, N. and Dmitrieva, T. (2021) Optimizing the Energy Efficiency of Higher Education Institutions. *E3S Web of Conferences*, **244**, Article 11029. <https://doi.org/10.1051/e3sconf/202124411029>
- [9] Schito, E. and Lucchi, E. (2023) Advances in the Optimization of Energy Use in Buildings. *Sustainability*, **15**, Article 13541. <https://doi.org/10.3390/su151813541>
- [10] Shahsavar, A., Ghadamian, H. and Saboori, H. (2023) Building Energy and Environmental Sustainability. In: Ma, H., Arıcı, M. and Shahsavar, A., Eds., *Building Energy Flexibility and Demand Management*, Elsevier, 3-15. <https://doi.org/10.1016/b978-0-323-99588-7.00006-7>
- [11] Opio, P. (2003) Household Energy Information Management System for Africa: A Ugandan Case Study. Master's Thesis, University of Cape Town. <https://open.uct.ac.za/>
- [12] Galvin, D., Leal Filho, W., Beans, C. and Escarré, R. (2017) Building Climate Change Resilience in East African University Campuses. In: Leal Filho, W., Azeiteiro, U., Alves, F., Molthan-Hill, P., Eds., *World Sustainability Series*, Springer International Publishing, 367-387. [https://doi.org/10.1007/978-3-319-47877-7\\_25](https://doi.org/10.1007/978-3-319-47877-7_25)
- [13] Ranadewa, K.A.T.O., and Chandanie, H. (2024) The Need for a Climate Database for Facilities Managers to Mitigate the Climate Change Implications on Buildings. *Proceedings of the 12th World Construction Symposium*, Sri Lanka, 9-10 August 2024, 1050-1063.
- [14] Kumar, S., Kumar Gupta, S. and Rawat, M. (2020) Resources and Utilization of Geothermal Energy in India: An Eco-Friendly Approach Towards Sustainability. *Materials Today: Proceedings*, **26**, 1660-1665. <https://doi.org/10.1016/j.matpr.2020.02.347>
- [15] Gupta, S.K., Dwivedi, V.K. and Kumar, N. (2021) Scenario of Small Hydro Power Plant (SHP) in India and Effects on Climate Change: An Eco-Friendly Approach Towards Sustainability. *IOP Conference Series: Materials Science and Engineering*, **1116**, Article 012043. <https://doi.org/10.1088/1757-899x/1116/1/012043>