Carbon Footprint of the Food Industry and ESG-Related Business Promotion

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Abstract. The carbon emissions of the food industry account for a significant proportion of the overall carbon emissions. Figuring out the carbon footprint of the food industry is a great way to find out the reason for the large amount of carbon emissions. In this part, the paper selected several variations that may have some influence on carbon emissions and did some intensive studies to figure out which one is the major factor. By analyzing through life cycle assessment and regression by Random Forest, it was figured that fertilizer is the most influential factor in carbon emissions, and focusing more on the usage of compound fertilizer and decreasing the usage of other kinds of fertilizer can effectively reduce the carbon emissions. Then the paper tried to figure out whether the reduction is realistic, and the paper did research in the financial field. The paper did an ESG score ranking of the fertilizer company, cultivated the investment weight in the portfolio, and did a risk rating of them. The research adopted the Grey Forecasting Model and quadratic Optimization Formulation to process data. Through the simple study of the carbon footprint of fertilizers and an analysis of the investment ratio of investors, it is finally found that to economically promote and support the development of carbon-reducing compound fertilizers by business is essential. Besides, it coincides with investors' interests..

Keywords: Carbon footprint; food production; ESG; fertilizer; financial derivatives.

1. Introduction

The concept "carbon footprint" is historically defined as "the total set of greenhouse gas(GHG) emissions caused by an organization, event, product or person." For nowadays, it is a crucial task to reduce carbon footprint.

In the past few years, to discover how to reduce carbon footprint in food production had been a hotter and hotter topic. From the current situation, the Main Pollutant of light industry, in which food, paper, leather and others majors, occupies the 50% of the total industrial emissions [1]. So that energy saving and emission reduction in light industry are arduous. In previous studies, it has been discovered that CH_4 emission is the main source of direct carbon emission, and indirect carbon emission is mainly due to application of chemical fertilizer, especially nitrogen fertilizer [2]. Besides, researchers had tried to transition nitrogen fertilizers to net-zero CO2 emissions and existed, which can contribute to climate and food security goals [3]. However, this method had a greater need in land, energy, and water than business-as-usual production, exacerbating land and water scarcity and the use of limited natural resources [3].

In most studies, the method Life Cycle Analysis AlLCA) has been widely used. It is a popular method in cultivating carbon footprint. It does an analysis of this whole process, based on an iterative process with four steps: goal and scope definition, inventory analysis, impact assessment, and interpretation [4-7].

Since the long term of studying in the past years have effectively benefits the reduction of carbon emission, but here are some problems we are still facing. It's hard to analyze how a single element effects other. Moreover, there are amount if variations in this study, which needs experts from all fields to work together.

After finding the element that contributes the most in carbon emissions in the agricultural period of food industry, methods need to be discovered to make the control of the usage of this element realistic. The first thing that need to be considered is the economic feasibility.

As companies work to limit the carbon emissions of their products to help protect the planet, new problems arise. While companies spend more effort to achieve this goal, they also raise the question of whether low-carbon has an financial impact on their performances [8]. More specifically, the companies worried about the increase cost of pollution and coomitment to low-carbon enironmental protection will increase the business burden on companies.

In such context, October 2005, the United Nations Environment Programme Initiative first came up with the concept of ESG in a Freshfields Report, which stands for Environmental, Social, and Governance. ESG is widely used to evaluate whether companies have a positive impact on the world, both humanely and naturally. With the popularization of this view, ESG has gradually attracted the attention of investors. The concept has also derived many quantitative standards. According to these criteria, many studies have found that ESG score does not have a negative impact on a company's economic operations [9].

From the perspective of financial market, environmental factors in ESG have no impact on the value development of a company rather than a positive impact [10]. Nevertheless, in the company's publicity, ESG can promote stakeholder's investment in the company and attract investors [11]. This means that focusing on ESG score in financial portfolio investment can effectively increase investor interest, guarantee the return of the portfolio, and support enterprises to comply with more environmentally friendly policies. The second half of this paper will analyze how to build a portfolio related to the industry that affect agricultural production’s carbon emission the most and maximize the profits.

The paper did an assumption on the result. The paper studied the agricultural period of food production and found several usage agricultural elements that may influence the total carbon emissions: fertilizer, irritation, film, pesticide, ploughing and diesel. The research may figure out one major factor, and do some further study in it. For the carbon emissions mostly contains carbon dioxide, nitrogen dioxide and so on. The main chemical elements that function in carbon emissions are carbon and nitrogen, and since nitrogen is one of the widely used fertilizer ingredient, the paper assumed fertilizer as the most influential factor. The paper is more likely to do a more detailed study in the elements that participate to influence the usage of this factor and see how they work. Meanwhile, investing the industry of producing this agricultural element may be a influential way to not only stimulate the agricultural period of food industry grow more environmental friendly, but also better profit the investors, by which can make the reduction of total fertilizer usage realistic.

2. Data analysis method and model analysis

2.1. Data introduction

Here we provide some basic advice for formatting your mathematics, but we do not attempt to define detailed styles or specifications for mathematical typesetting. You should use the standard styles, symbols, and conventions for the field/discipline you are writing about.

2.1.1 Crops

For the data of crops growing conditions, the research adopts the data frame “Crop recommendation”. This data frame shows how different conditions grow different crops. “N”, “P”, “K”, “temperature”, “humidity”, “pH”, and “rainfall” are contained as variations.

2.1.2 Emissions

For the data of the emissions of different elements, the data frame “Agricultural carbon emission data of 31 China provinces from 2000 to 2020” is adopted. It is a data frame presenting how different agricultural usage influenced the carbon footprint, and concluded how it changed by the year 2000 to

2020 in 31 provinces in China. Columns includes the usage of fertilizer, plastic film, agricultural diesel, pesticide, and the sown area, irrigation area, emissions of all kinds of agricultural elements, as well as total carbon emissions.

Moreover, here is a data frame presenting how different types of fertilizers are used during 2000 to 2022 in China. Columns includes the usage of fertilizer in total, N, P, K, compound fertilizer, and the carbon emissions of the usage of fertilizers.

2.2. LCA

In order to seperate the elements, LCA is essential. In this research, it is used to analyze the carbon footprint. But because of the limit of time and other conditions, it only contains part of the first two steps of LCA.

Here is a presentation of these two steps in figure 1:

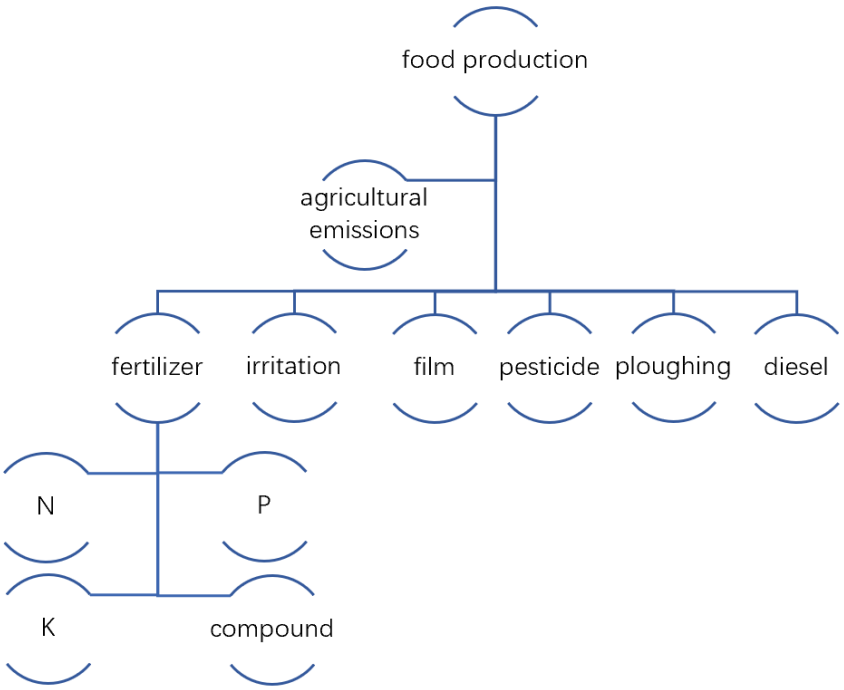


Fig. 1 LCA constructure

2.3. Introduction of computer model selection

Next, in order to make the relationship between elements clearer, the research adopts two ways to visualize the relationships of all variations: classification and regression.

First, classification is used to dispose the crops data. It can identify which crop can grow under which condition. Because the variations are numerous, the adopting confusion matrix is under consideration in order to show how well the model work when doing classification. Four models, decision tree, SVC, random forest and KNN are adopted.

Next, for the emission data, the research will show correlation between the carbon emissions and all variations. Regression is used to dispose the emission data. It can predict the trend of the emissions based on the usage of agricultural elements as well as different ingredient of the fertilizer. Four models, gradient boosting, KNN, random forest and decision tree are adopted.

As shown in figure 2 ,here is a presentation of the content of each part:

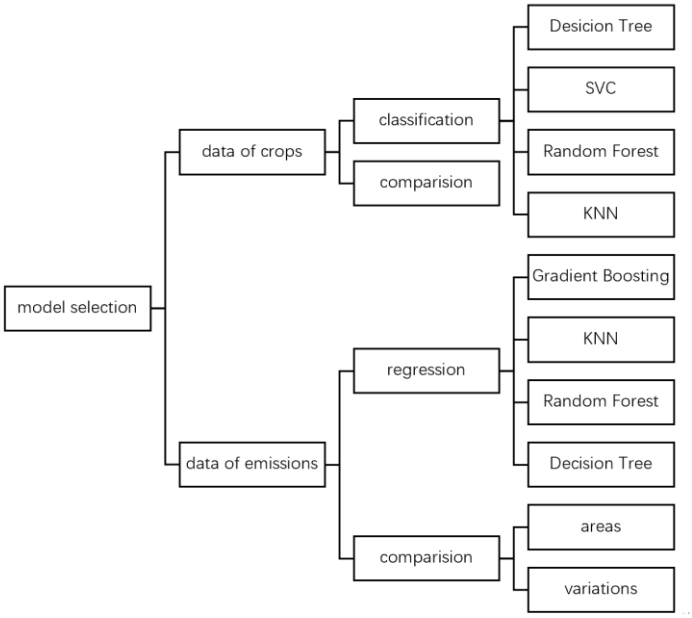


Fig. 2 model selection construction

2.4. Portfolio Analysis: Data and Analysis Method with Models

2.4.1 Data Selection

Period

Considering ESG-related financial derivatives are a relatively new concept and the information represented by stock price is time-sensitive, this paper only analyzes the data from December 2022 to December 2023 in a month.

Sample Stocks

Through the analysis of agricultural carbon emissions, this research will find which aspect has the biggest impact on agricultural carbon emissions, including fertilizer, film, fuel, pesticide, sown, and irrigation. After that, the paper will select the stock of the top 20 enterprises in the total market value of the industry, which is related to that aspect with the biggest impact, as the sample stocks for analysis. In addition, the 20 companies will be teamed into various groups based on their product characteristics to represent the investment bias of the general ESG-related portfolio.

For the judgment of market value, this paper will use the official data released by enterprises up to December 2023 as the benchmark to compare and make choices.

Individual Stock-Related Data Selection

1. ESG Score

ESG score is a scoring mechanism developed by quantifying the ESG benchmark proposed by the UN and evaluating whether an enterprise complies with ESG. The ESG score can more effectively classify high-quality and low-quality ESG enterprises.

This paper will use ESG scores from Wind as the correlated data set. This dataset comes from Wind's improvement of international Standards ISO 26000, SDGs, GRI Standards, SASB Standards, and TCFD Recommendations, which are more in line with China's ESG policy. Each company's ESG score will be updated monthly.

2. Stock Price

For financial derivatives, the stock price is an indispensable part of the analysis of investment data. Through the analysis and calculation of the stock price, the results and information can be obtained.

The stock price data of each enterprise selected in this paper is still from the Wind and updated in months. The analysis of the term “stock price” in this paper represents the analysis of the data set combined with the closing prices of 20 companies’ A shares on the last day of each month over 12 months

2.4.2 Analysis Method

1. Leading ESG Companies

Due to the scarcity and limited completeness of ESG score data, and given the requirement for only recent data, a Grey Forecasting Model was employed for analysis. This paper will determine whether the model is suitable for the stocks according to the extreme ratio interval. The posterior difference ratio of each sample stock would testify the accuracy of the model, and judge the fitting effect by the average relative error after prediction. The extreme ratio interval is (e^(-2/(n+1)), e^(2/n+1)) and all ESG scores should be in this interval, while the posterior difference ratio should be below 0.65. Also, the average relative error after prediction should be lower than 20%.

In addition, as all the data about ESG scores exhibit significant stability, predicting the value for the subsequent period (forecasting the ESG score for January 2023) and conducting an analysis thereof was deemed sufficient.

After predicting the representative ESG score of 20 companies, which is in total of 20 data, they will be ranked from largest to smallest, which means how well each company responds to the ESG policy.

This paper refers to the CNIIndex method to calculate the ESG benchmark index and excludes the bottom 20% of stocks of this ranking. This means that the remaining 16 stocks are identified as ESG-friendly and are included in the following portfolio investments as weighted security.

2. Portfolio Analysis

(1) Sharpe Ratio

The return and volatility (also referred to as risk) of a stock can be derived from its price. To maximize the profit of a portfolio, it is essential not only to maximize the return but also to minimize the risk. This leads to the application of the Sharpe Ratio.

The Sharpe Ratio is defined as the average return earned more than the risk-free rate per unit of volatility. According to the theorem, by maximizing this risk-adjusted return ratio, one can determine the optimal investment proportions of individual stocks within the portfolio.

(2) Risk-Free Securities

Although portfolios in China are mandated to hold a minimum of 5% in risk-free securities, this requirement does not significantly aid in maximizing the Sharpe Ratio.

Moreover, this paper primarily analyzes the investment proportions of different ESG enterprise groups within a specific industry. These are not related to risk-free securities, which can also create unnecessary impediments to percentage calculations.

Therefore, risk-free securities have been omitted in the calculations presented in this paper.

3. Optimization: Objective Function and Constraint

(1) Formulation

The formulation is shown below:

$$max_x \ \frac{\bar{r}^T x}{(x^T H x)^{\frac{1}{2}}} \tag{1}$$

$$s.t. e^T x = 1 \tag{2}$$

In this formulation,

$$\bar{r} = \begin{bmatrix} r_1 \\ \cdots \\ r_{16} \end{bmatrix}, x = \begin{bmatrix} x_1 \\ \cdots \\ x_{16} \end{bmatrix} \tag{3}$$

which $\bar{r}$ is the matrix of 16 stocks' expected return,

x is the matrix of 16 stocks' weights,

H is the covariance Matrix between stocks.

(2) Calculation of Expected Returns

For each stock, calculate the monthly return. This is a ratio of the difference between this month's stock price and last month's stock price divided by the last month's stock price. If the monthly return

is negative, it represents a loss. Otherwise, it represents a gain. There would be 11 monthly returns, and the expected return of each stock is the mean of these 11 data.

This calculation is also used to prevent any of the stocks with too high prices compared to others from getting inaccurately more weight, as a high price does not necessarily mean high return rate.

(3) Calculation of Covariance Matrix between stocks

After calculating the monthly return of each stock, the volatility, which is the average difference between the return of a month and the average return of 12 months, could be determined. This would give each stock one volatility data.

By pairing and calculating the correlation coefficient of each two stocks using their volatilities, it could form a matrix. This matrix is called the correlation matrix. By multiplying the corresponding standard deviation (volatility) of two stocks by each term of the correlation matrix, the covariance matrix could be obtained.

(4) Optimize and Plot

The result of the weight for each portfolio could be obtained by solving the formation using optimization strategies, which is generating 1000 random samples of portfolios with different weights for 16 stocks and demonstrating the best choice by analysing their volatility and return. Plotting the efficient frontier curve could visualize the maximum Sharpe ratio's location on the curve of an acceptable risk with the highest return.

4. Proportion of each group of stocks

After getting the weight of the 16 stocks, the stocks in the same group would be added together, which leads to the suggested investment inclination based on the characteristics of products for companies in the industry.

5. Risk Rating of the ESG Portfolio

Since the maximum Sharpe ratio is calculated, it is also possible to get the annual return and volatility (risk) of the ESG portfolio for further analysis.

According to the requirements of the "Guidance Opinions on the Applicability of Securities Investment Fund Sales" issued by the China Securities Regulatory Commission in 2007, this paper will calculate VAR values at 95% confidence interval and rate this ESG portfolio by table 1:

Table 1. Three Scheme comparing

Rating	**absolute VAR value**
R1	0%
R2	15%
R3	50%
R4	70%
R5	95%

As the expected annual return and expected annual volatility are known, the VAR value will be calculated as follows:

Annual Expected Return -1.65 X Volatility

3. Result

3.1. Food production——Agricutrual part analysis

3.1.1 Crops

First, the research did a pair plot of all variations in the data of crops. The pair plot shows the variation of different sources the crops need. In some plots, the area, or it can be called the usage variation, of the source remains narrow, which means there may be little things that can do to reduce the emission by changing the usage of it while not affecting the harvest of crops. Vice versa, in the wide part, there may be something that can do.

In the pair plot done in the research, there are different colors of scatters representing different kinds of crops. The variations in the data are conducted in group pairs. So, there are 49 plots in total in the pair plot, each plot shows a scatter plot of how the crops distributed under the variation.

In the plots that contain axes stand for “N”, “P”, and “pH”, the areas of the scatters representing all kinds of crops covered stretched in to long, wide areas parallel to the axes. In contrast, the other plots containing “temperature”, “humidity”, and “rainfall” showed thin, narrow areas, representing that the distribution of the crops under these variations have narrow distribution ranges, which make them hard to be adjusted to reduce the carbon emissions. Meanwhile, the plots containing axes “N”, “P”, “pH” show that they can be adjusted to reduce the carbon emissions.

If the research is more focused on the usage of fertilizer, and N, and P are related to fertilizer, pH will be temporarily out of consideration.

Next, it comes to the classification part.

Four computer models are adopted in this part, decision tree, SVC, random forest, and KNN. The research compared the four models by the GridSearchCV method. The result is in the table 2.

Table 2. Classification Models Accuracy Scores

Model name	Best score	Best param
decision tree	0.999393939	{'decisiontreeclassifier__splitter': 'random'}
svc	0.999393939	{'svc__C': 3, 'svc__kernel': 'linear'}
random_forest	1	{'randomforestclassifier__n_estimators': 8}
knn	0.988484848	{'kneighborsclassifier__n_neighbors': 5, 'kneighborsclassifier__weights': 'distance'}

Comparing the four different models, random forest works best according to the accuracy of classifying. Next, the research does some visualization, to draw a confusion matrix of the data of crops, using random forest.

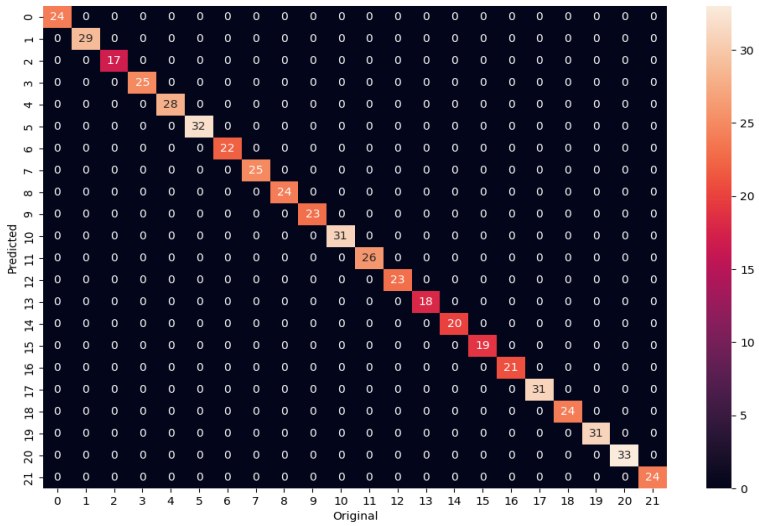


Fig. 3 Confusion Matrix

From figure 3, it can be easily found that most of the numbers concentrate on the diagonal line. This means, the classification model classified every sample into the right class. That means that the model works fine.

3.1.2Emissions

To begin with, to make the data of emissions easier to analyze, some summaries and visualizations are done.

First, they are summed up by year to show how each agricultural element’s emissions vary year by year from 2000 to 2022 the range of the whole country. Columns still include the usage of fertilizer,

plastic film, agricultural diesel, pesticide, and the sown area, irrigation area, emissions of all kinds of agricultural elements, as well as total carbon emissions.

Next, the research does some visualizations of the changing emissions of each agricultural element and the total emissions.

The research did a line chart and a pie plot to show the trend of the usage of different agricultural elements

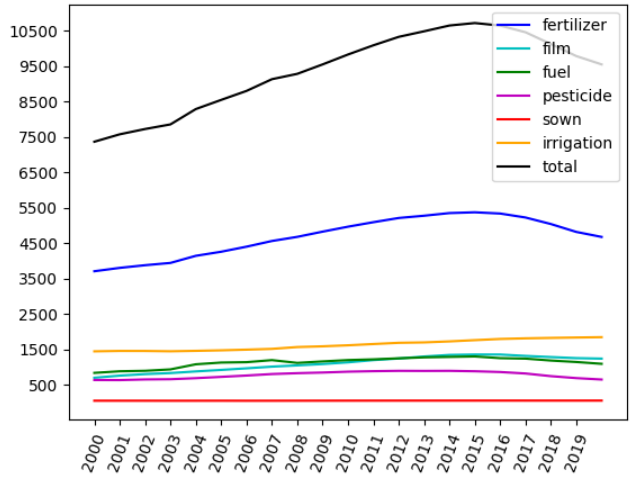


Fig. 4 Agricultural Carbon Emissions Line Chart

From the figure 4, it can be figured that the total carbon emissions increased year by year before 2015, then decreased in the year after 2015. This trend of change appears the same in the usage of fertilizer.

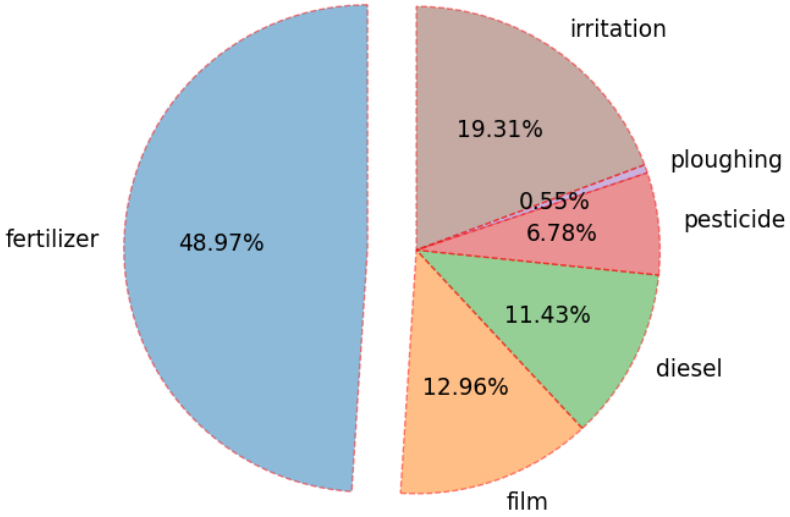


Fig. 5 Agricultural Carbon Emissions Pie Plot

From figure 5, it is easy to find that the usage of fertilizer is the one that plays the main role in agricultural carbon emissions. So the research furthers the study by the relationship between the usage of fertilizer and the agricultural carbon emissions.

In this part of the research, a regression model is established to better predict how the carbon emissions will be according to the usage of fertilizer and to further better control the carbon emissions.

There are four main kinds of fertilizers according to the variations of the ingredient, N, P, K, and compound. So the regression of the total emission is done based on the usage of the four main kinds of ingredients of fertilizers.

Four models are adopted, KNN, random forest, gradient boosting, and decision tree, and their accuracy is measured by three dimensions, mean-square error, mean absolute error, and R-squared. Their results are in table 3.

Table 3. Classification Models Accuracy Scores

model name	MSE	MAE	R^2
KNeighborsRegressor	28173.80882	138.696532	0.919958172
RandomForestRegressor	6968.579936	63.1306192	0.980202255
GradientBoostingRegressor	7947.688484	68.23835119	0.977420607
DecisionTreeRegressor	10345.50923	83.97684	0.970608395

From the comparison, random forest and gradient boosting play best in regression.
So the research does a prediction of the emissions using random forests. The result is in table 4.

Table 4. Emissions Prediction

N (10^4 tons)	P (10^4 tons)	K (10^4 tons)	Compound (10^4 tons)	emissions prediction (10^4 tons)
2381.42	819.19	605.13	1895.09	5229.436546
2399.89	828.57	617.71	1989.97	5263.622158
2164.11	705.73	399.57	983.69	3830.902116
2302.88	780.08	545.2	1608.6	4677.716557
2157.31	712.23	422.37	1040.35	3918.075747

From table 4, the total carbon emissions can be calculated by the usage of every kind of fertilizer. Also, a visualization is done using gradient boosting.

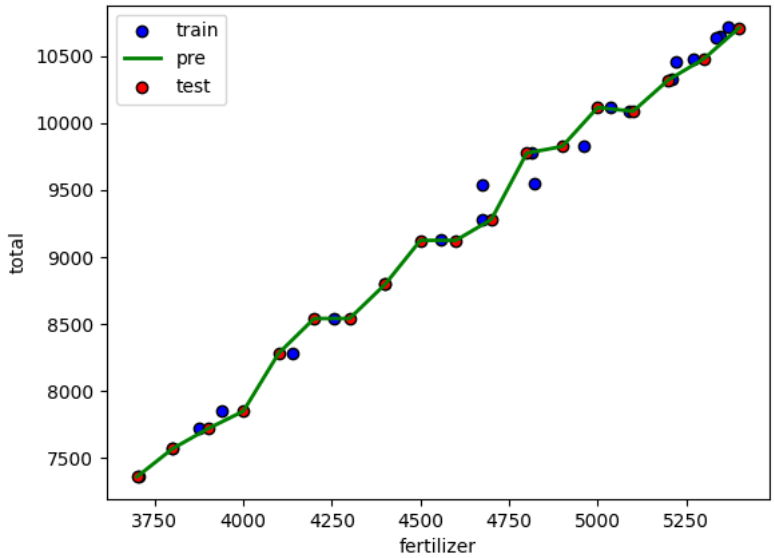


Fig. 6 Regression Visualization

In figure 6, the emissions prediction of the visualization is made based on the total usage of fertilizer instead of the multidimensional prediction based on the four kinds of ingredients of fertilizers.

Besides, the research also did another line plot to figure out how the usage of fertilizer and the total carbon emissions decreased after the year 2015.

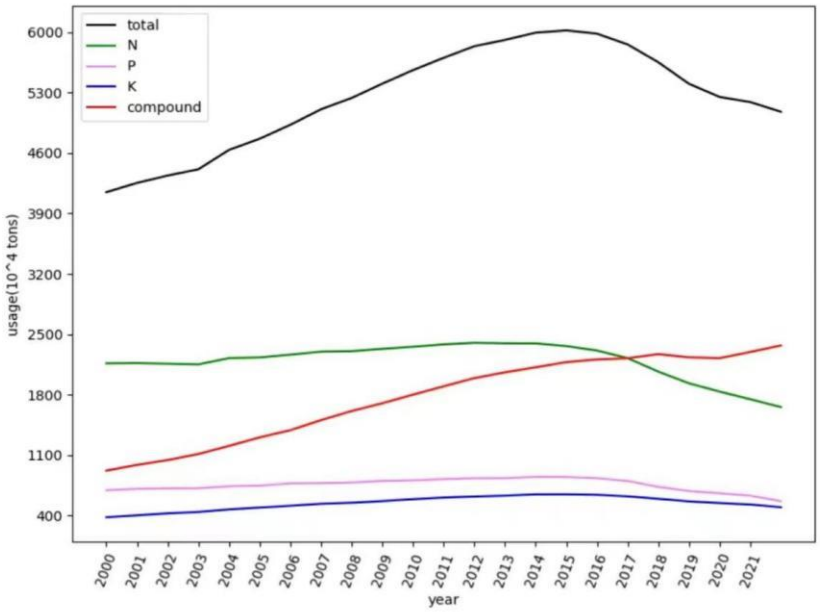


Fig. 7 Fertilizer Ingredient

Figure 7 was drawn according to the data of the usage of different ingredient of the fertilizer. From the line plot, the result can be found that, from the year 2015, the usage of the nitrogen decreased, and instead, the usage of compound fertilizer increased. The usage of the fertilizer decreased, but the usage of the fertilizer became more and more precise. This made full use of every piece of fertilizer.

3.2. Optimized ESG Portfolio: Composition and Characteristics

This paper has shown that the main cause of agricultural carbon emissions is the use of fertilizer products. Therefore, the portfolio focused on the fertilizer industry will be analyzed. Among them, the fertilizer industry companies mainly sell four major products, which are K fertilizer, compound fertilizer, P fertilizer, and N fertilizer. This research will take these four products as groups analyze the proportion of the companies corresponding to each product in the ESG portfolio, and make risk rate prediction of the portfolio.

3.2.1 Sample Stocks

Since 20 sample stocks are required and there are four categories, this paper will select five stocks with the highest total market value for each kind of product-oriented company. The company codes are listed in table 5:

Table 5. Sample Stocks

K Fertilizer	Compound Fertilizer	P Fertilizer	N Fertilizer
600251	002588	600096	600426
000792	002274	600141	000830
000408	000912	002312	000155
000893	002170	000902	002110
002545	000731	002539	600691

3.2.2 ESG Score Selection

After applying the Grey Forecasting Model and ranking the predicted ESG score, it is shown that the extreme ratio interval is (0.875, 1.143) for all stocks, and the extreme ratio for all ESG scores is in this interval. This means that the prediction model suits the ESG scores of the stocks. Other performance of the model and the predicted values are listed in table 6:

Table 6. Performance and Prediction

	Posterior Difference Ratio	**Average Relative Error**	**Predicted ESG Score**
600251	0.917	2.022%	5.992
000792	0.435	1.04%	6.789
000408	0.494	3.972%	6.577
000893	0.284	1.57%	4.338
002545	0.897	0.754%	6.579
002588	0.251	1.214%	5.449
002274	0.952	1.396%	5.000
000912	0.833	1.227%	5.529
002170	0.362	2.874%	5.448
000731	0.342	1.631%	6.070
600096	0.303	4.164%	8.326
600141	0.634	1.735%	6.013
002312	0.337	1.76%	5.152
000902	0.405	2.95%	4.994
002539	0.376	1.092%	5.523
600426	0.167	1.172%	5.079
000830	0.412	1.24%	5.815
000155	0.264	6.547%	8.001
002110	0.245	1.541%	6.007
600691	0.535	2.05%	4.948

As can be seen from the above table, although the posterior difference ratio of 600251, 002545, 002274 and 000912 stocks did not reach the standard of less than 0.65, the average relative error of each stock is much less than 20%. Also, model accuracy is not the most essential thing for this step. Therefore, this model is suitable for the prediction study of ESG scores.

By comparing the predicted ESG score, 600691, 002274, 000902, and 000893 stocks have the lowest value. This means that the management of these four enterprises does not have a good fit for sustainable development. As a result, these four stocks will no longer be considered sample stocks in a portfolio that focuses on encouraging companies to go low-carbon.

3.2.3 Portfolio Optimization

Using the Efficient Frontier plot, the approximate performance of this portfolio could be determined from the regions of the 1000 sample portfolios. In addition, the star points represent the position of the portfolio with a maximized Sharpe ratio on the Efficient Frontier line, as shown in figure 8.

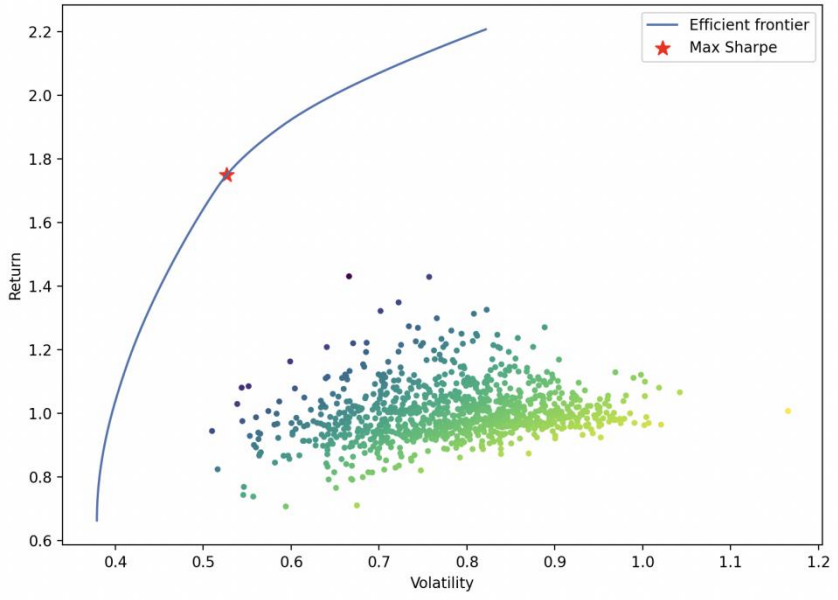


Fig. 8 Efficient Frontier with Random Portfolios

Judging by the dots representing random portfolios, they're all clustered on the lower side of the plot. This means that the portfolio is not effective, and its volatility has a wider range than the stable return. Therefore, the portfolio with the highest Sharpe ratio, which is represented by the star dot, would have a higher return and lower volatility value than the random portfolios.

After optimization, the proportion of each stock of this financial product is shown in table 7.

Table 7 Weight of Stocks

Company Name	Weight
000792	0
000408	0
002545	0
002588	0.6635
000912	0
002170	0
000731	0
000902	0.26219
600096	0
600141	0
002312	0
002539	0
600426	0
000830	0.07432
000155	0
002110	0

Most of the 16 stocks have not been weighted in the portfolio due to poor expected returns, and only three stocks have investment potential.

Among them, 002588 as the main company of compound fertilizer accounted for the majority of the total portfolio investment at 66.35%, after that is 000902 as the representative of P fertilizer with

26.219% followed by 000830 as the representative of N fertilizer with 7.432%. Companies that specialize in K fertilizer are not weighted in the Portfolio because of poor stock price performance or low ESG score.

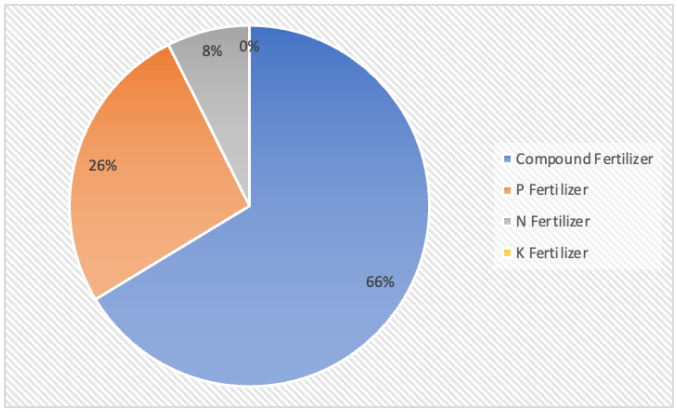


Fig. 9 Investment Proportion

From figure 9, it could be more intuitively confirmed that the main factors affecting the ESG-friendly Portfolio are the stocks of companies specializing in compound fertilizers, while companies specializing in P and N fertilizers play a smaller role, while potash fertilizer is ignored.

3.2.4 Risk Rating

Through calculation, the expected annual interest rate of this Portfolio is 174.9%, the volatility is 52.65%, and the Sharpe ratio is 3.32. It can be seen that the expected annual interest rate is relatively ideal. The volatility is large but within the tolerable range of normal investments. The Sharpe ratio is greater than 3, so the performance is good.

Converting the expected annualized interest rate and volatility into an absolute VAR value yields 88.0275%. Therefore, the Portfolio is R4-rated.

In summary, an ESG-friendly portfolio is suitable for investors who prefer high risk and high yield but are relatively conservative.

4. Conclusion

In the agricultural period, the paper did a process on crop data and figured out that the usage of nitrogen and phosphorus varies obviously in the same kinds of crop. That means these two agricultural elements can be adjusted to reduce the carbon emissions in actual production.

Moreover, compared with other agricultural elements, the usage of fertilizer contributes the most to the total carbon emissions. And in all kinds of fertilizers, reducing the usage of N fertilizer, P fertilizer, and K fertilizer, and increasing the usage of compound fertilizer can reduce the total emissions. Also, the usage of the ingredient of fertilizer can be used to predict the total carbon emissions, which makes it more convenient for precision fertilization.

Meanwhile, for the investment, the portfolio analysis indicates that the optimal portfolio, distinguished by higher returns and lower volatility compared the random sample portfolios, selectively invests in a few stocks with potential, primarily in the compound fertilizer sector. Companies in other fertilizer sectors like phosphorus and nitrogen are less represented, while those in the potash sector are excluded due to poor performance. Overall, this ESG-friendly portfolio demonstrates high risk and high yield characteristics, making it suitable for moderately radical investors seeking substantial returns.

The analysis reveals that compound fertilizers pose the greatest challenge. Consequently, investing in compound fertilizers emerges as a viable solution for facilitating the production of low-carbon compound fertilizers by enterprises. Notably, an examination of investment proportions indicates that compound fertilizers yield the highest returns. Hence, this approach achieves the twin objectives of carbon reduction and profitability.

From the results, it can be seen that among the six categories of factors related to agricultural production and affecting carbon emissions, fertilizer is the most important influencing factor. Among fertilizers, compound fertilizer is the main cause of carbon emissions.

From the investment point of view, the companies with each kind of fertilizer (N, P, K, compound fertilizer) as the main product, the companies with compound fertilizer as the main product deserve more attention and investment, since the shares of such companies are more profitable, while the ESG scores are eligible.

Therefore, as expected by the hypothesis, the main factors that need to be focused on and invested to encourage the reduction of carbon emissions coincide with those that can bring greater profits.

This research suggests that promoting carbon reduction and increasing return can coexist. In addition, it's a mutually beneficial situation for the business, for sustainability, and investors.

Upon identifying that the primary contributor to carbon emissions is fertilizer use, the paper advocates for economically incentivizing investments in enterprises linked to this sector to reduce carbon emissions. This approach aims to promote corporate commitment to ESG principles.

From an investor's perspective, the paper encourages the promotion of ESG-friendly portfolio offerings, providing a reference for investment allocation. This strategy is designed to support sustainable development while ensuring returns and managing risks.

The portfolio under consideration is categorized as an R4 derivative, indicating that investments in ESG (Environmental, Social, and Governance) related products remain a high-risk endeavor in the current era. Consequently, while such investments may appear to offer mutual benefits, they necessitate a degree of risk tolerance from investors. This inherent risk must be acknowledged and carefully managed to align with investor profiles and expectations.

For the more in-depth classification of fertilizers for analysis, only four types of fertilizers were selected in this paper. Organic fertilizer, however, is a murky area. To ensure the accuracy of this paper, organic fertilizers were not included in the scope of analysis.

Due to the novelty of ESG-related financial derivatives, the period chosen in this paper is relatively short when making predictions and analysis of the portfolio. In addition, as the fertilizer stock market has been depressed and had high volatility in the past year, although it will not have a strong impact on the final result, there will be errors.

This paper primarily concentrates on the business analysis of the fertilizer industry. However, it acknowledges that other sectors, notably irrigation, significantly impact carbon emissions and warrant further investigation. Additionally, there is potential for derivative research that integrates multiple related industries. Such an approach could enhance the diversification and scope of investment portfolios, thereby potentially improving overall investment performance.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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