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Assesment of CO_2 fluxes in the typical steppe of southern Western Siberia

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Abstract. For the first time, net ecosystem exchange (NEE) and ecosystem respiration (R_{eco}) were measured using the chamber method within the typical steppe of the Kulunda Plain, West Siberia, (Altai Krai), and gross primary production (GPP) was calculated. To identify the relationship between CO_2 fluxes and environmental factors, the following parameters were also measured: aboveground phytomass (AGP), photosynthetically active radiation (PAR), air temperature, soil temperature and soil moisture. The median (1Q, 3Q) NEE, R_{eco}, and GPP were -103 (-152, -66), 90 (74, 105), and -200 (-251, -151) mg C m^{-2} h^{-1}, respectively. The key factors of variability in NEE and GPP were aboveground phytomass, while for R_{eco} – soil moisture content in the 100 cm layer. Based on the obtained data, a neural network was successfully trained using the Levenberg-Marquardt algorithm (R^2_{train} = 0.9, R^2_{valid} = 0.9, R^2_{test} = 0.8; MSE_{train} = 335, MSE_{valid} = 647, MSE_{test} = 360; N_{train} = 50; N_{valid} = 11; N_{test} = 11), which will be used in the future to scale carbon fluxes in space and time.

Keywords. Carbon dioxide, summer fluxes, dry grassland, regional natural monument, south of Western Siberia, Kulunda Plain, Altai Krai.

Оценка потоков CO_2 в настоящей степи юга Западной Сибири

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Реферат. Впервые в пределах настоящей степи Кулундинской равнины, Западная Сибирь (Алтайский край), камерным методом были измерены чистый экосистемный обмен (NEE) и экосистемное дыхание (Reco), а также рассчитана валовая первичная продукция (GPP). Для выявления связи потоков CO_2 с факторами среды также измерялись следующие параметры: надземная фитомасса (AGP), фотосинтетически активная радиация (ФАР), температура воздуха, температура почвы и ее влажность. Медианные (1Q, 3Q) значения NEE, Reco и GPP составили -103 (-152, -66), 90 (74, 105) и -200 (-251, -151) мг С $м^{-2}$ $ч^{-1}$ соответственно. Ключевыми факторами изменчивости NEE и GPP были надземная фитомасса, а для Reco – влажность почвы в слое 100 см. На основе полученных данных успешно обучена нейронная сеть с использованием алгоритма Левенберга-Марквардта (R^2_{train} = 0.9, R^2_{valid} = 0.9, R^2_{test} = 0.8; MSE_{train} = 335, MSE_{valid} = 647, MSE_{test} = 360; N_{train} = 50; N_{valid} = 11; N_{test} = 11), которая в дальнейшем будет использоваться для масштабирования потоков углерода в пространстве и времени.

Ключевые слова. Углекислый газ, летние потоки, настоящие степи, памятник природы, юг Западной Сибири, Кулундинская равнина, Алтайский край.

Introduction

Finding ways to adapt to climate change requires refining regional estimates of the CO_2 and other greenhouse gas balance (Cenci, Biffis, 2025), which has been identified as a global priority at the national (Decree…, 2020; Strategy…, 2021) and international levels (IPCC, 2023).

Inventorying and long-term forecasting of the CO_2 balance is typically carried out using mathematical simulation methods, which require validation using regional field data. Furthermore, it is important not only to measure CO_2 fluxes at different spatial scales and types of terrestrial ecosystems, but also to explore and analyse their complex relationships with meteorological and environmental factors (Pillai et al., 2025). The most important of these are soil temperature and moisture, as well as the input of substrates from plants into soil biota (Hu et al., 2024). Also, the CO_2 balance of a particular ecosystem depends on local environmental conditions and land use types (Li et al., 2020; Wang et al., 2024). In international practice, studies on measuring CO_2 fluxes have been carried out mainly in forest and wetland ecosystems (Mazzola et al., 2021; Shokoufeh et al., 2021), while in steppe ecosystems such measurements are rare (Gilmanov et al., 2003; Perez-Quezada et al., 2010; Zhang et al., 2007; Wen et al., 2024). A detailed review of balance estimates of net ecosystem production (NEP) of CO_2 in the world's steppe zone based on instrumental measurements from 1997 to 2011 is presented in the paper by (Golubyatnikov et al., 2023). In Russia, there is also a prevailing interest in taiga forest and wetland ecosystems, where measurements are mainly organized using the eddy covariance (EC) method (Glagolev, 2010; Monitoring…, 2017; Kazantsev et al., 2018; Mamkin et al., 2019; Dyukarev et al., 2019; Kuricheva et al., 2023). This is partly due to the fact that forests account for 61% of Russia's total ecosystem area, tundra for 18%, swamps for 10%, and grassland ecosystems for 6%. Preserved and restored steppe ecosystems account for only 3.4%, with only 1% conserved in protected areas (Assessment..., 2023, p. 56). In the Altai Krai, natural steppes account for 2.9%, and restored steppes account for 7% of the region's total area. (Assessment..., 2023, p. 63). Moreover, the steppes are a critical component of biodiversity and are characterized by the largest soil carbon reserves in southern Russia.

A limited number of model estimates of net primary production (NPP) and ecosystem respiration (R_{eco}) have been obtained for steppe ecosystems in Russia (Titlyanova, Shibareva, 2017; Assessment..., 2023). These data are comparable with previous CO_2: NPP assessments for steppe ecosystems in Russia (Golubyatnikov et al., 2023). However, these model estimates require refinement to ensure a reliable accounting of steppe area, as well as the use of a broader set of factual data for validation (Assessments..., 2023). Among the instrumental measurements in steppe ecosystems, it is also worth noting the net ecosystem exchange (NEE) estimates using the EC method (natural background and fallow) in the Republic of Khakassia (Belelli Marchesini et al., 2007, Vuichard et al., 2008). Noteworthy are the R_{eco} estimates obtained using the EC method on the East European Plain within forest-steppe agroecosystems, mixed and broad-leaved forests during 2020-2022 growing seasons (Sukhoveeva et al., 2023). This confirms that direct instrumental ground-based measurements of CO_2 fluxes in steppe ecosystems in Russia are currently few and have not been conducted in the Altai Krai.

It should also be emphasized that greenhouse gas (GHG) emission datasets are often incomplete due to inconsistent reporting and difficulties in organizing ground-based observations, and recently there has been an increasing number of studies on filling these gaps and, in general, on estimating carbon emissions based on machine learning (Cullen et al., 2024; Feng et al., 2024; Al Nuaimi et al., 2025). Satellite remote sensing data (MODIS/Terra) for grass communities (Zhukov, Zhukova, 2023) and forest ecosystems (Rygalova et al., 2024) are also actively and successfully used to estimate GHG fluxes in the absence of ground-based measurements. In this regard, the purpose of this study is to evaluate CO_2 fluxes using static chambers and test machine learning methods for scaling CO_2 fluxes in space and time in conditions of a shortage (short series) of instrumental observations of fluxes and using only climatic parameters, which are usually easier to organize and long-term. To achieve this goal, ground-based instrumental measurements of CO_2 fluxes and related environmental factors were carried out for the first time in the arid meadows of the Altai Territory. The neural network was trained using short series data obtained using the Levenberg-Marquardt algorithm.

Materials and methods

Study Area

Measurements of CO_2 fluxes and associated environmental factors were carried out from July 22 to 25, 2024, at four measurement sites (MS) on the territory of the regional natural monument “Balochnaya system in Novokormikha” (protected area since May 6, 2014), located on the Kulunda Plain in the Altai Krai (coordinates: 52.143755, 80.086703, WGS84)[1)].

Climate and Weather Conditions

According to data from the nearest Roshydromet weather station in Volchikha (located 30 km southeast of the study site), average annual air temperatures from 1995 to 2024 ranged from 0.5 to 4.5°C, while precipitation over the same period ranged from 190 mm to 580 mm. In 2024, the average annual temperature was 4°C, and precipitation was approximately 400 mm, indicating warm and moist conditions during the measurement period. Over the past 5 years, the 2024 growing season was the most humid, but not the hottest, while the period from June to August was characterized by the highest average daily air temperatures. During the field work itself, rain was observed on July 22 (night and day), and also on the night of July 25.

Vegetation and Soils

The natural monument is a gully up to 15 m deep and overgrown with birch forest, and an adjacent flat area. The southwestern aspect of the gully is covered with steppe vegetation, and the northeastern one is covered with a community with a tree layer (*Betula pendula*). The bottom of the gully is composed of complexes of meadow and hydrophytic vegetation. The vegetation of the study area belongs to the class of typical steppe formations (Lavrenko, 1940; Lavrenko et al., 1991; Ronginskaya, 1963). Measurements of flows, environmental factors, and botanical descriptions were carried out on the flat area, where forb-feather-grass typical steppegrows on low-humus, medium-deep southern chernozems, classified as Chernozem according to the FAO classification, and Calcic, Chca according to the WRB classification[1]. During field geobotanical releves, two steppe communities were identified, named according to the dominant species of the identified sublayers. The communities are located 20 meters apart. The geobotanical releves were prepared using generally accepted methods and processed using the dominant-determinate system. They contain the following phytocoenotic data: phenological indices of dominant species, floristic diversity of communities, and total projective cover (PC). The dominants within each MS were identified. Latin plant names are given according to the International Plant Names Index[2)] (IPNI 2025). Four MS were established within these communities to measure CO_2 fluxes (Fig. 1).

[1)] Balochnaya system in Novokormikha [online], available at: https://minprirody-old.alregn.ru/directions/prirodnye_resursy/oopt/ooptAK/pamjatniki_prirody/pamjatniki_prirody_kraevogo_znachenija/balochnaja_sistema_v_novokormixe (accessed 30 June 2025) (in Russian).

[2)] International Plant Names Index (IPNI), available at: https://ipni.org (accessed 30 May 2025).

Figure 1. CO_2 flux measurement sites
MS 1-4 is marked as T 1-4, respectively. MS 1 and 4 are feather-grass wormwood steppe, MS 2 and 3 are fescue-feather-grass steppe

Рисунок.1. Площадки измерений (ПИ) потоков CO_2
На фото ПИ 1–4 обозначены как Т 1–4 соответственно. ПИ 1 и 4 – тырсоковыльно-полынная степь, ПИ 2 и 3 – типчаково-тырсоковыльная степь

Aboveground Phytomass

AGP was mown within each measurement site. Phytomass reserve (P) was calculated using the formula:

$$P = AGP_{raw} - (AGP_{dry}/S_{MS}), \tag{1}$$

where AGP_{raw} – weight of raw AGP in grams, AGP_{dry} – weight of dried AGP in grams, S_{MS} – area of measurement site in m^2. Drying was carried out in a drying chamber at a temperature of 105°C until an absolutely dry state was achieved.

CO_2 Flux Measurements

CO_2 fluxes were measured using the static chamber method using transparent and opaque chambers (closed with covers made of foil-clad polyethylene foam, which additionally reduced their heating). Transparent chambers were used to measure CO_2 fluxes: NEE, and opaque ones – for R_{eco}. GPP was calculated as the difference between NEE and R_{eco} (with negative values corresponding to the CO_2 sink from the atmosphere to ecosystems and vice versa). The chambers were made of transparent 4 mm thick organic glass in the shape of a parallelepiped (height – 70 cm, side dimensions – 34×34 cm, volume – 0.103 m^3) (Fig. 2). The chambers were equipped with samplers with silicone hoses. Settled well water was poured into a trough at the base, functioning as a water seal. The air in the chambers was mixed with a fan with an air flow rate of 0.88 m^3/min. To reduce the impact of foundation insertion on the soil gas profile, they were installed on July 22, 2024, 12 hours before the start of measurements. A portable infrared gas analyzer EGM-5 Portable CO_2 Gas Analyzer (PP-System, USA) with a concentration measurement error of <1% was used to measure the concentration of carbon dioxide over a range of 0-100,000 ppm. Measurements were carried out at each MS in triplicate in the morning from 9:30 to 11:30 am and in the evening from 4:00 to 6:00 pm. The exposure duration was 3 minutes. Specific CO_2 fluxes were calculated in the MatLab software package (MathWorks, Inc., USA) using the formula:

$$flux = 2aPMb\frac{H}{T + T_o}, \quad (2)$$

where $flux$ – specific CO_2 flux (mg C $m^{-2}h^{-1}$), a = 0.12 mg mol K/(kg J ppm), P – total pressure of the gas mixture (Pa), M – molar mass of gas (0.012 kg/mol for express flux in mg C m^{-2} h^{-1}), b – the rate of change of gas concentration in the chamber atmosphere (ppm/h; calculated as the slope of the line representing the increase in gas concentration in the chamber using the least squares method with weights, fitlm function, MATLAB), H – chamber height (m), T – temperature in the chamber at the end of the measurement (K), T_o – temperature in the chamber at the beginning of the measurement (K).

The absolute error of flux was estimated using the formula:

$$\Delta flux = 2aPM\frac{1}{T + T_o}(\Delta bH + |b|\Delta H). \quad (3)$$

Here Δb – error in determining the parameter b (ppm/h), ΔH – is the error in determining the camera height (m; assumed to be 0.05 m, which is mainly due to the inaccuracy of estimating the camera installation height due to surface unevenness). To compare the obtained instrumental estimates of GPP and NPP, the satellite remote sensing product MOD17A2HGF.061 (Terra Gross Primary Productivity) was used, which is an 8-day composite with a 500-meter spatial resolution of GPP values (Running, Zhao, 2021).

Ecological Factors

For continuous monitoring of air and soil temperature during daylight hours, autonomous Thermochron iButton DS1921 sensors (Dallas Semiconductor, USA) were installed at a height of 100 cm and a depth of 0.30 cm. They were set to measure at a frequency of 3 hours and had an accuracy of ±0.5°C. In the immediate vicinity of each MS, soil volumetric moisture content was measured in percentages at the surface once daily from 13:00 to 16:00 and then in 10 cm increments down to a depth of 100 cm using an express kit consisting of an NN-2 data logger and an ML3 ThetaProbe sensor (measurement accuracy of ±1%) (Delta-T Devices, UK). The total solar radiation (TSR) intensity was measured during daylight hours using a Janiszewski thermoelectric pyranometer connected to an EMS12 data recorder (Environmental Measuring Systems, Czech Republic), with continuous data recording during daylight hours at a frequency of 20 times/min. The measurement period was predominantly cloudless, so uniform conversion factors were used first from volts to kcal/cm^2 min (calibration coefficient – 0.12), and then to W/m^2 (coefficient – 698) (Photosynthesis…, 1989).

Statistical data processing and machine learning

Standard nonparametric statistics were calculated for the obtained data: the sample median for CO_2 flux measurements and environmental factors, and uncertainty characteristics – the first and third quartiles. Statistical hypotheses were tested using the Kruskall-Wallis test at a significance level of. The model (input: environmental factors; output: CO_2 fluxes) was developed using machine learning using the Neural Network Toolbox module in MATLAB. A standard two-layer feed-forward NN was used. The Levenberg-Marquardt algorithm was used for NN training, as it is the most universal method suitable for most problems. Furthermore, it has proven effective when working with small training sets and weak correlations between CO_2 fluxes and environmental parameters (Beale et al., 2010). The input parameters were checked for high internal correlation ($R^2 \geq 0.5$) using the correlation matrix. The original set of input and target data was divided (by default) into three subsets: the training subset "Training" (70%), which was used to adjust the neural network weights by minimizing the model error (Beale et al., 2010); the test subset "Testing" (15%), which was used to independently evaluate the performance of the trained model, and the validation subset "Validation" (15%), which was used to monitor training and stop testing if there was no improvement. The number of layers of neurons (10) in the hidden subset was selected empirically to achieve the highest training efficiency, which was expressed by the lowest MSE (Beale et al., 2010).

Results and discussion

During the fieldwork, geobotanical releves of the steppe communities and the measurement sites established within them were conducted. MS1 and MS4 were established in feather-grass-wormwood steppe communities: *Stipa capillata, Artemisia frigida, Festuca pseudovina*, *Koeleria pyramidata* (Fig. 2). MS2 and MS3 were established in fescue-feather-grass-steppe communities: *Stipa capillata, Festuca pseudovina* (Fig. 2). AGP was calculated at each MS (see Table 1).

As a result of measurements at the MSs, data were obtained on NEE and R_{eco}: CO_2, as well as associated environmental factors: air temperature at a height of 100 cm, PAR, soil temperature at the surface and at a depth of 30 cm, and volumetric soil moisture in a 100-cm layer with measurements every 10 cm. Based on these measurements, GPP: CO_2 was calculated. Results of all measurements are presented in Table 1.

To identify significant differences in the magnitude of CO_2 fluxes in the groups between the MSs, the Kruskal-Wallis test was used at a significance level of (Table 2). The differences that emerged for NEE and GPP (see Table 2) were most likely associated with the phytomass reserve (P). Higher values of NEE and GPP for MSs 1 and 3 are associated with higher productivity values – 291 and 419 g/m^2, respectively, and lower values of NEE and GPP for MSs 2 and 4 with lower values – 129 and 144 g/m^2 (see Table 1). We believe that the result of the R_{eco} test at MS4 (see Table 1) is due to moisture reserves in the meter-deep soil layer. A calculation of the moisture content (average for July 23-25) per 100 cm by MS revealed that MS4 (dominant: *Koeleria pyramidata*) recorded the lowest values – 175 mm. This compares to MS1 (dominant: *Artemisia frigida*) – 181 mm, MS2 (dominants: *Stipa capillata*, *Festuca pseudovina*) – 198 mm, and MS3 (dominant: *Stipa capillata*) –

193 mm. Moreover, comparatively low moisture content was also observed under MS1, which can be explained by the fact that *Artemisia frigida* is an indicator of arid conditions (Peat, Bowes, 1994).

Table 1. CO_2 fluxes and ecological factors of environment for MS 1-4 (median/1 quartile/3 quartile)
Таблица 1. Потоки CO_2 и экологические факторы среды по ПИ 1-4 (медиана / 1 квартиль / 3 квартиль)

Parameter	MS 1–4	MS 1	MS 2	MS 3	MS 4
NEE	-103/-152 /-66	-145/-159/-118	-68/-85/-56	-162/-200/-134	-54/-90/-41
R_{eco}	90/74/105	99/86/111	74/67/86	101/79/135	91/85/95
GPP	-200/-251/-151	-237/-266/-205	-149/-156/-134	-284/-310/-241	-157/-181/-137
P	218/140/323	291	129	419	144
PAR	1206/1007/1368	1057/777/1406	1240/1042/1387	1217/1100/1265	1204/1051/1362
T_{air}	31/28/34	31/27/34	32/28/34	32/29/34	32/28/34
T_0	29/27/37	28/27/38	29/27/37	31/27/38	31/27/37
T_{30}	22/22/22	22/22/22	22/22/22	22/22/23	22/22/23
W_0	22/20/24	21/20/21	23/20/25	22/20/25	22/17/25
W_{10}	18/17/19	18/17/21	18/18/23	19/18/19	17/17/18
W_{20}	16/15/18	15/13/18	17/15/26	15/13/20	16/16/18
W_{30}	13/13/14	13/13/14	15/13/16	13/13/18	13/11/14
W_{40}	15/14/16	15/13/16	16/15/16	15/14/16	12/11/14
W_{50}	14/13/15	14/13/15	15/15/16	13/13/14	13/12/13
W_{60}	14/13/16	14/12/16	16/15/16	15/14/16	12/12/14
W_{70}	16/14/17	16/13/18	17/17/18	15/15/18	14/14/14
W_{80}	17/17/18	18/13/19	17/17/18	18/15/19	17/16/19
W_{90}	19/17/20	17/15/20	17/17/18	22/19/22	20/15/21
W_{100}	22/20/24	19/16/20	24/23/24	24/23/26	20/19/22
W_{avg}	17/17/18	17/15/17	18/17/19	18/17/18	16/15/17

Footnote: the unit for specific CO_2 fluxes (NEE, Reco, GPP) is mg C m^{-2} h^{-1}, for phytomass reserve (P) is g/m^2, for temperatures are °C; soil moisture by depth (Wi) is volumetric moisture – %.

Table 2. Kruskal-Wallis test for significant differences in CO_2 fluxes in groups between MSs
Таблица 2. Тест Краскелла-Уоллиса на предмет значимых отличий по величине потоков CO_2 в группах между ПИ

MS	NEE	R_{eco}	GPP
1	A	A	A
2	B	B	B
3	A	A	A
4	B	AB	B

An independent estimate of GPP and NPP was obtained using MODIS/Terra satellite data. According to MOD17A2HGF, for the study area on July 23-28, 2024, GPP values fluctuated around 310 mg C $m^{-2}h^{-1}$, and NPP ~ 230 mg C $m^{-2}h^{-1}$. Thus, remote sensing generally agrees well with the median values for sites 1 and

3, whose plant communities are dominant in the study region. It should be noted that values of 300-310 mg C $m^{-2}h^{-1}$ are anomalous and exceed the long-term average (2000-2024) by 20%, which may be due to high humidity during the study period. Typically, the maximum in GPP according to MOD17A2HGF was observed in the period June 25 – July 5, but in 2024 it shifted to July 4-12 due to heavy precipitation, leading to an increase in soil moisture reserves. In this regard, the obtained data are more typical of conditions when vegetation has passed the peak of maximum development. Moreover, the year 2024 was generally different from previous years. For example, 2024 was noted in the Northern Hemisphere as the warmest and wettest in the series of instrumental observations since 1850[3)] (Global…, 2024). According to the Volchikha weather station (located 30 km southeast of the observation site), more precipitation fell during the growing season (May-September) of 2024 than in the previous four years – 254 mm (in comparison: 2020 – 148 mm, 2021 – 144 mm, 2022 – 133 mm, 2023 – 221 mm). Furthermore, our results on phytomass reserves within the MS range are highly comparable with those for the true steppes of Siberia and Kazakhstan, ranging from 60 to 226 g/m^2 (Titlyanova, Shibareva, 2017, p. 50). Despite the lack of calibration of the MOD17A2HGF product for typical steppe ecosystems of Eurasia and the anomalous climatic conditions in 2024, the MODIS data for the study period are quite close to the obtained ground-based GPP estimates.

The GPP reconstruction was based on the hypothesis of a correlation between ground-based instrumental observations of CO_2 fluxes (a short observation series) and variations in climatic factors. It was assumed that NN-based methods would allow extrapolation of the obtained relationships to a longer time range. To train the NN using cross-correlation, 8 of the 17 measured environmental factors were excluded. The exclusion threshold was a correlation coefficient (R) greater than 0.5 (in absolute value). As a result, the following predictors were selected for training the NN: phytomass reserve (P), air temperature at a height of 100 cm (T_{air}), soil temperature at a depth of 30 cm (T_{30}), soil moisture at depths of 10, 30, 60, 80, 90 cm (W_{10}, W_{30}, W_{60}, W_{80}, W_{90}). In the context of choosing predictors, we relied on the experience used in measuring NEE using the eddy covariance method. For example, in the typical steppe of Inner Mongolia, among the environmental factors influencing NEE, the authors highlight photosynthetically active radiation (PAR) and soil moisture at a depth of 20-30 cm (Wang, Wang, 2011). When measuring CO_2 fluxes using a similar method for typical steppe pastures, it was found that vapor pressure deficit and photosynthetically active radiation helped grasslands absorb atmospheric CO_2. At night, when temperature was above 0°C, the increases in air and soil temperature promoted vegetation respiration to release CO_2 (Chen et al., 2023). It was noted (Wang et al., 2024) that for the community of the closely related species Stipa krylovii, PAR showed a negative correlation with NEE (Wang et al., 2024). Based on the above, the current study considered air temperature at a height of 2 m, PAR, and soil moisture in the root layer (30 cm) as the main

[3)] Global Climate Highlights, URL: https://climate.copernicus.eu/global-climate-highlights-2024 (accessed: 29.01.2026).

predictors. Based on the results of the cross-correlation analysis, PAR was excluded from the discussed indicators. The results of NN training for predicting NEE, R_{eco}, and GPP fluxes are presented in Fig. 2.

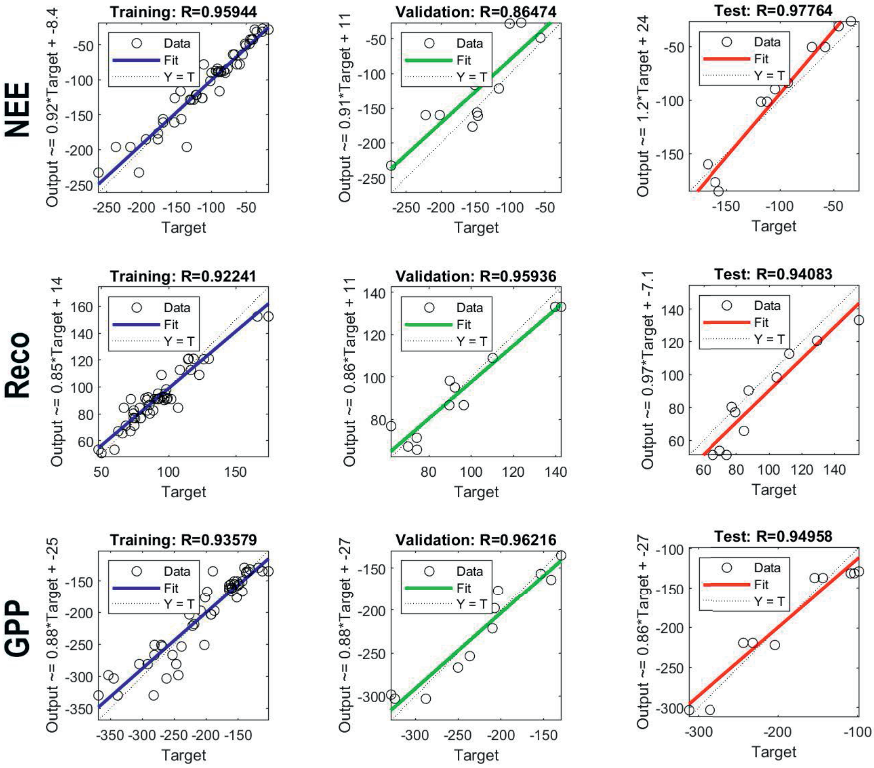

Figure 2. Results of training the NN for predicting the values of NEE, R_{eco} and GPP fluxes depending on environmental factors: phytomass reserve (P), T_{air}, T_{30}, W_{10}, W_{30}, W_{60}, W_{80}, W_{90}
Blue – training set, green – validation, red – test

Рисунок 2. Результаты обучения нейронной сети для предсказания величин потоков NEE, Reco и GPP в зависимости от экологических факторов: фитомассы растений (P), Твозд, T30, W10, W30, W60, W80, W90
Синий – обучающая выборка, зеленый – валидирующая, красный – тестовая

The correlation coefficients for all samples were equal to or greater than 0.9. The resulting NN can be used (primarily) for spatial scaling of CO_2 flux values due to the fact that the variability of the input parameters during the measurement period was insignificant. The applicability limits of the current neural network for the input variables P, T_{air}, T_{30}, W_{10}, W_{30}, W_{60}, W_{80}, W_{90} are as follows: 129-419 g/m^2, 24-44°C, 21-23°C, 17-23%, 11-18%, 12-16%, 13-19%, 15-22%; accordingly, inadequate results may be obtained beyond these limits. With further collection of field data under different temporal and environmental conditions, the NN should be further trained. AGP is a key parameter in carbon flux studies (Ilyasov et al., 2020). One of the study's hypotheses – to establish a link between NEE, R_{eco}, and plant community productivity – was also confirmed (see above). Furthermore, our results within the MS range are highly comparable with those for the dry grasslands of Siberia and Kazakhstan, ranging from 60 to 226 g/m^2 (Titlyanova, Shibareva 2017, p.50).

The good agreement between direct and satellite data in our study of the typical steppe, as well as in assessing the GPP of extrazonal forest ecosystems in the Altai Krai steppe (Rygalova et al., 2024), strongly suggests further productive work on the temporal and spatial extrapolation of ground-based data, as well as for the verification and possible calibration of remote sensing data in the region. It should be noted that progress is currently being made in improving the quality of remote sensing products, and MODIS data and ground-based measurements are being successfully used to develop and validate various models for estimating GPP at 10 km resolution (Wang et al., 2024).

Various types of NN have demonstrated satisfactory results in predicting GHG emissions, including backpropagation neural networks (BNNs) and recurrent neural networks (RNNs). These networks have their own advantages and disadvantages in terms of complexity and the accuracy of their results (Feng et al., 2024). In our case, a standard two-layer feed-forward neural network (FNN) was used. A similar example to our study, using a simple NN architecture and a limited set of input environmental parameters, was obtained in Indonesia for irrigated rice fields when predicting methane (CH_4) and nitrous oxide (N_2O). As in our case, air temperature, soil temperature, and soil moisture were selected as predictors (Chusnul et al., 2025). Clearly, rice fields have their own specific characteristics, primarily related to soil moisture regimes. However, the use of soil moisture as a predictor in modeling soil organic carbon content (Luo et al., 2020) and predicting carbon sinks (Humphrey et al., 2021) is becoming increasingly common. Air temperature, which we selected as one of the predictors, like atmospheric CO_2 concentration, is a clear and uncontroversial factor in influencing CO_2 sinks. Closely related to temperature, PAR is one of the most important factors influencing GPP (Yin et al., 2021). However, in our case, PAR and temperature were closely correlated, and using both parameters in the model could have introduced noise. Therefore, given that air temperature is clearly the leading factor, as well as the simple measurement technology and availability of data, we chose this parameter.

Conclusions

The work is devoted to measurements of CO_2 fluxes in the typical (true) steppe of the Altai Krai. Field chamber observations of CO_2 concentration served as the technological basis for the study. For the first time, estimates of such parameters as net ecosystem exchange, ecosystem respiration, and gross primary production were obtained for the region. Correlations were revealed between CO_2 fluxes and various environmental factors, such as aboveground phytomass, PAR, air temperature, soil temperature and moisture. The median (1Q, 3Q) NEE, R_{eco}, and GPP were, respectively: -103 (-152, -66), 90 (74, 105), and -200 (-251, -151) mg C m^{-2} h^{-1}. The key factor of variability in NEE and GPP was aboveground phytomass, while for R_{eco} it was soil moisture content in the 100 cm layer. Based on the obtained data, a neural network was trained using the Levenberg-Marquardt algorithm, which allows for GPP reconstruction using the above-mentioned climatic parameters, where $R^2_{test} = 0.8$. This research clearly requires further investigation, possibly including parallel observations using the eddy covariance method and, if possible, covering not only natural ecosystems but also agrocenoses (arable lands, pastures). Also of interest are measurements in the "arable land - field windbreaks" system, as studying the carbon sequestration potential of these systems is extremely relevant for both applied and fundamental research.

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