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ORIGINAL PAPER

Prediction of CO_2 emission from greenhouse to atmosphere with artificial neural networks and deep learning neural networks

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Abstract

The research aimed to model CO_2 flux from soil to atmosphere in greenhouse conditions, using multiple linear regression (MLR) artificial neural networks (ANN), and deep learning neural networks (DLNN). Following the purpose, crop species, soil temperature, soil moisture content, photosynthetic active radiation (PAR), and soil oxygen exchange were considered as input parameters and CO_2 flux as an output parameter. Levenberg–Marquardt learning function and logarithmic symmetric sigmoid transfer function were utilized in both ANN and DLNN. The optimal number of hidden layer neurons was determined through empirical observation, the model which produces the least mean absolute error value was chosen in each structure. Thus, ANN utilized 8 neurons, while DLNN utilized 14 neurons in the first hidden layer and 10 neurons in the second hidden layer. According to the result, CO_2 flux from soil to atmosphere was modeled using MLR with an accuracy of 95.63%, ANN with an accuracy of 95.56% and DLNN with an accuracy of 98.29%. Sensitivity analyses were conducted for both models to determine the pro rota efficiency of the input parameters on CO_2 flux. In the research, it was concluded that CO_2 flux from soil to atmosphere can be modeled in high accuracy, and deep artificial neural networks can have higher efficiency in similar works.

Keywords Greenhouse gas · Modeling · O_2 · PAR · Soil temperature · Soil moisture

Introduction

A lot of research has been done about the amount of CO_2 emitted from soil to the atmosphere in agricultural production. In all of these studies, the parameters affecting the CO_2 level were determined. The effects of factors such as organic matter content (Yu et al. 2020), microbial activity (Pramanik and Phukan 2020), soil tillage system (Luesma et al. 2020), fertilization amount and organic or inorganic nature of the fertilizer used (Rahman et al. 2020), soil moisture content (Zhang et al. 2020), soil temperature (Gao et al. 2020), aggregation condition of the soil (Dong et al. 2020), were examined on the amount of CO_2 emitted into the atmosphere.

Most of the research that modeling the amount of CO_2 emitted from the soil to the atmosphere has been done under field conditions. The number of studies conducted on modeling the amount of CO_2 emitted from the soil to the atmosphere in greenhouses is quite limited. In addition, in most of these studies, rather than CO_2, the concentration of other pollutant gases such as CH_4, NO_2 and NO_x released from the soil into the atmosphere was taken into account. Altıkat et al. (2019) stated that CO_2 dispersion increased in parallel with the increase in temperature and humidity content in their researches in which they examined the effects of soil type and soil temperature and humidity content on the amount of CO_2 emitted from the soil to the atmosphere. Also, it has been determined that CO_2 emission in normal soils is higher than saline soils. In the research, it was concluded that the manure wrapped on the soil surface causes more CO_2 emission than the manure left on the lower layers of the soil, and CO_2 emission increases due to the increase in the fertilizer norm.

ANN is an effective method to be used in the interpretation of parameters that do not have a linear relationship.

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ANN has been used in the modeling of atmospheric greenhouse gas concentrations, global warming, and other ecological issues frequently. Numerous studies have been conducted to model air quality and greenhouse gas emissions such as; the ANN was used the traffic and concentrations of pollutants (Viotti et al. 2002), dispersion of NO_2 (Nagendra and Khare 2006), modeling of the surface ozone concentration (Barcenas et al. 2005), net ecosystem exchange (He et al. 2006), CO_2 flux (Melesse and Hanley 2005). Also, ANN was used modeling forest ecosystems, vegetation, and soil change projections by researchers. Wang and Guan (2007) were used ANN for estimating forest biomass-based upon remote sensing, and Ito et al. (2008) predicted soil NNP using an ANN model.

Greenhouses are systems designed for production outside the natural growing seasons of plants, where the temperature, humidity, and ventilation needs are met by using various control systems (Choab et al. 2019). In recent years, changes in climates as a result of global warming have been attracting the attention of both governments and scientists, and there has been a significant increase in the number of researches conducted in this area (Liu et al. 2010). The increase of greenhouse gases such as CH_4, NO_2, and CO_2 in the atmosphere is one of the most important factors causing the increase of global warming (Pratibha et al. 2016). The adoption of technology-based production after the industrial revolution resulted in an increase of 700 μmol mol^{-1} of CO_2 in the atmosphere each year, and this situation caused in a 38% increase in atmospheric CO_2 compared to the pre-industrial period, and the temperature increased 0.6 °C over the past 100 years. (Lei et al. 2007). Over the years, they have been done a lot of research to observe these changes in climate. Besides, the various modeling techniques have been used to air quality interpret, model and predict of air quality (Choi et al. 2013; Garcia Nieto and Alvarez Anton 2014; Ishida et al. 2020; Lv et al. 2019; Schmidt et al. 2018; Zhang et al. 2019). However, most of the models did not produce positive results because the greenhouse gases in the atmosphere have been varying due to many factors, and there has been nonlinear relationship between them. Jung et al. (2020) modeled the temperature change with an accuracy rate of 96%, humidity change of 80%, and CO_2 change of 81% in their studies using the time series analysis method of deep neural networks to model the climate conditions within the greenhouse.

The purpose of this research is to model the amount of CO_2 emitted from the soil to the atmosphere in agricultural production under greenhouse conditions with artificial neural networks and deep artificial neural networks and to determine the effect levels by conducting sensitivity analysis of the parameters affecting CO_2 emission. Besides, the effectiveness of deep neural networks and artificial neural networks methods will be investigated in modeling studies.

Materials and methods

Experiment area

The experiments were carried out in greenhouses in the Agricultural Application and Research Center of Iğdır University. As experiment material, tomato, pepper, and cucumber plants were used, and seedlings were planted in April 2019. The drip irrigation method was used to distribute soil moisture homogeneously. In this method, drip irrigation

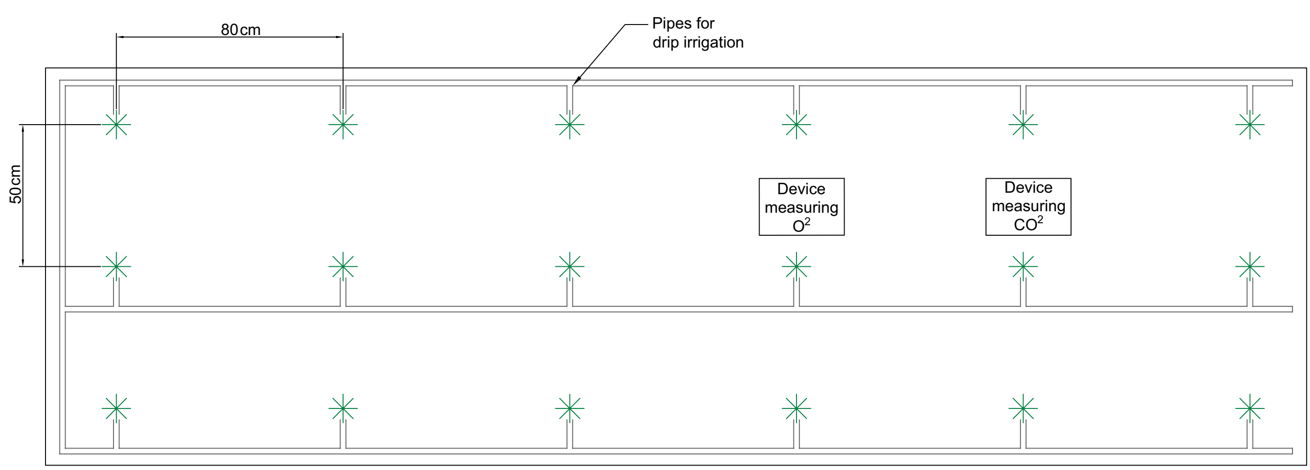

Fig. 1 Design of the experiment

Fig. 2 CO_2 and O_2 measurement instrument

pipes are placed in the root area of the plants. The plan of the experiment is given in Fig. 1.

To determine the level of CO_2 emitted from the soil to the atmosphere, the ACE brand CO_2 measuring device, which can measure according to the closed-loop method, was used (Fig. 2). The device runs on a 13 V battery and has sensors that can measure the changes in temperature and humidity under the ground. There is also a photosynthetically active radiation (PAR) sensor on the device. During the time from the start of the experiment to the conclusion, temperature, humidity, and PAR measurements CO_2 measurements were made simultaneously, and data on the device were recorded in the logger.

In the research, an undersoil oxygen measuring device was used to determine the change in soil oxygen capacity. The device consists of an oxygen sensor, battery, and data logger (Fig. 2). CO_2 and O_2 devices were placed between the rows of plants, and measurements were taken between 10:00 and 12:00 during the period until harvest. Oxygen measurements were made simultaneously with CO_2 measurements.

In this research, 426 data (6 parameters × 71 observation) were used for CO_2 flux prediction model. Soil temperature and moisture, photosynthetic active radiation, CO_2 and O_2 measurements were recorded at 30-min intervals with soil CO_2 exchange system and ICT oxygen measurement instrument.

Multiple Linear Regression (MLR), artificial neural networks (ANN) and deep learning neural networks (DLNN) methods were used to estimate the amount of CO_2 flux from the soil to the atmosphere. In the models, soil temperature, soil moisture, PAR, plant type, and O_2 level in soil were considered as input parameters; while CO_2 emitted from the soil to the atmosphere is considered as the output parameter.

The modeling with multiple linear regression

The MLR method was given in Eq. 1. In the equation, Y is model's predicted value, X is contaminant concentration, a_i, i:0…n, is coefficient of regression.

$$Y = a_0 + a_1x_1 + a_2x_2 + \cdots + a_nx_n \quad (1)$$

Artificial neural network (ANN) and deep learning neural network (DLNN)

In the ANN model, Levenberg–Marquardt was used as a learning function, and Linear functions were used as transfer functions. To determine the number of neurons in the ANN model, ANN network architecture has been tried in different neuron numbers, and the number of neurons that gave the minimum error was determined. As a result of the trials, it was decided to use ANN network architecture with neuron number of 8. ANN network architecture used in the research is given in Fig. 3.

Two hidden layers were used in the method of deep artificial neural networks. Levenberg–Marquardt was used as a learning function and Logarithmic-Symmetric sigmoid functions were used as transfer functions. To determine the number of neurons in the layers, the network was tested in different numbers of neurons, and models were made with the number of neurons that give the lowest MAE value (Table 1). Accordingly, in the DLNN method, the number of neurons in the 1st and 2nd layers was determined as 14 and 10, respectively. The architecture of the network used in the DLNN method is given in Fig. 4.

In the research, 70% of the data were used as the training set, 15% as the test set, and 15% as the verification set in both ANN and DLNN methods. The learning ability of the networks was decided by looking at the R values at the end

Fig. 3 ANN architecture

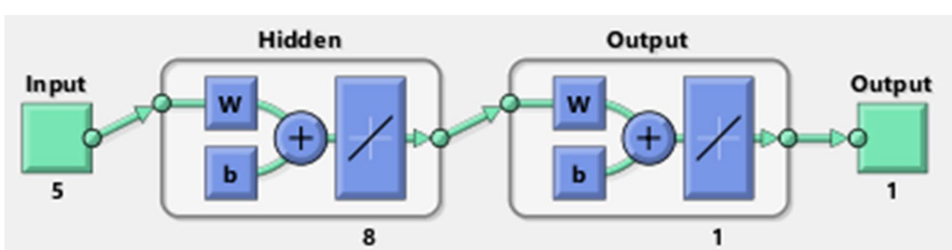

Table 1 MAE changes with different neuron numbers in DLNNs

Models	Learning function	Activation function	Neuron number		MAE
			1st hidden layers	2nd hidden layers	
DLNN1	Levenberg–Marquardt	Logarithmic- Symmetric sigmoid transfer fuctions	6	2	0.035
DLNN2			6	6	0.054
DLNN3			6	10	0.034
DLNN4			10	6	0.033
DLNN5			10	10	0.188
DLNN6			10	14	0.049
DLNN7			14	10	0.031
DLNN8			14	14	0.050
DLNN9			14	18	0.227
DLNN10			18	14	0.038
DLNN11			18	18	0.055
DLNN12			18	22	0.033

Fig. 4 DLNN architecture

of the training and verification of the network performances. As a result of the training of networks, it is concluded that the training and verification set is trained if the R values of the networks are close to 1. The MATLAB software was used in DLNN structures (R2019a). The MATLAB program is the most used software for modeling atmospheric pollution levels (Hagan et al. 1996).

Sensitivity analyses

In both methods, sensitivity analyses were performed on the models to determine the effect levels of input values on the CO_2 rate emitted from soil to the atmosphere (Aleboyeh et al. 2008). The following equality is used in determining the sensitivity tests (Eq. 2).

$$I_j = \frac{\sum_{m=1}^{Nh}\left(\left(\left|W_{jm}^{ih}\right| / \sum_{k=1}^{Ni}\left|W_{km}^{ih}\right|\right) \times \left|W_{mn}^{ho}\right|\right)}{\sum_{k=1}^{Ni}\left\{\sum_{m=1}^{Nh}\left(\left|W_{km}^{ih}\right| / \sum_{k=1}^{Ni}\left|W_{km}^{ih}\right|\right) \times \left|W_{mn}^{ho}\right|\right\}} \quad (2)$$

In the equation, I_j is the percentage of the relative importance of the jth input variable on the neurons, and W^{ih} and W^{ho} are the matrices of weights between input-hidden layer and hidden-output layer, respectively, N is the total number of neurons in the corresponding layer, respectively, and subscripts 'k', 'm' and 'n' are indices referring to the neurons in input, hidden and output layers, respectively.

Determining efficiency levels of the models

R^2 and MAE values were used to determine the accuracy of the models in both models (Eqs. 3, 4). The fact that R^2 value is close to 1 and MAE value to zero is accepted as an indicator that the model is correct.

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}\left(Y_{pi} - Y_{di}\right)^2}{\sum_{i=1}^{n}\left(Y_{di} - \bar{Y}\right)^2}\right) \quad (3)$$

Table 2 The statistical results for MLR analysis

	R^2	F	P	Estimated error variance
CO_2 flux	0.9563	288.9793	0.0000	0.0328

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_{pi} - Y_{di}\right| \tag{4}$$

In these equations; where, n is the number of observations, Y_{pi} is the predicted value for observation i, Y_{di} is the real value from observation i, and $\bar{Y}$ is the average of the real value.

Results and discussion

Result of multiple linear regression

In the research firstly, multiple linear regression models were used to estimate the CO_2 flux. For this purpose, plant type (Pt), photosynthetically active radiation (PAR), soil temperature (St), soil moisture content (Sm), and soil O_2 content (O_2) were used as input parameters for prediction of CO_2 flux. Table 2 illustrates the statistical results of the MLR. Examining Table 2, it can be seen that R^2 and P values are 0.9563 and 0.0000, respectively. The equation of the MLR model was given in Eq. 5. In addition, regression analyses of the MLR model and predicted—measurement values were given in Fig. 5a and b, respectively.

$$CO_2\ \text{flux} = 20.77 + 0.482x_1 + 0.00195x_2 - 0.2373x_3 - 0.27904x_4 - 0.6662x_5 \tag{5}$$

In this equation; x_1: Pt, x_2: PAR, x_3: St, x_4: Sm, x_5: O_2.

Table 3 Results of statistical analyses of ANN and DLNN

Models	R^2	MAE
ANN	0.9556	0.0661
DLNN	0.9829	0.0310

The results of artificial neural network (ANN) and deep learning neural network (DLNN)

In the research, statistical analyses of CO_2 models with artificial neural networks and deep artificial neural networks are given in Table 3. As can be seen from Table 2, the deep neural network model has lower MAE and higher R^2 value than the artificial neural network model. In the DLNN method, CO_2 fluxed from the soil to the atmosphere is modeled at an accuracy level of 98.29%, while this value is 95.56% in the artificial neural network model.

Network performances of the models are given in Fig. 6. When Fig. 6 is examined, it is seen that the R values of the training and verification process are above 0.95 in both models. According to these values, it can be concluded that both models do not memorize and the network structures created in both models are learned. In the research, the CO_2 emissions estimated and observed with the regression coefficients of both models are given in Fig. 7.

Results of sensitivity analyses

The results of sensitivity analysis were given in Table 4, and also Fig. 8 illustrates relative importance values for ANN and DLNN. In both models, it was determined that

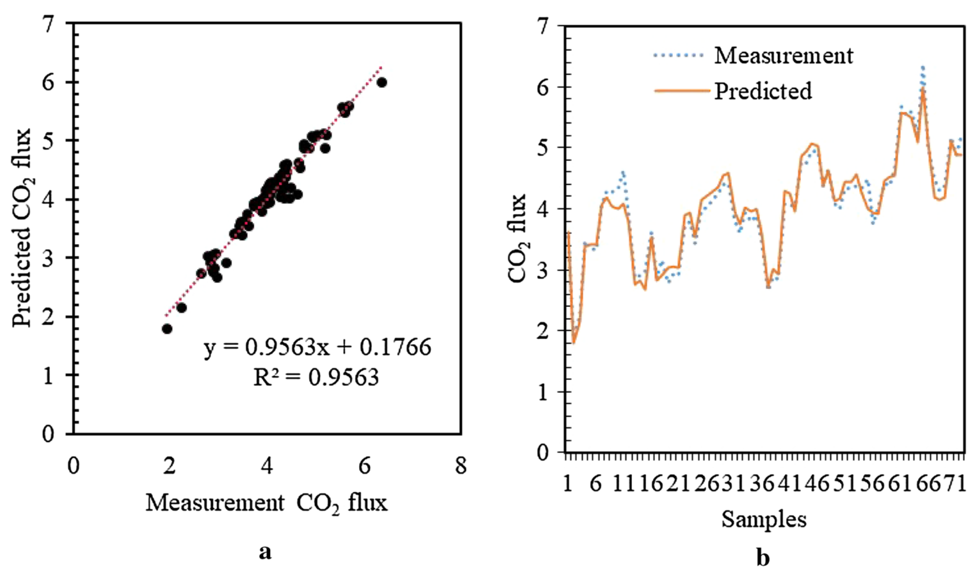

Fig. 5 Regression analyses of the models (**a**) and measurement-predicted CO_2 values (**b**)

Fig. 6 Training (**a**) and test results (**b**) of the models

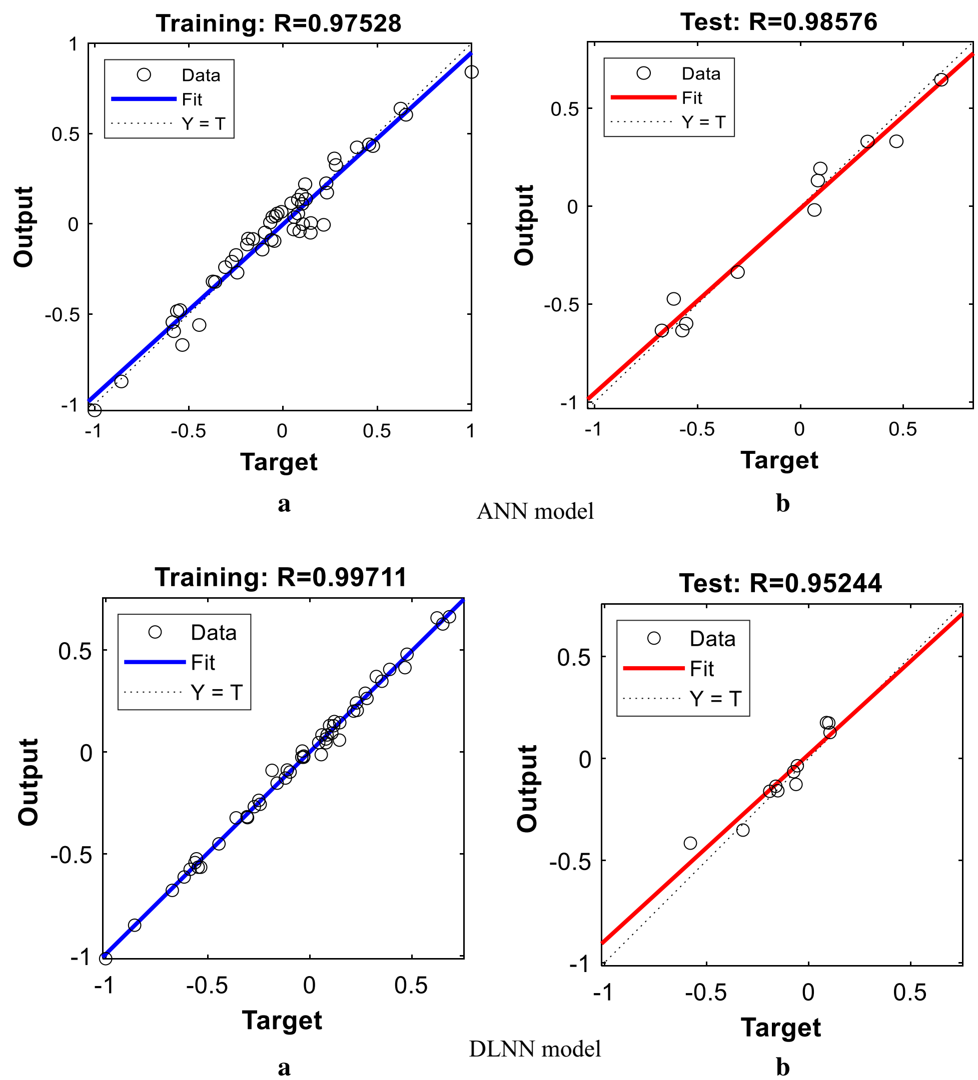

Table 4 The weights for DLNN and ANN

Deep learning neural network (DLNN)

Neuron number		W^{ih}					W^{ho}
		Inputs					Output
1st layer	2nd layer	Plant	PAR	Soil temperature	Soil moisture content	O_2	CO_2 flux
14	10	−0.64	3.03	0.0000	−3.55	0.42	−0.2201

Artificial neural network (ANN)

Neuron number	W^{ih}					W^{ho}
	Inputs					Output
	Plant	PAR	Soil temperature	Soil moisture content	O_2	CO_2 flux
8	0.227	0.229	−0.125	−0.784	−0.153	0.395

W^{ih} Input-hidden layer, W^{ho} hidden-output layer weights

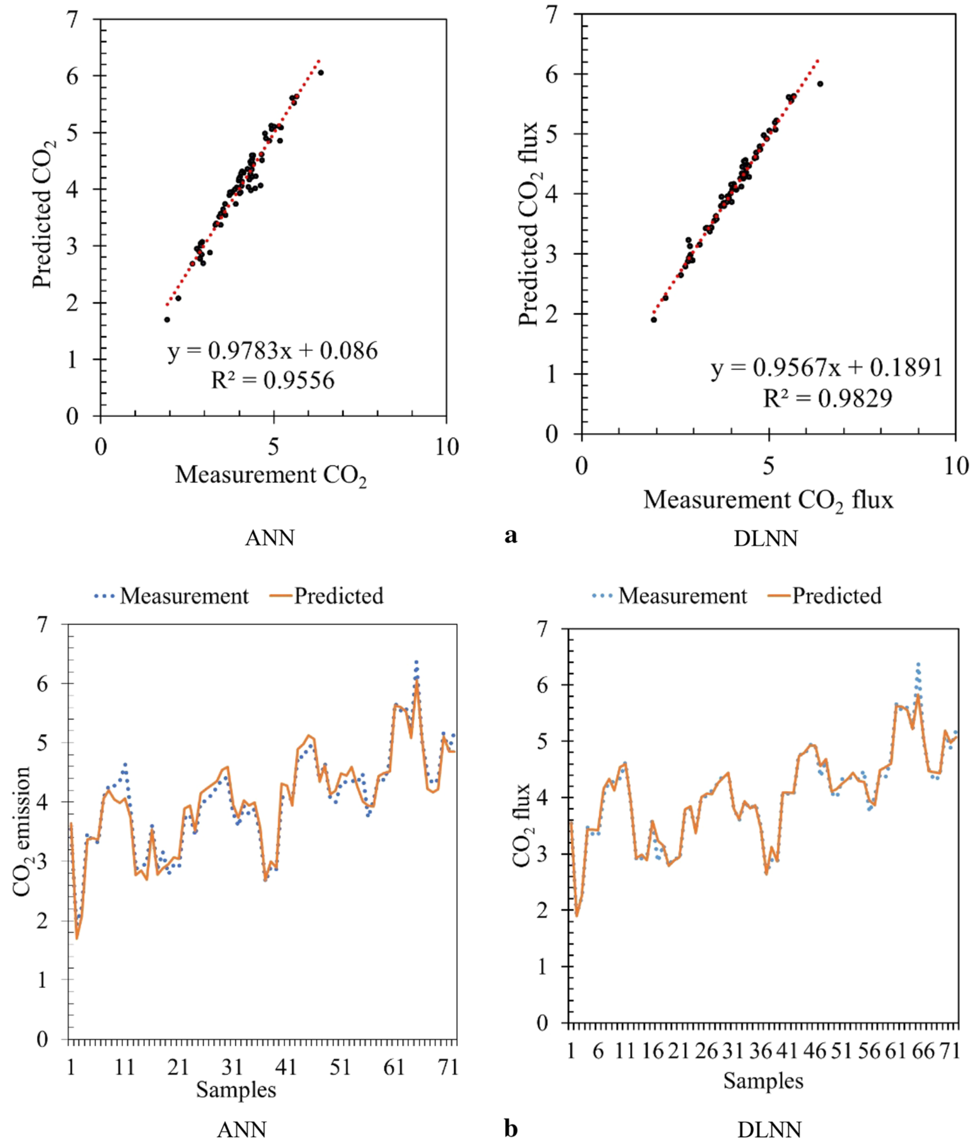

Fig. 7 Regression analyses of the models (**a**) and observed-predicted CO_2 values (**b**)

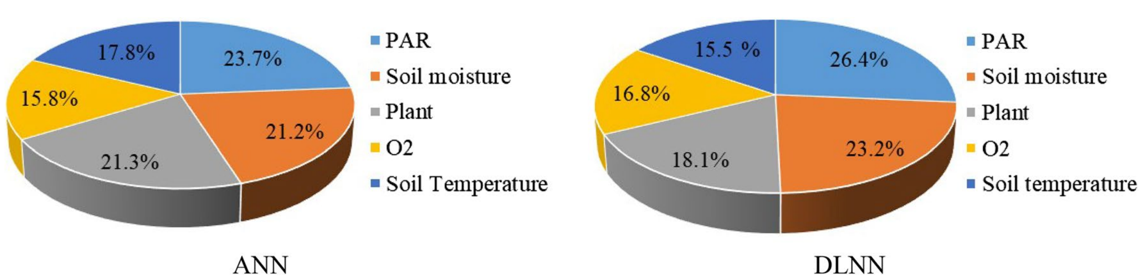

Fig. 8 Sensitivity analyses of the models

the most effective parameter on the amount of CO_2 emitted from the soil to the atmosphere is photosynthetically active radiation. The effect of photosynthetically active radiation on CO_2 emission was determined as 23.7% in the ANN method and 26.4% in the DLNN method.

In the research, CO_2 emitted from the soil to the atmosphere was modeled at a high accuracy level in both models. However, the accuracy rate in models created with deep neural networks was determined to be higher than artificial neural networks. The most important reasons for this are the number of hidden layers and the neurons used in deep artificial neural networks compared to artificial neural networks. In many studies, it has been emphasized that models using deep artificial neural networks have higher accuracy rates compared to other models.

Many studies are indicating that photosynthetically active radiation is effective in the amount of CO_2 emitted from the soil to the atmosphere. Vaczi (2019) and Altikat et al. (2018) stated in their studies that there is a directly proportional relationship between CO_2 emission and PAR. In studies to examine the relationship between soil temperature and CO_2 emitted into the atmosphere, it is emphasized that there is an increase in the rate of CO_2 emitted from the soil to the atmosphere depending on the temperature increase (Matthews et al. 2009; Eby et al. 2009). In hot environments such as greenhouses, the amount of CO_2 emitted from the soil to the atmosphere is more precisely affected by soil temperature (Wang et al. 2008) and soil moisture content (Sainju et al. 2010) than other factors.

Conclusion

In the study, soil temperature and humidity, soil oxygen capacity, photosynthetically active radiation, and plant type variables were used as input values in modeling the CO_2 level emitted from the soil to the atmosphere, and relative importance levels of these variables for CO_2 emission were determined in both models. Sensitivity analysis results showed a similar trend in both models. In the study, it was determined that the effect of photosynthetically active radiation level on CO_2 emission is proportionally higher than other variables. Photosynthetically active radiation is a variable that directly affects both soil temperature and soil moisture content. Subsoil moisture and temperature changes directly affect the microbial activities and by helping the organic matter decay rapidly in the soil, it helps to increase the micro and macro organism capacity of the soil and to transform the nutrients into the formation that plant roots can take. As a result, it can be said that the amount of CO_2 emitted from the soil to the atmosphere can be modeled at high accuracy in vegetative production under greenhouse conditions, and it will be more effective to use deep artificial neural networks in such studies.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

Aleboyeh A, Kasiri MB, Olya ME, Aleboyeh H (2008) Prediction of azo dye decolorization by UV/H_2O_2 using artificial neural networks. Dyes Pigm 77:288–294. https://doi.org/10.1016/j.dyepig.2007.05.014

Altikat S, Küçükerdem HK, Altikat A (2018) Effects of wheel traffic and farmyard manure applications on soil CO_2 emission and soil oxygen content. Turk J Agric For 42:288–297. https://doi.org/10.3906/tar-1709-79

Altıkat S, Küçükerdem HK, Altikat A (2019) The Response of CO_2 flux to soil warming, manure application and soil salinity. J Inst Sci Technol 9(3):1334–1342. https://doi.org/10.21597/jist.515501

Barcenas OP, Olivas ES, Guerrero JDM, Valls GC, Rodriguez JLC, Tascon SV (2005) Unbiased sensitivity analysis and pruning techniques in neural networks for surface ozone modeling. Ecol Model 182:149–158. https://doi.org/10.1016/j.ecolmodel.2004.07.015

Choab N, Allouhi A, El Maakoul A, Kousksou T, Saadeddine S, Jamil A (2019) Review on greenhouse microclimate and application: design parameters, thermalmodeling and simulation, climate controlling technologies. Sol Energy 191:109–137. https://doi.org/10.1016/j.solener.2019.08.042

Choi W, Paulson SE, Casmassi J, Winer AM (2013) Evaluating meteorological comparability in air quality studies: classification and regression trees for primary pollutants in California's South Coast Air Basin. Atmos Environ 64:150–159. https://doi.org/10.1016/j.atmosenv

Dong S, Zhang J, Li Y, Liu S, Dong Q, Zhou H, Yeomas J, Li YV, Gao X (2020) Effect of grassland degradation on aggregate-associated soil organic carbon of alpine grassland ecosystems in the Qinghai-Tibetan Plateau. Eur J Soil Sci 71:69–79. https://doi.org/10.1111/ejss.12835

Eby M, Zickfeld K, Montenegro A, Archer D, Meissner KJ, Weaver AJ (2009) Lifetime of anthropogenic climate change: millennial time scales of potential CO_2 and surface temperature perturbations. J Clim 2:2501–2511. https://doi.org/10.1175/2008JCLI2554.1

Gao X, Li W, Salman A, Wang R, Du L, Yao L, Hu Y, Guo S (2020) Impact of topsoil removal on soil CO_2 emission and temperature sensitivity in Chinese Loess Plateau. Sci Total Environ 708:1035102. https://doi.org/10.1016/j.scitotenv.2019.135102

Garcia Nieto PJ, Alvarez Anton JC (2014) Nonlinear air quality modeling using multivariate adaptive regression splines in Gijón urban area (Northern Spain) at local scale. Appl Math Comput 235:50–65. https://doi.org/10.1016/j.amc.2014.02.096

Hagan MT, Demuth HB, Beale M (1996) Neural network design. PWS Publishing Co. a Division of Thomson Learning, Boston

He HL, Yu GR, Zhang LM, Sun X, Su W (2006) Simulation CO_2 flux of three different ecosystem in China flux based on artificial neural network. Sci China Ser D-Earth Sci 49:252–261. https://doi.org/10.1007/s11430-006-8252-z

Ishida K, Tsujimoto G, Ercan A, Tu T, Kiyama M, Amagasaki M (2020) Hourly-scale coastal sea level modeling in a changing climate using long short-term memory neural network. Sci Total Environ 720:137613. https://doi.org/10.1016/j.scitotenv.2020.137613

Ito E, Ono K, Ito YM, Araki M (2008) A neural network approach to simple prediction of soil nitrification potential: a case study in Japanese temperate forests. Ecol Model 219:200–211. https://doi.org/10.1016/j.ecolmodel.2008.08.011

Jung DH, Kim HS, Jhin C, Kim H, Park SH (2020) Time-serial analysis of deep neural network models for prediction ofclimatic conditions inside a greenhouse. Comput Electron Agric 173:105402. https://doi.org/10.1016/j.compag.2020.105402

Lei XD, Peng CH, Tian DL, Sun JF (2007) Meta-analysis and its application in global change research. Chin Sci Bull 52:289–302. https://doi.org/10.1007/s11434-007-0046-y

Liu Z, Peng CH, Xiang WH, Tian D, Deng XW, Zhao MF (2010) Application of artificial neural networks in global climate change and ecological research: an overview. Chin Sci Bull 55:3853–3863. https://doi.org/10.1007/s11434-010-4183-3

Luesma SF, Cavero J, Bonilla DP, Martinez CC, Arrue JL, Fuentes JA (2020) Tillage and irrigation system effects on soil carbon dioxide (CO_2) and methane (CH_4) emissions in a maize monoculture under Mediterranean conditions. Soil Tillage Res 196:104488. https://doi.org/10.1016/j.still.2019.104488

Lv M, Li Y, Chen L, Chen T (2019) Air quality estimation by exploiting terrain features and multi-view transfer semi-supervised regression. Inf Sci 483:82–95. https://doi.org/10.1016/j.ins.2019.01.038

Matthews HD, Gillett NP, Stott PA, Zickfeld K (2009) The proportionality of global warming to cumulative carbon emissions. Nature 459:829–832. https://doi.org/10.1038/nature08047

Melesse AM, Hanley RS (2005) Artificial neural network application for multi-ecosystem carbon flux simulation. Ecol Model 189:305–314. https://doi.org/10.1016/j.ecolmodel.2005.03.014

Nagendra SMS, Khare M (2006) Artificial neural network approach for modelling nitrogen dioxide dispersion from vehicular exhaust emissions. Ecol Model 190:99–115. https://doi.org/10.1016/j.ecolmodel.2005.01.062

Pramanik P, Phukan M (2020) Enhanced microbial respiration due to carbon sequestration in pruning litter incorporated soil reduced the net carbon dioxide flux from atmosphere to tea ecosystem. J Sci Food Agric 100:295–300. https://doi.org/10.1002/jsfa.10038

Pratibha G, Srinivas I, Rao KV, Shanker AK, Raju BMK, Choudhary DK, Srinivas Rao K, Srinivasarao CH, Maheswari M (2016) Net global warming potential and greenhouse gas intensity of conventional and conservation agriculture system in rainfed semi arid tropics of India. Atmos Environ 145:239–250. https://doi.org/10.1016/j.atmosenv.2016.09.039

Rahman GKMM, Rahman MM, Alam MSA, Kamal MZ, Mashuk HA, Datta R, Meena RS (2020) Biochar and organic amendments for sustainable soil carbon and soil health. Carbon and nitrogen cycling in soil. Springer, Singapore, pp 45–85

Sainju UM, Stevens WB, CaesarTonThat T, Jabro JD (2010) Land use and management practices impact on plant biomass carbon and soil carbon dioxide emission. Soil Sci Soc Am J 74(74):1613–1622. https://doi.org/10.2136/sssaj2009.0447

Schmidt A, Creason W, Law BE (2018) Estimating regional effects of climate change and altered land use on biosphere carbon fluxes using distributed time delay neural networks with Bayesian regularized learning. Neural Netw 108:97–113. https://doi.org/10.1016/j.neunet.2018.08.004

Vaczi P (2019) Autonomous in situ measurement of daily courses of the net CO_2 exchange rate in a moss from alpine environment. Czech Polar Rep 9(2):220–227. https://doi.org/10.5817/CPR2019-2-18

Viotti P, Liuti G, Genov PD (2002) Atmospheric urban pollution: applications of an artificial neural network (ANN) to the city of Perugia. Ecol Model 148:27–46. https://doi.org/10.1016/S0304-3800(01)00434-3

Wang SJ, Guan DS (2007) Remote sensing method of forest biomass estimation by artificial neural network models (in Chinese). Ecol Environ. 16:108–111. https://doi.org/10.3390/rs9030241

Wang XG, Zhu B, Gao MR, Wang YQ, Zheng XH (2008) Seasonal variations in soil respiration and temperature sensitivity under three land-use types in hilly areas of the Sichuan Basin. Aust J Soil Res 46:727–734. https://doi.org/10.1071/SR07223

Yu Q, Hu X, Ma J, Ye J, Sun W, Wang Q, Lin H (2020) Effects of long-term organic material applications on soil carbon and nitrogen fractions in paddy fields. Soil Tillage Res 196:1–7. https://doi.org/10.1016/j.still.2019.104483

Zhang L, Traore S, Ge J, Li Y, Wang S, Zhu G, Cui Y, Fipps G (2019) Using boosted tree regression and artificial neural networks to forecast upland rice yield under climate change in Sahel. Comput Electron Agric 166:105031. https://doi.org/10.1016/j.compag.2019.105031

Zhang H, Qian Z, Zhuang S (2020) Effects of soil temperature, water content, species, and fertilization on soil respiration in bamboo forest in subtropical China. Forests 11(1):99. https://doi.org/10.3390/f11010099