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A Generalised Additive Model and Deep Learning Method for Cross-Validating the North Atlantic Oscillation Index

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Abstract: This study introduces an innovative analytical methodology for examining the interconnections among the atmosphere, ocean, and society. The primary area of interest pertains to the North Atlantic Oscillation (NAO), a notable phenomenon characterised by daily to decadal fluctuations in atmospheric conditions over the Northern Hemisphere. The NAO has a prominent impact on winter weather patterns in North America, Europe, and to some extent, Asia. This impact has significant ramifications for civilization, as well as for marine, freshwater, and terrestrial ecosystems, and food chains. Accurate predictions of the surface NAO hold significant importance for society in terms of energy consumption planning and adaptation to severe winter conditions, such as winter wind and snowstorms, which can result in property damage and disruptions to transportation networks. Moreover, it is crucial to improve climate forecasts in order to bolster the resilience of food systems. This would enable producers to quickly respond to expected changes and make the required modifications, such as adjusting their food output or expanding their product range, in order to reduce potential hazards. The forecast centres prioritise and actively research the predictability and variability of the NAO. Nevertheless, it is increasingly evident that conventional analytical methods and prediction models that rely solely on scientific methodologies are inadequate in comprehensively addressing the transdisciplinary dimension of NAO variability. This includes a comprehensive view of research, forecasting, and social ramifications. This study introduces a new framework that combines sophisticated Big Data analytic techniques and forecasting tools using a generalised additive model to investigate the fluctuations of the NAO and the interplay between the ocean and atmosphere. Additionally, it explores innovative approaches to analyze the socio-economic response associated with these phenomena using text mining tools, specifically modern deep learning techniques. The analysis is conducted on an extensive corpora of free text information sourced from media outlets, public companies, government reports, and newspapers. Overall, the result shows that the NAO index has been reproduced well by the Deep-NAO model with a correlation coefficient of 0.74.

Keywords: North Atlantic oscillation; generalised additive model; deep learning; ocean–atmosphere interaction

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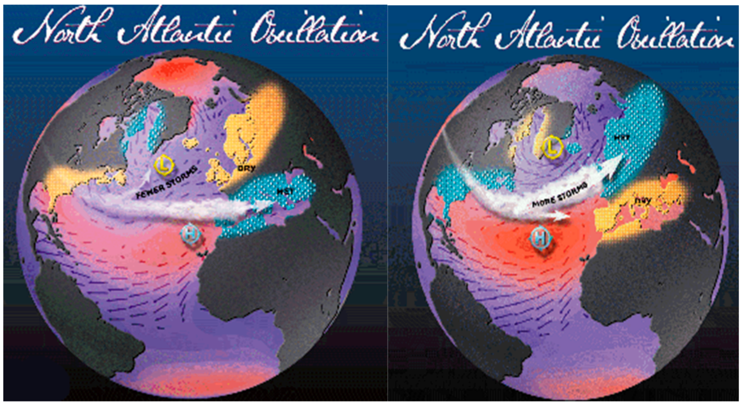
Citation: Wahiduzzaman, M.; Yeasmin, A. A Generalised Additive Model and Deep Learning Method for Cross-Validating the North Atlantic Oscillation Index. *Atmosphere* **2024**, *15*, 987. https://doi.org/10.3390/atmos15080987

Academic Editors: Tymon Zieliński and Anthony R. Lupo

Received: 6 July 2024
Revised: 26 July 2024
Accepted: 16 August 2024
Published: 17 August 2024

1. Introduction

The North Atlantic Oscillation (NAO) is the predominant way in which atmospheric variability occurs in the North Atlantic region [1–5]. It is characterised as the primary mode of daily to decadal oscillations of the wave. It regulates the primary meteorological patterns across the North Atlantic, North America, Europe, and to some extent, Asia. A negative phase (Figure 1a) of the NAO is linked to a substantial arching configuration of the jet stream in the North Atlantic and a southward-shifted storm track in Europe. Consequently, this results in colder and drier than average weather conditions in Northern Europe, while Southern Europe experiences wetter weather. An anomalous strength of the semi-stationary Icelandic low and Azores high-pressure regions is observed during a positive phase (Figure 1b) of the NAO. This phenomenon leads to a more zonal jet stream over the North Atlantic and a northward shift of the storm track over Europe. Consequently, Northern Europe experiences wetter and warmer weather, while Southern Europe encounters dry weather. Studying the variability of the North Atlantic Ocean and atmosphere will be a crucial area of focus for the climate and research in the coming decade [3–7].



(**a**) (**b**)

Figure 1. The North Atlantic Oscillation has two distinct phases: the negative phase on the left (**a**) and the positive phase on the right (**b**) [2].

The winter NAO has significant variability, exerting a considerable impact on weather patterns and climate dynamics throughout interannual to decadal time periods across North America, Europe, and Asia. The NAO variability is a result of internal atmospheric fluctuation, as well as intricate interactions between the atmosphere and the ocean. The variability of the NAO has significant implications for coastal populations, manifesting in various ways such as storm surges, high tide, atmospheric blocking resulting in persistent weather patterns, flooding and drought, sea ice formation, and coastal erosion [2–9].

Skilful forecasts are advantageous to the community. The relevance of winter windstorms to the food systems and insurance sector is significant. The influence of winter temperatures on energy pricing and the potential disruption of transport networks have been seen [8,9]. The enhancement of the NAO forecast also results in financial benefits by reducing electricity consumption during the winter season in Scandinavian nations through the implementation of hydropower generation and the energy market [10,11]. The NAO variability and prediction is an ideal test subject for developing innovative transdisciplinary research frameworks because of the strong connections between the atmosphere, the ocean, and society.

The NAO's adept forecasts [8–13] yield significant advantages for society, encompassing river dynamics, transportation, sea ice extent, energy production, water resource administration, insurance, and food systems. Notable instances include the effects on hydropower production and energy markets in Scandinavia, as well as the management of wind power in the UK [14–16]. There are a limited number of studies that rigorously quantify the impacts of the NAO. However, a significant challenge arises from the inherent difficulty in quantifying the socio-economic response to this phenomenon. This difficulty arises from the fact that a substantial portion of the pertinent information is disseminated through news portals and other communication media. Consequently, extracting and analysing this information for the scientific community is a complex task. The subsequent obstacle pertains to the formulation of the analysis–prediction framework [17–20]. Skilled NAO prediction is crucial for enhancing numerical models of atmospheric dynamics, which serve as the foundation for operational weather forecast services. However, the progress in these models is hindered by the intricate nature of the climate system and the models themselves. According to recent research [13], it has been proposed that the accuracy of the NAO winter forecast can be enhanced by integrating information regarding the external factors influencing the NAO tropical variability, such as the El Nino Southern Oscillation (ENSO) and the Madden–Julian Oscillation (MJO), Arctic Sea ice, and solar variability. The intricate interactions between the ocean and atmosphere are difficult to unravel using numerical models or standard analysis methods [13]. Therefore, the third task is to create a proficient model.

Novel data analysis approaches are emerging as viable alternatives to dynamical models. One illustration of Big Data analysis approaches encompasses the utilization of extensive text mining tools and the application of deep learning in time-series analysis. These techniques can be employed to examine the extensive textual resources (such as newspaper communications like the New York Times Annotated Corpus, social media, and public reports) with the aim of measuring the effects on the power generation sector and the decision-making process at the federal level concerning public services in the countries impacted by the NAO. But, it should be noted that much less useful information is available on the future NAO in the meteorological and oceanographic data used by previously published studies on predicting the wintertime NAO. Past weather information has been extracted based on whatever information was found. If information was found, then we coded this as 1, if not, then it was coded as 0. The techniques [17,20–22] have the potential to be utilised in the identification of optimal communication routes for prediction and forecast services, specifically in terms of facilitating the dissemination of information from the scientific community to society. In addition, there exist novel methodologies for the analysis and prediction of NAO variability. Various research has focused on analysing the portrayal of the NAO in climate models. An autoencoder (AE) is a neural network structure specifically created for the purpose of unsupervised learning. It operates in a comparable manner to Empirical Orthogonal Function (EOF) in terms of diminishing the dimensionality of data and extracting the most significant patterns. AE is distinct from EOF and able to extract intricate and nonlinear patterns. The study by Ibebuchi [23] utilised AE to condense the SLP anomaly data by employing the encoder. During the training process, the AE acquires the ability to reconstruct the input single-layer perceptron data by utilizing the decoder and the encoded representations. The reconstructed patterns are compared to the original input in order to calculate the loss, such as the mean squared error. This loss is then minimised during the training process. This technique facilitates the model in acquiring the fundamental patterns of the data.

This method incorporates a combination of meteorological and oceanic predictors. By incorporating pertinent predictors such as regional sea surface temperature/heat flow indices for oceanic predictors, ENSO, and indices designed to capture stratospheric variability, it is plausible that comparable methodologies might potentially improve the prediction of the NAO. The suggested effort is based on the use of these innovative methods to examine the elements of the atmosphere–ocean–society system (see to Figure 2 for further details).

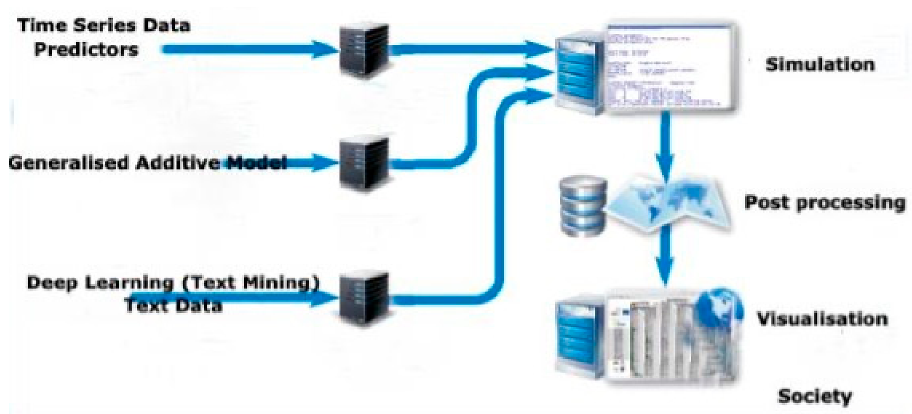


Figure 2. The overall procedures of proposed research study.

This paper aims to achieve the following important objective:

- The objective is to create a novel generalised additive forecast model, referred to as "DeepNAO," which integrates deep learning through text mining sources from textual resources. This model is used for cross-validating the NAO index.

2. Data and Methodology

2.1. Data

The NAO index is derived by projecting the NAO loading pattern onto the daily anomaly 500 millibar height field across a range of 0–90° N. The index can be found at https://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/norm.nao.monthly.b5001.current.ascii.table (accessed on 12 April 2024). The initial mode of analysis for the Rotated Empirical Orthogonal Function (EOF) analysis has been selected as the NAO loading pattern. This analysis utilises monthly mean 500 millibar height anomaly data spanning from 1950 to 2020, covering a latitude range of 0–90° N. Subsequently, each month within a given year has been assigned a singular numerical value.

2.2. Methodology

The approach depicted in Figure 2 encompasses several key stages, including data collection and preparation, exploratory analysis, data sampling for model fitting and testing, model prediction, and model evaluation. This section provides an explanation of various methods.

DeepNAO: The DeepNAO model is a software architecture that integrates the generalised additive model (GAM) with deep learning techniques. GAMs are a variant of linear regression that replacing the linear components with smooth transformations of the predictors [18,19]. The predicted value of the response or dependent variable Y in linear regression models is represented as a linear combination of the predictor variables X_1, X_2,..., X_p.

$$\mu = E(Y|X_1, X_2, \ldots, X_p = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_p X_p.$$

where $\beta_0, \beta_1, \ldots, \beta_p$ are regression coefficients to be estimated. In a generalised additive model, the linear terms are replaced by smooth transformations of the predictors:

$$\mu = E(Y|X_1, X_2, \ldots, X_p = \beta_0 + f_1(X_1) + f_2(X_2) + \cdots f_p(X_p).$$

Hence, where linear regression estimates the regression coefficients $\beta_0, \beta_1, \ldots, \beta_p$, the GAM estimates the smooth transformations $f_1, f_2, \ldots, f_p$.

Deep Learning

Deep learning is a crucial component of data science, encompassing statistics and predictive modelling. Deep learning greatly benefits data scientists who are responsible for gathering, analysing, and interpreting vast quantities of data, as it accelerates and simplifies this procedure. Deep learning involves the utilisation of neural networks that are composed of numerous layers of interconnected software nodes. Deep learning models are taught by utilising a substantial collection of labelled data and neural network designs. Deep learning programmes consist of numerous layers of interconnected nodes, where each layer progressively improves and optimises predictions and classifications based on the previous layer. Deep learning applies complex mathematical operations to its input and utilises the acquired knowledge to generate a statistical model as the output. The process of iteration persists until the output has attained a satisfactory degree of precision. The term "deep" was used to describe the number of processing layers that data need to go through. In order to attain a satisfactory degree of precision, deep learning algorithms necessitate access to vast quantities of training data and computational capacity, both of which were not readily accessible to programmers until the advent of Big Data and cloud computing. Deep learning programming has the capability to generate intricate statistical models directly from its iterative output, enabling it to produce precise prediction models from vast amounts of unlabelled, unstructured data [21,22].

This paper aims to utilise deep learning techniques to effectively record the impact of responses to historical events. The methodology employed in this study is based on the approach described by [22], which involves extracting event information that is pertinent to economic decision making from news corpora and subsequently utilising it to forecast stock markets [22]. The approach employs deep learning to represent both an immediate and enduring impact on the time-series data. This prediction model utilises the design of a multilayer perceptron. A total of 80% of the NAO data has been utilised for training, while the remaining 20% is allocated for testing purposes. A detailed description of the GAM and neural network can be found in the work of Wahiduzzaman et al. [24,25] and Ibebuchi [23].

We did not consider any specific predictors except the historical observations (which can be set out as limitations), where we have trained the model using 80% data and the NAO index has been used as both the input and output (Figure 3). The duration of the learning sample is 7 days, and 4 time steps a day have been considered. A 50-year time period has been considered. Smoothing has been done through the year is a variable. The end effect influences the quality of prediction as it does several iterations. Then, the iterations are averaged.

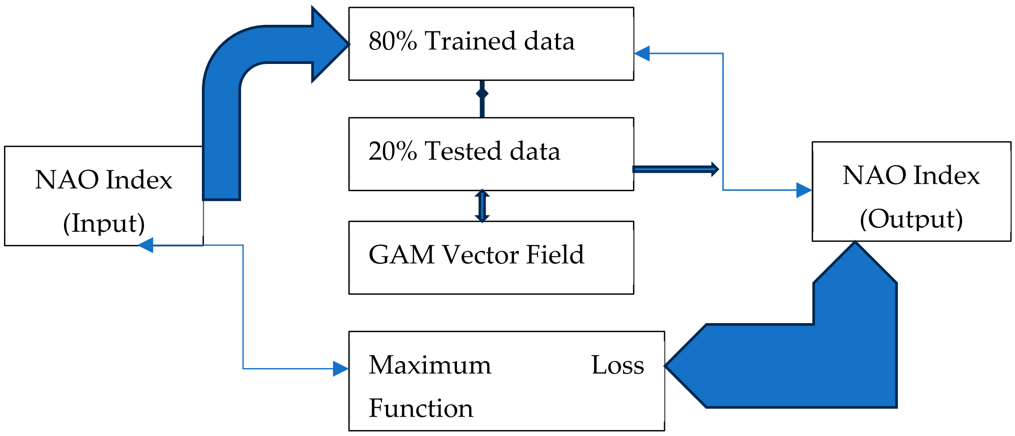


Figure 3. Flowchart of the work.

3. Results

In the current era, characterised by advanced computing capabilities, extensive data generation, and a vast influx of global information, the scientific community is confronted with the task of extracting and condensing crucial insights regarding the variability of the Earth's climate system from the continuously flowing data derived from observations and models. Additionally, there is a challenge in gathering and interpreting the indicators of the socio-economic response, which is necessary for the advancement of analysis tools and prediction models. These efforts aim to bolster societal resilience and prosperity. DeepNAO tackles three challenges in its reinterpretation of the traditional 'push–pull' problem [1].

A local weighted regression has been employed to evaluate time-series data and the correlation was 0.54, and then the GAM has been adjusted to the increments, utilising the velocities between consecutive places as its reaction. The velocities are derived by the process of data partitioning and subsequently computing the mean velocities (measured in degrees of latitude–longitude per day) across consecutive locations. Each component (x,y) of velocity is fitted with a distinct generalised additive model (GAM) in order to anticipate the velocity field. In this rudimentary model, we model each velocity as a continuous function of its corresponding position. After including the spline transformation, the correlation was 0.68. The estimated density is used as a basis for drawing samples. The estimate is treated as a Gaussian mixture, which represents the probability distributions of observations in the entire population. Initially, a component of the mixture is selected, and then a sample deviation is derived from that selection. The other data collected from reports are subjected to analysis using text mining techniques. Then, the correlation increased to 0.74.

The annual NAO value was compared using leave-one-out cross-validation with the GAM and Deep-NAO. It was noted that the GAM performed well in reproducing the NAO value, and the inclusion of the deep learning method with the GAM resulted in improved performance (Figures 4 and 5). In the Deep-NAO model, the text information will act as a layer that can be a variable into the model.

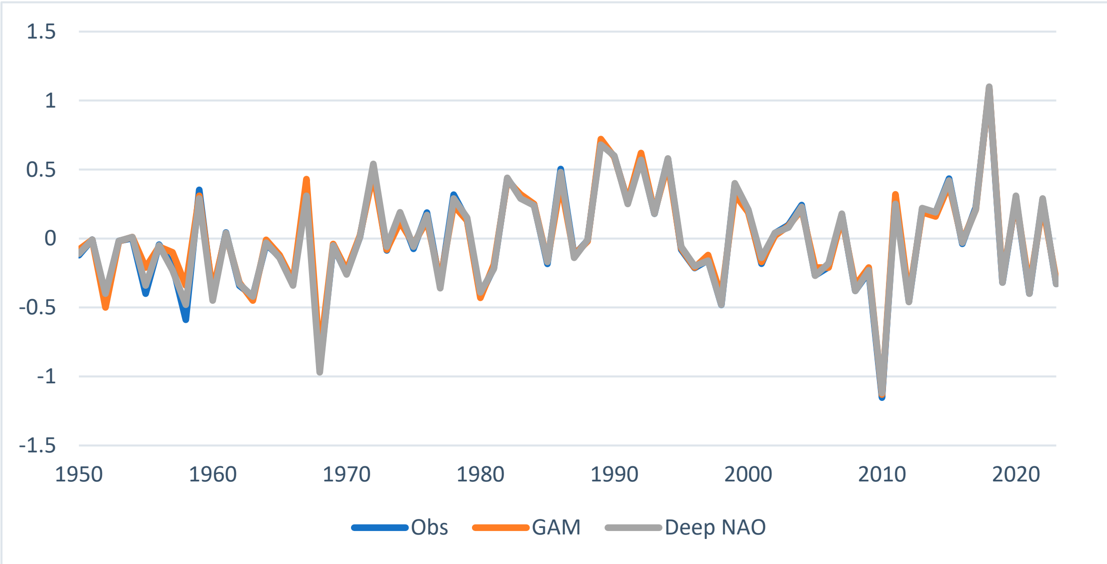


Figure 4. GAM and Deep–NAO replicate the annual NAO index using leave–one–out cross–validation. The observation is shown by the colour black, while GAM and Deep–NAO are coloured blue and red, respectively. The moving average of a year step is considered. Observation refers the gridded data of NAO index.

Figure 5. The plot displays the increasing (blue colour) and decreasing (orange colour) pattern of the difference in Deep–NAO compared with observation during 1950–2020. The year is shown in Figure 4.

4. Discussions

The authors [23] highlighted the promise of using data-driven techniques as a reliable tool for predicting the seasonal NAO and modelling air–sea interactions. While this work has significant advances, it is crucial to recognise the existence of some constraints. The existing causal discovery algorithms, which depend on data, have a constraint that restricts them to performing mutual causal analysis exclusively on data from a particular time period, often on a monthly basis. As a result, these systems lack the ability to analyse NAO occurrences that happen at specific times, such as during a particular season. However, due to the cyclical nature of NAO events, it is necessary to employ separate seasonal analysis and forecasting. Furthermore, the research undertaken by the authors in [23] suggests that causal discovery algorithms may encounter challenges in finding factors that have enduring impacts on NAO or those that exhibit teleconnections. Moreover, the use of data-driven methodologies can aid in predicting future events by utilising both past and current data. However, the accuracy of these predictions is greatly influenced by the quality and quantity of the accessible data. This study specifically examines monthly forecasts and utilises sea level pressure data dating back to 1899. The dataset consists of little more than 1300 monthly data points. Limited availability of data can lead to overfitting issues during model training. In addition, deep learning, which is an opaque method, lacks the ability to provide logical explanations for the gained attributes and their observable outcomes.

To overcome these limitations, future research can explore alternative areas of study. One possible topic to explore is the analysis of different algorithms for identifying causes. These algorithms should be able to assess occurrences of NAO (North Atlantic Oscillation) at certain time intervals and efficiently include seasonal fluctuations [26]. Further research should examine the use of additional remotely connected but important factors, such as El Niño Southern Oscillation (ENSO) events in the equatorial Middle and East Pacific, anomalies in sea surface temperatures (SST) in tropical regions, and the amount of snowfall. This research aims to improve the accuracy of forecasts. To address the issue of inadequate data, efforts were made to incorporate data from a wider range of sources. For example, using data from carefully integrated model simulations to gain an understanding of the fundamental physics of the model. Furthermore, it is imperative to develop methodologies that can effectively handle missing data, as this has the potential to improve the robustness of the models. Further study could explore methods for interpreting and visualising the fundamental representations of deep learning models to acquire a more profound comprehension of their tangible implications. These efforts have the potential to generate substantial insights into the underlying physical mechanisms and contribute to the validation of the models' predictions. Generally, data-driven approaches have limitations. However, there are many areas that could be explored in the future to overcome these limitations and improve our understanding of NAO dynamics and their effects [27].

In a distinct investigation, the authors in [28] analysed the influence of the El Niño Southern Oscillation (ENSO) on the atmospheric circulation during the initial winter period in the Euro-Atlantic region from 1979 to 2022. The analysis was performed utilising multiple reanalysis datasets. The study documented the El Niño Southern Oscillation (ENSO) atmospheric circulation trends from 1979 to 2022. The analysis found that the ENSO footprint had a better fit with the EAP than the commonly mentioned NAO pattern. The influence was associated with dipolar convection anomalies resulting from the El Niño Southern Oscillation (ENSO) in the Gulf of Mexico and Central America (GMCA). These irregularities can produce a sequence of Rossby waves that extend towards the north into the North Atlantic. This leads to the formation of a region of low atmospheric pressure south of Iceland and west of Ireland during El Niño occurrences. As a result, this causes an increase in El Niño Atlantic Precipitation (EAP).

Subsequently, the researchers [28] performed an investigation on the possible long-term variation in the early-winter ENSO teleconnection. An increase in the connection between the El Niño Southern Oscillation (ENSO) and the East Asian summer monsoon (EAP) was noted throughout the late 1990s. An evident EAP reaction was noted in the initial winter of the El Niño Southern Oscillation (ENSO) in the late 1990s. Before the late 1990s, the ENSO regression pattern had resemblances to a North Atlantic Oscillation (NAO) pattern. This observation suggests a possible shift in the early-winter ENSO teleconnection towards the Euro-Atlantic region in the late 1990s. Since the late 1990s, there has been a notable improvement in the GMCA precipitation response to the El Niño Southern Oscillation (ENSO). Although the TWEIO precipitation forcing is still in effect, the GMCA anomaly has had a notable impact on the TWEIO by causing an NAO anomaly. However, the GMCA precipitation has become significantly more susceptible to ENSO since the late 1990s. Although TWEIO precipitation forcing is still being used, the dominance of GMCA precipitation becomes prominent, resulting in the formation of an EAP by the stimulation of a north-propagating Rossby wave train.

The results of this study are consistent with earlier research that has demonstrated a discernible but restricted ability to predict the seasonal behaviour of the El Niño Southern Oscillation (ENSO)-related El Niño Atlantic precipitation (EAP) and the surface climate in the Euro-Atlantic region during the beginning of winter. The reduced strength of this signal is believed to be caused by the less accurate model simulation of tropical–extratropical teleconnections, which seems to be linked to the underestimated convection response to the El Niño Southern Oscillation (ENSO) phenomenon in the Gulf of Mexico and Central America (GMCA) region [28]. The results of our study highlight the importance of GMCA precipitation in the ENSO–EAP teleconnection, therefore confirming these claims. Moreover, the recent intensification of the ENSO–EAP teleconnection indicates a shift in the way the ENSO phenomenon affects the atmospheric circulation in the Euro-Atlantic region during the beginning of winter. The results of this study are important for understanding the ENSO teleconnection in early winter and improving the accuracy of seasonal climate forecasts in the Euro-Atlantic region.

The authors note that their findings are primarily based on observational data. They highlight the importance of incorporating information from modelling and CMIP6 simulations in future investigations. The study focused on analysing the effects of low-frequency Rossby waves resulting from the ENSO. The North Atlantic region is distinguished by a notable prevalence of atmospheric eddy–low-frequency flow feedback. Therefore, it may be essential to assess their potential consequences as well. In addition, the research mostly concentrated on the linear impacts of the ENSO. It is imperative to ascertain whether this link is influenced by the particular kind or variant of the ENSO. It is crucial to study how the ENSO teleconnections will be affected by changes in the future climate, particularly due to greenhouse warming. This is an intriguing topic for future research.

5. Conclusions

The NAO is a prominent pattern of atmospheric variability that takes place in the Northern Hemisphere, with a range of time intervals from daily to decadal. It has a significant influence on winter weather patterns across North America, Europe, and certain regions of Asia. Precise forecasts of the surface NAO are highly crucial for society in terms of planning energy consumption and adapting to harsh winter conditions, including winter wind and snowstorms. These circumstances can lead to property damage and interruptions in transportation networks. The analysis presented data from 1950–2020 where the Deep-NAO model has been trained for 50 years and tested for 20 years. Overall, the NAO index has been reproduced well by the GAM (with a 0.68 correlation coefficient) and Deep-NAO (with a 0.74 correlation coefficient). The fitness of the model increased when the GAM was incorporated with deep learning. The difference between observation and the model was very small. The model can be tuned through different or a combination of climate modes in the future to enhance the skill.

Author Contributions: M.W. initiated the project, conducted the data management and analysis, and drafted the manuscript. A.Y.—writng-review& editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Science Foundation of China (Project Number: 42250410325) and Ministry of Science and Technology, China.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data will be available upon reasonable request.

Conflicts of Interest: Alea Yeasmin was employed by E-3 complexity Ltd. The research was conducted in the absence of any financial or commercial interest.

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