Assessment of the potential and forecasting of carbon sequestration by agricultural crops using artificial intelligence*

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Abstract

The effectiveness of using information technologies in agriculture to support climate change adaptation and mitigation depends largely on the qualitative and quantitative characteristics of data collected through sensors, satellite monitoring, GIS technologies, drones, and other information- gathering tools. This article presents the development of a methodological toolkit for assessing the potential and forecasting carbon sequestration by agricultural crops using artificial intelligence. The ground-based installations were used to obtain the database-sensors that capture geolocation and sensors of physical characteristics such as humidity, temperature, and insolation, etc. Using the method of correlation and regression analysis, mathematical models were developed to predict the possible volumes of carbon dioxide sequestration depending on the size of sown areas and crop yields in the Ternopil region. It has been investigated that increasing the productivity of field crop agrocenoses is an important way to reduce the CO_2 content in the atmosphere and prevent further global warming on a planetary scale. To verify the accuracy of the obtained data and generate predictive analytics, the XGBoost gradient boosting method was applied. The application of this approach made it possible to increase the accuracy of predicting the volume of carbon dioxide assimilation by agrocenoses, taking into account the variability of yields and crop areas in different years. The results obtained allow us to predict potential changes in the ability of crops to fix CO_2 depending on climatic and farming factors, which is important for developing a strategy for sustainable agricultural production. The obtained results are the basis for further research on the use of artificial intelligence in carbon farming management.

Keywords

information technologies in agriculture, artificial intelligence, carbon farming, sustainability

1. Introduction

1.1. Problem statement

The application of climate change adaptation and mitigation measures in agriculture represents a set of innovative approaches to farming. In particular, the introduction of climate-

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neutral innovations in agricultural natural resource management are nature-based solutions for the development of precision agriculture, regenerative agriculture, and low-carbon agriculture itself. Such innovations are a synergy of carbon-neutral technologies and digital technologies to ensure the sustainable use of agricultural resources in the context of strengthening both food and climate security.

"Information technology in agriculture is used to generate yield maps, machinery movements; calculate the need for seeds, planting material, fertiliser; draw up a scheme of sown areas for future years; assess soil conditions; create an electronic field log with the ability to sort by harvest year; forecasting of technological operations for the next season or several years; preparation of reports with diagrams on the presence of diseases and pests, as well as weeds in the fields; division into groups of diseases [1], pests [2], weeds; keeping records of pesticides; recording climate forecasts and meteorological data" [3]; remote nitrogen monitoring in agricultural crops [4], etc. In this context, the effectiveness of information technologies in agriculture for climate change adaptation and mitigation is determined by the qualitative and quantitative characteristics of the database collected through sensors, satellite monitoring, GIS technologies, drones, and other digital tools. "The advantages of such information technologies are reduced consumption of water, nutrients and fertilisers, reduced negative impact on the surrounding ecosystem, reduced chemical runoff into local groundwater and rivers, increased efficiency, lower prices, etc." [5]. GIS-maps are of particular importance in this process, namely the use of geographic information technologies in agriculture, which enables the visualisation of current and future changes in precipitation, temperature, yield, plant health and, as a result, to determine the most suitable areas of the field for growing the relevant crops, to optimise the use of drip irrigation to avoid droughts by means of automatic or manual valve control. "Geoinformation systems allow you to choose the right layers, visualisation methods and indicators, developing a plan to suit your needs" [6]. The operational principle of such systems are illustrated in Figure 1.

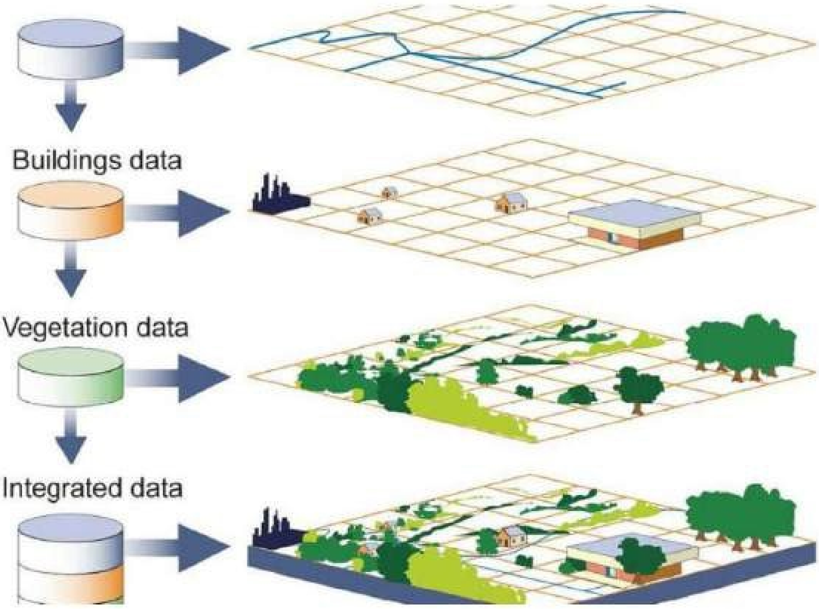

Figure 1: Principle of operation of geoinformation systems [6]

The "GIS technologies are a set of digital techniques that allow analysing the physical characteristics of the planet's surface. For better perception, the data obtained with their help is visualised. This information is used to create multi-layer maps, atlases, graphs, charts and interactive applications. The benefits of using GIS technologies for agriculture include increased yields and the development of precision farming, which increases the average yield of farms by 22% while reducing clean water consumption by 20%. In addition, the automation of machinery reduces the use of manual labour (for example, with the help of GIS solutions, one farm worker can operate four machines at the same time), saves fertilisers and plant protection products, and optimises associated costs (for example, the use of GIS reduces the cost of purchasing fuel, maintaining machinery and storing materials by 7-9%)" [5-6]. GIS technologies allow the company to collect databases on weather conditions and climate change in the following areas:

- "'Plant freezing' reports on low temperatures that threaten your winter crops;
- "Frost threat" highlights the days when the temperature dropped below -6℃ to assess the damage caused to early crops by frost;
- "Threat of drought" displays days with temperatures above +30 ℃ to assess damage from heat stress" [5].

One of the consequences of anthropogenic activities of mankind on the environment is global warming, which began in the middle of the second half of the twentieth century and continues to this day. Ecologists and climatologists believe that climate change is caused by an increase in the content of greenhouse gases in the atmosphere, in particular carbon dioxide. "Over the past 66 years, the CO_2 content has increased by 34.7%, from 315.2 ppm in 1958 to 424.6 ppm in 2024" [7].

1.2. Related work

One of the ways to reduce the CO_2 content in the atmosphere is through agricultural production, as agrocenoses can accumulate up to 1 Gt/year of carbon on a global scale [8]. "In agricultural practice, carbon farming is a method for capturing and sequestering carbon dioxide that enhance the capture and storage of CO2 in soil and vegetation, preventing its re- release. Examples include reforestation and the management of peatlands and wetlands" [9]. "According to EU Commission estimates, in Europe alone, carbon farming is expected to provide a total emissions reduction of 42 million tonnes of carbon dioxide by 2030" [10].

To address the issue of agricultural decarbonisation, artificial intelligence technologies are being applied. "Precision farming technologies based on artificial intelligence allow farmers to use resources such as water, fertilisers and pesticides more efficiently. In order to minimise the overuse of resources, reduce emissions associated with their production and application, using machine learning and data analytics algorithms, artificial intelligence can analyse various factors such as soil conditions, weather conditions and crop requirements. For example, AI- driven irrigation systems can significantly reduce water use and energy consumption, contributing to a lower carbon footprint. By preventing crop losses and reducing the need for chemical treatments, artificial intelligence can help reduce emissions associated with excessive pesticide use and freight transport" [11].

The study [12] proposed the use of remote sensing and soil sensing techniques, such as high-density electrical conductivity and electromagnetic induction sensors for instance, C- Mapper and ground penetrating radar, in combination with machine learning prediction models. The result is a proposed predictive carbon map of a soybean and corn field in Mississippi. The red dots on the map indicate the total number of ground data points collected. This field trial covers a huge area of 414 hectares. The predicted carbon map shows a high degree of accuracy with an average absolute error of only 0.149 (percentage of total carbon) and an average absolute percentage error of 14.2%.

Another way to prevent climate change goes with [13] proposing the use of agroforestry (using the example of the Neem tree, which has a higher carbon sequestration capacity by an average of 161% compared to other tree species in the tropics) as a cost-effective way to recycle carbon compared to other solutions in Tanzania. In particular, the application of artificial intelligence can intensify Neem tree-based agriculture to accelerate carbon sequestration. [14] presents a multi-channel convolutional neural network (CNN) based on the use of deep learning in combination with satellite data to improve the efficiency of estimating and predicting soil organic carbon content. Different time ranges, including multi-year and seasonal ranges, have been considered for generating composites. The study [15] conducted a predictive analysis based on the exponential smoothing model and life cycle assessment (LCA), which suggests that AI will reduce carbon emissions in agriculture by 2030 in India. To achieve this, it proposes measures to promote energy-efficient AI hardware, use renewable energy sources, optimise AI algorithms for energy efficiency, support precision agriculture (PA), and apply circular economy practices. The paper [19-20] presents an analysis of the use of AI tools in the agricultural sector.

A review of scientific papers confirms the relevance of carbon sequestration in agriculture. Of particular significance is the integration of remote sensing technologies and artificial intelligence to create and process a database. Attention is drawn to employ new technologies and the selection of plants with deeper root systems to mitigate climate change. However, in the context of climate change adaptation and mitigation in agriculture, an open challenge remains: how to accurately quantify and predict the amount of carbon dioxide, its removal and conservation by crops through carbon farming.

In view of this, **the aim of the article** is to develop a methodological toolkit for assessing the potential and forecasting the carbon sequestration of agricultural crops using artificial intelligence.

2. Materials and Methods

2.1. Methodology

Under martial law in Ukraine, there is a ban on the use of equipment installed on aircraft (e.g. drones). In view of this, ground-based installations were used to obtain the database-sensors that determine the coordinates and sensors of physical characteristics such as humidity, temperature, and insolation. The analytical data obtained were processed using correlation and regression analysis. For this purpose, a graphical model of the dependence of air temperature changes on a global scale on the content of carbon dioxide in the atmosphere was built in Figure 2.

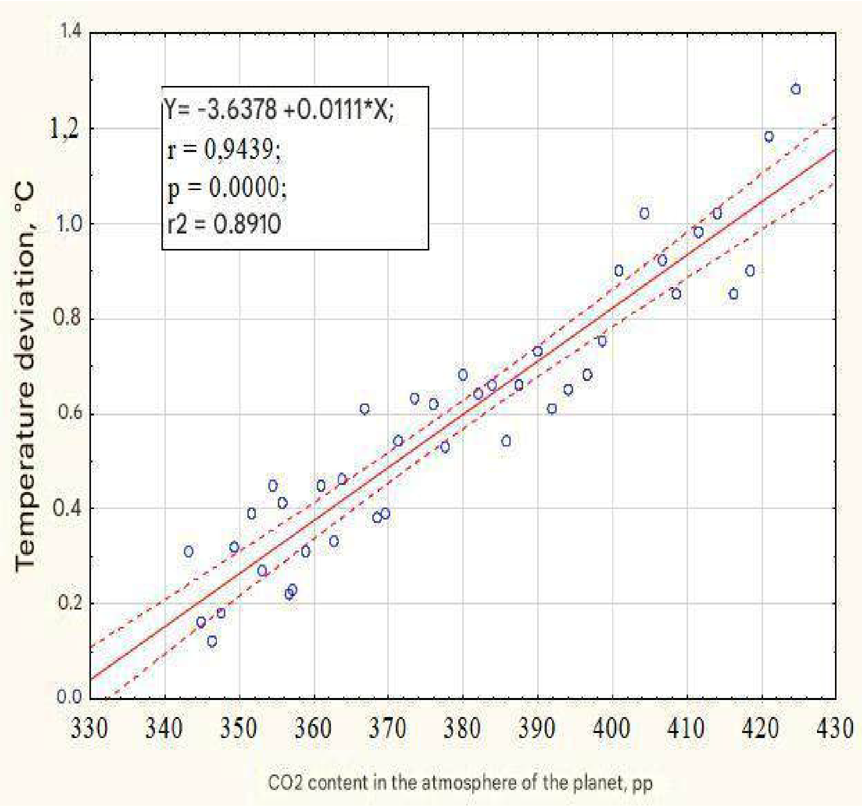

Figure 2: Correlations and regression equations between CO_2 content in the atmosphere and the Earth's temperature increase

A close direct correlation was found, as the correlation coefficient between the independent and dependent variables is 0.9439.

The regression equation Y=-3.6378+0.0111*X, where X is the content of carbon dioxide in the atmosphere, ppm, and Y is the deviation of air temperature, °C, reliably describes these relationships, since the probability of the null hypothesis (p) is 0.0000, which is less than 0.05.

Using the method of correlation and regression analysis, mathematical models were built to predict the possible volumes of carbon dioxide sequestration depending on the size of sown areas and crop yields in the Ternopil region. In order to determine the carbon sequestration potential of the main agricultural crops in the Ternopil region, the relevant calculations were made. The data from the State Statistics Service of Ukraine were used [16] on their sown areas and yields of main products.

To verify the accuracy of the data obtained and generate predictive analytics, we used the XGBoost gradient boosting method, which is one of the most effective approaches for working with tabular data. Its application is based on the ability to take into account complex dependencies between variables, high resistance to multicollinearity, and the ability to adaptively improve forecasting results through consistent training.

2.2. Case study

The total yield of absolutely dry biomass was calculated taking into account the dry matter content of the grown products. The amount of sequestered carbon was determined based on its average content in the plant biomass of field crops - 47% [17], and the amount of sequestered CO_2 was calculated using a coefficient of 3.7.

The study found that agrocenoses of winter and spring wheat in the Ternopil region can accumulate 169-21.4 t/ha of carbon dioxide, and their total crops are 4288.3 thousand tonnes (Table 1). For winter and spring barley, these figures are 13.5-15.1 t/ha and 294.2-363.5 thsd tonnes, respectively.

Corn is the leader in carbon dioxide sequestration among the crops grown in Ternopil region. During the growing season, it can accumulate 29.1-35.5 t/ha of CO_2 in biomass, and, taking into account the size of the harvested area, 955.4-1544.7 thsd tonnes.

Table 1
Calculation of CO_2 sequestration volumes by crops in Ternopil region

Years	Harveste d area, thud ha	Main crop yield, t/ha	Total biomass yield, t/ha a.s.e.	Amount of carbon sequestered, t/ha	Amount of sequestered CO_2, t/ha	Amount of CO_2 sequestere d by crops, thud tonnes
Spring and winter wheat						
2020	216,5	4,70	9,70	4,56	16,9	3652,3
2021	205,5	5,54	11,4	5,37	19,9	4086,3
2022	221,0	5,32	11,0	5,16	19,1	4220,0
2023	200,8	5,95	12,3	5,77	21,4	4288,3
Spring and winter barley						
2020	99,6	4,3	7,77	3,65	13,5	363,5
2021	83,6	4,48	8,09	3,80	14,1	317,9
2022	77,2	4,49	8,11	3,81	14,1	294,2
2023	78,5	4,82	8,70	4,09	15,1	321,2

Corn						
2020	144,0	9,26	17,5	8,23	30,5	1185,7
2021	176,0	9,87	18,7	8,78	32,5	1544,7
2022	121,4	8,85	16,7	7,87	29,1	955,4
2023	114,2	10,78	20,4	9,59	35,5	1094,7
Sugar beet						
2020	18,0	47,9	10,8	5,08	18,8	91,5
2021	16,7	53,5	12,1	5,68	21,0	94,8
2022	20,2	59,6	13,5	6,33	23,4	127,8
2023	22,5	55,4	12,5	5,89	21,8	132,5
Sunflower seeds						
2020	89,8	3,18	10,9	5,14	19,0	461,7
2021	83,2	3,34	11,5	5,40	20,0	449,3
2022	104,9	3,20	11,0	5,17	19,1	542,7
2023	100,2	3,47	11,9	5,61	20,8	562,2
Soybean						
2020	75,1	2,69	5,55	2,61	9,66	196,0
2021	83,7	3,05	6,30	2,96	10,9	247,6
2022	95,1	2,75	5,68	2,67	9,87	253,7
2023	94,4	3,84	7,93	3,73	13,8	351,7
Rapeseed						
2020	62,2	2,93	9,32	4,38	16,2	272,6
2021	68,7	3,82	12,16	5,71	21,1	392,5
2022	77,1	3,96	12,60	5,92	21,9	456,6
2023	102,5	3,01	9,58	4,50	16,7	461,4
Potato						
2020	56,5	16,2	15,9	7,46	27,6	421,2
2021	54,3	19,2	18,9	8,87	32,8	481,4
2022	54,4	17,7	17,4	8,17	30,2	444,4
2023	54,6	17,8	17,5	8,20	30,3	447,8

Oilseeds - sunflower, soybean and rapeseed - have a much lower sequestration capacity, as they assimilate 19.0-20.8, 9.66-13.8 and 16.2-21.9 tonnes of carbon dioxide per hectare, respectively.

For root crops (sugar beet) and tubers (potatoes), the volumes of carbon dioxide sequestration are 18.8-23.4 and 27.6-30.3 t/ha.

According to the averaged data on sown areas and yields, the potentially possible volume of CO_2 assimilation by agrocenoses of major crops in the Ternopil region is 7303.4 thousand tonnes.

Using the method of correlation and regression analysis, mathematical models were built to predict the possible volumes of carbon dioxide sequestration depending on the size of sown areas and crop yields in the Ternopil region (Table 2).

Table 2
Mathematical models of the dependence of CO_2 sequestration volumes on sown areas and crop yields in the Ternopil region

Crop	Regression equation
Spring and winter wheat	$У-4281,7922+20,0824*X_1+763,7612*X_2$
Spring and winter barley	$У= -285,9842+3,6494*X_1+66,5539*X_2$

Corn	У = -1070,8807+8,8104*X_1+107,5588*X_2
Sugar beet	У-109,6184+5,8366*X_1+2,0024*X_2
Sunflower seeds	У-521,0803+5,3184*X_1+158,403*X_2
Soybean	У-251,2182+2,6683*X_1+91,2005*X_2
Spring and winter rapeseed	У-332,6565+4,5301*X_1+109,8484*X_2
Potato	У-388,3006+7,0854*X_1+25,2557*X_2

The regression equations, where X(1) is the size of crops sown, thousand hectares, and X(2) is the yield, t/ha, describe the dependence of the amount of carbon dioxide absorbed on these variables.

Thus, increasing the productivity of field crop agrocenoses is an important way to reduce the CO_2 content in the atmosphere and prevent further global warming on a planetary scale.

To verify the accuracy of the data obtained and generate predictive analytics, we used the XGBoost gradient boosting method, which is one of the most effective approaches for working with tabular data. Its application is based on the ability to take into account complex dependencies between variables, high resistance to multicollinearity, and the ability to adaptively improve forecasting results through consistent training.

XGBoost's algorithm involves a step-by-step adjustment of the model by building an ensemble of decision trees, where each subsequent tree learns from the mistakes of the previous ones. The process begins with the initialisation of the base forecast, after which the deviations between the calculated and actual values are determined. Each new tree is aimed at minimising these deviations, which ensures gradual improvement of predictions.

An important step is the optimisation of the model parameters, which includes adjusting the depth of the trees, learning coefficients and applying regularisation to prevent overfitting. Thanks to the built-in feature selection mechanisms, the algorithm allows us to identify the most significant factors affecting the CO_2 sequestration process. Accuracy is assessed by cross-validation, which ensures the model's high generalisability.

```
import pandas as pd import
numpy as np import
xgboost as xgb
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# Data loading (initial set for model training) data
= {
   "Area_thousand_hectares": [200.8, 78.5, 114.2, 22.5, 100.2, 94.4, 102.5, 54.6],
   "Yield_in_tonnes_per_hectare": [5.95, 4.82, 10.78, 55.4, 3.47, 3.84, 3.01, 17.8],
   "CO₂_sequestration_in_tonnes_per_hectare": [21.4, 15.1, 35.5, 21.8, 20.8, 13.8, 16.7, 30.3]
}

df = pd.DataFrame(data)

# Definition of input variables (X) and target variable (y)
X = df[["Area_thousand_hectares", "Yield_in_tonnes_per_hectare"]]
y   =   df["CO₂_sequestration_in_tonnes_per_hectare"]

# Splitting into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42) #

Creating and training the XGBoost model
```

```
model = xgb.XGBRegressor(objective="reg:squarederror", n_estimators=100,
learning_rate=0.1, max_depth=4)
model.fit(X_train, y_train)

# Function for entering new data and forecasts def
predict_sequestration():
  print("Enter the data for the CO₂ sequestration forecast:")
  area = float(input("Sown area (thousand hectares): ")) yield =
  float(input("Yield (tonnes per hectare): "))

  new_data = np.array([[area, yield]]) forecast
  = model.predict(new_data)[0]

  print(f"Projected sequestration of CO₂: {forecast:.2f} tonnes per hectare")

# Run a forecast for user-entered data
predict_sequestration()

# Visualising the importance of features
xgb.plot_importance(model)
plt.show()
```

Code of the CO_2 sequestration forecast model

The application of this approach made it possible to increase the accuracy of predicting the volume of carbon dioxide assimilation by agrocenoses, taking into account the variability of yields and crop areas in different years. The results obtained allow us to predict potential changes in the ability of crops to fix CO_2 depending on climatic and agronomic factors, which is important for developing a strategy for sustainable agricultural production.

3. Conclusion

The application of information technologies in agriculture serves as a foundation for building comprehensive databases, performing in-depth analysis, and generating accurate forecasts. Artificial intelligence plays a crucial role to contribute to this issue. This study aimed to develop a methodological toolkit for assessing the potential of, and forecasting, carbon sequestration by agricultural crops using artificial intelligence. The issue of carbon sequestration in agriculture is relevant. The integration of artificial intelligence to create and process a database is particularly significant.

The analytical data collected were processed using correlation and regression analysis. The mathematical models were built to predict the potential volumes of carbon dioxide sequestration depending on the size of sown areas and crop yields in the Ternopil region. The relevant calculations were also conducted to determine the carbon sequestration potential of major agricultural crops in this region. The findings indicate that increasing the productivity of field crop agrocenoses is an effective means of reducing atmospheric CO_2 levels and mitigating further global warming on a planetary scale.

In order validate the accuracy of the data obtained and generate predictive analytics, the XGBoost gradient boosting method, which is considered to be one of the most effective approaches for working with tabular data, was used. Its application is based on the ability to take into account complex dependencies between variables, high resistance to multicollinearity, and the ability to adaptively improve forecasting results through consistent training adaptively. The application of this approach made it possible to increase the accuracy of predicting the volume of carbon dioxide assimilation by agrocenoses, taking into account the variability of yields and crop areas in different years. The resulting models enable the anticipation of potential shifts in the CO_2 fixation capacity of crops under varying climatic and agronomic factors (conditions), which are essential for the developing a strategy for sustainable agricultural production. The findings of this study provide the basis for further research into the application of artificial intelligence in carbon farming management.

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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