Running title：Regional Vulnerability for Africa Swine Fever

Assessment of Regional Vulnerability to Africa Swine Fever in China Based on a DEA Model

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ABSTRACT

In this study, we introduce the vulnerability index to measure the regional ASF epidemic and present the ASF severity ratings of 31 provincial regions of China. The index is defined based on the data from investigation, national statistical yearbook and reports. The data to be used includes pig breeding, financial resources, human resources, epidemic information of ASF and price fluctuation from the 31 regions. Then we use the data envelopment analysis (DEA) model to define the vulnerability index, the relative severity values for each region which quantitatively reflect the damage degree caused by the epidemic of ASF. The method allows us to provide a systematic classification for regional vulnerability level of ASF in China. Using the index, we find that the vulnerability of the whole country is at a high level, and there is no regional aggregation phenomenon. The vulnerability level of the 31 provinces are quite different and the provinces with high vulnerability level are dispersive geographically. For the five major prevention and control zones for ASF in China, the northern region has the highest vulnerability level, while the level of eastern zoon is the lowest.

Key words: African swine fever (ASF), Epidemic, DEA model, Regional vulnerability, Damage

Introduction

On August 3, 2018, China confirmed the first African swine fever (ASF) case in Shenyang, Liaoning Province (Zhou et al., 2018). This marked the ASF, the biggest killer of pigs in some countries for nearly 100 years, has broken into China. Subsequently, the ASF epidemic has developed from single spots to regions, rapidly spread across the whole country.

It was until April 2019 that the epidemic has swept all provinces, autonomous regions and municipalities of China (ASFRMARA, 2020). As of November 2019, statistics from China Animal Health and Epidemiology Center (CAHEC) showed that there were 21544 pigs were infected, 13800 died, at least 1.1 million killed in reported 160 cases. 31 provincial regions have suffered varying degrees of losses in pig industry, see Figure 1. It is worth noting that the exact situation may be more serious due to undiscovered cases or abnormal dispose. The death of pigs and the reduction of pig production capacity caused by ASF have resulted in a severe shortage of pork supply, which not only changed the pattern of breeding industry in China but also alternated the supply-demand relationship of related markets. Consequently, the prices of live pigs in each province have experienced a significant soar in the last eighteen months (see Figure 2).

According to the current epidemic trend of ASF in China, although the probability of large-scale recurrence of ASF may be very low, the factors leading to potential outbreaks still remains high, and the epidemic has been continuing and may last for a long time to come. Meanwhile, there are great variations in pig breeding mode, density and epidemic prevention capacity among the provincial regions of the country. In order to strengthen the prevention and control of ASF, coordinate the movement regulation of live pigs and pork products, and plan the layout of related industries in a unified way, the Ministry of Agriculture and Rural Affairs (MARA) of China issued a draft plan for regional prevention and control of ASF and other major animal epidemics on February 18, 2019 (RPCPMAD, 2019). In this plan, according to geographical proximity, complementary production and marketing, etc., the 31 provinces (including autonomous regions and municipalities) are divided into five zones, namely, the Northern, the Northwest, the Eastern, the Central South and the Southwest zone. See Table 1 for details. At present, six provinces in Central South zone took the lead to explore the experience for the prevention and control of ASF in China (PWRPCMAD, 2020).

The national wide outbreaks of ASF has brought severe damage and threat for the Chinese national pork industry. It is not only essential but also imperative to assess the severity and quantify the regional damage caused by the ASF outbreaks in different provinces (regions). The assessment will be also conducive to the current prevention and control which will help the evaluation for the purpose of adjustment of the related policies for the national investment and promotion of the pork industry in the country.

In order to quantify the epidemic damage, we introduce the term of vulnerability which has been widely used in measuring of natural disasters (drought, flood, earthquake, etc.). The vulnerability of regional epidemic will describe the extent or possibility of regional damage due to the adverse impact of the outbreaks of ASF. The concept of vulnerability is originated from disaster science, which refers to the sensitivity of disaster victims to damage and injuries (Connor et al., 2005 and Metzger et al., 2005). It has been widely applied to many other fields, ranging from ecology, public health, climate change to sustainable science, etc. However, due to different research objects and disciplinary perspectives, every field defines vulnerability according to distinctive features with different connotations. Natural sciences such as natural disasters and climate change treat vulnerability as the degree or possibility of damage caused by adverse effects of the disaster (White, 1974 and Cutter, 1996). However, social sciences such as poverty and sustainable livelihoods regard vulnerability as the ability of the system to withstand adverse effects and pay more attention to analyze the causes of vulnerability (Bogard,1988 and Adger,1999).

Last decades have witnessed the great improvements of methodology in disaster evaluation. One outstanding paradigm is to treat the process of disaster occurrence as an "input-output" system, and adopt a data envelopment analysis (DEA) model to quantify the regional vulnerability. DEA is a mathematical method to evaluate the relative effectiveness of decision making unit (DMU) by mathematical programming based on statistical data. In essence, it is a systematic evaluation model of "input-output" operation efficiency. The basic principle is to take each evaluated unit as a DMU, and then evaluate it with the weight of each input and output. This method was first proposed by Farrell in 1957 for analyzing the agricultural productivity in England (Farrell, 1957). Later, Chames et al. (Charnes et al., 1978) established a multi-input and output efficiency evaluation model (CCR model) with fixed scale reward. DEA method does not need to preset the function relationship and estimate the weight parameters, which can avoid the influence of subjective factors and improve the objectivity of evaluation. There have been many both in theories and applications of DEA method since it was first developed. For example, Yiming Wei et al.(Wei et, al., 2004) systematically introduced the DEA method to evaluate the relative severity of disasters in various regions. According to the annual government statistical data from 1989 to 2000 in China, a regional vulnerability analysis model was established to analyze the vulnerability of the mainland. Dapeng Huang et al. (Huang et, al., 2012) used the theory of DEA to analyze the vulnerability of flood disaster in China. Jianyi Huang et al. (Huang et, al., 2013) constructed DEA input-output model application of regional natural disaster system from three aspects of regional natural disaster hazard, regional bearing body exposure and regional natural disaster loss degree, and studied regional vulnerability level of natural disaster in China. DEA theory also has an important application in forest management and resource utilization. Limaei SM et al. (Limaei, 2013) used a traditional DEA model and a two-stage DEA model to evaluate the efficiency of 14 Iranian forest companies and forest management units. In addition, DEA model is widely used in health care (hospitals, doctors), education (primary and secondary schools, universities), banking, manufacturing, fast food restaurants and retail stores (Anderson, 2002).

To quantify the vulnerability of the ASF in regions or provinces in China, we collect the statistical data including pig breeding, the total number of staff and workers in township animal husbandry and veterinary stations, and GDP in 31 provinces in 2017. We also collect the epidemic data of ASF and the monthly average price of live pig from August 2018 to November 2019 by investigation of CAHEC and sources on the webs. Using those collected data, we establish a DEA model to evaluate the vulnerability for each province. After getting the relative efficiency value, which quantitatively assess the relative severity of ASF in each province, we then put forward the regional classification of ASF in China according to vulnerability indices. Finally, we provide graphic explanation about this outbreak which would benefit policymakers to adjust the prevention and control strategies as well as identify the urgent priority regions.

Method and Data

Ethics Statement

The research proposal leading to the study received ethics approval from the China animal health and epidemiology center (CAHEC) of MARA. Ethical approval for the survey was obtained from the Division of Epidemiology Survey within CAHEC which handles the ethics approval of field studies conducted by their staff in China.

DEA model

In this study, we use the classical CCR model proposed by Charnes, Cooper and Rhodes (Charnes et al., 1978) to get the relative efficiency value to measure the regional vulnerability of ASF in different provinces of China.

Assuming that there are n decision-making units $DMU_j (j = 1,2, \dots n)$, i.e., the region unit for vulnerability assessment; each DMU_j has m inputs and s outputs. The input vector can be written as $X_j = (x_{1j}, x_{2j}, \dots, x_{mj})$, x_{ij} is the input of the j-th decision-making unit for the i-th type of resource. The output vector is $Y_j = (y_{1j}, y_{2j}, \dots, y_{sj})$, y_{ij} is the output of the j-th decision-making unit for the i-th type of production. For a DMU j_0, the CCR model is given as (Charnes et al., 1978):

$$\begin{cases} \min \theta - \varepsilon({e_1}^T s^+ + {e_2}^T s^-) \\ s.t.\, \lambda^T X_j + s^+ = \theta X_{j_0}, j = 1, \dots, n, j \neq j_0, \\ \lambda^T Y_j - s^- = Y_{j_0}, \\ \lambda = (\lambda_1, \lambda_2, \dots, \lambda_n)^T \geq 0, \\ s^+ \geq 0, s^- \geq 0, \\ {e_1}^T = (1,1, \dots, 1)^T \in E_m, \\ {e_2}^T = (1,1, \dots, 1)^T \in E_t, \end{cases}$$

where λ_j is weight variable; S^- and S^+ are the slack variables; ε is non-Archimedean infinitesimal, generally taking $\varepsilon = 10^{-6}$, θ $(0 \leq \theta \leq 1)$ is the effective value of DMU j_0, that is, the relative efficiency of input relative to output.

According to the model structure and algorithms of DEA, if the θ score of one DMU j_0 is close to 1, it indicates that unit j_0 has a high input-output ratio, namely high efficiency for production. In the case of natural hazards like the impact due to the outbreak of ASF, it implies that the region has a higher potential or higher degree to be damaged. In other words, the region has a higher vulnerability index. On the other hand, a lower θ score implies that the concerned region has a relatively low vulnerability. When $\theta = 1$, the ratio of input to output is at the optimal production frontier, so the production efficiency of the region reaches the maximum. That is, the damage caused by the disasters is maximized and regional vulnerability to the outbreak of ASF can reach the highest.

Indicator selection

In this paper, the evaluation model of regional epidemic vulnerability and the input-output index system based on DEA will be constructed to analyze impact of ASF on pig breeding industry. According to the feature of outbreaks and epidemic course, there are significant differences of the impact of ASF in different regions, regardless the frequency of cases or the number of dead pigs (Figure 1). What's more, there were also significant variations in pig breeding production, financial and human input among provinces before the outbreaks (Figure 3 and Figure 4). If taking the regional vulnerability of ASF epidemic as a negative "production activity", what we will take as major input for the "production activity" will include live pigs, the number of veterinarians, GDP, while the "output" will be the damage or loss caused by the disease, such as, the number of pigs lost, the price fluctuation of pigs and related pork products, etc. Therefore the resulting DEA efficiency value obtained from the calculations will indicate the vulnerability of the region. The greater the efficiency is, the higher the vulnerability index will be.

So far, we have defined the basic principle and formulation of DEA model for evaluating the vulnerability of ASF in a give region. The selected indicators should be representative of the vulnerability of all regions, we therefore select pig stocking density, normal slaughtering volume, total number of employees in town animal husbandry and veterinary station and GDP as input indicators for the province, where the proportion of stocking density and normal slaughtering volume reflect the exposure risk of the region. The greater values of input indicators are, the higher exposure risk of pig breeding system will be which will lead to a higher score of the vulnerability; the total number of employees and GDP of the regional animal husbandry and veterinary station reflect the recovery ability under the epidemic situation. The more employees of the animal husbandry and veterinary department in the region, and the higher the GDP are suggests the stronger recovery and resistance ability to the epidemic which will lead to a lower vulnerability index of the region. . The number of outbreaks, the total number of dead pigs (dead by disease and culling) and the price fluctuation of live pig (Wai sanyuan) are selected as output indicators, which comprehensively reflect the epidemic losses. For initializing the DEA model, we set j=1, 2, …, 31, (total 31 provinces, autonomous regions and municipalities in China). The component elements $x_{1j}, x_{2j}, x_{3j}, x_{4j}$ of input vector X_j refer to the stocking density, normal slaughtering volume, total number of employees and GDP of the animal husbandry and veterinary station in the j-th province, respectively. The componentsy_{1j}, y_{2j}, and y_{3j} of output vector Y_j represent the number of outbreaks, the total number of dead pigs (dead and slaughtered) and the price increase of pigs (Wai sanyuan) in the j-th province, respectively.

Analysis of spatial clustering characteristics of vulnerability

Moran's index (Moran's I) is a mature and ideal method for global clustering test. It tests whether there are similarity and correlation between adjacent cells in the whole area cell, and judges whether the phenomenon or attribute value has aggregation property in space. The formulas of Moran's I is defined as (Moran,1950)

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(V_i - \bar{V})(V_j - \bar{V})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}},$$

with $S^2 = \frac{1}{n}\sum_{i=1}^{n}(V_i - \bar{V})^2$ and $\bar{V} = \frac{1}{n-1}\sum_{i=1}^{n} V_i$.Here n is the number of research units; V_i and V_j are the vulnerability values of unit i and unit j respectively; $\bar{V}$ is the average vulnerability value of all units; S^2 is the variance of vulnerability; W_{ij} is the spatial weight of element i and element j. The value of I is generally between -1 and 1. The value I approaching 1 indicates that there is a spatial pattern of similar attribute clusters in regional units; the value I approaching - 1 indicates that there is a spatial pattern of different attribute clusters in regional units; if $I = 0$, there is a random distribution or spatial autocorrelation does not exist.

Data sources

Data source of input variables. As the ASF started in China in the second half of 2018, we used the pig stocking density, normal slaughtering volume, the total number of employees in animal husbandry and veterinary stations and GDP of each province in 2017 before the outbreaks to measure the overall exposure level and resilience of each province. The pig stocking density was obtained by dividing the pig stock volume at the end of the year by the region area. The data include the pig stock at the end of the year, normal slaughtering volume, the total number of employees in animal husbandry and veterinary station are all from China animal husbandry and veterinary Yearbook 2018 (CAHVYB, 2019). And the regional area and GDP are from the website of National Bureau of statistics of China (DA, 2020).

Data source of output variables. The data on ASF epidemic used in this paper are all from the official data published by MARA (ASFRMARA, 2020). Here, we choose each province as a unit to count the number of ASF outbreaks and the total number of pig deaths due to disease deaths and culling from August 2018 to November 2019. Two sets of data about ASF epidemic are used to reflect the degree of direct damage caused by the epidemic. Taking the price increase of live pigs (Wai sanyuan) within 15 months after the outbreak as a representative, the monthly average price data from August 2018 to November 2019 were collected by browsing website (MAPP, 2020), and then the monthly average price increase in each province was calculated to reflect the impact of ASF on the market.

The data sets used to compute the vulnerability for the 31 provinces are summarized in Table 2.

Result Analysis

Combined the collected data with the DEA model, we calculate the vulnerability of each province since the outbreak of ASF in China by DEAP 2.1 software (Herrero et al., 2002). Using the vulnerability value of the epidemic, we then use ArcGIS (ArcMap10.2) software to make the spatial distribution map (see Figure 5), and grade the vulnerability of the epidemic by natural split point method (Table 3).

Spatial distribution characteristics of regional ASF vulnerability

Compared with the vulnerability values of the 31 provinces, we find that the vulnerability level of ASF epidemic in the whole country is high with an average vulnerability close to 0.52, and the regions with high vulnerability level are scattered. from the local regional or provincial point of view, as shown in Table 2, eight provinces in China (Fujian, Qinghai, Beijing, Liaoning, Shanghai, Hainan, Tibet, Ningxia) have higher vulnerability level with average vulnerability of

0.93; ten provinces including Shandong, Henan, Hebei, Jiangxi, Hubei, Sichuan, Guangdong, Jiangsu, Hunan and Jilin province all have a lower vulnerability level with the average vulnerability of 0.19. The rest of the 13 provinces have a vulnerability value range from 0.25 to 0.75. Remarkably, the vulnerability values are different over most of the provinces. Some regions have higher vulnerability levels than others, while their exposure and the recovery levels and incidence rates of ASF are all low, such as Tibet and Qinghai. The difference of vulnerability values suggests that each province should establish its own management policies in combination with their own particularity. For example, the Northeast region should focus on preventing the importation cases due to its special geographical location close to Russia.

In addition, by defining the spatial weight W_{ij} of unit i and unit j as the distance between the corresponding provincial capitals, the corresponding weight is calculated by using the geographic longitude and latitude of each provincial capital, and then calculated I = -0.2244 with $\bar{V}$ = 0.52, S^2= 0.098. The Moran's index is negative and close to zero, which again shows that the spatial aggregation effect of the vulnerability distribution of ASF is not significant. The differences of vulnerability among epidemic regions are large, and the distribution of provinces with high vulnerability level are relatively divergent, reflecting the current prevention and control policies have played an important role in combating the epidemic of ASF.

Based on the epidemic vulnerability values of each province, the average vulnerability values of five zones were then calculated. The results showed that the overall pattern of regional epidemic vulnerability was as follows: Northern (0.63) > Northwest (0.62) > Southwest (0.53) > Central South (0.46) > Eastern (0.36), northern and northwest zones showed the high efficiency (high vulnerability). However, the outbreak efficiency in the eastern is significantly lower (low vulnerability). It should be noted that the vulnerability values of the northern and the northwest are approximately calculated by the related value of the whole Inner Mongolia, because the province is selected as the regional unit in this study.

Classification of regional vulnerability to ASF

According to the vulnerability level, we classify the vulnerability of the epidemic by the natural split point method operated automatically by the ArcGIS software, and then divide all provinces into 4 groups with vulnerability levels change from light, medium, high and severe as shown in Table 3.

There are different levels of vulnerability in different regions, among which nearly One fifth of the provinces, Qinghai, Beijing, Liaoning, Hainan, Tibet and Ningxia, are the key areas for epidemic prevention and control. Therefore, it is suggested to formulate the regional plan for the prevention and control of ASF, reduce the regional vulnerability level and improve the ability of prevention and control of the epidemic.

Conclusion and Discussion

Using the DEA model for vulnerability assessment of natural disasters, we develop a frame work to assess the relative vulnerability level of ASF in different regions of China. The new quantifying index provides a novel method for the evaluation of regional epidemic severity, and serve as an important indicator for the study on the prevention and control of ASF.

There are great temporal and spatial variations in pig breeding production, financial revenue, human investment, outbreak and impact degree among 31 provinces in China. By selecting representative indicators and using the DEA method, we present a comprehensive analyze of the vulnerability level of each province. The vulnerability index allows the policymakers and industry stakeholders to intuitively understand the severity and spatial distribution of ASF in China from different perspective.

According to the scope of the current national implementation of the prevention and control of ASF, in contrast, the northern region has the highest level of vulnerability, while the eastern region has the lowest. Therefore, it is suggested that China's regional control plan for ASF should focus on the northern and northwest regions in the future. Because the severely vulnerable regions are distributed in the whole country, the epidemic prevention and control countermeasures in each region should be more focused. For regions with high vulnerability level, it is necessary to strengthen the investment and improve the ability of prevention and control of the epidemic. In addition, at present the "point- to-point" transfer of pigs and their products is required to be carried out in all regions (i.e. the pigs are directly transferred from farms to slaughterhouses, while the pigs and piglets are transferred from farms to farms). Due to the differences in the vulnerability levels of neighboring provinces, the supervision and management policies for pig transfer and transportation should continue to be strengthened, especially pig transport supervision for pigs from areas with high vulnerability level to areas with low vulnerability level.

It is worth noting that the results of this study are based on the analysis of relevant data that were published. Some reports showed that the actual number of deaths (due to disease deaths and culling) in China may be much larger than that published (ECASF, 2019). If there is any deviation of epidemic data due to concealment, omission and other reasons in practice, the current results may have some limitations. Therefore, the relevant departments of each province should deeply understand the situation of pig breeding and epidemic situation, and timely find out the impact of ASF in the current situation. In particular, national authorities should develop an effective epidemic evaluation system to strengthen the evaluation of epidemic prevention and control work in each province, which is not only conducive to understanding the overall situation and local regional scope of the epidemic, but also to the timely adjustment and introduction of ASF prevention and control policies.

Data availability statement

The data used to support the findings of this study are included in the article (see subsection Data sources or Table 2). Detailed data sources are as follows:

1. The China ASF epidemiological dataset that support the findings of this study are available in the website of Ministry of agriculture and rural affairs, PRC. The link of the raw data is [http://www.moa.gov.cn/gk/yjgl_1/yqfb/]. 2. The gap in the price of live pig (Wai sanyuan) for the last 15 months since the outbreak form August 2018 to November 2019, where the monthly average price data were collected from the website [https://bj.zhue.com.cn/zoushi.php]. 3. The data include the pig stock at the end of the year, normal slaughtering volume, the total number of employees in animal husbandry and veterinary station are all from China animal husbandry and veterinary Yearbook 2018[ISBN: 9772095996186, China Agriculture Press, Beijing, 2019, page 167-235]. 4. The GDP of each province is from the website of National Bureau of statistics of China [http://data.stats.gov.cn/easyquery.htm?cn=E0103].

Author contributions

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Conflicts of interest

All authors report there are no conflicts of interest related to the present article

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