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Predictive Machine Learning Models for Assessing the Effects of Land Use and Climate Change on Food Affordability in the UK

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Predictive Machine Learning Models for Assessing the Effects of Land Use and Climate Change on Food Affordability in the UK

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Abstract

This research analyses the complex trilateral relationship, land use pattern, climate change and consumer affordability of food products in the UK based on the data set collected from Food Agriculture and Organisation (FAO) from 1961 to 2022. Though agriculture contributes minimally to the UK's GDP, it plays a very major role in economic stability and in building resilient and sustainable planet. Artificial intelligence is a critical tool that helps in understanding, forecasting and predicting patterns on the complex multidimensional data. This paper aims to apply AI techniques on the data to understand the patterns and dependencies. Initially, the data extracted from the FAO is analysed to understand the trends and the relationship between the attributes is identified using correlation matrix. Several hypotheses are framed, and classification and prediction machine learning algorithms are applied on them. Trend analysis reveals that a decrease in carbon dioxide emission is caused by expansion in the forest land with a very steady high increase in the cost of buying a healthy diet in the UK. Several machine learning models are applied on land use and climate emissions and the support vector regressor shows the highest performance with an R-squared value of 0.96. Furthermore, classification models are applied to get relation between the high and low forest growth regions where the decision tree and the random forest achieved the highest accuracy of 0.8. This research provides valuable insight into the fact that increasing the agriculture land does not reduce the affordability to buy healthy food. Hence, to economically stabilize, the UK should come up with different policies and measures to provide affordable healthy food to people and not just by increasing the agriculture land it can be achieved.

CCS Concepts

• **Computing methodologies → Machine learning algorithms**.

Keywords

Agriculture, Climate Change, CO2 Emissions, Consumer Affordability, United Kingdom (UK), Machine Learning, Sustainable Development Goals (SDGs)

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1 Introduction

Agriculture contributes only 0.6 percent of the United kingdom's GDP. Despite the minimal contribution, it plays a major role in the country's economic stability and acts as a foundation to build a resilient and sustainable planet. The growth of agriculture practices extends beyond the grassland and farmland cultivation which includes the mixed and hybrid farming practices, livestock management etc.

Several challenges hinder the growth of deploying new and modern agricultural practices and to maintain a stable agriculture production which are either caused by natural or man-made disasters. Natural impacts to building a sustainable agriculture platform includes forest fires, livestock management, greenhouse gas emissions, water quality maintenance, flood, extreme rainfall etc; and man-made impact include extreme fertiliser or pesticide usage, dietary changes, sudden disease outbreaks etc. All these together contribute to the poor decision making in creating a healthy agricultural environment. Artificial intelligence (AI) is evolving as an excellent tool in modern agriculture. Many of the applications that AI involves include processing remote sensing satellite images on farmland, building predictive machine learning models to monitor the croplands, detect weeds, forecast landslides and deforestation etc. These tools are either used on a large scale or on a small scale to forecast agricultural trends, detect anomalies and support the decision making of the government agencies and assist them in policy making.

This research paper aims to study the trilateral relationship between the land use patterns, the climatic change and the consumer affordability of food products in the UK with data collected from 1961 to 2022. The research paper also presents a comprehensive analysis of all three factors and applies several predictive machine learning models that forecast the future land use patterns and examines how climate changes would affect consumer affordability. Overall, this research provides valuable insights for building sustainable agricultural planning under the context of climate and consumer affordability. The objective of the paper is to connect to the 2015 United Nations Sustainable Development Goals (SGDs): SGD 2 - Zero Hunger, SGD 12 - Responsible Consumption and Production and SGD 13 - Climate Action. The proposed research aims to connect all three SGD; by forecasting the people's affordability and maintaining responsible food thereby attaining Zero Hunger and ascertain the effects of climate change on agriculture land use patterns.

1.1 Climate Change and Agriculture in the UK

The UK meteorological office (Met Office) in United Kingdom provides national weather and climate information. The 2021 report from Met Office says that UK is experiencing warm winter and dry summer which is expected to intensify throughout the 21st century [11]. The main reason behind this would be reduced vegetation and increased greenhouse gas emissions. Agriculture, being a sensitive industry, relies much on the climate where even a small increase in temperature may reduce the growth or productivity of crops like wheat or barley [14]. For example, in the last five years, crop production decreases at the Somerset level which is one of the low-lying agricultural landscapes in the UK with rich agricultural landscapes [15, 20].

Smart Farming: The technology 'smart farming' involves embedding AI and Internet of Things (IoT) together in the farm management[8]. The smart management setup involves deploying IoT sensors in the farmland that predicts the soil moisture, nutrient level in the soil, forecasts the climate and through mobile app it notifies the farmer what must be done and helps the farmer in timely decision making [25]. This approach is being applied worldwide to increase crop production and to educate the farmers on the know-how. However, building and deploying the automated IoT setup demands collecting large amounts of data through the IoT sensors; applying complex machine learning models by AI experts to learn and predict based on the suitable objectives. Moreover, there could be no generic AI-IoT model that could be applied globally on all the farmlands, and it's subject to be modified based on the specific land and crop requirement [7].

textbfPrecision agriculture: Though smart farming and precision agriculture seems to resemble same, there is a subtle difference between them [8]. Precision agriculture is a subset of smart farming and focuses on the optimal use of the spatial land and finds ways to improve crop production. It's mostly adopted in commercial farming. While smart farming can be adopted in conventional farmlands as it's a holistic approach and not all the parameters in it can be controlled. However, it maps all the external parameters and builds sustainable agriculture across the value chain [24].

1.2 AI in Smart Farming and Precision Agriculture

Several technologies are applied in real time that utilise machine learning and deep learning models on the data generated from agricultural farmland. While it comes to IoT devices the data contains numerical information generated by the IoT sensors and images of the farmland are also captured through remote sensing satellites or drones for spatial land analysis. The data that is generated might be unstructured and can include numerical information, images, video or other customised formats suitable to the devices deployed [18]. Hence, there is a demand for building tailored models suitable to the needs of the application, the objectives and based on the type of data [10].

2 Literature

The UK is situated between latitudes 49° to 61° North and longitudes 8°W to 2°E enjoys a marine temperature with adequate rainfall and long growing season. The terrain includes flat plains, rocky mountains that are ideal to grow different variety of crops like wheat, barley, and potatoes and is rich in dairy farming.

In 1985, around 75% of the total land in the UK was used for agriculture. This percentage remained constant with mild fluctuation until 2000 but with the start of the 21st century, there is a decline in the agricultural sector and in 2024 it stands at 69% with a decrease of 1.5% from 2023 (Figure 1). This reduction is approx. 261,430 hectares which have been removed or stopped from cultivation. All the data is extracted from [21]. These decisions are not made willingly by small-scale farmers, but are the result of economic instability, cost of rising price of inputs and outputs needed for cultivation, socio-cultural attributes and change in the climate have played a significant role to this decline in percentage.

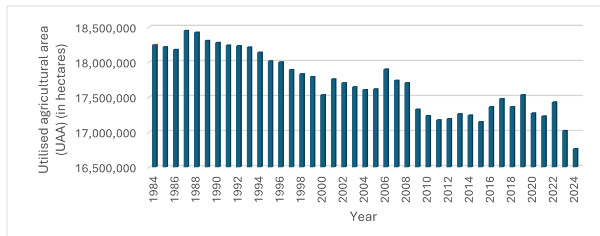

Figure 1: UK's Utilised Agriculture area from 1984 to 2024.

Grasslands contribute a significant role in environmental balance. A decline in the grassland would disturb the habitat of birds and lead to loss of carbon stores – Grasslands are major source of carbon reservoir [30]. In UK, the permanent grassland area decreased from 9,729,565 hectares in 2023 to 9,379,643 hectares in 2024, overall 3.6% decrease over the year (Figure 2). A significant decrease is seen in the livestock and chicken production numbers.

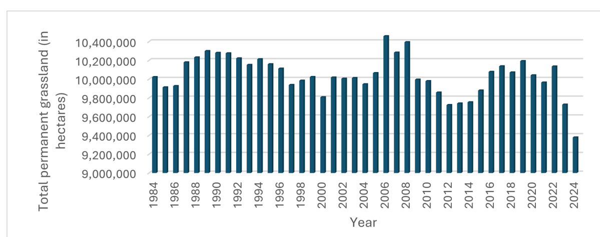

Figure 2: UK's Permanent Grassland from 1984 to 2024.

A noteworthy achievement is the CO2 emissions in UK have come to a decline in 2024 as compared to the past few years (Figure 3 and Figure 4). However, among the different sectors that emit CO2, domestic transport contributes 30%, building and product uses contribute to 21%, waste contributes to 5% (Figure 5). A slight increase in the temperature across 2022 to 2024 is one of the notable causes of reduction in CO2 emissions. The warmer temperature reduced the necessity to use the heating system by the people and the large-scale industries, leading to lower CO2 emissions. The global and national CO2 emission rate contribute to climate change as they are interrelated factors.

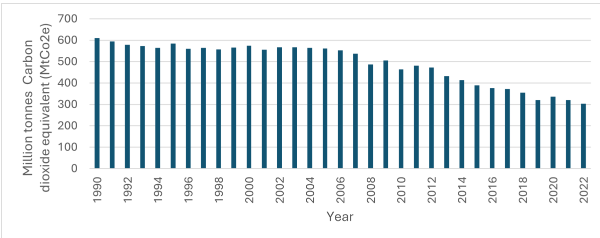

Figure 3: Net CO2 emissions (emissions minus removals) 1990 to 2022

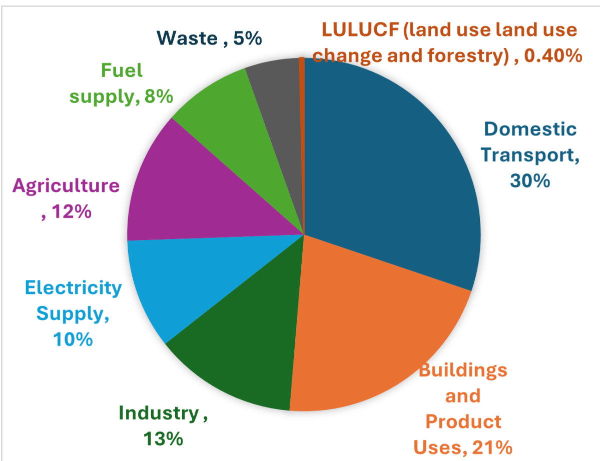

Figure 4: Provisional UK territorial greenhouse gas emissions statistics 2024

2.1 Challenges in Empowering farmers using AI in Agriculture Industry

Incorporating machine learning and deep learning technology into agriculture requires educating the farmers in the know-how of embedding them into their everyday life. The commercial farming industry reaps the benefit of this technology using IoT devices. However, to meet the different needs of the agriculture industry, almost 60% of the farmers should be using this technology in conventional farming. The farmers must be educated on the benefits of Graphical User Interface (GUI) App [16]; the know-how of installing the Apps; the installation procedure of the sensors or the setup; the usage of sensors; in some advanced cases knowing how to deploy the drone; capturing the images and videos and understanding the Geographical Positioning System (GPS) [13]. Most Importantly, the ways of how the output from these apps can be used to decision making to enhance the productivity of the agricultural process (Figure 5).

In the study, the author discusses how to educate farmers in Kenya [29], Africa [35], and it turns out to be successful in just three months. In the UK, agri-tech is deployed widely, DEFRA and IUK have introduced the Farming Innovation Program where IUK investigate the technology development, and DEFRA adoption and diffusion of technology into farming lands, monitoring etc. Since the past decade, significant growth and innovation has been seen in the UK Agri-tech industry [23]. The UK Agri-tech firms can be grouped into 7 categories: Agricultural Sciences, Automation, Drone Technology, Management Platforms, Precision Farming, Remote Sensing and Vertical Farming (Figure 6). The Agri-hub [22] and Agri-Investor [4] connects farmers, funders and industrial partners who can collaborate by sharing ideas and solve potential challenges encountered. Additionally, the UK has attracted a higher number of Agri-tech investors which includes the start-ups and commercial partners [5].

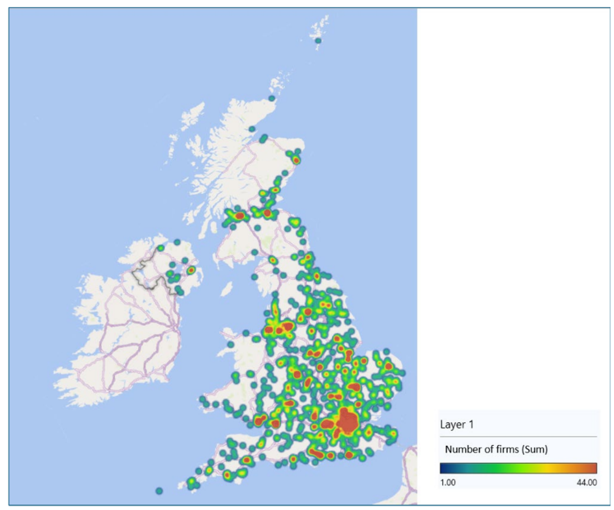

Figure 5: Net CO2 emissions (emissions minus removals) 1990 to 2022

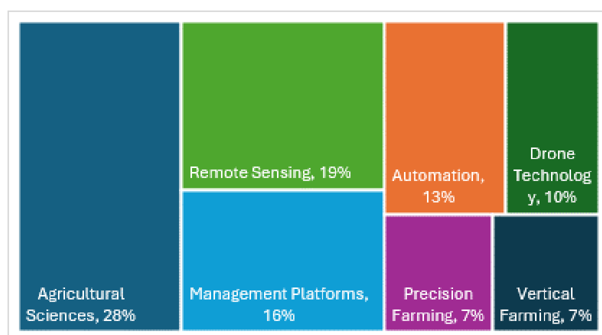

Figure 6: Dominant Agri-tech sub-sectors and their percentage of contribution

2.2 Machine Learning algorithms in Agriculture

Several review papers are published that focus on the different algorithms that are applied into Agriculture. A few notable existing works are cited here: disease detection in plants include [1, 3, 37], weed detection in farmlands [34, 38], predicting the overall productivity [26, 32] and IoT in agriculture [9, 31, 33].

An IoT and AI based automated decision-making system is proposed in [36]. It detects the anomalies in the dry beans data set using multilayer perceptron's, naive bayes and support vector machines. These algorithms identify strong deviation in the data set and enable timely decision making to protect the agricultural soil from further damage. The hybrid algorithm with random forest and neural network attained an accuracy of 92% in anomaly detection whereas SVM model achieved an overall accuracy of 93%. Additionally deep learning algorithms like MobileNetV2, VGG16, and InceptionV3, are applied to classify the soil types where MobileNetV2 achieved a higher accuracy of 97%. Though accuracy and other factors are considered for evaluating the performance of the system, the computational cost of deploying the IoT devices and the IoT devices could have been explored.

The moisture in grapes is detected using five different deep learning models namely: long short-term memory (LSTM), bidirectional – LSTM, long short-term memory (BI-LSTM) and gated recurrent unit (GRU), GoogleNet-R, and ResNet-50-R in [6]. This is a non-invasive method that uses Radio Frequency (RF) sensing to determine the optimal ripening period of grapes. RF sensors are employed to collect data from the grape clusters. The five learning models embedded with feature optimisation are applied on the RF data and the performance metrics namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and R2 score are captured. The GRU with Particle Swarm Optimisation (PSO) produces the optimal values for RMSE, MAE and R2 score with values 0.29, 0.22 and 0.92 respectively. The feasibility of deploying this to small scale farmers and robustness need to be assessed as they are the most important challenges with short-shelf-life fruit like grapes.

Machine learning and deep learning models namely random forest, XG boost, Convolutional Neural Networks (CNN) and LSTM is applied to predict the crop yield in [7] on the data extracted from the Indian government website from 1997 to 2000. The Random Forest algorithm achieves the highest accuracy of 98.96% and the CNN generates a test loss of 0.00060 demonstrating the optimal models for crop yield prediction.

2.3 AI in Climate and Agriculture

Several literature work explore by applying AI to analyse the impact of climate on agriculture productivity [35][36][37][38]. One of the important factors that directly connect the climate, and agriculture, is Green House Gas (GHG) emissions. The study [12] applies machine learning models to predict the GHG emissions from animal agriculture In Turkey. The livestock population data set, the manual management practices data set, and the climate-based information are collected and machine learning algorithms namely random forest, gradient boosting decision trees are employed to predict N2O, CH4, CO2 concentration. It was observed that by reducing the number of features the model's performance improved. An extensive result of the different GHG emissions is recorded and among all the models, CatBoost model proves to be robust in making accurate predictions.

2.4 Machine Learning algorithms across images and videos captured through remote sensing

An evolutionary fuzzy based system is applied on GEO-GRADLE and LUCAS SSL soil-based libraries [17]. This data set generated from soil spectroscopy and contained varying attributes and complex dimensions. To process the very large, big data, the algorithm is created in two tires: the first tier includes the soil granularities per feature and in the second tire DECORUM an evolutionary fuzzy based algorithm is created to execute in a distributed environment. The distributed algorithm with bootstrap loading outperformed the serial version. This paper exhibits the usage of a big data environment to analyse the large dimensional spectroscopy data.

Hyperspectral image processing is one of the outgrowing areas in the stream of Big data, AI and agriculture. One such methodology is applied in [28] for crop classification that detects the spectral similarities in crops. Dimensionality reduction algorithms, supervised classification algorithms and support vector machines are applied to classify and identify six different varieties of crops, achieving an overall accuracy of 98.07%.

Machine learning algorithms like Random Forest, Support Vector Regression and Gradient Boosting Machines are applied to the forecast the rice yield production at diverse tropical climate in India [2, 19, 27]. These models are applied on climate-based data including rainfall and temperature and the remote sensing data. The model has shown to be cost-effective and can be used on a large scale, especially for Indian farming, to predict rice yields accurately.

3 Dataset

The Food and Agriculture organisation (FAO), FAOSTAT data set from the United States is a global database containing information about the food and agriculture statistics. It contains information about the crop production, food cost, Emissions, food trade, food security and other information related to agriculture for around 245 countries. This is a freely accessible data set, and it is regularly updated to reflect the current trends.

4 METHODOLOGY

This research paper aims to study the trilateral relationship between the land use patterns, the climatic change and the consumer affordability of food products in the UK with the data collected from 1961 to 2022.

4.1 Understanding the Trend analysis

The three datasets that contain information about the land use pattern climate change and consumer affordability of food products are extracted and the trend patterns from them is analysed as an initial step as shown in graph (Figure 7).

The observations from the Exploratory Data Analysis (EDA) show that the CO2 emissions gradually decrease, the forest land shows modest expansion with a slight decrease in 2022, the cost of health diet shows a steady increase in 2022.

Pearson's correlation coefficient is applied to find out the relationship between the three factors and a weak negative correlation is found between the carbon dioxide emissions and the forest land which clearly states that the increase in the forest land reduces the concentration of CO2 in the air. A positive correlation is seen

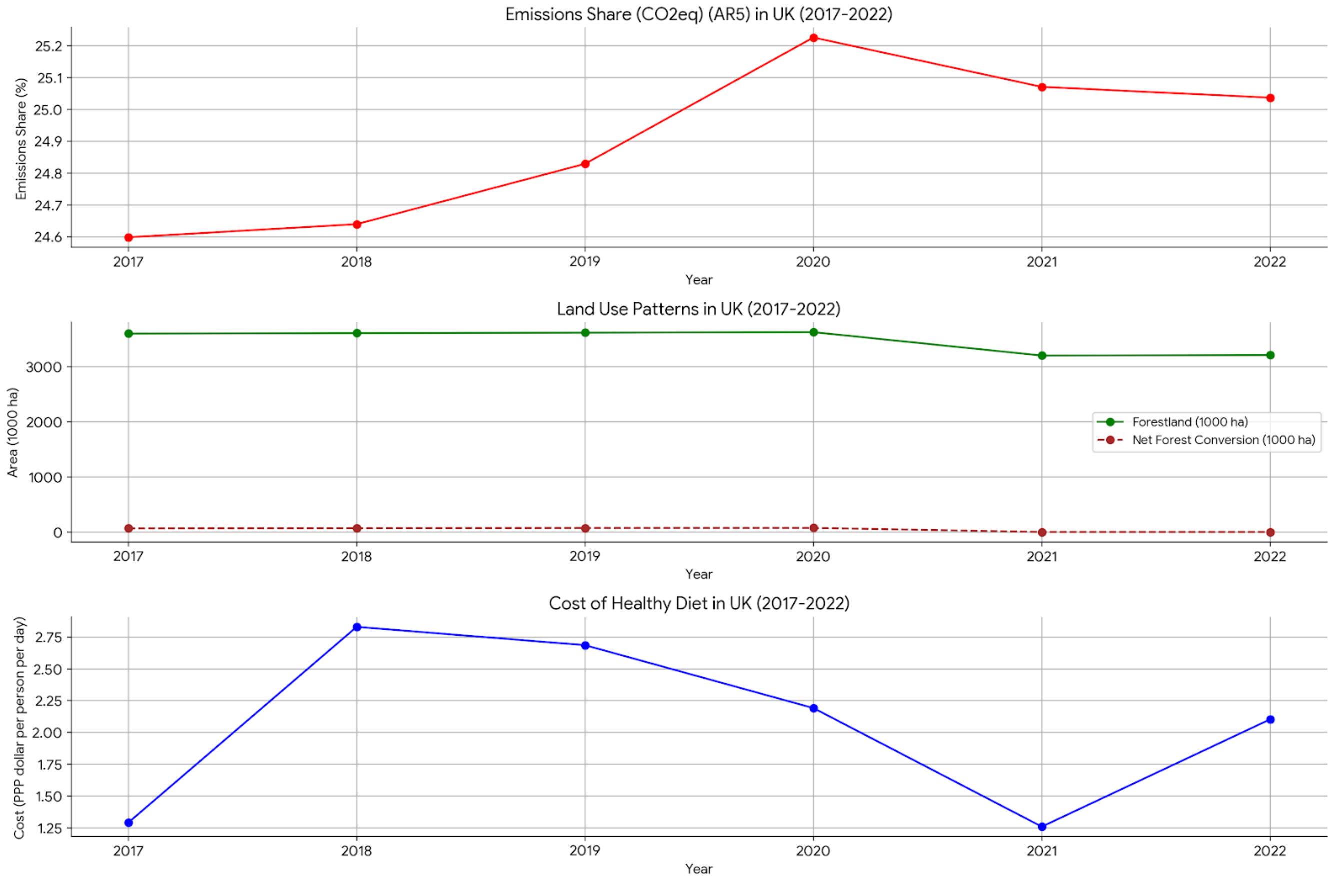

Figure 7: Trend analysis of land use patterns, climate change, and consumer affordability of food products in the UK

between the cost of a healthy diet and forest conservation; this is counter-intuitive, suggests that increasing forest land increases the cost of a healthy diet but there are other factors that need to be considered like the global food price inflation etc. hence with this we may not be able to conclude. A weak negative correlation is seen between carbon dioxide emissions and the healthy diet. The results of the Persons correlation coefficient are shown as heatmap below (Figure 8).

4.2 Different regression models applied for comparison

The below Figure 9 is the comparison of the results from applying various machine learning regression models to the land use and climate emissions dataset (1990-2022).

The regressor models performance MSE and R-square values are plot below in the Table 1.

The MSE and R2 are the metrics that are applied to analyse the performance of the model. The lower the MSE indicates a good performance and a higher R2 indicates that the target variable struggles with too much variance from the other independent variables. Of all the four different regressor models that is applied the Support Vector Regressor (SVR) proved to be the best performing model with the lowest MSE and highest R2. So, this shows that SVR captures the underlying patterns and relationships in the data very

Table 1: Regressor models performance

Model	Mean Squared Error (MSE)	R-squared (R2)
Linear Regression	0.0289	0.9242
Decision Tree Regressor	0.024	0.9371
Random Forest Regressor	0.0919	0.759
Support Vector Regressor (SVR)	0.0132	0.9654

Table 2: Classification models performance

Model	Accuracy	F1-Score
Linear Regression	0.2857	0.4444
Decision Tree Regressor	0.8571	0.8
Random Forest Regressor	0.8571	0.8
Support Vector Regressor (SVR)	0.5714	0.5714

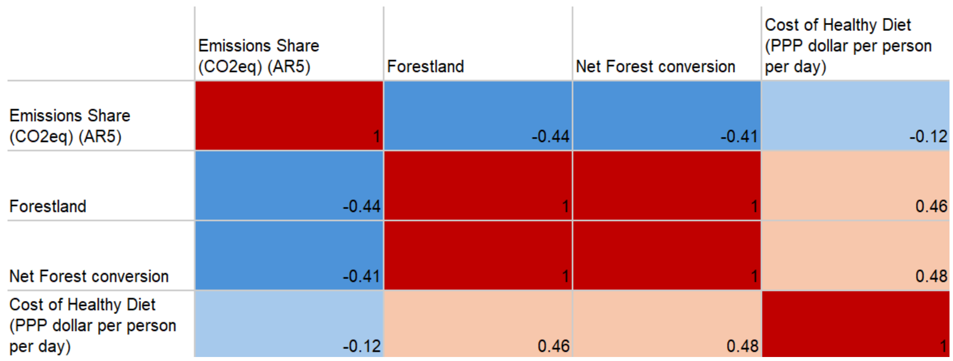

Figure 8: A heatmap that provides a visual representation of the three variables

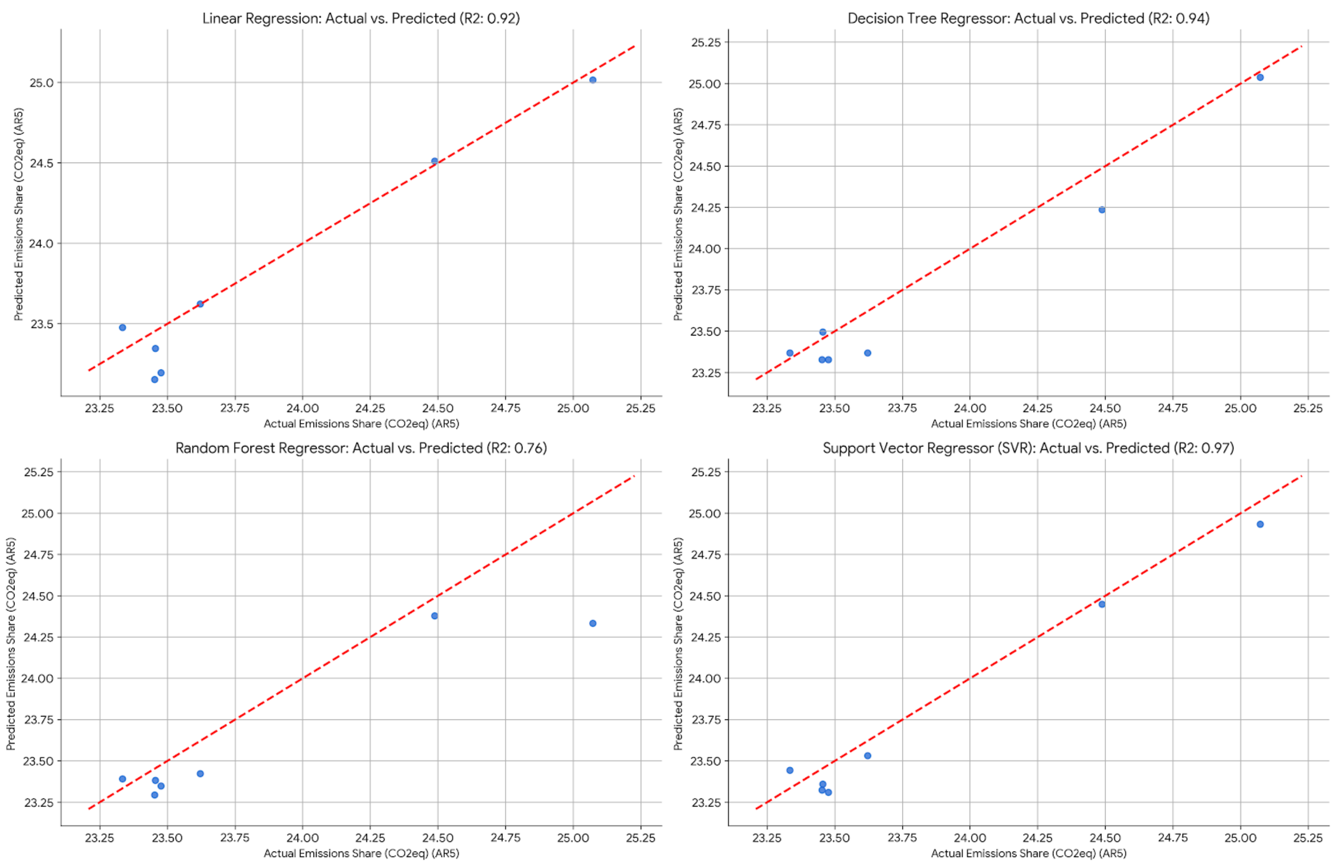

Figure 9: Results of regression models

accurately as compared to the other models. The decision tree regressor, however, performed better than linear regressor model. The random forest regressor showed the lowest performance because the random forest produces excellent results with large datasets. However, in this case the size of the data set is quite small for the random forest to identify their relationships.

4.3 Analysis on the Land use Dataset

The hypothesis that is chosen is classify the high forest growth and the low forest growth areas and apply machine learning models for classification. Results are shown in the Table 2. The decision tree classifier and the random forest classifier achieved in higher accuracy of 0.85 showcasing that they accurately classify the high forest growth and the low forest growth areas

5 CONCLUSION

The research identified the relationship between the land use pattern, climate change and consumer affordability of food products in the UK from 1961 to 2022. The study successfully explored multidimensional aspects of the relationship through a very detailed exploratory data analysis and by applying prediction and classification algorithms. As a first step the trend analysis identified slight decrease in the carbon dioxide emission in the UK with the expansion of the forest land. However, the cost of healthy diet showed a steady increase noticeably in 2022 post COVID. Relationship between the climate change and the agriculture land pattern was identified using correlation and regression analysis. It was observed that negative correlation is seen between the carbon dioxide emission and the forest land which reflects that an increasing forest cover may contribute to reducing carbon dioxide emissions. Models were applied to predict the carbon dioxide emission where the SVR achieved a higher prediction as compared to other regressor models. Furthermore, classification models are applied to differentiate the high and low forest growth periods, and the highest accuracy is achieved by decision tree and random forest classifier. This research offers a significant relationship between the agriculture and the policy making because either way with the decrease in carbon dioxide and the increase in the land for agriculture did not decrease the affordability to the healthy food. This study shows the relation between the three sustainable development goals namely: zero hunger, responsible consumption and climate action. The future extended research would be to analyse the data set in a granular level covering longer timeframes and by adopting specific cultivation practises with specific economic indicators and the climate data. An advanced time series analysis models can further enhance to understanding of the interdependencies between each of the parameters.

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