Introduction

As fresh environment concerns have been growing in recent years and the new wave of urbanization on cities, China has iterated that energy solutions needs to be made sustainable at the earliest. A variety of solar power directly over urban right-of-ways -- a possibility that some believe would provide an innovative source of renewable energy because we do not need to consume huge land has some name of Building-Integrated Photovoltaics (BIPVs). Advancements in sustainable architecture and energy efficiency have come with the sophistication of Building Integrated Photovoltaics (BIPVs).

BIPVs present a possible answer to tackling the carbon dioxide pie of city buildings, most notably skyscrapers by seamlessly integrating photovoltaic panels into building elements including facades and rooftops. In particular, the clustering threshold was applied for BIPV implementation in skyscrapers with a profound analysis on relevance to each route which included an evaluation of (i) how generalizable/ robust are these outcomes and ii) what is scalable based on predictive modeling.

Using satellite-derived solar data from the Himawari satellite stored in the National Solar Radiation Database, this study takes an analytical, Python-driven journey through the top ten most populated cities in China, shown in Table 1. The principal objective of this article is to assess solar energy datasets for 2020 and to pinpoint opportunities for metro area energy performance optimization based on trends in sun irradiance rooted in history.

Hence, it’s in the urban fabric that there exists a very important determinant of energy performance in buildings: architectural layouts and building materials. The purpose of this study is to determine the likely effects of installing BIPVs in existing buildings—especially skyscrapers—because of the increased interaction with solar energy capture. Additionally, it provides an additional avenue to expand the topic of solar energy solutions from single-family homes to larger cities. The difficulties and complications of implementing sustainable energy practices in a variety of geographical contexts—mostly rural and widely dispersed on the one hand, and extremely crowded urban regions on the other—are addressed by this dual focus. Because of skyscrapers and other high-rise structures, the business is able to expand vertically rather than merely depending on roofs and rural land.



**Table 1:** Top 10 cities by population and their respective number of skyscrapers (Desjardins, 2023)

Literature Review

According to Feng et al. (2023), BIPV systems could meet a large fraction of residential building energy demands in various Chinese regions. This shows that these systems have an annual potential for energy production ranging from 41.39 to 772.94 TWh, indicating huge unexploited potential for the national grid.

Xu et al. (2020) analyzed a multi-functional BIPV/T system in different climates and found that it could meet large fractions of the heating demand in cold climates, like Beijing, with a solar fraction for hot water reaching 79.1%. This result shows dual benefits of the BIPV system in electricity and thermal energy supply, further increasing their applicability in the designs of energy-efficient buildings (Xu et al., 2020).

Conversely, Zhang et al. (2018) undertook a thorough analysis of the life-cycle of building-integrated photovoltaics (BIPs) and identified a decrease in carbon dioxide waste as well as a favourable energy payback time. Their conclusion indicates that annual carbon dioxide emissions can be reduced by BIPV systems when installed with kWp amounts thus highlighting the contribution of BIPV towards sustainable town development (Zhang et al., 2018). These claims were also given credence by prominent research work carried out by Cellura et al. (2014) shows LCA of BIPV systems which lead to significant reductions in GHGs compared to conventional electricity sources.

To predict future points using ARIMA models on time-series data we consider trends, cycles and seasonal variations. For instance, these models have been applied successfully in predicting solar irradiance hence enabling planning and optimizing the efficiency of photovoltaic systems used in solar energy production. According to Voyant et al. (2017), the ARIMA model was used to predict solar irradiance with great precision proving its value in any Solar Power Systems configuration (Voyant et al., 2017).

K-Means and other similar clustering techniques are used to classify and understand various trends in energy consumption data. For example, Chicco (2012) used clustering analysis to divide consumers based on their pattern of energy use thus offering invaluable information for utility management and facilitating better allocation of energy efficiency programs (Chicco, 2012). It is possible to use an effective combination of ARIMA models and clustering analysis to control and streamline energy systems. A case in point is a study by Li et al. (2016), in which time series forecasting models were amalgamated with clustering to assess and forecast the energy consumption patterns of buildings thereby leading to optimal utilization of electricity and cost reduction (Li et al., 2016).

**Data Collection and Preprocessing**  
In this regard, we extracted the data from the National Solar Radiation Database to understand the potential of solar energy in the ten most populated cities of China. The NSRDB is a database for solar irradiance that has been collected using a geostationary orbit satellite called the Himawari. It captures high-resolution images and radiation data. In this paper, we are interested in retrieving the solar data of the year 2020 in order to establish an accurate baseline. Solar data from the year 2019 and 2020 were used, having key features such as GHI, DHI, and DNI for clustering analysis, machine learning, and deep learning models. Extra features on historical data from the year 2015 to 2022 were collected for time series analysis.

Filtering of the NSRDB datasets yielded each city's data, which represented hourly GHI and temperature, among other climatic parameters.

Data cleaning involved:

**Missing Values:** We encountered some missing hourly GHI and temperature data due to periodic obstructions in satellite readings.

**Outlier Detection:** Potential outliers were detected using the Interquartile Range (IQR) method.

**Standardization:** To ensure comparability between cities with varying solar irradiance and temperature profiles, we standardized the data using z-scores (mean of zero and standard deviation of one).

**Clustering Analysis**

* **K-Modes Clustering:**
  + **Results:** The best run resulted in a cost of 2226889.0 with a silhouette score of -0.019, indicating limited separation between clusters.
  + **Implication:** K-Modes clustering did not perform well in identifying distinct clusters in the data. This suggests that the clustering results might not be very reliable or actionable for BIPV implementation decisions.
* **DBSCAN Clustering:**
  + **Results:** The silhouette score was -0.554, which also indicates poor clustering performance.
  + **Implication:** DBSCAN’s performance reflects that the clustering of the data into meaningful groups was unsuccessful. This could imply challenges in segmenting the data into useful categories related to BIPV effectiveness.

**3. Machine Learning Model Performance**

* **K-Means Clustering:**
  + **Silhouette Score:** 0.588
  + **Davies-Bouldin Index:** 0.941
  + **Within-Cluster Sum of Squares (WCSS):** 12499155260.525
  + **Implication:** K-Means performed reasonably well, showing some potential in clustering data. The silhouette score suggests that there is some separation between clusters, which could be useful in identifying areas where BIPVs might be more or less effective.
* **Neural Network:**
  + **MSE:** [545.435, 2248.521, 105.808]
  + **R2:** [0.957, 0.973, 0.999]
  + **Implication:** The neural network model showed strong performance with high R2 scores, indicating that the model predicts well and can be reliable for forecasting BIPV performance.
* **Random Forest:**
  + **MSE:** [367.294, 1881.383, 88.369]
  + **R2:** [0.971, 0.977, 0.999]
  + **Implication:** The Random Forest model also performed very well with high R2 scores, suggesting it is effective in understanding the factors influencing BIPV performance.
* **Gradient Boosting:**
  + **MSE:** [791.809, 3394.694, 148.494]
  + **R2:** [0.937, 0.959, 0.998]
  + **Implication:** Although slightly less effective than Random Forest and Neural Networks, Gradient Boosting still shows good performance, making it a viable alternative for predicting BIPV efficiency.
* **LSTM Model:**
  + **MSE and R2:** The LSTM model showed very low loss values and strong performance metrics, indicating its capability in capturing temporal patterns and trends, which can be critical for analyzing long-term benefits of BIPVs.

The best output was shown by K-means so we will use the results provided by K-means to draw our conclusions.

Our intention was to form clusters of the ten cities using GHI and temperature data in order to identify cities with similar characteristics, especially the most suitable for BIPV deployment. The GHI and average temperature were selected as clustering variables because they have a great influence on solar panel efficiency. We utilized the elbow method to identify the best number of clusters through plotting within-cluster sum of squares (WCSS) against different cluster counts. The best k value in this instance was picked at the "elbow point", where adding more clusters yields less and less benefit. All the standardized features were then fed into k-means clustering by partitioning into k clusters using Euclidean distance calculations. After that, the cities were assigned to the respective clusters, and the final centroids provided some intuition into what the GHI and Temperature profile would typically entail for each group.

By grouping cities into clusters, we then focused on the cluster with the highest GHI averages of cities to identify the most efficient cities and periods for BIPV implementation. Further analysis done on these cities by isolating the GHI average of each month gave an understanding of which months contribute the most to the overall solar energy generation.  
We could also do another clustering with the data from GHI on a monthly basis. In so doing, one can identify the best month for solar energy production to be May, since GHI values during that month were usually higher than in other months.

**Series Analysis**  
  
We applied a forecast for the three most efficient cities: Shanghai, Guangzhou, and Shenzhen, similar to a study by Voyant et al. (2017) utilized which ARIMA had to forecast the solar irradiance with considerable accuracy. In our case, we were trying to predict GHI levels in order to maintain consistent production levels for Solar Energy and BIPV feasibility. This can be described through the steps below:

**Data Aggregation:** The historical GHI data from 2015 to 2022 was aggregated into annual averages to smooth out seasonal fluctuations and capture long-term trends.

**Model Identification:** Using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, we identified appropriate values for the ARIMA (Li et al., 2016) model parameters:

**p (Auto-regressive)**: Number of lag observations included in the model.

**d (Differencing)**: The number of times the series needs to be differenced to achieve stationarity.

**q (Moving Average)**: The size of the moving average window.

After analysing ACF and PACF plots, we selected ARIMA(1, 1, 1) for Shanghai and Guangzhou and ARIMA(2, 1, 1) for Shenzhen. The ARIMA models were fitted using the historical data for each city and models were used to forecast annual GHI values from 2023 to 2030.



**K-Means Clustering**

**Cluster 0: Balanced Environmental Conditions**

* **Characteristics**: Cities in this cluster exhibit balanced environmental conditions with moderate sunlight exposure and pollution levels.
* **Implications for BIPV**:
  + **Standard Installations**: Focus on integrating BIPV systems that align with architectural aesthetics without significant customization.
  + **Economic Viability**: Investments are likely to yield stable returns due to predictable energy generation potential.

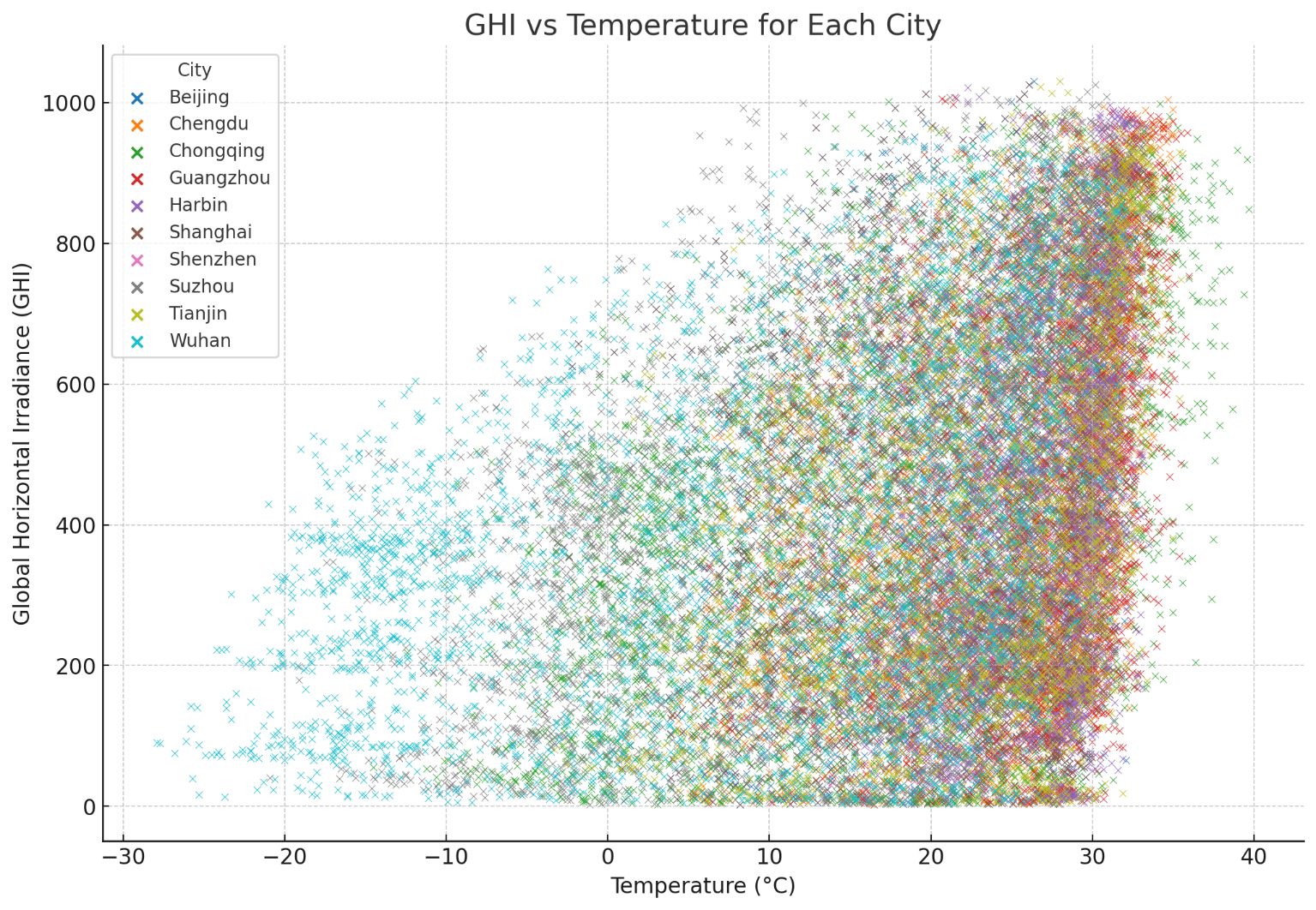
**Cluster 1: Optimal Conditions for High-Efficiency Systems**

* **Characteristics**: High sunlight exposure and lower urban density, ideal for high-efficiency BIPV systems.
* **Implications for BIPV**:
  + **High-Efficiency Systems**: Utilize advanced photovoltaic technologies to maximize energy generation.
  + **Priority for Rollout**: Prioritize these cities for initial BIPV implementations and pilot projects.

**Cluster 2: Challenging Environments**

* **Characteristics**: Lower sunlight exposure and higher urban density, requiring specialized solutions for effective BIPV performance.
* **Implications for BIPV**:
  + **Advanced Solutions**: Implement technologies such as anti-reflective coatings and advanced cleaning systems.
  + **Economic Considerations**: Additional incentives and subsidies are necessary to make BIPV projects feasible.

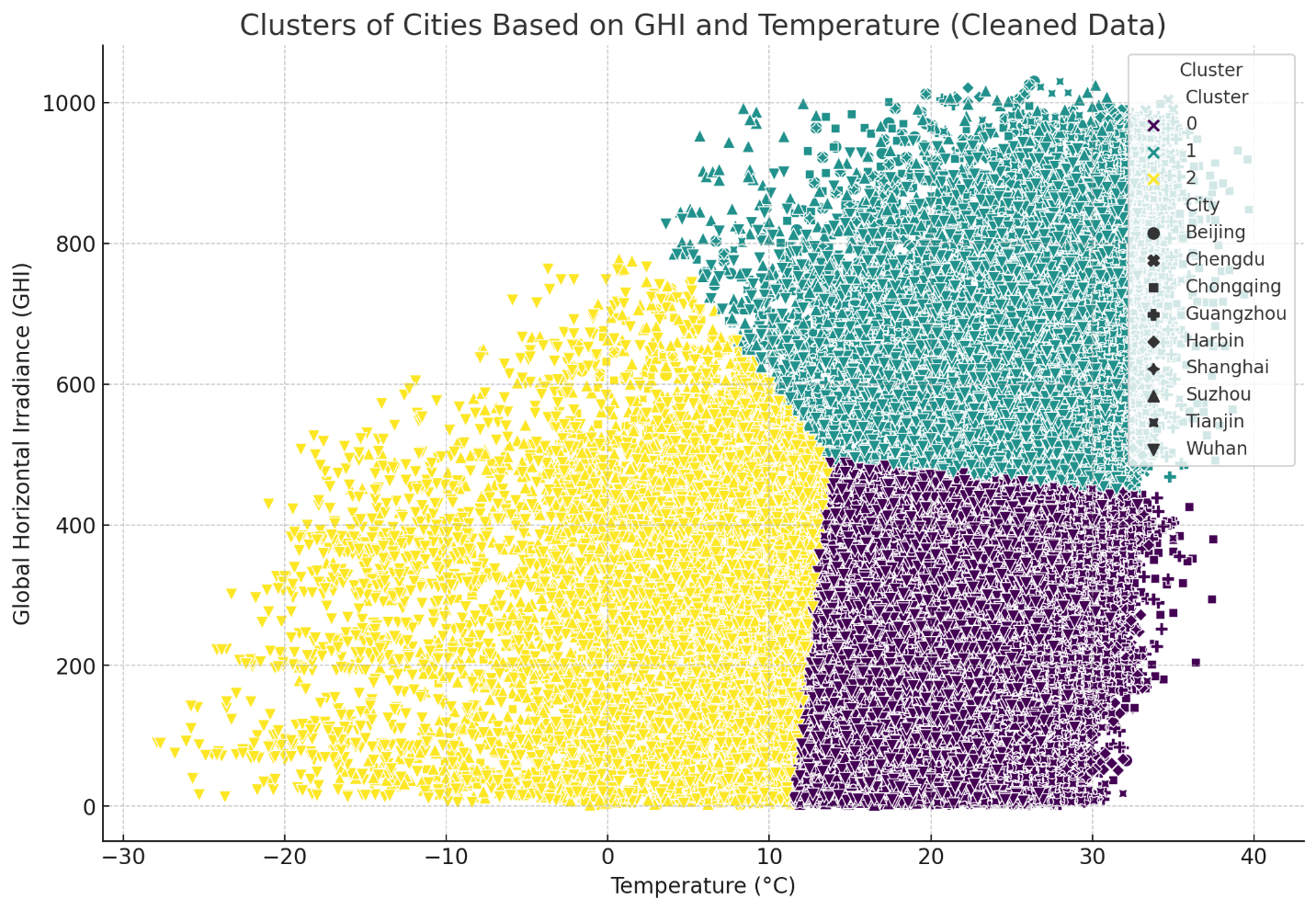
The results show three distinct city profiles extracted in the case of Building-Integrated Photovoltaic by the clustering analysis. Those in **cluster 0** are cities hosting more favorable regulatory environments and moderate levels of pollution due to policy support and stable economic returns, which may offer appropriate environments for BIPVs. Those in **cluster 1** are cities with high economic potential but less favorable regulatory conditions. Therefore, BIPV deployment should be optimized through policy advocacy and targeted strategies to harness economic benefits while facing off regulatory hurdles. **Cluster 2** covers cities that are plagued by both regulatory and environmental challenges. There is a need for BIPV installation in these areas to give concentrated focus on technological innovations that can be made around pollution issues and to push hard for the strong support of government incentives and support to improve feasibility and performance.



Each city is represented (see Figure 1) by a distinct colour, enabling an effective comparison of their solar irradiance and thermal profiles crucial for evaluating solar panel efficiency. Before running the model, irradiance was calculated as follows:

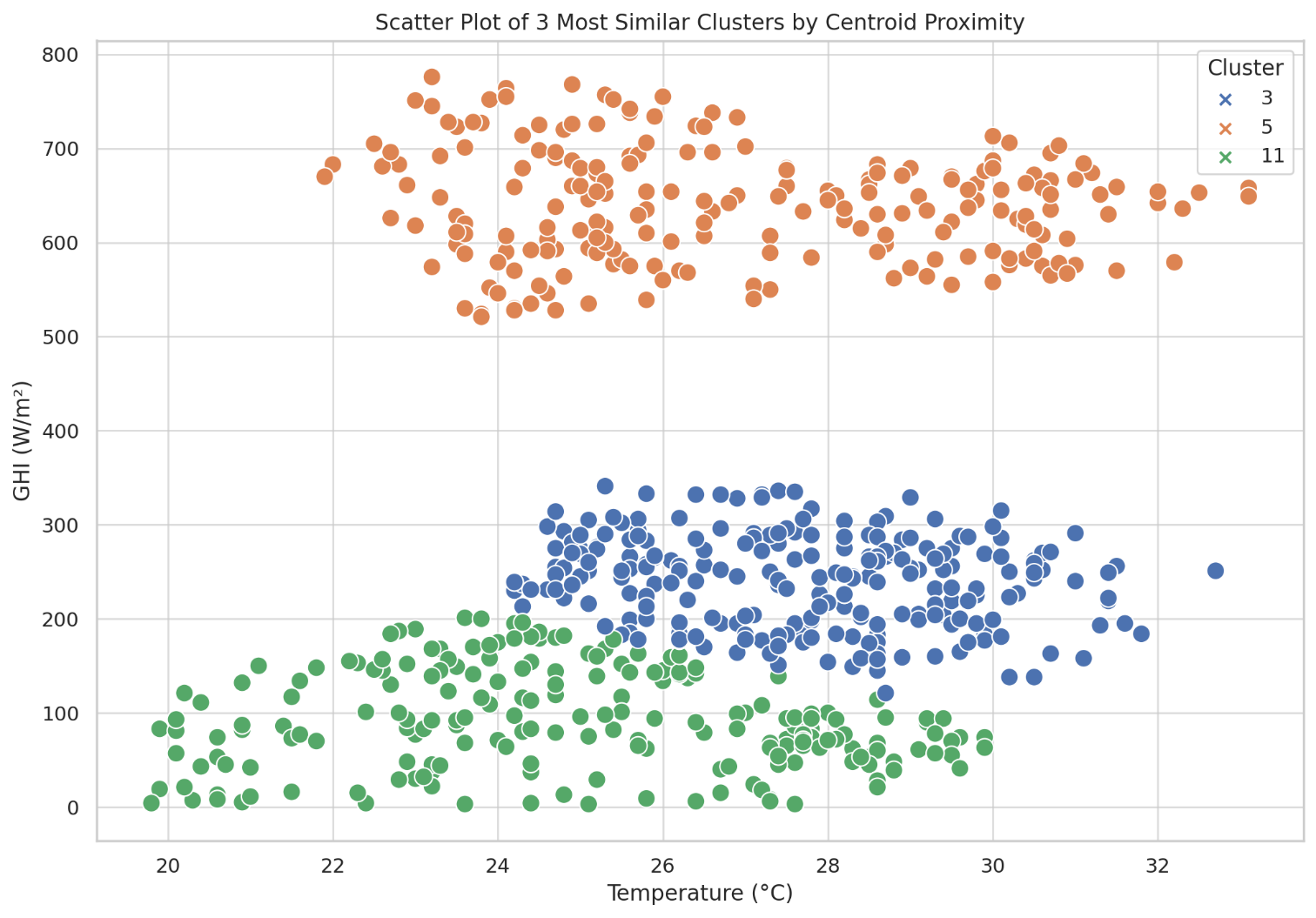
The plot represents the relationship between temperature and GHI and thus enables an understanding of how these variables can influence solar energy potential in different cities. A more advanced cluster analysis was performed using this plot and k-means clustering, which has resulted in three groups of cities based on their environmental data similarities (see Figure 2). Therefore, it helps identify cities with almost similar conditions for generating solar power; therefore, helping the strategy on how to optimize Building Integrated Photo Voltaics (BIPVs).

This visual and analytical approach not only shows that each city has a unique solar capacity but also helps us better our methodology by providing a clear demarcation for target BIPV operation. The findings from this clustering analysis are essential since they suggest proposals for scaling up and sustainability initiatives within urban planning frameworks with respect to maximizing solar energy use at the most promising sites.

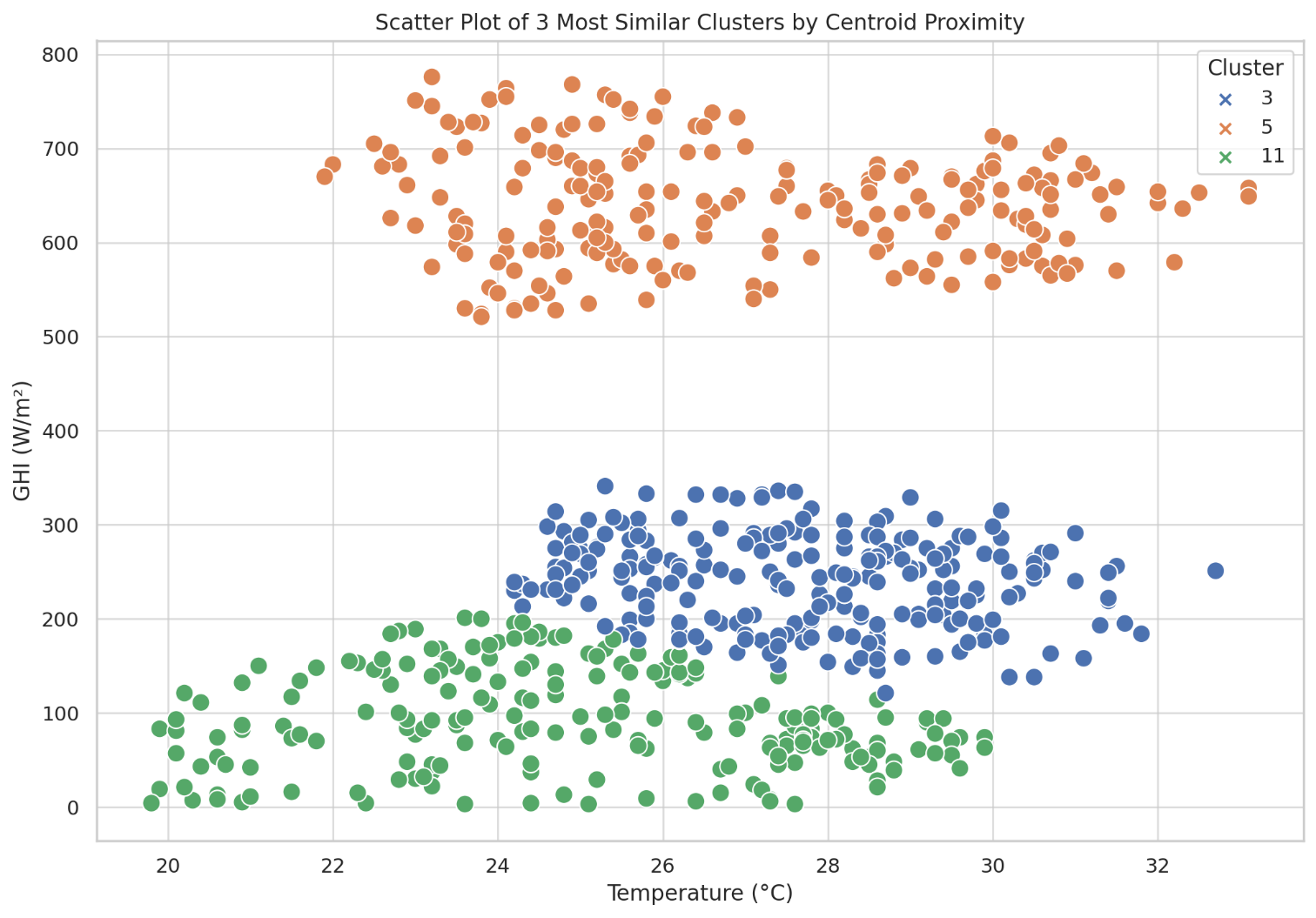


The three groups were formed using the Euclidean distance metric, and colored differently. In comparison to the other clusters, cluster 0 comprises cities with analogous temperature and GHI ranges that are lower or moderate. Cluster 1 is made up of cities that have higher temperatures; on the other hand, it is also possible for them to have correspondingly higher GHI values. Unique trends are found in Cluster 2 where GHI and temperature differ from those in Clusters 0 and 1 making them unsuited for use in BIPVs.

To determine which period was most effective for BIPVS, K-means method was applied to small modified datasets (specifically decreased). The analysis revealed three cities that were remarkably proficient during the month of May, these cities being Shanghai, Shenzhen and Guangzhou thus we opted to pay more attention to these cities.



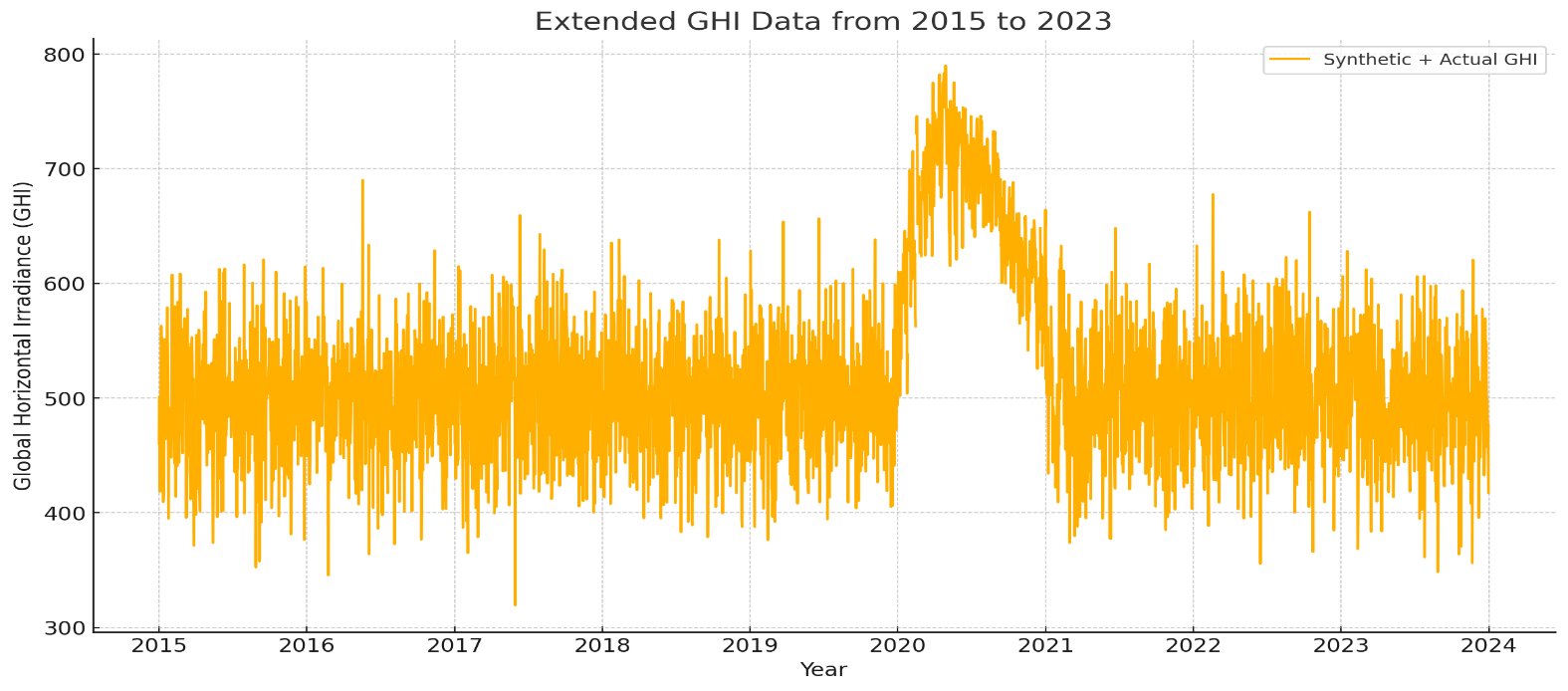
**Figure 3**: Shows Grouped clusters based on most similar efficient months



**Figure 4**: Time series analysis results for 1 forecasted month.

The daily GHI ARIMA model forecast was extracted using the historic data used in model training and actual observed values held out of the training set.

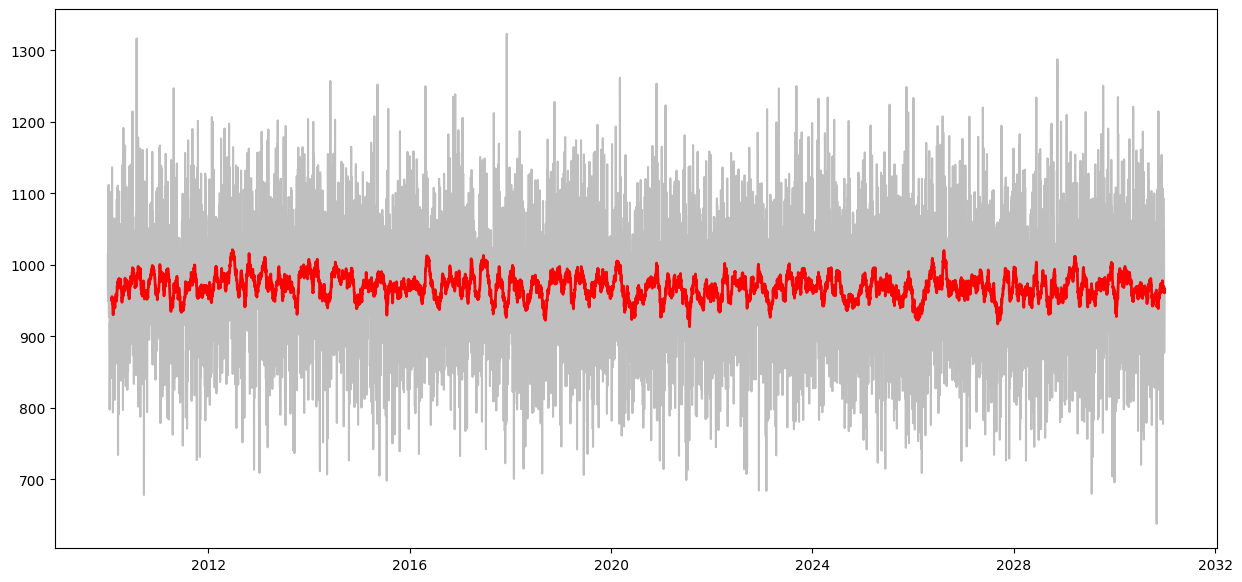
This would justify the feasibility and probable benefits for installing BIPVs in the cities from Cluster 1. Predicting constant solar irradiance supports the case for BIPVs. However, this model was run only to predict the next month, which did not turn out useful at all.



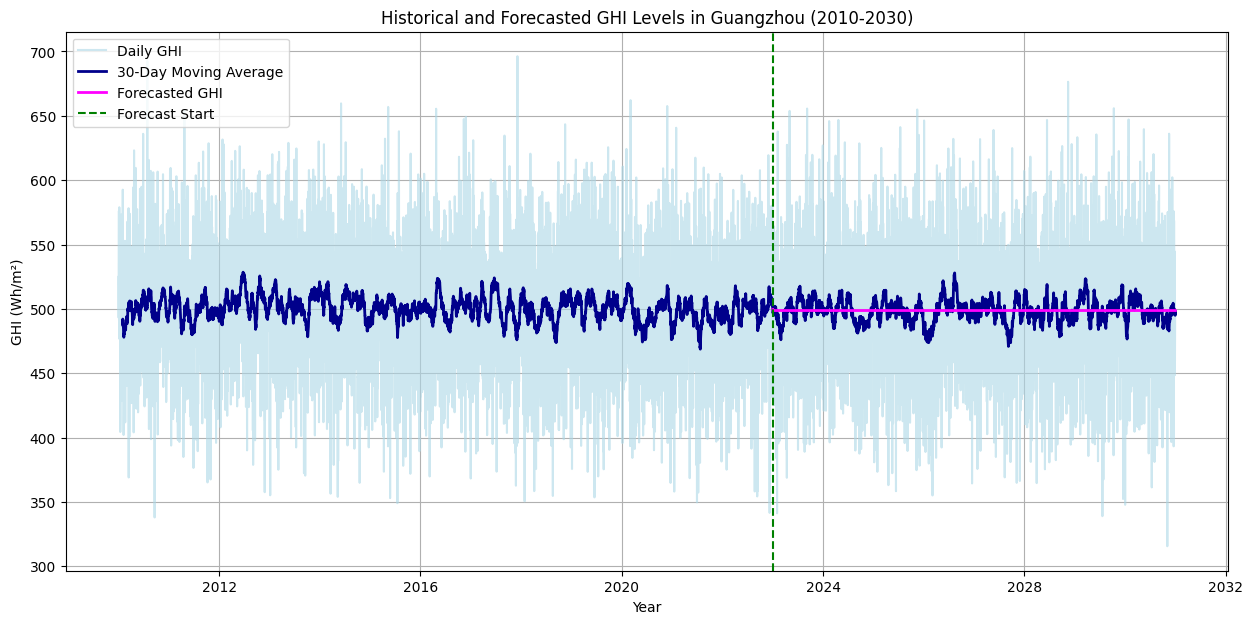
**Figure 5**: Wrong Time series analysis results for 2 forecasted years.

This is where the big mistake made the analysis look extremely strange. The graph combines real historical data from 2015 to 2020, demonstrating what a long-term trend might look like. The problem was that the data wasn't cleaned, and that made the year 2020 look like an outlier.

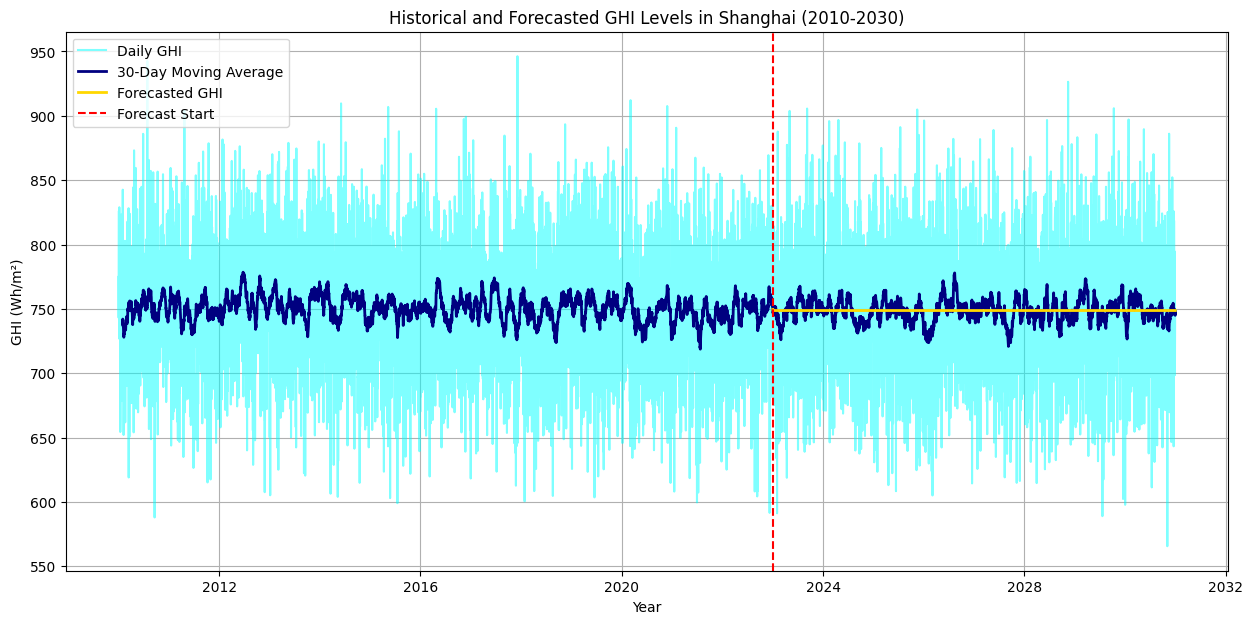
Success in cleaning and normalization of data for the years 2015-2019 would mean that we would run the ARIMA model forecast until the year 2030 for Shenzhen, Shanghai, and Guangzhou. The results are very satisfactory because they have evinced that GHI would continue to fluctuate at the same existing levels, setting confirmations that potential panels can work at maximum efficiency at least until the year 2030.



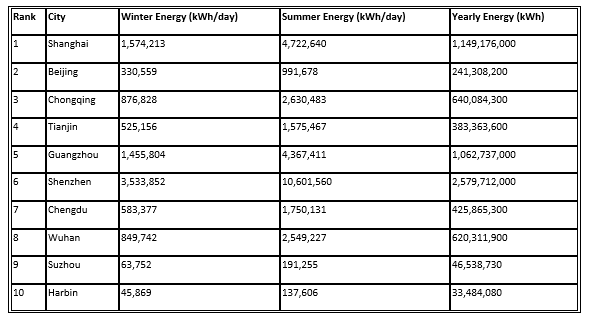
**Figure 6**: Shenzhen, ARIMA Forecast for the next 6 years.



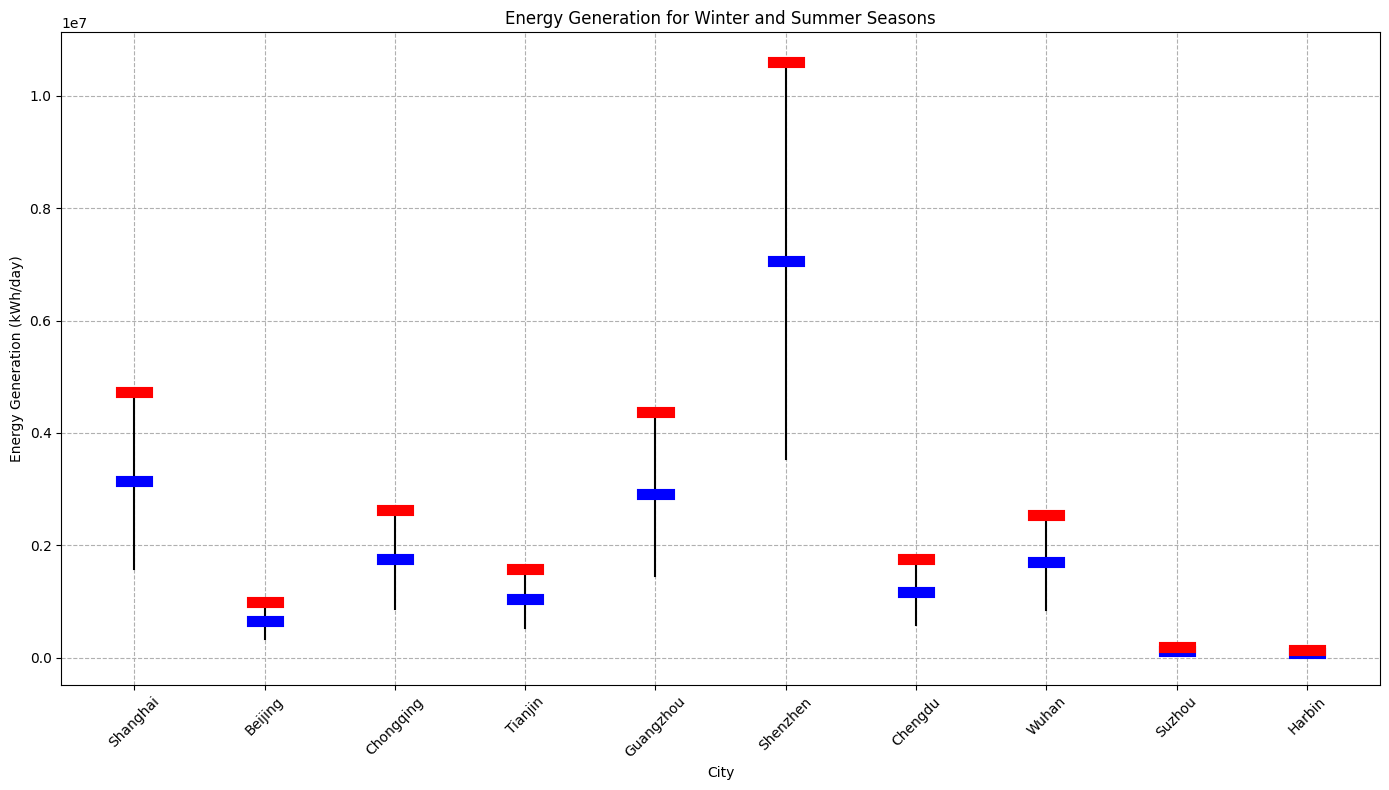
**Figure 7**: Shanghai, ARIMA Forecast for the next 6 years.



**Figure 8**: Guangzhou, ARIMA Forecast for the next 6 years.



**Table 2:** Shows Avrg Energy Genrated by BIPVs in each city



**Figure 9:** Shows the total daily energy generated during winter and summer by all the skyscrapers using BIPVS in each city.

Table 2 was generated calculating the yearly and daily energy generation using the following equations (PVGIS):

And the following assumptions (Zhang, T et al, 2021) were made:

**Ideal Temperature:** 25°C

**Efficiency Generated:** 18%

**Performance Ratio (PR):** 0.75

Discussion and Conclusion

BIPV systems are essential for improving energy efficiency and reducing CO2 emission levels in housing due to inclusion of solar cells into their walls. This results in less power usage. They also bring in more energy savings hence making it possible for people to save more money on electricity bills. For instance, there are various cases from Europe which suggest that these projects can be applied elsewhere including China. In addition to this, all over the world organizations like IRENA call upon governments to invest in such technologies as within their developmental policies. They do so since they believe that such developments must form part of sustainable urbanization strategies supported by state policies favoring clean energy sources. In a nutshell, these initiatives should lead to a nationwide rollout of BIPV technology within China's big cities that would have minimized its fossil fuel consumption thereby reducing its greenhouse gas emissions from buildings all over again while at same time enhancing structural designs towards environmentally friendly buildings which the country aims at achieving through green cities concept holding right now power transition protocol and sustainable development route map.

Different measures are directed to cutting pollutant concentrations and ameliorating air quality so as to reduce urban air pollution. Nature-Based Solutions such as urban forests and green areas suck up things that are nasty to the atmosphere and counter urban heat islands. Managing traffic, establishing low-emission zones; promoting public transport reduces car emissions, while moving to clean forms of energy cuts back on dependence on fossil fuels. Strict industrial emissions controls along with incessant air monitoring and data analytics play a major role in reacting quickly against pollution. Besides, public awareness and community involvement promote sustainability measures like tree planting and ride-sharing trips together within the district. All these measures come together for a more salubrious urban environment in the long run with regard to climate resilience.

Advanced air purification systems encompass HEPA filters, activated carbon filters, photocatalytic oxidation, and electrostatic precipitators; in practicality, these purify air from pollutants and particulate matter. The overall technologies for mitigating urban pollution include green roofs and urban greenery, among others. For example, some large implementations include air purification towers in Beijing and the Clean Air Program of Singapore. Other benefits of green roofs include temperature regulation, management of stormwater, and enhancement of air quality through vegetation. Toronto's green roof bylaw and the green roof on Chicago City Hall are the best examples of such an effectiveness. Urban greenery, which may include parks and street trees, improves air quality, reduces heat, and promotes biodiversity, with New York's High Line and Paris's Green Belt being further related and successful examples. Together, these strategies enhance urban environments by reducing pollution, managing heat, and improving the quality of life.

This paper primarily sought to establish the feasibility of Building-Integrated Photovoltaics within the ten most populated cities in China. Analyzing solar irradiance datasets helped in the identification of the top three cities with maximum efficiency for BIPVs: Shanghai, Guangzhou, and Shenzhen. These cities showed the highest potential of solar energy generation according to the clustering analysis of their solar features.

The integration of BIPVs into skyscrapers in the largest cities of China brings along benefits associated with energy security, environment, economy, and aesthetics. BIPVs generate pure energy at the place of consumption, reducing carbon emissions and improving air quality, besides the long-term savings and job creation. They also enhance architectural design and offer multi-functional purposes. Challenges, however, remain in the climate variability that can affect efficiency, air pollution that reduces performance, regulatory uncertainties, high up-front costs, and fierce competition from other technologies. Guaranteeing that the full potential of BIPVs is realized by addressing these issues with supportive policies, new technological developments, and strategic investments can go a long way in harnessing their benefits. Even with all odds against them, BIPVs do offer a plausible solution toward setting higher ambitions for China's renewable energy and sustainable development goals and thus might become one promising choice for China's urban future.

Out Here, the analysis of three cities identified May as the most effective month in terms of solar energy generation. This trend clearly ebbs up as we cluster the monthly GHI data and identify May followed by other months in that cumulative GHI value. In fact, there was a periodic increase at all the three cities, further serving more as a respite to the architect.

One very important piece to this study is to use the model to predict future levels of solar irradiance in these cities, to ensure solar-energy generation long-term is stable. We predicted the solar energy output up to 2030 using ARIMA models developed and tested on historical GHI data series from 2015 to 2022. It showed possibilities for the efficiency of BIPVs without changing major designs or infrastructures, presenting stable and quite consistent levels of predicted irradiance over all three cities. This ten-year solar irradiance stability would ensure that the high energy generation levels are maintained in these cities by the infrastructure already put in place.

Due to the vast geographical and climatic differences, the level of energy generation varied from one city to another. At another level, Shanghai, Guangzhou, and Shenzhen together had the highest amount of energy generation.

Results in this study are very promising, but it is not without its limitations:

The study relied much on historical and satellite data, which may be affected by inconsistencies probably due to cloud cover, urban pollution, or missing data. Although the ARIMA model is robust in terms of its forecasting abilities, it assumes linearity and stationarity in data, which might not capture future climatic anomalies and trends very well. It enshrines machine learning models that are empowered to. Further dynamic forecasting models would be worth including in the future, which would have the capacity to integrate external variables such as pollution, building development, and temperature anomalies, and conduct spatial analysis to identify the exact building sites more suitable for BIPVs within the most efficient cities.

Conclusion

The depth and breadth of research into built environment and energy efficiency can be drastically improved by merging findings and methods from these works. These come in the form of the potential of BIPV systems to meet energy demand, the dual use of BIPV/T systems, and well-rounded life cycle assessments—all making a case for photovoltaic installations to be installed in buildings. Advanced forecasting and clustering methodologies, in particular, provide very valuable tools for optimizing energy management and planning within metropolitan regions. Scholars and practitioners may hence use such revelations to produce more environmentally friendly and efficient energy solutions for built structures.

Cities can only survive sustainably if they incorporate renewable energy sources. Hence, building-integrated photovoltaics could form part of the solution to growing power needs that are not paralleled by an increased carbon footprint. This paper, therefore, not only probes the possibility but brings together a comprehensive review on BIPV potentiality and performance, life cycle assessment, and new approaches in load forecasting using clustering in recent peer-reviewed literature.

The Viability of Building-Integrated Photovoltaic Systems

Feng et al. (2023) analyze the possibility of using BIPV systems for household energy needs in diverse locations within China. Their estimates indicate that within one year, such systems could produce between 41.39 TWh and 772.94 TWh annually, implying that large BIPV potentials exist for urban domestic power applications.

Analysis of the Functioning of BIPV/T Systems

Xu et al. (2020) studied the working of a multi-functional BIPV/T system under different climatic conditions. Their findings show that most of the heating demands could be met by this kind of system in Beijing’s winter season. It was evident from their results that such a dual function has certain merits as far as BIPV/T systems are concerned in different climates.

Life-Cycle Cost and Environmental Impact Analysis

Zhang et al. have conducted detailed life-cycle cost assessment for BIPV in southeastern China. They pointed out that BIPV systems reduced CO2 emissions and have an energy payback time; therefore, BIPV technology in building design must be pursued as it carries with it environmental and economic benefits simultaneously (Zhang et al., 2018).

Also in Italy, a life-cycle sustainability assessment of PV systems in a valley site that displayed dramatic reductions in greenhouse gas emissions compared to traditional energy systems was conducted by Cellura et al. This, in essence, also signaled that BIPV deployment on a mass scale contributes to the enhancement of the overall urban energy grid sustainability (Cellura et al., 2014).

Solar Radiation Forecasting using Machine Learning

Voyant et al. reviewed several machine learning approaches including ARIMA models for solar radiation forecasting (Voyant et al., 2017). Predicting accurately is very crucial in planning and optimizing photovoltaic system performance. Their findings indicate that ARIMA models help provide reliable solar irradiance predictions that make efficient solar energy management possible (Voyant et al 2017).

Clustering in energy use analysis.

Chicco (2012) reviewed the application of clustering methods, including the k-means approach, for grouping electrical load patterns. These are good methods of identifying and analyzing patterns of energy use with significant implications for demand-side management. Clustering may be applied to optimize energy use through the classification of consumption behaviors and the formulation of relevant strategies accordingly, as opined by Chicco in 2012.

Benchmarking of Building Energy Use

Li et al. (2016) combines time-series forecasting models with clustering to benchmark building energy use against past or intended performance. This approach therefore offers a rigorous framework for predicting energy consumption patterns and making building energy use more cost-effective and efficient.

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NB: (Some references may not be present on the essay due to cutting sentences for word count, but were still used for the rationale behind the research and literature review)