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Physics-Informed Machine Learning for Air Temperature Prediction Using Surface Energy Balance–Based Feature Engineering

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Abstract: Precise predictions of air temperature are critical to environmental studies and climate research. However, conventional machine learning algorithms have a disadvantage in that, while performing well on capturing non-linear relationships, their physics interpretations can be poor. In this study, a physics-informed machine learning (PIML) model is proposed using Surface Energy Based (SEB) -based feature engineering techniques applied to ensemble models. The meteorological dataset for the Delhi region from NASA POWER for 2023–2025 was employed for this analysis. For testing purposes, two types of ensemble models are considered, including Random Forest and Gradient Boosting Machine (GBM) in both pure data-driven and physics-informed configurations. The physics-based features such as net radiation, sensible and latent heat proxies, vapor pressure deficit (VPD), and energy imbalance were included through feature engineering. Performance evaluation was done based on Root Mean Square Error (RMSE) and coefficient of determination (R^2). The results reveal a marked improvement in the accuracy of predictions, where the physics-based GBM model lowers RMSE from 1.54°C to 1.17°C and attains an R^2 of 0.968. It can be seen that integrating physical knowledge in machine learning models is beneficial for enhancing predictive accuracy and robustness making it a promising approach for environmental data analysis.

Keywords: *Physics-Informed Machine Learning, Surface Energy Balance, Air Temperature Prediction, Gradient Boosting, Random Forest, Vapor Pressure Deficit, Environmental Data Analysis.*

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I. INTRODUCTION

Air temperature forecasting is vital in many fields, including climatic research, farming, and environmental monitoring. In recent years, machine learning models have been used extensively for predicting temperatures due to their capacity to develop highly sophisticated correlations between various environmental factors. Ensemble models like random forests and gradient boosting models have been successful when applied to tabular environmental data [1, 2].

On the contrary, conventional machine learning approaches depend solely on data without considering any of the physical laws that govern atmospheric events [3]. Such a flaw may make the machine learning models constructed not be generalizable and understandable, particularly in cases where there is limited data or changing weather conditions. This need for a combination of physics-based knowledge and machine learning led to the development of PIML.

One of the basic laws that dictate the exchange processes between surface and atmosphere is Surface Energy Balance (SEB), wherein energy from the net radiation is distributed into sensible heat, latent heat, and ground heat flux [4]. The integration of these physical laws to machine learning models can enhance consistency and predictability.

Current studies in this field use Physics-Informed Neural Networks (PINNs) whereby the physics principles are incorporated into the loss function [5]. Although such methods have proved useful, they are costly in terms of computations and implementation. An easier alternative is to engage in physics-guided feature engineering whereby one derives and uses features that are meaningful physically in training a machine learning algorithm [6, 7].

In the current study, a physics-inspired model is created via the inclusion of SEB-derived features in ensemble models for forecasting air temperature. Data for meteorological variables are acquired from NASA's POWER data portal to

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create models that are purely data-driven as well as physics-inspired. The two models are compared with Random Forest and GBM approaches to evaluate the impact of incorporating physical knowledge.

The primary purpose of this study is to prove the efficiency of physics-informed feature engineering as an approach that can considerably improve the performance of machine learning algorithms for environmental tasks.

II. LITERATURE REVIEW

The coupling of physical properties and machine learning for enhanced predictions of environmental and thermal predictions is gaining momentum from recent researches. Machine learning techniques like Random Forest and Gradient Boosting exhibit great predictive powers in atmospheric and thermal systems, but suffer from the limitation of lacking physical insight and being inconsistent in adverse conditions. As shown by Tyler McCandless et al. [8], machine learning models could greatly enhance the performance of sensible heat and moisture flux predictions as compared to existing surface layer theory models. Likewise, emerging physics-inspired works have integrated energy balance equations into machine learning models for predicting temperatures. The constrained LightGBM algorithm that was designed for land surface temperature estimation exhibited higher accuracy levels and improved extrapolation ability during extreme weather events due to the incorporation of Surface Energy Balance (SEB) based physical features [9]. Similarly, in another study, the use of physics-inspired ensemble learning algorithms was demonstrated for temperature predictions during urban heat waves, revealing greater robustness than that of traditional data-driven techniques [10]. Moreover, hybrid physics-informed algorithms have also been employed for predicting river and lake temperatures, wherein the use of heat balance equations has enhanced their physical plausibility and predictive power [11]. Building on these advancements, the current study proposes a physics-informed ensemble learning algorithm for air temperature predictions.

➢ *Objectives of the Study*

The primary goals of the current study are the following:

- Development of machine learning models for air temperature prediction based on meteorological data
- Application of physical principles derived from the Surface Energy Balance in modeling
- Comparison between pure data-driven models and physics-informed models
- Performance analysis of ensemble techniques such as Random Forest and Gradient Boosting
- Identification of the effect of incorporating physics-informed factors on the prediction accuracy

➢ *Data Set Description*

The data used in this work was acquired from the NASA POWER data portal that offers authentic meteorological data in the public domain. The data corresponds to the Delhi region and covers a period ranging from 2023 to 2025 in daily frequency. The data includes atmospheric variables such as air temperature, solar radiation, relative humidity, wind speed, and pressure at the surface. The data is essential to understand the thermodynamic principles that governs temperature variations.

III. METHODOLOGY

In the current research work, the approach used for air temperature prediction is based on incorporating physics-based knowledge into ensemble models of machine learning. The entire method is composed of the following steps: data collection, data processing, feature generation based on physics knowledge, building the model, and evaluation of results.

The pre-processing phase was completed in order to have consistency and quality data. Proper measures were undertaken in order to address missing values, and the column of the date variable was transformed into appropriate date time format. The time dependency for temperature fluctuation was taken into account by generating lag features such as yesterday temperature. For integrating physics knowledge in the model, physics features were obtained based on the Surface Energy Balance (SEB) which governs the exchange of energy between the Earth's surface and the atmosphere.

- Surface energy balance equation: $R_n = H + LE + G$

Where,

R_n = net radiation,

H = sensible heat flux,

LE = latent heat flux and

G = ground heat flux

Since full flux measurements are rarely available, physically motivated proxy features were constructed.

- Net radiation was approximated from incoming solar radiation using a constant surface albedo assumption. If there is only solar radiation R_s (W/m²), net radiation can be approximated as:

$R_n = (1-\alpha)\, Rs$

Where,

α = surface albedo, for vegetation or mixed land surfaces, $\alpha = 0.23$

Sensible heat and latent heat fluxes were represented using simplified proxy formulations based on wind speed, temperature, and relative humidity [12].

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- True sensible heat flux is: $H = \rho\, c_p\, C_H\, U\, (T_s - T_a)$,

Where ρ = air density (≈ 1.225 kg/m³), c_p = specific heat of air (≈ 1005 J/kg·K), C_H = transfer coefficient (~ 0.001–0.01), U = wind speed (m/s), $T_s - T_a$ = surface-air temperature difference

Since surface temperature is usually unavailable, surface temperature can be correlated with solar radiation. So proxy is applied, Hproxy = U× (T_s− T_a). This preserves the physical idea that more wind implies more sensible heat exchange and higher radiation implies stronger temperature gradient [13].

- True latent heat flux: $LE = \rho L_v C_E U\,(q_s - q_a)$, Where L_v = latent heat of vaporization, $q_s - q_a$ = humidity gradient. Latent heat flux depends on moisture availability (humidity), radiation and air movement. The full equation needs humidity gradients and surface conditions, which is not available in dataset. Without full humidity gradients, LE_{proxy} = RH×Rs or LE_{proxy} = U×RH

Where RH tells how much moisture is available and Rs (solar radiation) is the energy driving evaporation. More sunlight implies more evaporation and more humidity implies more water available. If using second equation it can inferred that wind enhances evaporation and humidity provides moisture [14].

Since we don't have exact measurements, we estimate latent heat using humidity and radiation. Radiation-based proxy (RH × R_s) is preferred because evaporation mainly depends on available energy.

- Ground heat flux was estimated as a fraction of net radiation. Ground heat flux is typically:

$G \approx 0.1 R_n$ for daily averages.

- Vapor pressure deficit (VPD) was calculated using temperature and relative humidity to represent atmospheric moisture demand.

Saturation vapor pressure: $e_s = 0.6108\, exp\left(\frac{17.27\,T}{T + 237.3}\right)$

Actual vapor pressure: $e_a = RH \times \frac{e_s}{100}$

Vapor pressure deficit: $VPD = e_s - e_a$

VPD is physically interpretable and highly correlated with latent heat flux. This is a particularly strong environmental variable.

- An energy imbalance, computed as the difference between net radiation and the estimated components of the fluxes, was used as another environmental feature.

Energy Imbalance = R_n - (H_{proxy} + LE_{proxy} + G)

This feature is crucial because when there are violations of physical constraints in the modeled temperature, the value of this term is expected to be very high [15]. As direct measurement of these energy fluxes was unavailable, their estimates using simplified bulk formulas and proxies were obtained. These are physically meaningful variables that help the learning process of the model. [16, 17].

In this work, two ensemble machine learning algorithms have been applied: Random Forest and Gradient Boosting Machine (GBM). These two machine learning methods were used in two ways: (i) purely data-driven approach, where only the original meteorological predictors and time-based predictors were used, and (ii) physics-inspired approach, where the derived SEB predictors are also considered alongside the original predictors. The principle of Random Forest involves building several decision trees via bootstrapping and averaging their outputs [18], whereas Gradient Boosting algorithm builds decision trees successively, each correcting the mistakes of the preceding one [19, 20].

The data set was partitioned into training and testing sets at a ratio of 80:20. Each of the models was trained on the training set and tested on the testing set to ensure that there was no bias during evaluation. Model evaluation was performed using regression metrics such as Root Mean Squared Error (RMSE) and the coefficient of determination (R^2). These measures help to determine how well the model can predict temperature.

The comparison was conducted on four models, which include Random Forest (no physics), Random Forest (with physics), Gradient Boosting (no physics), and Gradient Boosting (with physics). The comparison enables a better evaluation of the impact that the incorporation of physics into the model can have. Moreover, the importance of the features is also evaluated to analyze their significance in predicting the temperature.

Table 1 Performance Comparison of Pure and Physics-Informed Machine Learning Models for Air Temperature Prediction

Model	RMSE	R^2
RF Pure	1.539929	0.944775
RF Physics	1.293109	0.961059
GBM Pure	1.535368	0.945101
GBM Physics	1.168407	0.968207

As can be observed from Table 1 that the inclusion of physics-related attributes resulted in improved prediction performance. The best result was achieved using the Gradient Boosting model with physics-informed attributes, where RMSE dropped from 1.54 to 1.17 while R^2 increased to 0.968. It shows how essential it is to include physical properties in

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machine learning using feature engineering. It is highlighted in the study that Gradient Boosting outperforms Random Forest because of its ability to learn sequentially using meteorological data.

IV. RESULTS AND DISCUSSION

The predictability of the physics-informed machine learning approach suggested here has been investigated using several statistical and visualization techniques for the purpose of determining its accuracy, stability, and physics interpretability. A plot of the predicted vs. experimentally observed temperature is presented in Fig. 1. Most of the data points are very close to the theoretical 1:1 line. Therefore, it can be concluded that the physics-informed Gradient Boosting approach predicts temperatures with high accuracy and minimal error at all temperatures.

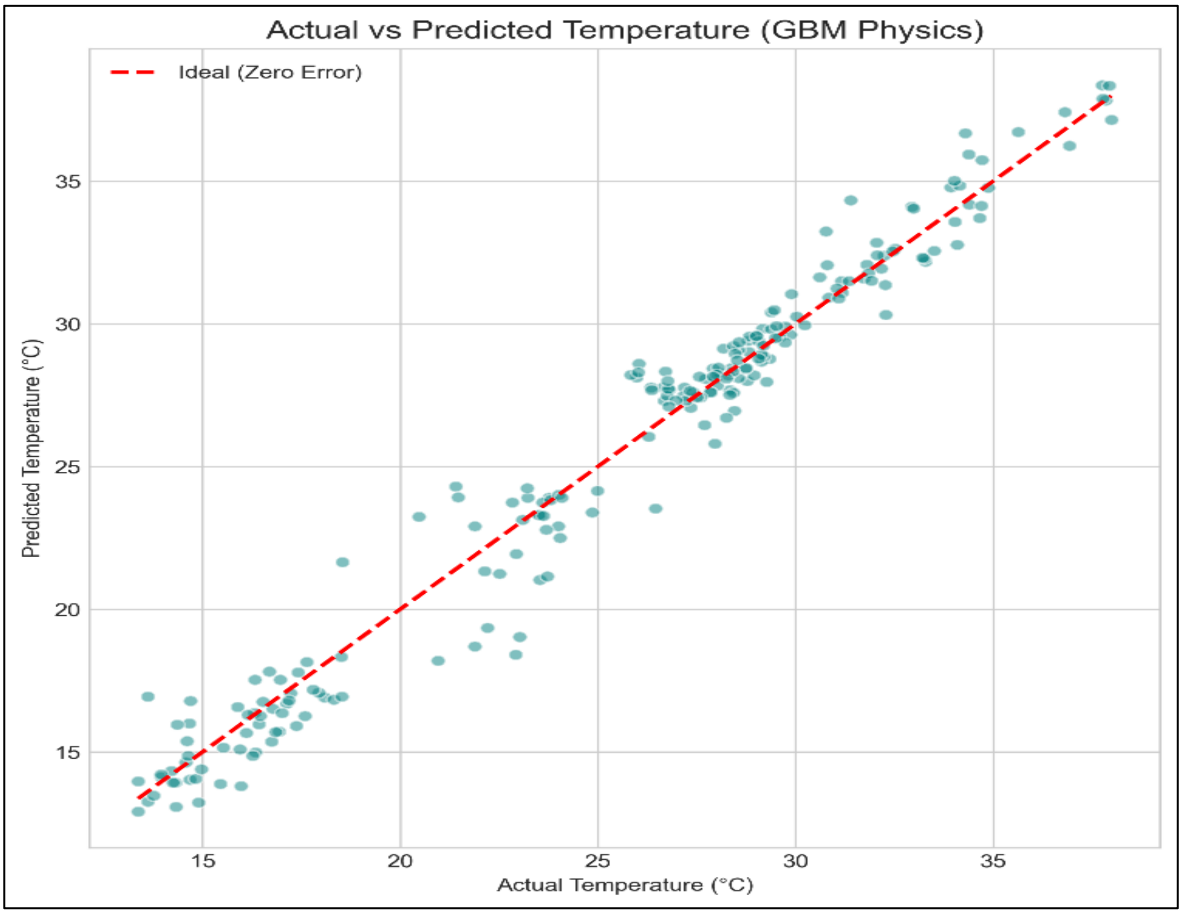

Fig 1 Actual vs Predicted Temperature (GBM Physics Model)

A scatter plot, as depicted in Figure 1, has been generated in order to depict a comparison between the observed air temperatures and those estimated with the help of Gradient Boosting algorithm based on physics. The dashed red line, in the figure, depicts the ideal fit, where the ratio is 1:1, hence implying no error in estimation and observation.

From the scatter diagram, it can be seen that all points lie on the line, suggesting a very good fit of prediction and observation. This suggests that the model is a good predictor of the relationship between weather phenomena and air temperature. The scatter of the data points along the line is quite low, which shows the low level of errors in the forecasting and high precision of the model. There are some minor departures from the straight line, particularly around the medium range of temperatures between 20-25 degrees Celsius, where there could be either under- or over-predictions. When the temperature increases, i.e., beyond 30 degrees Celsius, the predictions correlate with the real values, so the model functions well at such temperatures. The model functions well when the temperature falls below 18 degrees Celsius.

Overall, the linear relationship between the data points and the theoretical curve indicates that the ability of the Gradient Boosting model to predict the temperature based on the physics principles is highly accurate, supported by the low RMSE value and the high R^2 values obtained in this study.

The performance of the model through time is shown in Figure 2, which displays the predictions and observations of the temperature at different points in time. In particular, it is noteworthy that the model has the ability to predict both the short-term and long-term changes in the temperature, from summer to winter. The close alignment between the two curves demonstrates strong generalization capability.

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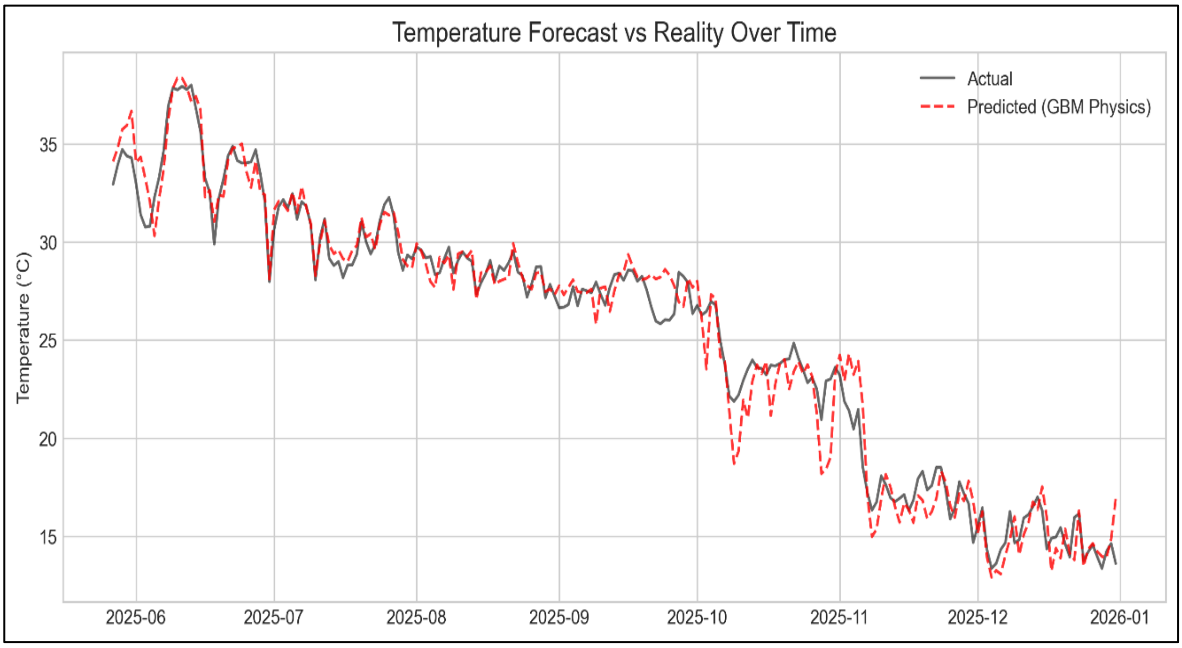

Fig 2 Time Series Comparison of Actual and Predicted Temperature

The Figure 2 shows how time influences the actual temperature and the predicted temperature through the use of the gradient boosting model. It is quite obvious from the above figure that the model can be used to forecast the temperature trends within certain time. This includes both short-term and long-term trends such as slow decline in temperatures from summer to winter.

However, despite the differences that may exist at certain points due to the abrupt change in temperatures, the overall correlation between the two graphs is quite significant. This level of inconsistency is expected due to the erratic nature of the weather patterns and the limitations within the data input. The similarity in results only adds to the validity of the model.

This can be clearly observed from Figure 3 based on the performance of the models in terms of RMSE after incorporating physics-informed variables into the model. Both the Random Forest and Gradient Boosting models exhibit good results after introducing physics-informed variables. From the figure, the lowest value of RMSE is obtained from the physics-informed Gradient Boosting model, confirming its superior predictive performance.

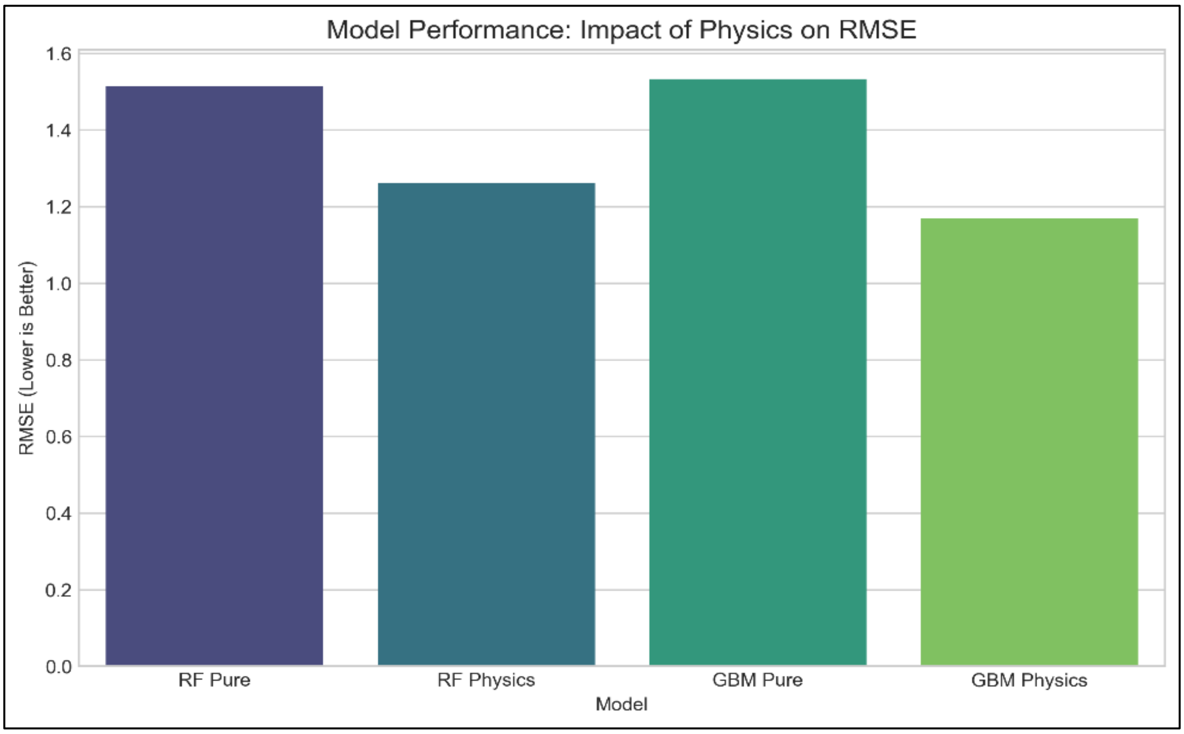

Fig 3 Comparison of Model Performance (RMSE) for Pure and Physics-Informed Models.

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Figure 3 shows the comparison between the accuracy of the prediction from four models: Random Forest (pure model), Random Forest (physics-informed model), Gradient Boosting Machine (pure model), and Gradient Boosting Machine (physics-informed model). The measure used to assess accuracy is the root mean square error (RMSE), where smaller values indicate superior outcomes.

As evident from the graph, the performance of both the models, after introducing them with knowledge about physics, is better than the models based only on data. In other words, in case of Random Forest, the RMSE decreases from 1.51°C to 1.26°C. Also, for the case of Gradient Boosting Model, it decreases significantly from 1.53°C to 1.17°C.

It is clear from the models that among all the models, the Gradient Boosting model informed by physics is the most efficient. This shows that the incorporation of physics-informed features along with sequential learning proves to be beneficial for the prediction.

For better understanding of the underlying factors affecting the model predictions, we can have a look at the importance of features, which has been shown in Figure 4. We see that surface pressure plays an important role, followed by vapor pressure deficit, and energy imbalance. This highlights the importance of atmospheric thermodynamics and validates the effectiveness of incorporating physically meaningful features.

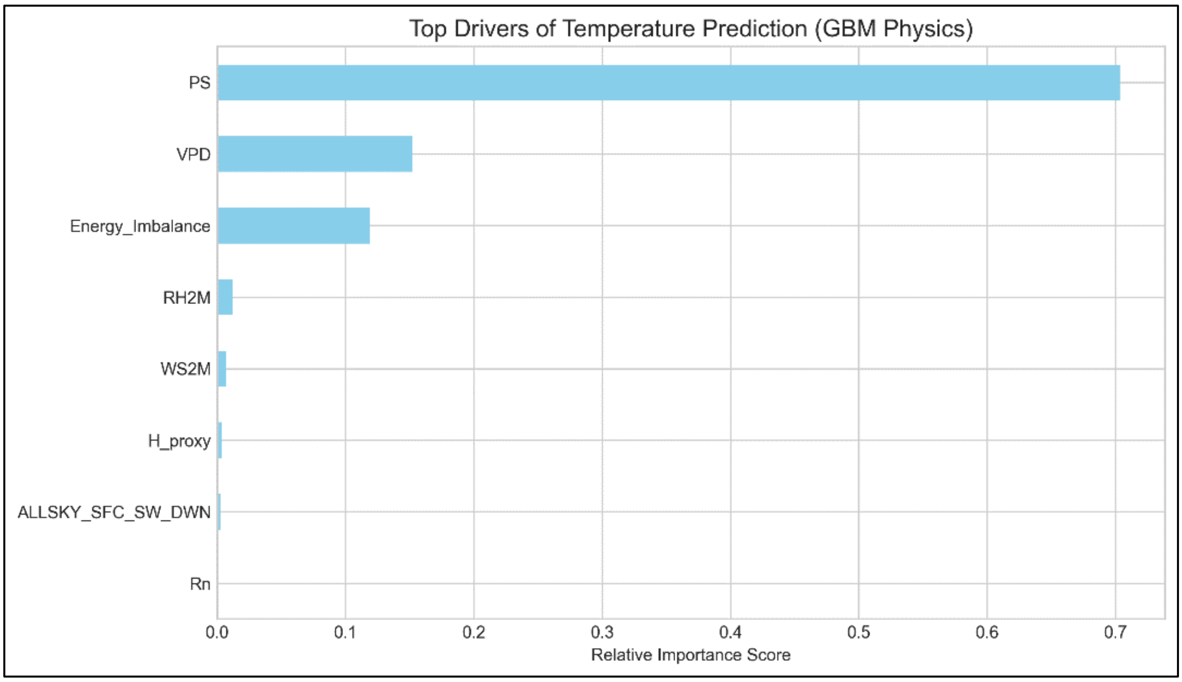

Fig 4 Feature Importance for Temperature Prediction (GBM Physics Model)

Figure 4 shows the impact of input variables used to build the physics informed gradient boosting model on the air temperature. The values of feature importance show the extent to which the input features help reduce the errors in predictions when learning.

It can be seen that pressure at the surface level (PS) is the most important variable, having the highest contribution compared to other input variables. Therefore, we can say that atmospheric pressure is a key factor affecting air temperature.

In addition to the meteorological features mentioned above, it can be noted that among the physics-related features, VPD and energy imbalance play a key role in predicting temperature [21, 22]. It is worth emphasizing that the importance of these two features reflects the importance of atmospheric moisture and energy balance processes in determining the temperature.

However, relative humidity (RH2M), wind speed (WS2M), and the proxy for sensible heat flux (H_proxy) have relatively less importance. The feature ALLSKY_SFC_SW_DWN, which represents incoming solar radiation at the surface under all-sky (cloudy and clear) conditions, exhibits relatively low importance despite being a key driver of surface heating and evaporation. This may be due to its influence being indirectly captured through derived features such as energy imbalance and latent heat proxies. Variables such as incoming solar radiation, net radiation (Rn), among others, based on the concept of direct radiation, have very little significance if the resulting features are available in the model, and thus it means that the model relies on the processed features to improve its efficiency [23]. In general, feature importance analysis shows the relevance of physics-based features in enhancing the efficiency of the model.

The reliability of the model is analyzed using the residuals shown in Figure 5. Residuals exhibit no definite trend but randomly vary around zero, and thus it reflects the unbiasedness of the model. The relatively high variation of residuals in predicting extremely high temperatures is attributed to the difficulty in prediction of dynamic behaviour.

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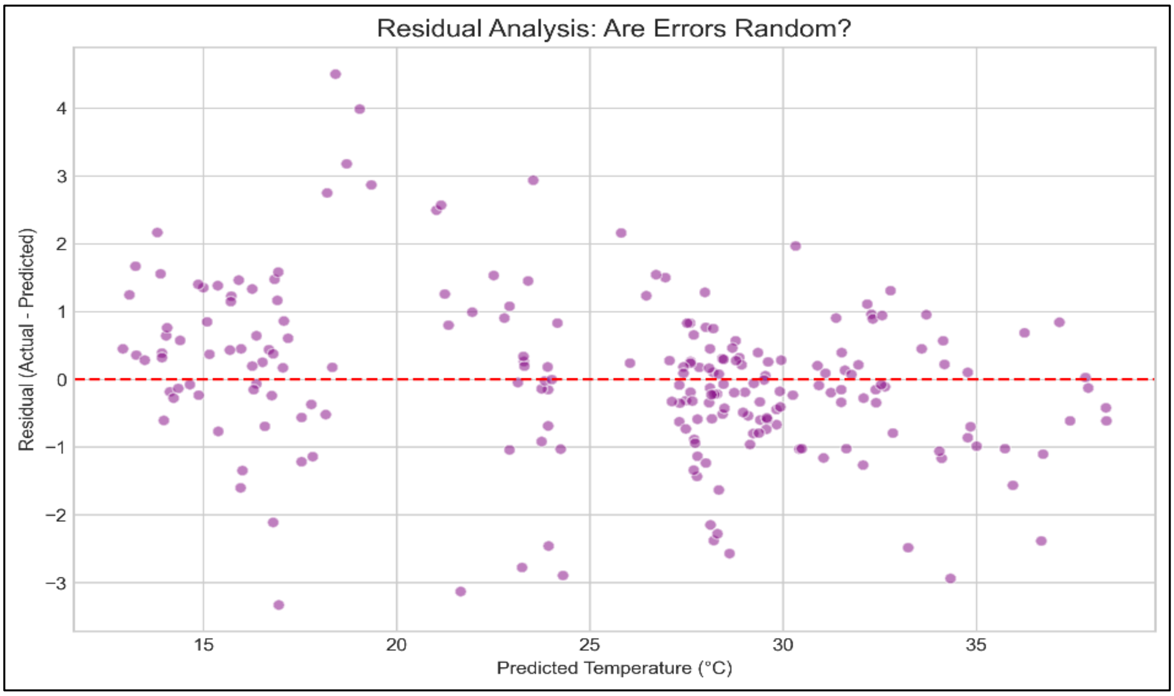

Fig 5 Residual Analysis of the Physics-Informed GBM Model

Figure 5 displays the residual plot for the physics-based Gradient Boosting model. Here, the residual (difference between the actual and predicted temperatures) is plotted against the predicted temperature value. The horizontal dashed line indicates zero error.

From this figure, it can be seen that the residuals are randomly spread around zero, indicating that the model has no bias and do not consistently overestimate or underestimate temperature. But some trends could be noticed. First, when considering low temperatures (around 14-18°C), there is a larger dispersion in the residuals, showing somewhat greater variability in the prediction error. On the contrary, at middle temperatures (around 26-30°C), residuals tend to cluster near zero, implying enhanced accuracy in the model's predictions in this range. Moreover, at higher temperatures, there seems to be a trend towards negative residuals, which indicates an overestimation in some cases by the model. Also, there seem to be several outliers present that might reflect sudden changes in the weather or lack of data in the input variables. In general, the distribution of residuals does not have a strong systematic component, which means that the physics-informed model can be considered to be properly calibrated.

A closer look at the forecast errors is provided in Figure 6, where the absolute forecast errors of both models are depicted over time. It can be seen that the physics-informed model shows better stability of predictions due to lower values of errors, particularly during periods of high variability, demonstrating improved robustness.

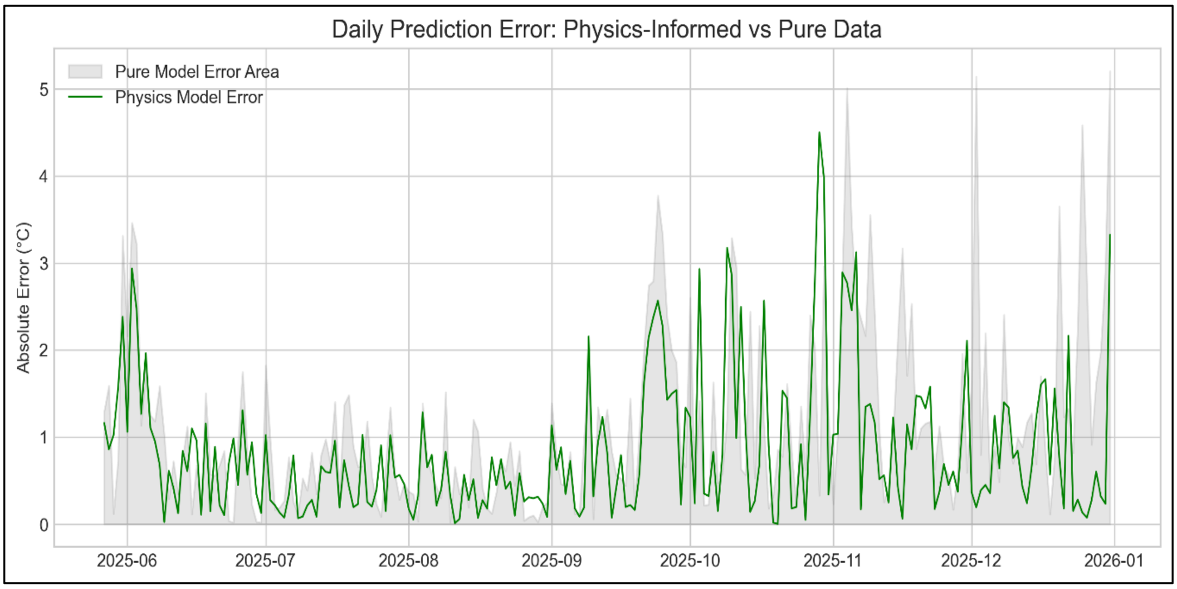

Fig 6 Daily Prediction Error Comparison Between Pure and Physics-Informed Models.

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Figure 6 presents the variation in errors in predicting values daily for both the pure and physics-informed models. The horizontal axis is time (dates), while the vertical axis is the magnitude of prediction errors in degree Celsius. The grey shaded region represents the magnitude of errors in the pure model, while the green line represents the magnitude of errors in the physics-informed model.

It is clear from the above graph that the physics-informed algorithm has lower error rates in comparison to the pure algorithm for the vast majority of the time periods. As one may notice, the green line lies inside or below the gray-shaded area. Thus, inclusion of physics-based features enhances accuracy. As one may notice, the distinction between both algorithms can be clearly seen when variability is high, as in such periods the pure algorithm demonstrates a substantial growth in error rates in comparison to the physics-informed algorithm, whose error rates remain considerably lower. However, there are instances when the two algorithms exhibit high errors, particularly when sudden changes in temperature occur. This phenomenon is expected given the limitations of the input data and the fluctuations in weather patterns. To conclude, the plot clearly illustrates the effectiveness of the physics-based algorithm in minimizing the average prediction error, as well as increasing the consistency of the model.

The applicability of the suggested methodology in extreme weather scenarios can be analyzed by referring to Figure 7. It can be observed that the physics-based model generates lower RMSE values when the temperature exceeds critical levels, demonstrating its superior performance in extreme temperature scenarios.

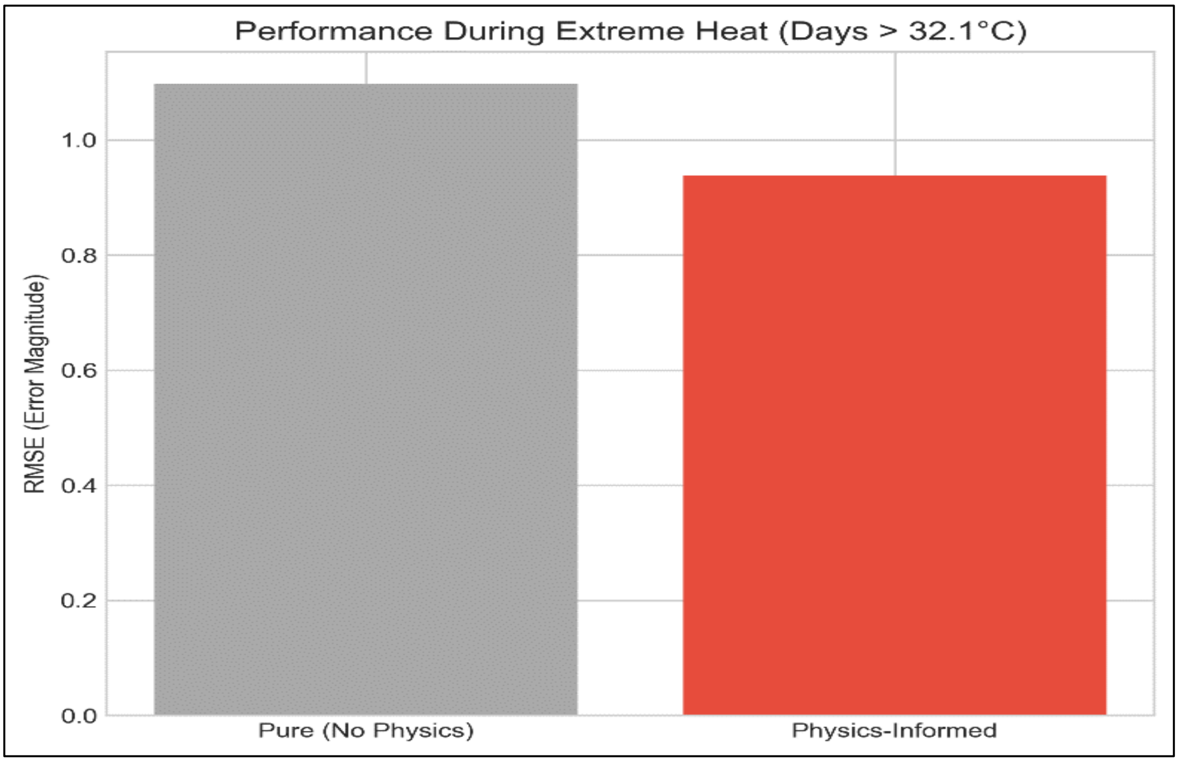

Fig 7 Model Performance During Extreme Heat Conditions

The graph in Figure 7 provides a comparison of the performance of the data-driven approach and the physics-informed approach when predicting under extremely hot weather, which is characterized by a daily temperature exceeding 32.1°C. The value on the Y-axis measures the Root Mean Square Error (RMSE) value, depicting the extent of prediction error.

It can be seen from the graph that the physics-informed approach performs better in terms of lower RMSE values under extremely high temperatures than the pure approach. While the pure approach produces errors of around 1.10°C, the physics-informed approach lowers this error rate to about 0.94°C. The improved error rate when there are high temperatures indicates that the physics-based approach is much better at handling extreme atmospheric phenomena than the other models. The improvement may be linked to the incorporation of physically relevant features like vapor pressure deficit and energy imbalance, which come into play during extreme temperatures. Thus, we can conclude that the results of physics-based machine learning improve not just the predictive ability, but also make the model more reliable during high-impact weather phenomena.

Variations in model accuracy according to the season have been shown in Fig. 8. It can be seen that the least error occurred during monsoons, while the maximum errors took place during winters. This indicates that the model was unable to account for complicated weather conditions such as fog and temperature inversion that exist during winters.

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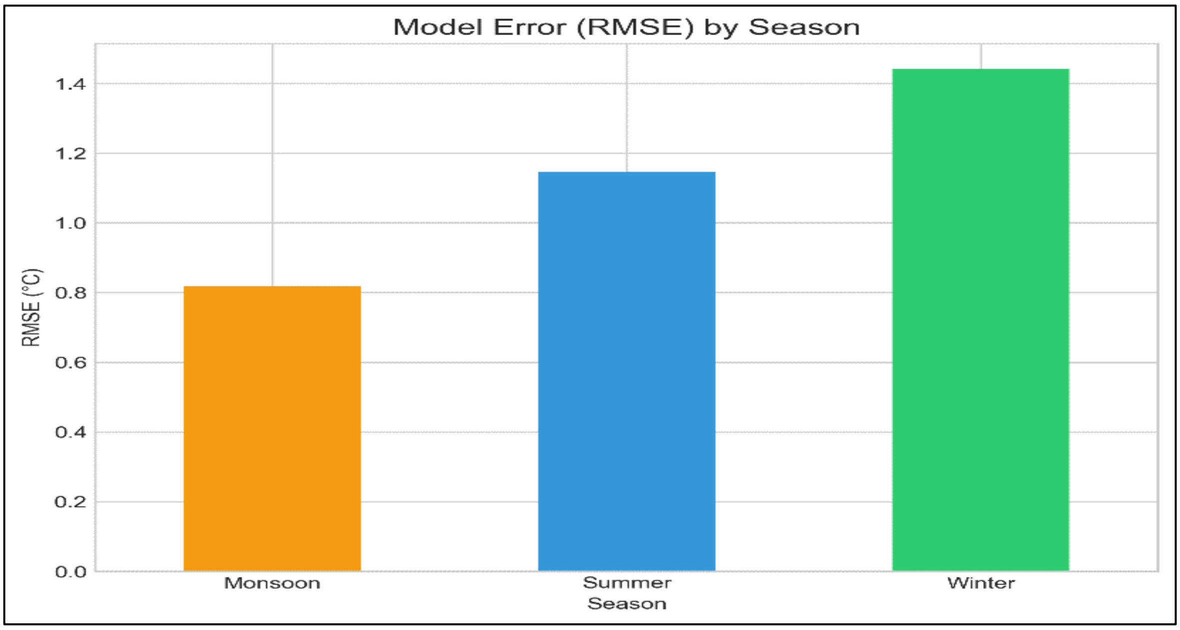

Fig 8 Seasonal Variation in Model Error

Figure 8 shows the changes in error predictions (RMSE) of the model in various seasons such as monsoon, summer, and winter. The vertical axis of the figure above shows the RMSE which is basically the value of prediction errors for each season.

It is clear from Figure 8 that the prediction error is minimal for the model when it predicts in the monsoon season, which has an RMSE of about 0.81°C. However, in the summer season, the error is increased to 1.14°C. On the other hand, the highest prediction error is recorded in winter with an RMSE of 1.44°C, indicating that the model finds winter conditions more challenging to predict accurately. The superior performance of the model during monsoon is due to the stability of the atmosphere as well as the considerable influence exerted by humidity-related factors, such as vapor pressure deficit, which are properly modeled in the regression equation. During winter, however, the atmospheric processes that take place are complicated and difficult to capture using the input variables, including the occurrence of temperature inversion, fog, and reduced solar radiation, hence resulting in higher prediction errors.

From the above, it is clear that the effect of atmospheric changes should be considered while building a model to predict the temperature. From the results, it is clear that the performance of the model during the winter season is poor, and therefore incorporating some more variables into the model would be necessary in order to accommodate atmospheric variations such as temperature inversion and fog.

Finally, the error distribution is presented in Figure 9. The error distribution in the physics-informed model is more concentrated and not highly skewed as compared to the other model. This shows that the physics-informed model has less variability and few outliers, hence it can be termed more accurate.

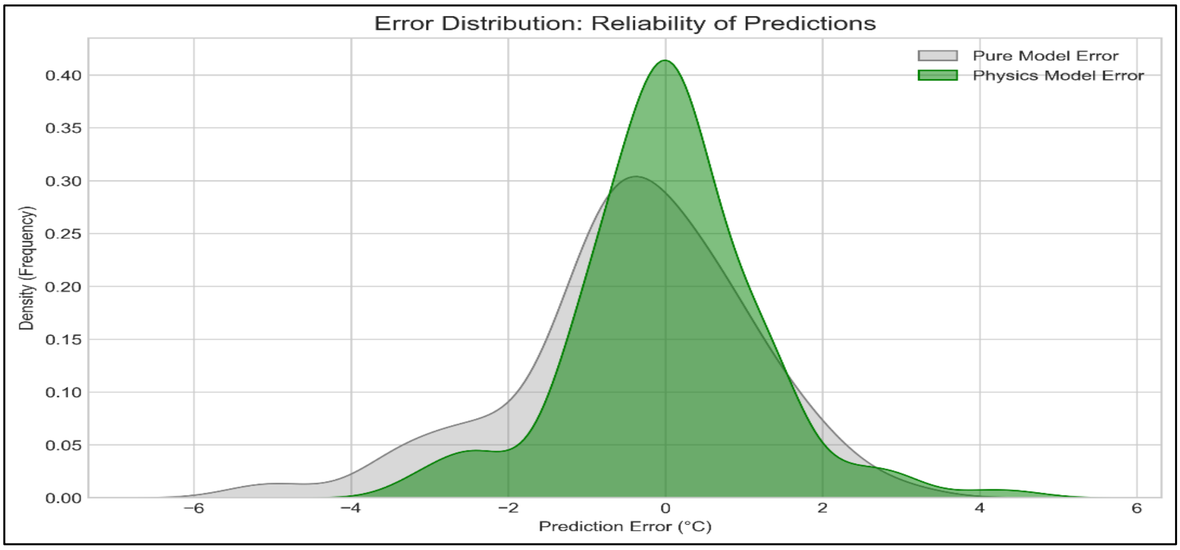

Fig 9 Error Distribution for Pure and Physics-Informed Models.

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As illustrated in Figure 9, the distribution of errors in prediction is plotted for both the pure and physics-based models. On the X-axis, the error in prediction (Actual − Predicted Temperature) is shown. The Y-axis denotes the frequency of errors in the prediction. As can be seen from the above graph, the error distribution for the physics-based model has a more pronounced peak centered on zero as compared to the pure model. It implies that most predictions made using the physics-based model contain minimal errors, whereas the pure model contains more dispersed error distributions. In addition to that, the physics-informed method also displays fewer large-scale errors (positive and negative alike), implying a smaller number of cases of large-scale under/over-estimations. The decreased variance seen from the graph is an indication of a more accurate predictive power of the physics-informed method.

Thus the physics-informed model does not just improve accuracy on average, but also increases reliability by minimizing variance and eliminating extremes. However, some asymmetry may be present, depending on the circumstances, although the overall errors are close to zero.

As we can conclude from all of the above, the combination of physical and machine learning methods shows very good prediction accuracy and stability. It is an efficient approach that helps to predict any environmental phenomenon.

V. CONCLUSION

The physics-informed machine learning framework was constructed for predicting air temperature by combining physical features with ensemble learning methods. From the results, we can see that the introduction of physics-based parameters improves the performance of the models. In both cases, we observe a decrease in error rate with the inclusion of physics-based parameters in the model, where the physics-based gradient boosting achieves the highest performance. We observe that the improved accuracy of RMSE indicates that the integration of physical knowledge into machine learning models increases the performance.

We also have visual evidence of the effectiveness of our models through graphical representations. The closeness of the values predicted by the models to the actual value confirms the effectiveness of the model. Time series analysis indicates that the model can predict seasonal effects well. The feature importance results demonstrate that physically relevant predictors such as vapor pressure deficit and energy imbalance play an essential role in the model.

Residuals and errors indicate that the application of the physics-based method allows obtaining stable and bias-free forecasts, as they exhibit lower variance and error rate. Moreover, the method demonstrates high robustness during challenging situations, such as extreme hot days, which is highly valuable from a practical perspective. To sum up, this work confirms that the employment of physics-informed machine learning can be considered an extremely efficient strategy for environmental forecasting, as it helps improve the accuracy, stability, and physicality of the predictions.

FUTURE SCOPE

Despite the success shown by the current study in the effectiveness of the physics-informed machine learning model, there are several areas that can be further investigated to improve the methodology.

For example, it is important to incorporate other environmental variables such as cloud coverage, soil moisture, and aerosols in order to simulate more complex atmospheric dynamics. Utilization of data obtained at different times (such as hourly data) might prove helpful in modeling more rapid changes in the weather.

For this current research, the approximations of different elements of energy balance have been used due to the absence of data regarding their direct flow rates. Future studies could make use of data sets that include information about their direct flow rates so as to develop more physically plausible models. This will certainly help in improving the representation of the interaction between surface and atmosphere.

Another promising avenue is that one related to including information about the spatial scale in modeling by using models with multiple sites/locations or regional modeling. It will be possible to include information on how temperature dynamics behave in multiple places and hence construct models that are generalizable.

The methodology of machine learning can also be explored further by using hybrid models where information on physics is included together with the deep learning models. Another aspect of the proposed methodology is uncertainty quantification in order to determine how accurate the predictions made are.

In addition to this, another application of the framework could be extending it outside of weather prediction and into other environmental or climatic issues, such as heatwave prediction or climate change effects or renewable energy prediction, for example. This extension would increase the relevancy of the physics-informed machine learning framework on a global scale.

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