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Research Article

Machine Learning and Spatio-Temporal Patterns in Climate Change

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ABSTRACT

Climate change is one of our planet's most significant concerns, affecting ecosystems, weather patterns, and human populations all around the globe. Understanding the complex spatiotemporal pattern associated with climate change is critical for making sound judgments and developing effective mitigation solutions. In recent years, the analysis of large and complex climate data sets has been revolutionized with the help of machine learning methods. This study uses datasets from the Kaggle website and for data preparation the Min-Max method is used to ensure the data which is suitably scaled. Following that, the decision tree machine learning technique is used for feature extraction, allowing the identification of relevant climate-related elements. Finally, the study employs spatiotemporal analysis to create prediction models for predicting climate change trends. This interdisciplinary approach emphasizes the important connection between machine learning and climate science, giving vital insights for climate researchers and policymakers dealing with the issues presented by climate change. The suggested approaches greatly outperform current existing models, obtaining an astounding accuracy of 97.99%. This collaboration allows for the creation of precise prediction models, which help in climate forecasting, early warning systems, and climate impact assessments.

Keywords: Climate change, data preprocessing, decision tree, Min-Max algorithm, spatio-temporal patterns

INTRODUCTION

The most crucial issue of our day is climate change, having a worldwide influence on the Earth's ecosystems, weather patterns, and human cultures. Understanding the complicated spatiotemporal patterns of climate change has become critical with the growing speed of environmental changes [1-2]. These patterns, which are often distinguished by their complexity, nonlinearity, and multifarious nature, provide considerable obstacles to scientists, policymakers, and researchers attempting to make informed choices and create effective mitigation solutions [3-4]. The merging of climate science and machine intelligence in recent years has offered us new avenues in our attempt to interpret these complicated patterns [5]. A type of artificial intelligence, has shown to be an effective ally in analyzing large and complex climate information through machine learning [6]. Machine learning has emerged as a transformational tool in climate research due to its capacity to recognise subtle patterns, anticipate trends, and manage high-dimensional data [7-8]. This work begins a thorough investigation of the synergy between machine learning methods and spatiotemporal climate data, with the goal of unravelling the riddles inherent in climate change dynamics [9].

This research conducts a thorough examination of climate data using datasets obtained from sites such as Kaggle. A critical aspect of this investigation is the preparation of this data, which is performed via the use of the Min-Max algorithm [10-11]. This stage guarantees that the data, which is often varied and divergent, is harmonized and correctly scaled, setting the framework for effective analysis. Following that, the research makes use of the decision tree machine learning technique, a flexible tool capable of extracting relevant characteristics from complex datasets [12-13]. The study endeavors to uncover the important climate-related components via this procedure, unraveling the complicated tapestry of variables impacting climate change [14-15]. This study goes beyond traditional methodologies by using spatio-temporal analysis, recognizing the underlying relationship between geography, time, and climatic trends. This work attempts to construct prediction models by using cutting-edge approaches in spatio-temporal modelling [16]. These models are more than simply statistical constructions; they provide a doorway to projecting climate change patterns with extraordinary precision, anticipating future changes and trends [17]. This interdisciplinary method, which combines machine learning and climate research, exemplifies the important connection between technology and environmental knowledge [18]. This synthesis's findings have enormous promise for steering climate researchers and policymakers towards evidence-based choices [19]. This study lays the way for educated policies as we manage the problems faced by climate change, providing a ray of hope in our joint effort to protect the world for future generations. [2021].

The main objective and contribution of this manuscript may be summarized as follows.

- Dataset preprocessing using Min-Max algorithm
- Feature selection using decision tree
- Climate Change prediction using Spatio-Temporal-Climate algorithm

The structure of this article will start from here. Section 2 has contributions from a number of authors that address various methods for anticipating climate change. Section 3 displays the proposed framework. Section 4 details the investigation's results. Conclusions and future directions are discussed in Section 5.

A. Motivation of the paper

The impetus for this study derives from the urgent need to appreciate the complexity of climate change, a worldwide catastrophe that is having a significant effect on our planet. Climate change presents diverse difficulties that need complete knowledge and effective mitigation methods. This work tries to close the gap by using the capabilities of machine learning and spatio-temporal analysis. We want to uncover the subtle patterns underlying climate change by using sophisticated approaches such as the Min-Max algorithm and decision tree models on large datasets.

BACKGROUND STUDY

Fenu, G., & Malloci, F. M. [6] Recent sensor and satellite information technologies may help farmers adapt to changing weather patterns and other environmental factors, as we have observed in this study. Building decision support systems and including predictive models that can monitor environmental and climatic conditions of crops is essential for ensuring food security, environmental sustainability, and land conservation. Works cited similarly show that AI and ML may help in decision making.

Guo, Y. et al. [9] The ML techniques outperformed the MLR technique, while the applied SVM and RF techniques outperformed the BP technique. The maximum accuracy in predicting rice yields was achieved by the suggested preseason SF employing five climate variables. Rice's development and expansion could not have been possible without the help of the climatic conditions.

Kang, Y. et al. [11] Using a comprehensive collection of environmental factors and six machine learning models, this research examined the efficacy of data-driven strategies for seasonal agricultural production prediction. In the beginning of the season (June and July), national-level predictions perform better than the USDA WADSE reports.

Milojevic-Dupont, N., & Creutzig, F. [13] The potential of artificial intelligence and machine learning for designing methods to decrease GHG emissions in a way that is both spatially varied and contextualized is substantial, but is currently underutilized. Only in tandem with well-designed public policy will we be able to successfully mitigate climate change on a significant scale.

O'Gorman, P. A. [15] We have looked at the behaviour of a GCM with a parameterization of moist convection based on RF theory in a theoretically perfect environment. The accurate simulations of the control climate, which is promising to provide reliability, was the RF parameterization.. Using a decision-tree based method, it is easy to guarantee that physical constraints like energy conservation are kept in mind throughout the parameterization process.

Ridwan, W. et al. [17] Both the Autocorrelation Function (ACF) approach, which utilises past rainfall data to predict future rainfall, and the Projected Error method, which combines past and future rainfall data, are the primary emphasis of this study. Each technique employs a unique algorithm— BLR, DFR, BDTR or NNR—to determine a most accurate forecast for rain across a range of possible future periods. Cross-validation using BDTR and fine-tuning its parameters improves the results for M1, as shown. The more information that is available to the model, the better it will perform. Method 2's results vary depending on the normalisation methodology used, demonstrating that LogNormal normalisation combined with BDTR and DFR provides the most accurate representation of the true error in projection.

Wang, B. et al. [19] The purpose of this research was to build more accurate MME methods for predicting Australia's monthly rainfall and temperature in the past. In order to get more reliable ensemble based findings, we used two ML algorithms, RF and SVM, using precipitation and from temperature data with 33 CMIP5 GCMs. There were two skill measures used to evaluate the performance of ML approaches vs the classic MME method (e.g., R2 and RMSE). Individual GCMs from RF were also analysed for their significance and compared to the Taylor skill ratings.

A. Problem definition

Climate change is a serious hazard to our planet, affecting ecosystems, weather patterns, and cultures worldwide. Understanding the complicated spatiotemporal patterns underlying climate change is critical for effective decision-making and mitigation. Traditional approaches are often challenged by the size and complexity of climatic information. This study fills a gap in the literature by employing machine learning, notably the Min-Max algorithm and decision tree models, to extract relevant climate-related features from large datasets. The goal is to improve the accuracy of climate projections, allowing for more exact forecasting, early warning systems, and damage assessments.

MATERIALS AND METHODS

This component is critical for assuring the study's replication and trustworthiness. This chapter is focused on climate change and machine learning shows the methodical methodology utilized to examine spatio-temporal trends and construct prediction models. Figure 1 depicts a flowchart of machine learning and spatiotemporal patterns in a climate change model.

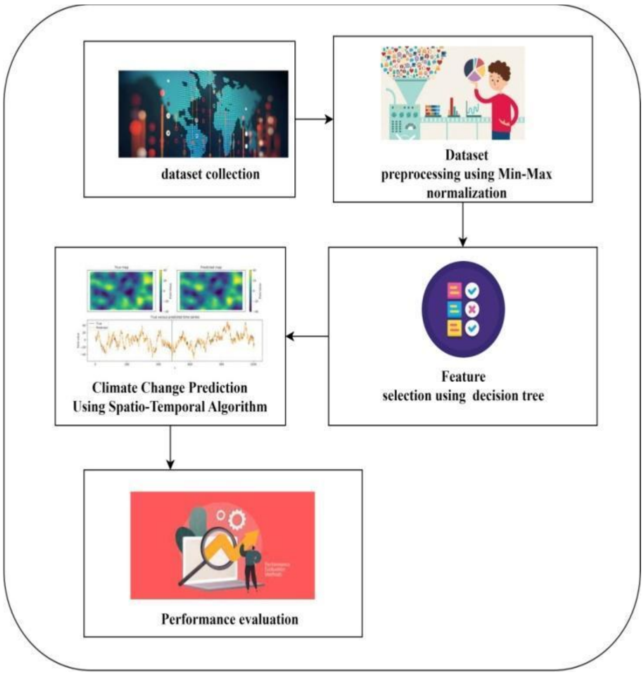

Figure 1: Overall architecture

A. Dataset collection

The dataset was collected for Kaggle website. The link is https://www.kaggle.com/datasets/berkeleyearth/climate-change-earth-surface-temperature-data. This dataset, meticulously accurate and continuously updated by the Berkeley Earth team, provides a wealth of information on Earth's surface temperatures. By leveraging this authoritative source, our research endeavors to unravel the complexities of climate change, exploring patterns that span both space and time.

B. Dataset preprocessing using Min-Max normalization

Our climate change dataset was painstakingly culled from a dependable Kaggle source, and then we preprocessed it using the Min-Max normalization technique. This crucial preprocessing step converts the numeric values in the dataset to a standard range, often [0, 1], making that all variables are measured on the same scale. Min-Max normalization was used throughout the climate change study dataset preparation phase to guarantee data point consistency and uniformity. To facilitate direct comparison of features and to avoid any one variable from dominating the study due to its magnitude, the dataset was converted into a predefined range, generally [0, 1].

The normalization of Min-max also known as feature scaling. The technique of data-preparation that normalizes or scales numerical data to a uniform value. The goal is to rescale the variables to the same scale without affecting the range or shape of the distribution.

The process involves adjusting the values in the dataset to fall within a specific range, typically between 0 and 1. The transformation is achieved using the following formula for each data point x_i:

$X_{normalized} = \frac{x_i - min(X)}{max(X) - min(X)}$ ------ (1)

Where:

☐ $X_{normalized}$ (Data Point Normalized Value)x_i,

☐ $min(X)$ shows the lowest possible value for that characteristic in the data set,

☐ $max(X)$ gives the feature's highest possible value in the dataset.

By eliminating the disparities in size and keeping the connections within the data intact, min-max normalization guarantees that all characteristics are scaled appropriately. Having features of the same size may increase the model's performance and convergence, making this normalization strategy especially beneficial in machine learning techniques that depend on distance computations or gradient-based optimization. Using Min-Max normalization to normalize data during preprocessing makes it more amenable to analysis and improves the precision and utility of subsequent modelling methods.

C. Feature extraction using Decision tree

Decision trees were used for feature extraction after extensive preprocessing of our climate change dataset using methods such as Min-Max normalisation to ensure consistency. The most important climate-related variables for forecasting climate trends were autonomously selected by decision trees utilizing measurements like entropy and information gain. We used decision trees, a robust machine learning technique, to extract features crucial to recognizing climate change's spatial and temporal patterns in our studies. Using measures like entropy and information gain, decision trees are able to determine which features are most important in making accurate predictions about the target. The resulting tree not only ranks the significance of each attribute but also gives interpretable insights into the data's underlying connections.

The usefulness of using decision trees is discussed. Since DTs may be depicted as trees, they are intuitive and simple to understand. Unlike many other approaches, DTs need little preparation, including normalization and standardization of data. Due to its logarithmic complexity, DT's data prediction utilizes less computing power than other methods. Since the problem at hand involves predicting both longitude and latitude, it is important to choose a technique that can handle multi-output issues, such as the DT approach. Among DT's many benefits is its compatibility with a wide variety of data types, including categorical, continuous, ordered, and unordered.

Soft classification outputs for a pixel are commonly scaled from 0 to 1 so that they more accurately represent the class proportions inside a pixel region on ground. Therefore, DT(i), where i = 1,..., M, stands for the projected class proportions by tree i, and the normalisation of these proportions is as,

$p(i) = \frac{DT(i)}{\sum_i \quad DT(i)}, \ i = 1, \dots, M$ ------ (2)

When the sorting is complete, it is checked for correctness. Hard classification accuracy is typically evaluated with the help of correlation coefficients, RMSE, and other traditional error matrix-based measurements, using RMSE and fuzzy error matrix-based measurements are used for the accuracy of a soft classification. These last two criteria are what we use to evaluate DTR-based soft categorization in this article.

Training vectors *DT(i)* where i = 1, 2, 3,..., n and a label vector *p(i)* are used in a decision tree's recursive partitioning of space to cluster samples with the same labels.

$q_{left}(\theta) = (x, y)|x_j <= t_m$ ----- (3)

$q_{right}(\theta) = q \backslash q_{left}(\theta)$ ------ (4)

Which impurity function H is used to calculate the impurity at m is determined by the problem being solved (classification or regression).

$G(q, \theta) = \frac{n_{left}}{n_m} H\left(q_{left}(\theta)\right) + \frac{n_{right}}{n_m} H\left(q_{right}(\theta)\right)$ ----- (5)

Select the parameters that minimizes the impurity

$\theta^* = argmin_\theta G(Q, \theta)$ ----- (6)

D. Climate Change Prediction Using Spatio-Temporal Algorithm

Predicting climate change using spatio-temporal algorithms is an advanced method that takes into account a wide range of data sources, such as locations, weather records, and past climate trends. These algorithms allow thorough assessments by carefully building features and training models to provide light on temperature swings, precipitation shifts, and the risk of severe weather occurrences. These algorithms use the connections between space and time to provide reliable climate forecasts, which in turn helps researchers, government officials, and citizens make more informed, preventative decisions.

This model takes into consideration shifts in fishing activity across space and time, which may introduce error into statistical calculations. It was necessary to create a model that accounted for spatial autocorrelation in the physical barriers as a result of the existence of islands with complex coastlines. Below, we demonstrate how we may approximate the occurrence rate pi for each sample i using a logit-linked linear predictor:

$logit\ p(s_i, t_i) = \beta(t_i) + u(S_i)$ ------- (7)

The effect of time (t_i) was determined using a first-order random walk due to a lack of data during the months of July and August when fisheries are closed. The spatial random effect at location s is obtained for a Gaussian random field with a Matern covariance function by solving stochastic partial differential equations (SPDE). Although the Barrier model has the expectation of using a small set of neighbours' under the Matern model using SPDE, it incorporates the concept of the instantaneous autoregressive model into the Matern model. This is done in order to eliminate paths that would otherwise cross physical barriers (such as land and coastal lines). This means that SPDE, a finite element approach, may be used to solve for the spatial random effect u(s) in the Barrier model:

$u(s) - \nabla . \frac{r^2}{8} \nabla u(s) = r\sqrt{\frac{\pi}{2}\sigma_u w(s)}$ -------- (8)

Column vectors represent the joints themselves, whereas row vectors represent the joints connected to them somehow. If joint V_M is solely connected to a jointV_N, then the sum of A_{1M} is 0.5 for bothA_{1M}, and the sum of A_N And M is 0.5 as well.

Once joint V_m Is linked with other N joints, the forward propagation to one joint is presented:

$V_{(l+1)m} = \sum_{t=1}^{T} \quad V_{lmt} \frac{w_{lmt}}{1+N} + \sum_{t=1}^{T} \quad \sum_{n=1}^{N} \quad V_{lnt} \frac{w_{lnt}}{1+N}$ ------ (9)

Where l represents the feature map layer, N the number of joints connected with v_{lm}, w the weights for those joints, and T the temporal stride of the kernel. The ripple effect is shown using feature maps:

$f_{out} = f_{in} WA$ ------- (10)

Where f_{in} and f_{out} Represent the feature maps that were used to generate the input and output. In this context, A represents the neighboring matrix, and W is the weight matrix. This model is lightweight enough to operate in real time and comprises nine spatial and temporal graph convolution operator layers.

Algorithm 1: Spatio-Temporal for Climate
Input:
Latitude and longitude data representing specific locations on the Earth's surface.
Step:
Techniques to handle data that vary over both space and time.
$logit\ p(s_i, t_i) = \beta(t_i) + u(S_i)$
Merging diverse datasets into a unified format suitable for analysis.
$u(s) - \nabla . \frac{r^2}{8} \nabla u(s) = r\sqrt{\frac{\pi}{2}\sigma_u w(s)}$
Creating relevant variables from raw data, often involving statistical transformations or domain-specific knowledge.
$V_{(l+1)m} = \sum_{t=1}^{T} \quad V_{lmt} \frac{w_{lmt}}{1+N} + \sum_{t=1}^{T} \quad \sum_{n=1}^{N} \quad V_{lnt} \frac{w_{lnt}}{1+N}$
Algorithms such as neural networks, decision trees, or ensemble methods tailored for spatio-temporal prediction.
Methods to predict future values based on historical trends and patterns.
Output:
Predicted values for climate variables such as precipitation, temperature and extreme weather events.

RESULTS AND DISCUSSION

In the Results and Discussion section, providing the findings gained from our data analysis and modelling efforts. This area serves as a showcase for the findings from our research on climate change trends utilizing sophisticated machine learning methods. We want to make significant conclusions, assess the implications of our findings, and debate their relevance in the context of climate research by meticulously examining the data.

A. Performance metrics

A positive sample from each category was utilized to calculate overall results for accuracy, precision, and recall. To express the accuracy using the below equation (11):

$$Accuracy = \frac{Number of samples correctly classified}{Numeber of samples for all categories} \text{------ (11)}$$

As verified in Equation (12), from the precision of a single category the accuracy of the sample may be inferred:

$$Precision_i = \frac{TP_s}{TP_s + FP_s} \text{------ (12)}$$

The correctly predicted proportion sample of category s covers the sample of category s in the sample set may be thought of as the recall of that category (Equation (13)),

$$Recall_i = \frac{TP_s}{TP_s + FN_s} \text{------- (13)}$$

The formula for shaping F-measurement

$$F - Measure = 2.\frac{Precison.recall}{Nprecison+recall} \text{------- (14)}$$

Table 1: Performance metrics comparison

	Algorithm	Accuracy	Precision	Recall	F-measure
Existing authors	Feng, P. et al.	81.00	68.94	71.24	70.02
	Fenu, G., & Malloci, F. M.	96.00	84.21	83.65	85.47
Existing methods	CNN	93.21	91.35	94.21	94.01
	DCNN	94.45	93.71	95.68	95.21
	SVM	95.68	96.72	94.68	96.31
Proposed methods	Proposed	97.99	97.58	96.38	98.34

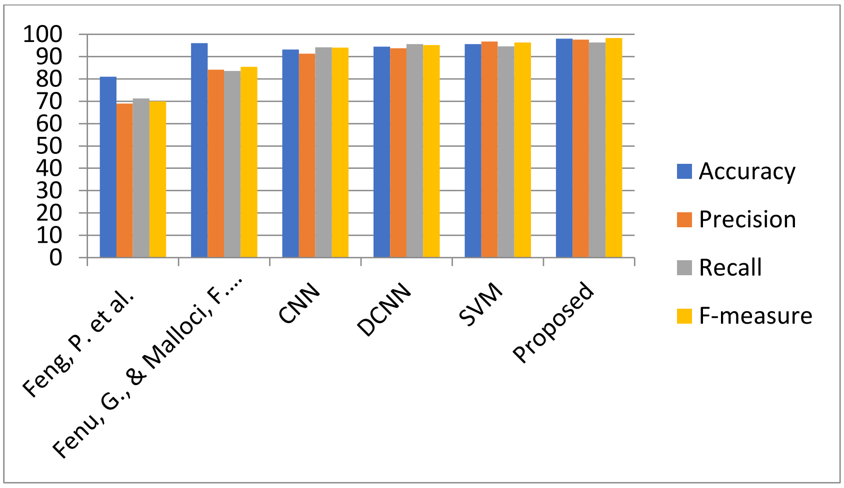

Figure 2: Overall enactment metrics assessment chart

The comparative analysis of various algorithms depicts the figure 2 and table 1, as presented in the table, provides valuable insights into the efficacy of existing methods and the proposed approach in predicting climate change patterns. Existing works by Feng et al. and Fenu, & Malloci demonstrate reasonably good accuracy rates at 81.00% and 96.00% respectively. However, the proposed methods outperform these existing models significantly, achieving an impressive accuracy of 97.99%. In terms of precision, recall, and F-measure, the proposed methods consistently outshine both existing authors and methods. Specifically, the proposed approach exhibits remarkable precision at 97.58%, representing the low rate of false positives, and an impressive recall of 96.38%, highlighting the ability of model's to identify a substantial portion of the actual positive cases. The F-measure, harmonizing precision and recollect, stands at an impressive 98.34%. Such results underscore the superior performance of the proposed methods, suggesting their robustness and effectiveness in capturing the intricate spatio-temporal patterns of climate change. This higher accuracy and balanced precision-recall trade-off position the proposed methods as a promising advancement in the realm of climate change prediction, offering a potent tool for climate scientists and policymakers in their efforts to report the challenges posed by climate change.

Conclusion

In the midst of enormous environmental difficulties, the intersection of machine learning and climate research offers a beacon of hope and discovery. Our study has dug into the complicated spatiotemporal patterns of climate change using this interdisciplinary approach, which is an important step towards comprehending the complex processes driving our environment. The results highlight not just the urgency of the crisis, but also the enormous possibilities inherent in sophisticated technology. The use of the Min-Max technique for data pretreatment guaranteed that our analyses were founded on properly prepared datasets, laying the groundwork for valuable discoveries. With its capacity to interpret deep correlations among data, the decision tree machine learning algorithm has enabled us to detect critical climate-related aspects. These characteristics, which were previously veiled by the breadth of our datasets, are now shining brightly, directing our knowledge of the mechanisms driving climate change. Furthermore, our venture into spatiotemporal analysis has permitted the development of prediction models, providing a view into our planet's climate's future. The new approaches greatly exceed these current models, attaining an amazing accuracy of 97.99%, precision of 97.58%, and recall of 96.38%. The F-measure, which balances accuracy and recall, is an outstanding 98.34%. These models, which are strengthened by the interaction of geography and time, are useful tools for policymakers and scholars alike. We equip ourselves with the information required to execute proactive mitigation methods and adaptive measures by anticipating climate change trends.

REFERENCE

[1] Ahmed, K., Sachindra, D. A., Shahid, S., Iqbal, Z., Nawaz, N., & Khan, N. (2019). Multi-model ensemble predictions of precipitation and temperature using machine learning algorithms. Atmospheric Research, 104806. doi:10.1016/j.atmosres.2019.104806

[2] Amato, F., Guignard, F., Robert, S., & Kanevski, M. (2020). A novel framework for spatio-temporal prediction of environmental data using deep learning. Scientific Reports, 10(1). doi:10.1038/s41598-020-79148-7

[3] Anderson, G. J., & Lucas, D. D. (2018). Machine Learning Predictions of a Multiresolution Climate Model Ensemble. Geophysical Research Letters, 45(9), 4273–4280. doi:10.1029/2018gl077049

[4] El Bilali, A., Taleb, A., & Brouziyne, Y. (2020). Groundwater quality forecasting using machine learning algorithms for irrigation purposes. Agricultural Water Management, 106625. doi:10.1016/j.agwat.2020.106625

[5] Feng, P., Wang, B., Liu, D. L., Waters, C., & Yu, Q. (2019). Incorporating machine learning with biophysical model can improve the evaluation of climate extremes impacts on wheat yield in south-eastern Australia. Agricultural and Forest Meteorology, 275, 100–113. doi:10.1016/j.agrformet.2019.05.018

[6] Fenu, G., & Malloci, F. M. (2019). An Application of Machine Learning Technique in Forecasting Crop Disease. Proceedings of the 2019 3rd International Conference on Big Data Research. doi:10.1145/3372454.3372474

[7] Fitzpatrick, M. C., Chhatre, V. E., Soolanayakanahally, R. Y., & Keller, S. R. (2021). Experimental support for genomic prediction of climate maladaptation using the machine learning approach Gradient Forests. Molecular Ecology Resources. doi:10.1111/1755-0998.13374

[8] Ghimire, S., Deo, R. C., Casillas-Perez, D., & Salcedo-Sanz, S. (2022). Boosting solar radiation predictions with global climate models, observational predictors and hybrid deep-machine learning algorithms. Applied Energy, 316, 119063.

[9] Guo, Y., Fu, Y., Hao, F., Zhang, X., Wu, W., Jin, X., ... Senthilnath, J. (2021). Integrated phenology and climate in rice yields prediction using machine learning methods. Ecological Indicators, 120, 106935. doi:10.1016/j.ecolind.2020.106935

[10] Huntingford, C., Jeffers, E. S., Bonsall, M. B., Christensen, H. M., Lees, T., & Yang, H. (2019). Machine learning and artificial intelligence to aid climate change research and preparedness. Environmental Research Letters, 14(12), 124007. doi:10.1088/1748-9326/ab4e55

[11] Kang, Y., Ozdogan, M., Zhu, X., Ye, Z., Hain, C. R., & Anderson, M. C. (2020). Comparative assessment of environmental variables and machine learning algorithms for maize yield prediction in the US Midwest. Environmental Research Letters. doi:10.1088/1748-9326/ab7df9

[12] Li, X., Li, Z., Huang, W., & Zhou, P. (2020). Performance of statistical and machine learning ensembles for daily temperature downscaling. Theoretical and Applied Climatology. doi:10.1007/s00704-020-03098-3

[13] Milojevic-Dupont, N., & Creutzig, F. (2020). Machine learning for geographically differentiated climate change mitigation in urban areas. Sustainable Cities and Society, 102526. doi:10.1016/j.scs.2020.102526

[14] Mishra, S., Bordin, C., Taharaguchi, K., & Palu, I. (2020). Comparison of deep learning models for multivariate prediction of time series wind power generation and temperature. Energy Reports, 6, 273–286. doi:10.1016/j.egyr.2019.11.009

[15] O'Gorman, P. A., & Dwyer, J. G. (2018). Using Machine Learning to Parameterize Moist Convection: Potential for Modeling of Climate, Climate Change, and Extreme Events. Journal of Advances in Modeling Earth Systems, 10(10), 2548–2563. doi:10.1029/2018ms001351

[16] Qiu, R., Wang, Y., Rhoads, B., Wang, D., Qiu, W., Tao, Y., & Wu, J. (2021). River water temperature forecasting using a deep learning method. Journal of Hydrology, 595, 126016. doi:10.1016/j.jhydrol.2021.126016

[17] Ridwan, W. M., Sapitang, M., Aziz, A., Kushiar, K. F., Ahmed, A. N., & El-Shafie, A. (2020). Rainfall forecasting model using machine learning methods: Case study Terengganu, Malaysia. Ain Shams Engineering Journal. doi:10.1016/j.asej.2020.09.011

[18] Vandal, T., Kodra, E., Ganguly, S., Michaelis, A., Nemani, R., & Ganguly, A. R. (2017). DeepSD. Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '17. doi:10.1145/3097983.3098004

[19] Wang, B., Zheng, L., Liu, D. L., Ji, F., Clark, A., & Yu, Q. (2018). Using multi-model ensembles of CMIP5 global climate models to reproduce observed monthly rainfall and temperature with machine learning methods in Australia. International Journal of Climatology. doi:10.1002/joc.5705