Journal of Informatics and Web Engineering

Vol. 3 No. 2 (June 2024) eISSN: 2821-370X

Temporal Climatic Shifts in Henan Province: A 16-decades Perspective Through Regression, SARIMA, and NAR Modeling

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Abstract - Global warming is having a significant impact on all aspects of human production and life. This study employs a cross-sectional analysis to investigate the temporal dynamics of average temperature changes in Henan Province, China, from 1851 to 2012. Utilizing the Berkeley Earth Surface Temperature Data and the Daily Meteorological Dataset of China National Surface Weather Station v3.0, we applied regression analysis, Seasonal Autoregressive Integrated Moving Average (SARIMA), and Nonlinear Autoregressive Network (NAR) models to predict temperature trends. Results indicate a significant warming trend over the 160-year period, with the models demonstrating strong predictive performance, albeit with some variability. The study underscores the increasing temperatures' implications for the province's agricultural sustainability and ecological balance. This study highlights the urgency of understanding and mitigating climate change's impacts, particularly in Henan Province, China, for the sake of agricultural sustainability, water resources, and public health. The research findings contribute valuable insights and methodologies to climate data analysis, aiding future predictions and policy-making efforts.

Keywords- Climatic predict, Temperature change, Henan Province, Data-driven analysis, SARIMA model; NAR network

Received: 17 January2024; Accepted: 19 March 2024; Published: 16 June 2024

I. INTRODUCTION

Climate change and global warming represent some of the most pressing challenges facing humanity in the 21st century[1] The escalating impacts of climate change are far-reaching[2], affecting ecosystems, biodiversity, agriculture, and human health across the globe. The Earth's climate system is incredibly complex[3], intertwined with various elements including atmospheric conditions, ocean currents, and terrestrial ecosystems, all of which contribute significantly to the planet's overall health and stability. The escalating rise in global temperatures[4], driven predominantly by human activities such as fossil fuel combustion and deforestation, is causing substantial alterations in weather patterns, leading to more frequent and severe weather events, and affecting biodiversity and ecosystems worldwide [5].

The importance of understanding and mitigating the effects of climate change cannot be overstated. The Earth's climate is a key determinant of biodiversity and the functionality of ecosystems[6], which in turn are crucial for services essential to human survival, such as food production, water supply, and disease regulation. Moreover, climate change

Journal of Informatics and Web Engineering
https://doi.org/10.33093/jiwe.2024.3.2.12

Published by MMU Press. URL: https://journals.mmupress.com/jiwe

poses a unique challenge[7] to human production and livelihoods, potentially exacerbating resource scarcity, and economic inequality, and causing displacement of populations [8].

In light of these challenges, there is a growing need for detailed, region-specific climate studies[9]. This paper focuses on Henan Province, China, a region that has experienced notable climatic variations in the past century. Henan, with its significant agricultural output and population, is particularly susceptible to the impacts of climate change. Understanding the temperature trends in this region is therefore crucial for developing adaptive strategies to mitigate the adverse effects on agriculture, water resources, and public health[10].

Our research aims to analyze the year-by-year average temperature changes in Henan Province from 1841 to 2012. Through this historical lens, we seek to uncover patterns and trends that could inform future climate predictions and policy-making. The study is grounded in a cross-sectional approach, employing methodologies from data science, computer science, and climate science.

To achieve a comprehensive analysis, we employ various methodological approaches, including regression analysis, Seasonal Autoregressive Integrated Moving Average (SARIMA) models, and deep neural networks. These methods provide a diverse perspective on the data, allowing for a robust understanding of temperature trends. Each technique offers unique insights: regression analysis helps identify linear trends and correlations, SARIMA models are adept at capturing seasonal variations and patterns, and deep neural networks leverage their predictive power to model complex, non-linear relationships in the data.

The comparative analysis of these methods is a core aspect of this research, enabling us to evaluate their respective strengths and weaknesses in the context of climate data analysis. This approach not only enhances the reliability of our findings but also contributes to the broader field of climate data analysis by providing a detailed assessment of various predictive methodologies.

Our analyses have led to the conclusion that the temperature in Henan Province has shown a gradual increase over the past 150 years. This finding aligns with global trends of rising temperatures and provides a specific regional context to the broader narrative of climate change. It also serves as a case study for the application of diverse data science techniques in climate research, offering insights that could be applied in other regions and contexts.

The following sections are organized as: Section II Related Works: Reviews existing literature and studies related to climate change, with a focus on temperature analysis and predictive modeling techniques. Section III Materials and Methods: Details the methodologies used in the research, including data sources, data processing techniques, and descriptions of the regression analysis, SARIMA, and deep neural network models. Section VI Results and Discussion: Presents the findings from the analyses and discusses their implications, comparing the effectiveness and insights derived from each methodological approach. Section V Conclusion: Summarizes the research findings, discusses the limitations of the study, and suggests areas for future research.

II. LITERATURE REVIEW

The field of climate prediction has witnessed significant advancements over the past few decades, propelled by improvements in data collection, computational methods, and a deepening understanding of climate dynamics. This section reviews key studies that have contributed to this field, focusing particularly on methods relevant to our study of temperature trends in Henan Province.

Kashinath et. al.[11] survey methods for integrating physics and domain knowledge into ML, and through ten case studies, demonstrate their successful application in weather and climate forecasting. This approach results in more physically consistent models with shorter training times and better data efficiency. Pokhrel et. al. [12] predict the hydrological responses to climate change in the upstream catchment of the Kase River basin having an area of 225 km2 by using the MIKE SHE model and GIS. The data generated from RCM 20 (Regional Climate Model) were utilized under scenario 1 to predict the future period 2081 – 2100 in the river basin.

Using physical models, Lertzman-Lepofsky et. al. [13]estimate the frequency of exceeding the thermal optimum (T) or critical evaporative water loss (EWL) limits, with and without shade- or water-seeking behaviors. Lertzman-Lepofsky et. al. also conclude that temperature and water loss act synergistically, compounding the ecophysiological risk posed by climate change, as the combined effects are more severe than those predicted individually. Chen et. al. [14] conclude that climate change and Land Use/Land Cover (LULC) change both have an important impact on the rainfall-runoff processes. They establish the SWAT (Soil and Water Assessment Tool) model for the Jinsha River Basin, and use the method of scenarios simulation to study the runoff response to climate change and LULC change.

Kimura et. al. [15]adopt deep neural networks (DNNs) to understand the long-term relationships between air temperature and surface water temperature, because DNNs can easily deal with nonlinear data, including uncertainties, that are obtained in complicated climate and aquatic systems. Continuous data (i.e., air temperature) ranging over 150 years to pre-training to climate change, which were obtained from climate models and included a downscaling model, were used to predict past and future surface water temperatures in the reservoir.

Under the condition of future climate change, the center of gravity of Cossus Linnaeus will move to high latitudes. Danneyrolles et. al.[16] investigate the effects of climate, tree species composition, and other landscape-scale environmental variables upon boreal forest regrowth following clearcut logging in eastern Canada. Predicted increased regrowth rates were mainly associated with increased temperature, while changes in climate moisture had a minor effect. A called DCT(“discrete cosine transform”)-based least-squares predictive model is proposed by Yang [17] for forecasting hourly AQI (“air quality index”) from time-series analysis or data-driven modeling perspective.

Lee et. al.[18] develop statistical reservoir inflow forecast models for a reservoir watershed, based on hydroclimatic teleconnection between monthly reservoir inflow and climatic variables. The predictability of such a direct relationship has not been assessed yet at the monthly time scale using the statistical ensemble approach that employs multiple data-driven models as an ensemble.

Xu et. al.[19] focus on the application of a hybrid arima–svr model based on the spi for the forecast of drought—a case study in Henan province, China. The hybrid ARIMA–support vector regression (SVR) model proposed is based on the advantages of a linear model and a nonlinear model. Comparing the measured data with the predicted data from the model shows that the combined ARIMA–SVR model had higher prediction accuracy than the single ARIMA model and that the predicted results 1–2 months ahead show reasonably good agreement with the actual data.

Ayaz et. al. [20] compare various empirical models and data-driven algorithms to predict ET0 using various climate variables. The dataset consists of daily meteorological data over a period of 51 years (1965–2015) for Hyderabad, the largest city of the Indian state, Telangana, with a semi-arid climate. The multilayer perceptron (MLP) and radial basis function (RBF) neural networks were employed to predict these three land surface temperatures (LST) series. Ojo et. al.[21] conclude that soft-computing intelligence techniques especially multilayer perceptron networks are suitable for the prediction of land surface temperature series over Nigeria for practical purposes.

These studies collectively underscore the complexity and multidisciplinary nature of climate prediction. They highlight the need for continuous innovation in methodological approaches and emphasize the importance of region-specific models to address local climate challenges.

III. MATERIALS AND METHODS

A. Data Collection

1) Berkeley Earth Data

The Berkeley Earth Surface Temperature (BEST) project offers one of the most comprehensive datasets for global land temperatures. Developed by a team of scientists aiming to address the limitations of existing temperature data, it provides a new and independent analysis of Earth's surface temperature records.

BEST combines 1.6 billion temperature reports from 16 pre-existing data archives, offering an extensive temperature record. It includes both land and ocean readings, although our study primarily utilizes land temperature data. The dataset spans from the 1750s to the present, with a focus on land temperature data starting in the 1800s. It provides monthly temperature averages, allowing for long-term trend analysis. It uses advanced statistical techniques to address common issues in climate data, such as data discontinuity, station moves, and instrument changes. The dataset undergoes rigorous quality controls and bias adjustments, ensuring high data accuracy. The dataset offers near-global coverage, filling gaps in areas where conventional datasets have limited reach. Table 1 shows the key meteorological elements in the BEST.

Table 1. Key Meteorological Elements In BEST (the Berkeley Earth Surface Temperature)

Data	Example
Date	1855-01-01
Average Temperature	-1.79
Average Temperature Uncertainty	1.186
State	Henan
Country	China
Latitude	36.17N
Longitude	130.23E

Due to the incomplete coverage of meteorological data for China and other regions in the early years of this dataset, the data for Henan Province in China are available from 1841 until 2012, for which records are available. However, the early meteorological data records have large errors and low reliability, so in this study, the meteorological data for the 10-year period from 1841 to 1850 are discarded, and thus we focus on the climate change in Henan Province, China, between 1851 and 2012, which is a period of 161 years.

We focus on data relevant to Henan Province, China, from the mid-19th century to 2012.

2) Meteorological Dataset of China National Surface Weather Station (MDC) (v3.0)
The MDC v3.0 is a specialized dataset focused on China’s meteorological conditions, managed by the China Meteorological Administration. It provides detailed meteorological observations from various surface weather stations across China.

Concentrated on China, this dataset provides a detailed insight into the country's climatic conditions. It includes daily measurements of basic meteorological elements like temperature, precipitation, and wind speed. The dataset's daily resolution allows for a more granular analysis of recent climate trends. The MDC v3.0 covers nearly 60 years, providing a valuable record of China's recent climatic history. As an official dataset, it follows strict data collection and processing protocols, ensuring high accuracy and reliability. We utilize the DMDC v3.0 dataset to analyze more recent and detailed climatic trends in Henan Province, focusing on the period it covers. This dataset complements the broader historical perspective provided by the BEST dataset.

B. Data Preprocessing

1) Preprocessing of Berkeley Earth Data
We preprocessed the Berkeley Earth data in the following 4 steps.

- Geographic Filtering: We extract data relevant to Henan Province. This involves identifying and isolating temperature records from geographic coordinates corresponding to this region.
- Time Period Selection: Given our study's focus, we select the time range from the earliest available records to 2012.
- Calculating Annual Averages: To maintain consistency with the DMDC v3.0 data and to facilitate year-on-year trend analysis, we convert monthly averages into annual averages.
- Data Cleaning and Normalization: We address any missing or anomalous data through interpolation and other statistical techniques. The data is then normalized to ensure comparability with the DMDC dataset.

2) Preprocessing of MDC v3.0 Data
We preprocessed the Meteorological Dataset of China National Surface Weather Station (MDC) (v3.0) in the following 3 steps.

- Data Extraction and Selection: We extract data for Henan Province, ensuring the temporal overlap with the BEST dataset for comparative analysis.
- Data Quality Assurance: We conduct a thorough quality check, verifying the accuracy and consistency of the data points.
- Data Alignment with BEST: To ensure coherence in our comparative analysis, we align the DMDC v3.0 data with the preprocessed BEST data in terms of temporal coverage and format.

A critical aspect of our methodology is maintaining consistency between the two datasets, particularly in terms of temporal resolution and geographical relevance. We employ various statistical methods to analyze and interpret the data, including trend analysis, anomaly detection, and correlation studies.

IV. RESULTS AND DISCUSSIONS

A. Geographic Location Analysis of Henan Province

Henan Province, located in the central part of China, is a region with diverse climatic and geographical characteristics, playing a significant role in both historical and contemporary contexts. In this section, we delve into a detailed description of Henan Province, focusing on its location, climatic characteristics, and geography.

1) Location of Henan Province

Henan Province lies in the east-central part of China, a crucial link between the northern and southern parts of the country. It is bounded by several provinces: Shaanxi to the west, Hebei to the north, Shandong to the northeast, Anhui to the southeast, and Hubei to the south. The Yellow River, one of the most significant rivers in China and a cradle of ancient Chinese civilization, flows through the northern part of the province, contributing substantially to the region's historical and cultural identity. The location of Henan Province in China is shown in Figure 1.

Figure 1. Location of Henan Province in China

2) Climatic Characteristics of Henan Province

Henan experiences a continental climate, with distinctive seasonal variations:

- Temperature Variability: The province experiences hot summers and cold winters. Average summer temperatures typically range around 27°C, but can exceed 35°C during heatwaves. Winters are cold with average temperatures around freezing, though colder spells can bring temperatures well below 0°C.
- Precipitation Patterns: Henan receives varied precipitation throughout the year. The province sees most of its rainfall during the summer months, influenced by the East Asian monsoon. This seasonal rainfall is crucial for agriculture, particularly for crops like wheat and maize. The annual precipitation averages between 500 to 900 mm, but can vary significantly across different areas of the province.
- Seasonal Extremes: The region is prone to extreme weather events, including droughts, floods, and occasional severe storms, particularly in the transition periods between seasons.

3) Geography of Henan Province

Henan's geography is diverse, ranging from mountainous terrains to fertile plains:

- Mountainous Regions: The western and southern parts of Henan are dominated by mountain ranges, such as the Funiu and the Tongbai mountains. These regions have a significant impact on the local climate, often experiencing lower temperatures and higher precipitation compared to the plains.
- Plains and Basins: The North China Plain extends into the northern part of Henan, characterized by flat, fertile land. This region, particularly along the Yellow River, is one of China's most important agricultural areas, known for its high productivity.
- River Systems: Apart from the Yellow River, Henan is home to several other major rivers, such as the Huai and the Luo. These rivers not only play a critical role in irrigation and agriculture but also influence the local climate, especially in terms of humidity and precipitation patterns.
- Urban and Rural Landscapes: Henan has a mix of urban and rural areas. Major cities like Zhengzhou and Luoyang are rapidly urbanizing and industrializing, which influences local microclimates. In contrast, vast rural areas, predominantly in the agricultural plains and mountainous regions, maintain a more natural landscape.
- Ecological and Environmental Issues: The province faces several ecological challenges, including air pollution, soil erosion, and water scarcity. These issues are exacerbated by the province's rapid industrial development and intensive agriculture.
- Biodiversity: Despite environmental pressures, Henan is home to a variety of flora and fauna, particularly in its mountainous regions. These areas provide critical habitats for numerous species and contribute to the overall ecological diversity of the province.

The geographical and climatic diversity of Henan Province makes it an interesting and complex area for climate studies. Understanding the interaction between these geographical features and climatic patterns is crucial for accurate climate modeling and prediction. This complexity adds both challenges and opportunities to our study, as we seek to analyze and understand the temperature trends and their implications in this region.

B. Climate Change in the Past 160 Years

Figure 2 illustrates the trend of average annual temperatures in Henan Province over a span of approximately 160 years, from around 1850 to 2010. Compared to the temperature in 1860, the temperature in 2010 has risen more than 2 degrees. We summarized and analyzed the average temperatures over these 16 decades.

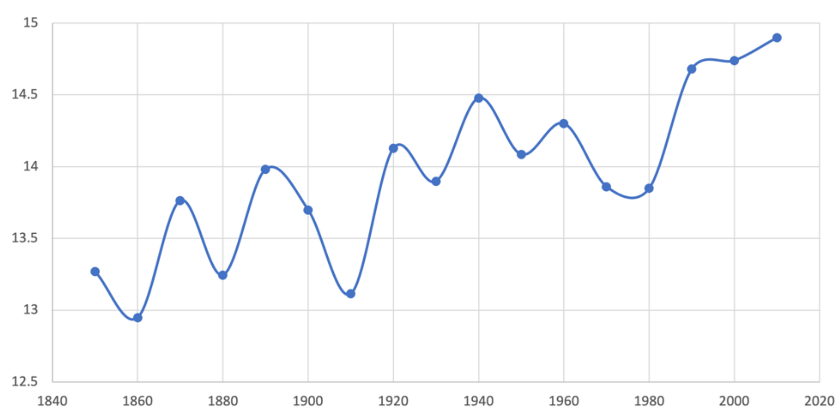

Figure 2. Average temperature change of Henan Province in the last 160 years

There is a discernible upward trend in average temperatures over the period, indicative of warming. This pattern is consistent with global observations of climate change and rising temperatures. The graph exhibits significant fluctuations from decade to decade, which is normal in climate data due to natural variability. However, despite these fluctuations, the general trend shows an increase.

The period from 1850 to around 1910 shows notable variability. This could be due to a smaller number of data sources, less accurate temperature recording methods at the time, or natural climatic variations. Late 20th Century to Early 21st Century Rise: There is a sharp increase in average temperatures from around 1970 onwards, with particularly steep changes in the last few decades of the record. This corresponds with the global increase in temperatures associated with anthropogenic climate change.

The rise in average temperatures in the latest part of the graph is of particular concern, as it suggests an acceleration in warming. This could have significant implications for Henan Province's agriculture, water resources, and overall climate resilience. The upward trend in temperatures could be influenced by several factors, including increased greenhouse gas emissions, urban heat island effects from expanding urban centers in Henan, and changes in land use and cover.

C. Prediction Base Linear Regression Model

A dot graph is shown in Figure 3. The graph displays the analysis of the annual average temperature data for Henan Province from 1851 to 2012 using a regression model. Each blue dot represents the actual recorded annual average temperature for a given year. The spread of the dots suggests variability in temperature from year to year. The yellow dots denote the temperatures predicted by the regression model for each corresponding record number. These predictions are the result of the model's attempt to fit a line that best represents the trend in the actual data.

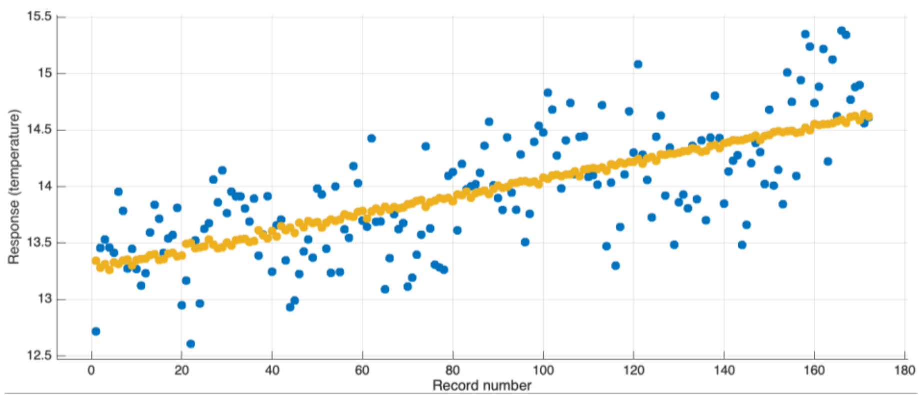

Figure 3. Temperature prediction base on regression model

The yellow dots form a clear ascending trend line, suggesting that the regression model has identified a long-term trend of increasing temperatures over the time period analyzed. The regression model's predictions align well with the actual data, indicating a long-term warming trend, with year-to-year variability reflecting the complex nature of climatic changes in the region.

D. Prediction Base SARIMA Model

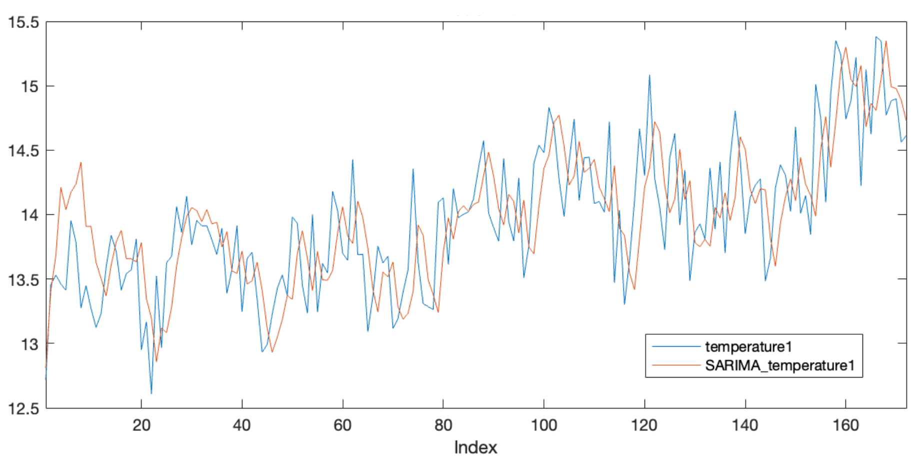

Figure 4. Temperature prediction base on regression model

The Figure 4 depicts the results of a SARIMA (Seasonal Autoregressive Integrated Moving Average) model applied to the annual average temperature data of Henan Province from 1851 to 2012. Blue line represents the actual recorded temperatures each year, showing fluctuations over time. Red line Depicts the temperatures predicted by the SARIMA model. The close alignment with the blue line suggests that the model has a good fit with the actual data. The SARIMA model parameters indicated (autoregressive order of 1, degree of integration of 2, and seasonal period of 11) are designed to capture both the trend and seasonal components in the data. The seasonal period of 11 is set to linked with sunspot activity, which is known to have an approximately 11-year cycle that can affect climate patterns.

The model can be described as:

$$(1 - \phi_1 L)(1 - L)^2 y_t = c + (1 + \theta_1 L + \theta_2 L^2 + \theta_3 L^3)\varepsilon_t \quad (1)$$

The SARIMA model appears to fit the actual data well, capturing the central trend and seasonal variations in the temperature data of Henan Province. In summary, the SARIMA model's predictions align closely with the actual observed data, suggesting it is a suitable model for analyzing and forecasting the annual average temperature in Henan Province within the historical range it was trained on.

E. Prediction Base NAR Network Model

The graph below represents the results of a Nonlinear Autoregressive Network (NAR) model applied to the annual average temperature data of Henan Province from 1851 to 2012.

As Figure 5 shown, Training Targets (blue dots) represents actual temperature data points used to train the model. Training Outputs (blue crosses) represents the model's predictions on the training dataset. Validation Targets (green dots) represents actual temperature data points used to validate the model. Validation Outputs (green crosses): The model's predictions on the validation dataset. Test Targets (red dots) represents actual temperature data points used to test the model. Test Outputs (red crosses) represents the model's predictions on the test dataset. Model Response (black line) represents this line represents the model's overall predictions across the combined training, validation, and test datasets. It provides a continuous prediction curve that the model has learned based on the input data. Error Bars (orange lines) represents these vertical lines indicate the error or deviation between the actual data points and the model's predictions. The length of the bar represents the magnitude of the error for each data point.

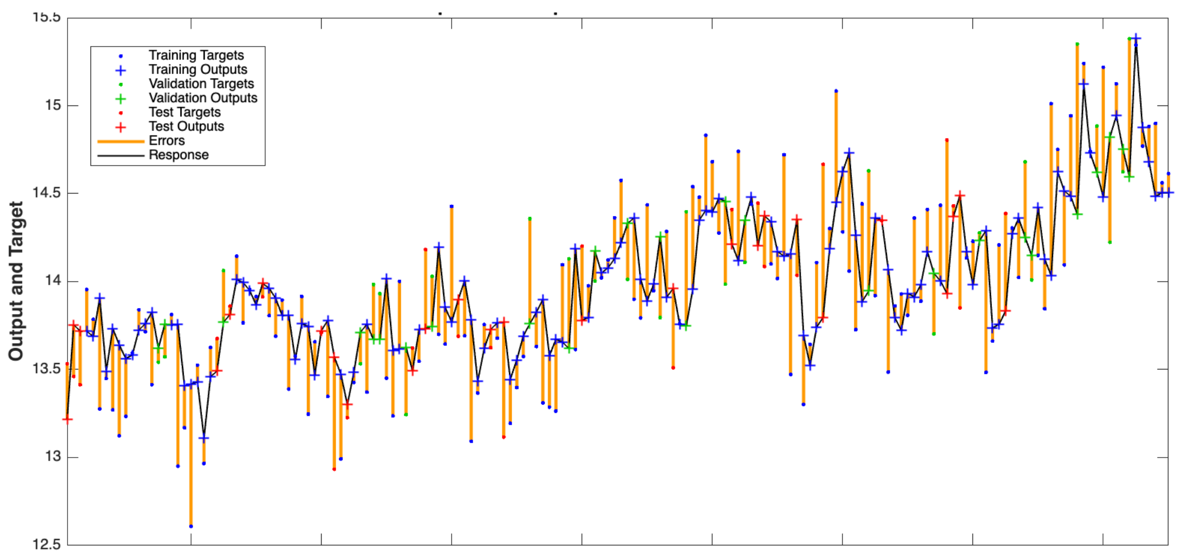

Figure 5. Temperature prediction based on NAR Network model

The black response line closely follows the trends of the actual data points (dots), which suggests that the model has learned the underlying pattern of the data well. The NAR model seems to perform well in capturing the annual temperature trends in Henan Province, with relatively small errors for most data points. The model's effectiveness in the test phase is indicative of its potential utility for future temperature predictions, although the instances of larger errors should be further investigated to improve the model's accuracy.

V. CONCLUSION

This paper presents a comprehensive analysis of long-term temperature trends in Henan Province, China, from 1851 to 2012, employing various statistical and machine learning models. Utilizing the Berkeley Earth Surface Temperature Data and the Daily Meteorological Dataset of China National Surface Weather Station (v3.0), the study integrates global and local data sources to capture a detailed climatic profile of the region.

The analysis began with preprocessing steps, including geographic filtering of the Berkeley dataset to isolate Henan-specific data, converting monthly to annual averages, and normalizing to ensure consistency with the MDC dataset. Regression analysis, SARIMA, and Nonlinear Autoregressive Network (NAR) models were then applied to the preprocessed data to model and predict temperature trends.

The regression model identified a clear warming trend, consistent with global observations of climate change. The SARIMA model, with parameters tailored to the dataset's seasonality, provided a nuanced fit capturing the cyclical nature of climate variability. The NAR Network model further refined the predictions, closely tracking the actual temperatures and demonstrating the capability to model complex, non-linear interactions within the data.

All models confirmed a significant increase in Henan Province's temperatures over the 161 years. This trend carries profound implications for regional agricultural practices, water resource management, and ecological sustainability. Limitations of this study include its exclusive focus on temperature trends, reliance on historical data with potential limitations, omission of future projections, and potential uncertainties associated with the methodology and model assumptions. Future research could focus on exploring the specific drivers of temperature trends in Henan Province, examining the impacts beyond agriculture, assessing vulnerability and adaptive capacity, and including other climatic variables.

ACKNOWLEDGEMENT

The authors received no funding from any party for the research and publication of this article.

AUTHOR CONTRIBUTIONS

Lin Qing: Conceptualization, Formal Analysis, Methodology, Writing, Validation
Ang Ling Weay: Investigation, Methodology, Resources, Supervision
Shao Yiyang: Data Curation, Visualization, Review & Editing
Sellappan Palaniappan: Resources, Supervision

CONFLICT OF INTERESTS

No conflict of interests were disclosed.

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