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Spatial Disparity and Efficiency of Science and Technology Resources in China

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Abstract: In the knowledge economy era, science and technology (S&T) resources are getting more and more important in shaping regional competiveness and building regional innovation capacity. As such, the spatial distribution of S&T resources is a key to understanding regional development and disparities. By designing an input-output indicator system, this paper develops an evaluation model to examine the spatial distribution of S&T resources in China and assess their spatial efficiency. Moreover, the paper tries to explain spatial differences in the efficiency of S&T resources in China. Major findings are: 1) the input and output of S&T resources in China shows a clear T-shaped spatial structure, i.e., concentrated mainly in the coastal region and along the Changjiang (Yangtze) River; 2) the efficiency of S&T resources in China displays strong spatial disparities, with the level of efficiency descending from the east to the west while high efficiency appearing in only several clusters; 3) the utilization rates of S&T resources in most provinces are quite low, resulting in low efficiency of S&T resources allocation. The paper suggests that the utilization rate of S&T resources should be raised and the commercialization of S&T outputs should be enhanced to improve the efficiency of S&T resources in China.

Keywords: science and technology resources; resources spatial allocation; resources-utilization efficiency; China

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1 Introduction

With the advent of the knowledge economy, the knowledge-based industry has become an emerging but competitive sector in the world. There is wide recognition that science and technology (S&T) resources are becoming the driving force for national and regional development (Buswell, 1983; Malecki, 1997; Xu, 2003; Mu and Qu, 2008). Economists emphasized the role of S&T innovations in economic development in classical theories, such as the neoclassical growth theory, the technology imperfect diffusion theory, as well as the theory of technology gaps (Grossman and Hepoman, 1994; Romer, 1994). Scholars in regional science and geography also stress the importance of technology in structuring and restructuring regional, national and international economic landscapes (Storper and Walker, 1989). Under this situation, S&T gap is frequently cited as a significant factor in explaining regional economic variations (Fagerberg, 1994; Fagerberg *et al.*, 1997). As such, governments are allocating vast resources in S&T field, to promote regional economic growth and to enhance their position in future competition (Malecki, 1987; Fischer *et al.*, 1994; Malecki, 1997; Sun, 2000).

Recent research has been focused on innovation activities, especially the location and clustering of these activities (Markusen *et al.*, 1986; Feldman, 1994; Feldman and Florida, 1994; Guerrero and Sero, 1997). Studies of S&T resources from which innovation capacity is built have been very insufficient, especially in de-

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veloping countries like China. In addition, with the tradition of stressing production system in the past, China had long ignored the key role of S&T resources in development, which led to a great many problems in the field of inappropriate allocation of S&T resources (Liu, 1999; Ding, 2005). Against this background, it has become one of the central concerns of the Chinese government to understand the present spatial distribution and efficiency of S&T resources and to learn how to improve the allocation of these resources. Indeed, since the end of the last century, the allocation of S&T resources has been attracting more and more academic attention in China. However, the existing studies are mainly from the perspective of management and economics (Wei and Wu, 2005; Li and Li, 2010), which ignore the spatial attributions of S&T resources.

This paper takes the allocation of S&T resources as a typical input-output system and designs an S&T input-output indicator system, and then uses the entropy method to analyze the spatial disparity of S&T resources in China and employs the Data Envelopment Analysis (DEA) model to examine the spatial efficiency of the resources. The analyzing unit in this paper is provincial-level administrative unit. Due to lack of data, Hong Kong, Macao and Taiwan are not included. Firstly, we will synthesis the selected indicators into three indexes by the entropy method, namely the investment in S&T resources, direct knowledge output and indirect economic benefit, which are used to examine the spatial allocation of S&T resources. Secondly, we will compute the relative efficiency of S&T resources of each analyzing unit by using the Charnes-Cooper-Rhodes (CCR) model of the DEA approach. Lastly, we will try to find reasons behind the huge spatial disparities of the efficiency of S&T resources in China and give suggestions on improving the efficiency. Therefore, it will be beneficial for enriching the economic geography to dig into spatial allocation of S&T resources, and also will provide a new angle for the study of social resources.

2 Data and Methodology

2.1 Data and indicator selection

S&T resources—consisting of human, financial, material, and information resources—are the foundation for all innovation activities. In a narrow sense, only human and financial resources are included in the definition of S&T resources (Zhou, 1999). Indeed, human resources are the only one that can have subjective initiative while financial resources are the foundation for creation and accumulation of all material wealth. To some extent, these two kinds of resources constitute the main part of S&T resources. Generally speaking, S&T human resources can be represented by the number of S&T personnel, the number of scientists and engineers, and the number of research and development (R&D) personnel, and S&T financial resources can be represented by the funding for S&T activities, expenditure on R&D, and the ratio of R&D expenditure to gross domestic product (GDP). In this paper, we will use the total R&D expenditure and full-time equivalent person-year of R&D personnel to represent the input of S&T resources (The Ministry of Science and Technology of the People′s Republic of China, 2002), which are commonly used internationally.

The output of S&T resources can be measured in many ways, e.g., the number of academic papers and books that represents direct achievements of scientific research, the number of invention patents that represents innovative technological achievements, the output of high-tech products that represents the degree of commercialization of S&T outputs. In particular, the number of SCI-, EI-, and ISTP-indexed papers is commonly used to measure the output of scientific research, while the number of invention patents is a vital indicator that embodies technological development. Both of them are termed direct knowledge output in this paper. In addition, the number of technological transaction contracts (TTC) reflects the degree of vitality of S&T activities and the capacity of transfer of S&T achievements into business. So does the output of high-tech products (OHP) because ongoing product innovation is a response to fierce market competition, and R&D activities are the foundation of such innovation. Thus, TTC and OHP are two major indicators reflecting indirect output of S&T resources, and they are termed indirect economic benefit.

In addition, an important principle of the DEA approach is that the number of decision-making units must exceed twice the number of input and output indicators. Otherwise, the accuracy of efficiency evaluation with the DEA model would decrease. Therefore, when the number of decision-making units is fixed, it is necessary to reduce as far as possible the number of variables in the input-output indicator system in order to improve accuracy. Table 1 shows the input-output indicator system of S&T resources. Since the input-output system is

Table 1 Input-output indicator system of S&T resources

Category	Indicator	Explanation
Input of S&T resources	Total R&D expenditure	S&T financial resources
	Full-time equivalent person-year of R&D personnel	S&T human resources
Output of S&T resources	Number of academic papers	Direct knowledge output
	Number of invention patent granted	Direct knowledge output
	Output of high-tech products	Indirect economic benefit
	Number of technological transaction contracts	Indirect economic benefit

generally time-lagged (Hu and Liu, 2009), we choose two years as the lag period, i.e., the output in 2009 arises from the S&T resources invested in 2007. All the data in this paper were from surveys on S&T activities. The surveys were conducted annually and covered all S&T activities. The survey results were officially published in the Chinese Science and Technological Statistical Yearbook (National Bureau of Statistics of China, 2008; 2010).

2.2 Methodology

In 1978, Charnes *et al*. (1978) developed a new systematic analyzing method for appraising relative efficiency—Data Envelopment Analysis (DEA). This is a nonparametric statistical method that can be used to evaluate those decision-making units (DMUs) that are of the same type and have multiple input and output items. When a comparison or evaluation of several units of the same type is required based on monitoring input and output data, the DEA method is one of the best. The input data are the amounts of investment when the units are engaged in particular activities, and the output data are the achievements at the end of those activities (Wei, 1988; Yang and Xie, 2002).

The allocation system of S&T resources is a typical input-output system. Through an analysis of the input and output indicators of S&T resources in different units using the DEA method, we can examine the relative efficiency in different units and find out the factors that affect the inefficiency. The DEA method includes several models, such as CCR, BCC (Banker-Charnes-Cooper), and C^2GS^2 (Charnes-Cooper-Golany-Seiford-Stutz). In this paper, we select the classic CCR model to study the allocation efficiency of S&T resources in China. As a first step, it is necessary to integrate all the six indicators in the input-output indicator system into three indexes using the entropy method (Zou *et al*., 2006), i.e., the investment in S&T resources, the direct knowledge output, and the indirect economic benefit. In the m indicators, n evaluating objects, the value of information entropy of the jth index (e_j) is as follows:

$$e_j = -K\sum_{i=1}^{n} Z_{ij} \ln Z_{ij} \qquad j = 1, 2, \ldots, m \tag{1}$$

where the value of K is equal to $1/\ln n$; and Z_{ij} is equal to $1/n$.

Suppose the weight of the jth index (W_j) is as follows:

$$W_j = h_j / \sum_{j=1}^{m} h_j \tag{2}$$

where h_j represents the information efficiency of the jth index, and equals to the difference between 1 and e_j.

As Table 1 shows, the input variables are the S&T human and financial resources, and the output variables are the knowledge output and economic benefit resulting from the investment. Suppose we have a set of n peer DMUs, {DMU$_j$: j = 1, 2, …, n}, which produce multiple outputs, y_{rj} (r = 1, 2, …, s), by utilizing multiple inputs, x_{ij} (i = 1, 2, …, m). Let the inputs and outputs for DMU$_j$ be $X_j = (x_{1j}, x_{2j}, \ldots, x_{mj})^t$ and $Y_j = (y_{1j}, y_{2j}, \ldots, y_{sj})^t$ respectively, so the CCR model is as follows:

$$\min \theta$$

$$s.t.$$

$$\begin{cases} \sum_{j=1}^{n} X_j \lambda_j + S^- = \theta X_0 \\ \sum_{j=1}^{n} Y_j \lambda_j - S^+ = Y_0 \\ \lambda_j \ge 0, S^+ \ge 0, S^- \ge 0 \end{cases} \tag{3}$$

where θ ($0 < \theta \le 1$) is the efficiency value; λ_j is the weight variable of the the jth index; S^- and S^+ are respectively slack variable and surplus variable. According to the DEA model, if the value of θ is very close to 1, it results in a high input-output ratio, which represents high efficiency of resources allocation. When the value of θ is equal to 1, the input-output level in the DMU is located in the optimal production frontier, and the allocation efficiency is at its highest. When the value of θ is less than 1, S^+ and S^- must be positive. And through the value of S^+ and S^-, we can identify the main affecting factors and to what extent the efficiency could be improved.

3 Spatial Pattern of Input-output of S&T Resources

3.1 Spatial disparity of input of S&T resources

In recent years, China′s investments in S&T resources have been increasing annually. However, the investments show a great spatial disparity among provinces. With the entropy method, we integrate the two indicators measuring the input of S&T resources into one index. Then, we measure this index by statistical clustering of ArcGIS. The analysis is shown in five classes—the highest as the first class and the lowest as the fifth.

As shown in Fig. 1, the input of S&T resources in China is very much unevenly distributed. The coastal region witnesses higher inputs with all the six highest provinces in the region. The central provinces mainly rank the second and third levels while the western provinces are mainly at the fourth and fifth levels. Overall, the spatial distribution of S&T resources in China is featured by a T-shaped structure, that is, provinces with higher input are located in the coastal region and along the Changjiang (Yangtze) River. In the coastal region, provinces with highest input are concentrated in three major metropolitan regions, i.e., the Beijing-Tianjin-Hebei region, the Changjiang River Delta and the Pearl (Zhujiang) River Delta. These are also the most developed regions in China in terms of economic indicators.

Provinces at the second level include, in descending order, Sichuan, Liaoning, Hubei, Henan, Shaanxi and Tianjin, and their integrated index is between 0.22 and 0.50. Except for Liaoning and Tianjin, all these provinces are in the central and western regions, and they are also the most populated provinces. To some extent, it is the stock of greater human resources and existing S&T institutions established before the opening up and re-

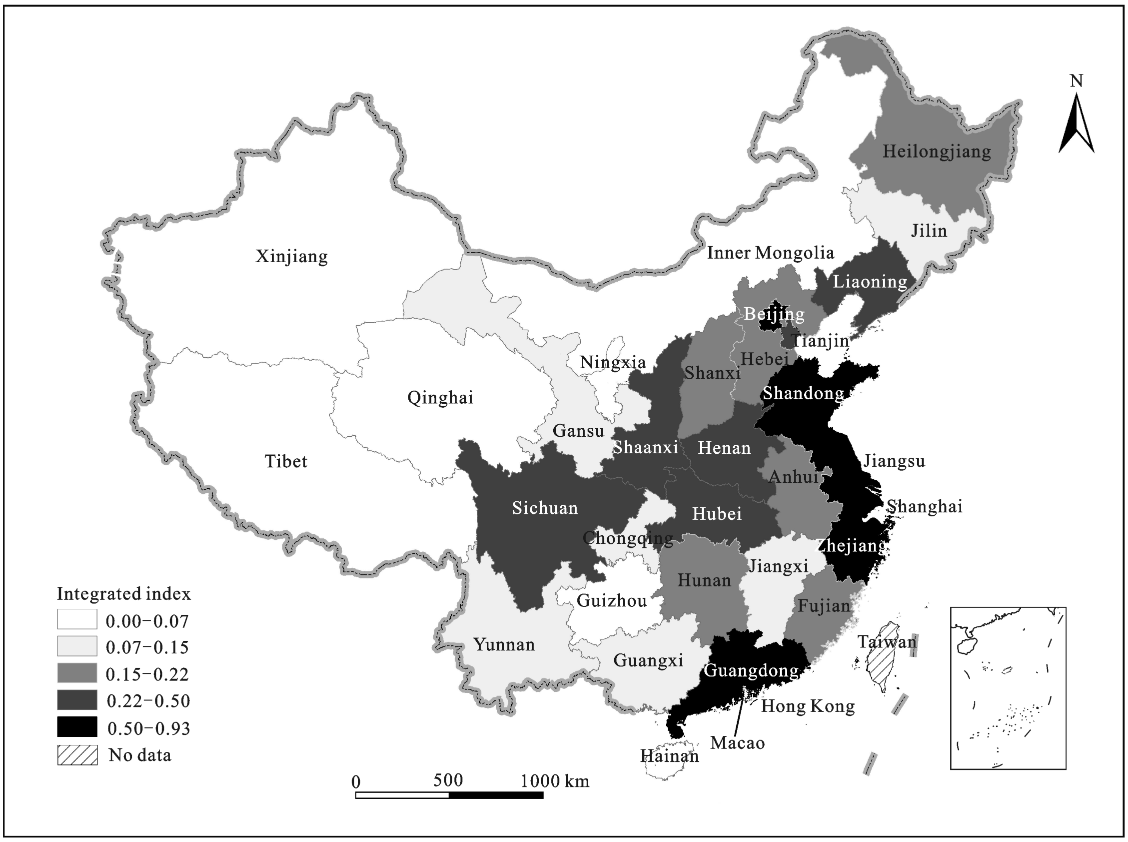

Fig. 1 Spatial disparity of input of S&T resources in China in 2007

form that make these central and western provinces enjoy higher inputs of S&T resources. Provinces at the third level include, in descending order, Fujian, Hebei, Anhui, Hunan, Heilongjiang and Shanxi, and their integrated index is between 0.15 and 0.22. Provinces at the fourth level are, in descending order, Jilin, Chongqing, Jiangxi, Guangxi, Gansu and Yunnan, and their integrated index is between 0.07 and 0.15. The remains are at the fifth level with the integrated index less than 0.07. The provinces at the fourth and fifth levels are also the lagging regions in China in terms of economic indicators. Thus, in general, the level of input of S&T resources in China is positively correlated with the level of economic development.

3.2 Spatial disparity of direct knowledge output of S&T resources

In recent years, the direct knowledge output of S&T resources in China, measure by the number of academic papers and invention patents, witnessed a significant increase. From 2004 to 2008, China rose from the sixth to the second largest country in the world in terms of the number of academic papers, and its share in the total number of papers of the world increased from 4.4% to 10.2%. The number of invention patents granted increased from 12 683 in 2000 to 93 706 in 2008, more than seven times in the eight years. To reveal the spatial disparities of direct knowledge output among provinces, we firstly integrate the two indicators representing the direct knowledge output into one index using the entropy method, and then employ the statistical clustering method of Natural Breaks in ArcGIS to divide provinces into five classes according to the rule of the minimum difference inside a class and the maximum difference among classes.

As shown in Fig. 2, the spatial distribution of direct knowledge output is extremely uneven. In general, the direct knowledge output in China witnesses a laddered spatial distribution in a descending order from the coastal to the western regions. Coastal provinces are mainly at the first and second levels, central provinces are mainly at the third and fourth levels, while most western provinces at the fourth and fifth levels. The only two exceptional provinces in the western region are

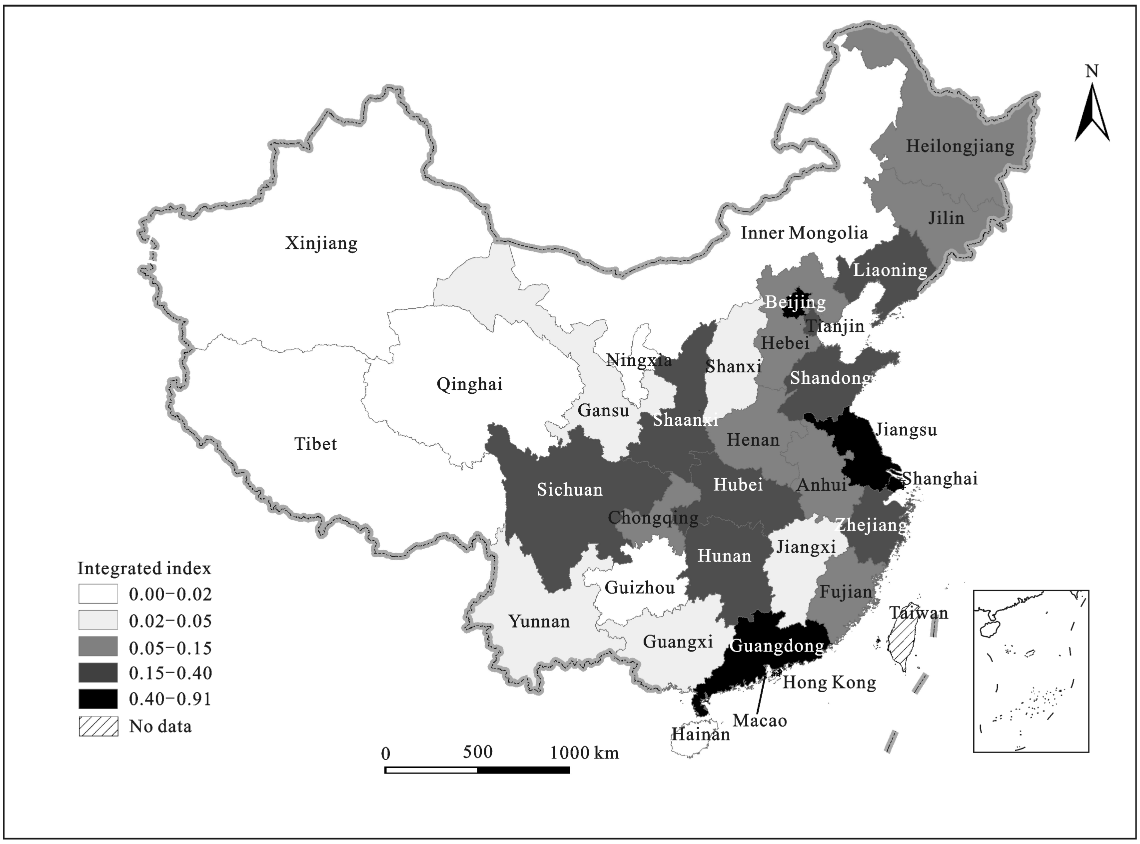

Fig. 2 Spatial disparity of direct knowledge output of S&T resources in China in 2009

Shaanxi and Sichuan, which rank the second level.

Provinces at the first level include Beijing, Guangdong, Shanghai and Jiangsu, all of which are located in the three main metropolitan regions. In particular, Beijing and Guangdong rank the first in terms of the number of academic papers and invention patents granted. Provinces at the second level are Zhejiang, Shandong, Hubei, Liaoning, Shaanxi, Hunan, Sichuan and Tianjin, which are scattered in the coastal, central and western regions. Provinces at the third level are Heilongjiang, Anhui, Jilin, Henan, Fujian, Hebei and Chongqing, and they are mainly located in the northeastern and central regions. Provinces at the fourth level are Shanxi, Gansu, Yunnan, Jiangxi and Guangxi while provinces at the fifth level are Guizhou, Inner Mongolia, Xinjiang, Ningxia, Qinghai, Hainan and Tibet. All of them except Hainan are located in the central and western regions. Indeed, the spatial pattern of direct knowledge output is similar to that of the input of S&T resources.

3.3 Spatial disparity of indirect economic benefits of S&T resources

Figure 3 shows the spatial distribution of indirect economic benefits of S&T resources in China. In China, the spatial disparity of indirect economic benefits is much more pronounced than that of input and direct knowledge output of S&T resources. Most provinces witness low indirect economic benefits. The several provinces enjoying high indirect economic benefits are Beijing, Guangdong, Jiangsu and Shanghai, and all of them are located in the three major metropolitan regions. Beijing and Guangdong are at the first level, and they represent two distinct types of S&T development. Beijing has the strongest administrative power in China while Guangdong enjoys the best market mechanism. Jiangsu and Shanghai belong to the second level, and there is quite a big gap between them and Beijing/Guangdong. For example, Jiangsu is half less than Guangdong in terms of the calculated value of indirect economic benefits. Provinces at the third level include Tianjin, Shandong, Zhejiang, Sichuan and Fujian while those at the fourth level are Hubei, Hunan, Anhui, Shaanxi, Chongqing and Liaoning. The remaining 15 provinces are at the fifth level, and they are mainly located in the western region. Overall, in China, the spatial pattern of indirect economic benefits of S&T resources does not have a close

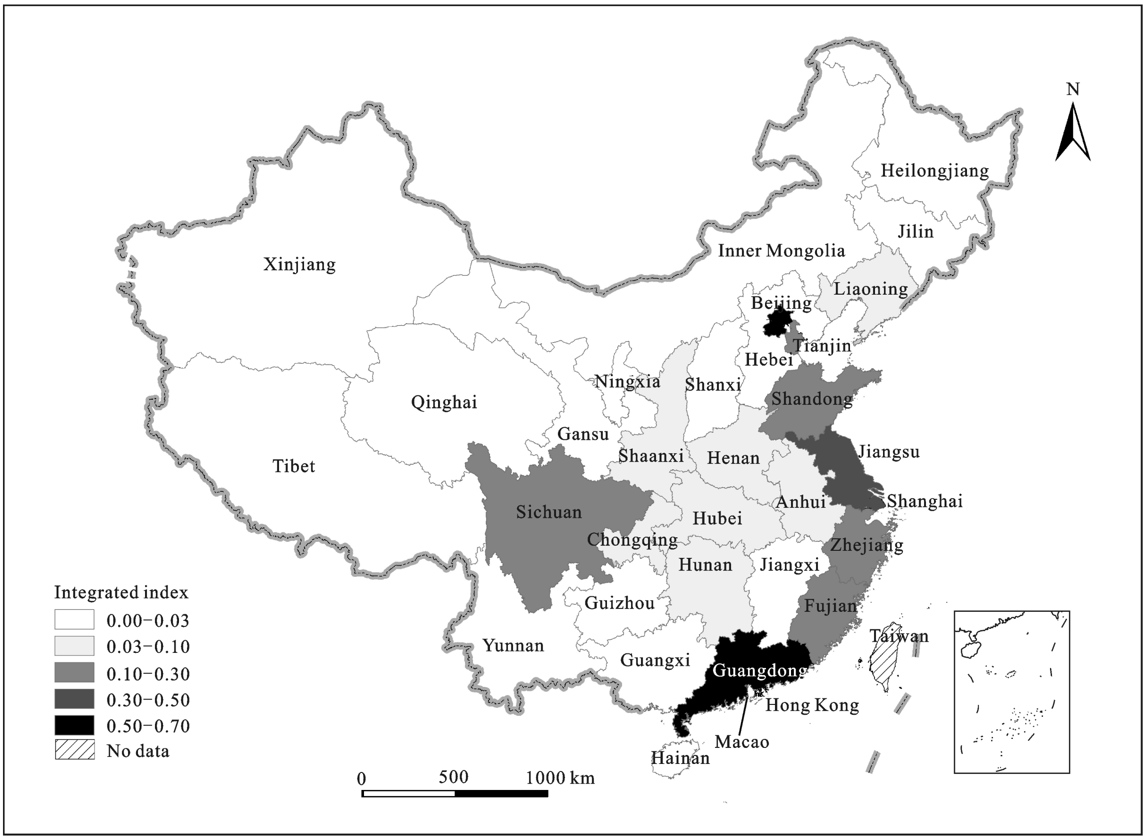

Fig. 3 Spatial disparity of indirect economic benefits of S&T resources in China in 2009

positive correlation to that of input and direct knowledge output of S&T resources, which indicates that the rate of application of direct knowledge output in business is still low in most provinces in China.

4 Allocation Efficiency of S&T Resources

4.1 Spatial pattern of efficiency of S&T resources

Through calculation of the input-output indicator system of S&T resources by using the CCR model of the DEA approach, we can get the value of θ to represent the allocation efficiency of S&T resources. Then, we divide provinces in China into five classes with the value of θ, in descending order from the first level to the fifth level. The computing results are shown in Fig. 4 and Table 2.

In general, the allocation efficiency of S&T resources in China is not featured by a laddered spatial structure, i.e., in a descending order from the coastal to the western regions, but by scattered distribution. Provinces with the highest level of efficiency of S&T resources are Beijing, Tianjin, Shanghai, Guangdong, Hunan, Heilongjiang and Hainan. The second level consists of Hubei, Shaanxi, Gansu, Fujian and Jilin. Among the provinces at the first and second levels, Hunan, Hainan, Heilongjiang and Gansu are eye-catching because they are the ones with quite low direct knowledge output and indirect economic benefits. The high value of efficiency of these four provinces can be attributed to the low input of S&T resources, but not the high output. Table 2 shows that the number of provinces at each level is by and large the same. However, regional composition at each level is different. Coastal provinces have a higher share in number of provinces at the first and second levels while the central and western provinces have a higher share at the fourth and fifth levels, which indicates in general the coastal region is superior to the inland region in term of the allocation efficiency of S&T resources.

It should be noted that the efficiency value calculated by using the CCR model of the DEA approach represents only the relative efficiency of S&T resources, which reflects the relative position of each province

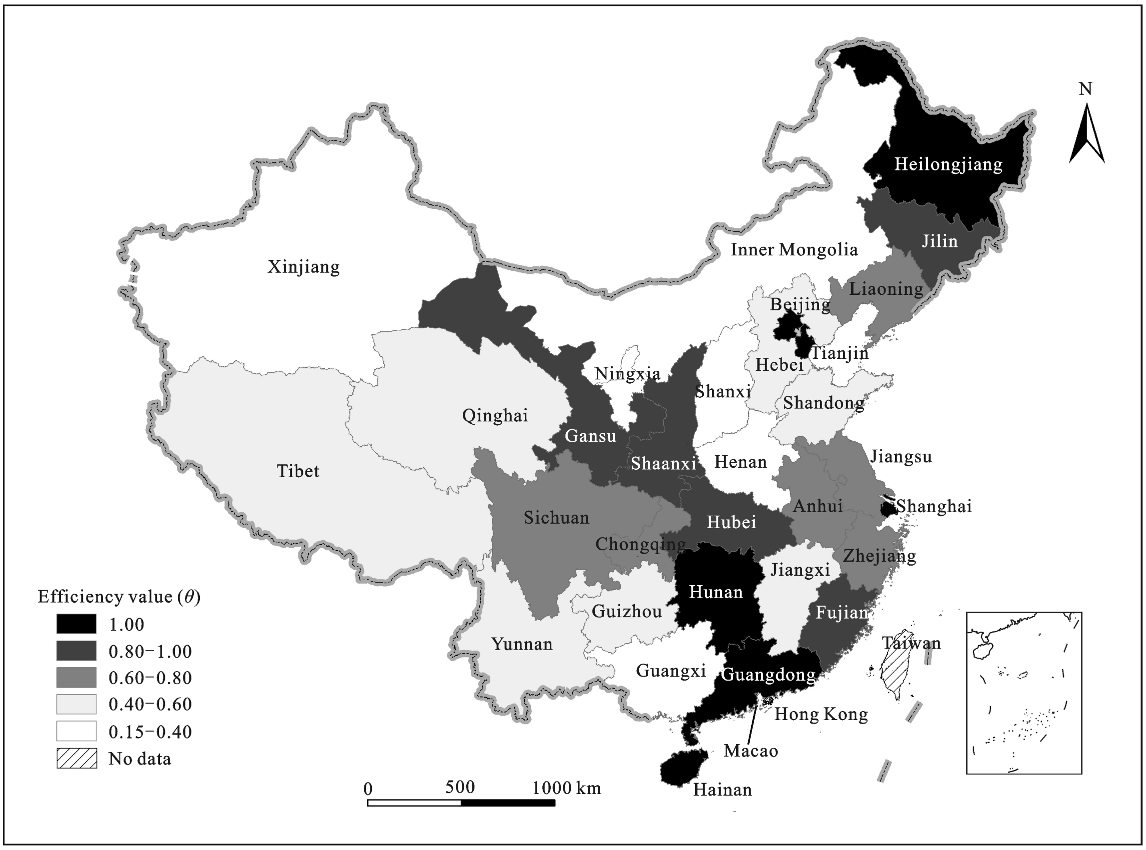

Fig. 4 Spatial disparity of allocation efficiency of S&T resources in China in 2009

among all the provinces. By comparing the three rankings of input, direct knowledge output and indirect economic benefits, as shown in Table 3, we can find the reasons behind spatial differences in the allocation efficiency of S&T resources. For example, Jiangsu ranks the second among all the provinces in input of S&T resources, but it ranks the fourth and third respectively in direct knowledge output and indirect economic benefits,

Table 2 Allocation efficiency of S&T resources in China based on CCR model

Efficiency value	Level	Province	Regional distribution
$\theta = 1.0$	First	Beijing, Guangdong, Hainan, Heilongjiang, Hunan, Shanghai, Tianjin	7 in total, 6 in the eastern, 1 in the central
$0.8 < \theta < 1.0$	Second	Hubei, Shaanxi, Gansu, Fujian, Jilin	5 in total, 2 in the eastern, 1 the central , 2 in the western
$0.6 < \theta < 0.8$	Third	Jiangsu, Sichuan, Zhejiang, Anhui, Chongqing, Liaoning	6 in total, 3 in the eastern, 1 in the central, 2 in the western
$0.4 < \theta < 0.6$	Fourth	Guizhou, Yunnan, Shandong, Qinghai, Tibet, Hebei, Jiangxi	7 in total, 2 in the eastern, 1 in the central, 4 in the western
$0.15 < \theta < 0.4$	Fifth	Henan, Guangxi, Shanxi, Xinjiang, Inner Mongolia, Ningxia	6 in total, 2 in the central, 4 in the western

Table 3 Ranking of input-output indicators of S&T resources in China

Province	Input	Direct knowledge output		Indirect economic benefits	
	Ranking	Ranking	Change compared to input ranking	Ranking	Change compared to input ranking
Beijing	1	1	→	1	→
Jiangsu	2	4	↓	3	↓
Guangdong	3	2	↑	2	↑
Shandong	4	6	↓	6	↓
Zhejiang	5	5	→	7	↓
Shanghai	6	3	↑	4	↑
Sichuan	7	11	↓	8	↓
Liaoning	8	8	→	10	↓
Hubei	9	7	↑	11	↓
Henan	10	16	↓	15	↓
Shaanxi	11	9	↑	12	↓
Tianjin	12	12	→	5	↑
Fujian	13	17	↓	9	↑
Hebei	14	18	↓	22	↓
Anhui	15	14	↑	16	↓
Hunan	16	10	↑	13	↑
Heilongjiang	17	13	↑	17	→
Shanxi	18	20	↓	19	↓
Jilin	19	15	↑	18	↑
Chongqing	20	19	↑	14	↑
Jiangxi	21	23	↓	20	↑
Guangxi	22	24	↓	26	↓
Gansu	23	21	↑	21	↑
Yunnan	24	22	↑	23	↑
Inner Mongolia	25	26	↓	25	→
Guizhou	26	25	↑	24	↑
Xinjiang	27	27	→	30	↓
Ningxia	28	29	↓	28	→
Qinghai	29	30	↓	27	↑
Hainan	30	28	↑	29	↑
Tibet	31	31	→	31	→

which makes its efficiency of S&T resources low. On the contrary, Gansu ranks the twenty-third in input of S&T resources, but it ranks twenty-first in both direct knowledge output and indirect economic benefits, which allows its rank in efficiency of S&T resources quite high. Therefore, the measurement result of efficiency of S&T resources does not mean whether or not S&T resources are sufficient in a province. That is, even if the value of θ of a province is higher, it does not indicate that the province has strong S&T resources.

4.2 Coupling relationship between efficiency and input-output system

Although the efficiency of S&T resources reflects input, direct knowledge output and indirect economic benefits, the spatial pattern of allocation of S&T resources can be understood more deeply if the coupling relationship among them is analyzed. Based on value calculated above, we can re-classify the three synthesized indexes into three new levels in descending order, i.e., high, medium and low. The first two classes are re-classified as high, the third class as medium, and the two lowest classes as low. By such re-classification, we can divide all the provinces into 14 types, as shown in Table 4.

There are five types of input-output relations in the high allocation efficiency category. They are: 1) high input, high knowledge output and high economic benefits (Beijing, Guangdong and Shanghai), which indicates the strongest comprehensive strength in China; 2) high input, high knowledge output and medium economic benefits (Tianjin), which indicates the link between S&T activities and economic development is weak; 3) medium input, high knowledge output and low economic benefits (Hunan), indicating high output of S&T activities but weak link between S&T output and economic development; 4) medium input, medium knowledge output and low economic benefits (Heilongjiang); and 5) low input, low knowledge output and low economic benefits (Hainan). The last two types seem to suggest that these two provinces have tried to best use their weak S&T input although they are far behind in S&T development.

There are nine types of input-output relations in the low allocation efficiency category. They are: 1) high input, high knowledge output and high economic benefits (Jiangsu), indicating there is plenty of room for improving the allocation efficiency; 2) high input, high knowledge output and medium economic benefits (Shandong, Zhejiang and Sichuan), indicating weaker link between S&T activities and economic development; 3) high input, high knowledge output and low economic benefits (Liaoning, Hubei and Shaanxi), indicating very weak link between S&T activities and economic development; 4) high input, medium knowledge output and low economic benefits (Henan), indicating both low output efficiency and weak link between S&T activities and economic development; 5) medium input, medium knowledge output and medium economic benefit (Fujian), indicating a medium level of output efficiency; 6) medium input, medium knowledge output and low economic benefits (Hebei and Anhui), indicating lower input and weaker link between S&T activities and economic development; 7) medium input, low knowledge output and low economic benefits (Shanxi), indicating both lower output efficiency and weaker link between S&T activities and economic development; 8) low input,

Table 4 Coupling relationship between allocation efficiency and S&T input-output system

Input-output relation	High allocation efficiency	Low allocation efficiency
H input, H output, H benefit	Beijing, Guangdong, Shanghai	Jiangsu
H input, H output, M benefit	Tianjin	Shandong, Zhejiang, Sichuan
H input, H output, L benefit		Liaoning, Hubei, Shaanxi
H input, M output, L benefit		Henan
M input, H output, L benefit	Hunan	
M input, M output, M benefit		Fujian
M input, M output, L benefit	Heilongjiang	Hebei, Anhui
M input, L output, L benefit		Shanxi
L input, M output, L benefit		Jilin, Chongqing
L input, L output, L benefit	Hainan	Jiangxi, Guangxi, Gansu, Yunnan, Inner Mongolia, Guizhou, Xinjiang, Ningxia, Qinghai, Tibet

Notes: H: high; M: medium; L: low

medium knowledge output and low economic benefits (Jilin and Chongqing), indicating weak link between S&T activities and economic development; 9) low input, low knowledge output and low economic benefits (the remaining 10 provinces).

5 Countermeasures to Improve Efficiency of S&T Resources

From the above analysis, we know that there are two main factors affecting the efficiency of allocation of S&T resources; one is redundancy of input (i.e., deviation of input) while the other is deficiency of output. However, we are unable to identify which of the two factors play a leading role in each province. Thus, we have to make further investigation. From the DEA model, we know that when the value of θ is equal to 1, the DMU′s input-output level is at the optimal production frontier and the allocation efficiency of S&T resources attains 100%. When the value of θ is less than 1, the DMU′s input-output level does not reach the optimal production frontier, and the gap between the optimal value and actual value can be measured by the value of S^- and S^+. S^- represents redundancy of input while S^+ stands for deficiency of output. Analyzing the gap can reveal the main factors leading to low efficiency of S&T resources in a particular province.

Provinces with input redundancy of human and financial resources include Chongqing, Liaoning, Guizhou, Yunnan, Shandon, Qinghai, Tibet, Hebei, Jiangxi, Henan, Guangxi, Shanxi, Xinjiang, Inner Mongolia and Ningxia, where the ratio of input redundancy is over 60%. Indeed, in most provinces in this category (except Chongqing, Liaoning, Guizhou and Yunnan) the ratio of input redundancy is as high as 100%. It is clear that although the lack of S&T resources has been widely recognized, the waste of these resources is still a big issue in most regions in China. In particular, in the central and western regions, the failure to make full use of S&T resources is the main reason behind low efficiency.

Provinces with low output of high-tech products include Gansu, Yunnan, Qinghai, Guangxi, Xinjiang and Inner Mongolia, where the ratio of output deficiency is between 60% and 96%. All these provinces are located in the western region. They have weak linkages to other provinces and are far from international market, resulting in weak innovation capacity and low output of high-tech products. Provinces with small number of technological transactions include Hubei, Shaanxi, Fujian, Jilin, Jiangsu, Sichuan, Zhejiang, Anhui, Guizhou, Shandong, Tibet, Hebei, Guangxi, Shanxi and Xinjiang, where the ratio of output deficiency is between 60% and 100%. The common issue faced by the provinces in this category is the lag between S&T activities and business, resulting in low commercialization of S&T outputs. Provinces with small number of academic papers include Tibet and Qinghai, where fundamental scientific research is very weak. Provinces with small number of granted invention patents include Gansu and Fujian, indicating weak capacity of technological innovation. Overall, the ratio of deficiency in direct knowledge output in most provinces in China is below 60%, which means there is still some room for increasing direct output efficiency but not very big.

Based on the above analysis, reasons behind the low allocation efficiency of S&T resources in China can be summarized as the following two points. One is that all the provinces with the allocation efficiency lower than 100% (i.e., $\theta < 1$) witness input redundancy and low rate of commercialization of S&T outputs. The other is that the lower a province′s efficiency is, the higher its input redundancy is, and the lower its commercialization rate is. In particular, those provinces with $\theta < 0.5$ have a very high level of input redundancy and very low rate of commercialization. In terms of commercialization rate of S&T outputs, 28 provinces have considerable room for improvement in technological transactions and 23 provinces have potentials in raising high-tech output rate.

As the allocation efficiency of S&T resources involves both the input and output sides, improvement can be achieved by reducing input redundancy and raising output efficiency as well as strengthening the link between S&T activities and business. On the input side, most provinces in China have a high level of input redundancy, indicating a large room for improvement. This is especially true for such provinces as Shandong and Qinghai, where the redundancy ratio is more than 100%. On the output side, all provinces except for Tibet, Qinghai, Gansu and Fujian do not have great potentials in raising direct knowledge output (i.e., academic papers and invention patents) while most provinces have considerable room for achieving more indirect economic benefits. Therefore, to raise the efficiency of S&T resources in China, on the one hand, existing S&T resources should be made full use and new inputs should be guided by market needs; on the other hand, every efforts should be made to promote the commercialization of S&T outputs, i.e., to increase the contribution of S&T activities to economic growth.

Of course, the allocation of S&T resources is not a simple program; it involves not only the input and output factors, but also institutional factors. The latter is not discussed in this paper, but that does not mean it is not important. Indeed, the improvement of the allocation efficiency of S&T resources in China has to be made against the institutional context. In particular, an effective combination of market forces and government interventions to promote innovation of enterprises is essential.

6 Conclusions

On the one hand, being important strategic resources, S&T resources have great potentials in boosting economic growth. On the other hand, being rare resources, S&T resources should be allocated efficiently to promote socio-economic development. By designing a S&T input-output indicator system, the paper develops an evaluation model to measure the allocation efficiency of S&T resources. With the model, it examines the spatial pattern and disparities of S&T resources in China and evaluates the allocation efficiency of these resources. The paper also points out reasons behind low allocation efficiency of S&T resources in China and suggests countermeasures to improve the efficiency. Major findings of the paper are: 1) the input and output of S&T resources in China shows a clear T-shaped spatial structure, i.e., concentrated mainly in the coastal region and along the Changjiang River; 2) the efficiency of S&T resources in China displays strong spatial disparities, with the level of efficiency descending from the east to the west and high efficiency appearing in only several clusters; 3) the utilization rates of S&T resources in most provinces are quite low, resulting in low efficiency of S&T resources allocation.

The present study on allocation efficiency of S&T resources in China has limitations and shortcomings. First, due to data accessibility, the study is confined to province-level analysis, and is not able to produce refined research results that rely on prefecture-level data. Second, due to the complicated input-output relationships of S&T activities, indicators used in this paper may not be able to tell the full pictures of S&T inputs and outputs although they have been commonly used. Thus, future studies on this topic can move in two directions. One is to do case studies of selected prefecture-level administrative units to examine the dynamics of S&T resources allocation. The other is to testify the indicators used in the paper by case studies and fix the input-output indicators to cover more information of S&T activities.

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