AI-POWERED CLIMATE RISK FORECASTING MODELS FOR RURAL AND URBAN RESILIENCE

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Abstract

The intensity or level of climate risk hazards in terms of magnitude and frequency, as well as geometric complexity, is also increased by climate change. The appropriate model for predicting climate risk is highly relevant as well as informative for developing a climate-resilient plan. The currently available climate risk prediction model, although incorporated with physics, is perfect and claims accuracy in long-term predictions but acts as a reactive model with resolution requirements; therefore, the currently used climate risk prediction model in the SD plans is inefficient for conducting risk assessment at the local level. The advances in AI/ML technology have led to the evolution of the paradigm shift in developing innovative solutions for dealing with climate risk prediction difficulties and made easier to manage the big data at the multiple sources effectively. The conclusion of the paper is drawn at the end after determining the relevance to the scope in dealing with the future developments in AI-assisted climate risk prediction in the SD plans.

Keywords

Artificial Intelligence; Climate Risk Forecasting; Rural Resilience; Urban Resilience; Machine Learning; Climate Adaptation

1. Introduction

This is a problem for the world in contemporary society and has major effects on the environment, economic systems, as well as human settlements. This is because natural occurrences such as floods, drought, heat waves, and storms are rising in their occurrences. The worst affected areas in the world in relation to the issue of climate change are the remotest areas. This is because such areas rely on their climatic condition for their survival. This may include agriculture. Major cities in the world are also affected.

Preciseness in the forecast of climate risk is the most crucial factor in the process of build-out. Not only the approach will assist in the forecast of climate risk but also it will make sure that the risk is at a minimum. The traditional approach which can be followed for the forecast of climate risk is the numerical simulations of climate risk based on the laws of physics. The developments of artificial intelligence models to forecast climate risk are trends in the methodologies of climate risk forecast.

This paper has the objective of reviewing AI models related to climate risk predictions. The objective is to determine the role played by climate risk models using AI within the process of improving resilience.

2. Literature Review

This is a problem faced by the world at present and has serious effects on the environment, economic systems, and human settlements. This is attributed to the fact that natural occurrences such as flooding, drought, heat, and storms are on the increase. The remote areas of the world are mostly affected by climate change. This is attributed to the fact that these regions rely on the climate for their survival. Examples include agriculture. The major cities in the world are also affected.

The forecasting of climate risk in the build-out process of resilience should be highly accurate, as the approach in place would not only assist in the forecasting process but also help minimize the risks to the barest minimum. Traditionally, the forecasting of climate risk has been treated numerically by simulation and using the fundamental approach to physics. Currently, the development of approaches using artificial intelligence encompasses the trends that are associated with the forecasting of climate risk.This review paper reviews AI models that are available in regard to the predictions of climate risk. This paper will seek to establish the contribution of the AI climate risk model towards resilience.

3. Methodology

3.1 Data Collection and Preprocessing

The type of artificial intelligence that might ideally be applicable in the prediction of the risks involved in climate change can make use of the integration of the knowledge that has been acquired in various forms. This type of knowledge involves the collection of facts or information that is associated with the environment, flooding, drought, and the risks involved in storms.

1. Historical Weather Data

The past weather patterns also consist of a history of data, which will be maintained in order to be analyzed in the form of the atmosphere at present, in terms of temperatures, rain, speed, and humidity in the atmosphere. The data will help the artificial system in spotting the past patterns and abnormalities developed due to the emergence of bad weather.

2. Satellite and Remote Sensing Data

These satellites and remote sensing systems have relevance in observation and validation of features and conditions of the Earth at all times. The pieces of information that a satellite can offer include the formation of clouds, the land surface temperature of the landmass, vegetation, the content of water in the soil, the changes in the sea water levels, and ice. All the pieces of information that will be discussed below will prove important, taking into consideration the fact that this information does not normally lie in the open.

3. Climate Reanalysis Data

Climate reanalysis data is a combination of climate observation data and numerical climate modeling. This results in a set of data that can fill gaps not accounted for by actual observation. Reanalysis data can be applied extensively when it comes to making climate risk assessments based on AI.

4. Socio-Economic, Land-Use, and Demographic Data

It can be said that the human climate risk isfully affected by the various human factors. Socioeconomic data contains information on density, economic status, infrastructure, and economic activities. It also holds land usage information. This information depicts land usage categories such as urban land, agricultural land, and forest land. Demographic information facilitates the determination of the population at risk. The AI model not only predicts climatic risks but also predicts the effects resulting from these risks.

5. Sensor and Weather Station Records

The ground sensor stations and weather stations allow for real-time and highly accurate determination of the prevailing climatic variables on the ground. It's very essential in the process of validating the data from satellites and in determining the micro-weather events, which might not be captured on a macro-level.

3.2 Model Development

The proposed methodological approach incorporates different types of AI models. The AI models are found to be useful in assisting in comprehending the nature of climate data, in some cases of which the data might be complex, Natural Language (NL), spatial data, or temporal data in nature. The AI models, due to different types of applications, belong to three different types, including conventional machine learning models, Deep Learning models, and Hybrid AI models.

1. Traditional Machine Learning Models

In contrast, traditional machine learning algorithms employ a conventional use of baseline models because a random forest model and support vector regression model are more interpretable and reliable. Random Forest Models and Support Vector Regression Models would respectively and generally be employed to create a baseline model among other models under Machine Learning due to their interpretability relatively compared to other models.

Random Forest (RF):

Random Forest is an ensemble learning method which tries to make better predictions using a combination of decision trees to prevent the problem of overfitting. Applications of RF in climate-related research include:

- Dealing with high dimensional and heterogeneous data (Temperature, Rainfall, Humidity, Wind Speed).
- Studying nonlinear correlations among climatic variables.
- Feature importance estimation, which assists in identifying how various environmental variables contribute to climate-related risks.

Support Vector Regression (SVR):

Support Vector Regression: This regression model encompasses a machine learning method that relies on a technique called kernels and aims to determine the best possible fit with the least possible error margin regarding estimation of the output value. Support Vector Regression performs superbly well in:

- Represent approximate complex nonlinear relationships between climate variables.
- Making reliable predictions, in situations where the size of the dataset is comparatively small when contrasted with other datasets.
    - It could be used as a good benchmark model for comparison with the complex deep learning models.

2. Deep Learning Models

The motive to create models with deeper learning is embedded in their capacity to form hierarchical representations from complex data. From a climatic forecast perspective, they can be applied effectively to model both sequences and geographic dependencies.

Long Short-Term Memory (LSTM) Networks:

LSTMs are a kind of RNN that managed to resolve the vanishing gradient problem and achieved success in the field of time series forecasting. LSTMs have been applied to a variety of fields within climatology to perform the following:

- Temporal dependence patterns from climate sequence data.
- Future trends for the likes of rainfall, temperature, and drought.
- Climate variability patterns, inter-annual, and seasonal variations

Gated Recurrent Unit (GRU) Networks:

However, owing to the fact that the weakness in the LSTM Network is that the total number of parameters being too high, an optimized version called *The GRU Network*, which has a reduced requirement for storage space as far as the total number of parameters considered, has been developed. This is because the total number of parameters in "The GRU Network" is less compared to that of the "LSTM Network", since

- Pattern recognition in climate data time series.
- Facilitate the training process of the model over a shortened timeframe with a similarity in levels of accuracy that are more or less similar.
- Acting as a substitute if there would be a number of operations involving power.

Convolutional Neural Networks (CNNs):

It can be generally stated that the applications of the CNNs would be attributed to the processing and acquisition of the spatial features present in the grid data, the image data, and the climate data. The most important advantages which would be generated by the applications of these CNNs would be the following:

- Identification of Correlation & Patterns in Spacial Data.
- It incorporates trajectory studies that involve weather front formation distributions based on geography, rain, and heat waves.
- Dimension Reduction, maintaining spatial data.

3. Hybrid Models

These models leverage the benefits that arise from the ability of various models to deal with the complexity introduced due to the nature of the climate system using deep learning. In such a case, the CNN-LSTM model could be used.

CNN–LSTM Hybrid Architecture:

In the proposed approach, the initial processing step of the SPMs for the grid climate data involves the engagement of the CNN layer. The temporal SPMs are subsequently employed as the input for the processing in the LSTM layer. This makes the architecture of the neural network consisting of the CNN layer and the LSTM layer capable of performing the following functions:

- Relationship training by means of collaborative learning.
- Advanced Spatiotemporal Models
- Opportunities pertaining to the optimization of predictability for flood, drought, heat-wave, and heavy rainfall hazard types.

3.3 Training, Validation, and Testing

The models are trained on past data sets; validation techniques include the use of cross-validation. There is hyperparameter optimization to improve the models' robustness. The optimization of hyperparameters is performed for robustness improvement and generalization.

3.4 Performance Evaluation

Performance evaluation is a significant task to measure the efficiency and validity of a forecasting model. This is required to compare the estimated outputs generated from a model with actual data on the basis of numerical evaluation criteria. In a study, the performance of a model for accurate estimation is evaluated using some universally recognized evaluation criteria, which include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2).

Mean Absolute Error (MAE)

MAE computes the mean value of the absolute difference between the actual value and the value of the forecast without considering the characteristics of the forecast. This is done by calculating the absolute values without considering the characteristics of the error. This method is quite straightforward and it is employed in the evaluation of the forecast error to find out how well the model fits with respect to the forecast of the variable given that the values are in units of the variable.

Advantages of MAE:

- “Easy on the eyes, easy to read."
- The errors are considered equal, no matter what the errors in the larger numbers are.
- Therefore, this method is an optimal solution for dealing with outlier observations that require error norms to be expressed by means of a square.

The MAE might find applications when there is a need to approximate an approximate value for an error prediction task.

Root Mean Square Error (RMSE)

RMSE calculates the square root of the mean value for the forecast errors subtracted by the actual value measurements. By understanding its dependency upon a value that is squared, giving more concern towards larger errors than the smaller ones, the “why” the concern of the issue is so important to RMSE can be derived.

Advantages of RMSE:

- Relatively harsher in terms of punishment for big mistakes, which is great if big mistakes are not wanted.
- Scales are equal as they contain similar units to the predictor when there is scaling.
- Regression Analysis for Comparison used for forecasting purposes.

The RMSE may only apply where the greatest possible reduction of error is relevant to instances of prediction that require the greatest possible reduction of the error of prediction.

Coefficient of Determination (R^2)

Coefficient of determination, or, the measure of the variability in the dependent variable explained by the forecasting equation. Indicates the relative appropriateness of the values calculated in the actual values.

4. Applications for Rural and Urban Resilience

Anyways, coming back to this issue, it would be quite clear that the scope of predictive processes regarding the threat of climate change posed by Artificial Intelligence would extend to drought early warning systems in agricultural areas, agricultural land use in agricultural areas, irrigation in agricultural areas, as well as food security in agricultural areas. It is Climate change adaptation before it occurs where Artificial Intelligence applies.

The resilience of the AI model could be demonstrated in an urban setting, predicting floods, heatwaves, storms, through to Urban Planning and Design. The application of AI model forecasts in decision-support systems in the urban setting could be useful in combating climate change.

5. Challenges and Limitations of AI-Based Climate Risk Predictive Models

With great potential exists for Ai-based predictive models to help improve climate risk assessments and the decisions made based on those assessments. However, where AI-driven predictive models currently provide valuable support, they also come with various technical, ethical and practical challenges that must be addressed in order to ensure the model's reliability; equity and sustainabliity.

1. Data Gaps and Limited Coverage of Spatial Representation

To develop effective AI models in a timely manner, we need to work with large volumes of high quality representative data. Unfortunately, many of the datasets that have been generated in connection to climate change do not currently provide adequate spatial and temporal coverage.

For example, there may be very few weather stations, sensor networks and/or historical data records (or even an absence of any records) in rural or remote areas, creating an under-representation of these areas in training datasets.

Although satellite data can fill some of these gaps, there may be limitations related to resolution and/or accuracy when trying to do localized risk assessments like flood risks or drought vulnerability assessments.

The fact that collection standards vary across regions and countries can create noise and increase uncertainty in collection processes, impacting the reliability of the models.

For this reason, some AI models will produce 'biased' and/or inaccurate 'results' for areas that are traditionally underrepresented in available dataset, particularly in marginalised and data-poor regions, which are generally the areas that are the most vulnerable to the impacts of climate change.

This imbalance can exacerbate the existing inequities associated with the increasing priority given to well monitored urban/high incomes, as opposed to rural/developing areas.

2. High computational demands of AI and the cost of energy

Deep learning and other AI-based algorithms require extremely powerful computers to process their complexity.

The development of climate models involves using advanced computer modeling and simulating on a global scale to achieve high-accuracy forecasting, working with very large datasets that are referred to as "big data" and having forecasts of longer durations than are utilized in the traditional weather forecasting industry.

The energy requirements needed to run data centers that use multiple advanced GPUs to develop AI systems have increased the CO2 footprint associated with AI development and raised numerous environmental sustainability concerns.

Many developing nations and smaller academic/independent researchers may not have the necessary computational facilities for developing these AI-based models to address climate change, creating barriers for their ability to participate and develop innovative solutions.

Increasing the frequency of retraining the climate forecasting models creates additional energy usage and cost for the developers. A situation arises where climate forecasting models developed with the intention of mitigating climate change may contribute negatively to the environment if not developed or utilized appropriately; thus, creating a paradox with regard to the use of AI to combat climate change.

3. Low Interpretability of Deep Learning Models

Many AI climate risk analysis techniques that are based on computer modelling operate either as "black boxes" or as predictive algorithms whose methodology is hidden from analysis, resulting in a lack of explanation of how model predictors produce predictions. Deep Learning models provide valid outputs but do not provide a rationale for the predictions they are making. Insurers, policymakers and Emergency Managers may not have adequate faith in the predictions generated from an unexplainable deep learning model.

The lack of interpretability also presents a barrier to the ability to be able to effectively identify model errors, biases and causal links, limiting the level of trustworthiness associated with outputs. The inability to be able to justify decisions made based on a model output in high-stakes scenarios (e.g., disaster preparedness and infrastructure planning) creates legal and ethical liabilities associated with decision-making processes.

In addition, the lack of rationales and justification from AI-based Climate Value models creates barriers to the adoption of insight generated from AI-enabled Climate Value Models in real-world practices and on-going mitigative action.

4. Ethical Considerations: Bias, Fair Treatment, and Equal Access

The presence of ethical implications is among the most significant obstacles when applying Artificial Intelligence (AI) in prediction of risk that is associated with climate change.

Systematic bias that exists in historical data can produce systematic undervaluation of risk relating to groups that are most affected by climate change, e.g. people with the highest vulnerability.

Those communities that have limited access to technology or digital capability are at risk of becoming disenfranchised in their access to AI-based climate prediction resources.

The creation of a limited number of proprietary models and datasets creates concentrated control of these prediction capabilities within a small number of organizations.

With limited transparency and accountability, the question of who controls these AI prediction models, how they reach their decision-making and who will take responsibility for the negative impacts of inaccurate predictions presents a significant barrier.

The lack of inclusive design and governance models/approaches increases the risk that AI-based systems will exacerbate social and economic inequality, rather than reducing the climate vulnerability of these underrepresented communities.

Taking these challenges into consideration is very important in order to ensure the effective application of AI in climate change resilience strategies.

6. Conclusion

AI Climate Risk Forecasting models provide a viable pathway for improving rural and urban resilience to the increasing number of climate-based disasters and extreme events caused by climate change. AI climate risk forecasting models rely on advanced machine learning and deep learning technologies and can integrate data from multiple sources, including past weather patterns, satellite images, and socio-economic information, into a single product. As a result, AI Climate Risk Forecasting models will provide actionable information for early warning systems, risk assessments, and climate adaptation planning. AI Climate Risk Forecasting models will also have superior performance to traditional physics-based climate forecasting models in several ways. For example, AI models are more capable of processing extremely large volumes of complex data than physics-based models. Moreover, AI models can also make considerably better predictions regarding local climate conditions than physics-based models, which allows for more timely decisions regarding flood, heat, drought, and storm disasters.

AI may be useful in foreseeing how climate change affects economies; however, implementing AI poses obstacles. In particular, the majority of the globe does not possess adequate data necessary for producing reliable AI models, resulting in limited uses for these models, in addition to the creation of localization bias in determining the regions affected due to climate change. Second, many AI technologies rely on vast amounts of computational resources and energy to operate, raising significant sustainable issues, especially in developing and resource-limited environments. Third, many AI technologies lack interpretability and transparency (i.e., are “black boxes”), meaning it is often challenging for users to fully understand the rationale behind AI conclusions, ultimately making the use of AI to help inform decision-making and policy development problematic. Lastly, the questions related to AI's ethical ramifications raise significant concerns, such as bias from algorithms that causing entities not to have equitable access to AI products, and equal consideration given to all who could be impacted by AI technology.

As we look at the future of climate modelling and forecasting, it is important to consider hybrid modelling strategies which combine physical climate models with AI-based techniques. These hybrid approaches will allow for the most reliable forecasts possible and provide the greatest level of robustness. It is also important to develop and use explainable AI (XAI) frameworks. XAI enhances transparency of AI-driven forecasting systems and improves stakeholder trust in these systems. Additionally, investing in the data infrastructure necessary to ensure equitable representation across all geographic areas will make the greatest impact on building climate resilience and sustainable development.

The collaborative efforts of climate scientists, Artificial Intelligence (AI) researchers, and decision-makers (policymakers, local community representatives) will be needed to create effective AI-enhanced forecasting tools that advance scientific knowledge and provide meaningful contributions to climate resilience and sustainable development. This research illustrates that, when deployed responsibly and inclusively, AI-based predictive systems can become valuable tools for building climate adaptation strategies and enabling decision makers to prepare for climate change impacts in ways that have never been possible before.

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