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Research Article

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A Robust and Comprehensive Food System

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Abstract The food system affects all aspects of human existence, such as economy, politics, environment, health, culture, etc. It is a multi-factorial, multi-level, multi-objective interconnected and inter-constrained system. To address the issues of food system evaluation and optimization and policy support, we develop an EPSE framework, which allows us to evaluate and optimize food system development and provide corresponding countermeasure suggestions. In the process of evaluation and prediction, we resort to these methods of data processing and statistical analysis, such as entropy weight method, grey prediction. The evaluation results show that changing the priority of food systems through policy interventions can have a benign impact on the restoration of environmental development as well as on the global development system. The timing of development under policy intervention will also vary across indicators, but the overall target achievement time occurs in about 10 years. Based on the numerical results and analysis, we give several suggestions for a robust and comprehensive food system.

Keywords Food systems, Entropy Method, GM(1,1), Optimization Methods, Sustainability

Introduction

The food system is the foundation for human survival and development in the wake of globalization. It includes not only production, processing, and transportation, but also ensures that the demand for nutritionally adequate, high-quality food is guaranteed on a global scale. The production, processing & packaging, distribution & retail, and consumption of food are essential components of human life, and filling the bellies of people around the world as much as possible is a major undertaking [1].

Although the concept of food systems has long been proposed, how to meet efficiency, profitability, sustainability, and equity at different levels simultaneously is particularly critical in the face of increasing globalization and the rampant COVID-19 epidemic and progressive agroecological degradation. Therefore, it is worthwhile to consider how to assess the current food body system, determine the optimal route and expand the system appropriately [2].

Outline of the Approach

Inspired by the TEEB AgriFood framework, we have developed an EPSE framework based on ***efficiency***, ***profitability***, ***sustainability*** and ***equity***, which consists of three levels: the main system, the subsystem and the indicator layer [3]. The main system is the food system, the subsystems are efficiency, profitability, sustainability and equity, and the indicator layer is made up of 42 indicators based on the subsystem screening (Fig. 1.).

To evaluate and predict the food system and consider similarities and differences of each country, we collect data from China and the U. S. in recent years and measure the current development status of the food system based on the EPSE framework. The following is a brief introduction to the data analysis and data estimation methods used in this paper.

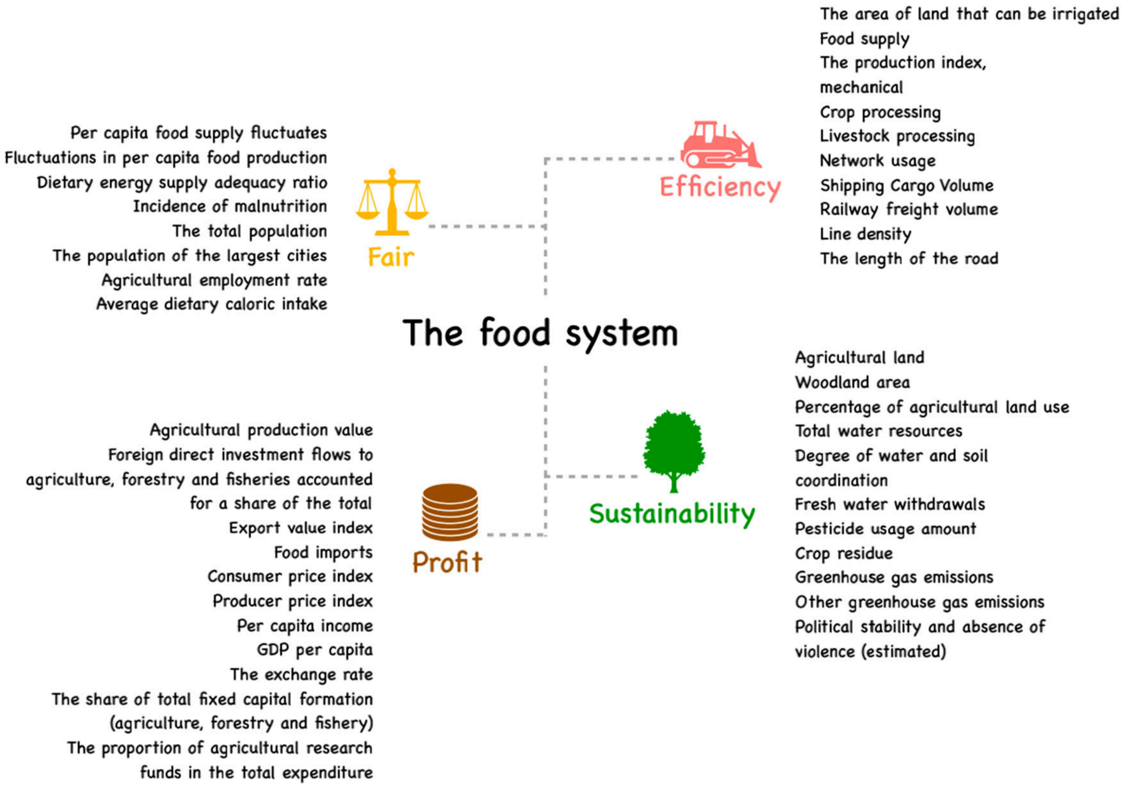


Figure 1: Structure of the EPSE framework

Objective and Subjective Entropy Method

Unlike the traditional entropy model, we add the subjective evaluation ***J*** in the data normalization process, so as to prevent the situation that the standard value of ***0*** leads to the non-existence of weights. In other words, the value of ***J*** is the subjective assignment of the evaluation subject, which makes the improved entropy method a combination of subjective and objective methods [4].

The following is an example of model calculation of ***Efficiency*** in subsystems, with ***a*** regions and ***b*** indicators in each subsystem, which can form the original data matrix of evaluation indicators.

First step: make evaluation indicators being dimensionless.

$$E = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1b} \\ e_{21} & e_{22} & \cdots & e_{2b} \\ \vdots & \vdots & \ddots & \vdots \\ e_{a1} & e_{a2} & \cdots & e_{ab} \end{bmatrix} \tag{1}$$

For positive indicators:

$$e_{ij}^{'} = \frac{e_{ij} - \min\{e_j\}}{\max\{e_j\} - \min\{e_j\}} \times J + (1 - J) \tag{2}$$

For negative indicators:

$$e_{ij}^{'} = \frac{\max\{e_j\} - e_{ij}}{\max\{e_j\} - \min\{e_j\}} \times J + (1 - J) \tag{3}$$

Where, $e_{ij}^{'}$ is the standard value of each evaluation indicator, $\min\{e_j\}$ is the minimum value of all evaluation indicators in the efficiency subsystem, $\max\{e_j\}$ is the maximum value of all evaluation indicators in the efficiency subsystem.

Second step: calculate the entropy value of the ***j-th*** evaluation indicator in the efficiency subsystem.

$$s_j = -k\sum_{i=1}^{a}\left[\frac{e_{ij}^{'}}{\sum_{i=1}^{a} e_{ij}^{'}} \cdot \ln\left(\frac{e_{ij}^{'}}{\sum_{i=1}^{a} e_{ij}^{'}}\right)\right] \qquad k = \frac{1}{\ln a} \tag{4}$$

Third step: calculate the weight of the ***j-th*** evaluation indicator in the efficiency subsystem.

$$w_j = \frac{1 - s_j}{\sum_{j=1}^{b}(1 - s_j)} \tag{5}$$

Final step: calculate the composite score of the efficiency subsystem for the ***i-th*** region.

$$(E)z_i = \sum_{j=1}^{b}(E)w_j \cdot e_{ij}^{'} \tag{6}$$

Following the above steps, the composite scores of the other three subsystems can be calculated, and then repeat the steps to apply the composite score data of the subsystems to calculate the composite score of the main system, which is the composite score of the food system (Fig. 2.).

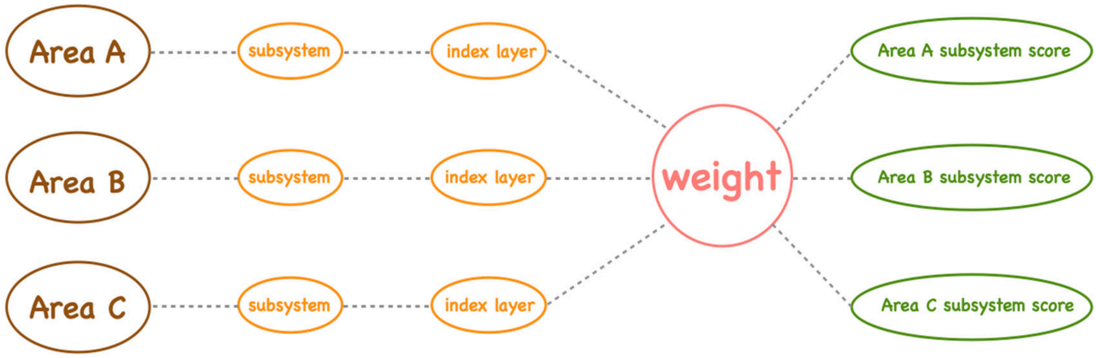


Figure 2: Calculation schematic of the objective and subjective entropy method

Grey Prediction Model

After the evaluation of the food system under the EPSE framework, some of the indicators that have the greatest impact on the overall score of the main system have been highlighted. Thus, Some policy could be taken to improve the corresponding indicators, and the data trend before and after policy intervention can be compared in the GM(1,1) model[5].

First step: construct the original data time series.

$$r^{(0)} = \left(r^{(0)}(1), r^{(0)}(2), \cdots, r^{(0)}(i)\right) \tag{7}$$

Second step: examine and process the data.

$$\lambda(k)=\frac{r^{(0)}(k-1)}{r^{(0)}(k)} \qquad k=2,3,\cdots,i \tag{8}$$

If all the stage ratios $\lambda(k)$ fall within the tolerable coverage range $\Psi=\left(e^{-\frac{2}{i+1}},e^{\frac{2}{i+1}}\right)$, the time series can be used as the data of model GM(1,1) for the grey prediction. Otherwise, necessary transformation processing (such as translation transformation, etc.) is needed to make the time series fall within the tolerable coverage range.

Third step: sequentially accumulate the original data time series.

$$r^{(1)}=\left(r^{(0)}(1),r^{(0)}(1)+r^{(0)}(2),\cdots,\sum_{j=1}^{i}r^{(0)}(j)\right) \tag{9}$$

Forth step: construct the data matrix ***A*** and the data vector ***Y***.

$$A=\begin{bmatrix} -\frac{1}{2}\left(r^{(1)}(1)+r^{(1)}(2)\right) & 1 \\ -\frac{1}{2}\left(r^{(1)}(2)+r^{(1)}(3)\right) & 1 \\ \cdots & \cdots \\ -\frac{1}{2}\left(r^{(1)}(i-1)+r^{(1)}(i)\right) & 1 \end{bmatrix} \qquad Y=\begin{bmatrix} r^{(0)}(2) \\ r^{(0)}(3) \\ \cdots \\ r^{(0)}(i) \end{bmatrix} \tag{10}$$

Fifth step: Calculate the whitening equation correlation coefficient.

$$\hat{u}=\left(\hat{a},\hat{b}\right)^{T}=\left(A^{T}\cdot A\right)^{-1}A^{T}Y=\begin{pmatrix}\hat{a}\\ \hat{b}\end{pmatrix} \tag{11}$$

Sixth step: Establish and solve the whitening equation.

$$\frac{dr^{(1)}(t)}{dt}+ar^{(1)}(t)=b \tag{12}$$

$$\hat{r}^{(1)}(k+1)=\left(r^{(0)}(1)-\frac{\hat{b}}{\hat{a}}\right)e^{-\hat{a}k}+\frac{\hat{b}}{\hat{a}} \tag{13}$$

Subsequently, the prediction series value $\hat{r}^{(1)}(k+1)$ and the model-reduced series prediction value $\hat{r}^{(0)}(k+1)$, where $\hat{r}^{(1)}(1)=\hat{r}^{(0)}(1)=r^{(0)}(1)$ is taken, can be brought in to obtain the prediction series from $\hat{r}^{(0)}(k)=\hat{r}^{(1)}(k)-\hat{r}^{(1)}(k-1)$.

Seventh step: the derived time series of the predicted data are subjected to error testing.

$$\rho(k)=\left|1-\left(\frac{1-0.5\hat{a}}{1+0.5\hat{a}}\right)\lambda(k)\right| \tag{14}$$

Final step: the actual data time series values and the predicted data time series values are plotted for analysis. The development of the selected indicator data without policy interference can be observed, so that the policies related to the indicators can be better optimized and policy analysis can be performed to achieve controllability and predictability for the optimal development of the system (Fig. 3.).

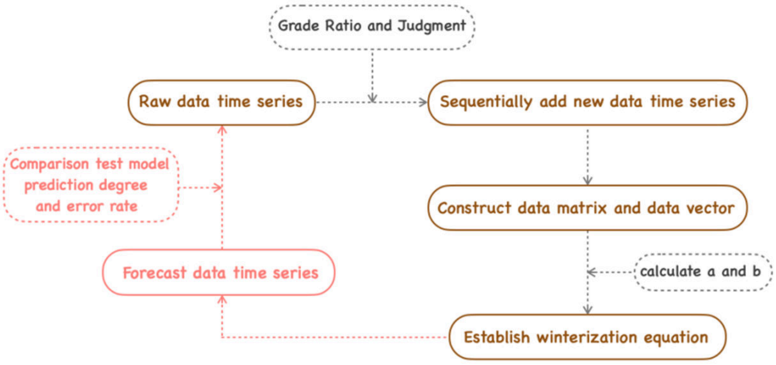


Figure 3: Calculation schematic of the GM(1,1)

Policy Optimization

On the basis of the EPSE framework, we have chosen China and the USA as examples. When we increase the composite score of the sustainability subsystem, the system score increases; when we increase the composite score of the fairness subsystem, the composite score does not rise as much as in the previous case, because the optimization of the indicator level data under fairness leads to a decrease in the profitability composite score.

Under the objective and subjective entropy method, the indicators with greater weight are crop residues, other greenhouse gas emissions, GDP per capita, machinery, agricultural employment, percentage of agricultural land use and income per capita.

In order to optimize the food system, we put the Sustainability first. We must develop green agriculture in order to achieve sustainable agriculture. We propose relevant policies to achieve the goal of sustainable agriculture and analyse their benefits and costs (Fig. 4.). The relevant policies are: agricultural non-point source pollution policy, planned grazing policy, reforestation policy, science and technology innovation policy, efficient supply policy, efficient fertilizer policy and land use rights(tenture) transfer policy [6].

- The advantage of agricultural non-point source pollution policy is that it can remediate the already polluted land and at the same time protect the land for pollution, thus playing a role in protecting the environment and preventing the spread of pollution, the cost is that it requires a lot of initial investment in human and material resources, government attention and intervention.
- The benefits of a planned grazing policy are that it promotes animal movement and reduces the probability of livestock being infected by disease, and the costs are that production performance is not high and livestock are not easily managed.
- The benefit of the reforestation policy is that it allows the forest area to be retained at a high level, at a cost to the government.
- The benefits of STI policy are that it can transfer surplus rural labour, increase land productivity and move from traditional to modern agriculture by improving rural technology and competitiveness, and the costs are that it requires government investment in scientific research and national training of high-tech talent.
- The benefit of an efficient supply policy is that the required supply can be met quickly, the cost is that the high rate of output can burden the land and make it less fertile.
- The benefits of an efficient fertilizer policy are that it reduces the amount of fertilizer used but achieves better results for our health and the environment, while the costs are that the use of fertilizer causes environmental pollution.
- The benefit of the land tenture transfer policy is that it allows the State to plan agricultural land more efficiently and increase productivity.

Policy	Level of linkage			
	Efficiency	Profitability	Equity	Sustainability
Agricultural non-point source pollution	Moderate	Moderate	Moderate	Strong (Crop residue Greenhouse gas emissions Other greenhouse gas emissions)
Planned grazing	Weak	Moderate	Moderate	Strong (Percentage of agricultural land use Degree of water and soil coordination)
Green agriculture	Strong (The area of land that can be irrigated)	Moderate	Strong (Political stability and absence of violence)	Strong
Grain for green	Weak	Moderate	Strong	Strong (Agricultural land)
Science and technology innovation	Strong (Machinery Network usage)	Strong (The proportion of agricultural research funds in the total expenditure)	Moderate	Strong
Efficient supply	Strong (Food supply Index of production)	Moderate (Price index Export value index)	Moderate (Capita food supply fluctuates Fluctuations in per capita food production Dietary energy supply adequacy ratio)	Moderate
Highly efficient fertilizer	Strong	Strong	Moderate	Weak (Pesticide usage amount)
Land tenure transfer	Moderate	Strong	Moderate	Weak (Woodland area)

Figure 4: Relevance of the subsystem to the policy

Empirical Analysis

Evaluation and Optimization

The original composite score of China's food system is 0.417, where the efficiency, profitability, sustainability and equity scores are 0.333, 0.459, 0.894 and 0.389 respectively. After the policy optimization, the measured score of China's food system is 0.529. Similarly, the original food system of U.S. had a composite score of 0.396 and four subsystem scores of 0.360, 0.459, 0.823, 0.387. After the policy optimization, the food system score of U.S. is 0.602 (Fig. 5.).

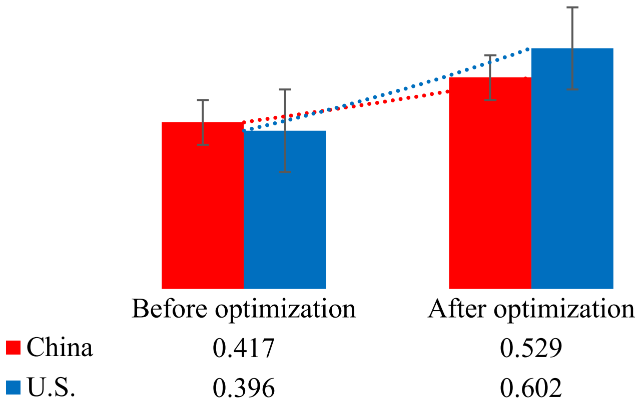


Figure 5: Score of the food system before & after policy optimization

Predicted Occurrence of Food System

Due to the sheer volume of data, we have selected two of the most representative indicators that contribute to sustainability and equity: percentage of agricultural land use and income per capita.

As the Fig. 6. shows, per capita income is steadily increasing in both China and the U.S. The model calculates that China will grow from the original figure of USD18,170 to USD21,800 at an annual growth rate of 6 percent, which will be achieved by 2023; similarly, the U.S. will grow from the original figure of USD63,600 to USD76,300 at an annual growth rate of 4.627 percent, which will be achieved by 2024.

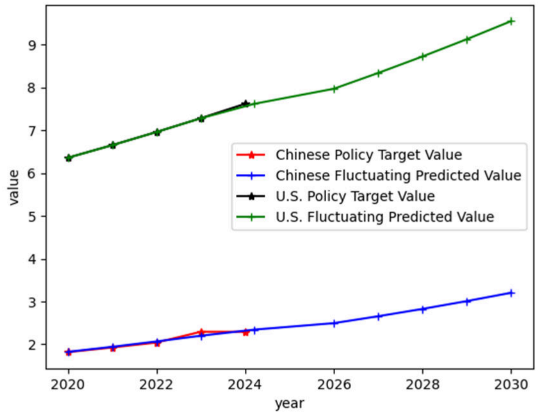
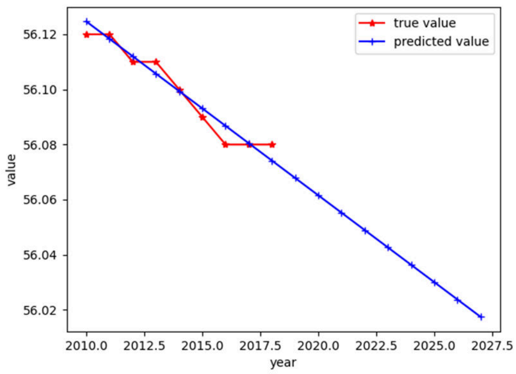


Figure 6: Projected per capita income for China and the U.S.

However, Fig. 7. calculated from GM(1,1), agricultural land utilization tends to decline in the absence of government intervention in both countries, so effective policies related to agriculture are needed. As the Fig. 8. shows, the target is calculated to be 58.88 percent for China and 46.58 percent for the U.S., with an annual growth rate of 0.844 percent for China and 1.973 percent for the U.S., to be achieved in 2028 and 2023 respectively. It takes 7 years to optimize the composite score to 0.529 prediction for China and 10 years to optimize the composite score to 0.602 prediction for the United States.



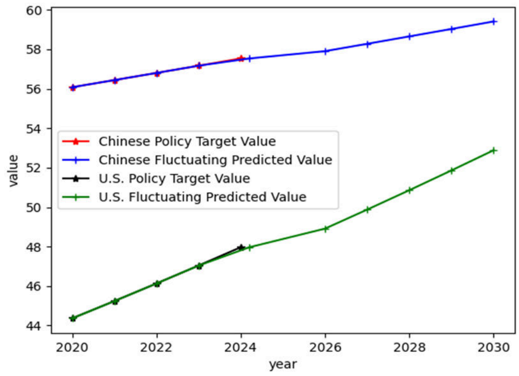


Figure 7: Agricultural land utilization in the absence of government intervention

Figure 8: Agricultural land utilization for China and the U.S. in the government intervention

Conclusions

Changing the priority of food systems through policy interventions can have a benign impact on the restoration of environmental development as well as on the global development system. The timing of development under policy intervention will also vary across indicators, but the overall target achievement time occurs in about 10 years. In developing countries, where technology and automation are lagging behind, there can be no significant increase in the volume and value of production in the short term, which means that the corresponding costs and benefits cannot change significantly; but at the same time, the slow pace of industrialization allows for better control over the sustainability of the system after policy implementation. The developed countries, on the other hand, have been able to achieve a significant increase in costs and benefits after policy interventions because of the rapid development of industrialization, high technology and automation over a long period of time; at the same time, however, there is no guarantee of short-term optimization of the environment, which means that there is greater volatility in terms of sustainability and equity.

Further Discussion

For a broad food system, i.e., without considering the food system as a subsystem of the global development system, the food system in the EPSE framework we have built exists as a single food system. In this regard, we also need to build a larger framework system to evaluate and optimize the food system. The food system as the main system may need to exist as a subsystem of the global development system, and the application of the model requires an additional layer of nesting, i.e., the model is more scalable. For smaller food systems, the model can still be used. Moreover, a dynamic food system evaluation and optimization simulation needs to be studied to replace the food system construction under the static indicator system.

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