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Remote Sensing-Based Analysis of Residential Electricity Consumption Drivers in Tabriz's Cold Semi-Arid Climate Using Machine Learning and Deep Learning

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ABSTRACT

Objective: This study investigates the climatic and urban factors influencing residential electricity consumption in Tabriz, Iran, a city with a cold semi-arid climate, using remote sensing data and machine learning (Random Forest, LightGBM) and deep learning (LSTM, CNN) models.

Methods: Bi-monthly data from 2008 to 2023, including LST (day/night), NDVI, NDBI, NDWI, DMSP-OLS/VIIRS Nighttime Lights, Precipitation, Relative Humidity, Solar Radiation, Sunshine Hours, and AQI (NO_2, O_3, Aerosol), were used. Electricity consumption data were obtained from the Tabriz Electricity Distribution Company. Variables were Z-score normalized and processed in Google Earth Engine. Four models—Random Forest (RF), LightGBM, LSTM, and CNN—were implemented in Google Colab. Performance was evaluated using R^2, RMSE, and MAE, with feature importance assessed via SHAP analysis.

Results: Random Forest outperformed others (R^2=0.91, RMSE=0.29, MAE=0.17), effectively capturing nonlinear relationships. Key drivers were NDWI (0.228), Night Light (0.211), and Solar Radiation (0.189), highlighting water scarcity, urbanization, and radiative heating impacts. LightGBM showed moderate performance (R^2=0.64), emphasizing NDBI and Precipitation, while LSTM and CNN underperformed ($R^2<0$) due to limited data and non-sequential variables. SHAP and residual analyses confirmed RF's robust, stable predictions with minimal bias compared to LightGBM's scale-dependent errors and deep models' irregular residuals.

Conclusions: In Tabriz's cold semi-arid climate, residential electricity consumption is driven by NDWI, urbanization (Night Light), and solar radiation. These reflect increased heating/cooling needs due to low precipitation, urban heat islands, and rising temperatures. Green infrastructure and passive solar design are recommended to mitigate demand. This approach suits data-scarce regions, with potential enhancements via household behavioral data integration.

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Introduction

Residential electricity consumption constitutes a significant portion of global energy demand, heavily influenced by environmental and climatic factors such as temperature fluctuations, precipitation patterns, and the broader impacts of climate change. These factors shape household behaviors and energy needs, particularly through the demand for space heating and cooling, which accounts for a substantial share of household energy use worldwide. As global warming intensifies, rising temperatures are expected to increase cooling demand, potentially leading to significant spikes in electricity consumption in vulnerable regions. For instance, simulations in California suggest that higher temperatures driven by human-induced climate change could increase household electricity consumption by up to 55% by the end of the century, even in scenarios with stable population levels (Auffhammer et al., 2011). Similarly, in G7 economies, cold days have a stronger positive impact on electricity demand for heating compared to hot days for cooling, indicating an asymmetric effect of extreme temperatures (Emenekwe et al., 2022). In China, temperature changes have driven up household electricity consumption, though this effect may be moderated or "crowded out" by income growth, which alters household adaptation strategies (Zhang et al., 2021). Environmental variables such as snowfall and rainfall further amplify consumption, as observed in Tibet, where climate contributes approximately 16.46% to total household electricity use, with urban effects being more pronounced in certain months (Xia et al., 2021). Globally, future scenarios under various socio-economic pathways project that by 2050, improved efficiency could reduce carbon dioxide emissions from residential heating by 34 to 52%, but rising cooling demand in warmer climates may offset these gains without targeted mitigation efforts (Mastrucci et al., 2021). Understanding these dynamics is critical for developing sustainable energy policies that balance environmental resilience and equitable access to electricity.

In arid climates, residential electricity consumption is significantly shaped by environmental and climatic factors, which, due to the extreme conditions characteristic of these regions, drive distinct energy demand patterns. Arid climates, defined by low precipitation and high temperatures, often experience intense heat and prolonged dry periods, necessitating substantial energy use for cooling and water-related activities. Key factors include temperature intensity, humidity levels, solar radiation, and seasonal variations, all of which directly influence reliance on air conditioning, ventilation, and other energy-intensive systems. For example, high temperatures in arid regions such as the Middle East or parts of the southwestern United States lead to increased cooling demand, which can account for a significant portion of household energy consumption (Al-Zayer & Al-Ibrahim, 1996). Additionally, socio-economic factors such as population growth and urbanization interact with climatic variables, further amplifying electricity consumption in these areas (Isaac & van Vuuren, 2009).

The interplay between environmental conditions and energy consumption has been extensively studied. Research indicates that temperature variability in arid climates significantly impacts peak electricity loads, particularly during summer months when cooling demand surges (Sailor & Pavlova, 2003). Moreover, urban heat island effects in rapidly growing arid cities exacerbate cooling needs, leading to higher per capita electricity consumption (Santamouris et al., 2015). Understanding these factors is vital for developing sustainable energy policies and improving energy efficiency in residential settings, particularly as climate change intensifies temperature extremes and alters precipitation patterns in arid regions (Diffenbaugh et al., 2007).

Temperature is the primary climatic factor influencing residential electricity consumption. Extreme heat and cold significantly increase electricity use, mainly due to the heightened demand for air conditioning and heating. For example, each additional day with average temperatures exceeding 32°C can raise annual household electricity consumption by approximately 9%, as households rely more on air conditioners to manage heat stress (Zhang et al., 2022; Su & Ullah, 2024). Similarly, colder days drive up electricity demand for heating, with research indicating a "V-shaped" relationship between temperature and electricity use—consumption spikes as temperatures deviate from a comfortable range in either direction (Pablo-Romero et al., 2024; Li et al., 2023). This impact varies across demographics and regions: urban and rural households, as well as different income groups, respond differently to temperature extremes, with rural residents often showing greater sensitivity to cooling needs due to limited infrastructure (Da et al., 2023; Du et al., 2020).

Precipitation and relative humidity also significantly influence electricity consumption. Increased precipitation, particularly snowfall, elevates electricity use during cold seasons as households depend more on electric heating systems (Xia et al., 2022). High humidity levels intensify discomfort during hot periods, increasing the reliance on cooling appliances (Sarkodie et al., 2021). These factors directly affect thermal comfort and cooling requirements. For instance, high humidity amplifies perceived heat, leading to greater air conditioning use, while precipitation can temporarily cool surfaces, slightly offsetting cooling needs (Imran et al., 2021). Other meteorological factors, such as wind speed and dew point temperature, are critical predictors of climate-sensitive electricity loads, affecting both the intensity and timing of residential energy consumption (Mukherjee & Nateghi, 2017).

Solar radiation and surface albedo (the reflectivity of surfaces) further shape local microclimates and building heat loads. Higher solar radiation elevates indoor temperatures, increasing the need for cooling, while lower albedo in urban areas (darker surfaces) exacerbates urban heat islands, driving up electricity demand for air conditioning (Hu et al., 2020; Sarkodie et al., 2021). The duration of sunshine hours also influences energy use by affecting both artificial lighting and cooling requirements (Imran et al., 2021; Hu et al., 2020). Land surface temperature (LST), influenced by urbanization and land cover changes, plays a critical role. Higher daytime LST, driven by urban expansion and reduced vegetation, increases cooling demand, particularly in built-up areas (Imran et al., 2021; Zhao et al., 2024). Areas with lower vegetation (indicated by lower NDVI) and fewer water bodies (lower NDWI) exhibit higher LSTs, amplifying cooling needs and electricity consumption. Conversely, higher NDVI and NDWI, reflecting more greenery and water bodies, are strongly negatively correlated with LST, reducing local temperatures and cooling-related electricity demand. In contrast, a higher NDBI (indicating more built-up areas) correlates positively with LST, intensifying urban heat and electricity use (Abulibdeh et al., 2024; Patel et al., 2023; Zhao et al., 2024).

Urban heat islands, characterized by elevated nighttime LSTs, sustain higher electricity demand even after sunset, as residential and commercial areas retain heat due to urban morphology and land cover (Abulibdeh et al., 2024; Patel et al., 2023). Nightlight intensity, a proxy for urbanization and socioeconomic activity, is closely linked to increased residential electricity consumption, driven by greater appliance ownership and lifestyle demands (Beyer et al., 2020; Sarkodie et al., 2021). Additionally, ambient air pollution, such as NO_2 and O_3 concentrations, often correlates with urban density and energy use. Although not directly tied to electricity consumption in the referenced studies, higher pollution levels can lead to avoidance behaviors, such as staying indoors and using air conditioning more frequently, indirectly increasing electricity demand (Mukherjee & Nateghi, 2017). Together, these climatic and environmental factors interact to shape residential electricity consumption patterns, with urbanization and land use changes amplifying their effects.

The combined effects of these environmental and climatic drivers are expected to intensify with ongoing climate change. Projections indicate that, without mitigation, residential electricity consumption could increase by up to 47% in some regions by the end of the century due to rising temperatures alone 1Full text used68. This underscores the importance of integrating climate adaptation and mitigation strategies into energy planning and policy (Zhang et al., 2022, Su, & Ullah, 2024, Zheng et al., 2020). Tabriz, located in the cold and semi-arid climate of northwest Iran, faces growing challenges in residential electricity consumption, exacerbated by climatic, environmental, and infrastructural factors. Currently, frequent power outages lasting over two hours daily, particularly during peak consumption seasons, have become a major concern for residents and urban authorities. These outages stem from a combination of factors, including aging electricity transmission and distribution networks, insufficient production capacity relative to rising demand, and the impacts of climate change. Rising land surface temperatures (LST) due to human activities such as extensive urbanization and reduced vegetation cover, coupled with global warming, have intensified air temperatures, increasing energy demand for heating during cold winters and cooling during increasingly warm summers. Additionally, reduced precipitation, particularly snowfall, has limited energy production in hydroelectric plants, further straining the electricity grid. Analyzing residential electricity consumption in Tabriz using satellite and remote sensing data is essential for several reasons. First, the analysis of these data enhances understanding of the impact of climatic variables—such as land surface temperature, albedo, solar radiation, reduced precipitation, and rising temperatures—on residential electricity demand, particularly in the context of declining power generation from Tabriz's thermal cycle power plants due to fuel shortages. Second, this study can leverage accessible, open-source data to identify key factors influencing electricity consumption in a developing country like Iran, where significant data limitations exist. Finally, this analysis is critical for developing local policies aimed at optimizing energy consumption, with an emphasis on climatic and environmental variables and the impacts of climate change in Tabriz. This study can contribute to sustainable urban planning and the reduction of environmental impacts from high energy consumption in the city.

Methods and materials

- **Study area and data**

Tabriz, located in northwestern Iran, exhibits a cold semi-arid climate with dry summers, cold winters, and moderate spring conditions (Fig. 1). The city's climate is shaped by its altitude (~1,350 m), BSk (Cold semi-arid climate), and proximity to Lake Urmia, which has influenced local weather patterns and microclimates. Tabriz's mean annual temperature is approximately 13°C, with maximum summer temperatures reaching 35.2°C. Annual precipitation averages around 380 mm, with most rainfall occurring outside the dry summer months (Sreedevi et al., 2021, Heydari & Movaghari, 2025). Recent decades have seen a statistically significant upward trend in average temperatures and a decline in annual precipitation, especially since the 1980s. The mean annual temperature increased from 11.76°C to 13.32°C after 1994, while mean annual precipitation dropped from 316 mm to 261 mm. Climate projections indicate further temperature increases (up to 4.9°C by 2100) and decreasing precipitation under high-emission scenarios (Imani et al., 2024, Ghazi & Jeihouni, 2022, Nourani & Paknezhad, 2022). Urbanization has led to notable microclimatic changes. Tabriz experiences daytime cool islands and intense nighttime heat islands, with negative daytime surface urban heat island (SUHI) values and positive nighttime SUHI values. These patterns are expected to persist, with a decreasing trend in daytime SUHI for spring and summer (Koushesh Vatan et al., 2025). Urban morphology, building density, and orientation significantly affect local thermal comfort and microclimate, with optimal building configurations mitigating extreme temperatures (Karimimoshaver & Shahrak, 2022, Akbarzadeh & Bavali, 2024).

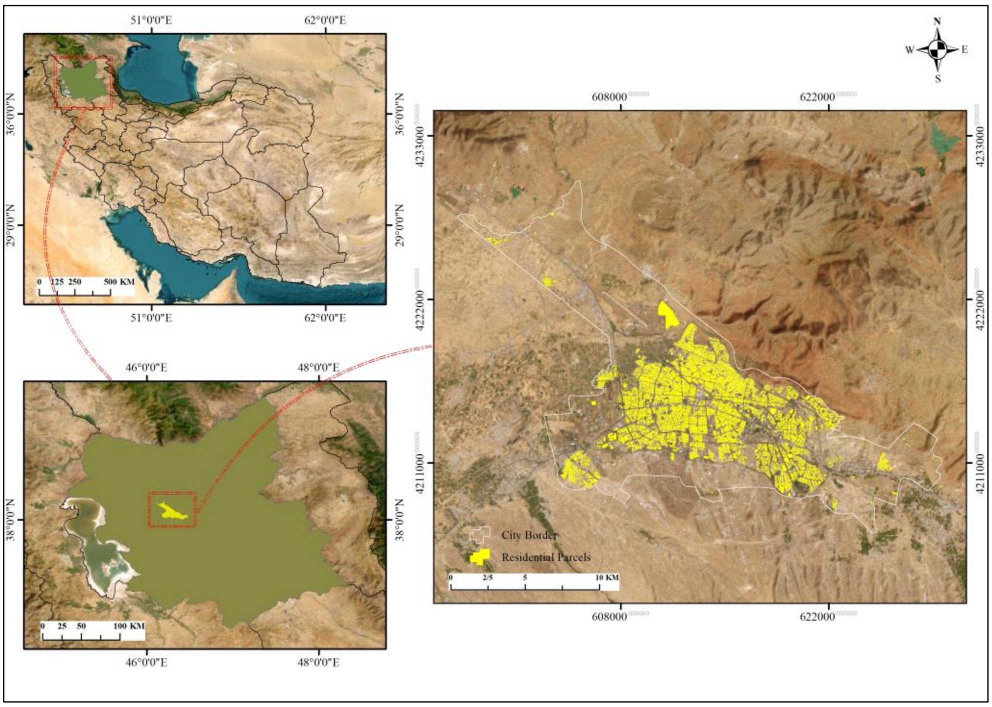


Figure 1. Study area

Table 1. Data used in this study

Variable	Source / Dataset	Spatial Resolution	Notes
Air Quality Index (AQI)	Sentinel-5P: Aerosol Index, NO_2, O_3	~7 km	Calculated as max Z-score of normalized NO_2 (µg/m³), O_3 (µg/m³), Aerosol Index;
LST Daytime	MODIS MOD11A1	1000 m	Celsius
LST Nighttime	MODIS MOD11A1	1000 m	Celsius
NDVI	Landsat 5/7/8	30 m	calculated via NIR/Red ratio
NDBI	Landsat 5/7/8	30 m	calculated via SWIR/NIR ratio
NDWI	Landsat 5/7/8	30 m	calculated via NIR/Green ratio
Nighttime Lights	DMSP-OLS (2008–2011), VIIRS DNB (2012–2023)	1000 m	Merged DMSP & VIIRS
Precipitation	ERA5-Land Daily Aggregates	~9 km	Converted from meters to mm
Relative Humidity	ERA5-Land Daily Aggregates	~9 km	Calculated from 2m temperature & dewpoint
Solar Radiation	ERA5-Land Hourly	~9 km	Converted from J/m² to MJ/m
Sunshine Hours	ERA5-Land Daily Aggregates	~9 km	Approximated from surface solar radiation; max radiation = 25 MJ/m²/day
Residential electricity consumption	Tabriz Electricity Distribution Company	City-level	Dependent variable

In this study, environmental, climatic, and urban data were collected for the period 2008 to 2023 (Persian calendar years 1387–1402). All independent variableswere derived from remote sensing datasets and processed using Google Earth Engine (https://earthengine.google.com/). The dependent variable, residential electricity consumption, was provided by the Tabriz Electricity Distribution Company (https://toztab.ir/). All datasets were aggregated into bi-monthly periods, and mean values were computed for each period. The Air Quality Index (AQI) was also calculated by combining the Z-scores of Aerosol Index, NO_2, and O_3 for each bi-monthly period and included as one of the independent features in the predictive models. Due to the differing units and scales across the datasets, all variables were standardized using Z-score normalization. The Z-score of each variable was calculated as the deviation of the observed value from the mean divided by the standard deviation, ensuring comparability across features and mitigating the dominance of variables with larger numeric ranges.

To predict residential electricity consumption, two machine learning models such as Random Forest (RF), LightGBM, and two deep learning models such as Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNN) were applied. The models were implemented in Google Colab (https://colab.research.google.com/) and optimized using cross-validation. For tree-based models, feature importance was extracted to quantify the contribution of each independent variable.

- **RandomForest**

Random Forest (RF) represents an ensemble machine learning technique that amalgamates numerous decision trees to enhance predictive accuracy and robustness. The inherent randomness in RF manifests at two primary dimensions, as illustrated in (Fig. 2). Firstly, it involves the stochastic selection of feature subsets; rather than employing the entirety of available features for each constituent decision tree, RF randomly samples a fraction of these features to serve as inputs for training individual trees (Joo et al., 2022). Secondly, randomness extends to the sampling of training instances, wherein each decision tree is trained on a bootstrapped subset drawn with replacement from the original dataset. For classification tasks, the final RF prediction is determined via majority voting across the outputs of all trees, whereas in regression scenarios, it computes the arithmetic mean of the individual tree predictions. As a versatile ensemble approach, RF leverages bootstrapped datasets and random feature subsampling to aggregate predictions, thereby mitigating overfitting (Kooshesh Vatan et al., 2021). Within the domain of geosciences, RF has gained prominence for applications such as land cover categorization, susceptibility mapping for natural hazards, and ecological simulations, owing to its efficacy in managing high-dimensional and spatially heterogeneous datasets.

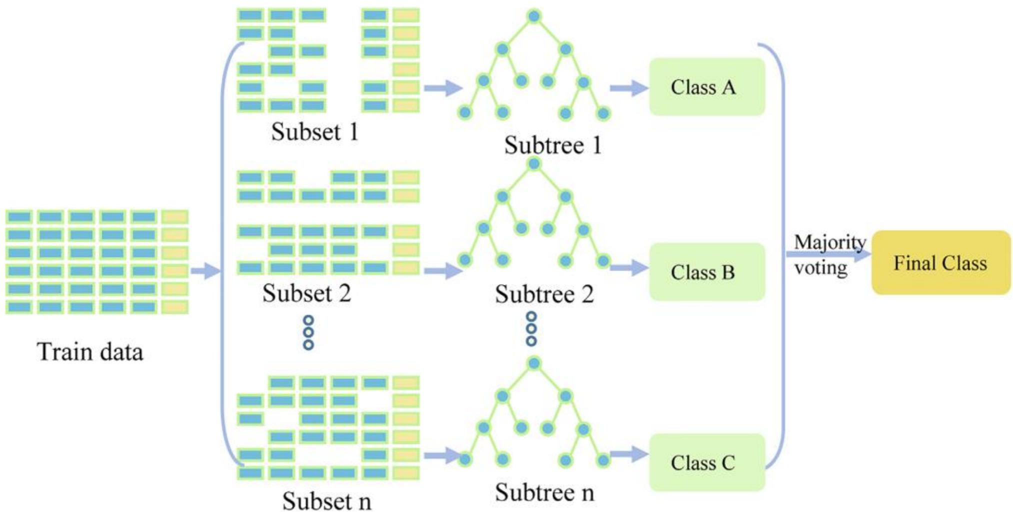


Figure 2. Diagram of Random Forest (Wang et al., 2022)

- **LightGBM**

LightGBM constitutes a gradient boosting decision tree (GBDT) paradigm designed for efficient scalable learning (Ke et al., 2017). Broadly, GBDT frameworks iteratively ensemble weak base learners into a potent predictive model by optimizing residuals derived from a specified loss objective (Chen & Guestrin, 2016). Although this sequential integration confers superior performance relative to parallel ensemble methods like random forests—where trees are constructed independently—it often entails elevated computational demands, limiting applicability to expansive datasets. To surmount these constraints, the LightGBM architecture introduced by Ke et al. (2017) incorporates optimizations such as histogram-based splitting, leaf-wise growth strategies, and exclusive feature bundling, yielding substantial efficiency gains over conventional GBDT implementations.

- **LSTM**

Long Short-Term Memory (LSTM) networks extend the foundational architecture of Recurrent Neural Networks (RNNs) to effectively capture prolonged sequential dependencies while alleviating the vanishing gradient challenge inherent in standard RNNs. The core LSTM unit comprises three regulatory gates that modulate information flow: The forget gate employs a sigmoid activation to selectively discard irrelevant prior state information, factoring in the current input and preceding hidden state; outputs range from 0 (complete erasure) to 1 (full retention) (Siami-Namini et al., 2019). Complementarily, the input gate governs the assimilation of novel data through a dual mechanism: a sigmoid layer identifies update-worthy elements, while a hyperbolic tangent (tanh) layer produces candidate values for state augmentation. Finally, the output gate utilizes a sigmoid function to filter cell state components for emission, followed by tanh scaling to bound values between -1 and 1 (Sherstinsky, 2020; Elshewey et al., 2025).

- **CNN**

Convolutional Neural Networks (CNNs) are deep learning models optimized for processing structured grid-like data, excelling in tasks requiring spatial feature extraction. Their architecture leverages backpropagation to learn hierarchical feature representations through modular components: convolutional layers apply trainable kernels to detect local patterns like edges, reducing parameter complexity via sparse connectivity; Rectified Linear Unit (ReLU) activation accelerates training by zeroing negative values; pooling layers, typically max-pooling, downsample feature maps to lower computational load and enhance invariance; fully connected layers integrate local features for global inference; and the output layer, often using Softmax, produces probabilistic predictions (Alzakari et al., 2024; Li et al., 2021; Elshewey et al., 2025).

- **Model accuracy**

To evaluate the accuracy of the models comparative analysis include coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) calculated based on the equations shown below (Choi, 2021, Kooshesh Vatan et al., 2025):

$$R^2 = 1 - \frac{\sum_i^n \left(SST_i^{real} - SST_i^{estimated}\right)^2}{\sum_i^n \left(SST_i^{real} - \overline{SST^{real}}\right)^2}$$

$$\overline{SST^{real}} = \frac{1}{n}\sum_i^n SST_i^{real}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(A_i - \hat{P}_i\right)^2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|A_i - \hat{P}_i\right|$$

Results

The comparison of models revealed that RandomForest outperformed others in predicting electricity consumption in Tabriz, achieving an R^2 of 0.91 with low errors (RMSE = 0.29, MAE = 0.17). Its success stems from effectively capturing complex, nonlinear relationships between climate variables and land cover factors. By contrast, LightGBM showed moderate results with an R^2 of 0.64, explaining only part of the consumption variability. Deeper models, LSTM and CNN, performed poorly, with negative R^2 values (-0.88 and -4.76, respectively), failing to detect data patterns and underperforming the baseline. This can be linked to limited data size, the non-temporal nature of variables, and the need for intricate tuning in these networks.

Table 2. Model comparison table

	MAE	RMSE	R^2
RandomForest	0.1718	0.2904	0.9148
LightGBM	0.3387	0.5960	0.6414
LSTM	1.1042	1.3945	-0.8838
CNN	2.0763	2.4388	-4.7616

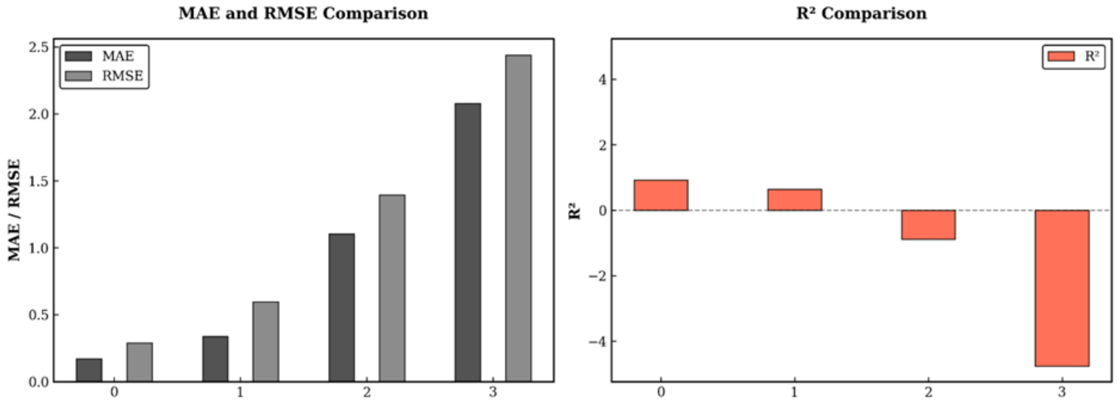
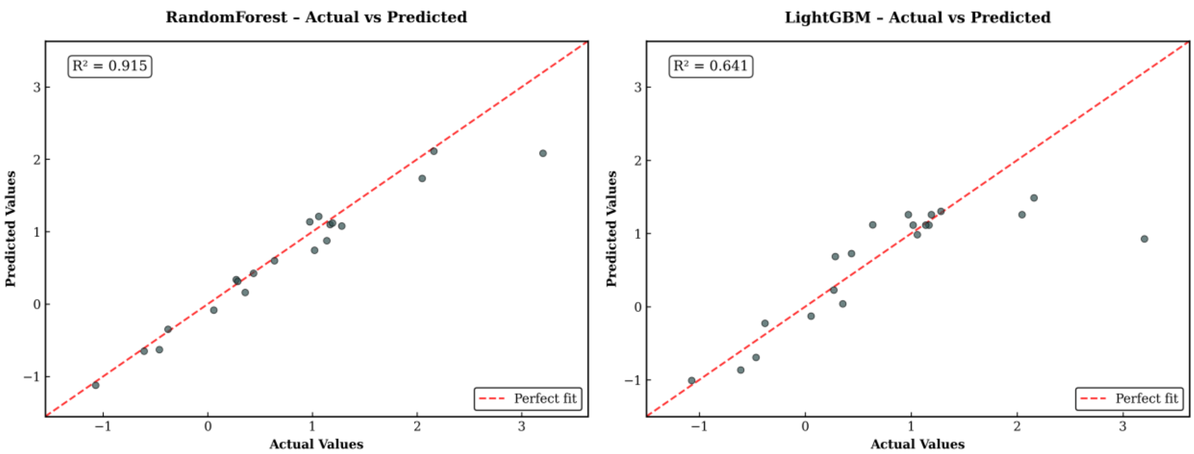


Figure 3. Model performance comparison

Overall, the results highlight that in Tabriz's cold semi-arid climate, simpler tree-based models like RandomForest offer superior performance compared to complex deep learning approaches. Model choice should align with data characteristics and local climate conditions.



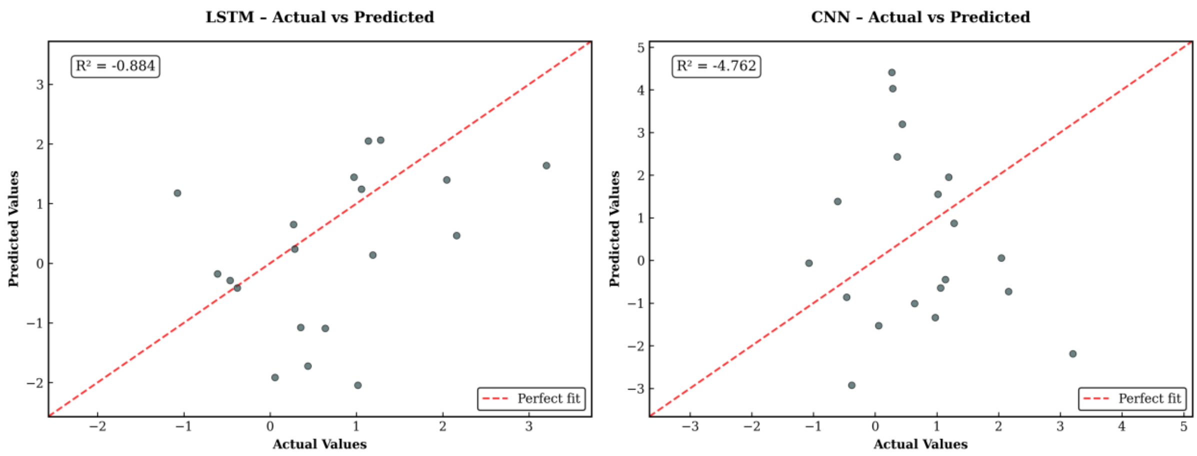
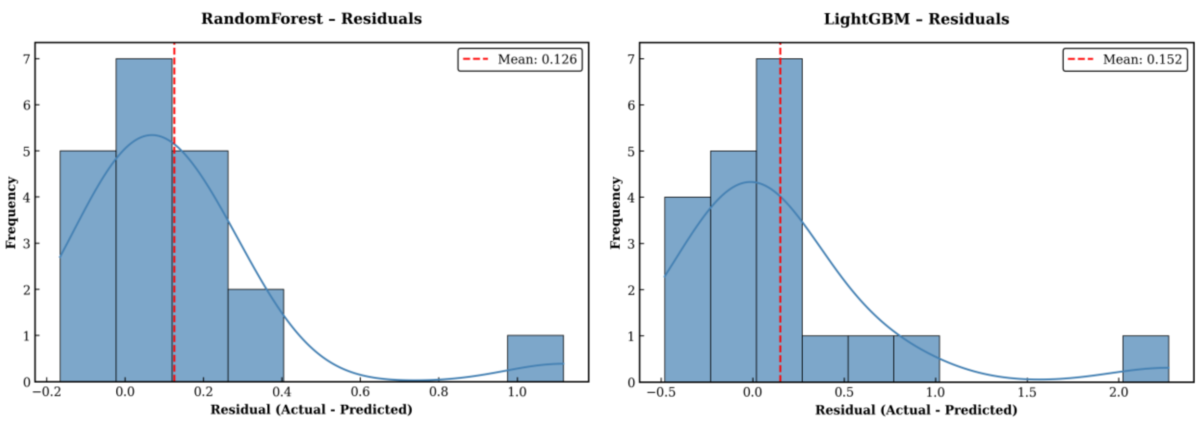


Figure 4. Models actual vs predicted scatter plots

Analysis of the Actual vs. Predicted plots reveals that only the RandomForest model achieved substantial alignment between observed and predicted electricity consumption values. In this model, data points cluster closely around the 1:1 correlation line, with minimal scatter, indicating that discrepancies between actual and predicted values are generally small. This aligns with the model's high R^2 and low RMSE and MAE values, demonstrating its ability to accurately capture electricity consumption patterns. In contrast, the LightGBM model's plots show moderate correlation with actual data but exhibit greater scatter around the 1:1 line, particularly at higher consumption levels, where noticeable deviations occur. This suggests that LightGBM is less accurate in predicting higher consumption values, often underestimating them. The LSTM and CNN models' plots stand in stark contrast. Both display significant scatter, lacking any coherent alignment with actual data. In many instances, predicted trends even move inversely to actual values, clearly explaining their negative R^2 values. These plots underscore the neural networks' inability to discern patterns in the climatic and spatial data linked to energy consumption in this study. Overall, the Actual vs. Predicted plots confirm that while LightGBM achieves some degree of correlation with actual data, only RandomForest delivers consistently accurate and reliable predictions. Other models, particularly neural networks, fail to effectively represent electricity consumption behavior in Tabriz's climatic conditions.



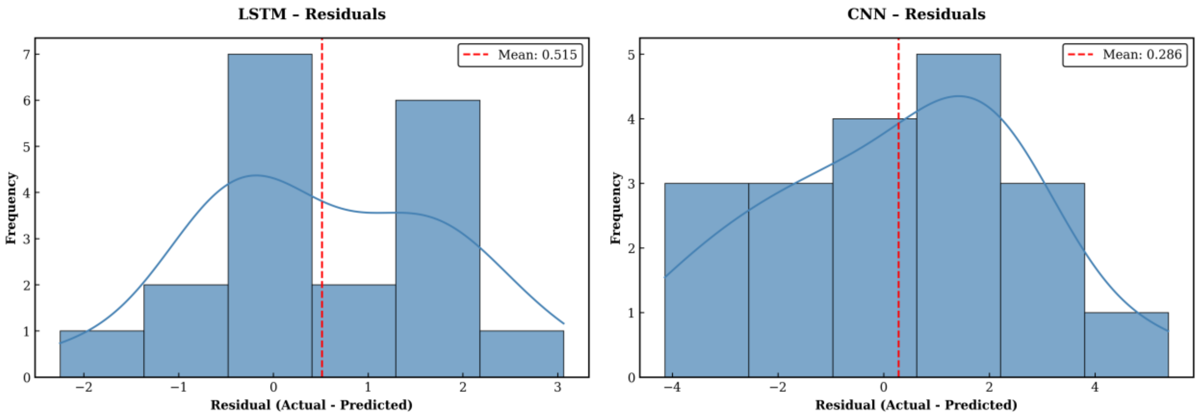


Figure 5. Models residual plots

The analysis of residual plots provides a clearer picture of the models' accuracy and stability. For the RandomForest model, residuals are evenly distributed around the zero axis, showing no discernible pattern. This indicates that prediction errors are uniformly distributed across different levels of electricity consumption, with no evidence of systematic bias. This characteristic underscores RandomForest's strong generalization ability and its capacity to avoid overfitting. In contrast, the LightGBM model exhibits wider and less symmetric residual scatter. At lower consumption levels, the model tends to overestimate, while at higher levels, it underestimates actual values. This error pattern suggests a scale-dependent bias, highlighting LightGBM's limitations in capturing extreme or outlier energy consumption behaviors. The error patterns for the LSTM and CNN models are markedly different and highly irregular. The residuals show significant scatter and large deviations from the zero axis, indicating that these models not only fail to capture the overall consumption trend but also produce substantial prediction errors. Rather than a random distribution, the residual patterns suggest unmodeled structures in the data, pointing to fundamental weaknesses of these neural networks in this dataset context. The residual plot analysis reveals that only RandomForest produces balanced and non-systematic errors. LightGBM suffers from scale-dependent bias, while the deep learning models exhibit severe error scatter. Consequently, in Tabriz's climatic conditions, tree-based models like RandomForest not only offer higher prediction accuracy but also demonstrate superior stability and error behavior compared to other approaches.

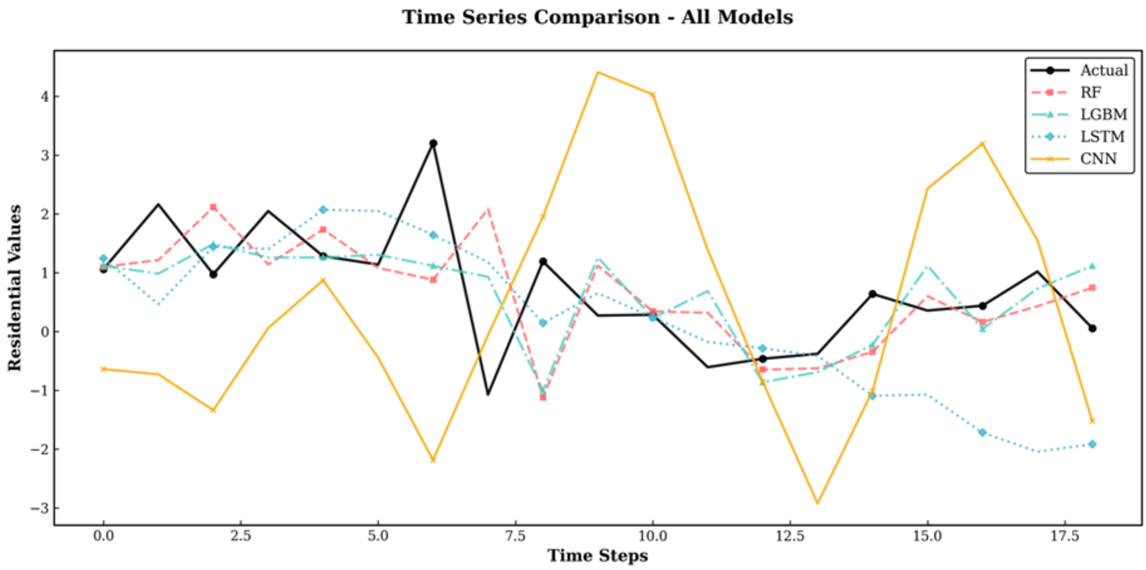


Figure 6. Time series comparison

The comparison of time series for actual versus predicted electricity consumption reveals that only the RandomForest model successfully captures the fluctuations in consumption throughout the study period with reasonable accuracy. This model closely tracks the overall trend and seasonal variations, with minimal discrepancies between the peaks and troughs of the time series. This indicates that RandomForest effectively reproduces not only the average consumption but also the dynamic patterns and short-term fluctuations. The LightGBM model shows partial alignment with actual data, but deviations are more pronounced during peak consumption periods (seasonal highs). It tends to overlook smaller, mid-term variations, focusing primarily on the general trend, which leads to reduced prediction accuracy during periods of sharp consumption fluctuations.

In contrast, the LSTM and CNN models exhibit poor performance, failing to establish meaningful correlation with actual data. Their time series outputs lack alignment with real consumption patterns, with peaks and troughs poorly represented and predictions occasionally moving in opposition to actual trends. This highlights the neural networks' inability to capture electricity consumption patterns in the context of Tabriz's dataset, potentially due to insufficient long-term data or weak temporal structures in the input variables. The time series comparison confirms that RandomForest is the only model capable of accurately reflecting the dynamics of electricity consumption. LightGBM captures the general trend to some extent, while deep learning models prove largely ineffective.

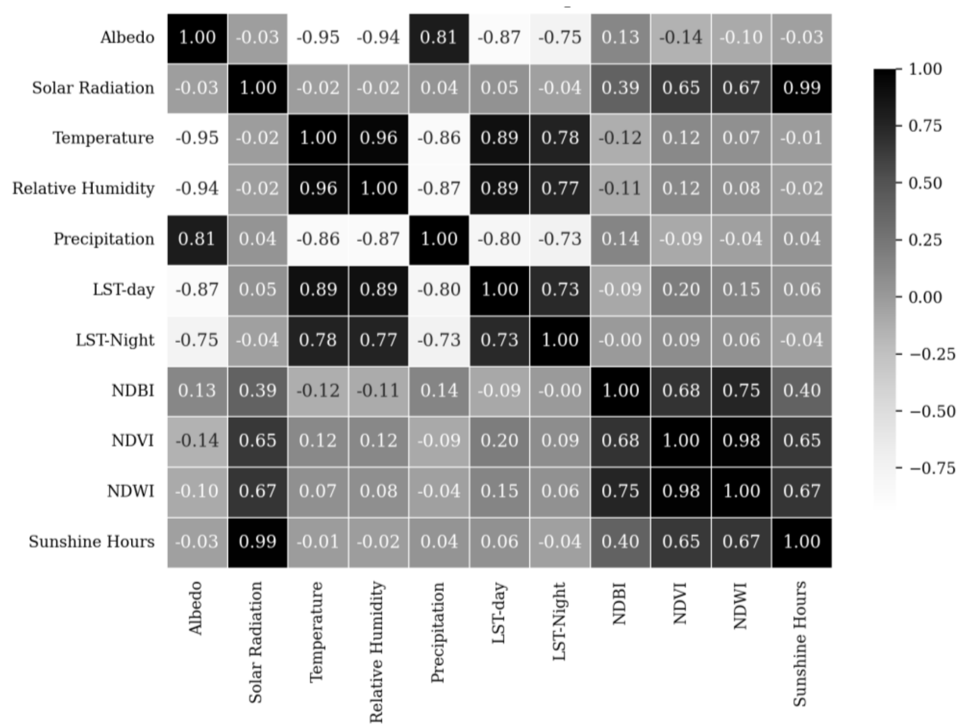


Figure 7. Correlation matrix of input features

The analysis of the correlation matrix of input variables reveals a complex, multidimensional pattern of relationships among climatic and environmental indices. Notably, thermal indices such as temperature and land surface temperature (LST, both day and night) exhibit strong positive correlations, reflecting their shared dependence on Tabriz's prevailing climatic conditions. This is particularly significant in a cold semi-arid climate, where diurnal and radiative temperature variations directly influence domestic energy consumption, particularly for heating and cooling needs. Surface cover indices, including NDVI, NDWI, and NDBI, also display distinct correlation patterns. A positive correlation between NDVI and NDWI highlights the linkage between vegetation cover and surface moisture availability. Conversely, NDBI shows an inverse relationship with these indices, primarily indicating the dominance of built-up surfaces and reduced thermal-moisture efficiency in the environment. This is noteworthy for electricity consumption, as increased built-up area density typically correlates with higher cooling demands. Other variables, such as solar radiation, sunshine hours, and albedo, show moderate correlations with thermal indices, suggesting an indirect influence on energy consumption variations. Rather than acting independently, these variables amplify or modulate the effects of primary thermal and surface cover factors. Air quality indices (e.g., AQI) exhibit weak or no significant correlations with radiative and thermal variables, appearing largely independent. This aligns with variable importance analyses, which indicate their minimal contribution to predicting electricity consumption.

Table 3. Feature-Importance Comparison Across 4 Models:

Feature	RF	LGBM	LSTM	CNN
NDWI	0.228	0.031	0.000	0.000
Night Light	0.211	0.064	0.101	0.023
Solar Radiation	0.189	0.117	0.213	0.000
Relative Humidity	0.131	0.037	0.000	0.070
NDVI	0.106	0.070	0.000	0.148
Temperature	0.060	0.050	0.000	0.084
LST-day	0.015	0.035	0.000	0.244
LST-Night	0.013	0.080	0.106	0.161
AQI	0.011	0.008	0.114	0.098
NDBI	0.010	0.190	0.145	0.072
Albedo	0.009	0.000	0.206	0.000
Sunshine Hours	0.008	0.112	0.078	0.073
Precipitation	0.008	0.207	0.037	0.028
NDWI	0.228	0.031	0.000	0.000

The comparison table of variable importance across the four models offers clear insights into the differences and similarities in how each algorithm identifies key factors influencing electricity consumption. According to the table, in the RandomForest model, the NDWI index holds the highest importance (0.228), followed by Night Light (0.211) and solar radiation (0.189). These findings suggest that in Tabriz's semi-arid climate, surface moisture and water resources, alongside artificial lighting intensity and solar energy, are the primary drivers of electricity consumption patterns. In contrast, the LightGBM model assigns greater importance to NDBI (0.190) and precipitation (0.207), emphasizing physical and hydrological features. While RandomForest prioritizes a balanced combination of water, radiation, and artificial lighting, LightGBM focuses more on patterns related to built-up density and precipitation. The LSTM model attributes the highest importance to solar radiation (0.213), albedo (0.206), and NDBI (0.145). This combination reflects the model's sensitivity to continuous and ordinal variables tied to land surface variations and radiation. However, the overall poor performance of LSTM indicates that highlighting these variables alone was insufficient for accurate predictions. For the CNN model, LST-Day (0.244) and LST-Night (0.161) are the most influential, followed by NDVI (0.148) and AQI (0.098). This pattern aligns with CNN's strength in detecting spatial and visual patterns, such as thermal and vegetation changes. Nevertheless, the model's general weakness in reproducing electricity consumption trends limits the practical value of its variable importance rankings.

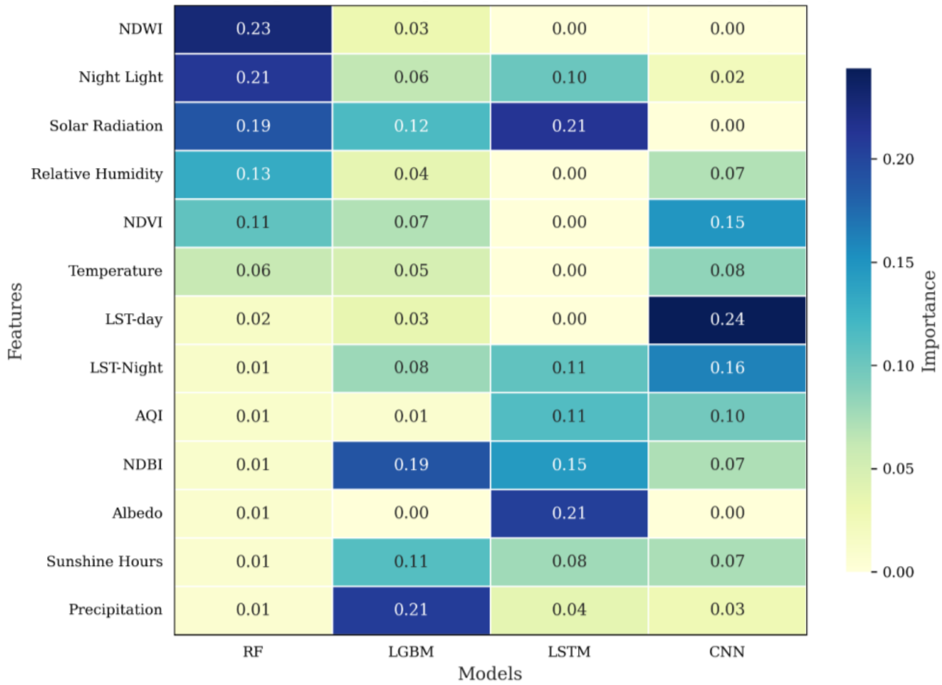


Figure 8. Feature Importance Comparison Across Models (Sorted by RF)

The Feature Importance Comparison Across Models (Sorted by RF) chart effectively highlights these differences. Sorting by RandomForest reveals that key variables identified by RF, such as NDWI, do not carry consistent importance across other models. Notably, NDWI, the top variable in RandomForest, has the lowest weight in LightGBM, LSTM, and CNN. Conversely, variables like NDBI and precipitation, less significant in RF, rank higher in LightGBM and LSTM. Similarly, CNN's emphasis on LST-Day and LST-Night, which have lower importance in RF, underscores its distinct approach to pattern extraction. Overall, the table and chart analysis indicate that while all models share some overlap in identifying influential variables, only RandomForest successfully captures a balanced mix of natural (water, radiation, moisture) and human-related (night light, built-up areas) factors. This aligns closely with its superior performance in predicting electricity consumption.

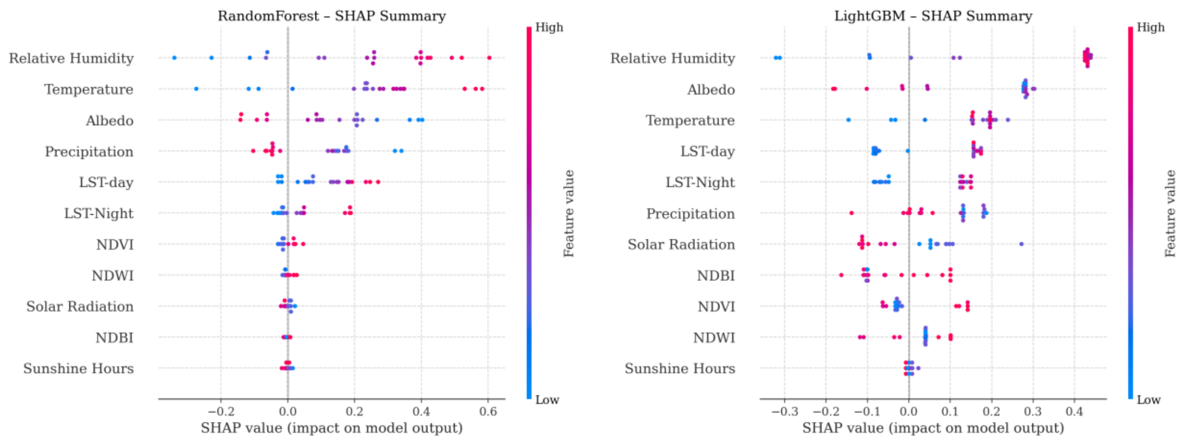


Figure 8. SHAP summary of RF and LightGBM models

The SHAP Summary plots for the RandomForest and LightGBM models effectively illustrate how input variables influence electricity consumption predictions. For the RandomForest model, SHAP values highlight NDWI, Night Light, and solar radiation as the most impactful variables. These variables exhibit relatively stable and consistent effects across the entire data range, successfully explaining electricity consumption patterns. The dense clustering of points around these variables and their clear directional impact indicate that RandomForest not only achieves high accuracy but also offers strong interpretability.

In contrast, for the LightGBM model, NDBI, precipitation, and sunshine hours emerge as the most influential variables. However, the SHAP values display a more heterogeneous distribution compared to RandomForest. The significant scatter and sharp variations in the impact of these variables suggest that LightGBM is more sensitive to extreme and nonlinear data conditions, but this comes at the cost of reduced stability and generalizability. Overall, the SHAP analysis confirms that RandomForest outperforms LightGBM not only in statistical metrics but also in the transparency and consistency of variable contributions. This advantage underpins its superior accuracy in predicting electricity consumption in Tabriz's semi-arid climate.

Discussion

The findings of this study demonstrate that machine learning models, particularly tree-based algorithms, provide robust tools for predicting domestic electricity consumption in cold, semi-arid climates such as Tabriz, Iran. The RandomForest model achieved superior performance with an R^2 of 0.91, RMSE of 0.29, and MAE of 0.17, outperforming LightGBM (R^2= 0.64) and the deep learning models LSTM and CNN (with negative R^2 values of -0.88 and -4.76, respectively). This aligns with prior studies in similar cold, semi-arid regions, such as Tibet, where climatic factors like snowfall and rainfall account for approximately 16.46% of domestic electricity consumption, with urban effects more pronounced in specific months (Xia et al., 2021). Similarly, in arid climates like the Middle East or the southwestern United States, elevated temperatures drive cooling demands, constituting a significant portion of household energy use (Al-Zayer & Al-Ibrahim, 1996). RandomForest's success in Tabriz stems from its ability to effectively model nonlinear relationships between climatic variables and consumption.

The prominence of the NDWI (Normalized Difference Water Index) as the most influential feature in RandomForest (importance score: 0.228) underscores the critical role of surface moisture and water availability in modulating electricity consumption in Tabriz's cold, semi-arid climate. Reduced precipitation, particularly snowfall increases reliance on thermal power plants, amplifying NDWI's relevance as an indicator of water scarcity's impact on heating and cooling demands (Xia et al., 2021; Xia et al., 2022). This finding is consistent with studies in arid regions, where hydrological indices strongly correlate with peak energy loads, especially in areas with urban heat island effects that intensify cooling needs (Santamouris et al., 2015; Abulibdeh et al., 2024; Patel et al., 2023). Night Light (importance: 0.211) and solar radiation (0.189) further highlight human and radiative factors: Night Light, as a proxy for urban development, plays a key role in explaining consumption patterns, reflecting global trends where urban expansion drives energy use (Beyer et al., 2020; Sarkodie et al., 2021). Solar radiation emphasizes daytime heating, aligning with increased cooling demands in arid climates (Hu et al., 2020; Imran et al., 2021). SHAP analysis reinforces this, showing NDWI's consistent positive impact on predictions, where low moisture levels elevate land surface temperatures, intensifying electricity reliance in Tabriz, akin to temperature-driven consumption increases observed in China, though moderated by income growth (Zhang et al., 2021).

In contrast, LightGBM's emphasis on NDBI (importance: 0.190) and precipitation (0.207) reflects a focus on urban morphology and hydrological extremes in Tabriz's climate, partially explaining consumption trends but exhibiting scale-dependent bias in residual plots. This aligns with forecasting challenges in arid climates, where irregular precipitation and urban heat island effects influence peak loads (Sailor & Pavlova, 2003; Mukherjee & Nateghi, 2017). The poor performance of LSTM and CNN models is attributed to dataset characteristics, including non-sequential variables and limited temporal depth, which hinder their ability to extract meaningful patterns, as evidenced by irregular residual distributions and inverse trends in time-series comparisons. This is consistent with the heightened sensitivity of such models to climatic data in semi-arid regions like Tabriz (Li et al., 2023; Pablo-Romero et al., 2024). CNN's focus on LST-Day (importance: 0.244) highlights the utility of remote sensing, where indices like LST, NDVI, and NDWI, derived from satellite data, capture urban heat island effects on consumption (Zhao et al., 2024; Abulibdeh et al., 2024; Patel et al., 2023).

These results validate the use of remote sensing to model energy consumption in Tabriz's cold, semi-arid climate, where satellite-derived indices like LST, NDVI, NDWI, and NDBI effectively capture complex relationships between climatic factors and electricity demand. For instance, the negative correlation of NDVI and NDWI with LST indicates reduced cooling demand through vegetation and water presence, while positive NDBI-LST correlations amplify urban heat island effects (Imran et al., 2021; Hu et al., 2020; Zhao et al., 2024). This approach is particularly valuable in developing countries like Iran, where data limitations are common, and aligns with global projections suggesting that rising temperatures could increase cooling demand by up to 55% in vulnerable regions (Auffhammer et al., 2011). The asymmetric temperature effects in Tabriz, with greater heating demand on cold days than cooling on warm days, mirror findings in G7 economies (Emenekwe et al., 2022), and remote sensing accurately captures these dynamics. However, limitations such as the omission of household behavior suggest future research could integrate remote sensing data to inform energy efficiency policies (Mastrucci et al., 2021; Diffenbaugh et al., 2007; Isaac & van Vuuren, 2009).

This investigation validates the efficacy of remote sensing data in modeling the climatic determinants of domestic electricity consumption in the cold, semi-arid climate of Tabriz, Iran. Satellite-derived indices, including NDVI, NDWI, and LST, accurately elucidate the intricate interplay among urbanization, land surface temperature, and energy demand, corroborating global projections of up to a 55% increase in cooling demand in climatically vulnerable regions. This methodology is particularly advantageous in data-constrained developing nations such as Iran, providing a robust framework for evidence-based energy policy formulation and underscoring the importance of green infrastructure to ameliorate urban heat island effects. Future studies could enhance predictive precision by integrating remote sensing data with household-level behavioral data, thereby advancing sustainable energy management strategies to address the challenges posed by climate change. Based on the study's insights, the following recommendations are proposed:

- **Advancement of Urban Green Infrastructure and Built Environment Optimization**

Decreased vegetation cover (NDVI) and surface water availability (NDWI), alongside increased urban density (NDBI), are key drivers of elevated land surface temperatures and heightened electricity consumption. To counter this, expanding urban green spaces with drought-resistant native species, redesigning dense urban areas to incorporate permeable surfaces, and minimizing impermeable materials like asphalt and concrete can effectively moderate ambient temperatures, mitigate urban heat island effects, and reduce cooling energy demands. Such strategies also promote sustainable management of scarce water resources.

- **Adoption of Passive Solar Design and Climate-Responsive Technologies**

High solar radiation and extended sunshine hours in Tabriz significantly contribute to cooling energy requirements. Implementing passive solar design in building architecture—through optimized orientation, effective shading systems, enhanced thermal insulation, and high-albedo materials—can substantially lower both heating and cooling energy needs. Furthermore, integrating solar energy solutions, such as photovoltaic systems, can transform thermal loads into renewable energy sources. This combined approach enhances energy efficiency and reduces dependence on conventional power grids.

Conclusion

This study demonstrates that machine learning models, particularly RandomForest, leveraging remote sensing data, provide robust tools for predicting domestic electricity consumption in the cold, semi-arid climate of Tabriz. The superior performance of RandomForest (R^2=0.91) compared to LightGBM, LSTM, and CNN underscores its capability to model nonlinear relationships among climatic variables such as NDWI, Night Light intensity, and solar radiation. These findings align with global studies projecting up to a 55% increase in cooling demand in vulnerable regions (Auffhammer et al., 2011) and highlight the critical influence of hydrological and urbanization factors on energy consumption in arid climates (Xia et al., 2021; Santamouris et al., 2015). Satellite-derived indices like NDVI, NDWI, and LST enable precise identification of urban heat island effects and moisture deficits, which are exacerbated in Tabriz by reduced precipitation and rising land surface temperatures, posing challenges to energy infrastructure (Abulibdeh et al., 2024; Zhao et al., 2024). This approach is particularly vital for data-scarce developing countries like Iran, facilitating the development of sustainable energy policies. Future research should focus on integrating remote sensing data with household behavioral data to enhance prediction accuracy and bolster climate-resilient energy management strategies (Mastrucci et al., 2021; Diffenbaugh et al., 2007).

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