Journal of Industrial Engineering and Applied Science
Journal Home: http://jieas.suaspress.org/ | CODEN: JIEAAE
Vol. 2, No. 6, 2024 | ISSN 3005-6071 (Print) | ISSN 3005-608X (Online)

FSMM: Food System Monitoring Model for Re-optimization

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Abstract: The unstability of global food system have aroused growing attention worldwide [6, 7]. Althrough there is sufficient food produced to feed every person, many people in the world are suffering from hunger. Moreover, the current food system is harmful to the environment. As our global population continues to rise, the ability to produce more food while sustaining, and even improving, the health of our environment counts.

The FSMM(Food System Monitoring Model) provides score rank using entropy weight and subjective weight to evaluate the current state of the food system for most countries in the world. It contains 9 individual features to measure multiple aspects, including efficiency, profitability, sustainability and equity.

Considering the future trend of the food system, we apply Gray Forecast Model to forecast the next 5 years of the development of the food system to figure out the time for each country to change into equity and sustainability.

To find out the relation between external factors and food system, The FSMM uses Boosting Regression Model to find the correlation between the scores and 10 indicators which represent the influences of energy use, government, agriculture, social factors and population ratio. The FSMM fits the data from 178 countries from 2000 to 2019. After simulating and adjusting the parameters to decrease the loss of the model, we gets the importance rate of each indicator.

We find the indicators whose importance rate change significantly when the food system is optimized for equity and sustainability. And we use these indicatos as dependent variable and apply Linear Regression to fit by using the yields of the wheat, meat and vegetables as independent variable. By doing this, We find out the direct impact of re-optimization on the food system.

We finally get the importance rate and the coefficient of two regression model and analyze the specific influence of various factors on the food system and compare the differences between the influence on developing and developed countries.

After the overall analysis of the influence on developed and developing countries, we pick some specific developing and developed countries to analyze and discuss the scalability and adaptability of the model.

Keywords: Boosting Regression, Linear Regression, FSMM, Entropy Weight, Data Mining, Supervised Learning, Energy Use.

Disciplines: Applied Mathematics. **Subjects:** Mathematical Modeling.

DOI: https://doi.org/10.70393/6a69656173.323433 **ARK:** https://n2t.net/ark:/40704/JIEAS.v2n6a11

1 INTRODUCTION

food system is a complex web of activities involving production, processing, transport, and consumption. Although the current food system around the world yields enough grains to feed population worldwide, inequality and unsustainability exists. According to FAO's estimation, 161 million children under five years of age are chronically malnourished, and over two billion people suffer with micronutrient deficiencies. Moreover, the pursuit of profitability and efficiency leads to massive emission and pollution, harming our sustainable use of trees and water. Consequently, Humans and other species' living situation runs down.

Since the current food system poses potential threat to the ecosystem and human health, re-optimizing the system is imperative. Despite food system's complexity, we need to change the way in which food is produced and distributed[8].

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It is important to balance the efficiency and profitability with equity and sustainability, or go one step further, optimizing the latter.

Artificial intelligence (AI) has shown tremendous promise in addressing complex, multifaceted challenges across various domains. In finance [10], AI has been employed for market forecasting [28]. It also excels in analyzing heterogeneous data, such as using co-attentive neural networks [15, 18] for user identity linkage from mobility data [9] and improving multi-modal steganography with adversarial learning to optimize text-image matching [1, 13]. Furthermore, AI [16, 17] shows power in construction [2, 4, 11] and other fields [25].

In this paper, we address the challenge of optimizing food system by developing a series of AI models [26]. We apply these models to evaluate food system and identify differences, benefits and costs when changing the priorities of a food system. We also forecast how long will a modified system take effect. Finally we use our models both in developed and developing countries to verify our achievements and discuss the scalability and adaptability of our models to make sure it is feasible in different situations.

2 DATA PROCESSING

2.1 Data Sources

We select data that contains 186 countries from 2000 to 2019 and the data is about agricultural and environmental factors, such as Producer Price Annual Value, Emissions (CO2eq) (Energy), Per capita arable land area, etc. from The Food and Agriculture Organization (FAO) and World Bank, we also derive political data which contains Conflict and Disaster Stock Displacement Number and other indexfrom Internal Displacement Monitoring Centre(IDMC).

2.2 Data Cleaning

2.2.1 Missing Data and Outliers

The raw data has missing values that would influence our modeling result. To cope with this drawback, we processed our original dataset as follows:

If lack of specific series of data continues for some year, we will use the nearest year's data to replace all missing data.

If this series of data is not available in all years, world's average value will be applied to all vacant series instead.

To cope with outliers, we use formula related to interquartile range:

$$IQR = x_{75\%} - x_{25\%}$$

Our method is: if the value of the data is higher than Figure A, which is defined as upper quartile plus 1.5IQR (interquartile range), this data will be defined as outliers and its value will be replaced by the value of Figure A. If the value of the data is lower than Figure B defined as upper quartile plus 1.5IQR, this data will also be defined as outliers and its value will be replaced by the value of Figure B.

2.2.2 Data Decomposition

When processing Political indicators, we choose WGI index provided by World Bank economists Caufmann et al.. This index is composed of six main indicators and has thirty-six variables in the original database [4]. These data may have multicollinearity and taking all these variables into consideration can be time-consuming. Many approaches are available for data decomposition. Here we use Principle Component Analysis(PCA).

Part of original variables

Number	Variable
1	Control of Corruption: Percentile Rank, Lower Bound of 90% Confidence Interval
2	Government Effectiveness: Estimate
3	Political Stability and Absence of Violence/Terrorism: Estimater
4	Regulatory Quality: Percentile RankUpper Bound of 90% Confidence Interval
5	Rule of Law: Number of Sources
6	Voice and Accountability: Standard Error

Given a set of data $X_{m\times n}$, the mean vector of each attribute of the original matrix is $\bar{X}$, Find the covariance matrix of the original matrix

$$Cov(X) = \frac{1}{m}(X - \bar{X})^T(X - \bar{X})$$

Calculate the eigenvalues and eigenvectors of the covariance array. The eigenvectors corresponding to the largest k eigenvalues are selected to form the matrix $W_{n\times k}$. Then we can calculate the Data matrix after dimensionality reduction:

$$Z_{m\times k} = X_{m\times n}W_{n\times k}$$

As for how to select k, Choose different k values, and then keep calculating using the following equation to select the smallest k value that can satisfy the conditions of the following discriminant:

$$\frac{\frac{1}{m}\sum_{i=1}^{m} \| x^{(i)} - x_{approx}^{(i)} \|^2}{\frac{1}{m}\sum_{i=1}^{m} \| x^{(i)} \|^2} \le t$$

Let $t = 0.85$, then two completely new variables are obtained to represent the political factors: Law&Political Stability and Government Management. We can believe that these two variables have a good description of each country's political situation considering all original variables together.

3 ASSUMPTIONS AND JUSTIFICATION

In order to simulate real-life conditions and make complex systems easier to evaluate and monitor, we make the following assumptions and justifications and modification:

A comprehensive food system involves many aspects

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including agriculture, ecology, climate, population, etc. and it is impossible to model every possible scenario. Therefore, we have made a few assumptions and simplifications , each of which is properly justified.

The data we collect from online databases is both reliable and internally consistent. Since our data sources are all the websites of international organizations such as The Food and Agriculture Organization, it is reasonable for us to assume the data has high quality.

The rate of change of each index over time is relatively stable, and will not change drastically in a short time. The rate stability is the basis of the Gray Forecast Model to forecast the future trend of the re-optimization.

The equity and sustainability is largely depend on per capita harvested area, the emissions of Greenhouse gases, the food production, etc..

The efficiency and profitability is largely depend on Food CPI, food inflation, net export value and PPI.

4 NOTATIONS

Symbols	Description
Efficiency	Synthetic Efficiency indicators
F_{CPI}	Consumer Price Indices
F_{inf}	Food Inflation
Profitability	Synthetic Profitability indicators
P_{ne}	Net export Value
P_{PPI}	Producer Price Annual Value
Equity	Synthetic Equity indicators
E_p	Production
E_d	Displacement Numbers
Sustainability	Synthetic Sustainability indicators
S_{CH4}	CH4 Emission
S_{CO2}	CO2 Emission
S_{LA}	Per capita arable land

5 EQUITY AND SUSTAINABILITY ORIENTED MODEL

5.1 Entropy Weights

To optimize the existing food system that focuses on efficiency and profitability in terms of equity and sustainability, we need to first build an evaluation model based on the existing food system. We first calculate the entropy weights of each indicator from efficiency and profitability indicators.

For efficiency and profitability, we choose **four indicators** to quantify the impact of these types of elements on current food system [20].

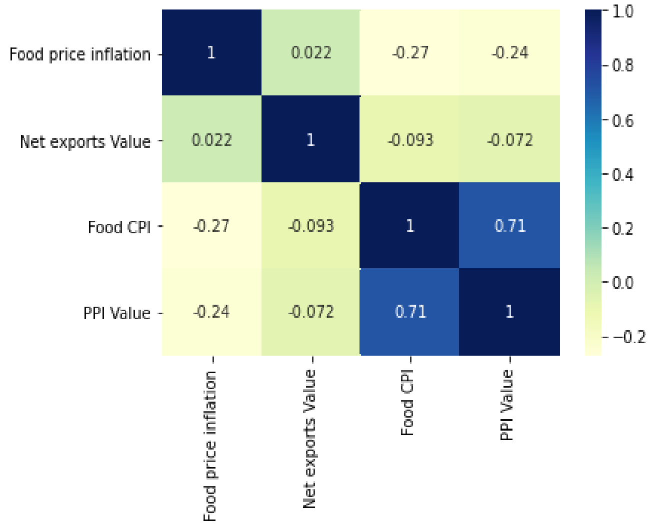
Consumer Price Indices (Food) directly shows consumers' purchasing power within a nation, including all kinds of crops and stocks. Appropriate Indices mean that its value is neither high or low and inform us that this nation's food supply is in the normal value.

Food Inflation measures the ease of access to food, especially those who have low standard of living. High food inflation usually indicates that this nation's food system is on the verge of collapse.

Net Exports Value shows the amount which exceeds this nation's total food consumption requirements. High net exports value protect nation's food security as extra food prodution gain profits when safe, but when this nation suffer from disasters or other incidents, these extra food can be distributed during emergency time.

Producer Price Annual Value reflects farmers' profitability and capacity. Although this index is to some exent related to CPI, it sees food system from a different angle and is helpful for us to research farmers' state.

These four indicators' coefficient is shown below:



COEFFICIENT

The raw data is first normalized . The raw matrix experience positivization , which means that all indicator types are uniformly transformed into maximum type indicators. For the intermediate type indicator Food Inflation, Net Exports Value, the following formula is used:

$$M = \max\{|x_i - x_{best}|\}, \tilde{x}_i = 1 - \frac{|x_i - x_{best}|}{M}$$

where:

x_i = original data

x_{best} = this type of data's best value

$\tilde{x}_i$ = data after normalization

For the interval-type indicators Consumer Price Indices (Food) and Producer Price Index, the positivation formula is as follows:

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$$M = \max\{a - \min\{x_i\}, \max\{x_i\} - b\}, \tilde{x}_i = \begin{cases} 1 - \frac{a-x}{M}, x < a \\ 1 \quad , a \le x \le b \\ 1 - \frac{x-b}{M}, x > b \end{cases}$$

where $[a, b]$ represents the best interval.

After obtaining the normalized data p_{ij} of the original data, we apply the entropy weighting method and calculate its entropy value and variability coefficient and finally determine the weight of each indicator:

$$e_j = -\frac{1}{\ln n}\sum_{i=1}^{n} p_{ij}\ln(p_{ij}), \quad g_j = 1 - e_j$$

$$W_j = \frac{g_j}{\sum_{i=1}^{m} g_j}, j = 1,2,3\ldots\ldots m$$

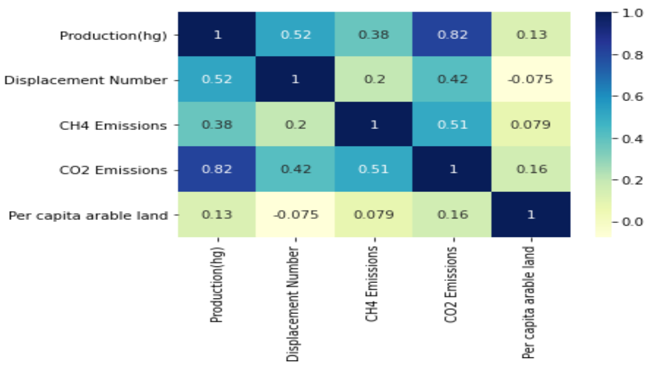
The same treatment is performed for the indicators measuring equity and sustainability. These indicators are also chosen after thorough consideration.

Emissions of CH4 and CO2 directly reflects the extent to which the whole system is polluted. So every environmentalist shopes to decrease these emissions or at least control its growth.

Per Capita Arable Area decreases when a coutry has more contaminated lands or suffered by natural disasters and wars. More unfortunately, this decrease is often irreversible. This is why we choose this factor to represent sustainability.

Production and **Conflict and Disaster Stock Displacement Number** is highly realted to a nation's equality because of their high correlation to people's living rights. A country where endless turmoil exists has low production and high displacement number.

These five indicators' coefficient is shown below:



COEFFICIENT

For the minimum value indicators Displacement, Emission, the formula

$$\tilde{x}_i = max - x_i$$

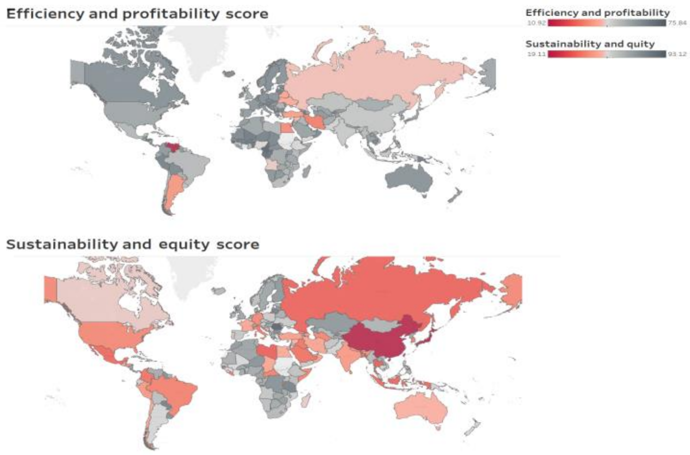
is used to convert them to extreme values. For the maximum value indicator Production, Per Capita Land, only normalization is required.In this way, we obtain the scores Y_1 for efficiency and profitability and Y_2 for equity and sustainability of the food system in each country for each year by using the following formula:

$$score_{Y_1} = \gamma_1 F_{CPI} + \gamma_2 F_{\inf} + \gamma_3 P_{ne} + \gamma_4 P_{PPI}$$
$$score_{Y_2} = \beta_1 E_p + \beta_2 E_d + \beta_3 S_{CH4} + \beta_4 S_{CO2} + \beta_5 S_{LA}$$

That is to say we did the following calculation:

$$score = n \times \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} \times \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}$$

The difference between Y_1 and Y_2 is the change of the priority of the system. The inconsistency in the selection of indicators is why the existing system differs from the optimized system.



FOOD SYSTEM SCORE

5.2 Gray Forecast Model

The optimized system takes a long time to reach the optimal state. Since data is previously normalized, the values of the five indicators representing fairness and sustainability are equal to 1 when the optimal state is reached. We use the gray model to forecast each country's score for the next 6 years (2020-2025) and our data is qualified for the requirements to do gray forecast model. Given the element sequence data

$$x^{(0)} = \left(X^{(0)}(1), X^{(0)}(2), \ldots, X^{(0)}(n)\right)$$

process accumulation to generate a (1-AGO) sequence

$$x^{(1)} = \left(X^{(1)}(1), X^{(1)}(2), \ldots, X^{(1)}(n)\right)$$

where

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \quad k = 1, \ldots, n$$

Define

$$Z^{(1)} = \left(z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n)\right)$$

$$\hat{a} = (a, b)^T$$

where

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$$z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1)$$

a=development coefficient

b=gray action

Next, modeling the gray differential equation of GM(1,1) and shadow equation

$$x^{(0)}(k) + az^{(1)}(k) = b$$

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b$$

Final forecasting equation is as follows:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = \left[x^{(0)}(1) - \frac{b}{a}\right](1-e^{a})e^{-ak}, \quad k = 1,\dots,n-1$$

Checking forecast value is essential. Calculate the result of $\varepsilon(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)}$, $k = 2,\dots,n$, if $\varepsilon(k) < 0.2$, it meets basic requirements if $\varepsilon(k) < 0.1$, it meets higher requirements, and the mean value of $\varepsilon(k)$ in our model is about 0.03.

After calculation, we arrive at the amount of change in the indicators for 6 years, and the amount of change needed to reach optimality is $5 -$ countries 2019 scores. The years required δt to reach optimality is thus

$$\delta t = \frac{5 - \text{country 2019 score}}{\text{amount of change over 6 years for each country}} \times 6$$

5.3 Taking Systems into Effect

The average value of the $\varepsilon(k)$ for more than 100 countries is around 0.04 by gray forecast, and all countries except China can pass the relative residual test. The reason why China cannot pass the residual test is that China is more polluted, has an emission score of 0, and has a huge amount of food production, population, and food consumption. Therefore, China cannot complete a good system in terms of profit maximization because of tight market, and in terms of sustainable development, it is difficult to change the current situation of China's food system, and it can only maintain a flat development in the future development, so it is difficult to complete a sustainable transition based on the recent 20 years of data.

Moreover, since the results show that only 54 countries are satisfied with moving toward sustainability, the remaining countries are having difficulty completing sustainability development. According to current standards, sustainability development is slow, and most countries need about 100 years to maintain the good operation of their food systems and to make the transition to sustainability. Therefore, it is difficult to fully achieve the goal of sustainability under the current policy. However, there are a few countries that can make the sustainability transition in the foreseeable future:

sustainability transition

Country	Iceland	Indonesia	Angola	Benin	Greece	Uzbekistan	Lebanon	Senegal
Year	6.716	7.578	13.780	15.948	18.011	23.482	23.993	25.141

Based on the results, we found that Iceland, Indonesia, and Angola are able to complete the transition to sustainability after 6,7,13 years, respectively. According to data, Iceland is a small island country with low production capacity and a food importer, but because of its small population base and low demand for food, the CPI Food is not high and can maintain a healthy development.

Iceland has become a model of modern economic development driven by renewable energy. Therefore, within six years, Iceland will be able to transform its food system to meet the requirements of sustainability. Similar to Iceland, Indonesia is also a food importer and has done an excellent job of environmental protection in recent years, so Indonesia will be able to achieve a sustainable transition in the foreseeable future.

Although Angola is a developing country located in the middle of Africa and a food importer on account of its high demand for food and high consumption index, Angola's CPI Food is small and its food system is relatively healthy, and because Angola's CO2 and CH4 emissions are low, it is at the forefront of environmental protection in the world, so it will be able to complete a sustainable transformation in more than 10 years.

6 ANALYSING BENEFITS AND COSTS

6.1 Boosting Regression

Researching the benefits and costs of the food system after the change of priorities can be started with some indirect indicators to study the impact of external changes on food production [5]. Eleven indirect indicators were selected, firstly, yield was selected from within the food system, and then seven other indicators were selected from the environmental system and socio-economic system, which are closely related to the food system [21].

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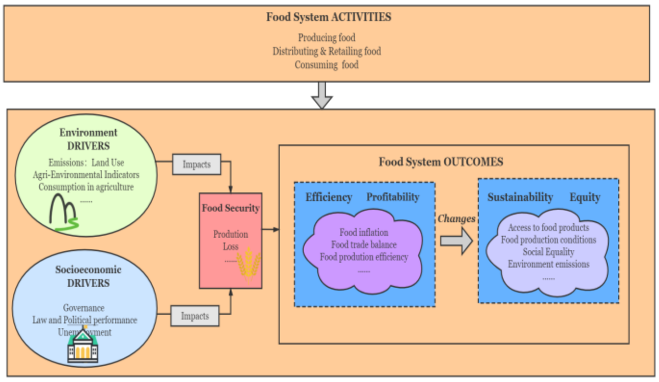
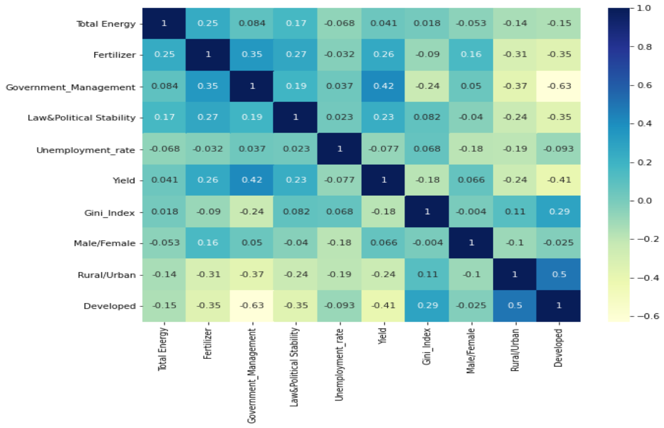


INTRODUCTION TO EVALUATION MODEL

However, only 10 indicators were finally filtered because of the high autocorrelation coefficient between Consumpiton Agriculture and total energy, so we removed Consumpiton Agriculture.



CORRELATION COEFFICIENT

Since there are 10 features in total, we calculate the Pearson coefficients and find that they do not have great correlation and the operability to decomposite. The correlation between each independent variable and the dependent variable is complicated, and the multiple linear regression model cannot be used to fit to find the relationship. Therefore, we choose a regression model based on a decision tree [12].

However, using only one decision tree usually does not result in a good fit, so we want to take advantage of the computer's iterative computing power to fit the data using multiple trees in parallel. Parallel operation allows us to evaluate the results of a tree after it has ended decision, and to reduce the loss value by a greedy algorithm (local optimal solution) so that each iteration reduces the loss at the same time to reduce the error of the previous tree. So we firstly define an evaluation function for each tree:

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t)$$

To optimize this function faster, we use the **gradient descent** method to optimize the loss function. We can use a second-order Taylor expansion at $f_t = 0$ and the objective function is independent of the previous loss, so we remove the loss term to obtain the following figure:

$$L^{(t)} \approx \left[\sum_{i=1}^{n} g_i\, f_t(x_i) + \frac{1}{2} h_i {f_t}^2(x_i)\right] + \Omega(f_t)$$

where g_i denotes the first-order partial derivative of L with respect to f and h_i denotes the second-order partial derivative of l with respect to f. Because it is a regression task, we define the loss function as MSE (mean square error):

$$g_i = \frac{\partial l}{\partial f} = f(x_i) - y_i$$

$$h_i = \frac{\partial^2 l}{\partial f^2} = 1$$

Since each $f_t(x_i)$ corresponds to a leaf node w_i, so we can replace f_t with w_i, so we rewrite that objective function to get

$$\tilde{\mathcal{L}}^{(t)} = \sum_{j=1}^{T} [\left(\sum_{i \in I_j} g_i\right) \omega_j + \frac{1}{2}\left(\sum_{i \in I_j} h_i + \lambda\right) \omega_j^2] + \gamma T$$

We obtain the optimal weights based on this objective function by using the extreme value property of the derivative being 0 to find the partial derivatives of w_j:

$$\omega_j^* = -\frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda}$$

Substituting the optimal weights back into the original function gives us the final scoring function for the performance of the decision tree f_t:

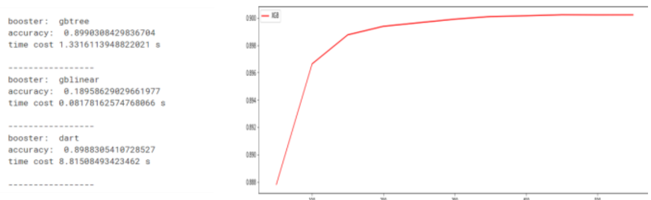
$$\tilde{\mathcal{L}}^{(t)}(q) = -\frac{1}{2} \sum_{i=1}^{T} \frac{\left(\sum_{i \in I_j} g_i\right)^2}{\sum_{i \in I_j} h_i + \lambda} + \gamma T$$

The basic step of the algorithm should be to iterate through all segmentation methods for all features, select the one with the least loss, get two leaves, and then continue the iteration. The iterations can be executed in parallel. The total formula is as follows:

$$\mathcal{L}_{split} = \frac{1}{2}\left[\frac{(\sum_{i \in I_L} g_i)^2}{\sum_{i \in I_L} h_i + \lambda} + \frac{(\sum_{i \in I_R} g_i)^2}{\sum_{i \in I_R} h_i + \lambda} - \frac{(\sum_{i \in I} g_i)^2}{\sum_{i \in I} h_i + \lambda}\right] - \gamma$$

6.2 PARAMETER ADJUSTMENT

This integrated learning method based on many decision trees is called Boosting, and each tree is called Base Learner. In this experiment, we first selected decision trees, regression trees, and dart trees as the base learners to compare the accuracy and runtime respectively, and we found that the accuracy of decision trees and dart trees matched and the running time of decision trees was faster, so we chose decision trees as our base learners.

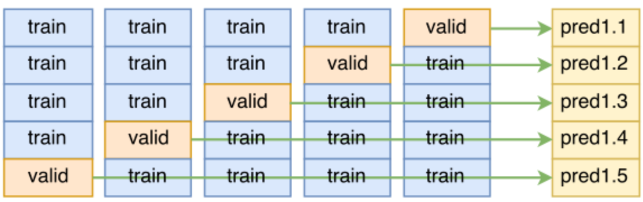


BASE LEARNER AND TREES SELECTION

When using Boosting to fit, the choice of the number of base learners is crucial, which is related to the complexity of our Boosting model. Too few learners tend to be underfitting and too many learners will make model too complex. In the fitting process, as the number of base learners increases, the accuracy of the fitting is rising, and it has converged when the number of base learner reaches about 400, and more base learners do not help us make better decisions, so we set the number of base learner at about 400.

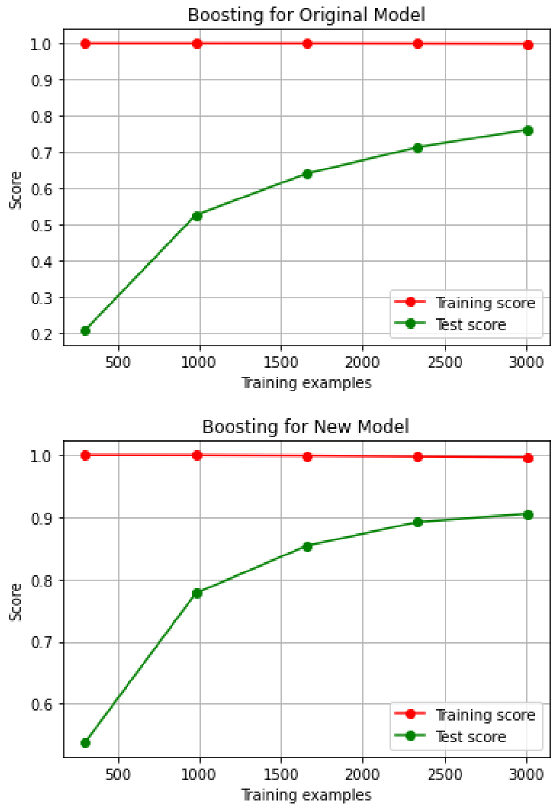
In order to evaluate the model, we divide the data into training data and testing data, where the testing data is not involved in training and is used for the evaluation of the final model. In addition, when we decide the parameters of the boosting model (including the number of base learners and the type of base learners), we divide the training data into a part of the training data as the validation data for adjusting parameter, and then evaluate the model by the test set, so that the model can match the data outside the training set.

We use K-Fold cross validation which divides the original data into K groups, make each subset of data into a validation set separately, and set the rest of the K-1 subset data as the training set, so that K models will be obtained. These K models are evaluated in the validation set separately and the final error MSE (Mean Squared Error) is summed and averaged to obtain the cross-validation error. It utilizes a limited amount of data and the evaluation results can be as close as possible to the performance of the models on the test set.



K-FOLD CROSS VALIDATION

Finally, we fit the regressions of the original model and the new model scores using 10 independent variables, and the fit of the original model reached about 76% with an average MSE of about 0.09; the fit of the new model reached about 90% with an average MSE of 0.04.



RESULT OF NEW MODEL

6.3 Result of Regression

The weight ratio of the original model and the new model is as follows:

weight ratio

Weight	T-E	Fert	G-M	LPS	U_r	Yield	Gini	M/F	R/U	Dev
Original	17%	6%	13%	14%	6%	11%	9%	9%	10%	6%
New	26%	6%	9%	2%	7%	5%	7%	12%	10%	17%

Where

$$T - E = \text{TotalEnergy}$$
$$\text{Fert} = \text{Usage Amount of Fertilizer}$$
$$G - M = \text{Government Management}$$
$$\text{LPS} = \text{Law\&Political Stability}$$
$$U\_r = \text{Unemployment rate}$$
$$M/F = \text{Proportion of Male/Female}$$
$$R/U = \text{Ratio of Rural/Urban}$$
$$\text{Dev} = \text{Developed or Developing Country}$$

We can find that both in the original model and the new model emphasizing equality and sustainability, the indicator of agricultural energy use is a very important measure, and it is more important in evaluating equity and sustainability, while the other indicators contribute more evenly to the model. The original efficiency and profitability oriented model focuses more on political development and agricultural

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output, and the model has higher requirements to maintain the stability of political development and economic development in agriculture in a country, and the score of the original model gets higher as the government's management capacity, the emphasis on politics, and the output increases.

Changing the food model to an equity and sustainability oriented model requires more emphasis on Total Energy use, as many energy sources are non-renewable, this situation put stress on our ability to develop renewable energy and requires us to control usage on traditional energy. So for sustainability we need to reduce the use of energy emissions. The level of development of a country is also an important measure of the equity and sustainability oriented food model, because as a country becomes more developed, its level of sustainability is higher. In practical terms, in order to achieve a balanced sustainable development, it is necessary for developed country to drive developing countries to develop together, strengthen development cooperation to fully mobilize resources, and provide resources to developing countries to help.

The United Nations [24] officially proposed SDGs in 2015, pointing out that development must be based on a balance of social, economic and environmental sustainability. And it also shows that developed and developing countries have different performance in the equity and sustainability oriented food system. Further, we distinguish between developed and developing countries by training and separately calculating the weights:

differences between developed and developing countries

Model	Weight	T-E	Fert	G-M	LPS	U_r	Yield	Gini	M/F	R/U
Original	Developed	13%	9%	6%	17%	4%	5%	20%	19%	8%
	developing	19%	6%	10%	11%	8%	9%	8%	10%	18%
New	Developed	33%	3%	13%	3%	1%	6%	2%	27%	12%
	developing	32%	5%	11%	3%	8%	7%	8%	10%	16%

In the food system of efficiency and profitability, political factors, the Gini index plays an important role in the measurement of a country's efficiency and profitability oriented food system, because the country focuses on policy and national income stability. Low Gini index represents a smaller gap between rich and poor, and the smaller the gap between rich and poor, the higher the efficiency of the food system and the higher the country's score in the original model.

The developed countries also promote the development of profitability mainly through the influence of policies on the stability of the country. In the evaluation of efficiency and profitability for developing countries, Total Energy use has an important influence on the evaluation of efficiency and profitability, which indicates that the developing countries want to achieve efficiency improvement and profitability change, they need to pay more attention to energy use.

6.4 Internal Impact

We got the weight that changed the most and try to figure out the specific impact on the food system, so we proceed to analyze the impact of the transformation of the food model on the yields of vegetables, eggs, and wheat in a country. Because there are not many variables, We simply establish four linear regression models which use four indicators respectively as dependent variable and the yields of three main products as Independent variable.

$$Y_{\mathrm{i}} = \alpha + \beta_1 vegetables + \beta_2 meat + \beta_3 wheat$$

Overall, all four regression models passed the F-test, indicating that the fitted equations were statistically significant.

Four linear regression models also pass the significance test of regression coefficients since the significance test of regression coefficients can determine whether the effect of the independent variable on the dependent variable is significant. Therefore, all three variables passed the significance test and did not need to be excluded.

$$T-E = 51414.119 + 171.495 vegetable + 51.172 meat + 110.93 wheat$$
$$Yield = 45256.709 + 150.372 vegetable + 38.387 meat + 12172.25 wheat$$
$$Fert = 35.715 + 0.243 vegetable + 0.64 meat + 1.355 wheat$$
$$LPS = 0.226 + -0.001 vegetable + 0.13 meat + 0 wheat$$

In the previous analysis, it can be seen that the weight of total energy in the new model increases significantly due to the importance of sustainability and equity to the ecological environment. In the linear regression model of total energy, the most weighted factors are vegetables and wheat. Therefore, countries need to find more environmentally-friendly ways to produce vegetables and wheat. In contrast, energy savings have less impact on meat production.

On the other hand, the level of government management and development in laws are less important. In the fitted equation of Law and political stability, the regression coefficient of wheat is 0, which shows that the government's ability to govern and social laws are not affected by law and political stability [19]. The reduced importance of Law and Political stability in the food system will not change wheat production.Also ,the yield of vegetables has a negative relationship with law and political stability.

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6.5 Further Analysis of Different Countries

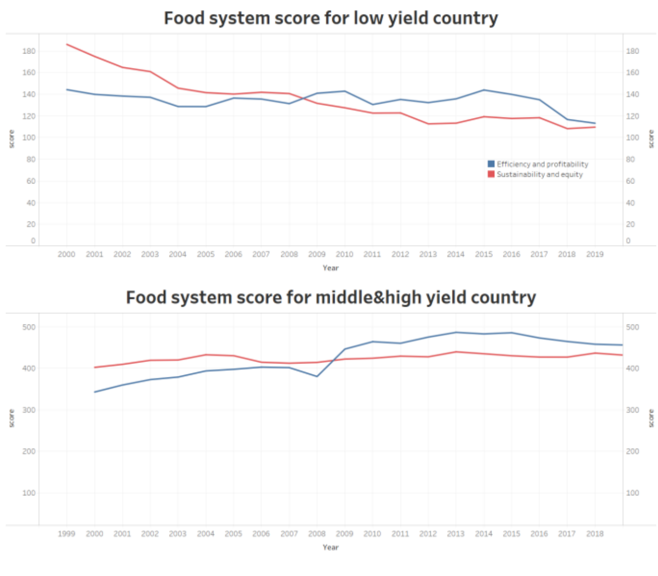
The level of food production plays a crucial role in the overall evaluation system. The importance of stable food production capacity is also emphasized in the UN definition of the basic concepts of food security. Therefore, we choose the food yield as an indicator of the level of agricultural production in developed and developing countries to further analyze the benefits of changes in the food system.

$$yield = \frac{quantity\ of\ agricultural\ products}{average\ area\ per\ unit\ of\ land}$$

Combining the upper quartile and lower quartile of the world food yield level with yield data, we classify countries into three categories of countries according to yield: low yield, middle yield , and high yield.

Geographical distribution of different yield countries. The high yield countries and the middle yield countries are mainly located in North America, Europe, Oceania, and parts of East Asia. Most of these countries are developed countries with leading agricultural production levels. Low yield countries are mainly located in Africa, parts of South America and Russia. Most of these countries are economically underdeveloped, and agriculture is limited by climate and technology. As a result, food production is low and food insecurity is likely to occur.

Performance at different times. Food systems in low yields countries show a slight decline in performance in sustainability and equity and a flat performance in efficiency and profitability. High and low yields countries show a flat performance in sustainability and equity and a slight overall increase in efficiency and profitability.

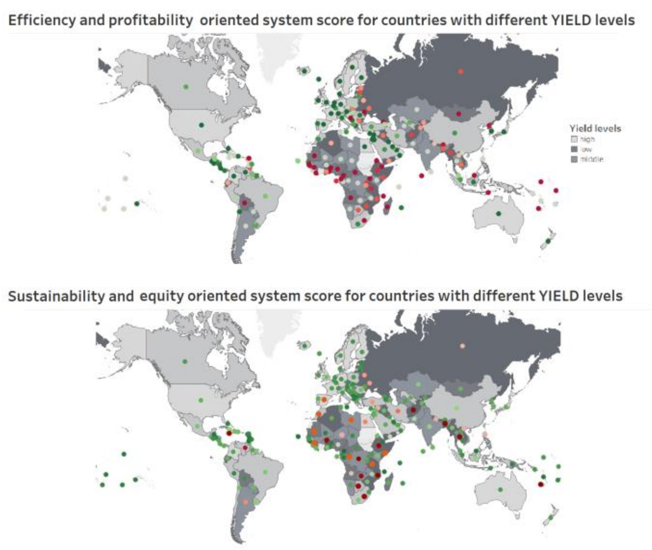


PRFORMANCE AT DIFFERENT TIMES AND COUNTRIES

1. Developing countries. In the original Efficiency and profitability oriented food system, developing countries with lower food yields score low. Geographically, they are mainly located in southern Africa, parts of Eastern Europe, parts of South Asia and some Pacific Island countries. In the case of Southern Africa, for example, most of the countries there are mainly developing countries. The impact of natural and social factors has left millions of people on the brink of poverty and hunger. Price instability, widespread poverty, underemployment, and economic instability also contribute to the deteriorating food security situation in many countries in the region. Food systems also have low profitability scores due to low food production and underdeveloped productivity in the region. Among developing countries, there are also some countries with high yields, abundant domestic food production. These countries are mostly exporters of food and thus have high efficiency and profitability scores.

In the sustainability and equity oriented food systems, developing countries with low yields have poorer food system sustainability performance, low priority for agricultural emissions, and low arable land per capita. In terms of equality in the food system, there is instability in food production and unequal access to food due to low food output and high numbers of people affected by conflict and natural disasters.

2. Developed countries. Developed countries with medium to high yields excel in the efficiency and profitability oriented food system. Take North American and European countries for example, such countries have advanced agricultural technology and higher level of agricultural production. At the social level, normal inflation and food CPI ensure the profitability and stability of food distribution and marketing. Although developed countries outperform developing countries in terms of sustainability and equity of the food system, they do not achieve high scores in sustainability and equity. Indicators which reflect sustainability and equity scores such as agricultural emissions need to be taken seriously.



GEOGRAPGICAL VIEW

Therefore, the transformation from efficiency and profitability orientation to equity and sustainability orientation requires a greater emphasis on Total Energy use and a transformation from developing to developed countries, and a balance between The transition from the efficiency and profitability orientation to the equity and sustainability orientation requires a greater emphasis on Total Energy use, a shift from developing to developed countries, and a balance between production and policy.

For developed countries, they need to drive the development of developing countries, allocate resources [23, 27] to narrow the gap between rich and poor countries in the world, and take into account environmental protection and sustainable energy use while developing, and reduce energy emissions. Due to the development of industrialization, it is not realistic to reduce energy emissions in a short period of time, which requires developed countries to change their original goal of profit maximization for the good operation of the world environment, and sacrifice a small part of the benefits to promote the development of an equal and sustainable food system.

Developing countries will receive some help from developed countries in the transformation process, but internally they need to adjust their population levels to take into account environmental protection while adjusting the rural-urban demographic structure, allowing the rural-urban population to transform into urban areas, and also reducing national unemployment through policy benefits.

For developing countries to achieve a healthy food system, economic and social changes are needed to increase the level of industrialization, food production, and economic development.However, industrialization can also have an impact on the ecological environment, so a balance between ecological and industrial development is needed to achieve a good food system.

7 FURTHER EXTENSION AND CASE STUDY

7.1 FSMM Extension for Developed and Developing Countries

The food system contains three aspects: environmental aspects, Socio-economic aspects, and food. Different countries perform differently in the three aspects, and there are differences in the development of each country in the three aspects. For different countries, we make appropriate adjustments to the independent variables of the boosting regression by selecting the variables that can reflect the characteristics of the countries. For developed countries, they pay more attention to the problems like environmental pollution and renewable energy in agriculture, so the indicator of **Renewable Energy Consumption** is added. For developing countries, food insecure is a core issue in the food system. Hunger, disease, and even death due to lack of food are the problems faced by some developing countries. Therefore, **the number of children dying under 5 years old** and **the number of hungry people** are added as new variables.

Types	Renewable energy consumption
Developed	0.27180973
developing	0.11180042

The comparison shows that the weight of Renewable Energy Consumption is much higher in developed countries than in developing countries which verifies that developed countries pay more attention to the use of new energy sources in the sustainability and equity oriented food system

Types	Death under 5	Number of hungry people
Developed	0.016867043	0.15131006
developing	0.119765356	0.33290072

For developing countries, Death under 5 has slightly effect on the sustainability and equity oriented food system. However, the weight of the number of children dying under 5 years old is still higher in developing countries than in developed countries. In real-world terms, developed countries are largely free from infant and child mortality due to lack of food. Another indicator, Number of hungry people, is strongly associated with the sustainability equity oriented food system in developing countries. This suggests that developing countries are underperforming in terms of equity in food access and that inequities need to be addressed.

7.2 Case Study:China and the United States

Let’s first pick the most developed of the developing countries, China, and the most developed country, the United States, for our analysis. In terms of data, China’s food production is in line with that of the United States, but because of China’s large population, food price inflation and Food CPI are very high and the overall food supply is uneven, making China a giant food importer. China’s food system is equivalent to an extreme and not a virtuous food system, more extreme than the United States, where food CPI and food inflation are low compared to China, but still at a high level compared to the world, so from the perspective of efficiency and profitability, the characteristics of these two countries reflect the problem of imbalance of food supply in developed countries.

From the perspective of equity and sustainability, these two countries are well industrialized, and they are not good examples of sustainability due to China’s large population, the uneven distribution of resources [14], and the serious gap between rich and poor in these two countries.

Combining these two aspects, China and the U.S. are at a disadvantage in either orientation of the food system. Although China is a developing country, it reflects the characteristics of a developed country in terms of various indicators, similar to developing countries in that

Journal of Industrial Engineering and Applied Science
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· Its influence in policy indicators is much lower than that of the US

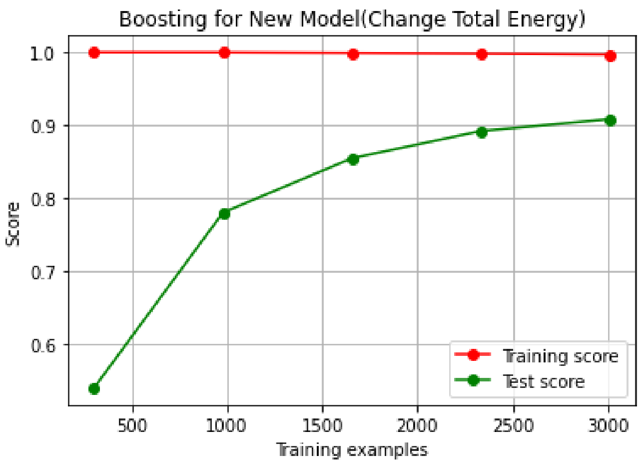
· Its larger share of Rural/Urban reflects that its overall urbanization level is still inferior to that of developed countries.

Therefore, as we suggested before, to achieve a good food system, China needs to improve its urbanization level and increase its political decisions to transform the food system to a good sustainable development. In other areas, the U.S. and China need to drive economic development in developing countries, transform energy, reduce greenhouse gas emissions, and transform to equity and sustainability.

8 SENSITIVITY ANALYSIS

Since Boosting Regression is a non-linear regression model based on a tree model, which has a strong degree of fitting ability and the ability to handle missing values, we will perform a sensitivity analysis on our model.

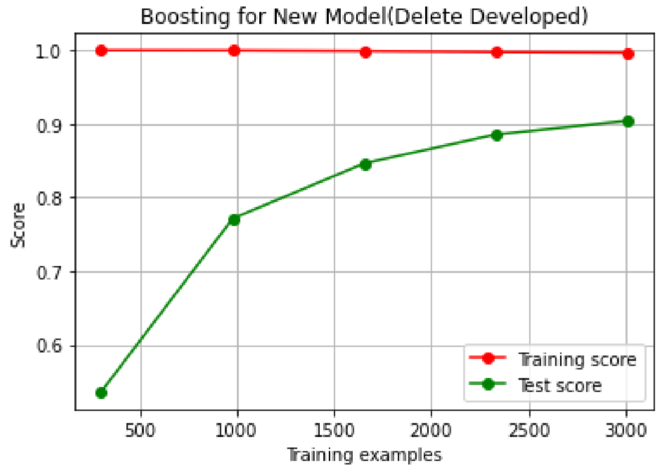
Previously, we found that the weight of Total Energy was very high, so we modified the real value of Total Energy and used Total Energy new = log(Total Energy) to reduce the variation of Total Energy to observe the degree of fit of the model regression, and the results are shown in the following figure:



BOOSTING FOR NEW MODEL(CHANGE TOTAL ENERGY)

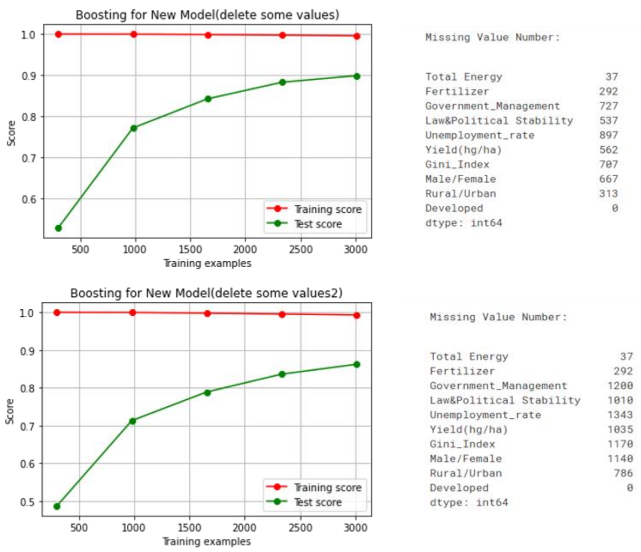
In the modified model, the weight of Total Energy is reduced to 23%, but it does not affect the fitting dgree of the model.

The variable Developed in the original model also had a high impact on the model, so we removed this variable to re-fit the model with the following results in figure below. We can find that the fitting degree of the model is close to the original model, and with enough features, the model does not reduce the fit of the model by one feature reduction.



BOOSTING FOR NEW MODEL(DELETE DEVELOPED)

We perform the removal of values to see how well the model fits. Since we are using the Boosting algorithm, missing values will be divided into two categories to perform gradient descent optimization, our regression is acceptable to have a certain number of missing values, so we will test to what exetent missing values will have an impact on the fitting degree of the model, the results are shown in figures below.



BOOSTING FOR NEW MODEL(DELETE VALUES)

With a total of 3600 data, we found that when the data were missing around 700 items, it did not affect the fit of the model, and when the data were missing 1200 items, the effect on the model was also subtle, and the model still had a fit of around 87%, so our model has a strong ability to handle sudden changes in values and missing values, and the fit does not change due to partial changes in values or missing values.

Through the above sensitivity analysis [22] steps, it can be seen that our model is robust, so the adaptability is correspondingly well, and we can obtain satisfying results in different regions. As for scalability, although our model is built on a worldwide basis, we can narrow down the data source of the model so that it can be applied to lower sizes of food systems.

9 STRENGTH AND WEAKNESS

9.1 Strength

We collected as many indicators and data as possible and processed them carefully to ensure that as much of the data as possible could be used.

The model has a wide range of application and can measure the level of development of any country in the global food system.

The model we bulit is robust, which maintains good explanatory power when some indicators change drastically.

9.2 Weakness

Despite the selection of a large number of indicators, there may still be some influencing factors that we do not take into account, and their inclusion in the model may weaken the explanatory ability..

Our model is based on data fitted to all countries in the world, and therefore cannot analyze the food system within a single country, but only the functioning of that country as part of the world food system.

The gray forecast model has convergence characteristics, so it amplifies the time to complete the sustainability transition for many countries.

10 CONCLUSION

Our main achievement is to establish the FSMM to monitor the changes in various indicators of the society after the re-optimization of the food system, and then to provide suggestions for future development.

We firstly build the different score rank model which uses use entropy weight and subjective weight to evaluate the food system before and after the reoptimization. Then we use the Gray Forecast Model to calculate the time for re-optimization in all countries. We found Iceland to be the fastest country to transform, taking 6 years.

Besides, we build the FSMM which uses worldwide data and monitor the food system of more than 170 countries to figure out the change of the importance rate of different indicators during the re-optimization, considering the aspects of environment ,social-economic elements and food production. Thus, we can quantify the benefits and costs of developed and developing countries during re-optimization. It suggests that countries should pay more attention to energy use.

We extend FSMM by using linear regression and add new indicators and combine the result and reality to provide suggestions for the health development of the food system. Finally we do sensitivity analysis, discuss the scalability and adaptability of FSMM.

ACKNOWLEDGMENTS

The authors thank the editor and anonymous reviewers for their helpful comments and valuable suggestions.

FUNDING

Not applicable.

INSTITUTIONAL REVIEW BOARD STATEMENT

Not applicable.

INFORMED CONSENT STATEMENT

Not applicable.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Not applicable.

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