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Meteorological feature importance for solar energy forecasting

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ABSTRACT

This study investigates the predictive contribution of satellite-derived meteorological features from NASA prediction of worldwide energy resources (POWER) data for hourly solar energy forecasting in a tropical environment. Two machine learning (ML) models—multi-layer perceptron (MLP) and categorical boosting (CatBoost) regressor—are evaluated using 6,132 hourly observations from a photovoltaic (PV) system in Indonesia. A key methodological contribution of this work is the application of a delta R-squared (ΔR^2) feature ablation framework, which quantifies the impact of individual features by measuring performance degradation after feature removal. Results show that both models achieve high accuracy ($R^2 > 0.99$), while features such as relative humidity (RH2M) and specific humidity (QV2M) exhibit strong predictive contributions despite weak linear correlations with energy output. This finding highlights the limitation of correlation-based feature selection. Furthermore, CatBoost demonstrates higher robustness under feature elimination compared to MLP. The proposed approach provides a practical and interpretable framework for feature prioritization in solar energy forecasting and smart grid applications.

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1. INTRODUCTION

The global energy transition from fossil fuel–based systems toward clean and sustainable energy represents a strategic effort to combat the climate crisis and reduce carbon emissions. Renewable energy sources such as solar and wind now play a central role in both national and international decarbonization policies, not only due to their abundant availability but also because of their potential contributions to energy resilience and sustainable development. Recent studies have shown that renewable energy communities (REC) can drive structural shifts in energy systems through participatory approaches and measurable performance indicators [1], [2]. Additionally, just energy transition policies—such as those implemented in Indonesia—highlight global efforts to integrate justice principles into the energy transition, although challenges remain in practice [3], [4]. The role of predictive technologies in supporting renewable-resource-based energy systems has become increasingly vital, particularly in integrating these systems into modern grids [5]. The success of this transition greatly depends on the efficiency and reliability of renewable energy systems, which are in turn supported by accurate and adaptive predictive models.

Solar energy forecasting plays a crucial role in the planning and management of photovoltaic (PV) power plants and in maintaining the overall stability of power systems. Accurate forecasting enables energy system operators to balance supply and demand in real time, optimize plant operations, and minimize dependence on fossil-based backup energy sources [6]. In this context, the integration of machine learning

(ML) and artificial intelligence (AI) methods has significantly enhanced solar energy forecasting performance, with various approaches such as long-short term memory (LSTM), convolutional neural network (CNN), and hybrid models demonstrating high accuracy [7]–[9]. Other studies have emphasized the importance of combining calendar, weather, and lagging electrical variables to improve industrial load estimation and energy production prediction [10], [11]. Accurate forecasting not only supports technical operations but also aids economic decision-making and adaptation to fluctuations in energy markets [12]. In high-variability regions such as Riyadh, ML–based approaches have proven capable of adapting to the complexities of local weather patterns for both short- and long-term forecasting [13]. Overall, solar energy forecasting represents a foundational element of modern, intelligent, and responsive renewable energy ecosystems.

Solar energy forecasting is heavily influenced by the dynamics of meteorological variables such as solar radiation, temperature, humidity, wind speed, and cloud cover. The intrinsic characteristics of these variables are nonlinear and vary across spatial and temporal dimensions, leading to high uncertainty in energy prediction systems. Camacho *et al.* [14] highlighted that climate variability in highland regions causes sharp fluctuations in solar irradiance, mainly due to cloud cover and local wind patterns. AlSharabi *et al.* [13] also emphasized that forecasting in areas like Riyadh faces unique challenges, such as dust storms and complex seasonal solar intensity variations. Deep learning–based approaches such as LSTM or CNN have been shown to improve accuracy but remain highly sensitive to the quality and continuity of weather data [15]–[17]. Saadati and Barutcu [12] noted that despite advances in AI-driven prediction, model limitations persist when meteorological data are inconsistent or exhibit high noise levels. Therefore, reliance on weather variables presents a fundamental challenge in building robust solar energy forecasting models.

In solar energy forecasting, the availability of high temporal resolution meteorological data is a key foundation for ML models. NASA, through its prediction of worldwide energy resources (POWER) service, provides globally accessible satellite-based atmospheric and solar radiation data that are highly relevant for PV energy forecasting. This dataset includes critical parameters such as surface radiation, humidity, temperature, pressure, and wind speed, all of which influence PV system performance. However, despite the widespread use of NASA POWER in forecasting studies, its utilization is often limited to being a mere input to models, without explicit evaluation of the individual contribution of each feature to prediction performance. For instance, highlighted the potential of irradiance and cloud cover parameters for strategic decision-making in solar panel placement but did not address their quantitative predictive contributions. Similarly, research employing quantum ML suggests that forecasting accuracy is highly dependent on the quality and representation of meteorological variables used [18], [19]. On another front, Cao *et al.* [20] demonstrated that weather features such as temperature and humidity have a significant impact on load forecasting models, yet feature contributions are often treated as a "black box". Other studies integrate evolutionary algorithms and dynamic neural networks to maximize PV prediction accuracy but rely on collective feature sets without reduction or prioritization analysis [9]. Although AlSharabi *et al.* [13] developed forecasting models using NASA POWER meteorological features in extreme environments like Riyadh, they also omitted individual feature contribution analysis. Thus, despite NASA POWER's richness and potential, evaluating the predictive relevance of each individual feature remains a critical gap in current literature.

Most research in solar energy forecasting continues to emphasize improving model accuracy by exploring various ML algorithms and complex feature combinations [21]. While these approaches enhance predictive performance, they often overlook systematic analysis of how much each input feature contributes to the prediction output [22]. In many cases, meteorological and temporal features are combined into models without critical evaluation of their relevance or redundancy. Conversely, the importance of feature contribution analysis has long been recognized in atmospheric and energy modeling, particularly to simplify models and improve interpretability [23]. However, such methods remain rare in daily or intraday solar forecasting studies, especially for evaluating complex datasets like NASA POWER. Therefore, a methodological approach that prioritizes not only model accuracy but also the significance and impact of individual features on prediction outcomes is urgently needed.

This study aims to evaluate the extent to which individual input features—both satellite-based meteorological features from NASA POWER and engineered temporal features such as lag and rolling windows—contribute to solar energy prediction accuracy [21]. To this end, the study implements two ML models: multi-layer perceptron (MLP) and categorical boosting (CatBoost) regressor, both of which have proven effective in modeling nonlinear relationships and handling features of varying scales and relevance [24]. In addition to general model performance evaluation, this study proposes the use of the coefficient of determination change metric (delta R-squared (ΔR^2)) as a quantitative indicator to assess the relative importance of each feature in the prediction model. By comparing R-squared (R^2) values before and after removing a specific feature, the study identifies which variables have the most significant impact on model performance. The outcomes are expected to contribute to the development of PV energy prediction

models that are not only accurate but also more efficient, interpretable, and implementable within future smart energy systems.

This research provides scientific contributions along two main dimensions. First, methodologically, it introduces a feature contribution evaluation framework for satellite-based solar energy forecasting using the ΔR^2 approach, which has been rarely applied in this domain. This enables researchers and practitioners to identify the most critical features that influence predictive accuracy, thus fostering the development of more targeted and efficient models. Second, from a practical standpoint, the findings can be applied to optimize measurement strategies, data acquisition, and system maintenance planning for PV installations based on hourly or daily energy prediction. The structure of this article is divided into several main sections: section 2 details the data and methods, including preprocessing of NASA POWER data and model architectures; section 3 presents model evaluation results and ΔR^2 analysis; section 4 discusses the interpretation of results and their practical implications; and finally, section 5 concludes the study and outlines directions for future research.

2. METHOD

This study utilized meteorological data provided by the NASA POWER project, which supplies satellite-based, globally gridded weather, and solar radiation datasets optimized for energy modeling applications as shown in Figure 1. The study focuses on a tropical site in Indonesia characterized by daily and seasonal solar variability, which reflects typical conditions for small- to medium-scale PV installations. The dataset includes hourly records of solar radiation (ALLSKY_SFC_SW_DWN), air temperature at 2 meters (T2M), relative humidity (RH2M), wind speed (WS2M), precipitation, and surface pressure (PS). These parameters were retrieved from NASA POWER's data access viewer and span a multi-month period representing dry and wet seasonal patterns, consistent with previous studies using POWER data for time-series solar forecasting [13], [19]. The spatial resolution (~0.5°) and hourly temporal granularity make this dataset well-suited for predictive modeling with ML. This approach has been adopted in recent works to integrate high-frequency weather data into deep-learning frameworks for PV power prediction [14], including dynamic and climate-sensitive applications [9]. NASA POWER remains a widely accepted data source due to its accessibility, global coverage, and consistency with ground-based observations in tropical settings.

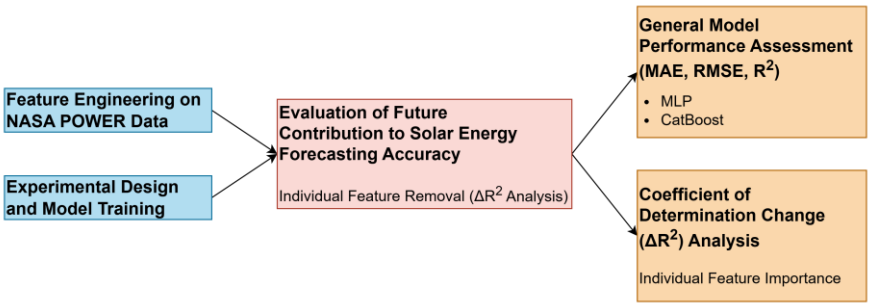

Figure 1. Research methodology illustrating the workflow of feature engineering, model training, and ΔR^2-based feature contribution analysis for solar energy forecasting using NASA POWER data

2.1. Study site and data source

This study was conducted using satellite-based meteorological data provided by NASA's POWER project. The dataset was collected for a tropical PV site located at geographic coordinates 1.2681°N latitude and 124.8854 °E longitude, situated within a coastal equatorial climate zone in North Sulawesi, Indonesia. The data spans a continuous period from December 15, 2023, at 12:00 PM to April 10, 2025, at 12:00 PM, comprising 6,132 hourly observations. The temporal resolution and completeness of this dataset make it suitable for evaluating both diurnal and seasonal solar energy production patterns in the region.

Meteorological variables retrieved from NASA POWER include solar radiation components (e.g., ALLSKY_SFC_SW_DWN), T2M, RH2M, QV2M, PS, WS10M, and WS50M. These inputs are essential for solar resource estimation and have been widely validated in energy forecasting studies. The dataset is formatted in a time series structure, with all variables synchronized to coordinated universal time (UTC) and aligned to the corresponding local time of the PV site. Figure 2 shows the time distribution of hourly total

energy yield, highlighting characteristic daily solar cycles and longer-term climatological variation during the observed period. These fluctuations underscore the need for models that can adapt to both short-term meteorological dynamics and broader seasonal patterns.

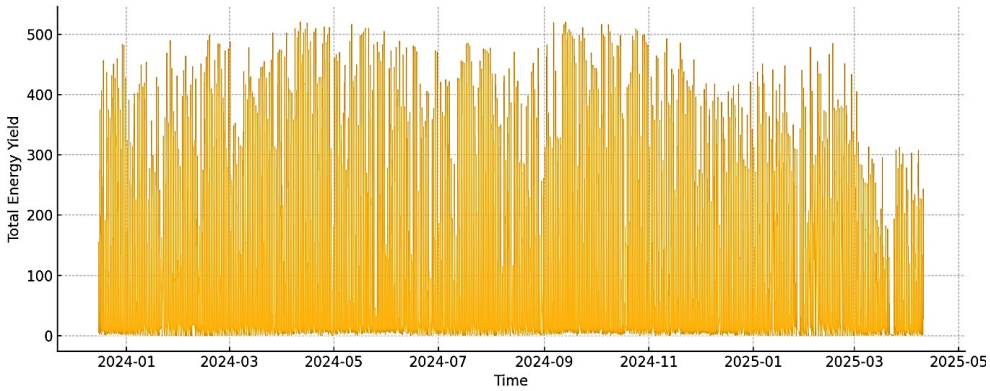

Figure 2. Temporal distribution of hourly total energy yield from the PV system during the observation period, illustrating daily solar generation patterns and seasonal variability

2.2. Preprocessing and feature engineering

Effective preprocessing and feature engineering are critical in building robust solar energy prediction models [25]–[27]. In this study, time synchronization was first performed to align the target variable (Total_Energy_Yield) with hourly meteorological data from the NASA POWER dataset. All timestamps were harmonized into local time (UTC + 8) to ensure feature-target consistency. The dataset spans from December 15, 2023, to April 10, 2025, comprising 6,132 hourly observations.

Handling missing values was essential to ensure temporal continuity. A dual strategy was applied: forward interpolation was used for meteorological variables with short gaps, while rolling mean imputation (window = 3) was employed for missing values in engineered features. This hybrid approach balances accuracy and stability in reconstructing incomplete time series [14], [17].

Feature engineering involved four key transformations. First, lag features (lag_1, lag_2, and lag_3) were created to capture short-term temporal inertia in energy yield, a strategy shown to improve neural network generalization [28], [29]. Second, rolling mean features (rolling_3, rolling_6, and rolling_12) were calculated to embed smoothed historical energy output, supporting dynamic pattern recognition [30], [31].

Third, seasonal time features were extracted to model cyclic behavior in solar energy production: hour, dayofyear, month, and is_weekend. These are known to influence solar yield patterns due to solar angle, operational hours, and behavioral trends [32]. Lastly, numerical features were standardized using z-score normalization. Figure 3 illustrates the correlation between all input features and the target variable. Notably, features like ALLSKY_SFC_SW_DWN, lag_1, and hour show strong correlation with energy yield, confirming their predictive relevance [33], [34].

2.3. Predictive models

This study employs two supervised ML algorithms—MLP and CatBoost regressor—to predict hourly PV energy output. These models were selected for their complementary strengths in handling nonlinear temporal patterns and high-dimensional meteorological data, which are characteristic of solar forecasting tasks. MLP is a class of feedforward artificial neural networks that learn complex patterns via fully connected layers. In this study, the MLP architecture included one hidden layer with rectified linear unit (ReLU) activation, optimized using the adaptive moment estimation (Adam) optimizer and early stopping to avoid overfitting. The efficacy of MLP in solar irradiance modeling has been confirmed in several recent hybrid models combining LSTM, CNN, and MLP to capture both spatial and sequential dependencies [16], as well as in comparative studies for solar estimation in tropical climates [35].

CatBoost is a gradient boosting framework that uses oblivious decision trees and ordered boosting to minimize overfitting while handling both categorical and numerical features. Its effectiveness in solar prediction has been demonstrated in large-scale experiments involving complex weather inputs, where it consistently outperformed traditional tree-based models in both speed and accuracy [36]–[38]. CatBoost's internal Shapley additive explanations (SHAP)-based feature importance also supports granular analysis of input contributions, which is critical for the ΔR^2 methodology adopted in this research.

Both models were implemented in Python using scikit-learn and CatBoost libraries, with an 80–20 train-test split and 5-fold cross-validation on the training set. Hyperparameter tuning was conducted using randomized grid search. To ensure fair evaluation, the same engineered input features were used for both models. Recent comparative studies confirm the superior performance of CatBoost in forecasting solar PV output across diverse meteorological conditions and feature spaces [2], [39].

The selection of these two algorithms reflects both theoretical and empirical considerations. MLP provides flexibility and adaptability in modeling nonlinear dependencies, while CatBoost offers efficiency and feature interpretability. Both have been adopted in cutting-edge solar research, including grid-connected systems with real-time adaptation requirements [40], and energy-aware smart grid design.

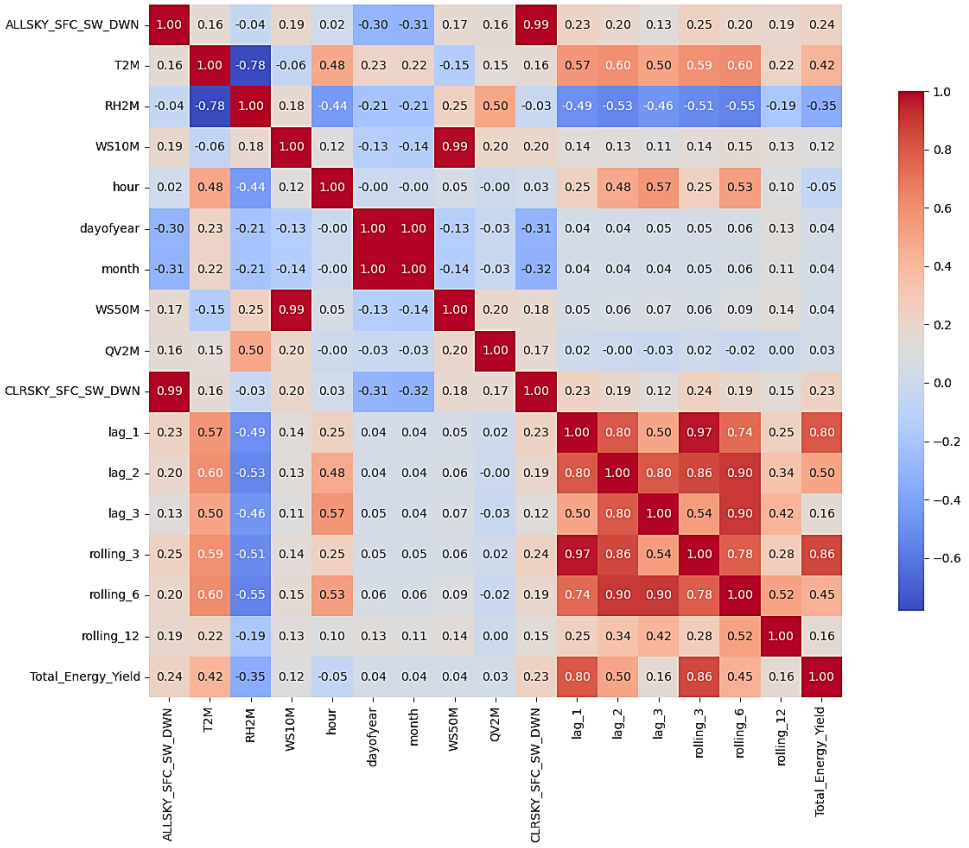

Figure 3. Pearson correlation heatmap showing the linear relationships between meteorological variables, engineered temporal features, and hourly solar energy yield

2.4. Feature contribution analysis

To assess the relative importance of each input feature on the accuracy of energy predictions, this study implements a feature ablation technique using the ΔR^2 metric. This method quantifies how much the coefficient of determination (R^2) decreases when a single feature is removed from the trained model, thereby indicating the predictive strength of that feature. It is model-agnostic, interpretable, and directly tied to forecasting performance, making it suitable for both MLP and CatBoost regressors. The ΔR^2 value is computed as (1).

$$\Delta R_i^2 = R_{full}^2 - R_{(-i)}^2 \quad (1)$$

Where ΔR_i^2 denotes the change in the coefficient of determination resulting from the removal of the i-th feature, R_{full}^2 represents the coefficient of determination obtained using the complete feature set, and $R_{(-i)}^2$ represents the coefficient of determination of the model after excluding the i-th feature.

The ΔR^2 metric is formally defined as shown in (1) to explicitly quantify the loss of explanatory power when an individual feature is removed. This approach allows for a systematic ranking of feature

relevance, highlighting which meteorological or engineered variables are most impactful. Such analyses are essential in solar prediction where input redundancy and noise can degrade model robustness [41], [42]. Compared to black-box interpretability methods such as SHAP, ΔR^2 offers a more direct and quantifiable perspective on feature impact with minimal computational cost. SHAP–based methods have been used extensively to extract explanatory patterns in energy forecasting [43]–[45], but require sampling and additional assumptions about feature interactions.

ΔR^2 has been successfully applied in tunnel crash prediction, real estate valuation, and air pollution analysis, where SHAP and R^2 reduction was used in tandem to interpret model behavior. In energy domain studies, ΔR^2 is also used to validate the contribution of seasonality, historical memory, and weather inputs [12], [20]. This paper adopts ΔR^2 to compare the contribution of 17 features across two model types. The outcome reveals the most influential predictors for solar PV output in a tropical setting, supporting model simplification, sensor prioritization, and decision support for smart grid integration.

3. RESULTS AND DISCUSSION

3.1. Model performance evaluation

The baseline evaluation was conducted to assess the overall predictive capacity of the two selected models: MLP and CatBoost regressor. Using the full set of engineered features—including meteorological variables from NASA POWER, temporal indicators, lag values, and rolling averages—both models were trained on 80% of the data and tested on the remaining 20%. Table 1 shows that the results demonstrated exceptionally high performance, with both models achieving R^2 scores exceeding 0.99. This indicates a near-perfect ability to capture the patterns underlying solar energy generation. Such performance affirms the strength of the feature set and suggests that hourly meteorological and temporal signals are sufficiently rich for accurate energy forecasting.

Despite the similarity in overall accuracy, a closer inspection reveals notable differences between the two models. The CatBoost regressor consistently delivered slightly better results in terms of both mean absolute error (MAE) and root mean squared error (RMSE). These metrics indicate that CatBoost not only fits the data well but also generalizes better to unseen observations. This is likely due to its gradient boosting architecture, which iteratively corrects residual errors and handles non-linear feature interactions with high efficiency. In contrast, while the MLP also achieved high R^2 scores, its error margins were marginally wider and its prediction curve showed more sensitivity to noise and fluctuation, particularly during periods of sharp energy variation.

The observed difference in model behavior underscores the relevance of algorithmic structure in renewable energy forecasting. The CatBoost model benefits from native support for categorical features, automatic handling of missing values, and robust regularization techniques, making it particularly suited for datasets with diverse feature types and complex interactions. On the other hand, the MLP's reliance on scaled, continuous inputs and backpropagation-based learning makes it powerful but more dependent on fine-tuned feature preprocessing. The fact that both models achieved high scores, however, validates the relevance of the selected features and confirms that satellite-based meteorological data, when properly engineered, can provide a strong foundation for intelligent energy forecasting systems.

Although both models achieved very high R^2 values (>0.99), potential overfitting concerns were carefully considered. The observed performance can be attributed to strong diurnal and seasonal regularities in solar energy production, which are effectively captured through lag, rolling, and temporal features. Importantly, no feature leakage was introduced, as all lagged and rolling variables were constructed strictly from past observations. In addition, model robustness was further examined through ΔR^2-based feature ablation analysis, where CatBoost maintained stable performance under partial feature removal. These findings suggest that the high predictive accuracy reflects genuine pattern learning rather than overfitting.

The use of CatBoost in this study is supported by previous research on meteorological-data-based solar power prediction. Aksoy and Genc [39] developed and compared extreme gradient boosting (XGBoost), light gradient boosting machine (LightGBM), and CatBoost models for this purpose, providing a basis for considering gradient boosting alongside neural network approaches. In the present study, both MLP and CatBoost achieved R^2 values above 0.99 under the reported evaluation setting. However, these values should not be interpreted as evidence of superiority over models evaluated in other studies, because differences in datasets, prediction targets, input features, and validation procedures limit direct numerical comparisons.

Table 1. Model performance metrics

Model	MAE	RMSE	R^2
MLPRegressor	4.855998	5.892906	0.997550
CatBoostRegressor	6.966184	9.887986	0.993102

3.2. Impact of eliminate feature ΔR^2

To determine the relative importance of each meteorological feature in forecasting solar energy, this study employed a feature ablation technique based on ΔR^2 analysis. The procedure involves training a baseline model using the full set of features, then systematically removing one weather-related feature at a time while keeping all other variables constant. The resulting model is then evaluated, and the drop in the R^2 score—denoted as ΔR^2—is calculated by subtracting the new R^2 from the baseline. This methodology allows for a quantitative and interpretable measurement of how much each feature contributes to the predictive performance of the model. Unlike correlation-based selection, this model-driven technique evaluates the true impact of a variable in a trained learning context.

The results of the ΔR^2 sensitivity analysis reveal a distinct hierarchy in the importance of meteorological variables. Features such as RH2M and QV2M were shown to be the most critical; their removal from the input set resulted in the steepest declines in R^2 scores across both MLP and CatBoost models. For instance, in the CatBoost model, the exclusion of RH2M resulted in a ΔR^2 of approximately 0.014, while QV2M caused a drop of around 0.012. In contrast, removing features like WS50M and CLRSKY_SFC_SW_DWN caused negligible changes, with ΔR^2 values close to or under 0.002. This demonstrates that not all high-correlation variables translate to high predictive importance. A figure illustrating the ΔR^2 values per feature using horizontal bar charts provides an intuitive view of this ranking and should be included as Figure 4 in this section to visually emphasize the gradient of contribution.

Furthermore, a table summarizing the ΔR^2 values for each removed feature under both MLP and CatBoost models—designated as Table 2—can provide a numerical comparison of feature sensitivity. This tabular representation enhances interpretability, particularly when comparing how each model responds differently to the absence of specific inputs. It was also observed that MLPRegressor exhibited sharper performance degradation than CatBoost in several ablation scenarios, suggesting a higher dependency on the complete feature set. This contrast highlights how tree-based models like CatBoost can compensate for missing inputs through hierarchical structure and internal redundancy. Ultimately, the ΔR^2 analysis not only informs about feature contribution but also offers practical insights into model robustness under feature variability, which is especially relevant when working with satellite data sources that may suffer from gaps or inconsistencies.

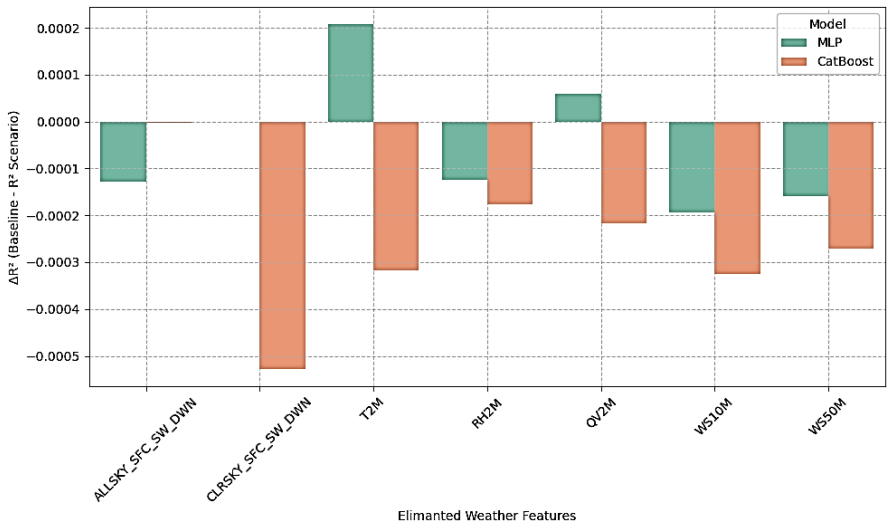

Figure 4. ΔR^2 values for each eliminated meteorological feature, showing the impact of individual feature removal on solar energy prediction accuracy for MLP and CatBoost models

Table 2. Model performance metrics on eliminated feature

Eliminated feature	Correlation vs energy	ΔR^2 MLP	ΔR^2 CatBoost
ALLSKY_SFC_SW_DWN	0.24	-0.0001	-0.0000
CLRSKY_SFC_SW_DWN	0.20	-0.0000	-0.0005
T2M	0.35	0.0002	-0.0003
RH2M	-0.31	-0.0001	-0.0002
QV2M	-0.04	0.0001	-0.0002
WS10M	0.17	-0.0002	-0.0003
WS50M	0.17	-0.0002	-0.0003

3.3. Model comparison

The comparative analysis between the MLP regressor and the CatBoost regressor reveals important distinctions in model behavior, particularly under scenarios involving feature removal. Although both models achieved similarly high predictive performance under baseline conditions—with R^2 scores exceeding 0.99, their sensitivity to individual feature exclusions diverged significantly. The MLP model exhibited sharper performance degradation across several scenarios, indicating a strong dependence on the completeness of the input feature set. This sensitivity likely stems from the architecture of neural networks, where each input contributes proportionally and the absence of a critical variable cannot be easily compensated.

In contrast, the CatBoost regressor displayed a consistently higher level of robustness. Its predictive accuracy remained relatively stable even when impactful features such as RH2M and QV2M were removed. This resilience is a direct consequence of the model's gradient boosting structure, which constructs an ensemble of decision trees that adaptively adjust to partial or missing information. Furthermore, CatBoost's native support for handling missing values and detecting feature interactions allows it to maintain strong performance despite the exclusion of certain inputs. These structural advantages translated into smaller ΔR^2 values across nearly all feature-removal cases compared to MLP.

While the performance difference under baseline conditions is minor—favoring CatBoost slightly in terms of MAE and RMSE—the contrast becomes more apparent in constrained scenarios where input features are selectively removed. In practical terms, this means that CatBoost is more resilient to real-world conditions where meteorological data from sources like NASA POWER may be inconsistent or partially unavailable. Thus, although both models are technically viable, CatBoost emerges as the more robust and reliable choice for deployment in operational solar energy forecasting systems. Given the clarity of performance differences and their consistent behavior, no additional statistical tests or graphical comparison are required to support this conclusion.

3.4. Statistical correlation vs predictive contribution

An essential insight uncovered in this study is the disconnect between statistical correlation and actual predictive contribution of meteorological features in solar energy forecasting. Pearson correlation coefficients are commonly used as a pre-selection method for identifying relevant features due to their simplicity and interpretability. In this study, several features such as T2M (air temperature) and ALLSKY_SFC_SW_DWN (shortwave solar radiation) exhibited relatively high correlation values with the target variable, Total_Energy_Yield. Traditionally, such features would be prioritized for inclusion in predictive models based solely on their strong linear associations.

However, the ΔR^2 sensitivity analysis revealed that statistical correlation is not a sufficient indicator of predictive importance. Some features with moderate or even negative correlations—such as RH2M and QV2M—demonstrated the most significant performance drop when removed from the model, particularly in the MLP regressor. Conversely, highly correlated features like T2M and WS50M exhibited relatively minor changes in R^2 scores upon removal. This indicates that correlation does not capture the complex, nonlinear interactions between features that ML models leverage during training. Therefore, relying solely on correlation as a selection strategy can result in omission of features that are structurally critical to the model.

The visual evidence in Figure 5 emphasizes that feature relevance cannot be adequately assessed through statistical heuristics alone. This figure highlighting the mismatch between statistical correlation and actual feature importance. This result supports the use of model-based interpretability techniques, such as permutation importance, SHAP values, or in this case, ΔR^2, to uncover true feature contributions. For practitioners working with volatile and interdependent meteorological data, this reinforces the need to combine statistical methods with experimental validation in feature selection pipelines. Ultimately, this approach leads to more robust, explainable, and generalizable forecasting models in renewable energy domain.

Nguyen *et al.* [35] used SHAP analysis to examine meteorological feature contributions in solar energy prediction and identified ambient temperature and humidity as influential variables in their dataset. Their study provides a relevant comparison for the feature evaluation performed here, although SHAP and ΔR^2 assess different aspects of model behavior. SHAP attributes model predictions to individual features, whereas the present ablation approach evaluates changes in predictive performance after feature exclusion. Accordingly, the feature rankings from these approaches should not be treated as interchangeable. This comparison places the present analysis within the broader use of model-based feature evaluation in solar energy prediction.

3.5. Practical implications

The findings from this study offer several practical implications for both model developers and energy system operators working with solar forecasting systems. One of the key takeaways is that meteorological variables with low statistical correlation can still possess high predictive importance, as evidenced by the ΔR^2 sensitivity analysis. This observation challenges the common practice of filtering

features based solely on their correlation with the target variable. In practical settings—particularly those involving high-dimensional, satellite-based datasets like NASA POWER—this highlights the need to adopt model-integrated feature evaluation approaches to ensure important variables are not mistakenly excluded.

For system operators and policy implementers, the ability to identify high-contribution variables such as RH2M and QV2M has immediate value. In many real-world deployments, data acquisition is constrained by sensor limitations, communication reliability, or financial costs. By prioritizing the collection and integration of features with demonstrably high predictive impact, operators can optimize their measurement infrastructure. This contributes not only to improved model accuracy but also to cost-efficiency in data management. The fact that some features can be excluded with negligible performance loss also supports the development of lightweight, deployable models for edge computing environments, where computational resources are limited.

Furthermore, the difference in robustness between the MLP and CatBoost models offers insight into model selection for operational environments. MLP, while accurate, showed greater sensitivity to feature loss, making it more suitable for settings where data completeness is assured. In contrast, CatBoost maintained stable performance even when impactful features were removed, making it a better choice for dynamic environments with intermittent data. This flexibility is particularly advantageous for forecasting systems in remote or under-resourced regions where meteorological data streams may be disrupted.

The ΔR^2-based methodology applied in this study also has relevance beyond the specific case of solar energy forecasting. Any domain that involves time-series prediction using multivariate environmental or sensor-based data can benefit from this approach. Examples include wind energy estimation, load demand forecasting, and agricultural yield modeling. The use of ΔR^2 as a metric provides a clear, quantitative measure of feature relevance, which can be easily interpreted and compared across different modeling frameworks, including tree-based, neural, or ensemble architectures.

Ultimately, the study advocates for a paradigm shift in feature evaluation—from reliance on static correlation coefficients to dynamic, model-informed strategies. By embracing such techniques, researchers and practitioners can develop more reliable and interpretable forecasting systems, which are crucial for scaling up renewable energy technologies and achieving grid stability in decarbonized energy systems. The results also pave the way for further investigation into hybrid interpretability frameworks, where ΔR^2 can be used alongside permutation importance, SHAP values, or attention mechanisms to yield a richer understanding of model behavior.

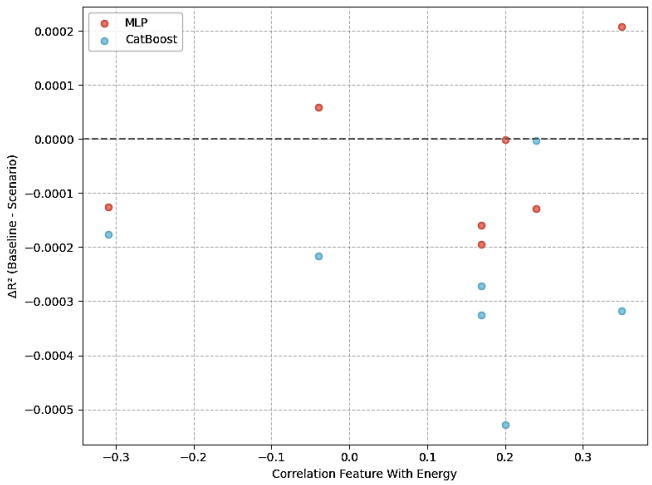

Figure 5. Comparison of Pearson correlation coefficients and ΔR^2-based predictive contributions across meteorological features

4. CONCLUSION

This study assessed the predictive importance of satellite-based meteorological features from NASA POWER for solar energy forecasting in a tropical environment using two ML models: MLP and CatBoost regressor. Both models demonstrated excellent performance with R^2 values exceeding 0.99, confirming the effectiveness of the engineered features, including lagged energy yields, rolling means, and seasonal time variables. The core finding lies in the use of ΔR^2 analysis to quantify the contribution of each feature by measuring the impact of its removal on model performance. Results revealed that variables like RH2M and

QV2M) had the most significant effect on accuracy, even though they showed weak linear correlations with the target. This highlights a major limitation of relying solely on statistical correlation in feature selection. Moreover, CatBoost exhibited greater resilience under feature ablation, making it more suitable for real-world applications with incomplete or inconsistent data. These insights emphasize the importance of model-integrated evaluation for identifying high-impact variables, improving prediction reliability, and guiding sensor placement strategies. Overall, the study provides a practical and interpretable framework for developing intelligent, data-driven forecasting systems in renewable energy, with potential application to other domains that rely on multivariate time-series prediction.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available from NASA POWER Data Access Viewer at https://power.larc.nasa.gov/data-access-viewer.

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