An Integrated Wavelet DAG-CNLA-SCM Structure with Recurrent Neural Networks for Climate Vulnerabilities Prediction

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***Abstract*—Advancements in Artificial Intelligence (AI) have yielded several machine learning and deep learning models that highlight correlation while failing to differentiate cause-and-effect relationships. Current methodologies, such as Granger Causality (GC), solely identify temporal causal linkages in which causes precede effects, hence neglecting contemporaneous associations. This paper introduced the integration of Causal Network Learning Algorithms (CNLA), Structure Causal Models (SCM), and Long Short-Term Memory (LSTM) networks to forecast climatic catastrophes. A Directed Acyclic Graph (DAG) is constructed utilizing the Temporal Causal Discovery Framework (TCDF) technique, which employs attention-based Convolutional Neural Networks (CNNs) to ascertain causal relationships between temperature and carbon dioxide (CO). The study examines the enduring issue of causality versus correlation in the relationship between temperature and CO with regard to climate change. Results reveal Europe undergoes the fastest warming at 0.80°C per decade, with Eastern Europe, particularly Ukraine, experiencing extreme warming at 1.21°C per decade. Northern Europe exhibits an unusual wavelet maximum power of 5.596, indicating complex periodic patterns. Despite distinct CO-temperature correlations, regression analysis shows emissions account for merely 0.032% of temperature variability. Time lag studies verify emission-temperature connections persist beyond 1–5 year temporal scales, endorsing emission reduction measures while highlighting geographic climate inequities affecting low-emission regions like Africa disproportionately.**

***Index Terms*—Causal Inference, Wavelet Analysis, Convolutional Neural Networks, Structure Causal Models, Causal Network Learning Algorithms, Artificial Intelligence, Granger Causality, Climate Change Prediction.**

I. Introduction

The words correlation and causation are sometimes used interchangeably, but semantically, they are not the same. The general link between two variables that show a growing or declining trend is correlation [1]. Conversely, causality, also known as cause and effect, occurs when the cause partially contributes to the effect, and the effect partially depends on the cause. Causal inference is the process of determining a cause-and-effect relationship based on the conditions of occurrence. Causal inference differs from correlation inference in that it examines how the effect variable responds to changes in the cause [2, 3].

According to Yao [4], it is a general belief that ”correlation does not imply causation.” A study found that girls who eat breakfast tend to be lighter than those who do not, suggesting that it can aid in weight loss. However, it is possible that these two events are correlated rather than causal. Girls who eat breakfast every day may have a healthier lifestyle, including regular exercise, sleep, and eating nutritious food, leading to a lighter weight. A healthier lifestyle is linked to both breakfast consumption and weight loss, making it a potential confounding factor in the causal relationship between the two.

Causality and causal inference are critical subjects in various scientific fields, providing essential insights into cause-and-effect interactions. Causality denotes the relationship between two occurrences in which one event (the cause) precipitates the occurrence of another event (the effect). The causal discovery can provide more robust insights by identifying causal predictors that are more likely to hold under future climate change scenarios [5]. Causal inference, conversely, involves approaches employed to ascertain these links, frequently utilising statistical tools to derive conclusions from data. The cause explains the “why,” whereas the effect explains the “what”.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have rekindled interest in causal inference due to the increasing availability of observational data. This fascination is evident in various fields, including economics, public policy, computer science, and health care [6]. Although Randomized Controlled Trials (RCTs) are the gold standard for causal inference, they are not always feasible. This is often due to ethical, legal, or economic constraints. Consequently, researchers have developed various methods to infer causation from observational data, including statistical methodologies and causal relational learning frameworks [7, 4].

Although ML algorithms have achieved exceptional predictive accuracy in a variety of domains, they frequently function as ”black boxes” in which the relationship between inputs and outputs is unclear [8]. In high- stakes domains such as healthcare, criminal justice, and climate change, where comprehension of the causal mechanisms behind decisions is essential, this unexplainability presents substantial challenges. Additionally, these algorithms frequently codify and amplify societal biases that are present in the training data, resulting in discriminatory outcomes that disproportionately affect marginalised social groups [9, 10].

Correlational relationships and statistical parity are the primary objectives of conventional methods for addressing these issues, including bias testing and feature importance methods. Nevertheless, these methodologies are unable to capture the underlying causal mechanisms responsible for both the unexplainable and bias issues. For instance, an ML algorithm may accurately predict higher default rates for specific demographic groups without determining whether this relationship is causal or merely reflects historical discriminatory practices embedded in the training data [8].

II. LITERATURE REVIEW

According to Keele [11], causal inference frameworks such as the possible outcome framework have opened several approaches to careful examination of observational data [4, 12]. It is important to understand the underlying assumptions in causal analysis since these frameworks often rely on identifying assumptions that allow researchers to interpret statistical data causally [11].

However, due to the complex interplay of several influencing elements, causal inference in human behaviour faces significant challenges. To address these problems, researchers suggest approaches such as triangulation, which combines theoretical frameworks with quasi-experimental methodologies [13]. Effective problem-solving requires that an individual comprehend intricate relationships; hence, causality has become an essential ingredient to effective learning and cognitive processes [14].

The continuous development of causal inference techniques has enhanced crucial information for empirical investigation and judgment in a variety of fields [15]. Because it offers improved methods for monitoring, conservation, and sustainable resource management, Artificial Intelligence (AI) has subsequently become indispensable in addressing global concerns [16, 17].

Runge [18] examined four causality inference algorithms in their work related to inferring causation from time series in Earth system sciences. The first was Granger Causality (GC), known to be limited to lagged causal dependencies and, furthermore, to have known deficiencies in the presence of sub-sampled time series and other issues. The multivariate extensions of GC fail if too many variables are considered or dependencies are contemporaneous due to time-sampling data. GC requires a time delay between cause and effect to identify causal directionality. If causation occurs almost instantaneously, or at least faster than the observable sampling interval, then causal directions cannot be identified in general.

Conversely, Causal Network Learning Algorithms (CNLA) are suitable for time series that are of a stochastic nature. The algorithm begins its classification with an empty or fully connected graph and the statistical criterion for removing or adding an edge. The common feature of these algorithms is that they assume the Markov condition. Causal network learning algorithms can incorporate time-order as a constraint (causes precede effects) and utilise a set of causal orientation rules to identify causal directions. The CNLA has only recently started to be applied in Earth system sciences, mainly focusing on climate science [20, 22]. The Markov equivalence is two contemporaneously dependent variables where the causal direction cannot be inferred with conditional independence- based methods [18]. The Structural Causal Models (SCMs) can identify causal directions in such cases because they permit assumptions about the functional class of models [18]. According to Perez-Suay and Camps-Valls [19], SCMs have not yet been applied in Earth system sciences except for one work in remote sensing [20, 21, 22].

The study by Huang [23] investigates the causality between multiple atmospheric processes and sea ice variations using three distinct data-driven causality approaches: Temporal Causality Discovery Framework, Non-combinatorial Optimisation via Trace Exponential and Augmented Lagrangian for Structure learning (NOTEARS),) and Directed Acyclic Graph-Graph Neural Networks (DAG-GNN). The static graphs generated by NOTEARS and DAG-GNN are well known to be good because the outcomes of the causality graph and the literature reviews from the models revealed better insights.

Machine learning, a subset of artificial intelligence, can generate multiple solution models for intricate environmental and climate-related challenges, including natural disasters, greenhouse gas emissions, biodiversity evaluation, agriculture, and meteorological and climatic modelling, providing invaluable information for addressing climate change issues [24, 25, 26, 27].

A. *Big Data Analytics Artificial Intelligence*

Big Data Analytics (BDA) and Artificial Intelligence (AI) have emerged as transformative agents in modern business and academic settings. Artificial intelligence, particularly ML, is crucial for using big data for improved predictive analytics, pattern recognition, and automated decision-making [28, 29, 30]. The use of AI technology, machine learning algorithms, and sophisticated data analytics tools allows organisations to extract substantial knowledge from large and complex datasets, hence enhancing strategic decision-making and fostering corporate success [28].

Decision-making in a smart environment where artificial intelligence (AI) and machine learning are at the forefront has become easier and faster with better privacy safeguards and necessitates ethical supervision [29]. The use of AI and ML in BDA has resulted in many advancements across multiple fields, including query optimisation, real-time predictive analytics, and improved data security [31].

B. Morlet Wavelet Data Analysis

The Morlet wavelet transform has become an effective instrument for the analysis of intricate signals in diverse fields. It is proficient at extracting fault characteristics from noisy vibration signals, especially in identifying compound faults in rolling element bearings [33]. The continuous wavelet transform employing the complex Morlet wavelet has demonstrated efficacy in detecting power frequency fluctuations and integer harmonics in power signals [34].

Detection and attribution of climate changes to internally generated natural climate variability and external natural and anthropogenic climate forces require methods that may simultaneously address time scale dependence and nonstationarity. Wavelet analysis represents a powerful and effective tool for analyzing non-linear and especially non-stationary time series. The two basic features that make wavelets an effective solution to the analysis of nonstationary processes with multiscale features or structures and scale-dependent relationships are their time-scale localisation property and their frequency-dependent windowing of the signals, that is, multiresolution decomposition analysis. These properties are especially useful for analysing complex signals that are 'non-stationary, have short-lived transient components, have features at different scales or have singularities' [35].

Gallegati [36] stated that wavelet analysis can address the issues of non-stationarity in time series by executing a local time scale decomposition of the signal, which is possible due to the signal, due to the finite support of the wavelet basis function. Furthermore, concerning alternative filtering techniques adept at analyzing diverse non-stationary signals, wavelet analysis achieves an optimal balance between temporal and frequency resolution due to its capacity to decompose a time series into distinct components, each possessing a resolution commensurate with its scale. The wavelet transform employs a flexible time-scale window that contracts for small-scale features and expands for large-scale features, providing excellent time resolution at high frequencies and superior frequency resolution at low frequencies. This characteristic is particularly advantageous for climatic applications, as most signals of practical significance exhibit high-frequency components over brief intervals and low-frequency components over extended periods [36].

III. METHODOLOGY

The study uses a global dataset that includes 169 countries on six continents, ensuring a vast geographical representation. The distribution comprises 41 African countries, 20 in the Americas, 49 in Asia, 5 in the Caribbean, 3 in Oceania, and 42 in Europe. Furthermore, the data set was classified into 20 separate regions, allowing for regional research while still providing a wide coverage of the world. This diverse data set strengthens the findings across different continents and allows continental comparisons, ensuring that the research takes into account different socioeconomic, cultural and geopolitical situations.

The data was gathered from different reputable platforms. ERA5, the fifth-generation global reanalysis data set generated by the European Center for Medium-Range Weather Forecasts (ECMWF) and produced by the Copernicus Climate Change Service, provided most of the monthly temperature data (158,613). This data set integrates historical observations from weather stations, satellites, buoys, and aircraft to produce a globally complete and consistent climate data set that spans atmospheric, land and oceanic conditions from 1940 to March 2025, with a resolution of 30 km. Additionally, carbon dioxide emissions (62,961) from 1960 to 2023 were collected from Globalcarbonatlas, while population (11,766), GDP (1,896), and educational index data (8,370) were gathered from the World Bank's Global Indicators database.

A thorough preprocessing was carried out. The data pre-cleaning includes data normalisation using the RobustScaler technique, replacing missing values with the mean value of the column, removing inconsistent data and outliers, and detrending and deseasonalizing data for a generalizable prediction. The Data Exploratory Analysis (DEA) was performed with wavelets (Morlets) for pre-analysis and to determine the CO_2 time lag exploration. A relational database (MySQL) generated view tables to improve data association and memory efficiency, resulting in 63,993 clean anomaly temperature records for analysis. All countries, regions, and continents were allocated unique identification numbers (primary keys) to ensure that all were captured in the data.

A Directed Acyclic Graph (DAG) Fig. 1 was created to illustrate how the confounders and the driver (cause) are related, using the Temporal Causal Discovery Framework (TCDF) algorithm that relies on attention-based Convolutional Neural Networks (CNN). Thereafter, both the Causal Network Learning Algorithms (CNLA) and the Structural Causal Model (SCM) integration was meant to identify the cause and the effect. A Long-Short-Term Model (LSTM), a version of a recurrent neural network built to predict climate crises. A cross-validation method was employed with a ratio of 80:20% of training and validation sets while retaining a holdout of 10% for the test.

IV. RESULT AND DISCUSSION

This study of global climate trends indicates significant and swift alterations in critical environmental variables. The baseline year was 1985, and the analysis spanned 41 years of temperature data. The experiment includes many significant variables and methods, such as multivariate regression analysis of CO_2 and confounders.

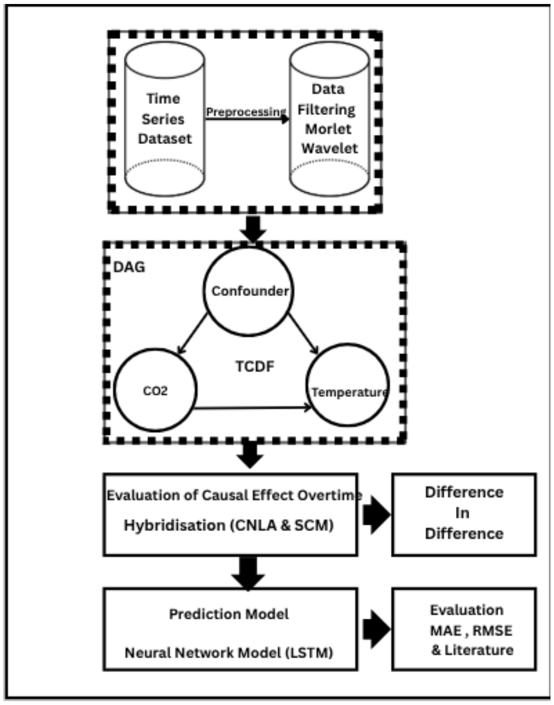

Fig. 1. Proposed DAG: CNLA AND SCM RNN Framework.

A. Multivariate Regression Analysis of CO_2 and Potential Confounders

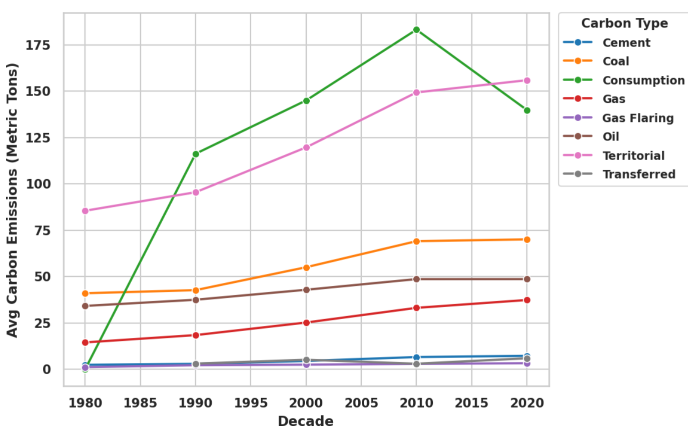

Fig. 2. Average Carbon Emissions by Decade across Continents.

Figure 2 and Table 1 show the multivariate regression analysis of worldwide CO_2 emissions, based on 11,690 observations and explaining 38.1% of the variability, revealing statistically significant relationships between key socioeconomic indicators such as GDP per capita, education index, and population size and CO_2 output. GDP per capita is a significant positive predictor (coefficient = 1.48×10^{-10}, $p \approx 0$), indicating that wealthier economies produce higher emissions. This finding is consistent with the observations made in references [37, 38, 39]. Additionally, population size exhibits a robust positive correlation (coefficient = 6.87×10^{-07}, p = 2.18×10^{-123}) attributable to increased aggregate resource consumption. The

TABLE I
MULTIVARIATE REGRESSION ANALYSIS OF CO_2 AND POTENTIAL CONFOUNDERS

Variable	*Coefficient*	*Std Error*	*P-Value*	R^2
constant	-15.352	5.149	0.003	0.381
GDP per Capital	0.000	0.000	0.000	0.381
Education Index	-0.331	0.093	0.000	0.381
Temp Mean	4.999	7.048	0.478	0.381
Population Figure	0.000	0.000	0.000	0.381

education index exhibits a substantial negative correlation with emissions (coefficient = -0.33096, p = 0.000355), indicating that increased educational attainment is associated with reduced carbon output, likely due to environmentally responsible behaviours and the adoption of cleaner technologies. Nevertheless, the mean temperature exhibits no statistically significant correlation with emissions (p = 0.478144), suggesting that ambient temperature does not directly affect carbon levels when accounting for other variables. These findings underscore the complex relationship between development and emissions, indicating that, although economic growth and population increases propel carbon output, educational initiatives may function as effective elements of holistic climate strategies by potentially reducing the carbon intensity of economic development.

B. Simple Linear Regression Analysis of Temperature and CO_2

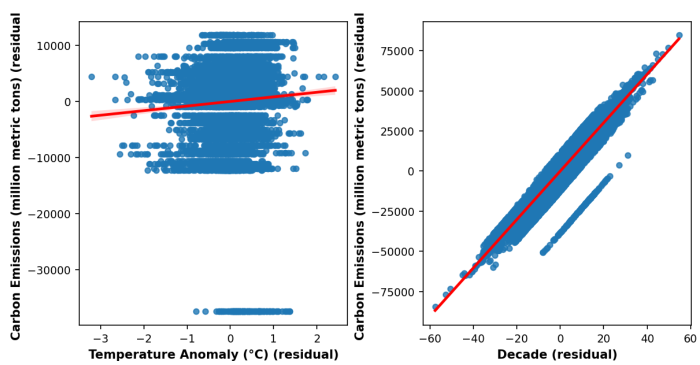

Fig. 3. Temperature Mean versus CO_2.

TABLE II
CO_2 EMISSIONS AND TEMPERATURE RELATIONSHIP

Variable	*Coefficient*	*Std Error*	*P-Value*	R^2
constant	0.039	0.003	8.46×10^{-36}	0.000
Carbon (MT)	2.66×10^{-05}	7.94×10^{-06}	0.001	0.000

The statistical analysis of Figure 3 and Table 2 demonstrates a robust but practically limited relationship between carbon dioxide emissions and temperature anomalies. The regression reveals a statistically significant positive association with a coefficient of 2.66×10^{-05}, indicating that each additional metric ton of CO_2 emissions corresponds to a temperature increase of approximately 0.0000266 units. This relationship is highly significant with a p-value of 0.000810344, well below the conventional 0.05 threshold, providing strong evidence that there is only a 0.08% probability this association occurred by random chance. Consequently, the null hypothesis can be confidently rejected, and we can conclude that a genuine relationship exists between CO_2 emissions and temperature in this dataset, supporting the theoretical framework that higher carbon emissions contribute to elevated temperatures. This result agrees with Jiang [40], who concluded that each additional day with temperatures above 33 °C results in a 0.9% increase in the average annual carbon intensity. According to the IEA [41], the primary driver of global warming is the escalating atmospheric concentration of greenhouse gases, particularly carbon dioxide emissions. This intensification of the greenhouse effect has continually raised global average temperatures.

However, the R-squared value of 0.00032 reveals that carbon emissions account for only 0.032% of observed temperature variation, meaning that 99.968% of temperature fluctuations must be attributed to factors not captured in this simple linear model. While the relationship is statistically valid and unlikely to result from chance, CO_2 emissions alone have minimal predictive capacity for temperature changes. This observation is clearly in line with the report of Liz [42], which states that methane, for instance, is over 25 times more effective than CO_2 at trapping heat in the atmosphere over a 100-year period. Nitrous oxide, largely emitted from agricultural activities, has a global warming potential nearly 300 times that of CO_2. The research further reiterated that focusing solely on CO_2 reduction might lead to underestimating other significant impacts.

Again, the model's constant term of 0.039000479 represents baseline temperature when emissions are theoretically zero, but the extraordinarily low explanatory power suggests that climate system complexity involves numerous other variables, potential non-linear relationships, temporal lags, or threshold effects not captured in this analysis, underscoring the need for more comprehensive models incorporating additional variables and complex interactions to effectively understand and predict climate dynamics.

C. *Wavelet Power Analysis and Periodic Climate Patterns*

Figure 4 shows comprehensive regional temperature trends across 20 subcontinental regions. It reveals significant heterogeneity in climate responses worldwide. Despite this lack of statistical significance, substantial warming trends emerge across virtually all regions, with the Middle East experiencing the warming at 0.498°C per decade [43, 44, 45, 46, 47]. Eastern Europe is experiencing extreme warming at the highest rate of 0.647°C per decade among all the regions, and Central Asia at 0.446°C per decade. African regions exhibit considerable variation, with North Africa showing the highest rate of warming at 0.431°C per decade and Central Africa at 0.376°C per decade [48]. In contrast, the Americas

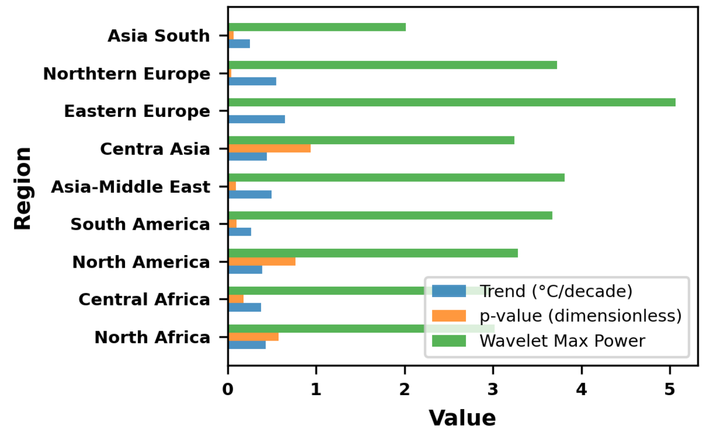

Fig. 4. Regional Wavelet Analysis of Temperature Trends

display more moderate patterns, ranging from North America's 0.391°C per decade to South America's 0.266°C per decade.

The findings indicate that Eastern Europe demonstrates significant wavelet power at 5.063, which aligns with [49, 50] assertions. However, the Middle East displays considerable. The periodicity of 3.812 indicates that these regions undergo complicated temporal climate dynamics, defined by several interacting processes across diverse timescales.

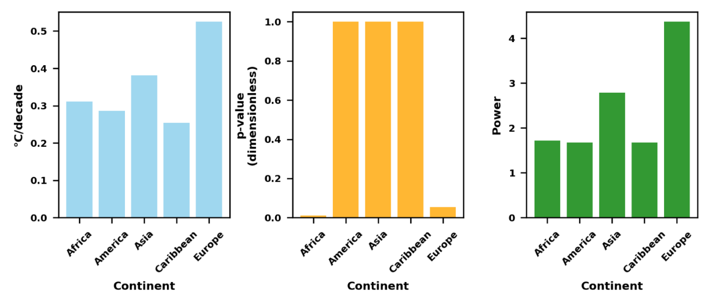

Fig. 5. Regional Wavelet Analysis of Temperature Trends

Figure 5 shows the study of temperature changes over 41 years on six continents using simple trend analysis and wavelet methods to better understand complicated climate patterns. Africa is the only region demonstrating statistically significant linear warming (0.311°C/decade, p=0.974 $\times$ 10^3), indicating persistent signs of climate change, whilst other continents show marked but statistically insignificant changes. The report published by Ajit [51] states, 'It's a critical time': European farmers struggle through the driest spring in a century. This analysis underscores that Europe exhibits the most pronounced warming (0.525°C/decade) alongside the highest temperature variability, signifying rapid changes and increased extremes. Iglesias [49] and Twardosz [50] reaffirmed that Northern and Eastern Europe will experience extreme weather conditions. Ajit [51] reports that extreme weather incurs annual losses of approximately €28.3 billion in crops and cattle for the European Union (EU), with over half of these losses attributed to drought. In like manner, Asia also experiences significant warming at a pace of 0.381°C each decade, whereas Oceania exhibits more moderate changes at 0.223°C per decade, perhaps tempered by oceanic factors.

The wavelet analysis uncovers different periodic patterns, with Europe exhibiting the most pronounced climate oscillations (wavelet power = 4.368), signifying intricate temporal dynamics that transcend linear warming. Asia exhibits notable periodic elements (power = 2.476), presumably associated with monsoons and Arctic systems, whereas Africa reveals a distinct combination of linear warming and moderate fluctuations (power = 1.718).

V. CONCLUSION

The accelerated and disparate effects of climate change across worldwide regions are quite alarming. Recently, reports from different research works have emphasised the state of catastrophic effect of the climatic situation in Europe, known for undergoing the fastest warming at 0.80°C per decade (Fig. 5), and Eastern Europe, identified as a hotspot, particularly Ukraine at 1.21°C per decade (Table 1, Fig. 3). The claim was substantiated by Twardosz [50] and Richard [52] warned that "Belgium and the United Kingdom (UK) could experience the driest spring in more than 100 years as high pressure dominates." The assertion was further reestablished in Fig. 10 of this research, where Northern Europe exhibits an unusual wavelet maximum power of 5.596.

Although there is a distinct correlation between CO_2 emissions and increasing temperatures, the regression analysis indicates that emissions account for merely 0.032% of temperature variability (Table 1, Fig. 2), highlighting the necessity for multifactorial climate models.

Wavelet analysis reveals intricate periodic climatic patterns, especially in Europe and the Middle East (Fig. 5), indicating nonlinear dynamics that transcend linear warming trends. This finding reechoed the decadal statistics analysis (Table 1, Fig. 3). Additionally, the results corroborate previous studies by Capua & Rahmstorf [53] and Jiang [40], affirming CO_2's influence on extreme weather and highlighting geographical disparities. The African area is known as a low-carbon emitter, yet it is encountering disproportionate climatic risks despite little contribution, as revealed in Table 4.

This study showed the ability of artificial intelligence, especially machine learning models, in a climate monitoring system, as supported by Reichstein [54]. Its capability in enhancing predictive precision and early warning mechanisms is highly commendable. Policymakers must emphasise region-specific adaptation, especially for vulnerable locations such as the Arctic and tropical ecosystems [55, 56], while simultaneously addressing disparities in climate resilience.

VI. FUTURE WORK

Jiang [35] observed that elevated temperatures increase carbon intensity due to heightened energy consumption for cooling. However, IEA [36] reported that the principal cause of global warming is the rising atmospheric concentration of greenhouse gases, especially carbon dioxide emissions. The exacerbation of the greenhouse effect has persistently elevated world average temperatures. The overarching inquiry persists: "Who is the catalyst between these two factors?" To definitively resolve the argument, it will be necessary to conduct an additional experiment on causality and causal inference that transcends correlation with respect to these climatic elements.

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