Prediction the Dynamic of Changes in the Concentrations of Main Greenhouse Gases by an Artificial Neural Network Type NARX

Alexander Sergeev[1,2, a)], Alexander Buevich[1,2, b)], Andrey Shichkin[1,2, c)], Elena Baglaeva[1,2, d)], Irina Subbotina[2, e)], Alexander Medvedev[1,2, f)], Marina Sergeeva[2, g)]

[1]Ural Federal University, Mira str., 19, Ekaterinburg, RUSSIA 620002
[2]Institute of Industrial Ecology UB RAS, S. Kovalevskoy str., 20, Ekaterinburg, RUSSIA 620990

[a)]aleksandrpsergeev@gmail.com
[b)]bagalex3@gmail.com
[c)]and@ecko.uran.ru
[d)]elenbaglaeva@gmail.com
[e)]iesub@mail.ru
[f)]Corresponding author: medvedev@ecko.uran.ru
[g)]marin@ecko.uran.ru

Abstract. The paper considered the use of one of the most accurate artificial neural networks for predicting time series - a nonlinear autoregressive neural network with external input (NARX) for predicting the dynamics of changes in the concentrations of the main greenhouse gases. The data were obtained in the course of monitoring the dynamics of changes in the main greenhouse gases on the Arctic island Belyy, Russia. The data of the surface concentration of methane, carbon dioxide, carbon monoxide and water vapor were used. A time interval of 168 hours was chosen for the study during the summer period (July-August 2016). The NARX model accurately predicted concentration changes for all greenhouse gases.

INTRODUCTION

The content of greenhouse gases in the atmosphere varies greatly in space and time, and their sources and sinks are very diverse and not well understood. Therefore, all the developed scenarios of the temporal dynamics of the global content of greenhouse gases are prognostic and can be carried out with a certain probability. For the implementation of such predictions, models based on artificial neural networks (ANN) [1] - [16], and, in particular, networks like NARX [17]-[20], are well suited. The NARX network is a recurrent dynamic multi-level feedback network. At its core, contains an autoregression model, which is used to describe systems with inertia. The predicted value depends on the previous values of the time series. The paper predicts changes in the concentration of several greenhouse gases by a model based on the NARX ANN. Water vapor (H_2O) is the main natural greenhouse gas. Carbon dioxide (CO_2) is the most important source of climate change, accounting for an estimated 64% of global warming. The main sources of carbon dioxide emissions into the atmosphere are the production, transportation, processing and consumption of fossil fuels (86%), the reduction of tropical forests and another biomass burning (12%). Methane (CH_4) has both natural and anthropogenic origin. It is estimated that methane accounts for about 20% of global warming. Carbon monoxide (CO) is not a greenhouse gas, but it affects chemical cycles in the atmosphere, which result in the formation or decomposition of other greenhouse gases [21].

International Conference of Numerical Analysis and Applied Mathematics ICNAAM 2019
AIP Conf. Proc. 2293, 120020-1–120020-4; https://doi.org/10.1063/5.0027183
Published by AIP Publishing. 978-0-7354-4025-8/$30.00

MATERIALS AND METHODS

Measurements of greenhouse gases carbon dioxide, carbon monoxide, methane, and water vapor were made on the Arctic Island, Belyy, YNAO, Russia. The island is located 9 km north of the Yamal Peninsula in the Kara Sea (Fig. 1).

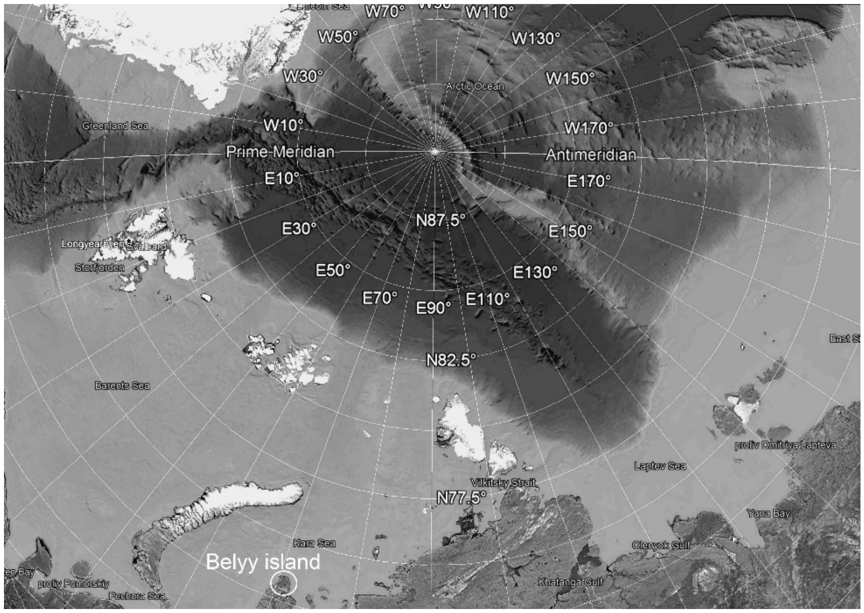

FIGURE 1. Place of measurements (Google Earth).

Concentrations of greenhouse gases and the main meteorological parameters (temperature, humidity, atmospheric pressure, wind speed and direction) were made by a cavity ring-down spectrometer Picarro G2401 and Vaisala AWS310 weather station. Gas concentrations and meteorological parameters were synchronized.

The time interval of 168 hours was divided into two parts. The first "long" part (144 hours) was used for train the model based on NARX. The second “short” (24 hours) was used only for forecasting and for comparing the predicted and measured data. The network structure was determined by computer simulation. The time interval and meteorological parameters were fed to the input, the hidden layer consisted of several neurons, and the output layer represented the gas concentration corresponding to the time interval. The Levenberg-Marquardt training algorithm was used for learning [18].

The number of neurons in the hidden layer in NARX was selected using the minimum mean square error (RMSE). The number of neurons ranged from 5 to 25. Each network was trained 500 times. Then the best of them was selected.

Indices mean absolute error (MAE) (1), RMSE (2), and the index of agreement (d), (a standardized measure of the degree of model prediction error and varies between 0 and 1, where a value of 1 indicates a perfect match, and 0 indicates no agreement at all [22] (3) was verified the predictive accuracy of each selected approach between the prediction and raw data from the training data set.

$$MAE = \frac{\sum_{i=1}^{n} |z_{mod}(x_i) - z(x_i)|}{n}, \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (z_{mod}(x_i) - z(x_i))^2}{n}}, \quad (2)$$

$$d = 1 - \frac{\sum |z_{mod}(x_i) - z(x_i)|}{\sum (|z_{mod}(x_i) - \overline{Z}| + |z(x_i) - \overline{Z}|)} \quad (3)$$

where $z_{mod}(\boldsymbol{x}_i)$ is a predicted concentration in location $\boldsymbol{x}_i$, $z(\boldsymbol{x}_i)$ is a measured concentration, $\overline{Z}$ is a mean concentration, and n is a number of points.

RESULTS AND DISCUSSION

The final neuron number in the hidden layer was 20 for NARX network. The indices given in table 1 show that the forecast of changes in the concentrations for all studied gases was carried out with sufficient accuracy.

TABLE 1. Accuracy assessment indices of the greenhouse gases concentration.

Gas	MAE	RMSE	d
H_2O	0.06	0.08	0.72
CO_2	1.80	2.16	0.80
CH_4	0.03	0.03	0.62
CO	0.002	0.003	0.82

It is especially important that the index of agreement d is high (with the exception of the indicator for CH_4). According to [22], this means a good accuracy of the model. Figure 2 visualizes the results of the forecast.

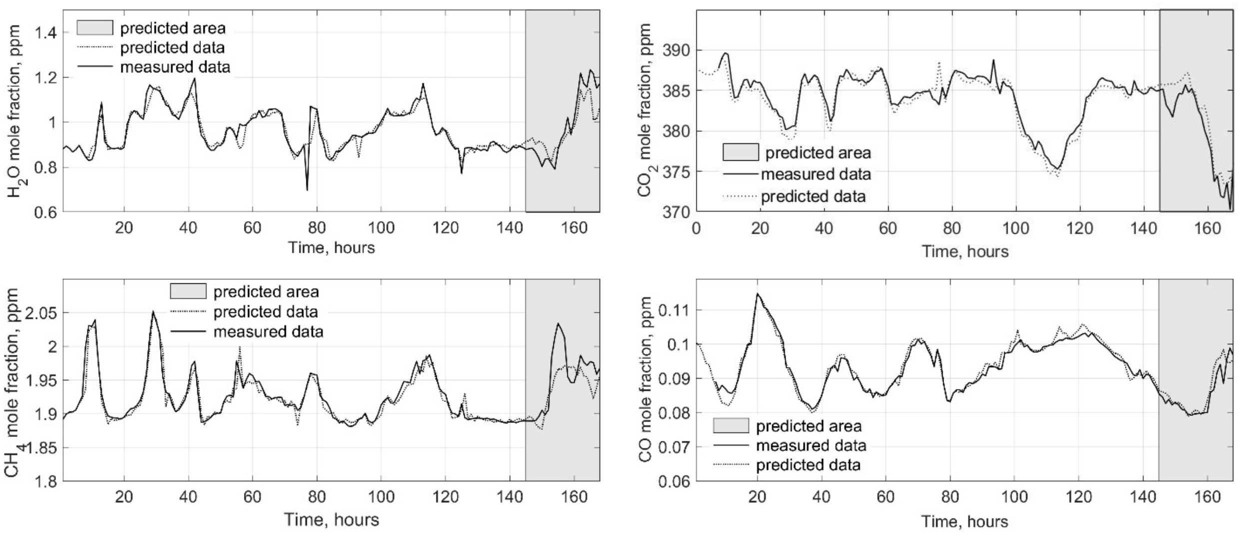

FIGURE 2. Visualization of the results of the prediction models based on NARX.

CONCLUSION

Due to the uncertainty of a number of climate feedbacks, the behavior of such a complex system as the atmosphere is difficult to predict. Even with the absolutely correct setting of changes in the concentration of greenhouse gases, the resulting change in the temperature of the system is difficult to determine unambiguously. Nevertheless, the authors believe that it is ANN-based models that can cope with such complex predictions.

REFERENCES

[1] A. Russo, F. Raischel and P. Lind, "Air quality prediction using optimal neural networks with stochastic variables", Atmos. Environ. 79, 822–830 (2013).

[2] A.P. Sergeev, A.G. Buevich, E.M. Baglaeva and A.V. Shichkin, "Combining spatial autocorrelation with machine learning increases prediction accuracy of soil heavy metals", Catena 174, 425–435 (2019).

[3] S. Stojadinovic, "Prediction of fly rock launch velocity using artificial neural networks", Neural Computing & Application 27, 515–524 (2016).

[4] D.A. Tarasov, A.G. Buevich, A.P. Sergeev and A.V. Shichkin, "High Variation Topsoil Pollution Forecasting in the Russian Subarctic: Using Artificial Neural Networks Combined with Residual Kriging", Applied Geochemistry 88(B), 188-197, (2018).
[5] A.V. Dmitriev, "Time series prediction of morbidity using artificial neural networks", Biomedical Engineering 47, 1, 43–45 (2013).
[6] G. Dimitrov, G. Panayotova, I. Garvanov, O. Bychkov, P. Petrov and A. Angelov, "Performance analysis of the method for social search of information in university information systems", in 3rd International Conference on Artificial Intelligence and Pattern Recognition (Lodz, Poland, IEEE, 2016), pp. 149-153.
[7] A. Erdil and E. Arcaklioglu, "The prediction of meteorological variables using artificial neural network", Neural Computing & Application 22, 1677–1683 (2013).
[8] K. Mohanty and T. J. Majumdar, "Using artificial neural networks for synthetic surface fitting and the classification of remotely sensed data", International Journal of Applied Earth Observation and Geoinformation 1(1), 78–84 (1999).
[9] G. Panayotova, G. Dimitrov, P. Petrov and O. Bychkov, "Modeling and data processing of information systems", in 3rd International Conference on Artificial Intelligence and Pattern Recognition (Lodz, Poland, IEEE, 2016), pp. 154-158.
[10] Z. Polkowski, J. Vasilev, D. Zajac and A. L. Florina, "A content analysis of existing educational portals for teaching data warehouse and business intelligence", Proceedings of the 8th International Conference on Electronics, Computers and Artificial Intelligence, ECAI 2016, 7861146 (2017), pp. 420-437.
[11] J. Vasilev, V.F. Turygina, A.I. Kosarev and Y.Y. Nazarova, "Mathematical optimization in environmental economics. Algorithm of gradient projection method", in International Multidisciplinary Scientific GeoConference SGEM 2016, Surveying Geology and Mining Ecology Management, (2016), pp. 349-356.
[12] Q. Zhou, H. Jiang, J. Wang and J. Zhou, "A hybrid model for PM2.5 forecasting based on ensemble empirical mode decomposition and a general regression neural network", Sci. Total Environ. 496, 264–274 (2014).
[13] Andrey Shichkin, Alexander Buevich, Alexander Sergeev, Alexander Medvedev, Alexandra Kosachenko, Anastasia Moskaleva, Marina Sergeeva, "Training Algorithms for Artificial Neural Networks for Time Series Forecasting of Greenhouse Gas Concentrations", AIP Conference Proceedings 2116, 200019 (2019).
[14] Sergeev A.P., Buevich A.G., Medvedev A.N., Spasov K.B., Kosachenko A.I., Moskaleva A.S., "On the Hybrid Models of Soil Contaminants Concentrations Predicting in Subarctic Region", AIP Conference Proceedings 1978, 440006 (2018).
[15] D.A. Tarasov, A.N. Medvedev, A.P. Sergeev, and A.G. Buevich, "Review and Possible Development Direction of the Methods for Modeling of Soil Pollutants Spatial Distribution", AIP Conference Proceedings 1863, 050014 (2017).
[16] Alexander G. Buevich, Alexander N. Medvedev, Alexander P. Sergeev, Dmitry A. Tarasov, Andrey V. Shichkin, Marina V. Sergeeva, and T. B. Atanasova, "Modeling of Surface Dust Concentrations Using Neural Networks and Kriging", AIP Conference Proceedings, 1789, 020004 (2016).
[17] M. Ardalani-Farsa and S. Zolfaghari, "Chaotic time series prediction with residual analysis method using hybrid Elman–NARX neural networks", Neurocomputing 73, 2540–2553 (2010).
[18] J.M. Jr. Menezes and G.A. Barreto, "Long-term time series prediction with the NARX network: An empirical evaluation", Neurocomputing 71, 3335–3343 (2008).
[19] E. Pisoni, M. Farina, C. Carnevale and L. Piroddi, "Forecasting peak air pollution levels using NARX models", Engineering Applications of Artificial Intelligence 22, 593–602 (2009).
[20] G. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model", Neurocomputing 5, 159–175 (2003).
[21] M.C. Serreze and R.G. Barry, "Processes and impacts of Arctic amplification: A research synthesis. Global and Planetary Change 77, 85–96 (2011).
[22] Willmott, C.J., "On the Validation of Models", Physical Geography 2, 184-194 (1981).