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Spatial Clustering of Electricity Consumption Patterns in Indonesian Higher Education Institutions

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Abstract – **Higher education institutions represent a significant contributor to electricity consumption in the public sector, particularly in developing countries such as Indonesia. This study aims to identify spatial patterns and provincial disparities in electricity consumption across Indonesian higher education institutions. This research method uses spatial autocorrelation analysis with Moran's I and hierarchical clustering based on Ward's method. The results show that the observed Moran's I (0.5129679) is higher than the expected Moran's I (-0.03030303), and the spatial pattern of electricity consumption by higher education institutions is clustered. This result is confirmed by the negligible p-value (0.0003618787 < 0.05), indicating a strong clustered spatial pattern. Hierarchical clustering was used to identify three groups of provinces based on electricity consumption levels. The findings highlight significant regional disparities in electricity consumption patterns and provide a quantitative basis for energy management strategies and sustainable higher education policy planning in Indonesia.**

Keywords: Electricity consumption, higher education institutions, spatial autocorrelation, Moran's I, hierarchical clustering, Ward's method, Indonesia

I. Introduction

Higher education institutions are major contributors to public-sector electricity consumption in developing countries such as Indonesia due to the growing number of students and the expansion of campuses [1]. Several universities have implemented predictive models and renewable energy initiatives to manage energy consumption and reduce emissions [2], [3]. However, the growth of digital transformation in higher education with regard to IoT devices and data centers has led to increased energy consumption [4]–[7]. Unregulated energy consumption not only increases operational requirements but also increases carbon emissions, thereby worsening the current global climate change dilemma [8]–[12].

Data-driven spatial methodologies, especially Geographic Information Systems (GIS), are currently employed to detect regional differences in electricity consumption [13]–[15]. Moran's I is one of the many methods used for spatial analysis, which is widely used to test for spatial autocorrelation among data on energy consumption [16]. Empirical studies have supported the view that Moran's I is useful for revealing spatial clusters of energy consumption, which are often linked to geographic, demographic, and structural characteristics [17], [18].

Regional disparities in Indonesian higher education institutions influence the distribution of electricity consumption, reflecting infrastructure development and energy access [19]–[21]. Investigations conducted in other nations, including China and India, show that spatial analysis provides important insights into improving sustainable energy management in the educational sector [22]–[24].

Moreover, the implementation of GIS for the spatial analysis of electricity consumption has proven effective as a strategy for promoting SDGs, especially those related to energy efficiency and the reduction of carbon emissions [25]–[27]. The analytical framework implemented in this study has significant potential to enhance energy management in Indonesia's higher education institutions, especially in view of the continuous growth in annual energy demand.

However, no study has systematically examined the spatial autocorrelation and provincial clustering of electricity consumption in Indonesian higher education institutions. Existing studies are mostly focused on aggregate sectoral consumption, forecasting models, or general regional clustering, without explicitly testing ~~of~~ whether electricity consumption in higher education institutions shows statistically significant spatial dependence across provinces. This limitation leads to an important research gap, since understanding spatial dependence is crucial for designing regionally coordinated and evidence-based energy management strategies.

This study aims to (1) measure the degree of spatial autocorrelation in the province-level electricity consumption of higher education institutions using Moran's I, (2) test the statistical significance of the result, and (3) identify the spatial clusters of consumption using hierarchical clustering based on Ward's method.

The findings are expected to provide empirical evidence on whether electricity consumption patterns show statistically significant spatial dependence and to provide a spatially-informed analytical framework for

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higher education institutions' energy management at the provincial level.

II. METHODOLOGY

This study employed a quantitative methodology based on spatial analysis to measure and explain electricity consumption patterns in Indonesia's higher education institutions. The methodological framework was combined with statistical data, GIS technology, and electricity consumption clustering in higher education institutions. This GIS and clustering method is computationally efficient because it uses clustering algorithms to analyze geolocation data, similar to previous studies, although it focuses on assisting occupants [28]. The procedural steps taken in this research are outlined below:

A. Data Collection

This research method begins with the collection of electricity consumption data in higher education in some Indonesian provinces. Furthermore, data on the administrative boundaries of provinces were obtained to enable spatial analysis. Geographic coordinates were used only for mapping and spatial visualization.

B. Spatial Weight Matrix

After obtaining electricity consumption data for each of the province's higher education institutions, a spatial weight matrix was built using a Queen contiguity approach based on provincial administrative boundaries to define spatial adjacency relationships between provinces. Under the queen criterion, two provinces are neighbors if they share either a common boundary or a common vertex. A binary adjacency matrix was first created in which neighboring provinces were assigned a value of 1 and all other entries were assigned a value of 0. The matrix was then row-standardized to make the province comparisons comparable. The resulting standardized row matrix was used in the calculation of Moran's I.

C. Moran's I Analysis

Moran's I is an index used to detect spatial patterns in a variable. In the current analysis, Moran's I is computed to assess the degree of electricity consumption concentration in a given area. In the analysis of spatial patterns, two types of Moran's I are commonly used. They are observed Moran's I and the expected Moran's I. The observed Moran's I is the Moran index usually calculated directly from the data. It is calculated using the following equation:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \quad \ldots\ldots\ldots\ldots\ldots \quad (1)$$

where

I = Moran's I

n = Number of observation areas (provinces and higher education institutions)

w_{ij} = Elements of the row-standardised Queen contiguity matrix

x_i = Observation value of electricity consumption at the location (i-th row area)

x_j = Observation value of electricity consumption at the location (the j-th column area)

$\bar{x}$ = Average observation value of the electricity consumption

The resulting Moran's I can be interpreted as representing five spatial patterns : weak, moderate, moderately strong, strong, and very strong, as shown in Table 1.

Table 1. Interpretation of Moran's I for Spatial Autocorrelation.

Moran's I	Interpretation
0.0–0.2	Weak
0.2–0.4	Moderate
0.4–0.6	Moderately Strong
0.6–0.8	Strong
0.8–1.0	Very Strong

Expected Moran's I is the theoretical value of Moran's I assuming that the data were distributed randomly. The expected Moran's I is given by the following equation:

$$E(I) = -\frac{1}{n-1} \quad \ldots\ldots\ldots\ldots\ldots \quad (2)$$

If the observed Moran's I is greater than the expected Moran's I, then the observed Moran's I is autocorrelated and forms a cluster. However, if the observed Moran's I is less than the expected Moran's I, the spatial pattern is scattered. If the calculated Moran's I is equal to the expected Moran's I, then the spatial pattern is random.

After analyzing Moran's I, a significance test was performed using the p-value. This value is important in proving that the detected autocorrelation pattern is significant.

D. Spatial Cluster Development

Spatial patterns of electricity consumption are reflected in clusters indicating differences in consumption among provinces' higher education institutions. These clusters help ~~to~~ show general patterns of electricity consumption, thereby providing an understanding of how it is used across regions. Spatial clustering was conducted using hierarchical clustering with Ward's method to identify provinces with similar electricity consumption characteristics. The squared Euclidean distance was used as a similarity measure, and all variables were standardized using Z-scores before clustering to ensure comparability. The dendrogram was analyzed to determine the optimal number of clusters by determining a significant increase in the linkage distance (fusion level), which represents a natural break between groups. Based on the dendrogram's cut-off criteria, three clusters were selected as they provided the most interpretable and statistically distinct grouping structure without excessive fragmentation.

Overall, the integration of spatial statistical analysis and hierarchical clustering offers a strong methodological framework for understanding regional electricity consumption patterns and supporting data-driven policy development in Indonesian higher education institutions.

III. RESULTS AND DISCUSSION

A. Results

In the first stage of the research, electricity consumption data for higher education institutions were collected by province. These data provide a clear overall picture of variation in electricity consumption in Indonesia and of disparities among higher education institutions.

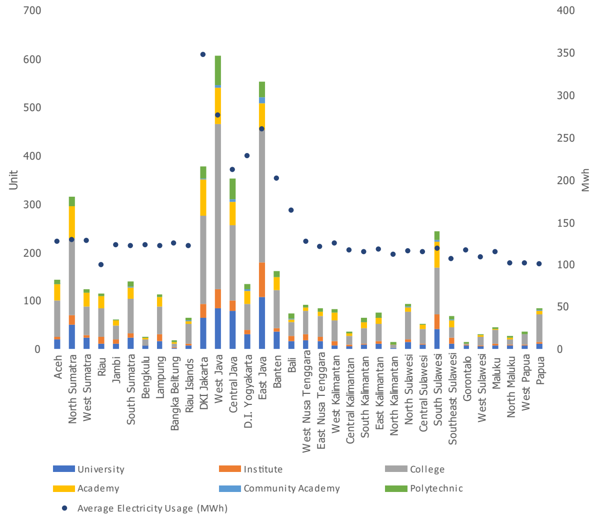

Figure 1. Distribution of higher education institutions and average electricity consumption (kWh) in Indonesian provinces

Data on electricity consumption in higher education institutions in various provinces in Indonesia were obtained from the official Statistik Captive Power publication distributed by *Badan Pusat Statistik* (BPS). This publication offers a large amount of information related to the number of higher education institutions, which includes universities, institutes, colleges, academies, community academies, and polytechnics, measured in units, in association with the average electricity consumption measured in kilowatt-hours (kWh).

As shown in Figure 1, the bar graph depicts the number of higher education institutions, such as universities, academic institutions, community academic institutions, colleges, and polytechnics. The line graph indicates the electricity usage across various higher education institutions in each province, by type, such as universities, institutes, academies, community academies, colleges, and polytechnics. This means that provinces with an urban center, such as Jakarta, West Java, and East Java, have significantly higher electricity consumption than other regions. Jakarta has the highest average electricity consumption. Provinces located in eastern Indonesia, such as North Maluku, West Papua, and Papua, have a lower average electricity consumption than other regions. The analysis of differences in electricity consumption across higher education institutions in each province is an advanced indicator of the need for spatial analysis.

Next, to obtain a geographical overview of the provinces, provincial administrative boundary data were used within a Geographic Information System (GIS) environment. Table 2 presents data on the locations of the provinces for mapping, based on their latitude and longitude coordinates.

Table 2. Longitudes and Latitudes of Indonesian Provinces.

Province	Longitude	Latitude
Aceh	4.28314552	96.94271
North Sumatra	2.30109413	99.1592
West Sumatra	-0.6937111	100.65117
Riau	0.44623367	101.76198
Jambi	-1.69790378	102.72143
South Sumatra	-3.21897964	104.1682
Bengkulu	-3.52159928	102.34665
Lampung	-4.91386926	105.02225
Bangka Belitung	-2.25307598	105.98738
Riau Islands	3.9158351	108.20227
DKI Jakarta	-6.20908997	106.8387
West Java	-6.91990729	107.60303
Central Java	-7.25880247	110.20493
D.I. Yogyakarta	-7.89508109	110.44686
East Java	-7.81636296	112.61345
Banten	-6.45446536	106.12149
Bali	-8.35542001	115.11618
West Nusa Tenggara	-8.63079183	117.85805
East Nusa Tenggara	-8.60460171	121.14352
West Kalimantan	-0.06858231	111.15311
Central Kalimantan	-1.60086204	113.41682
South Kalimantan	-2.95639307	115.38277
East Kalimantan	0.46339608	116.44696
North Kalimantan	2.87731512	116.18107
North Sulawesi	0.88305377	124.26728
Central Sulawesi	-0.98234669	121.08122
South Sulawesi	-3.62752945	120.15855
Southeast Sulawesi	-3.81028156	121.83345
Gorontalo	0.68711896	122.37404
West Sulawesi	-2.46098924	119.33948
Maluku	-3.20137669	129.46071
North Maluku	0.87122735	128.01526
West Papua	-2.10230269	133.14421
Papua	-4.54584624	138.72571

Spatial relationship evaluation was performed based on shared administrative boundaries between provinces using the Queen contiguity criterion. A binary adjacency matrix was created according to this criterion, and the provinces with a common boundary or a common vertex were given the value of 1, while the non-neighboring provinces were given the value of 0. The spatial matrix serves as the main instrument for understanding electricity consumption patterns in higher education institutions in a geographic and spatial context. Each element in the matrix is a binary spatial adjacency indicator (1 if the provinces share a common boundary or vertex, 0 if not). Then, the matrix was row standardized to allow comparability across provinces. Row standardization was applied so that the weights of neighboring provinces were set to 1 for each province.

With 34 provinces, a 34-by-34 matrix was developed. To model the spatial adjacency between provinces, a 34-by-34 row-standardized Queen contiguity matrix was constructed. Each element of the spatial weight matrix is the standardized adjacency relationship between provinces under the queen's contiguity. This spatial weighting approach is the foundation for the autocorrelation analysis by accurately calculating Moran's I for electricity consumption in higher education institutions in each province.

The calculation of Moran’s I was performed based on the row-standardized Queen contiguity spatial weight matrix. Table 3 shows the results of the calculation of the observed Moran’s I, the expected Moran’s I, and the p-value.

Table 3. Statistical Results of Moran’s I Spatial Autocorrelation Analysis

Parameter	Value
Observed Moran’s I	0.5129679
Expected Moran’s I	-0.03030303
p-value	0.0003618787

According to the calculation results, the observed Moran's I value was 0.5129679. This value indicates the fairly strong positive spatial autocorrelation between electricity consumption and the geographic locations of higher education institutions in each province in Indonesia. This positive spatial autocorrelation also implies that provinces with similar electricity consumption levels (low or high) tend to be geographically close.

After obtaining the observed Moran's I value, it was compared with the expected Moran's I value to determine whether the spatial pattern of electricity consumption of higher education institutions in Indonesia is ~~a~~ random, clustered, or dispersed. A random spatial pattern is specified when the observed and expected Moran’s I values are the same as the expected Moran's I value. A cluster spatial pattern is defined when the observed Moran’s I value is higher than the expected Moran’s I value. A dispersed spatial pattern occurs when the observed Moran’s I value is below the expected Moran’s I value.

The calculation results in the expected Moran's I value of -0.03030303. Referring to the observed Moran’s I (0.5129679) as greater than the expected Moran’s I (-0.03030303), the electricity consumption pattern by higher education institutions is a cluster pattern. This result is supported by a negligible p-value (0.0003618787) below 0.05. This provides strong statistical evidence that a significant spatial pattern exists in electricity consumption at higher education institutions (rejecting the null hypothesis that there is no spatial autocorrelation).

The statistical results demonstrate the importance of spatial patterns in determining electricity consumption in higher education institutions. Figure 2 shows the visualization of electricity consumption by higher education institutions across provinces in Indonesia. This image attempts to simplify the results and show the regional patterns.

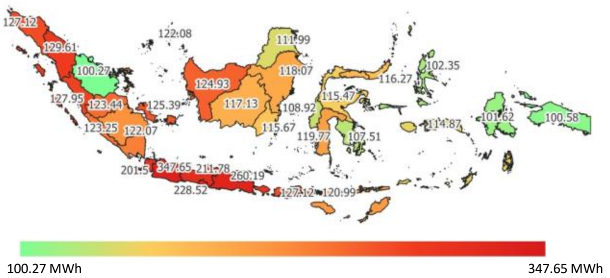

Figure 2. Spatial pattern of electricity consumption in Indonesian higher education institutions

Spatial analysis was performed to determine electricity consumption patterns in Indonesia’s higher education institutions and to form homogeneous groups by province. Variables that affect electricity consumption were included as dependent variables in each province, along with the effects of independent variables such as geography. The clusters were produced by hierarchical cluster analysis using Ward’s method to classify Indonesian provinces based on similar electricity consumption patterns. Then, a dendrogram shows the measured distances between clusters of provinces with similar electricity consumption characteristics.

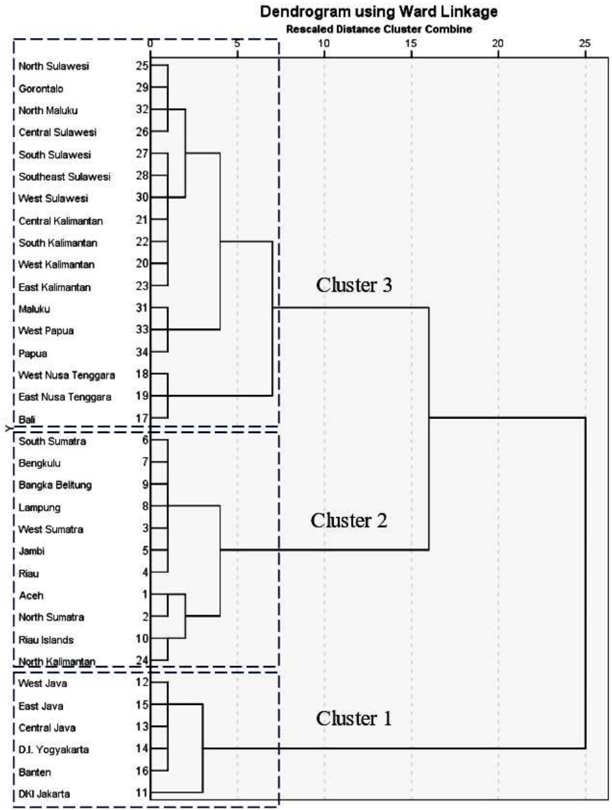

Figure 3. Hierarchical clustering dendrogram of provinces using Ward’s method based on electricity consumption in higher education institutions

This finding can serve as a basis for designing appropriate management strategies and formulating policies for electricity consumption efficiency in higher education institutions. Therefore, the formation of clusters of provinces with similar electricity consumption profiles among higher education institutions is a crucial step in supporting more efficient energy management and effective data-driven policies.

The dendrogram in Figure 3 illustrates the Indonesian provinces’ interrelationship with electricity consumption in higher education institutions. A hierarchical cluster analysis was performed using Ward’s method and the squared Euclidean distance to measure of how different the variables were. Cluster 1 comprises provinces with high electricity consumption. Some provinces of this cluster are DKI Jakarta, Banten, West Java, D.I Yogyakarta, Central Java, and East Java. These provinces are national centers of academic growth, marked by many continuities in higher education and research. From a policy perspective, these provinces are well-positioned to be hotbeds for research-based projects that will encourage advanced technology and support the Triple Helix framework (which includes government, industry, and academia). Cluster 2 covers provinces with moderate electricity consumption. Provinces included in this cluster are Aceh, North Sumatra, West Sumatra, Riau, Riau Island, Bangka Belitung, Bengkulu, Jambi, South Sumatra, Lampung, and North Kalimantan. These regions will have a high demand for middle-skilled workers, requiring the full potential of their workforce. However, interventions are required to assist certified training programs and strengthen partnerships between vocational schools and businesses. Cluster 3 includes provinces with ~~a~~ relatively few institutions and low electricity consumption. Several provinces in this cluster are located in eastern Indonesia, including Bali, West Nusa Tenggara, East Nusa Tenggara, West Kalimantan, Central Kalimantan, South Kalimantan, East Kalimantan, Sulawesi, Gorontalo, North Maluku, Maluku, and Papua. Given the low electricity consumption, access to higher education and building infrastructure are difficult. Policy measures for this cluster should focus on affirmative action, such as the establishment of educational facilities, the provision of scholarship programs, and the capacity building of lecturers.

The formation of clusters 1–3 demonstrates the relevance of spatial analysis in capturing the heterogeneity of regions and electricity consumption in higher education institutions. Identifying clusters with homogeneous consumption patterns within each province can provide an empirical basis for developing policy strategies to optimize electricity distribution and improve the efficiency of electricity consumption programs in higher education institutions. This spatial clustering approach can also be used to make data-driven decisions in planning and implementing improvements to Indonesia's electricity system.

B. Discussion

The results show a positive relationship between the presence of higher education institutions and electricity consumption levels, which is consistent to some extent with previous results, which found an association between the level of education and energy consumption in Indonesia [29]. However, fundamental differences exist in the approaches and units of analysis used. Previous studies analyzed the impact of education level on per capita energy consumption using the STIRPAT framework and a panel econometric approach, differentiating between Java and non-Java regions. Meanwhile, the current analysis focuses on the spatial dimension and clustering patterns of electricity consumption in higher education institutions, considering the geographical proximity between provinces. The spatial clustering pattern of higher education institutions in Indonesia demonstrates that geographical location is related to similar electricity consumption levels. This pattern indicates that electricity consumption dynamics are influenced by regional context rather than occurring in isolation. Thus, the spatial autocorrelation discovered using Moran's I not only indicates a statistical relationship but also reflects the structure of higher education development, which tends to concentrate in certain areas.

The use of Geographic Information Systems (GIS) technology to analyse spatial patterns of electricity consumption in higher education institutions is very important because this integration supports data-driven decision-making, especially in priority areas. Combining spatial methods with energy policy in Indonesia can improve electricity consumption efficiency not only in the higher education sector but also in other sectors. Integration, a key element of this research methodology, is also relevant in strengthening national energy policies, including greenhouse gas reduction strategies. However, a direct relationship between the management of electricity consumption in higher education and national carbon emissions cannot be directly concluded from the present analysis and requires further analysis.

The results of the provincial cluster analysis in Indonesia, based on electricity consumption in higher education institutions, were divided into three clusters. The number of clusters aligns with the studies of Y. Arvio, who clustered electrical load consumption using k-Means clustering [30], and Y. L. Berliana et al., who clustered electricity consumption levels by province in Indonesia using k-Means clustering [31]. Thus, the objects of analysis and the variables used are substantively different from the current investigation, which focuses specifically on electricity consumption in higher education institutions.

In addition, it is also strengthened by R. Utari et al., who clustered electricity distribution using the mean shift algorithm [32], S. Mulyadi et al., who used the mini-batch k-Means clustering algorithm [33], and M. Farid et al. using Density Based Spatial Clustering of Application With Noise (DBSCAN) algorithm [34], also strengthen this approach. However, previous studies focused on clustering based on numerical similarity. However, the approach in this study incorporates geographic linkages into the analysis structure. Therefore, the contribution of this analysis is the integration of cluster analysis with spatial dimensions through geographical weight and autocorrelation analysis, so that grouping is determined not only by numerical similarities in electricity consumption but also by the geographical connectedness between regions. Thus, the current research opens up the perspective of clustering in the study of electricity consumption in Indonesia by situating the higher education institutions in a more contextual spatial analysis framework.

Overall, the spatial clustering methodology of this study provides a more detailed picture of how location and educational outcomes on electricity consumption. These findings must be placed in the context of an initial analytical basis to support the formulation of more focused policies, rather than as final or comprehensive policy recommendations. These insights are helpful in developing strategies for sustainable electricity consumption, equitable educational growth, and long-term improvement planning.

While this analysis provides an overview of the spatial patterns of electricity consumption in higher education institutions, some limitations should be considered. The data used are secondary data at the provincial level, so it does not fully capture the variations in electricity consumption across the institutions of one province. Therefore, further research with more detailed provincial-level data is required to gain a better understanding of the determinants of electricity consumption in higher education institutions.

IV. CONCLUSION

This analysis examines the spatial distribution of electricity consumption in Indonesia's higher education institutions. The observed Moran's I value is 0.512, which is higher than the expected Moran's I value of -0.030303. This implies a huge spatial clustering pattern in electricity consumption. Furthermore, the p-value 0.00036 (p-value < 0.05) indicates a statistically significant spatial pattern. GIS-based thematic maps reveal clusters of high electricity consumption, mainly in cities with large higher educational institutions. Conversely, low electricity consumption clusters occur in areas with limited access to energy or operational activity. Further analysis shows that these consumption patterns result from a combination of geographic, demographic, and operational factors. The results show the potential utility of the geoinformation system (GIS)-based methods for understanding electricity consumption patterns on a larger scale (i.e., at the regional scale). The results also categorized higher education institutions into three groups based on electricity consumption. The formation of these clusters can offer initial insights for the creation of more specific energy-efficiency policies, especially in regions with ~~a~~ relatively high electricity consumption, while also promoting the consideration of electrification strategies in regions with ~~a~~ low energy consumption. This methodological framework has the potential to make analytical contributions to data-driven energy policy discussions. However, its use at the national level still requires further study by considering other heterogeneous variables across provinces and testing in other research contexts. However, the present analysis has a number of limitations, in particular the use of provincial-level aggregate data, which does not adequately reflect internal variation across institutions, and the limitations of the explanatory variables. Future research could combine other factors such as university accreditation level, lecturer functional position composition, and regional socio-economic variables to better understand the determinants of electricity consumption in higher education institutions. Furthermore, future research could develop an analysis of energy use intensity to obtain a more comprehensive understanding of electricity consumption patterns across the types and characteristics of higher education institutions based on each province's type of education.

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