Nat Hazards (2017) 87:1751–1764
DOI 10.1007/s11069-017-2846-y

ORIGINAL PAPER

Direct and indirect economic loss assessment of typhoon disasters based on EC and IO joint model

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Received: 19 January 2017 / Accepted: 24 March 2017 / Published online: 1 April 2017

Abstract In recent years, the typhoon disasters frequently occur, by which the economic loss caused is paid more and more attention. Combined with the uncertainty of real economy and the structure of detailed departments' classification, traditional input–output models are extended in this paper. Moreover, static and dynamic models of economy and input–output are, respectively, constructed to evaluate the direct and indirect economic loss caused by typhoon disasters for related industrial departments. It is shown that when referring our proposed static model, the four dominant departments' loss affected by typhoon in 2013 is 1271.9248 billion Yuan in total, accounting for 75.5303% of the total industrial product loss. In the case of the dynamic model, the longer the time of the sector returns to normal production, the bigger the cumulative economic loss caused by typhoon is.

Keywords Econometric models · Input–output model · Extend model · Time series

1 Introduction

Statistics from the meteorological department show that in the past 10 years from 1992 to 2001, natural disasters had caused the death of about 626,000 people and more than 2 billion people had been affected by the disasters. Meteorological disasters accounted for 90 percent of whole loss, which happen most frequently and affect most significantly (Wang et al. 2015a, b; Zhao et al. 2011). In all meteorological disasters, typhoon is the most severe disaster, which is accompanied by heavy rainfall, very easily leading debris flow,

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landslides and other secondary disasters. Therefore, it causes tremendous damages and losses (Noy 2015; Wang et al. 2016a, b, c, d). “China Meteorological Disaster Yearbook (2014)” shows that the area affected by typhoon disasters in China was 2670.1 thousand hectares by them in 2013, whereas the area of crop failure was 289.5 thousand hectares. Moreover, the population affected was as high as 19.222 million, and direct economic loss actually reached 126.03 billion Yuan. It can be seen that assessment of the economic loss caused by typhoon has a great representative significance (Noy and Vu 2010).

In recent years, scholars from all over the world have made remarkable achievements and have significant effects in the research area of typhoon. Niu et al. (2011) established a typhoon disaster model for coastal provinces and cities of the typhoon disaster loss to analyze and evaluate the factors of disasters; Shi et al. (2013) established the Shanghai typhoon disaster damage assessment model and assessed the typhoon disaster for Shanghai annual changes and regional distribution differences; Wu et al. (2014) used a static and dynamic input–output model to evaluate the associated economic losses of typhoon disaster in Jiangsu Province. Wang et al. (2016a, b, c, d) used different statistical methods to study the temporal and spatial distribution of tropical cyclones influencing China, and evaluated the economic losses caused by them from 1984 to 2015. Kerry (2005) studied the devastating changes in typhoon disasters over the past three decades and obtained their relationship with demographic changes; Mumby et al. (2011) used the time index to cluster the typhoon and further studied its impact on the ecosystem (Krishnamurthy et al. 2011; Vickery et al. 2009; Emanuel et al. 2008; Lou et al.2012).

The input–output (IO) model is based on input–output tables. As the workload of generating an input–output table is huge (once for every five years), it cannot correspond with statistical yearbook (2011). Therefore, this paper extends the IO model and constructs an econometric (EC) model based on the related part of the corresponding input–output table. Then, the EC + IO model can be obtained. This model can be used to predict the input–output table of each year, so as to improve the accuracy of the input–output model to evaluate the economic loss of disasters.

In terms of the joint model, West (1991) made an overview of Queensland using the established EC + IO model; Meng (2009) extended the traditional input–output model and analyzed the industrial structure of China in the past ten years; Rey (2000) examined the problems and opportunities for establishing the EC + IO model. There are also some scholars focusing on the study (Israilevich et al. 1997; Santos and Haimes 2004; Rose and Casler 1996).

The remaining parts of the paper are organized as follows. Section 2 is an introduction to the relevant model. In Sect. 3, the static and dynamic EC + IO models are established. Section 4 presents an empirical analysis of the direct and indirect economic losses caused by typhoon in China in 2013. In Sect. 5, discussions are reported. Finally, a conclusion is given in Sect. 6.

2 Model introduction

From the “line-balance” relationship of the value-type input–output table (Wang wu, et al. 2016), we can get:

$$\sum x_{ij} + Y_i = X_i, \tag{1}$$

Or in matrix:

$$AX + Y = X. \tag{2}$$

where x_{ij} is the number of sector i's products assigned to sector j, x_i is the total output of sector i, Y_i is the end-use of sector i, A is the direct consumption coefficient matrix, whose element is $a_{ij} = \frac{x_{ij}}{X_i}$.

(2) is equivalent to:

$$X = (I - A)^{-1}Y,, \tag{3}$$

where $(I - A)^{-1}$ is the Leontief inverse matrix.

From (1) we can see that the Y consists of four components: household consumption, government consumption, total capital formation and net exports (Meng 2009). Thus, an EC model can be established for these four sections, respectively. History data can be used to predict the required each sub-data of Y. Then, the end-use's sub-items can be substituted into the input–output model. In other words, the IO model is driven by the predictive results of the EC model. The model established by this connection is called the EC + IO model. In the past, EC + IO model was used in the researches of industrial structure, and there were few studies on disaster. This paper combines EC model with static IO model and dynamic IO model, respectively, to evaluate the direct and indirect economic losses caused by typhoon disaster.

3 Model building

3.1 Construction of the EC model

This section uses the relevant data from 1992 to 2012 Statistical Yearbook to establish the EC model. To eliminate the impact of price changes, the paper uses a constant price data (1978 = 100).

3.1.1 Resident consumption model

Due to the dual-society structure in China, the consumption model of urban residents has been established by using the per capita consumption and per capita disposable income of urban residents, whereas the consumption model of rural residents has been created by per capita consumption and per capita net income of rural households. Finally, we use the data to obtain the resident consumption models:

Urban residents' consumption equation:

$$LnC_t = -1.4556 + 0.7425 \times LnDIS_t + 0.1622LnC_{t-1}, \tag{4}$$

Rural residents' consumption equation:

$$LnC_t = -0.8350 + 0.9893 \times LnDIS_t + 0.1560 \times LnC_{t-1}, \tag{5}$$

where *Ln* is the natural logarithm (same as followed). For urban residents, *DIS* is per capita disposable incomes. For rural residents, *DIS* is per capita net incomes. C_{t-1} represents a former household consumption expenditure. According to the simulation results, we find that $\hat{R}^2 = 0.9951$ of Eq. (4), the value p is far less than 0.05 at significant level $\alpha = 5\%$, which shows that the equation we establish is significant. $\hat{R}^2 = 0.9890$ in Eq. (5), the value

p is much less than 0.05 at significant level $\alpha = 5\%$, which indicates that the equation we establish is significant.

3.1.2 Government consumption model

The model involves the total government consumption, economic construction expenditure and expenditure of science, education, culture and health. Finally, government consumption model is obtained:

$$LnG_t = -0.5874 - 0.4385 \times LnED_t + 0.9794 \times LnESC_t + 0.7476 \times LnG_{t-1}, \tag{6}$$

where G is government consumption, ED is the economic construction expenditure, ESC is expenditure of science, education, culture and health. $\hat{R}^2 = 0.9986$ in Eq. (6), the value p is less than 0.05 when the significant value of $\alpha = 5\%$, then the original hypothesis is rejected, which indicates that the equation is significant.

3.1.3 Gross capital formation model

Total capital formation is composed of gross fixed capital formation and increase in inventories. However, the changes in inventories are not very regular. In this paper, a function model of the total fixed capital formation is built, which involves an indicator of financial institutions loans. Finally, the total fixed capital formation model is obtained by using relevant data:

$$LnFCI_t = -0.7042 + 0.3763 \times LnCRE_t + 0.6659 \times LnFCI_{t-1}, \tag{7}$$

where FCI is the gross fixed capital formation, CRE is the financial institutions loans, FCI_{t-1} is the previous year's gross fixed capital formation. In Eq. (7), $\hat{R}^2 = 0.9977$, the value p is less than 0.05 when the significant value of $\alpha = 5\%$, then the original hypothesis is rejected, which indicates that the equation is significant.

We can get the gross capital formation in gross fixed capital formation (FCI) and increase in inventory (SI), as follows:

$$I_t = FCI_t + SI_t. \tag{8}$$

3.1.4 Net export model

Net exports are equal to that exports (EX) minus imports(IM). Considering the distribution of data in the various sectors, only one model of total exports is built in this paper. The model also involves indicators of gross domestic product and foreign exchange reserves. Finally we get the total export function model:

$$LnEX_t = 14.0786 - 1.0879 \times LnGDP_t + 0.7673 \times LnFR_t, \tag{9}$$

where GDP is the gross domestic product, ER is the foreign exchange reserves. In Eq. (9), $\hat{R}^2 = 0.9694$, the value p is less than 0.05 when the significant value of $\alpha = 5\%$, then the original hypothesis is rejected, which indicates that the equation is significant. Identities net exports expressed as follows:

$$EN_t = EX_t - IM_t. \tag{10}$$

3.2 Static EC + IO model

Y^1 is the predicted end-use part, (3) becomes:

$$X^1 = (I - A^1)^{-1} Y^1, \tag{11}$$

where A^1 is a prediction of direct consumption coefficient matrix. Its elements are $a^1_{ij} = \frac{x_{ij}}{\sum x_{ij} + Y^1_i}$, Y^1_i is an element of Y^1, $X^1_i = \sum x_{ij} + Y^1_i$ is an element X^1. By the formula (12), the final loss of product sectors can be seen as direct economic losses, that is $\Delta Y = (\Delta Y_1 \Delta Y_2, \ldots, \Delta Y_n)^T$. The total loss of production can be seen as:

$$\Delta X = (I - A^1)^{-1} \Delta Y. \tag{12}$$

Indirect losses (Wu et al. 2012) are $\Delta X - \Delta Y$.

In order to improve the accuracy of the various sectors' total product loss value assessment, in this paper, the complete consumption coefficient will be used for analysis. The complete consumption coefficient matrix at this time can be regarded as the predicted complete consumption coefficient matrix. Its relationship with the predicted direct consumption coefficient matrix is: $B^1 = (I - A^1)^{-1} - I$, then (10) can be converted to:

$$\Delta X = (B^1 + I)\Delta Y \tag{13}$$

Assuming that sector i suffers from a disaster, the final requirements of other sectors remain unchanged. From (11), we can obtain the total output of the change for all sectors:

$$\begin{aligned}
\begin{pmatrix} \Delta X_1 \\ \Delta X_2 \\ \ldots \\ \Delta X_i \\ \ldots \\ \Delta X_n \end{pmatrix} &= \begin{pmatrix} b^1_{11} & b^1_{12} & \ldots & b^1_{1i} & \ldots & b^1_{1n} \\ b^1_{21} & b^1_{22} & \ldots & b^1_{2i} & \ldots & b^1_{2n} \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ b^1_{i1} & b^1_{i2} & \ldots & b^1_{ii} & \ldots & b^1_{in} \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ b^1_{n1} & b^1_{n2} & \ldots & b^1_{ni} & \ldots & b^1_{nn} \end{pmatrix} \\
&+ \begin{pmatrix} 1 & 0 & 0 & \ldots & 0 & 0 \\ 0 & 1 & 0 & \ldots & 0 & 0 \\ 0 & 0 & 1 & \ldots & 0 & 0 \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & 0 & \ldots & 1 & 0 \\ 0 & 0 & 0 & \ldots & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ \ldots \\ \Delta Y_i \\ \ldots \\ 0 \end{pmatrix} \\
&= \begin{pmatrix} b^1_{1i}\Delta Y_i \\ b^1_{2i}\Delta Y_i \\ \ldots \\ b^1_{ii}\Delta Y_i \\ \ldots \\ b^1_{ni}\Delta Y_i \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ \ldots \\ \Delta Y_i \\ \ldots \\ 0 \end{pmatrix}.
\end{aligned} \tag{14}$$

In the above formula: $b_{ij}^1(i,j = 1,2,\ldots,n)$ is the predicted complete consumption coefficient. The total product loss of the ith sector is:

$$\Delta X_i = b_{ii}^1 \Delta Y_i + \Delta Y_i, \tag{15}$$

where ΔY_i is a direct economic loss of the ith sector, $b_{ii}\Delta Y_i$ is the indirect economic loss of the forecasted sector i. The total loss of production in other sectors is as follows:

$$\Delta X_n = b_{ni}^1 \Delta Y_i, \quad n \neq i. \tag{16}$$

The formulas (15), (16) above are the static EC + IO model for the predictive evaluation of departments' total product loss (Wang et al. 2015a, b).

3.3 Dynamic EC + IO model

Leontief built dynamic EC + IO model (Wang et al. 2016a, b, c, d):

$$X(t) - AX(t) - D[X(t+1) - X(t)] = U(t), \tag{17}$$

where D is the investment coefficient matrix (Zhang 2013), $D[X(t+1) - X(t)]$ is productive investment matrix, $U(t)$ is the ultimate net demand matrix, and $D[X(t+1) - X(t)] + U(t) = Y(t)$.

If the matrix $Q = -D^{-1}$, then Eq. (17) can be converted to:

$$X(t+1) - X(t) = Q[AX(t) + U(t) - X(t)] \tag{18}$$

The proportion of total economic losses for the ith sector is $l_i = \Delta x_i / x_i$, where Δx_i is the total economic loss of value of the ith sector, x_i is the total output of the ith sector, l_i is the total loss ratio element matrix L. Therefore, the matrix $L = X^{-1}\Delta X$. The proportion of the demand for the ith sector is $u_i^* = \Delta u_i / x_i$, where Δu_i is the needs of the ith sector loss values, u_i^* is an element of demand loss matrix U^*. Formula (18) can be expressed as:

$$l(t+1) - l(t) = Q[A^* l(t) + U^*(t) - l(t)], \tag{19}$$

among them $A^* = X^{-1}AX$.

The general solution of (19) is:

$$l(t) = l(0)e^{-Q(l-A^*)t} + \int_0^t QU^*(s)e^{Q(I-A*)(s-t)}\mathrm{d}s. \tag{20}$$

If the final demand sectors remain unchanged, then $U^* = 0$. Equation (20) becomes:

$$l(t) = l(0)e^{-Q(I-A^*)t}. \tag{21}$$

If t → ∞, the loss ratio $l(t) \to 0$, and the affected sector is back to normal. If only considering the ith sector, formula (21) can be changed as:

$$l_i(t) = l_i(0)e^{-q_i(1-a_{ii}^*)t}. \tag{22}$$

The total economic loss of sector i in the period t returned to normal output $X_i(t)$ can be expressed as

$$X_i(t) = x_{it} \int_{t=0}^{T} l_i(t)\mathrm{d}t, \tag{23}$$

where x_{it} is the output value of the ith sector in period t. The end-use portion of the input–output table for the year is forecast.

The dynamic EC + IO model predicts the end-use portion Y^1 of the input–output table. If input–output identity still holds, the total output of the ith sector is $X_i^1 = \sum x_{ij} + Y_i^1$. This will make the ith sector output value within the period t, similarly, the change in total output will make the loss rate also change, then formula (22) can be changed as follows:

$$l_i(t)^1 = l_i(0)e^{-q_i(1-a_{ii}^{*1})t}, \tag{24}$$

where a_{ii}^{*1} is a matrix element of $A^{*1} = X^{-1}A^1X$, and A^1 is the predicted direct consumption coefficient matrix.

The total economic loss of the sector i predicted by the dynamic EC + IO model during the time period t returned to normal production is:

$$X_i(t) = x_{it}^1 \int_{t=0}^{T} l_i(t)^1\mathrm{d}t, \tag{25}$$

where x_{it}^1 is the planned output of sector i in unit time.

4 Direct and indirect economic loss assessment of typhoon

4.1 Prediction of Y

By Eqs. (4), (5), (6), (7), (9), the total consumption of urban residents in 2013 was about 165,074.6892 billion Yuan, whereas the total consumption of rural residents was about 4711.38009 billion Yuan, and the total consumption was 212,188.49 billion Yuan. Government consumption in 2013 was 7889.81643 billion Yuan, while a total of fixed capital formation was 288,192.5586 billion Yuan, and total exports were 121,603.14396 billion Yuan.

4.2 Input–output table data

In this paper, the year of 2012 national input–output table contains 17 sectors. The data for the projected end-use portion of the 2013 input–output table are tabulated in Table 1. Due to the availability, the data flow of the middle part was still 2012 data.

According to the results in the table, the 2013 input–output table can be generated with flow-part data of the 2012 input–output tables from 17 sectors. Then, the estimated direct consumption coefficient matrix A^1 can be calculated.

4.3 Hazard data

"China Meteorological Disasters Almanac" (2014) shows that crops "affected area," "disaster area" and "low-yield area" are defined as those with the decrease in crop production due to natural calamities by 10, 30 and 80%, respectively. Therefore, the calculation method of crop yield loss percentage of the estimated final simplified as follows (Wu et al.2014):

Table 1 2013 national input–output table using the final prediction section

	End-use						Import (billion Yuan)	Other (billion Yuan)
	Final consumption expenditure		Gross capital formation		Export (billion Yuan)	Total end-use (billion Yuan)		
	Household consumption expenditure (billion Yuan)	Government consumption expenditure (billion Yuan)	Gross fixed capital formation (billion Yuan)	Changes in inventories (billion Yuan)				
Agriculture, forestry, animal husbandry and fishery	21,681.4	654.9	3752.3	3598.2	695.6	30,382.3	5118.8	622.4
Mining industry	174.0	0.0	0.0	617.6	414.7	1206.3	24,897.0	−203.8
Food and beverage manufacturing and tobacco manufacturing	40,207.6	0.0	0.0	1803.5	2492.9	44,504.0	3381.0	865.1
Textile, clothing and leather products manufacturing	11,857.1	0.0	0.0	342.3	14,180.1	26,379.5	2054.3	813.1
Coking gas and petroleum processing	3946.7	0.0	0.0	503.5	1044.6	5494.8	2881.7	−23.5
Chemical industry	6369.9	0.0	0.0	229.9	8795.6	15,395.4	12,306.7	−213.5
Non-metallic mining industry	541.1	0.0	0.0	−68.1	2378.6	2851.5	702.6	−264.9
Metal product manufacturing	524.1	0.0	3462.9	260.9	1443.4	5691.4	9765.0	−725.0
Machinery and equipment manufacturing	15,653.1	0.0	92,195.7	1332.5	52,561.7	161,743.1	45,853.3	550.0
Other manufacturing industries	3477.8	0.0	2138.4	843.0	8675.2	15,134.3	4313.3	144.5
Electricity, heat and water production and supply	3840.6	0.0	0.0	0.0	69.3	3909.9	22.2	−76.5

Table 1 continued

	End-use						Import (billion Yuan)	Other (billion Yuan)
	Final consumption expenditure		Gross capital formation		Export (billion Yuan)	Total end-use (billion Yuan)		
	Household consumption expenditure (billion Yuan)	Government consumption expenditure (billion Yuan)	Gross fixed capital formation (billion Yuan)	Changes in inventories (billion Yuan)				
Construction industry	0.0	0.0	156,263.8	0.0	688.3	156,952.1	228.4	494.6
Transportation industry	13,181.1	2127.1	11,856.2	299.9	5954.9	33,419.3	4005.2	36.5
Wholesale and retail trade, accommodation and catering	25,910.3	0.0	5656.1	876.0	10,978.3	43,420.7	1152.7	11.1
Real estate, leasing and business services	23,258.0	1226.1	0.0	0.0	3677.3	28,161.3	2795.4	43.1
Financial industry	10,248.7	1009.1	11,400.9	0.0	369.7	23,028.4	443.4	−54.5
Other services	30,996.5	73,881.1	1466.9	0.0	845.1	107,189.6	2106.2	34.4

$$\text{Proportion of crop yield loss} = \frac{\text{Affected area} \times 0.1 + \text{disaster area} \times 0.2 + \text{crops area} \times 0.7}{\text{Total sown area of crops}} \times 100\%. \tag{26}$$

Based on the type of disasters as well as the data recorded in the "China Statistical Yearbook" (2014), the estimated crop yield losses of 2013 due to typhoon caused ratio is about 0.6727%. In this paper, the crop yield loss ratio is approximately regarded as the yield loss ratio.

4.4 Empirical results of direct and indirect economic losses in the industrial sector

4.4.1 *Static EC + IO model assessment results*

In 2013, the direct economic loss ratio of typhoon disasters in China was 0.6727%, which was predicted by the national input–output table in 2013. The direct economic loss was 77.8483 billion Yuan by Eq. (15), (16) to predict the overall loss of products obtained in other sectors as shown in Table 2.

From Table 2, affected by typhoon disasters, the top five of the sectors' total loss are: agriculture, forestry, animal husbandry and fishery (968.2482 billion Yuan), food and beverage manufacturing and tobacco manufacturing (14.1835 billion Yuan), chemical industry (125.4101 billion Yuan), mining industry (82.2373 billion Yuan) and coking gas

Table 2 Total loss of departmental products

Number	Industry sectors	Loss value (billion Yuan)
1	Agriculture, forestry, animal husbandry and fishery	968.2482
2	Mining industry	82.2373
3	Food and beverage manufacturing and tobacco manufacturing	141.1835
4	Textile, clothing and leather products manufacturing	12.4335
5	Coking gas and petroleum processing	80.2557
6	chemical industry	125.4101
7	Non-metallic mining industry	9.5807
8	Metal product manufacturing	16.1863
9	Machinery and equipment manufacturing	13.4761
10	Other manufacturing industries	22.3758
11	Electricity, heat and water production and supply	65.5079
12	Construction industry	1.0359
13	Transportation industry	36.6812
14	Wholesale and retail trade, accommodation and catering	35.7076
15	Real estate, leasing and business services	23.6877
16	Financial industry	38.2418
17	Other services	11.5826

and petroleum processing industry (80.2557 billion Yuan). Throughout the table, due to the loss of the final product of agriculture, forestry, animal husbandry and fishery, the total social product loss is 1683.8319 billion Yuan. In addition to agriculture, forestry, animal husbandry and fishery, Table 2 also shows that the losses of the forefront of the list are more than the second industry-related departments, indicating that, compared with the tertiary industry, the second industry affected by the impact of typhoon damage is more sensitive. For the secondary industry, the loss of heavy industry is more serious than that of light industry. The main reason is that the input cost of heavy industry is higher than that of light industry. While the construction industry affected by agriculture, forestry, animal husbandry and fishery is less affected, so it gets minimum loss. For the secondary industry, the loss of heavy industry is more serious than that of light industry. The main reason is that the input cost of heavy industry is higher than that of light industry. While the construction industry affected by agriculture, forestry, animal husbandry and fishery is less affected, so it gets the minimum loss.

According to the proportion of total output loss from sectors of the economy, the loss ratio of the five largest sectors are: agriculture, forestry, animal husbandry and fishery (1.0624%), coking gas and petroleum processing industry (0.1855%), food and beverage manufacturing and tobacco manufacturing (0.1565%), mining (0.1535%) and electricity, heat and water production and supply (0.1294%).

Seventeen sectors are ranked by size, based on the total product loss value and total output loss ratio. It is considered that the sectors with high total loss and high total output loss ratio are the most influential sectors in 2013. There are four sectors among the top five for these two indicators: agriculture, forestry, animal husbandry and fisheries, mining industry, food and beverage manufacturing and tobacco manufacturing, coke gas and petroleum processing industry. In 2013, the total product loss value of the four industry sectors was 1271.9248 billion Yuan, accounting for 75.5303% of the entire industry sector and the total product loss.

4.4.2 Dynamic EC + IO model results

Typhoon disasters have bigger influence on the transportation sector. Due to that the dynamic EC + IO evaluation model is more suitable for the sectors which restore the original function. It is difficult to restore the original under the impact of the typhoon in a year, which is difficult to restore the original output levels under the impact of the typhoon in a year. Setting the typhoon disasters to the department of the original negative impact was 5%, namely the $l(0) = 0.05$. If the sector in the recovery period of 30 days return to 99% of the level of output, namely the $l(30) = 0.1$. Using the input–output tables of the nation's data in 2013, according to the formula (24), we can get q = 100, then the sector recovery system equation can be obtained:

$$1 - l(t) = 1 - 0.05 \times e^{-0.0713\times(1-0.2478)\times t} = 1 - 0.05 \times e^{-0.0536\times t}. \qquad (27)$$

The sector within 30 days of recovery curve is shown in Fig. 1.

The formula (25) shows that, when the transport sector recovery period is 30 days, the cumulative loss of value of the sector is 3.46533 billion. Similarly, when the recovery period is 10 days, 20 days, 60 days, the cumulative loss can be obtained in the transport sector in value of the recovery period (concrete results in Table 3). The data in Table 3 show that, when the recovery period is short, the impact and the loss of typhoon disasters on the transport sector and the whole economic system are smaller; whereas the longer, the larger.

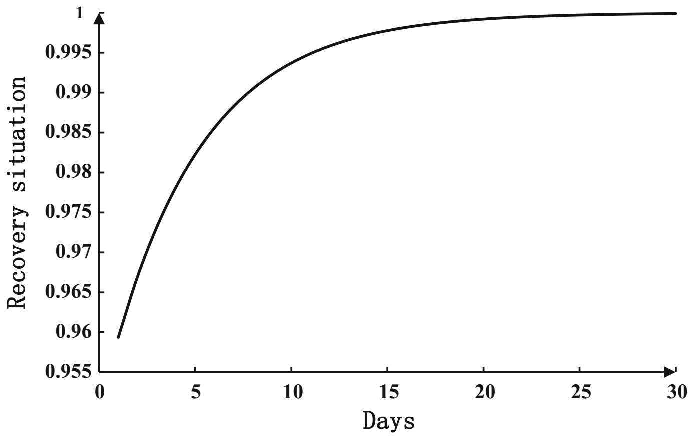

Fig. 1 30-day transportation industry recovery curve

Table 3 Different values of the cumulative loss of recovery in the transport sector

Recovery period (d)	Cumulative loss value (billion Yuan)
10	10.3959
20	23.1020
30	34.6533
60	62.3759

The data from Table 3 show that, when the recovery period is short, the impact and the loss of typhoon disasters on the transport sector and the whole economic system are smaller; whereas the longer, the larger. The sector loss value obtained by the dynamic EC + IO model is less than the sector loss value of the static EC + IO model in the shorter industry sector recovery period. This is because the static model obtaining the loss rate is the instantaneous value, the loss value from the loss rate and the annual output value of the division obtained, the default time is one year, so the loss is larger. And the loss rate of the dynamic model is exponentially decayed. The loss value is multiplied by the output value of the industry and then accumulated by the number of days of recovery. Therefore, the loss value is smaller.

5 Discussion

This paper establishes national static and dynamic EC + IO models. The joint model preserves the decomposition of the IO model department, adds the random term of the EC model and absorbs the advantages of the IO model and the EC model. The joint model not only reflects the meticulous departmental classification structure but also reflects the randomness, thus improves the theoretical model's ability by analyzing the practical problems. This is about the theoretical development and the requirements of real problems. At the same time, the national EC + IO joint model links the "China Statistical Yearbook" with input–output data. The data sequence of input–output non-programmed year are developed, which enhances the integrity of input–output data and extends the field of data application. Compared with the static EC + IO model, the dynamic EC + IO model incorporates the convalescence variable, which is more consistent with the actual situation. The theoretical basis of the model can be supported by Meng's research (2009).

In the case of using the static EC + IO model to assess the economic losses caused by the typhoon disaster, it is found that the sectors with the greatest impact of the typhoon disaster in 2013, namely the sum of the total product loss and the proportion of total output loss are agriculture, forestry, animal husbandry and fishery, mining, food and beverage manufacturing and tobacco manufacturing, coking gas and oil processing industry. The total value of these four product loss industry sectors is about 1271.9248 billion Yuan, accounting for 75.5303% of the total loss of the whole industry. The result is consistent with the findings of Wu et al. (2012). By using dynamic EC + IO model, we found that the shorter the recovery period, the smaller the total product loss; the longer the recovery period, the greater the total loss of departmental products. Wang et al.'s conclusion on the study of Beijing's haze in 2013 is in line with the conclusion of the article (2016).

Many scholars used the EC + IO model in the economic (Olson et al. 1991; Kim et al. 2016), this paper tries to use it for disaster and gets good results and the results are reasonable. The results of this work will help policy makers to understand better the typhoon disaster and its economic losses and reduce the loss caused by typhoon disasters through the introduction of relevant programs. In addition, the evaluation process of this paper can also be used for similar problems encountered in other regions.

6 Conclusion

The preparation of an input–output table is challenging and not continuous. Therefore, in this paper we use an econometric model to predict relative values of the input–output table. Obtaining input–output tables for gap years facilitates the prediction of the damage and losses caused by typhoon disasters. It has a very close relationship between various sectors. Therefore, during the assessment of the economic losses, it is more reasonable not only to calculate the direct economic losses caused by one disaster event for one industry, but also consider the total product loss of the disasters to other departments, even the whole economic system. According to the close correlation between industrial sectors, when affecting by a disaster, the relevant industry sectors should be sorted accordingly. This paper shows that the agriculture, forestry, animal husbandry and fishery sector, the mining industry, the food and beverage manufacturing and tobacco manufacturing, and the coking gas and petroleum processing industry are the most affected industrial sectors. The total product loss value of these industrial sectors accounted for a larger proportion of the entire economic system. When a typhoon disaster occurs, these sectors should be paid high attention. In the dynamic model, as the recovery period is shorter, the cumulative losses caused by typhoon disasters on the sectors and the entire economic system will be smaller. When a typhoon disaster occurs, the relevant departments should take measures to shorten the department recovery period, thereby to reduce the typhoon disasters losses.

Acknowledgements This work was supported by the Special Scientific Research Fund of Public Welfare Profession of China [Grant Number GYHY201506051], National Social and Scientific Fund Program [Grant Number 15BTJ019, 16ZDA047] and the Natural Science Foundation of China [Grant Number 71373131].

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