

Systematic Literature Review on Increase Climate Temperature During Global Heating

Hassan Sattar

Abstract— Climate change is a significant global issue caused by increased levels of greenhouse gases in the Earth's atmosphere, leading to rising surface temperatures and associated impacts. Machine learning and GIS can be used to analyze and understand the effects of climate change and to develop decision-making tools for adaptation and mitigation. This systematic review analyzed the use of machine learning and GIS in the development of climate temperature maps and found that these tools can be effective, but the accuracy of the maps depends on the quality of the data and modeling techniques used. Ensemble approaches and cross validation can be used to improve the accuracy and robustness of the predictions. Data-driven models, such as ANNs and LS-SVMs, have also been effective in predicting weather patterns and could be used for predicting temperature changes

Index Terms— climate change, climate temperature, global heating, machine learning, artificial intelligence, GIS, Remote sensing

I. INTRODUCTION

Climate change is a phenomenon that is occurring because of increased levels of greenhouse gases in the Earth's atmosphere. These gases trap heat from the sun and cause the planet's average surface temperature to rise, leading to a range of impacts such as more frequent and severe extreme weather events, rising sea levels, and changes in the distribution and behavior of plants and animals.

Machine learning and GIS may be utilized in a variety of ways to address climate change and associated challenges. Machine learning, for example, may be used to evaluate massive datasets containing climatic and environmental variables such as temperature, rainfall, and vegetation in order to better understand and anticipate the effects of climate change. GIS may be used to generate maps and visualizations of this data to assist academics and policymakers in comprehending the geographical patterns and trends in these variables. Furthermore, machine learning and GIS may be utilized to create decision-making tools and systems to assist policymakers and organizations in adapting to and mitigating the effects of climate change.[1] There have been many researchers who have studied and presented solutions for the prediction of weather conditions, including temperature. These efforts have involved the use of a variety of approaches, including statistical modeling, machine learning, and physical modeling.[1]

Based on the premise that the future would be similar to the past, statistical models forecast future weather conditions by

analyzing weather data from the past. These models might be basic, like linear regression, or more complicated, such as autoregressive integrated moving average (ARIMA) models.[1]

Machine learning models, on the other hand, use algorithms that can learn from data to make predictions. These models can be trained on large datasets of past weather data and use this training to make predictions about future weather conditions. Machine learning models can be more flexible and adaptable than statistical models but may require more data and computational resources to train and run.

Physical models, commonly called numerical weather forecasting models, use mathematical formulas to replicate the physical processes that control the weather. These models can be used to create precise forecasts of the weather since they are based on our knowledge of atmospheric physics and can be run on extremely fast computers. To enhance the accuracy of weather forecasts, physical models are frequently combined with information from weather monitoring.

The objectives of this systematic review were:

- To describe currently available method of climate change mapping
- To assess the modeling predictors used for developing climate temperature maps
- To describe methods used for climate changing mapping and discuss their applicability in the context of environmental

II. RESEARCH METHODOLOGY

Search terms and databases

The methodology of this review adheres to the guidelines for systematic reviews and meta-analyses outlined in the PRISMA[2]. The time frame for this review was from **October 2015 to October 2022**. Seven years data we have taken for this review. This review included a search of the following electronic databases: **IEEE Explore, Springer, and ACM**. In the initial phase of our multi-level approach, we used IEEE Explore and conducted plain text searches using a combination of keywords and Boolean operators. The searches were based on 10 different sets of keywords from the following categories: (1) climate change, global heating, global temperature (2) geographic tools (e.g., remote sensing, GIS), and (3) machine learning and artificial intelligence and

in addition, we also search in grey literature. We did not impose any restrictions on the time frame or language of publication in our search. our search was limited to English language sources. We used Mendeley to combine the results of our search and removed duplicates paper into our datasets. To determine which studies would be included in our review, we employed a two-step process once we had obtained the search results. In the first step of the selection process, we reviewed the titles and abstracts of the articles obtained from the search results and excluded those that were not relevant to the topic. We also searched the bibliographies of the reviewed articles. We reviewed the full texts of studies that were relevant to our research questions, including those that were uncertain for inclusion based on their titles or abstracts.

A. Inclusion and exclusion criteria

We only considered full-text articles for inclusion in our review if they met the following criteria: (1) the use of machine learning algorithms to detect global temperature (2) To detect climate change based on GIS/Remote sensing and we excluded those articles into search that (1) not used machine learning algorithm (2) not used remote sensing and geographic information technique **Fig 1**.

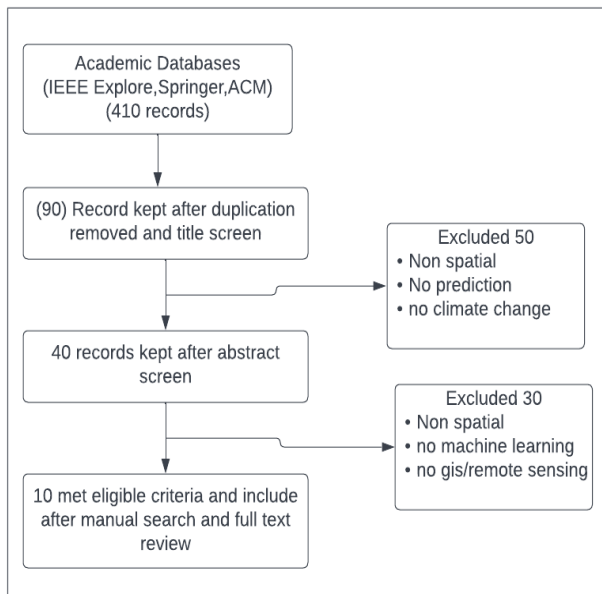


Fig. 1. Flow diagram of article inclusion/exclusion process

III. DATA COLLECTION METHODS

Predicting temperature changes in a particular region is a complex task that involves understanding various factors that can impact temperature, such as atmospheric conditions, topography, and human activities. Ensemble approaches, which involve combining the predictions of multiple models, can be useful in this context as they can provide a more accurate prediction by accounting for the uncertainty inherent in any single model.[3] There are several machine learning

algorithms that can be used to predict temperature changes, including linear regression, decision trees, and neural networks. The choice of algorithm will depend on the specific characteristics of the data and the prediction task at hand. In addition to the choice of algorithm, it is also important to consider the quality and quantity of the data being used for the prediction.

In general, machine learning models work by training on a large dataset of past temperatures and then using that training to make predictions about future temperatures. The performance of the model can be evaluated by comparing the predicted temperatures to actual temperatures and measuring the error between the two. By continuously improving the model through this process, it is possible to achieve increasingly accurate predictions of temperature changes in a particular region.[3]

A. GHCN

The Global Historical Climate Network (GHCN) is a dataset that contains records of temperature observations from around the world. The GHCN is used by scientists and researchers to study global climate patterns and trends, including changes in temperature over time. The data in the GHCN is divided into various categories, such as temperatures by major cities, states, and countries. These approaches involve combining the predictions of multiple models to create a more accurate prediction. The proposed ensemble approach for predicting temperature changes in major cities is based on three models that have shown good performance in terms of the evaluation metrics you mentioned: correlation, accuracy, R2, root mean squared error (RMSE), and total time. [3]

B. Cross Validation

Cross validation is a technique that can be used to evaluate the robustness of the selected models. It involves dividing the data into a training set and a test set and using the training set to train the models. The models are then tested on the test set to evaluate their performance. This process is repeated multiple times, with different splits of the data, to get a more reliable estimate of the model's performance. By performing cross validation on the best performing models, you can check how well the models are able to generalize to new data and determine if they are robust enough to be used for predicting temperature changes. To compare the performance of multiple machine learning models on a given dataset to determine which model is the most accurate. By running the dataset on 15 different regression models, you can evaluate the performance of each model and compare their accuracy in predicting temperature changes.

The top three machine learning models with the highest accuracy among the 15 existing models can then be selected for further analysis. Cross validation can be used to evaluate the robustness of these models and determine how well they generalize to new data. The chosen models are **Decision Tree, Variable Ridge Regression and Conditional Inference Tree**

If the results of the cross validation show that the Decision Tree model has the highest accuracy rate among the top three models, this may be a good choice for predicting temperature changes. However, it is important to consider other factors, such as the complexity of the model and the amount of data it requires, when making a final decision about which model to use **Table 1**.

TABLE I
VARIOUS MACHINE LEARNING MODELS

| Model Name | Method Argument value | Type | Packages | Tuning Parameters |
|--|-----------------------|------------|----------|-------------------|
| Bagged Mars | bagEarth | Dual Use | Earth | nprune, degree |
| Conditional Inference Tree | Ctree | Dual Use | Party | Mincriterion |
| Decision Tree | Class | Dual Use | Rpart | None |
| EARTH | bagEarth | Regression | Earth | Nprune |
| Independent component Regression | Icr | Regression | fastICA | n.comp |
| K Nearest Neighbour | Knn | Dual Use | - | K |
| Least Angle Regression | Lars | Regression | Lars | Fraction |
| Mars | bagEarth | Dual Use | Earth | nprune, degree |
| Neural Network | Nnet | Dual Use | Nnet | Size, decay |
| Non negative Least Square | Nnls | Regression | Nnls | None |
| Non Convex penalized Quantile Regression | Rqnc | Regression | rqPen | Lambda,penalty |
| Principal Component Analysis | Pcr | Regression | Pls | Ncomp |
| Projection | Ppr | Regression | None | Nterms |

| | | | | |
|--------------------|--------|------------|-----------|-------------|
| Pursuit Regression | | on | | |
| Relaxed Lasso | Relaxo | Regression | Relaxo.pl | Lambda, phi |

C. ANN

In recent times, data-driven models have proven to be effective in predicting weather patterns. A variety of data-driven techniques have been applied to weather forecasting in both linear and nonlinear frameworks. Among these techniques, Artificial Neural Networks (ANN) and Least Squares Support Vector Machines (LS-SVM) are two of the most widely used. LS-SVM performs well for temperature prediction.[4]

D. SKSC

Soft Kernel Spectral Clustering (SKSC) is a technique for clustering data points based on the similarity of their feature vectors. It is often used in data-driven modeling because it can identify groups of similar samples, which can be useful for tasks such as classification or regression.

Elastic net is a feature selection method that combines the L1 and L2 regularization techniques from Ridge Regression and Lasso Regression, respectively. It is often used in high-dimensional data sets to select the most relevant features and reduce the risk of overfitting. In the context of temperature prediction, using SKSC to identify similar samples and Elastic net for feature selection can help build a more accurate and robust model. By training the model on a set of similar samples, it may be able to better capture the patterns and trends present in the data. Additionally, using Elastic net to select only the most relevant features can help prevent the model from being influenced by noise or irrelevant information in the data

E. LS-SVMs

Least Squares Support Vector Machines (LS-SVMs) are a type of support vector machine (SVM) that can be used for regression tasks. They work by finding the hyperplane in a high-dimensional feature space that maximally separates the data points into different classes or categories. LS-SVMs differ from traditional SVMs in that they use a different objective function, which is based on minimizing the sum of squared errors rather than maximizing the margin between the data points.[5]

In the proposed temperature prediction method, features are selected independently in each cluster using Elastic net, and then LS-SVM regression is used to learn the data within each cluster. The predicted values from the LS-SVMs are then averaged based on the membership of the test point to each cluster. By using this approach, the model can take advantage of the local structure of the data, which may improve the accuracy of the predictions.

It is good to see that the performance of the proposed method is competitive with existing weather temperature prediction sites. This suggests that the combination of Soft Kernel

Spectral Clustering, Elastic net, and LS-SVM regression can be an effective approach for temperature prediction.[4]

Develop a climate change resilient heatwave prediction model using machine learning algorithms such as support vector machines (SVM), random forest, and artificial neural networks [6]. The motivation for this study was the observation that many forecasting models have shown low skill or have failed due to changes in the relationship between predictors and predictands in the context of global climate change. By using machine learning algorithms, the authors hoped to develop a model that would be more resilient to these changes and able to produce more accurate heatwave forecasts. It's worth noting that the success or effectiveness of this model would depend on the quality of the data and the specific characteristics of the predictors and predictands being used. [6]

F. Linear model climate detection

Machine learning techniques such as generalized linear model (GLM), boosted regression tree (BRT), and maximum entropy (Maxent) were used to simulate the effects of climate change on the distribution of Banj oak, a tree species found in the mid-Himalayas in the Kumaon region of Uttarakhand. The accuracy of these models was evaluated using metrics such as the area under the curve (AUC) and receiver operating characteristics (ROC) curves. The results of this study suggest that machine learning can be used to improve the accuracy of species distribution models, which can be useful in understanding the impacts of climate change on different species and their habitats. This information can be used to develop strategies to mitigate or adapt to these impacts, and to better understand the potential impacts of climate change on biodiversity. It's worth noting that species distribution models are just one tool among many that can be used to understand the impacts of climate change on biodiversity, and that other approaches such as experiments, field observations, and modeling may also be useful.[7]

G. Electronic Devices climate detection

Early detection of the weather temperature is a problem. Once approach to address this problem is the use of electronic devices that can detect and continuously monitor weather events. These devices should be equipped with various sensors to measure various physical quantities related to the occurrence of these events, such as temperature, humidity, air pressure, and pollution. By continuously monitoring these quantities in real-time, it is possible to gain a better understanding of the conditions that may lead to the triggering of weather phenomena. [8]

This search implemented on North-East African because its most effective part of climate change detection instead of all over the world. In this study, the authors used machine learning techniques to analyze the connection between greenhouse gas emissions and climate change. They used essential climate variables as a basis for their machine learning models, which were designed to predict short- and long-term

changes in climate variables. The goal of this method was to develop an ML model that could be used to inform climate adaptation and mitigation efforts, as well as to identify the levels of greenhouse gas concentrations that should be maintained to avoid climate events and crises.[9]

H. Social media climate detection

Social media can be used as a data source to survey public perceptions and attitudes towards climate change. It is still difficult to automatically determine people's attitudes towards climate change based on their social media content. This study analyzed public discussions about climate change and global warming on Twitter in 2016. The data used for the analysis was taken from Twitter.

The objectives of this study were:

- To create an optimized Deep Neural Network (DNN) classifier to identify users who deny climate change based on their tweets.
- To investigate the temporal patterns of climate change discussions on Twitter and the factors that influence them.

The results of this study show that the DNN model developed was able to identify climate change deniers with a high level of accuracy, achieving an overall accuracy of 88% based on the content of their tweets. This demonstrates the effectiveness of the model in identifying users with this specific viewpoint.[10]

IV. RESULT

Results Predicting temperature changes in a particular region is a complex task that involves understanding various factors that can impact temperature. Machine learning algorithms can be used to make these predictions, and the performance of the model can be evaluated by comparing the predicted temperatures to actual temperatures. Ensemble approaches and cross validation can be used to improve the accuracy and robustness of the predictions. Data-driven models, such as ANNs and LS-SVMs, have also been effective in predicting weather patterns and could be used for predicting temperature changes. **Table 2**

| Methods | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|-----------------|-----|---|-----|-----|-----|-----|-----|-----|---|-----|
| Regression | yes | | yes | | | | | | | |
| SVM | | | | yes | yes | yes | yes | | | |
| SKSC | | | | yes | | | | | | |
| GLM | | | | | | | yes | | | |
| GMS | | | | | yes | | | | | yes |
| Neural networks | | | | | | | | yes | | |

Table 2

V. CONCLUSION

In conclusion, Climate change is caused by the buildup of greenhouse gases, which trap heat in the Earth's atmosphere and contribute to rising global temperatures. The increase in greenhouse gases is largely the result of human activities, such as burning fossil fuels and deforestation. so predicting temperature changes in a particular region is a complex task that involves understanding various factors that can impact temperature. Machine learning algorithms can be used to make these predictions, and the performance of the model can be evaluated by comparing the predicted temperatures to actual temperatures. Ensemble approaches and cross validation can be used to improve the accuracy and robustness of the predictions. Data-driven models, such as ANNs and LS-SVMs, have also been effective in predicting weather patterns and could be used for predicting temperature changes. It is important to consider the complexity of the model and the amount of data it requires when making a final decision about which model to use

REFERENCES

- [1] J. J. Nay, M. der Linden, and J. M. Gilligan, "Betting and Belief: Prediction Markets and Attribution of Climate Change," in *Proceedings of the 2016 Winter Simulation Conference*, IEEE Press, 2016, pp. 1666–1677.
- [2] A. Liberati *et al.*, "The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration.," *PLoS Med.*, vol. 6, no.

- 7, p. e1000100, Jul. 2009, doi: 10.1371/journal.pmed.1000100.
- [3] Himika, S. Kaur, and S. Randhawa, "Global Land Temperature Prediction by Machine Learning Combo Approach," in *2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, Jul. 2018, pp. 1–8. doi: 10.1109/ICCCNT.2018.8494173.
- [4] Z. Karevan and J. A. K. Suykens, "Clustering-based feature selection for black-box weather temperature prediction," in *2016 International Joint Conference on Neural Networks (IJCNN)*, Jul. 2016, pp. 2722–2729. doi: 10.1109/IJCNN.2016.7727541.
- [5] R. S. Ebrahimi, S. Eslamian, and M. J. Zareian, "Groundwater level prediction based on GMS and SVR models under climate change conditions: Case Study—Talesh Plain," *Theor. Appl. Climatol.*, 2022, doi: 10.1007/s00704-022-04294-z.
- [6] N. Khan, S. Shahid, T. Bin Ismail, and F. Behlil, "Prediction of heat waves over Pakistan using support vector machine algorithm in the context of climate change," *Stoch. Environ. Res. Risk Assess.*, vol. 35, no. 7, pp. 1335–1353, 2021, doi: 10.1007/s00477-020-01963-1.
- [7] Z. Khan, S. A. Ali, F. Parvin, M. Mohsin, S. K. Shamim, and A. Ahmad, "Predicting the effects of climate change on prospective Banj oak (*Quercus leucotrichophora*) dispersal in Kumaun region of Uttarakhand using machine learning algorithms," *Model. Earth Syst. Environ.*, 2022, doi: 10.1007/s40808-022-01485-5.
- [8] S. Salheddine, S. Ouissal, B. Malek, M. Abderraouf, and B. André-luc, "Development of an intelligent electronic sentinel for the monitoring and detection of meteorological phenomena due to global climate change," in *2020 International Conference on Advanced Aspects of Software Engineering (ICAASE)*, Nov. 2020, pp. 1–7. doi: 10.1109/ICAASE51408.2020.9380123.
- [9] S. K. Ibrahim, I. E. Ziedan, and A. Ahmed, "Study of Climate Change Detection in North-East Africa Using Machine Learning and Satellite Data," *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 14, pp. 11080–11094, 2021, doi: 10.1109/JSTARS.2021.3120987.
- [10] X. Chen, L. Zou, and B. Zhao, "Detecting Climate Change Deniers on Twitter Using a Deep Neural Network," in *Proceedings of the 2019 11th International Conference on Machine Learning and Computing*, 2019, pp. 204–210. doi: 10.1145/3318299.3318382.