Evaluative Index System of Coal Mine Ecological Security based on SEM Modeling

Xiaoling Ke[1], Amal Mougharbel[2], Min Feng[1]
[1]School of Economics and Management
China University of Geosciences
Wuhan, 430200, P. R. China
[2] Business Administration Department
International Technological University
CA, 95113, USA
kxlcug@163.com, amougharbel@itu.edu

ABSTRACT: *This paper applies structure equation model, which is capable of processing variables and their relationship, in ecological security analysis of coal mining areas. Based on the collection of data from questionnaires and in-depth interviews, and then by using SPSS and AMOS software, it analyzes the factors of the ecological security in coal mining areas, sets up the paths in the model, and establishes an evaluative index system for ecological security in coal mining areas. The research results prove that this model has a good emulation effect, and that it can reflect the relationship between ecological security factors. The model has good interpretive potential, and can be used in practice.*

Keywords: Ecological Security, Mining Area, Structural Equation Model, AMOS

Received: 18 September 2015, Revised 19 October 2015, Accepted 25 October 2015

1. Introduction

According to the China Coal Industry Association's preliminary statistics, in 2013 the national coal production was at around 3.72 billion tons, with an annual consumption amounting to 3.61 billion tons. According to the situation of China's coal demand from 2013 to 2030, China Coal Peak Forecast Report predicts that by 2020, the total coal demand will reach a peak of about 4.1 to 4.7 billion tons per annum[1]. Heavy reliance's on coal mining, while it provides an impetus for economic development, is damaging to the ecological security of coal mining areas, mainly in the atmosphere, water, land and other natural resources. It also damages biodiversity and causes natural disasters. It is of vital practical significance to mitigate the increasingly prevalent conflicts between coal mining and environmental protection, and to establish a scientific and reasonable early warning indication system. Which will help us locate major factors for ecological security, so as to reduce natural disasters and the destruction of ecological resources, and to provide the basis for subsequent evaluation criteria in ecological security.

This paper takes two coal mines as examples, and analyzes the relationship among factors and variants of coal mine ecological security, by means of structural equation modeling, which can process variants and their relationships. It designs paths of models and builds a structural equation model of the ecological security evaluation index system of coal mine areas from the aspects of pressure, status, response, and performs a comprehensive analysis of the factors affecting the ecological security of coal mine areas.

2. Basic Principles of a Structure Equation Model

2.1 Introduction of Structure Equation Modeling

Structure equation modeling is a way to analyze relationships between variables using a covariance matrix of variables[2]. Speraman and Tucker proposed factor analysis, and Sewall Wright proposed path analysis, which helped the emergence of SEM. Because factor analysis and path analysis have their own advantages and disadvantages, the Swedish statistician Jorcskog integrated their respective structural formulae as a general framework for data analysis in 1973, in order to combine their strengths. This is the structural equation model [3]. Today, structural equation modeling has become an important multivariate analysis method and is widely used in the fields of genetics, sociology, psychology, economics and so on. Compared with traditional statistical modeling, a structural equation model has the following advantages [4] :(1) It allows errors in the independent variable in regression equations; (2) It can handle multiple dependent variables simultaneously; (3) It can simultaneously measure variables and process their relationship in a model; (4) It allows a more flexible model setup.

2.2 Basic Principles of Structure Equation Modeling

As structural equation model describes the relationship between the various variables in the form of a road map and establishes a hypothetical model. The lines with arrows indicate the relationship between variables in the road map. Single arrows indicate effect or a causal relationship, double arrows indicate correlation, and the correlation coefficient shown as the coefficient on the lines are called path coefficient[3] .

Variables in structural equations are divided into observed variables and latent variables. Those that can be measured directly are observed variables, otherwise they are latent variables. Latent variables representing the same observed variables share some common characteristics in terms of variance and covariance. Observed variables should be adjusted for measurement errors. Latent variables are further categorized into exogenous variables and endogenous variables according to their relationship with each other. Endogenous latent variables are variables determined by other latent variables, and exogenous latent variables are variables determined by observed variables. Because exogenous latent variables cannot be completely represented by their observed variables, they have to come with residuals which stand for things beyond measurement and therefore unexplainable.

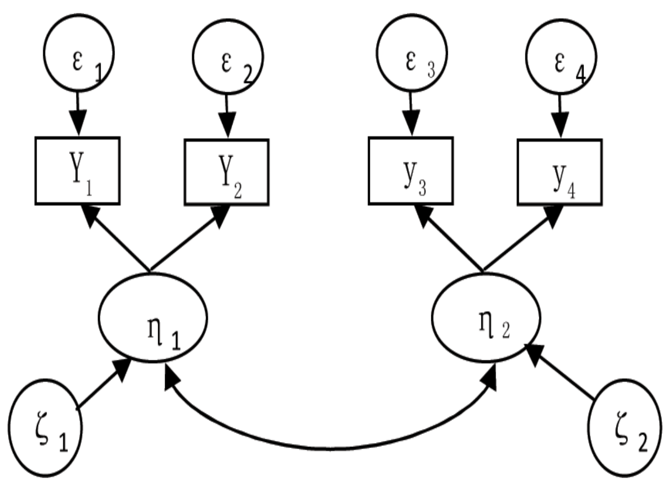

Figure 1. A complete structural equation model

A complete structural equation model (Figure 1) generally consists of two parts, the measurement model and the structural part of the model. Measurement models describe the relationship between latent variables and their observed variables. The formula is:

$$x = \Lambda x \xi + \delta \qquad (1)$$
$$y = \Lambda y \eta + \varepsilon$$

where x is the exogenous observed variable in dimension $q \times 1$; y indicates the endogenous observed variables in dimension $p \times 1$; $\wedge x$ is the load matrix between the exogenous observed variables in $q \times n$ dimension and latent variables; $\wedge y$ indicates the load matrices of observed variables in $p \times m$ dimension and endogenous latent variables; δ indicate errors of exogenous observed variable x in $q \times 1$ dimension; ε indicates the error of endogenous observed variable y in $n \times 1$ dimension[3]. The main function of the measurement model is to confirm factor analysis, to investigate whether the observed variables can be used as a measure of latent variables.

Structural models describe the relationship between latent variables. The following is the equation:

$$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta \qquad (2)$$

in which ξ indicates exogenous latent variables, η represents endogenous latent variables, B represents relationships between endogenous latent variables, Γ indicates load of exogenous and endogenous latent variables, and ζ indicates residuals of latent variables [4].

The analysis process of a structural equation model includes:

(1) Model setup. Based on previous research and theory, the initial theoretical model is designed, the properties of variables and the relationship between the variables are stated, and the above equations are formulated as well as the path coefficients in the equations.

(2) Estimation of model parameters. There are a variety of methods for estimating the parameters of the most common ones being: the robust, the weighted least squares and the maximum likelihood estimation method.

(3) Model evaluation and revision. After the estimation of model parameter, the overall emulation effect of the model will be evaluated. If the model does not emulate well, modifications of parameters or their relationship are needed to adjust the model. If the model fits, the results will be analyzed.

3. Definitions of Model Variables

Due to the particularity and complexity of the ecological security system in coal mines, the evaluation of its evaluative index system is different from other types of evaluative systems of ecological security. It should reflect the real parameters in coal mining areas and the basic characteristics.

In order to avoid subjectivity and arbitrariness in modeling, the present paper selects the P-S-R (pressure-status-response) model as a framework presented by the Organization for Economic Cooperation and Development. Based on previous literature, in-depth discussions and field research, a relational table of the variables of coal mine ecological security evaluation, will illustrate how the relationship is designed, showing the relationship between latent variables and observed variables in Table 1. Latent variables in coal mine ecological security are classified into three categories: ecological security pressures, ecological security status, and ecological security response.

Pressure refers to the ecological security pressure and threat in the process of coal mining, including but not limited to population pressure, natural resources pressure, pollution pressure and so on; status refers to the specific situation of ecological security in a coal mining area in a period of time, including coal mine resource quality and environmental quality; response refers to measures taken in response to threats to the ecological security of coal mining areas, including technological capacity and investment in order to improve the environment ecologically. Each latent variable is reflected by a number of observed variables.

4. Questionnaire Design and Data Collection

For a quantitative analysis of the scales of the impact of variables in the table on ecological security, we combine questionnaires and in-depth interviews. Data were collected from Yejiashan mine and Haiyuan Mine, which belong to Chibi Mining Ltd., Hubei Province. Topic options uses Likert scale questionnaire of five set points system [4], with the number “1 to 5” indicates varying degrees from “*no*”, “*little*”, “*medium*”, “*relatively high / large*” ,”*very high / large*”. Surveyees fill out the questionnaires according to their understanding of the ecological condition in the coal mines. In addition, the certainty and the time used to fill out the form are also collected in order to improve the accuracy of the questionnaire.

Data acquisition is mainly questionnaire-based, supplemented by a few in-depth interviews. A total of 100 questionnaires were distributed, 86 were returned, of which 84 were valid questionnaires. The efficiency of the questionnaires is 84%.

Latent variables	Observed variables	Observation perspective
Ecological Security Pressure （B_1）	population density pressure （D_1）	population pressure
	Mining total pressure （D_2）、tons of ore land area （D_3）	land pressure
	Water pressure （D_4）	water pressure
	Industrial waste load pressure （D_5）	pollution pressure
Ecological Security Status （B_2）	vegetation coverage （D_6）、air quality （D_7）、water (source) pollution index (D_8)、land resources destruction index （D_9）、solid waste dumps disaster index （D_{10}） human health （D_{11}）	Environmental Quality
Ecological Security Response （B_3）	per capita industrial output（D_{12}）、eco-construction investment intensity （D_{13}）、pollution control input intensity （D_{14}）	Investment capacity
	Industrial waste processing capacity （D_{15}）、solid waste utilization capability （D_{16}）、mine workers quality （D_{17}）	Technological capability

Table 1. Variables relational table of coal mining area ecological security evaluation

5. Assumptions of the Model

The ecological security assessment of coal mining area requires a complex system. In order to clarify the relationships between the various factors of ecological security, we make the following assumptions regarding the relationships between observed variables and the relationships between latent variables and other latent variables. We use observed variables, such as population density, total mining, area of land occupied by tons of ore, water consumption, and industrial emissions and so on, to describe the ecological security pressure of mines. A higher value of variables shows greater pressure. So the followings are the assumed relationships between them:

Assumption H_1: Population density, total volume of mining, the size of the area of land occupied by tons of ore, water usage, industrial waste load have a positive impact on ecological security pressure;

By the same token, there is an assumed relationship between ecological security status, its observed variable, response and its observed variables:

Assumption H_2: Vegetation coverage, air quality, human health have a positive impact on the ecological security status;

Assumption H_3: Water (source) pollution, destruction of land resources, solid waste dumps disasters have a negative impact on ecological security state;

Assumption H_4: Per capita gross industrial output, ecological construction investment, pollution control investment and industrial waste processing capacity, solid waste utilization capacity, mine worker quality have a positive impact on ecological security response.

Ecological security pressures, ecological security status and ecological security response have the following assumed relationships:

Assumption H_5: Ecological security pressure has a negative impact on the status of ecological security;

Assumption H_6: Ecological security pressure has a positive impact on ecological security response;

Assumption H_7: The shake of ecological security has a negative impact on ecological security response;

After assuming these relationships, we can build the model. The structural equation model is in the form of a path diagram. Latent variables are represented by ellipses, observed variables by rectangles, single straight arrow indicates causal relationship, two-way arrows indicate correlation. The model is shown in Figure 2:

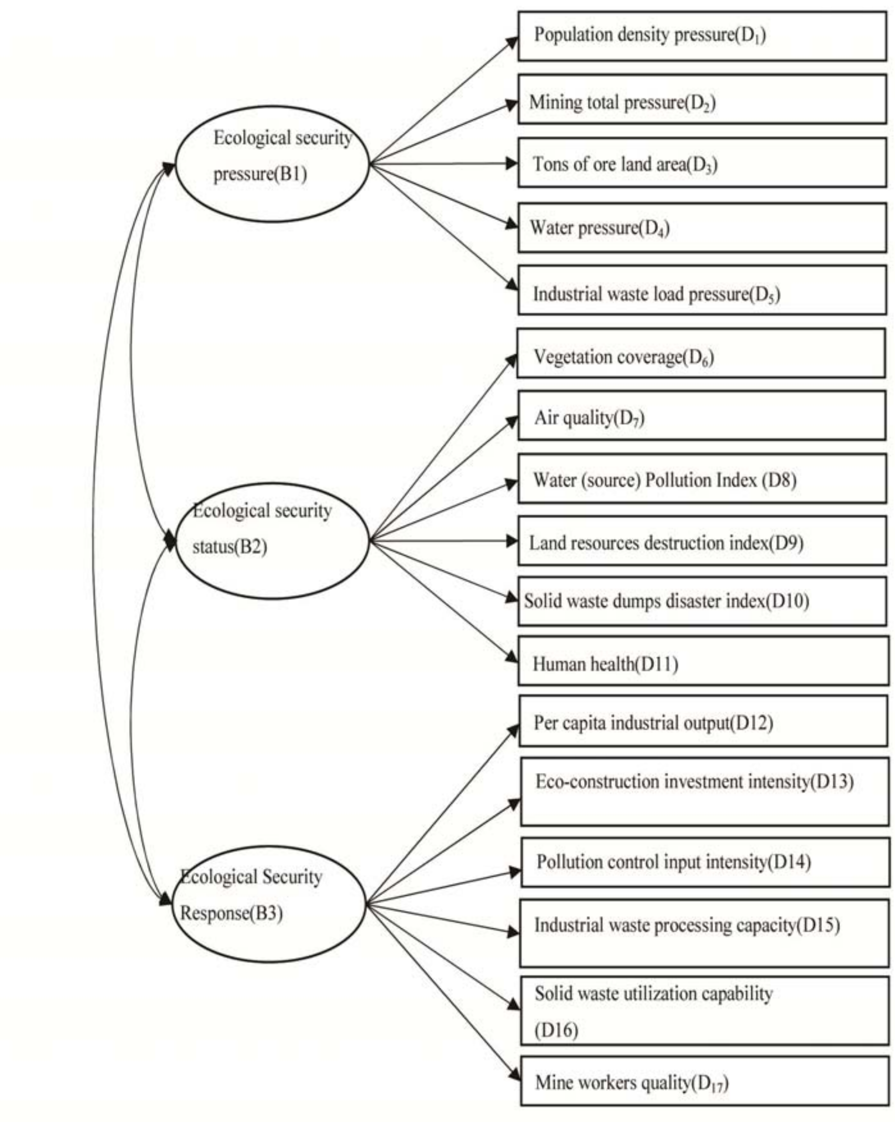

Figure 2. Evaluative index system of the ecological security of coal mine

6. Structural Equation Modeling Analysis

Structural equation modeling includes measurement model and structural model stages, in which the measurement model includes data normality test and assessment of validity and reliability of measuring tools, while the structural model measures the explanatory power of the evaluative model and the significance of the assumed paths. This study paper uses SPSS20 and AMOS 21 software to complete these studies.

6.1 Measurement Model Test

6.1.1 Normal Distribution Test

The estimation method used by structural equation model is maximum likelihood estimation, which requires data to be multivariate normal distribution, to ensure an unbiased, consistent, progressive and effective estimation. Therefore it is necessary to test data normal distribution. By using AMOS 21 the data are be tested, and the results are shown in Table 2. Skew represents skewness, c.r. represents skewness coefficient, kurtosis represents kurtosis, and c.r. represents kurtosis coefficient, Multicariate represents multi latent variable kurtosis test coefficient. According to "38 *principles*" proposed by Kline, RB (1998), all skewness coefficient of observed variables are less than 3, kurtosis coefficients are less than 8, and multi latent variables kurtosis test coefficient is 18.645, less than 19.6, indicating observed variables follow normal distribution.

6.1.2 Validity and Reliability Test

Test validity is the extent to which a test accurately measures what it purports to measure. The more consistency there is between the results of the measurement and with the characteristics of the object, the higher the validity of the best [5]. In this paper, exploratory factor analysis (EFA), the average variance extracted (AVE) and confirmatory factor analysis (CFA) are used

observed variables	skew	c.r.	kurtosis	c.r.
D_1	0.320	1.123	-0.276	-0.485
D_2	-0.144	-0.505	-0.500	-0.879
D_3	0.217	0.761	-0.434	-0.762
D_4	0.174	0.612	-0.281	-0.493
D_5	-0.213	-0.747	0.117	0.205
D_6	-0.270	0.279	-0.346	0.552
D_7	-0.093	-0.328	-0.545	-0.958
D_8	-0.236	-0.827	-0.384	-0.674
D_9	-0.103	-0.360	-0.520	-0.912
D_{10}	-0.335	-0.177	-0.185	-0.324
D_{11}	0.012	0.042	0.489	0.859
D_{12}	0.267	0.938	-0.363	-0.638
D_{13}	0.837	0.279	0.445	0.552
D_{14}	0.095	0.333	-0.295	-0.518
D_{15}	0.243	0.854	-0.400	-0.703
D_{16}	0.061	0.214	-0.565	-0.993
D_{17}	0.195	0.684	0.047	0.082
Multicariate			97.894	18.645

Table 2. Results of normal distribution test

Model	AVE	KMO	Bartlett's test of sphericity		Standardized load ranges		
B_1	0.6884	0.839	sig=0.000		0.742-0.958 *		
B_2	0.7534	0.877	sig=0.000		0.597-0.995 *		
B_3	0.7337	0.817	sig=0.000		0.622-0.969 *		
Model	CMIN/DF	RMR	NFI	IFI	CFI	GFI	RMSEA
B_1	2.484	0.032	0.955	0.973	0.972	0.937	0.224
B_2	1.853	0.018	0.979	0.990	0.990	0.943	0.108
B_3	3.675	0.024	0.950	0.963	0.962	0.828	0.191

Table 3.Validity test results

Note: * represents possibility: P<0.001

to test validity. A measurement scale consisting of the Cronbach A coefficient and composite reliability (CR) is used to test reliability.

First, by using SPSS 20 for factor analysis, the KMO coefficient of the three latent variables and Bartlett's test of test are obtained. The KMO coefficient is larger than the standard line and achieves an appropriate level. Bartlett's test of sphericity passes the significance test with a result of 0.000. Judging from the satisfactory results of each of the three measurement models, the appropriate data have satisfied the evaluation criteria, indicating the sound emulation of the models. The results of the validity test are shown in Table 3.

Reliability refers to the reliability of measurement tools which reflects how consistent, stable, and reliable the measured results are. High reliability coefficients reflect more consistent, stable and reliable results [5]. Reliabilities are reflected by using the Cronbach A coefficient and composite reliability in measurement scales. Research results show that reliability is best when the Cronbach A coefficient is between 0.71 and 0.93. The CR in this measurement scale is in all instances above 0.9, much higher than the threshold of 0.7, which indicates the high reliability of this study. The specific results of the analysis are shown in Table 4. In sum, we believe that the scale of this study has good validity and reliability, and that the model can effectively measure the ecological security status of coal mining areas.

Model	Cronbach α	CR	Standardized load ranges
B_1	0.912	0.9162	0.742-0.958 *
B_2	0.711	0.9368	0.597-0.995 *
B_3	0.927	0.9310	0.622-0.969 *

Table 4. Reliability analysis results

Note: * represents possibility: P<0.001

6.2 Structure Model Test

6.2.1 Model Fitting and Correction

Structural model testing mainly evaluates emulation fitness, interpretive capacity, and the level of significance of assumed paths. This paper adopts maximum likelihood estimation in fitting, and the results of model fitting fall into 3 classes and 7 fitting indices, including 2 absolute fitting indices (CMIN / DF, RMSEA) and 3 relative fitting indices (CFI , IFI, NFI) and 2 minimalist fitting indices (PNFI, PCFI) [3].

The model fitting results are shown in Table 5. It can be seen that the variables CMIN / DF, CFI, IFI, PNFI, PCFI variables have satisfied the evaluation criteria. RMSEA and NFI do not fulfill the evaluation criteria, but the deviation is within an acceptable range. Based on the above analysis, the overall model fits.

Type	Index	Fitness	Corrections	Criteria
Absolute Fitness Index	CMIN/DF	2.634	2.559	≤ 3
	RMSEA	0.150	0.146	< 0.1
Relative Fitness Index	NFI	0.858	0.864	> 0.9
	CFI	0.905	0.911	> 0.9
	IFI	0.907	0.912	> 0.9
Simplified Fitness Index	PNFI	0.662	0.685	≥ 0.5
	PCFI	0.698	0.694	≥ 0.5

Table 5. Model fitness and correction

After completing the fitting analysis of the model, we should further optimize the model. Optimization is based on the coefficient of modification indices. As the output from AMOS 21 shows, the maximum coefficient of Modification Indices is only 5.615, which means that the change does not enhance the fitness of the model significantly. Therefore, the model will not be modified.

6.2.2 Model Interpretation and Analysis

Model explanatory power is reflected by multivariate squared coefficient (R2), which is distributed with in the range 0-1. The higher the value, the stronger the explanatory power. As shown in Table 6, the minimum R2 value is 0.338 and the maximum is 0.986. According to the general requirements for structural equation, when the value of R2 is greater than 0.3, it is supposed to have a good explanatory power [6].

Observed variable	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8
R^2	0.907	0.500	0.766	0.560	0.718	0.589	0.356	0.986
variable	D_9	D_{10}	D_{11}	D_{12}	D_{13}	D_{14}	D_{15}	
R^2	0.899	0.917	0.895	0.748	0.899	0.816	0.338	

Table 6. R^2 value of the model

7. Conclusions

We test the assumed relations (H1 ~ H20) to ascertain whether the coefficients go with the assumed relationship. If they are in accordance, then the assumed relation is valid. If not, then the assumed relationship should be modified or deleted. Figure 3 shows the standardized path coefficient of the model. It is found that the 7 assumed relationships all passed the test.

The standardized path coefficients of the five observed variables of ecological security pressure (population density pressure, total mining pressure, land area of ton ores, industrial waste water, and pressure load pressure) are 0.699; 0.839; 0.871; 0.641 and 0.952, indicating that of all the five observed variables, the variable which is the most sensitive to ecological security threats is industrial waste load pressure. This is because industrial waste has the most severe and direct influence on ecological security.

Heavy waste load pressure means heavy pollution, severe impact on the environment,, and therefore the pressure to maintain ecological security is greater.

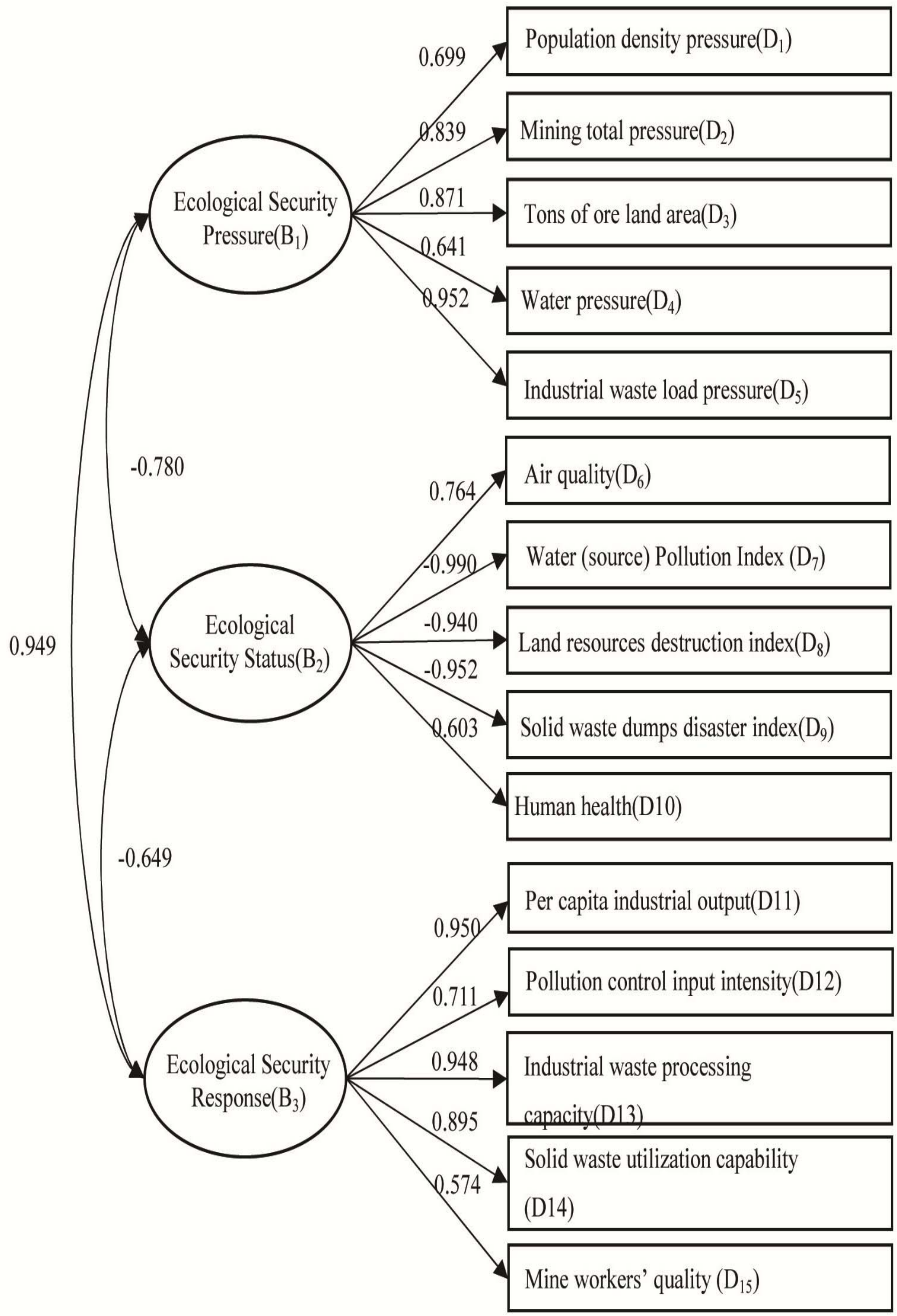

Figure 3. The standardized path coefficient of the model

The standardized path coefficient of the five observed variables of ecological security status (mining area air quality, water bodies (source) pollution index, land resources destruction index, solid waste dumps hazard index and human health index) are 0.764; -0.990; -0.940;0.952 and 0.603. This shows that water (source) pollution index is the best indicator of the ecological security status of coal mining areas. This is because water is most vulnerable to pollution.

Among the standardized path coefficients of the five ecological security responses (per capita industrial output, pollution control input intensity, industrial waste treatment capacity, solid waste utilization capacity and mine workers' quality) at values of 0.950; 0.711; 0.948; 0.895; 0.574 respectively. It is industrial waste processing capacity that provides the best ecological security response, because it directly determines the ability to reduce industrial waste pollution which has the largest impact on ecological security.

The correlation coefficient of pressure and status is 0.780. The correlation coefficient of pressure and response is 0.649, and the correlation coefficient of pressure and response is 0.949. In terms of their impact on the other two latent variables, pressure has the largest impact; Response has the second largest impact, and status the third. Arguably, it is because pressure is the first stage in ecological security maintenance. According to our findings above, pressure has a dominant role in its relation with status and response.

The correlation coefficient between pressure and response is the largest. This is because response is designated on the basis of pressure, the impact and the link between the two being the largest. Partly because ecological security response is ecologically safe and is designed pressure. Pressure is the root cause of the ecological impact of ecological security, ecological security and ecological security states only exons pressure, therefore, highly relevant. On the other hand is due to ecological security response by the people to implement, efficient, fast, short term, namely the implementation is complete, always ensure close contact between the two.

In summary, the evaluative index system of coal mine ecological security passes the test of structure equation model. The whole system has sound theoretical and statistical bases. It can comprehensively and objectively reflect the variables and their relationship and therefore has a good explanatory power.

8. Acknowledgements

This work is supported by Research Foundation of Humanities and Social Sciences of Ministry of Education of China No. 13YJC630065, by the Fundamental Research Founds for National University, China University of Geosciences (Wuhan) No. CUGW110201, by the open foundation of Research Center of Resources and Environmental Economy in CUG No. 2011B011and by the open foundation for Research Center for Digital Business Management.

References

[1] Meijing Net .(2014). http://www.nbd.com.cn/articles/2014-03-04/813974.html (2014-03-04)

[2] Lin Song .(2008). Principle of structural equation model and AMOS application. Wuhan: Huazhong Normal University Press.

[3] Wangji Chuan., Wang Xiaoqian., Jiang Baofa. (2011). Structural equation modeling: Methods and Applications. Beijing: Higher Education Press, 2011, 32-35.

[4] Zhu Zhen. (2009). Modern service enterprise e-ready impact on e-commerce capabilities: An Empirical Study of Enterprise Resource. *Information System Journal*, 3 (1), 34 - 47.

[5] HAU Kit-tai., Wen Zhonglin., Cheng Zijuan. (2004). Structural equation model and its application. Beijing: *Education Science Press*, 86-90.

[6] Rongtai Sheng. (2009). AMOS and research methods. Chongqing: Chongqing University Press, 32-35.

Author Biographies

Xiaoling, Ke. (1980), Ph.D., is an associate professor at the School of Economics and Management, China University of

Geosciences in China. Now she is a visiting scholar in USA. Her research interests are decisions under uncertainty and corporate sustainable development. In recent years, she began to pay attention to the sustainable development of resource-based enterprises. Some of her researches have been supported by government funding, such as Social Science and Humanities Funds of China Ministry of Education.