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Exploring the Correlation Between Temperature and Other Factors in North America (2001-2020)

Yiming Liu[1*†], Shan Li[2†], Xi Zheng[3†], Maokun Lin[3]

[1]*School of Emergency Management, Nanjing University of Information Science and Technology, Nanjing, China*
[2]*School of Remote Sensing & Geomatics Engineering, Nanjing University of Information Science and Technology, Nanjing, China*
[3]*Fuzhou No.3 High School, Fuzhou, China*
**Corresponding Author. Email: 7702130@qq.com*
[†]*These authors contributed equally to this work and should be considered as co-first author.*

Abstract. This study inquires into the association of temperature anomalies with the different climatic factors in North America from 2001 to 2020 and investigates this through the use of a Random Forest model. Forecasting on monthly temperature anomalies was made, based on cloud cover, wind components U and V, and radiation. This model showed a high training R^2 of 0.908, which suggests a good fit for the training data, and had a low mean cross-validation R^2 of 0.259, indicating overfitting. The most important features were the TOA net radiative flux, with relatively important contributions from TOA shortwave and longwave radiation. The other features are less important, but all factors influence temperature anomaly features. The results also found to be very deviant from the observations in 2008 and 2016, which might be due to catastrophic weather incidences in those years like severe winters, hurricanes, and El Niño, which most probably affected the model predictability. This kind of analysis forms the background for the understanding of future studies where it is proved that more comprehensive climate models with additional climatic variables need to be included to increase the predictive performance.

Keywords: Temperature Anomalies, North America Climate, Random Forest Model, Climatic Factors, Extreme Weather Events.

1. Introduction

The phenomenon of global warming has become an irreversible trend, as evidenced by the extreme heat waves that occurred in 2023, affecting vast areas of North America, Europe and China. These heat waves have broken heat records in many areas, for example, Phoenix had 30 days with daily highs at or above 110°F (43.3°C) and record nighttime lows that never fell below 97°F (36.1°C) [1]. Rising global temperatures have significant impacts on material and energy cycles and on human survival and development.

Lately, there appears to be quite a need for studying climate change and its driving factors in North America with the growing consequences of global warming. The time frame of research,

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2001-2020, is chosen because of its richness in a number of key events on climate change that are crucial for understanding modern climate change. North America is a significant contributor to the change in global climate and exhibits some unique regional climatic characteristics. This has made North America an ideal location for studying regional climate phenomena. The purpose of the study is to detect drivers for temperature anomalies in North America (30°–70° N, 140°–60° W, Figure 1) during 2001–2020 and explore the spatial and temporal characteristics during this period.

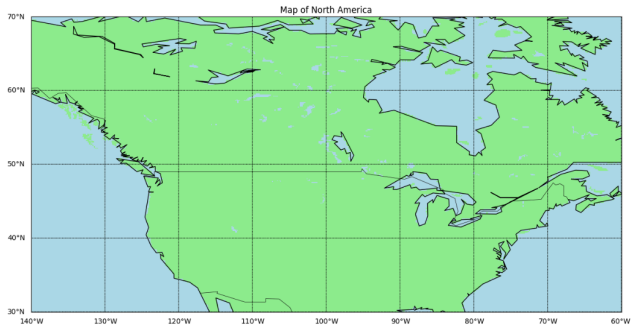


Figure 1. Study area

In the previous works, the scholars noted the importance of radiation, cloudiness, and wind for surface temperature. Aumann et al. (2012) researched the sensitivity of surface temperature with respect to reflected shortwave radiation, net incoming radiation and outgoing longwave radiation at a global scale, which indicates that these types of radiation are closely connected with changes in global averaged surface temperatures, especially under warming scenarios where interannual anomalies become larger [2]. Similarly, Aun et al. (2020) addressed the influence of cloud cover on solar UV radiation in Antarctica, demonstrating that variability of such clouds does not just have impacts on UV radiation intensity but rather is strongly correlated with local wind speed and temperature variations [3]. Elaborating on the scope of atmospheric factors, Fei et al. (2023) took the monthly variation patterns of U and V components of wind to a global level, relating their values strongly with that of temperatures, especially in the light of climate change, where such correlations have grown even stronger [4].

There are also many methods from researchers to further understand the complicated interaction of climatic factors and temperature. Han et al. used correlation analysis in testing for the relationship that exists between climatic factors and NDVI (Normalized Difference Vegetation Index). The results came out significant statistically, although the correlation coefficients were very low [5]. In order to take into account such complex relationships in a more comprehensive way, many authors have recently switched to using Random Forest models. For instance, in the work by Zhang et al. (2022), this model was used to find how the human factor and climate change have influenced the runoff, where effective simulation and quantification of these contributions were made [6].

The present work will enumerate the driving factors of temperature changes in North America through correlational analysis and the Random Forest model. This way, identification and understanding of key variables along with a focused review of anomalous years—say, 2008 and 2016—our research is conducive to a full understanding of regional climate dynamics that aids in the development of more accurate predictive models.

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2. Data and method

2.1. Data

The surface temperature anomaly data are obtained from the Goddard Institute for Space Studies Surface Temperature Analysis (GISSTEMP v4) [7] dataset. Temperature data at 1000 hPa, sea level pressure data and wind data are sourced from the ERA5 [8] reanalysis dataset, produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). We choose the data of cloud cover at 500 hPa and radiation data at the top of the atmosphere, including shortwave, longwave and net radiation, from the Clouds and the Earth's Radiant Energy System (CERES)Energy Balanced and Filled (EBAF) [9] dataset.

2.2. Data analysis method

2.2.1. Standardization

We have standardized the data with the aim of converting features with different scales to the same scale so that their mean is equal to 0 and standard deviation is equal to 1. This preprocessing improves the rate of convergence and prediction performance of the model in the case where the features have different dimensions and magnitudes. For a feature vector X , the formula for standardization is Equation (1). $X_{standardized}$ is the standardized feature value, X is the original feature value, μ is the mean of the feature, σ is the standard deviation of the feature:

$$X_{standardized} = (X - \mu)/\sigma \tag{1}$$

In this study, we standardized each feature variable and target variable, which eliminates the differences in dimensions and magnitudes between different features.

2.2.2. Moving average and correlation analysis

All data we used are in period 2001-2020, and we used the monthly data. Latitudinal weighting is important when analyzing grid-based data. Therefore, we use the latitude-weighted method to calculate the average per year. A five-year moving average is applied to surface temperature anomaly data to smooth time series to estimate or highlight potential trends [10]. Scatter plots were created to investigate the relationships between surface temperature anomaly and the following variables: wind speed, wind direction, cloud cover, longwave radiation, shortwave radiation, net radiation, and sea level pressure. We draw scatter plots and linear regression was performed on calculating the trend, correlation, and significance. We also visualized the data, with using spatial series plots to illustrate the change of spatial distribution of anomalies and true values.

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2.2.3. Random Forest model

Table 1. The parameters in Random Forest

Parameters	value
N-estimators	50
Random_state	42
Min_samples_split	2
Min_samples_leaf	1
Max_depth	'none'
Max_features	'sqrt'

2.2.3.1. The introduction of Random Forest model

The core idea of the method is to randomly sample the dataset with putback, generate multiple subsets, train a decision tree for each subset, and finally get the prediction results through the voting mechanism or averaging mechanism. Invented by Leo Breiman in 2001, Random Forest applies random feature selection and Bagging to handle high-dimensional data and nonlinear relationships efficiently [11].

2.2.3.2. Construction and training

In this study, we use Random Forest model to predict temperature anomalies. Through grid search, we determined the optimal parameters of Random Forest model as Table 1.

We use the standardized characteristic matrix X_{scaled} and target variables y for model training. For each decision tree T_i, we have Equation (2) and the ultimate prediction is derived by averaging the outcomes from each of the decision trees: Equation (3), where $\hat{y}$ is the final prediction and N is the number of decision trees (i.e., n_estimators).

$$\hat{y}_i = T_i(X_{scaled}) \tag{2}$$

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N}\hat{y}_i \tag{3}$$

2.2.3.3. The evaluation of the model

We use the 5-fold cross-validation method, where the data is segmented into 5 subsets, and each time 4 of them are used for training and 1 subset for validation, which is repeated 5 times, finally the average R^2 is calculated. The cross-validation of R^2 is Equation (4), where y_i is the actual value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean of the actual values.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}\left(y_i-\bar{y}\right)^2} \tag{4}$$

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We also used the entire training set X_{scaled} and the target variable y for prediction to calculate the model's R^2 and Mean Squared Error on training set. The formula for R^2 on training set is the same as the formula for the R^2 score on the cross-validation.

We compared the actual temperature with the predicted temperature and calculated the residuals. The plot of the residual distribution (Figure 2) shows that the residuals show an approximately normal distribution with a mean close to zero, which indicates that the model predicts comparatively accurately in most cases.

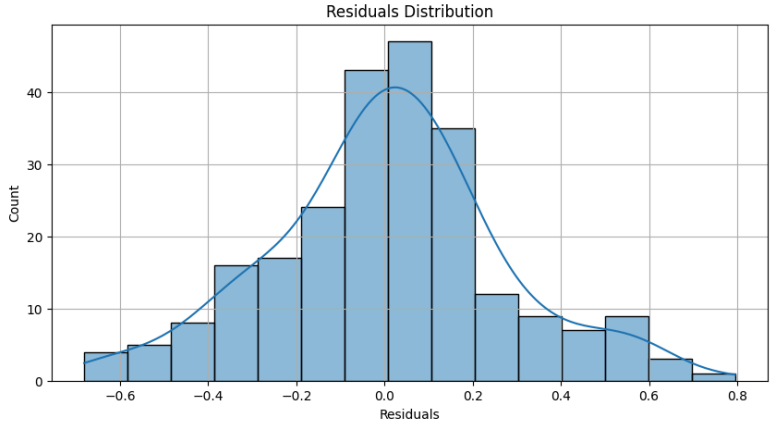


Figure 2. The plot of the residual distribution

The plots of the comparison between actual and predicated temperature (Figure 3) show that the predicted values for most of the samples are closer to the actual values, indicating that the model is able to predict temperature anomalies comparatively accurately in most cases. However, there are some sample points where the predicted values have significant differences from the actual values, which we think is due to the presence of extreme conditions at these sample points or the model's weak generalization ability in these cases.

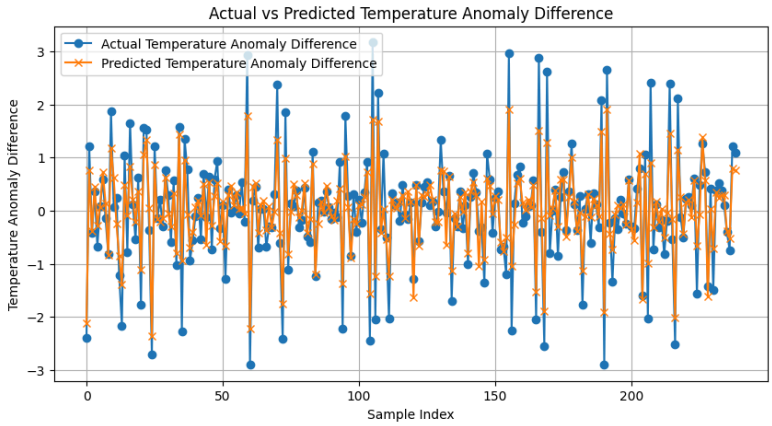


Figure 3. The comparison between actual and predicated temperature

2.2.3.4. The importance analysis of variables

The importance of a feature in this study is measured by accumulating the reduction in the Mean Squared Error of this feature in all decision trees. In Equation (5), $\mathrm{Impurity}(n_{parent})$ is the impurity of the parent node, $\mathrm{Impurity}(n_{left})$ and $\mathrm{Impurity}(n_{right})$ are the impurities of the left and right

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child nodes, respectively, N_n is the number of samples of the node n, and $N_{n_{left}}$ and $N_{n_{right}}$ are the number of samples of the left and right child nodes, respectively. Finally, the bar chart of variable importance is plotted to show the importance of each feature.

$$\Delta Impurity\,(n) = Impurity\,(n_{parent}) - \left(\frac{N_{n_{left}}}{N_n} Impurity\,(n_{left}) + \frac{N_{n_{right}}}{N_n} Impurity\left(n_{right}\right)\right) \quad (5)$$

3. Results and discussion

3.1. The correlation between parameters and temperature is not significant

We selected six parameters to explore meteorological influences. Initial correlation analysis indicated that there is some correlation between each meteorological parameter and temperature anomalies, though the correlation of individual variables is low (Table 2). Longwave radiation, shortwave radiation, net radiation, cloud cover, u and v component of wind all showed high significance, with p-value of 0.0287, 0.000134, 0.00197, 0.0433, 0.0507 and 0.0507 respectively. The impact of a single meteorological parameter on temperature anomalies is limited, necessitating the use of a random forest model to handle complex nonlinear relationships.

Table 2. Correlation and significance between temperature and other factors

	correlation	p-value
longwave radiation	-0.14	0.0287
shortwave radiation	-0.24	0.000134
net radiation	-0.20	0.00197
Cloud	0.05	0.0433
u-wind	0.13	0.0507
v-wind	0.18	0.00475

3.2. The Random Forest model has some predictive ability but is limited by the amount of data

We balanced the model across different features to maximize prediction accuracy. Cross-validation showed an average R^2 of 0.26, indicating moderate predictive ability. R^2 reached 0.91 on the training set, significantly higher than the cross-validation results, indicating model overfitting.

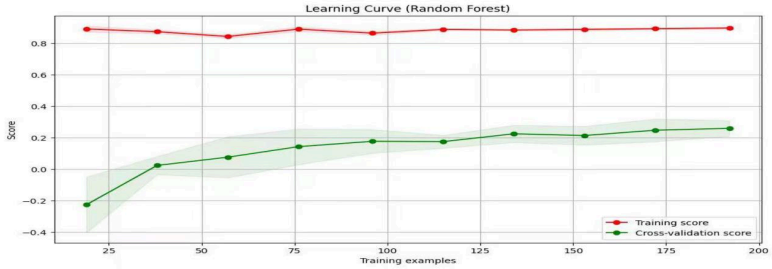


Figure 4. Learning curve of Random Forest model

This phenomenon was also evident in the learning curve (Figure 4). As the number of training samples increased, the training set scores remained high, while cross-validation scores were

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relatively lower but gradually increased, suggesting that the model's overfitting was due to insufficient data.

After calculations, the model predicted the average temperature anomalies for 240 months from January 2001 to December 2020 and compared these with the actual values (Figure 5). Additionally, the average annual temperature anomalies for each year were calculated (Figure 6). The results show that, although the overall trends are generally consistent, there were significant discrepancies in the model's actual values compared to predictions for 2008 and 2016, with 2008 being excessively cold and 2016 excessively hot.

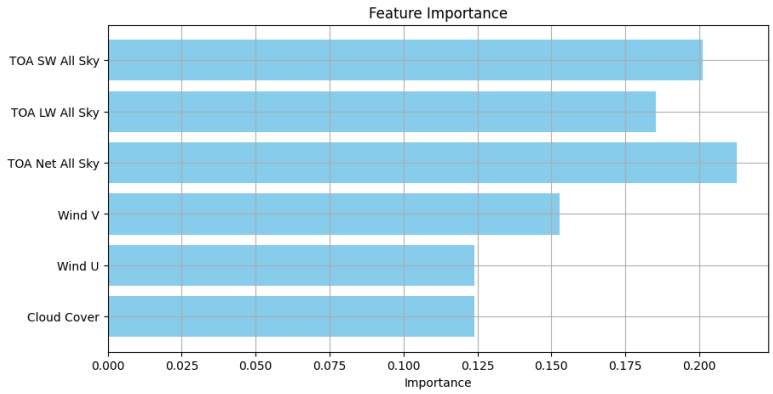


Figure 5. Average temperature forecast and true value

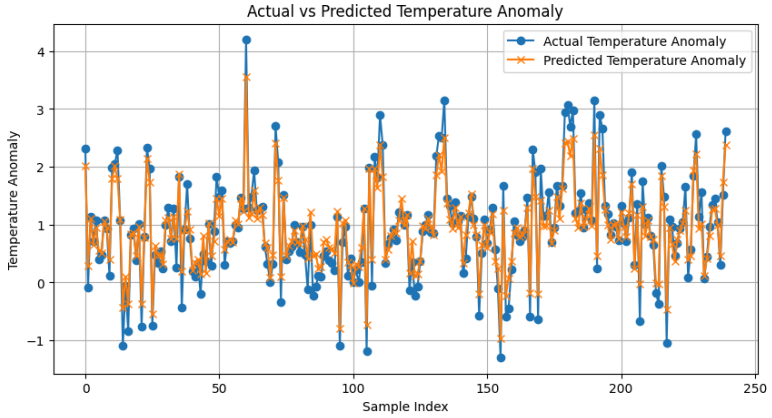


Figure 6. The average annual temperature anomalies for each year

3.3. The TOA net radiation under all-sky conditions plays the most important role in influencing air temperature

We also calculated the feature importance in Random Forest model and found that TOA (Top of Atmosphere) net all-sky radiation (Net All Sky), shortwave all-sky radiation (SW All Sky), and longwave all-sky radiation (LW All Sky) are the most influential factors in predicting temperature anomalies. Wind speed (U and V components) and cloud cover also have significant importance. Figure 7 displays the importance scores of each feature.

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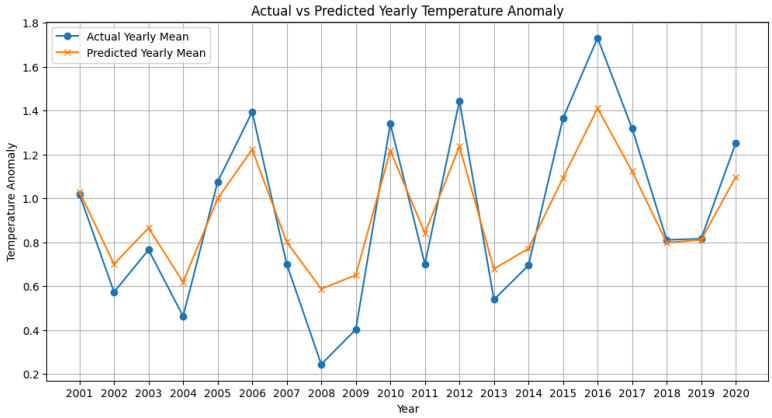


Figure 7. The importance scores of each feature

The TOA net all-sky radiation holds the highest importance in the model, demonstrating that radiative transfer processes have a significant impact on temperature anomalies. These processes involve the reflection, absorption, and re-radiation of solar radiation after it enters the Earth's atmosphere, playing a crucial role in changes to surface temperatures. Net all-sky radiation integrates the effects of both longwave and shortwave radiation, reflecting the atmosphere's overall regulatory effect on radiation, thus ranking highest in feature importance. TOA shortwave all-sky radiation and longwave all-sky radiation respectively represent the transmission and exchange processes of solar and Earth radiation within the atmosphere. Shortwave radiation primarily includes energy from the sun, while longwave radiation is mainly the energy released from the Earth's surface and atmosphere into outer space. Both are significant in predicting temperature anomalies as they directly affect Earth's energy balance and temperature distribution. However, North America is just one region, and its energy budget is influenced by both atmospheric exchange and surrounding energy sources, hence showing lower correlation in linear regression.

Wind speed (U and V components) and cloud cover, though ranked lower in feature importance, still influence temperature anomalies. The U and V components of wind speed represent horizontal movements in the atmosphere, which by affecting the interaction between warm and cold air, play a significant role in the temperature distribution both locally and over larger areas. Strong wind speeds can accelerate the movement of cold air southward or warm air northward, leading to rapid temperature changes in a short period. Moreover, wind speed also regulates heat exchange between the ocean and land, particularly in coastal areas, where changes in wind speed can significantly affect the temperatures of coastal waters, thereby indirectly impacting land temperature anomalies [12].

Cloud cover influences surface temperatures through the radiative transfer process. The explanation for this is that their presence can decrease the sum of solar radiation on surface; for example, during the day, reflection on the thick clouds may be high enough to reduce the energy received on the surface and hence the temperatures. At night, however, the clouds perform as an insulating media and take in, to later re-emit, the long-wave radiation from the surface. This obviously is against heat loss, and thus temperatures during the night are relatively higher. Radiation transfer by clouds is, therefore, a dual process of complex nature that has important implications for temperature change. Besides, the height, thickness, and type of clouds could affect temperature changes in various ways. It is found that while cirrus-like high-altitude clouds provide small direct shading of the surface, at the same time, their albedo and absorption effects in the atmosphere are large; lower clouds, for instance stratocumulus and nimbostratus, provide a strong radiation

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blockage at the surface [13,14]. Hence, successful forecasting of temperature anomalies requires not only the number of clouds but also their detailed analysis involving precise cloud types. One has to consider diverse meteorological elements and their interactions to enhance the degree of accuracy and reliability in constructing and predicting models for climate.

3.4. The weakened polar vortex and La Nina caused the abnormally low temperatures in 2008

The Arctic oscillation have a potent effect on northern hemisphere winter climates. In the negative phase, there are increased chances that cold polar-regional air will move southward into middle latitudes; such movements almost always bring very cold weather conditions. The negative phase of the Arctic oscillation is behind the extremely cold winter in 2008, when frigid air masses moved down south from the Arctic region, leading to temperatures considered off the scale and even blizzard conditions in North America's Midwest and Northeast [15]. Meanwhile, another key factor supporting this southward shift of cold air is the weak polar vortex. A high-altitude low-pressure system, the polar vortex allows the frigid Arctic air to spill over large portions towards mid-latitudes if it weakens; it is also the culprit for severe cold weather events [16]. The 2007-2008 La Nina event caused cooler sea surface temperatures along the equatorial eastern Pacific Ocean. This leads to a shifting global atmospheric circulation pattern and worsens colder and drier winters in North America. Besides, La Nina strengthens the polar vortex to an even greater level, making it easier for cold air masses to head southwards [17]. When these freezing polar air masses (frontal cyclones) encounter air masses with higher temperatures, they lead to widespread snowfall and blizzards. Such cyclonic activity is common in the winter months and occurs in high levels during La Nina years [18], one of the biggest factors contributing to December snowstorm events.

Over the summer period, Hurricane Ike inflicted substantial devastation upon Texas and Louisiana states. Through substantial release of latent heat energy, tropical cyclones induce alterations in temperature and humidity distribution within the atmosphere, consequently exerting influences on regional as well as global climatic conditions. The formidable gales accompanied by torrential downpours associated with Hurricane Ike not only had direct impacts on coastal temperatures but also induced modifications to atmospheric circulation patterns via intricate ocean-atmosphere interactions [19]. Moreover, these vigorous winds along with copious precipitation contribute to a redistribution of thermal energy within oceans. Subsequent to hurricane occurrences, surface cooling effects are observed across oceans leading to consequential atmospheric cooling phenomena which further impact climates spanning from coastlines to inland regions [20].

3.5. The strong El Niño phenomenon and its complex interactions with global weather patterns caused the abnormally high temperatures in 2016

The warmest temperatures ever observed in North America took place in 2016, largely due to a strong El Niño. Record-equatorial Middle Eastern Pacific Ocean waters, due to their size, are changing global weather patterns through extremely complex ocean-atmosphere interactions. The higher the amount of heat energy released into atmosphere from warm ocean waters, the more the amplitude of convective activity grows and the stronger the global temperature surge builds up [21,22]. In the meantime, under El Niño, extreme weather has spiked with scorching heat waves and massive droughts shattering temperature records in multiple states across the United States. These extreme weather occurrences include prolonged periods of high temperatures and extended dry spells that further create temperature anomalies.

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4. Conclusion

In conclusion, the current study will serve as an analytical basis for the interaction of temperature anomalies with other factors of climatic influence in North America from 2001 to 2020. Even though the random forest model was very accurate on the training data set, cross-validation has shown that probably more data are needed to avoid overfitting. The massive prediction errors found in the extreme weather event years of 2008 and 2016 also are indicative of the fact that such anomalies in climate models should be considered. This research opens the ground for future studies, with insights granted on the determinants of temperature variations and their predictions. Further work in this domain is essential not only to help increase the effectiveness of the climate prediction models but also to understand and mitigate the impacts of climate change better. The focus of future works should be towards integrating more extensive datasets with advanced modeling techniques capable of capturing the nuances of climatic interaction.

Authors' contributions

Yiming Liu: served as the corresponding author, conceived the study, led the group, provided resources, contributed to methodology, formal analysis and model validation, wrote the original draft, conceptualized the research, conducted the literature review, and contributed to paper revision.

Shan Li: Conducted formal analysis; wrote the introduction, and reviewed and edited the manuscript; performed literature review, investigation, supervision, and led paper revision.

Xi Zheng: Performed correlation analysis, provided resources, contributed to the methodology and formal analysis, wrote the methodology section, and its review; performed literature review, and contributed to writing the final manuscript.

Maokun Lin: Contributed to the literature review and drafted the introduction section.

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Yiming Liu, Shan Li and Xi Zheng contributed equally to this work and should be considered co-first authors.

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