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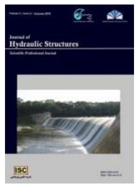

A Novel Deep Learning Method for Forecasting ENSO

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Abstract

Ability of predicting climate phenomena enables international organization and governments to manage natural disasters such as droughts. El Niño Sothern Oscillation (ENSO) is one the most influential and crucial phenomenon follows with large scale climatic events and can be used for predicting droughts and floods all around the world. Due to such a great importance, a new Convolutional Neural Network method based on augmented data (ACNN) for predicting ENSO on a relatively long period is developed in this research. The method is developed based on CNN to forecast ENSO six month earlier. Sea Surface Temperature (SST) anomaly maps are given to the model as the predictors and Niño 3.4 Index is the predictand. The method applies convolutional tensors to extract features from the maps, and delivers them to a fully connected neural network to discover connections between Niño Index and the features. A tricky augmentation process is used to increase the number of input data to compensate lack of observations. The model's skill correlation is over 0.83 for January-February-March season, while, the original CNN method' correlation is 0.71. The model can be executed on GPUs of a laptop without any need to super computers. The feature that makes it a great tool for predicting ENSO even for research institutions in low income countries.

Keywords: ACNN, El Niño, Forecast, SST, Augmentation.

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1. Introduction

Variability of El-Niño Southern Oscillation (ENSO) has many tele-connections with most of anomalies around the world. Thus, the ability to forecast this phenomenon is crucial for governments and international organizations 1. For instance, there is an Uncertainty for

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governments and water resource managers whether to reserve water to compensate incoming drought or releasing water behind dams' reservoirs to be prepared for incoming floods.

Despite scientists' decades of endeavor, prediction of ENSO accurately still remains as a challenge [2,3]. However, duo to existence of frequent and recursive factors in ENSO and its connection to oceanic variability it can be concluded that this phenomenon is predictable [4]. This is possible even with the surprising behavior of equatorial Pacific Ocean anomalies during several La-Nina events that lasted longer in recent years [5]. In addition, highly frequent equatorial winds are less predictable that make the prediction harder [6]. In contrast, some clues are being discovered. SST anomalies outside equatorial Pacific Ocean can lead to an ENSO event with a time-lag more than one year [7].

On the other hand, in recent years, large scale numerical models have been developed to understand climatic drivers to improve man's ability to forecast future climate [8]. However, numerical methods such as 3D finite element method [9] require high computational costs to discretize the earth entirely in the domain of the problem. They also encounter the problems to enforce boundary conditions. Despite developing more recent methods such as iso-geometric methods [10,11] for imposing boundary conditions and meshfree methods [12,13] for eliminating time consuming meshing process, modeling large scale models remains a challenge. Moreover, calculating uncertainty is necessary to predict climate variation in both short and long runs [14,15]. Uncertainty can occur due to our lack of knowledge about important drivers in the future such as anthropogenic activities, change in greenhouse gasses, aerosols, volcanos, and solar radiation [16-18]. Uncertainties also arise in numerical modeling because of grid size issues, some simplifying methods in discretizing differential equation, and issues in enforcing boundary conditions [19,20]. Another uncertainty source is internal variability on earth climate which is inherent in the nature of these phenomena [21-23].

Chaotic behavior of atmospheric system might imply that decreasing the uncertainty is impossible [24-26]. However, more observations are needed to prove this hypothesis. Fortunately, in 2020 Smith et al. [27] after scrutinizing six decades of retrospective atmospheric forecasts concluded that despite the differences between climatic models and their weak results, decadal variability in the climate of North Atlantic Ocean is predictable. This discovery is important due to different circulation models of CMIP5 [28] and CMIP6 [29] which show discrepancy for different parts of European continent. Smith et al.argue that using relatively simple statistical methods and extracting the main signal out of climatic data, the average temperature of Europe is predictable in a decadal scale. Moreover, they say that low level of signal-noise ratio in general circulation models (GCM) is a weakness that should be solved to reach lower uncertainty. This research also proves that despite huge investment on these sophisticated GCMs, they cannot detect every precursor, and relatively cheap statistical methods or methods based on artificial Intelligence can present better predictions to some extent.

ENSO make a great impact on climate of different parts of the globe [30-32]. Therefore, there is room for more research to discover triggering mechanism [33-35] and precursors [36,37]. For example, previous works have emphasized on the Warm Water Volume (WWV) in the equatorial Pacific Ocean as precursor of ENSO [38]. Since Oceanic Memory, based on Delayed Oscillator Theory [39] or Recharge Oscillatory Theory [40,41], relies on Wave Adjustment Process, a peak WWV occurs usually 8 months before El Niño [42]. Ham et al. [43] showed that sea surface temperature (SST) anomalies in Tropical North Atlantic (TNA) in the beginning of spring, using Rossby Wave response to source of temperature anomaly in TNA and local ocean-atmosphere interaction along Inter-Tropical Convective Zone in semitropical north Atlantic, can be used for ENSO forecast.

One of the strongest models in predicting ENSO is the Japanese SINTEX-F [44-47]. This model is a couple ocean-atmosphere model with high resolution that present most accurate predictions for lead times ranging from one to two years, so it is used as a benchmark at most of recent researches [48,49]. However, the problem is that these kind of sophisticated methods have high computational cost and require powerful super computers which are not usually affordable for lower income countries. With a normal desktop computer, such methods can only be used for modeling simpler engineering problems [50-52]. To fill this gap, machine learning methods have shown great potential to solve huge and complicated problems without the need for complete knowledge about physical phenomena and their defining partial differential equations [3,53]. They also are independent from complex boundary conditions.

Considering the arguments above, it can be concluded that ENSO can be predicted more accurately in the future. By the advent of big data era, deep learning has outperformed human abilities in recognizing hidden patters through raw data and images. Especially, convolutional neural networks (CNN) have represented brilliant results in the analysis of multi-dimensional arrays [54-57]. Therefore, CNN can be applied to find connections between precursors and predictand indices. Ham et al. [49] successfully applied CNN for the prediction of ENSO for lead times up to 18 months. Their work outperforms all state-of-the-art GCM models like SINTEX-F for all lead times ranging from 1 to 18 months. It uses SST anomaly data and heat content anomaly maps as the predictors. They use 21 GCM models output as well as SODA (Simple Ocean Data Assimilation) reanalysis data as the input of their model. However, obtaining, storing and processing such a massive data takes so much time and resources so their presented model is categorized sophisticated one in terms of feeding the model; the work that lies outside the capability of powerful personal computers.

2. Method

All Deep Learning (DL) models need high quality data to be able to predict or find patterns. Without reliable data these methods are nonsense. So, feeding the model with sound and related data is the first step in creating a reliable DL model. In this work SST anomaly maps for three consecutive months were applied as the predictors. The SST data were processed to create SST anomaly maps. Then, they were cropped from 55* S to 60* N to simplify the data and deleting icy polar areas. The SST data were obtained from Beijing Climate Centre, China Meteorological Administration (BCC-CSM1.1-m) [58].

The predictand is Niño 3.4 Index which is SST anomaly averaged over the area 120* to 170* west and from 5* to 5* north as shown in Fig. 1. This index is one of the most used indices in the literature and is rationally related to the selected input data [49,59].

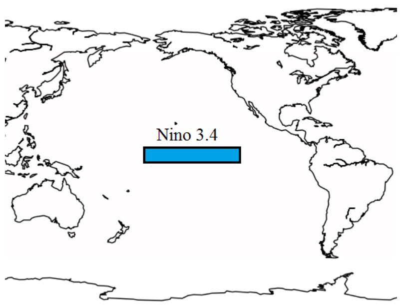

Figure 1. Niño Indices sown on Pacific Ocean map.

One of the biggest barriers to apply CNN effectively in predicting climate is lacking of big data. Sea surface temperature is only available from 1871 [60] so, for each month we merely have access to almost 150 anomaly maps [49]. To overcome this problem scientist have proposed some solutions. Ham et al. used 21 CMIP5 data to increase the number of data. This idea works great but needs huge RAM capacity as well as timely effort to obtain and process the data. Here we present a simple but powerful method to augment the input data for prediction ENSO for lead time of 6 months. Data augmentation is one the most attractive fields of study in machine learning that has been successfully applied in different fields of study [61-66]. In this method, we augment the available data by some noisy versions of the main data. The formulae of created augmented data is as follows:

$$\overline{\mathrm{SST}_\mathrm{i}} = \mathrm{SST}_i + \mathrm{p}(x) \tag{1}$$

Where $\overline{\mathrm{SST}_\mathrm{i}}$ is the new map of SST anomalies of a specific month, SST_i is the available SST anomaly map of the month and $\mathrm{p}(x)$ is the probability density function of the normal distribution. The probability density function is a type of continuous probability distribution which first derived by both Gauss and Laplace independently [67]. This function represents distributions that usually occur in nature and often is called the bell curve because of its characteristic shape (Fig. 2).

The general form of probability density is:

$$p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}} \tag{2}$$

Where μ is the mean of the distribution, σ is the standard deviation, and σ^2 is the variance.

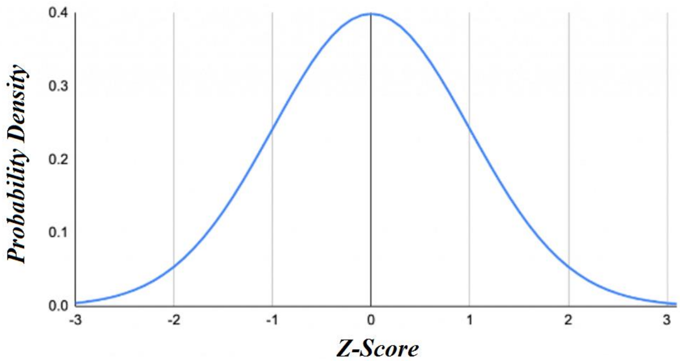

Figure 2. The probability density function or normal distribution.

Fig. 3 Shows augmented SST map created based on January, 1863 SST anomaly map. The random noisy spots can be seen in the map (Fig. 3a).

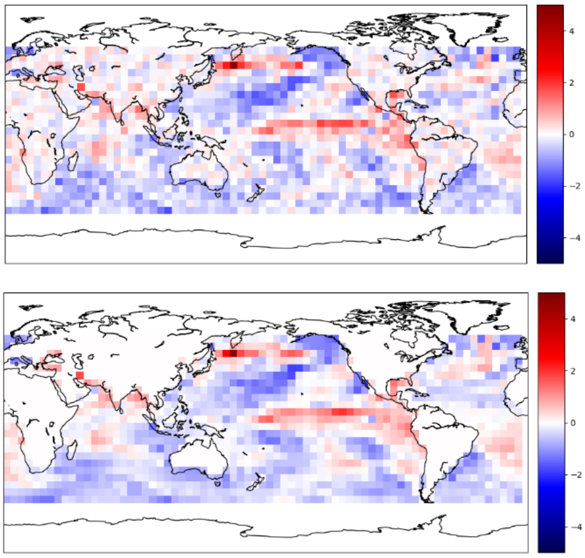

Figure 3. SST anomaly map of January 1863 versus augmented one.

The proposed CNN model is composed of 4 convolutional layers in between lies 4 2×2 max-pooling layers with same padding (Fig. 4). Initial weights of convolutional layers are chosen randomly based on a normal distribution. The last convolutional layer is connected to one fully connected layer. The number of neurons in the fully connected layer is 20 and the number of convolutional filters is chosen to be 20 as well. The hyper parameters of the network that are mini batch and epoch are set to be 500 and 1000 respectively. Mean Absolute Error function [68] is applied as the cost function as follows:

$$MAE = \frac{\sum_{i=0}^{n} |y_i - y'|}{n} \tag{3}$$

Where y_i is interpolated result of a specific epoch and y' is the observed Niño 3.4 Index.

A Rectified Linear Unit (RELU) is used as the activation function. RELU is a piecewise linear function that its output is zero unless it is positive [69]. When it is positive the output will be the input itself as follows:

$$R(z) = \begin{Bmatrix} z & z > 0 \\ 0 & z <= 0 \end{Bmatrix} \tag{4}$$

3. Results

In this work, ENSO was predicted 6-month earlier for each of 12 months. The input period ranges from 1861 to 1970 and the output interval is 1986-2017. The training input data for were created based on BCC-CSM1.1-m, and the validation and label data were obtained from Global Ocean Data Assimilation System reanalysis (GODAS) models. Niño 3.4 Index calculated based on GODAS anomaly maps from 1861 to 2002 applied for output layer of training stage [70]. GODAS anomaly maps and corresponding Niño index from 1986 to 2017 used for validation stage. To validate the ability of the proposed CNN model to predict ENSO, we calculate the correlation of results with observation data. As the prediction output is a vector, the following Pearson correlation equation was leveraged to compare prediction skills of the two methods:

$$r = \frac{\sum(x_i y_i) - n\bar{x}\bar{y}}{\sqrt{\sum(x_i^2 - n\bar{x}^2)\sum(y_i^2 - n\bar{y}^2)}} \quad (5)$$

Where x_i is the observed values of Niño 3.4, $\bar{x}$ is the mean of x vector, y_i is the predicted vector of Niño 3.4, and $\bar{y}$ is the mean value of vector y. The threshold of the forecast correlation to be judged as a reliable prediction is 0.5 according to the literature [49]. Fig. 5 shows the correlation skill of the ACNN. The ACNN method shows a good overall correlation and represent a very good correlation for seasons other than spring. In order to better evaluation of the method, the results are compared to those of CNN method, which is the most accurate method in this field to the date. The bubbles diameter shows the uncertainty of the results. According to Fig. 5, ACNN improves CNN method in both increasing accuracy as well as decreasing uncertainty. The accuracy reduction in spring is due to the spring barrier which makes every climatic prediction hard for this period [71,72].

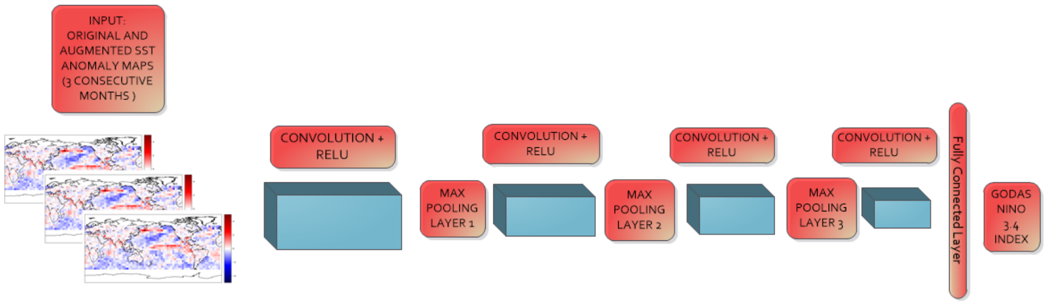

Figure 4. CNN Architecture.

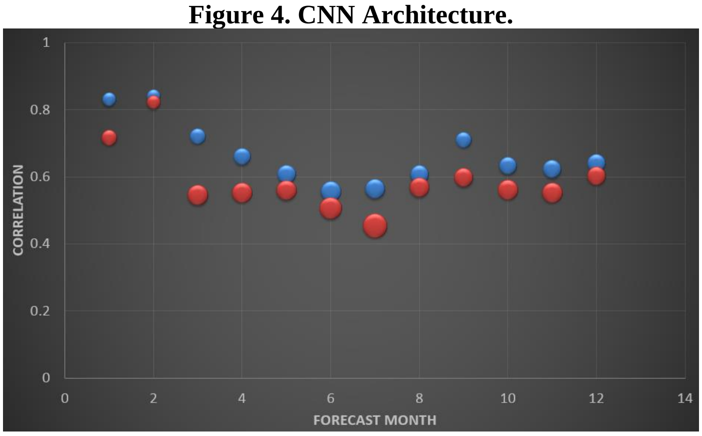

Figure 5. Correlation skill of ACNN for ENSO prediction.

As shown in Fig. 6. the ACNN model correctly forecasts the Niño 3.4 amplitude of FMA (February-March-April) season. The time series of predicted ENSO have a good agreement with observed values. Another time series comparison is done in Fig. 7 in which predicted Niño 3.4 index well forecasts the phenomenon, however, for spring season (JJA) the skill of forecast is not as good as other seasons. In order to ensure reliability of the method, results from the most advanced GCM method called SINTEX-F is also depicted on the chart. The comparison proves the superiority of ACNN method even over numerical methods.

The El Niño of 1997 is captured in both predictions but in Fig. 6 the amplitude of the phenomenon is predicted more accurately.

Convergence rate of the method is demonstrated in fig. 8. The method is a fast convergent method with a monotonic and smooth convergence that can readily be executed on GPUs of a PC or laptop without any need to super computers.

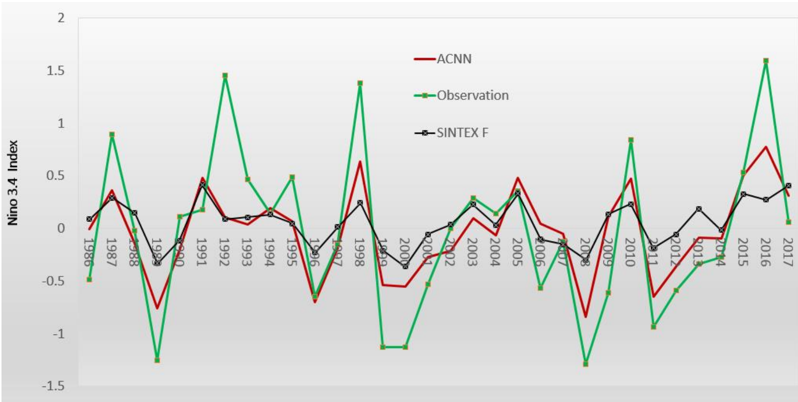

Figure 6. Comparison of predicted and observed time series for FMA (February-March-April) season.

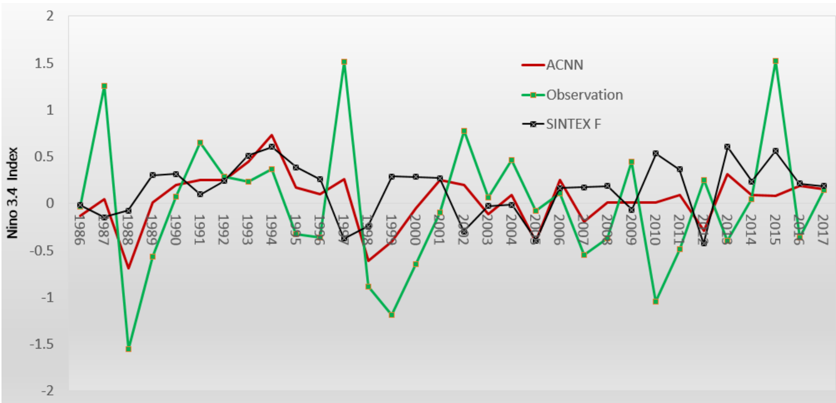

Figure 7. Comparison of predicted and observed time series for JJA (June-July-August) season.

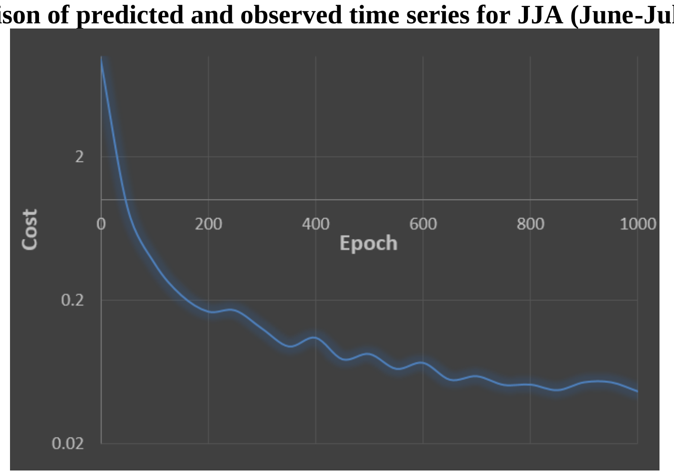

Figure 8. Convergence rate of ACNN method.

4. Conclusion

By the advent of deep learning methods, having knowledge about possible future events is going to be a reality. In this way forecasting large scale phenomena such as ENSO provides great benefits for governments all around the world. In this research, a new CNN Method presented to forecast ENSO six month earlier. The method receives noisy augmented SST anomaly data as the input data and delivers Niño 3.4 Index as the output. Preparing the input data for the model is far more convenient than other sophisticated CNN methods. This method uses convolutional process to extract features from SST anomaly maps, and then uses a fully connected neural network to classify them and finding connections between Niño Index and the features. The results compared with reliable GODAS data, and shows a very good agreement with the observation. The amplitude of ENSO is predicted well, too. The best model's skill correlation is over 0.83 that occurs in January-February-March season, and the lowest is over 0.57 due to spring barrier. Thus, the method outperforms the CNN method that its correlation ranges from 0.45 to 0.81. The model can be executed on GPUs of a PC or a laptop without any need to supercomputing; The feature that makes it a great tool for predicting ENSO even for research institutions in low income countries. These characteristics makes it ideal for fast and reliable predictions of ENSO several months earlier.

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