Application of a neural network model to forecasting of El Niño and La Niña

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Abstract. In this paper, a possibility to forecast El Niño and La Niña by using an artificial intelligence model based on neural networks is studied. The quality of such a long-term climate forecast is assessed too. A set of global climatic indices of atmosphere-ocean system oscillations in 1950-2019 is used as input parameters of the model. The Nino3.4 index is calculated by using monthly average 500mb geopotential height and sea surface temperature fields from NCEP/NCAR reanalysis data sets. A verification of the model is carried out by using a control sample of 1950–1957. Additionally, the same indices of 1872-1947 are calculated by using 20th Century Reanalysis (20CR) data sets to test the model. A possibility to predict the Nino3.4 index for 2 to 7 months is shown. However, in spite of a high-level reconstruction of the index dynamics, increasing the time of forecasting is accompanied by decreasing its quality. With 20CR data it is shown that the model is able to successfully predict the beginning of 75% of El Niño and La Niña for 3 months, 66% of the events for 5 months, and only 52% for 7 months in advance.

1. Introduction

The El Niño-Southern Oscillation (ENSO) phenomenon is the strongest global interannual climatic signal of the ocean-atmosphere system of the Pacific equatorial zone. It is characterized by extreme quasi-periodical 2-7 years change of the sea surface temperatures (SSTs) and sea level pressures. The ENSO includes two episodes opposite in sign: warm (El Niño) and cold (La Niña).

In 20th century the scientists identified several typical features of the ENSO phases. It was considered that El Niño is characterized by the eastward transfer of warm equatorial waters, the alignment of the thermocline near the South American coast, weakening of the Walker cell intensity, and a shift of the atmospheric action centers at the equator [1, 2]. La Niña is characterized by the westward transfer of warm equatorial pool, the thermocline levelling up near the South American coast, and intensification of the Walker cell [3]. The Nino3.4 index is usually applied for definitions of El Niño and La Niña events. It is calculated as an SST anomaly in the Nino3.4 region located in the equatorial Pacific within the coordinates (5°S – 5°N, 170°W –120°W).

Manifestations of the ENSO are noted in weather and climate anomalies not only over the Tropical Pacific, but in extra-tropical regions too, through the "atmospheric bridge" [3, 4, 5]. The consequences of these events often lead to serious casualties and economic losses [6, 7]. However, despite the improvement of the modeling approaches and the development of technologies for El Niño and La Niña monitoring, the forecasting of these events remains imperfect [8]. The fact is that, despite many
studies [2, 3, 4, 6, 7] and available examples of successful El Niño modeling [9], the mechanism of El Niño and La Niña formation is still one of the most important scientific problems.

In the present paper, we try to use a method based on artificial neural networks (NNs) to forecast the beginning of extreme ENSO phases. NN is a subsection of artificial intelligence in which signals are processed using phenomena similar to those in neurons of living organisms. The first ideas to create the neural networks were proposed at the end of the 19th century by Warren McCulloch and Walter Pitts, who proposed the first neuron binary model [10]. As a result of development of the neural networks theory, in 1975 Paul John Werbos proposed a new method of machine learning – backpropagation [11]. The backpropagation algorithm is currently considered as one of the most efficient machine learning algorithms for multilayer NNs.

Previously we attempted to use the NN to forecast. Methods based on NNs were used to predict the Southern Oscillation Index [12]. However, at that time the atmospheric oscillation indices of the subequatorial and equatorial Pacific were not used between input parameters in the NN model, and the set of indices of the Southern Hemispheric baric systems was not complete. In this paper, the quality assessment of the Nino3.4 index forecasting using a NN model is made.

2. Data and methods
Monthly SST data sets from the Met Office Hadley Centre (HadISST) were used to calculate the Niño 3.4 index. It was calculated as the difference between the observed values and the 30-year moving average. Atmospheric patterns were selected based on the results of the space-time correlation analysis between the Nino 3.4 index and baric atmospheric fields. The monthly indices of selected atmospheric patterns were calculated and used in the proposed model. Space-time correlation analysis and calculation of the atmospheric indices were carried out using monthly 500mb geopotential heights and sea level pressures of NCEP/NCAR reanalysis data sets for the available period of observations (1948-2019). The study also includes a retrospective forecast. In this case the atmospheric indices were calculated using 20th Century Reanalysis V2c (20CR) data in 1870-1947. Thus, the following ocean-atmosphere system indices were used for modeling: the North Atlantic Oscillation (NAO), the Arctic Oscillation (AO), the East Atlantic Oscillation (EA), the Scandinavian Oscillation (SCAND), the Polar Oscillation (POL), the West Pacific Oscillation (WP), oscillations between the East Atlantic and West Eurasia (EA/WR), between the eastern and northern parts of the Pacific (EP-NP), between the Pacific and North America (PNA), oscillations in the middle latitudes of the Northern Hemisphere (MNH) and Southern Hemisphere (MSH), the South Atlantic Oscillation (SAO), the South Pacific Oscillation (SPO), oscillations between the South Atlantic maximum and the South Ocean minimum located south of the coast of Africa (SA/S), the South Indian Ocean Zonal Oscillation (SIZO), the South Indian Ocean Meridional Oscillation (SIMO), the Equatorial Oscillation between the Pacific Ocean and Indonesia (EP/EI), Equatorial Oscillation between the Atlantic and Pacific Oceans (EA/EP), the sum of the geopotential heights of middle latitudes over the Pacific Ocean (MNP/MSP) and the average pressure in equatorial latitudes (EqO).

Unidirectional hetero-associative neural network (one hidden layer) with a teacher was used for Nino 3.4 forecasting. The neurons of input, hidden, and output layers are represented by a sigmoidal bipolar function: \( f(x) = \tanh(\beta x) \) [10, 13]. The set of the above-mentioned atmospheric indices was used as input parameters. The model was trained using the backpropagation algorithm.

From paper [14] it is known that the quality of the NCEP/NCAR reanalysis data is better than that of the 20CR reanalysis data, which can be explained by differences in the algorithm of assimilating meteorological data by reanalyses. Therefore, in this paper we will use the NCEP/NCAR reanalysis data for modeling. The series of simulated parameter values and input atmospheric indices were divided into training, test, and control samples. In an earlier paper of the authors [15] it was shown that 30-year periods must be used for the testing and training to improve the quality of model training. In the present study, the sample for 1958-1987 was used for training and the sample for 1988-2019, for testing. The control sample did not participate in the modeling process. The eight-year period of 1950-1957 was considered as a control sample. It included two La Niña events (1949-1951 and 1954-
1956) and two El Nino events (1951-1952 and 1957-1958). Additionally, to estimate the forecasting in advance, a retrospective forecast was carried out on the basis of an efficient model for 1872-1947.

The process of adaptation of the models included three stages: pre-processing, modeling, and final processing of the results [15]. The first stage can be divided into 2 parts. First the series of each of the input indices was converted into four series: the original index, the same index with 30-year variability removed, and the same two series using a three-month average sliding filter. Averaging windows are the empirical choice of the authors. Thus, groups of series were formed, and each of them corresponded to one atmospheric index. After that the correlation between the atmospheric indices and the predicted parameter was calculated. During the filtering process, the selected indices were ranked by the correlation coefficient. Repetitions were excluded for the group of series of each index. As a result, 22-24 indexes were fed into the model input.

Modeling. The practical modeling showed that the behavior of the NN is not always predictable. The model not always had satisfactory results when run on the basis of indices selected at the preliminary stage, probably because it used indices not related directly to the modeled parameter or some input indices were not orthogonal. Therefore, the model was run many times with different combinations of input parameters selected at the preliminary stage. For each NN combination at the time of maximum training the correlation was calculated between the actual and estimated values in the test sample. The maximum training was determined on the basis of a comprehensive assessment of the Euclidean distance and correlation coefficients of the training and test samples [15]. The NN combinations, the NN parameters at the time of maximum training, and the correlation estimates were recorded in a log file.

At the final stage, on the basis of the obtained correlation coefficients of the model data with the test sample, selection of the 20 best NN combinations was performed. Since the test sample is involved in the ranking, it is probable that the selected NN combinations are mistakenly trained or retrained. Therefore, additional independent assessment of the trained model results was carried out using the control sample. If one or more NN combinations were significantly different from the rest, these combinations were excluded. Further, an ensemble was calculated from the remaining NN combinations, and its compliance with the control sample was checked.

For this, the correlation coefficient was calculated:

\[ r = \frac{\text{cov}(x_i, y_i)}{\sigma_x \sigma_y} \]  

(1)

where \( \sigma_x \) and \( \sigma_y \) are the standard deviations (SD or \( \sigma \)) of the samples \( x \) and \( y \), which represent the simulation result and the observed Nino 3.4 index; the root mean square error (RMSE or E):

\[ \text{RMSE} = \sqrt{\frac{\sum(x_i - y_i)^2}{n}}, \]  

(2)

and the ratio of the RMSE to the standard deviations.

3. Results and discussion

The ability to predict the Nino 3.4 index was studied for each month taking into account different forecasting in advance from 2 to 9 months.

First we will evaluate the correlation coefficients between the model calculations for the forecast for 2, 3, 4, 5, 7, and 9 months and the observed Nino 3.4 index for each month within the test sample (1988-2018). The differences of intra-annual values are demonstrated in Figure 1. It shows that, on average, the correlation coefficient is smaller in June, July, August, and September. This may be due to the fact that the El Niño and La Niña events begin mainly from May to July. The correlation coefficients decrease with an increase in the advance forecasting for the months from July to January, and they are approximately equal for February, March, April, and June. The lowest correlations are typical for the 9-month advance forecast and the highest correlations, for the 2-month advance forecast.
Figure 1. Estimation of correlation coefficients for different forecasting in advance: from 2 to 9 months.

Next, we evaluate the quality of modeling in the control sample. Table 1 shows the statistical characteristics ($r$, $E_{r}$, $E/\sigma$) calculated by formulas (1) and (2), and the SD of the NN combinations ensemble ($\sigma_{m}$). It can be noted that the correlation of the control sample (all months for 1950-1957), as well as in the case of the test sample, decreases with increasing time of forecasting in advance and the RMSE and SD of the NN combinations ensemble increase. All these indicators lead to the conclusion that the quality of modeling worsens with increasing time of forecasting in advance.

Table 1. Assessment of the model quality for each month and the entire period. $Adv$ is the forecasting in advance of 2 to 9 months, $r$ is the Pearson correlation coefficient, $E_{r}$ or RMSE is the root mean square error, $E/\sigma$ is the the ratio of RMSE to standard deviations of the Nino3.4 index, and $\sigma_{m}$ is the ensemble standard deviation.

|       | Adv     | 2   | 3   | 4   | 5   | 7   | 9   | Adv     | 2   | 3   | 4   | 5   | 7   | 9   |
|-------|---------|-----|-----|-----|-----|-----|-----|---------|-----|-----|-----|-----|-----|-----|
| Jan   | $r$     | 0.95| 0.94| 0.89| 0.86| 0.73| 0.78| $r$     | 0.97| 0.88| 0.96| 0.92| 0.90| 0.90|
|       | $E_{r}$ | 0.45| 0.49| 0.55| 0.40| 0.53| 0.64| $E_{r}$ | 0.27| 0.39| 0.30| 0.28| 0.40| 0.33|
|       | $E/\sigma$ | 0.65| 0.70| 0.79| 0.57| 0.77| 0.92| $E/\sigma$ | 0.35| 0.52| 0.40| 0.37| 0.52| 0.44|
|       | $\sigma_{m}$ | 0.35| 0.37| 0.40| 0.46| 0.47| 0.61| $\sigma_{m}$ | 0.17| 0.27| 0.43| 0.36| 0.31| 0.37|
| Feb   | $r$     | 0.91| 0.83| 0.83| 0.80| 0.70| 0.75| $r$     | 0.95| 0.98| 0.86| 0.80| 0.93| 0.93|
|       | $E_{r}$ | 0.42| 0.43| 0.34| 0.44| 0.50| 0.41| $E_{r}$ | 0.22| 0.17| 0.35| 0.42| 0.24| 0.24|
|       | $E/\sigma$ | 0.66| 0.68| 0.53| 0.68| 0.79| 0.65| $E/\sigma$ | 0.32| 0.25| 0.50| 0.60| 0.34| 0.34|
|       | $\sigma_{m}$ | 0.42| 0.29| 0.39| 0.31| 0.27| 0.35| $\sigma_{m}$ | 0.21| 0.25| 0.40| 0.33| 0.39| 0.39|
| Mar   | $r$     | 0.89| 0.87| 0.77| 0.81| 0.73| 0.84| $r$     | 0.95| 0.93| 0.96| 0.90| 0.88| 0.87|
|       | $E_{r}$ | 0.32| 0.34| 0.38| 0.31| 0.38| 0.32| $E_{r}$ | 0.28| 0.32| 0.26| 0.48| 0.45| 0.52|
|       | $E/\sigma$ | 0.60| 0.63| 0.73| 0.59| 0.72| 0.59| $E/\sigma$ | 0.35| 0.40| 0.32| 0.61| 0.57| 0.65|
|       | $\sigma_{m}$ | 0.20| 0.23| 0.18| 0.28| 0.26| 0.27| $\sigma_{m}$ | 0.33| 0.37| 0.29| 0.35| 0.43| 0.37|
| Apr   | $r$     | 0.96| 0.82| 0.81| 0.85| 0.67| 0.87| $r$     | 0.95| 0.91| 0.93| 0.92| 0.94| 0.84|
|       | $E_{r}$ | 0.19| 0.35| 0.36| 0.33| 0.45| 0.32| $E_{r}$ | 0.30| 0.36| 0.35| 0.35| 0.39| 0.61|
|       | $E/\sigma$ | 0.30| 0.55| 0.57| 0.52| 0.72| 0.51| $E/\sigma$ | 0.38| 0.46| 0.45| 0.44| 0.50| 0.77|
|       | $\sigma_{m}$ | 0.14| 0.23| 0.22| 0.23| 0.28| 0.27| $\sigma_{m}$ | 0.39| 0.34| 0.36| 0.33| 0.41| 0.48|
| May   | $r$     | 0.95| 0.75| 0.82| 0.77| 0.60| 0.75| $r$     | 0.97| 0.83| 0.81| 0.83| 0.95| 0.93|
|       | $E_{r}$ | 0.25| 0.45| 0.34| 0.37| 0.47| 0.40| $E_{r}$ | 0.32| 0.63| 0.63| 0.67| 0.48| 0.58|
|       | $E/\sigma$ | 0.41| 0.74| 0.56| 0.60| 0.77| 0.66| $E/\sigma$ | 0.31| 0.62| 0.62| 0.66| 0.47| 0.56|
|       | $\sigma_{m}$ | 0.14| 0.27| 0.34| 0.31| 0.31| 0.32| $\sigma_{m}$ | 0.38| 0.24| 0.37| 0.31| 0.46| 0.46|
| Jun   | $r$     | 0.90| 0.82| 0.78| 0.82| 0.87| 0.91| $r$     | 0.92| 0.93| 0.92| 0.91| 0.98| 0.97|
|       | $E_{r}$ | 0.30| 0.33| 0.38| 0.35| 0.29| 0.28| $E_{r}$ | 0.43| 0.39| 0.51| 0.51| 0.36| 0.52|
|       | $E/\sigma$ | 0.50| 0.54| 0.63| 0.59| 0.49| 0.47| $E/\sigma$ | 0.51| 0.46| 0.60| 0.59| 0.42| 0.60|
|       | $\sigma_{m}$ | 0.31| 0.22| 0.25| 0.34| 0.27| 0.41| $\sigma_{m}$ | 0.33| 0.39| 0.47| 0.45| 0.46| 0.48|
|     | $r$     | 0.92| 0.85| 0.84| 0.84| 0.84| 0.79| $E_{r}$ | 0.32| 0.40| 0.41| 0.42| 0.42| 0.51|
| All time | $E/\sigma$ | 0.41| 0.53| 0.55| 0.55| 0.55| 0.63| $\sigma_{m}$ | 0.28| 0.29| 0.34| 0.34| 0.36| 0.39|
Now we compare the modeling results for the 3- and 9-month advance forecasts with a real Niño3.4 index during the control sample period. Figure 2 shows the time course of the observed and calculated Niño3.4 index smoothed by a 3-month sliding filter. In the time of two-year La Niña (1949-1950) it can be seen that the presence of a negative SST anomaly is during the first mature phase of this phenomenon in the model calculations, despite a slight weakening of the index. As for the second minimum of this La Nina event in 1950, the model of forecasting in advance of 3 months shows it well, but the model of forecasting in advance of 9 months has rather high index values, in connection with which one can even make an erroneous conclusion on premature completion of the La Niña. In this case the erroneous conclusion about early completion of the La Niña may be made. Following the considered La Niña, the 1951 El Nino event occurred. Both models predict it well. The dynamics of this modelled El Nino evolution is somewhat overestimated as compared to the real Niño3.4 index. The graph shows that extreme ENSO events were absent from 1952 to 1954, but the model of forecasting in advance of 9 months erroneously indicated the presence of a weak El Niño in 1953. The beginning of the two-year La Nina (1954-1956) was determined by both models with a delay of 4 months, but the dynamics were modeled well. The start of the 1957 El Nino was predicted by the models a month later, and the dynamics were generally overestimated.

Next, we evaluated the results of a retrospective forecast of the Nino3.4 index. For this forecast, the 20CR reanalysis was used. Since the algorithms of assimilating the data in 20CR and NCEP/NCAR reanalyses differ, there are some differences in the geopotential and baric fields [14]. Therefore, when analyzing the results of retrospective modeling, emphasis was placed on qualitative assessment. First some statistical characteristics were estimated. Fig. 3 shows that the best similarity with the real index is observed in the 3-month advance forecast (Fig. 3a). The correlation of this model is 0.75, and the RMSE is 0.56 °C (the presence of fluctuations in the model index during the El Niño and La Niña can be explained by a high RMSE). Models with the ability of forecasting 5 and 7 months in advance noticeably do worse modeling of the Nino3.4 index. The correlation of these models with the Nino3.4 index is 0.61 and 0.46, and the RMSE is 0.67 °C and 0.77 °C, respectively. Figure 4 shows the time course of the Nino 3.4 index and modeling 3, 5, and 7 months in advance. All graphs are smoothed out by a 3-month moving average filter. It can be seen that the model with the forecast of the 3-month period describes the Nino3.4 index better.

![Figure 2](image_url)

**Figure 2.** Three-month mean average Niño 3.4 (red line), forecasting Niño 3.4 3 month in advance (green line) and 9 month in advance (blue line) for 1950-1957. The threshold for El Niño and La Niña selections is shown by a dotted line.
Figure 3. The ratio of the observed and modeled Niño 3.4 index 3 (c), 5 (b), and 7 (c) months in advance for 1872-1947.

Figure 4. Three-month mean average Niño 3.4 (red line), forecasting Niño 3.4 3 months in advance (dotted line), 5 month in advance (pointed line), and 7 month in advance (blue line) for 1872-1909 (a) and 1910-1947. The threshold for El Niño and La Niña selections is shown by a green line.
Table 2. Assessment of the possibility of predicting the start and maximum phase of El Niño (EN) and La Niña (LN) events in advance. Adv is forecasting 3, 5, 7, and 9 months in advance, $r$ is the Pearson correlation coefficient. If the modeled index is delayed, the value is negative.

| ENSO | Years | max(min) \( nino3.4 \) / duration | Adv=3 \( r=.75 \) | Adv=5 \( r=.61 \) | Adv=7 \( r=.46 \) | Adv=9 \( r=.40 \) |
|------|-------|----------------------------------|----------------|----------------|----------------|----------------|
|      |       | start max. phase | start max. phase | start max. phase | start max. phase | start max. phase |
| EN   | 1872  | -0.97/8   -3 0 | -1 5 1 | -1 -8 0 | - | - |
| EN   | 1873  | -1.06/15  -1 | - | - | - | - |
| EN   | 1875  | -0.89/14  -1 | - | - | - | - |
| EN   | 1877  | 2.71/17   0 -1 5 -1 | -1 -8 0 | - | - |
| EN   | 1885  | 1.03/5    -1 | - | - | - | - |
| EN   | 1886  | -1.16/13  -3 0 | -2 -7 0 -7 -2 | - | - |
| EN   | 1888  | 2.37/16   0 0 5 +2 | -1 -7 1 | - | - |
| EN   | 1889  | -2.12/16  -3 1 5 1 | -1 -6 2 | - | - |
| EN   | 1892  | -1.30/22  +3 1 +1 3 | - | - | - | - |
| EN   | 1895  | 0.75/5    -2 2 -3 5 0 | -1 | - | - | - |
| EN   | 1896  | 1.64/9    -1 -1 +1 4 +1 -2 | - | - | - | - |
| EN   | 1899  | 1.59/15   -3 2 | - | - | - | - |
| EN   | 1902  | 1.61/12   0 1 2 -1 -7 1 -6 1 | - | - | - | - |
| EN   | 1903  | -0.94/5   | - | - | - | - |
| EN   | 1904  | 1.46/17   0 -4 -2 | - | - | - | - |
| EN   | 1909  | -1.32/17  0 -1 2 1 -1 -1 2 | - | - | - | - |
| EN   | 1911  | 1.51/6    -3 2 | - | - | - | - |
| EN   | 1916  | -1.69/9   | - | - | - | - |
| EN   | 1918  | 1.36/10   0 2 0 +2 0 +2 -2 0 | - | - | - | - |
| EN   | 1924  | -0.98/9   -1 1 5 1 | - | - | - | - |
| EN   | 1925  | 1.50/13   | - | - | - | - |
| EN   | 1931  | 1.75/12   0 -1 2 1 -1 2 -1 2 | - | - | - | - |
| EN   | 1933  | -1.22/10  -2 1 | - | - | - | - |
| EN   | 1938  | -1.00/10  -3 6 0 | -1 0 0 0 | - | - |
| EN   | 1940  | 1.15/8    -3 6 0 | -1 0 0 0 | - | - |
| EN   | 1941  | 1.39/14   0 5 3 4 +1 4 | - | - | - | - |
| EN   | 1942  | -1.44/9   0 0 | - | - | - | - |

Let us analyze the possibility of predicting upcoming of El Niño and La Niña events in advance. Table 2 shows all recorded extreme ENSO phases from 1872 to 1947. As a criterion, it was assumed that the Nino3.4 index should be greater/less than 0.5/ -0.5 °C and that the duration of the anomaly should exceed 5 months. If the beginning of the phenomenon was determined by the model with a delay greater than the time of forecasting in advance, then it was believed that the model does not reproduce its beginning. Thus, the model with a 3-month advance forecast predicts 20 from 27 extreme events. It is slightly more than 74%. Note that 7 event starts could not be modeled (5 events from 7 are La Nina). The model with 5-month advance forecast predicts 18 events from 27. This is slightly more than 66%. If the forecasting in advance is 7 months, 14 from 27 extreme events were predicted, while in the case of forecast of 9 months only 9 from 27 events were identified in advance.

It is obvious that the quality of the retrospective forecast is much worse in comparison with the forecast with the control sample. There may be several reasons for this: the use of other data in the retrospective forecast, low availability of input data during assimilation by the 20CR reanalysis for 1872-1947, and the “memory” of the model, which was trained and tested in one climate but verified in another climate. It follows that before each forecast the neural network model must be retrained based on new data.
4. Conclusions
With a neural network model, a possibility of a Nino 3.4 index long-term 2-9 month advanced forecast was studied in this paper. The quality of the model was assessed by using NCEP/NCAR reanalysis and 20CR data.

On a test sample, the quality of the modeling worsens with increasing time of forecasting. The correlation coefficients between the observed and modelled indices for 2-3 months in advance are 0.95–0.85, while in the case of a 7-9 month advance forecast they are reduced to 0.91–0.76.

On a control sample, the quality of the NN model does not change fundamentally when the series is evaluated as a whole. The model calculations for a 3 month forecast showed a correlation coefficient of 0.92, while for a 9 month one it is 0.79 with the observed ENSO index. The RMSE and ensemble standard deviation increased with increasing time of forecasting. A qualitative comparison of the El Niño and La Niña forecasting on the control sample showed no significant disagreement with the observed indices when modeling for 3-9 months in advance. At the same time, in forecasting for 9 month in advance, erroneous ENSO events are sometimes modelled.

A retrospective forecast, carried out for an additional verification by using reanalysis data of 20CR in 1872-1947, showed a possibility of successful forecasting of up to 75% of the events of El Niño and La Nina for 3 months, up to 66% in forecasting for 5 months, and only up to 52% in forecasting for 7 months.

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