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Analysis

Effect of agricultural economic growth on sandy desertification in Horqin Sandy Land

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ABSTRACT

Using traditional methods, this paper gave assessment to the extent of sandy desertification and the changes of land use in eight counties in Horqin Sandy Land over the period 1980–2010. A coupling model was established on the base of general Environmental Kuznets Curve (EKC) model to better understand the roles of economic growth and other factors to sandy desertification in an integrated framework. To avoid the bias owing to the data discordance and the autocorrelation in time series data, Unit Root Test was applied and an ARDL model was established to improve the EKC model. The results showed that there was a positive linear correlation between the extremely severe sandy desertification per capita and the real agricultural GDP per capita in the short run, while there was a Kuznets Curve in the long run, showing the effect of economic growth as both the pressure on land and the capability to alleviate the risk of sandy desertification in different phases. The effect of economic growth on sandy desertification was greatly influenced by exogenous factors, including strategy factors, climatic factors and the extent of sandy desertification itself.

1. Introduction

As the definition given by the United Nations Convention to Combat Desertification (UNCCD), desertification refers to the land degradation in arid, semi-arid and dry sub-humid areas resulting from various factors including climatic variations and human activities (UNCCD, 2004). Because of the complexity of the mechanism of desertification, it is quite difficult to identify the exact role of specific variable in the context of the synergistic effect of various driving factors of desertification. In particular, the interaction between economic factors and desertification is still far from being fully understood. As the population increases steadily and the economy continues to grow, the earth's capacity of supporting human beings is diminished (Skonhoft and Solem, 2001). Many projects have been designed and implemented to better understand the roles of economic factors and to prevent the deterioration of ecological systems (Abdelgalil and Cohen, 2007). For instance, the project MEDALUS developed physically-based models to describe environmental processes and land use changes in different scenarios of socio economic development (European Commission, 2001b). Another example, the project DESERTLINKS searched for a common methodology with social-economic indicators for desertification monitoring and management (European Commission, 2001a). Different aspects of social-economic activities in various regions were discussed in these projects, like land use, water utility, grazing culture and etc. However, the interaction between specific economic factor and desertification remained unclear especially in temporal and spatial dimensions (Hillel and Rosenzweig, 2002; Mohamed, 2011; Sánchez-Arcilla et al., 2011; Salvati et al., 2013b; Sun et al., 2006).

Sandy desertification is the most severe issue among all types of desertification in Northern China where the fragility of the ecosystems is predetermined by inherently harsh physical conditions, such as sparse vegetation, continental climate, sandy soils and water deficiency (Chen and Tang, 2005; Wang et al., 2002, 2004, 2008). Under the special ecological conditions, grazing and cultivation are the traditional ways of agricultural production in Northern China, which provide the family income to meet the basic needs for the survival of local people (Démurger and Fournier, 2011). Because the ecological systems are vulnerable and the technologies for agricultural production are backward, many people are very poor in these regions (Fu and An, 2002; Jiang, 1999). The inner demand of increasing family income may lead to excessive human activities, resulting in the frequent rapid expansion of sandy desertification (Blazey, 2012; CCICCD, 2002; Ci and Yang, 2010; Démurger and Fournier, 2011; Huang et al., 2009; Liu, 2012; Sjögersten et al., 2013; Sun et al., 2006; UNCCD, 2004; Wang et al., 2008).

Obviously, economic growth is one of the most important anthropogenic driving factors of sandy desertification (Salvati et al., 2011; Skonhoft and Solem, 2001; Zilio and Recalde, 2011). For decades, researchers made efforts to explore the mechanism of sandy desertification with the economic driving factors, such as land use, etc. (Wang et al.,

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2002, 2006, 2008). Some researches claimed that sandy desertification was largely attributed to a range of agricultural production factors mainly, including over-grazing, over-reclamation, and extensive cutting (Hai et al., 2002, 2003; Yu-Zhu and Han-Min, 2007; Zhao et al., 2005). The reclamation would destruct the original ground vegetation and deteriorate the chemical or physical properties of soil. The grazing would destroy the vegetation coverage of grassland and destruct the soil's crust layer through livestock's crunching and trampling. The urgent demand for increasing family income would violently change the land cover in the desertified regions in Northern China.

However, as the driving mechanism of sandy desertification is so complex that it is very difficult to assess the relative role of specific factor under an independent condition, plenty of researchers would not accept the economic factors as main cause of sandy desertification. They claimed that historical records and archaeological evidence indicated sandy desertification in Northern China was likely influenced by climate change and geomorphological processes with specific trends in temperature, drought and wind regime (Hillel and Rosenzweig, 2002; Peters et al., 2012; Salvati et al., 2013a; Turkes, 1999; Wang et al., 2006; Yang et al., 2005; Zhu and Chen, 1994). The divergence of different disciplines lead to the long time dispute about the main cause of sandy desertification (Sun et al., 2006). The focus on this debate detracted much needed attention from studies of specific factor in the context of a combined effect of all kinds of factors (Ge et al., 2006; Wang et al., 2008).

Recently, the scientists realized that it was much more important to identify the roles of specific factors in a coupling context before comparing the contribution of different types of factors to sandy desertification (Wang et al., 2006, 2012; Xiaodong et al., 2013; Xu et al., 2011). To achieve this goal, coupling quantitative methods should be developed to combine the dynamics of ecological processes and the effect of economic growth (Wang et al., 2005, 2006; Xu et al., 2009, 2010). Statistic models, such as linear regression models and principal component analysis models, were frequently used in recent studies (Xu et al., 2011). For instance, Salvati et al. (2011) investigated the correlation between the vulnerability to land degradation and some socioeconomic indicators with regression models separately. These quantitative methods were widely questioned. Some researchers believed that the role of the driving factors should not be tested individually and separately (Bagliani et al., 2008; Saboori et al., 2012). They also believed that there could be inevitable biases in these models due to the dissonance of the different sources of data, especially when the spatial or temporal effect of the factors were considered (Khan and Khan, 2009; Wang et al., 2012; Xu et al., 2009, 2011).

The absence of coupling methods contributed to the confusion about the exact role of economic growth to sandy desertification. As Environmental Kuznets Curve (EKC) models were widely used to uncover the relationship between environmental degradation and economic growth (Agras and Chapman, 1999; Ahmed and Long, 2012; Bagliani et al., 2008; Grossman and Krueger, 1991, 1995; Stern, 2004), they might be used as references to improve the coupling methods in sandy desertification researches. As initially proposed by Simon Kuznets, the EKC concept was portrayed as an inverted U shaped relationship between income and income inequality (Ahmed and Long, 2012; Kuznets and Simon, 1995). This finding attracted global interest (Bulte and van Soest, 2001). Since the early 1990s, the EKC has been applied to a range of studies examining economic growth and environmental degradation (Bowman, 1997; Dinda, 2004; Farshad and Zinck, 1993; Glomm and Ravikumar, 1998; Grossman and Krueger, 1995; Stern et al., 1996; Zaki, 1997). In these EKC models, the quadratic item even cubic item of economic factor was included to better describe the non-linear change of the effect of economic factor (Cox et al., 2012; David, 2004; Stern et al., 1996). And also, several types of EKC models were developed to give specific explanation to the correlation between various variables, including square form model, cubic form model, logarithm form model and etc. (Bulte and van Soest, 2001; Dinda, 2001; John and Pecchenino, 1994; Kadekodi and Agarwal, 1999). Hence, EKC models could help to establish the coupling models for identifying the relative roles of economic growth to sandy desertification (Arrow et al., 1995).

Of course, the EKC models were criticized by many researchers. They claimed that many attempts failed to find an inversed-U shaped curve or other specific shaped curves (Choumert et al., 2013). The results in different cases could vary widely (Choumert et al., 2013; de Freitas and Kaneko, 2012; Yang et al., 2015). Too much enthusiasm was engaged in interpreting the existence or non-existence of the inversed-U shaped curve, while the real interaction between economic growth and environmental degradation was insufficiently explained. Furthermore, most of the EKC models were applied to the issues of pollution, and only a few of them were applied to the ecological issues (Ahmed and Long, 2012; Bagliani et al., 2008; Caviglia-Harris et al., 2009; Chiu, 2012; Culas, 2007; Damette and Delacote, 2012; Huang et al., 2009; Mills and Waite, 2009). In ecological issues, the interaction between different types of factors was more complex. The results of EKC models could still be biased owing to the existence of the autocorrelation in temporal or spatial dimension (Dinda, 2003; Ekins, 1998; Zang, 1998). For instance, current economic growth could be influenced by that in the last year, and local policy factors, climatic elements and geomorphological variables could be greatly influenced by those in neighboring regions. Further theoretical studies should be conducted to improve the EKC models to solve the problems (Dinda et al., 2000; Liu, 2012; Panayotou, 1997). To date, such attempt was seldom found in sandy desertification related researches (Rozelle et al., 1997).

It was much more important to give assessment on the exact role of economic growth on sandy desertification than to argue for the existence or non-existence of a specific shaped curve. A time series analysis would provide better framework to study the relationship between economic growth and sandy desertification. Autoregressive distributed lag (ARDL) model was regarded as a preferential technique for cointegration analysis in datasets with limited number of observations (de Freitas and Kaneko, 2012). It was first introduced by Pesaran and Shin (1999). Based on the general-to-specific modelling technique, the ARDL model took sufficient number of lags to capture the data generating process in a dynamic framework to avoid the bias of the autocorrelation (Kanjilal and Ghosh, 2014; Rushdi et al., 2012). It could provide both the short-run and the long-run information from a small sample collection.

This paper aims to analyze the interaction between sandy desertification and economic growth in Horqin Sandy Land in both the short run and the long run, in the context of synergistic effect of climatic variables and policy factors. Therefore, the main objectives of this paper are to (1) establish an integrated coupling model based on EKC model, incorporate the data of different sources into the same analysis framework, including economic indicators and ecological indicators; (2) extract ecological indicators from satellite images with traditional methods of sandy desertification assessment and land use analysis; and (3) improve the EKC model with Unit Root Test and *ARDL* techniques to eliminate the influence of the non-stationarity that is caused by time series data.

2. Method

2.1. Study area

Horqin Sandy Land (118°35′-123°30′E; 42°21′-45°15′N) is located in the east of Inner Mongolia of China, as shown in Fig. 1. As one of the four largest sandy lands in China, Horqin Sandy Land has an average annual precipitation of 360–500 mm which varies widely in spatial and temporal dimensions. It belongs to the agro-pastoral region in Northern China. Grazing and cultivation are the two main types of human activities in this region. Due to the fragile ecological system and improper management of natural resources, Horqin Sandy Land has been seriously desertified, particularly since over-grazing and over-cultivation occurred in different historical periods. To bring desertification under

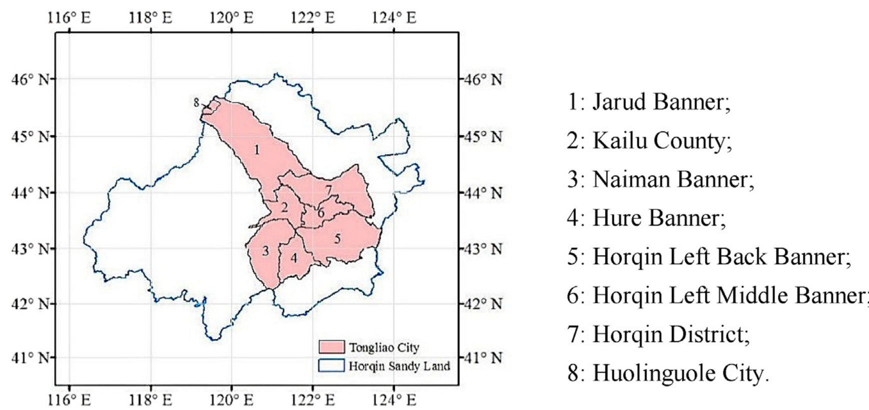

Fig. 1. The geo-location of the study areas.

control and reduce its influence on grasslands and farmlands, some ecological restoration projects are implemented in the area, including the 'Grain for Green Project', the 'Beijing and Tianjin Sandstorm Source Controlling Project', and the 'Three-North Shelterbelt Project'.

Tongliao city suffers the most severe sandy desertification and represents the key area of Horqin Sandy Land. It is centrally located in Horqin Sandy Land (119°15′–123°43′E, 42°15′ to 45°41′N). It covers an area of 59535 km^2 and consists of eight counties, including Huolinguole City, Jarud Banner, Kailu County, Tongliao City, Horqin Left Middle Banner (Horqin LM), Horqin Left Back Banner (Horqin LB), Hure Banner, and Naiman Banner. Sand-covered land is mainly distributed in the north-central and south-central regions of Tongliao, and partly in the northern regions. The main sand-covered land types include fixed and semifixed sand dunes which accounted for 35.7% and 33.4% of the entire sand dune area in Tongliao City, respectively. Agricultural activities in Tongliao play a vital role in the process of sandy desertification in the way of accelerating the soil exposure and the wind erosion.

2.2. Improved EKC model for Horqin Sandy Land

2.2.1. General model

Sandy desertification is caused by both climatic variables and human activities at different scales respectively. The human activities and climatic variables have synergistic effect on the change of the extent of sandy desertification. This paper develops an improved EKC model that consists of both variables, as shown in Eq. (1):

$$D = f\left(Y, Y^2, Z\right) \quad (1)$$

where D is the extent of sandy desertification, which is obtained with traditional method for sandy desertification assessment, Y is the indicator representing the real agricultural *GDP*, and Z represents all the other explanatory variables besides Y that play important roles in the process of sandy desertification, including climatic variables and ecological restoration instruments. The coefficient of item Y^2 reveals the changing trend of the correlation between Y and D. Taking the squared item of a variable into consideration would help to reveal the effect of the trend and the changing rate of the specific factor on sandy desertification.

Among all climatic variables which greatly influence the process of sandy desertification, precipitation, particularly annual precipitation, helps to improve vegetation cover and decrease sand transport, thereby significantly contributing to ecosystem rehabilitation. With low precipitation, surface vegetation becomes sparse and the proportion of surface soil being turned into sandy soil becomes relatively large. Therefore, the indicator of the precipitation A_t is included in the model as an explanatory variable to represent the function of the climatic variables.

Ecological restoration instruments also change land cover, greatly influencing the process of sandy desertification. As a result of the implementation of the various ecological restoration projects, vegetative cover and the area of woodland has achieved some improvement. Here, we use the area of woodland, W_t, in the model to represent the impact of the ecological restoration instruments as another explanatory variable.

Specially, the logarithmic form of the equation helps to avoid the disturbance of the unit of different variables. The expanded EKC model for Horqin Sandy Land is proposed as Eq. (2):

$$\ln(D_t) = \alpha_0 + \alpha_1 \ln(aGDP_t) + \alpha_2[\ln(aGDP_t)]^2 + \alpha_4 \ln(W_t) + \alpha_5 \ln(A_t) + \varepsilon_t \quad (2)$$

where t is the time period, D_t is the per capita area of desertified land, which represents the extent of sandy desertification, $aGDP_t$ is the per capita real agricultural GDP, W_t is the per capita area of wood land, which represents the intensity of ecological restoration projects, A_t is the annual precipitation, and ε_t is the standard error term. The values of the coefficients (α_i) indicate the different roles of various explanatory variables to the extent of sandy desertification.

2.2.2. Indicator for the extent of sandy desertification D_t

Classification of remote sensing images is a traditional way for assessing the extent of sandy desertification and computing the area of sandy desertified lands. Generally, sandy desertification is classified into four types: slight, medium, severe, and extremely severe. According to standard definitions, sandy desertification is highly related to vegetation cover. Thus, two indicators of Geomorphological Features – the Proportion of Bare Sand Land and Vegetation Coverage – are used to represent the degree of sandy desertification at a specific time, as shown in Table 1.

Geomorphological features are quite important for identifying the characteristics of any land use type using Landsat images. Sand land has usually been divided into two types — fixed sand dune and semi-fixed sand. Semi-fixed dune was sand dunes with less than 30% of vegetative cover, while fixed sand dune was those with more than 30% vegetative cover. Field investigation helps verify Geomorphological features.

The indicator of the Proportion of Bare Sand Land is helpful for reflecting extreme land degradation. Most sandy desertification assessment research use the proportion of bare sand land for quantifying the status of land cover. Generally, a region is considered to be severely desertified when the proportion of bare sand land is over 50%, while it is considered to be slightly desertified when the proportion of bare sand land is below 5%.

The Vegetation Coverage Index (*FVC*) is also helpful for reflecting the status of land cover in the context of the entire ecosystem. To

Table 1
The criteria for sandy desertification classification in northern China.

Classification	Geo-morphological features	Proportion of bare sandy land (%)	Vegetation coverage (%)
Extremely severe	Continuous mobile sand-dune matrix	>50	0–10
Severe	Mobile sand-dune matrix interspersed with fixed and semi-fixed sand dunes	25–50	10–30
Medium	Shifting sand patch or dense shrub or bush-mound everywhere, obvious surface	5–25	30–60
Slight	Spotted shifting sand points or deflation points	<5	>60

calculate the Vegetation Coverage Index, *NDVI* is previously calculated as Eq. (3):

$$NDVI = (\rho_{nir} - \rho_{red})/(\rho_{nir} + \rho_{red}) \tag{3}$$

where *NDVI* stands for the Normalized Difference Vegetation Index, which can be used to assess whether the target being observed contains live green vegetation or not, ρ_{red} and ρ_{nir} stand for the spectral reflectance measurements acquired in the visible (red) and near-infrared regions, respectively, which are identified from the satellite images. *NDVI* portrays the dominant plant reflectance at any spot on the land surface with the contrast of acquired data in visible and near-infrared spectral regions. Higher *NDVI* means more plant reflectance. Based on the *NDVI*, the Vegetation Coverage Index at any spot on the land surface can be calculated as Eq. (4):

$$FVC = (NDVI - NDVI_{\min})/(NDVI_{\max} - NDVI_{\min}) \tag{4}$$

where *FVC* is the Vegetation Coverage Index, and $NDVI_{\max}$ and $NDVI_{\min}$ are the maximum and minimum *NDVI* values of the given region, respectively.

2.2.3. Indicator for the intensity of ecological restoration Instruments W_t

The ecological restoration instruments have obvious influence on vegetative cover, especially for woodland. The area of woodland (W_t) is used to reflect the implementation of ecological restoration projects. Remote sensing methodologies are used to compile satellite images and extract the indicator of area of different land use types. Radiometric calibration, geometric correction, and cloud removal are conducted for all of these images. All images are georeferenced to the WGS_1984UTM Projected Coordinate System with a geometric precision of 0.5 pixels. Then, geometrical corrections and classifications are made. Seven land use types are identified including irrigated cultivated land, dry farmland, woodland, grassland, resident land, surface water, and bare sand land.

2.3. Data processing

2.3.1. Data sources

Satellite remote sensing data are used as the basic data for computing the area of bare sand land and area of woodland. US Landsat MSS images with a spatial resolution of 80 by 80 m, and TM/ETM images with a spatial resolution of 30 m by 30 m, are used in this paper. The Landsat satellite images are taken in 1978, 1985, 1990, 1995, 2000, 2005 and 2010, respectively. All spectral data are collected in summer, mainly in July or August. A total of 77 scenes of images are processed, with 11 scenes for each year respectively, as shown in Table 2. Agricultural GDP and population data are drawn from statistical year books. The data of the precipitation are obtained from the China Meteorological Data Sharing Service System.

2.3.2. Data interpolation

Because of the difficulties of data acquisition and processing, data for D_t and W_t are not temporally continuous. Traditionally, the skill of data interpolation will be used to better interpret the trend of the variables in temporal dimension, as shown in Eq. (5):

$$f(t) = f(t_1) + (f(t_2) - f(t_1))(t_2 - t_1)/(t_2 - t_1) \tag{5}$$

where t_1 and t_2 are the time periods, t refers to a given year between t_1 and t_2, $f(t)$ is the indicator being extracted from satellite images of year t, such as per capita area of desertified land D_t, and the per capita area of wood land W_t.

2.3.3. Model validation

When estimating the relationship between sandy desertification and its causes, it is important to produce unbiased, consistent estimates. However, some variables could be time dependent. In this situation, Eq. (2) could not reveal the real correlation between the independent variables and dependent variable. Some extended analysis should be added to the model.

Unit root test is firstly implemented to test for the order of the variables, in order to identify whether the variables are stationary or not. The Augmented Dickey Fuller (ADF) test is used for all the variables, as Eqs. (6)–(8):

$$\Delta h_t = \theta h_{t-1} + \sum_{i=1}^{m} \varphi_i \Delta h_{t-1} + \varepsilon_t \tag{6}$$

$$\Delta h_t = \xi + \theta h_{t-1} + \sum_{i=1}^{m} \varphi_i \Delta h_{t-i} + \varepsilon_t \tag{7}$$

$$\Delta h_t = \xi + \varphi_t + \theta h_{t-1} + \sum_{i=1}^{m} \varphi_i \Delta h_{t-i} + \varepsilon_t. \tag{8}$$

Where h is the tested variable, t is the time period. This article tests the null hypothesis of $\theta = 0$, which represents the existence of a unit root and indicates that the time series data of h is non-stationary. The test procedure is from Eqs. (8) to (6). It stops when the hypothesis is rejected by any of the three models, or it finishes after Eq. (6) is tested. The t statistics of estimated parameter θ is calculated and compared to critical values to decide whether to accept the null hypothesis. If the t statistics is lower than the critical value of τ distribution, then the null hypothesis of non-stationarity can be rejected, but if it is greater than the critical value of τ distribution, then the null hypothesis is accepted.

Table 2
The satellite remote sensing data being used in this paper.

Year	Type	WRS	Path/row
1978	Landsat MSS	WRS1	128/30, 129/29, 129/30, 129/31, 130/29, 130/30, 130/31, 131/28, 131/29, 132/28, 132/29
1985/1990/1995/ 2000/2005/2010	Landsat TM/ETM	WRS2	119/30, 120/29, 120/30, 120/31, 121/29, 121/30, 121/31, 122/28, 122/29, 123/28, 123/29

When variables are time dependent, an autoregressive distributed lag model (ARDL) is established to reduce the influence of time-dependency and to test for the long-run equilibrium relationship among the time series data, as Eq. (9):

$$\begin{aligned}\Delta \ln D_t = \beta_0 &+ \sum_{s=1}^{p}\beta_{1s}\Delta \ln D_{t-s} + \sum_{s=1}^{p}\beta_{2s}\Delta \ln(aGDP_{t-s}) + \sum_{s=1}^{p}\beta_{3s}\Delta[\ln(AGDP_{t-s})]^2 \\ &+ \sum_{s=1}^{p}\beta_{4s}\Delta \ln W_{t-s} + \sum_{s=1}^{p}\beta_{5s}\Delta \ln A_{t-s} + \lambda_1 \ln D_{t-1} + \lambda_2 \ln(GDP_{t-1}) \\ &+ \lambda_3[\ln(GDP_{t-1})]^2 + \lambda_4 \ln W_{t-1} + \lambda_5 \ln A_{t-1} + U_t \end{aligned} \tag{9}$$

where β_0 is drift component, U_t is the white noise, and p is the lag length of independent variables. The terms with summation signs represent the error correction dynamics. The terms with coefficients of λ_i correspond to the long-run relationship.

To analyze with the ARDL model, the first step is to test the null hypothesis, H_0: $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = 0$. If the null hypothesis is accepted, there is no long-run relationship between the independent variables and dependent variable, which means non-existence of co-integration. If the null hypothesis is rejected, the alternative hypothesis is accepted, H_1: $\lambda_1 \neq 0$, $\lambda_2 \neq 0$, $\lambda_3 \neq 0$, $\lambda_4 \neq 0$, $\lambda_5 \neq 0$, which means the existence of long-run relationship exists between the independent variables and dependent variable.

F test is conducted to test the existing of long-run relationship among the variables. The *F* statistics are compared to the critical values which are provided by Pesaran et al. (Pesaran and Pesaran, 1997; Pesaran et al., 2001). If the calculated *F* value is greater than the upper bound of critical values, null hypothesis will be rejected. On the contrary, if the calculated *F* value is below the lower bound of critical values, the null hypothesis can be accepted. However, when the *F* value falls in between the two bounds of critical values, the test is inconclusive.

When applying *F* test to the model of Eq. (9), it is quite important to decide the lag length *p* in advance. Schawrtz–Bayesian criteria (SBC) and Akaike's information criteria (AIC) are used to choose the optimal lag length for each variable. The SBC is used to select the smallest possible lag length. The AIC is used to select the maximum relevant lag length. After the selection of the ARDL model by AIC and SBC criterions, the long-run relationship among variables can be estimated. The error correction model (ECM) is estimated as Eq. (10).

$$\begin{aligned}\Delta \ln D_t = \beta_0 &+ \sum_{s=1}^{p}\beta_{1s}\Delta \ln D_{t-s} + \sum_{s=1}^{p}\beta_{2s}\Delta \ln(aGDP_{t-s}) + \sum_{s=1}^{p}\beta_{3s}\Delta[\ln(aGDP_{t-s})]^2 \\ &+ \sum_{s=1}^{p}\beta_{4s}\Delta \ln W_{t-s} + \sum_{s=1}^{p}\beta_{5s}\Delta \ln A_{t-s} + \theta \cdot \mathrm{ECM}_{t-1} + U_t \end{aligned} \tag{10}$$

where ECM_{t-1} is the error correction term, which indicates the speed of the adjustment and shows how quickly the variables return to the long-run equilibrium.

3. Results and analysis

3.1. The extent of sandy desertified D_t

The area of extremely severe sandy desertified land in Tongliao City was shown in Table 3. The results indicated that sandy desertification expanded during the period 1980 to 1995. Then, sandy desertification rapidly reversed after 1995. In 2010, the sandy desertification in Tongliao City was greatly reversed. In spatial dimension, different counties suffered different extent of severe sandy desertification, while in most counties sandy desertification expanded before 1990 and reversed after 1990. Naiman Banner and Horqin Left Back Banner, which were located in the south of Tongliao City, suffered more from severe sandy desertification, while Huolinguole Banner suffered the least, which had the least total area and was located in the north of Tongliao City. Fig. 2 showed the results of sandy desertification assessment.

Table 3
The area of extremely severe sandy desertification in Tongliao City (km^2).

Banner	1980	1985	1990	1995	2000	2005	2010
Huolinguole	54.4	45.5	62.4	375.7	295.5	140.3	20.0
Kailu	232.8	267.0	268.8	277.6	35.8	28.3	18.1
Horqin D	215.4	242.5	259.6	198.0	15.1	10.4	9.6
Horqin LB	984.4	1097.2	1264.4	1365.8	620.7	519.2	354.7
Horqin LM	299.3	546.7	685.1	655.4	544.1	420.7	206.1
Hure	606.5	635.1	792.0	780.2	475.9	364.1	182.0
Naiman	995.0	1227.7	1190.0	767.8	867.5	621.9	337.7
Jalud	663.2	809.8	818.0	574.8	231.8	203.9	116.8

Table 4 showed the area of extremely severe sandy desertification per capita in Tongliao City. The area of extremely severe sandy desertified land per capita varied in spatial dimension, so that Local people faced different extent of sandy desertification individually in different counties. Huolinguole Banner suffered the biggest area of severe sandy desertification per capita among all counties, although it had the least area of severe sandy desertification in total. So, people faced heavier extent of sandy desertification individually in Huolinguole Banner than people in other counties. Horqin District suffered the least area of extremely severe sandy desertified land per capita.

In temporal dimension, the area of extremely severe sandy desertified land per capita presented a trend of increasing since 1980, but it decreased after 1990, 1995 or 2000 in different counties respectively. For instance, the area of extremely severe sandy desertified land per capita increased in Huolinguole from 302.2×10^{-4} km^2 in 1980 to 459.1×10^{-4} km^2 in 1995, and it decreased to 114.7×10^{-4} km^2 in 2010.

3.2. The area of woodland W_t

In most counties, the area of woodland per capita increased obviously from 1980 to 2010, as shown in Table 5. For instance, it increased from 390.0×10^{-4} km^2 to 437.2×10^{-4} km^2 in Jalud Banner, while it increased from 37.4×10^{-4} km^2 to 46.0×10^{-4} km^2 in Horqin Left Middle Banner. Among all counties, it increased by 50% in Huolinguole and Horqin Left Back Banner, while it decreased by less than 12% and 5% in Kailu and Horqin District respectively. The implementation of ecological restoration strategies obviously increased the vegetation cover in Horqin sandy Land during the period from 1980 to 2010.

In spatial dimension, the area of woodland per capita varied much between the counties. Jalud had the biggest area of woodland per capita, while Horqin District had the least.

3.3. The results of ADF test

After the data interpolation, the time series of D_t and W_t of all counties were obtained. To avoid the problem of spurious regression, the variables with time series data were tested with *ADF* method, as shown in Table 6, in which k was the degree of augmentation that was automatically determined by the *ADF* test. The variables $\ln(D_t)$, $\ln(aGDP)$, $(\ln(aGDP))^2$ and $\ln(W_t)$ were non-stationary ($k > 0$). The order of integration were one for $\ln(D_t)$, $\ln(aGDP)$, $(\ln(aGDP))^2$ and $\ln(W_t)$, so that these variables were $I(1)$. The variable $\ln(A_t)$ was stationary ($k = 0$), so that $\ln(A_t)$ was $I(0)$. Most of the results could be accepted at a significance of 5%.

The results of unit root test suggested that k is not greater than one for any variable at any county, indicating that none of the variables was $I(2)$ or beyond. *ADRL* techniques could be employed to test the existence of the long-run equilibrium relationship – co-integration – among the time series variables.

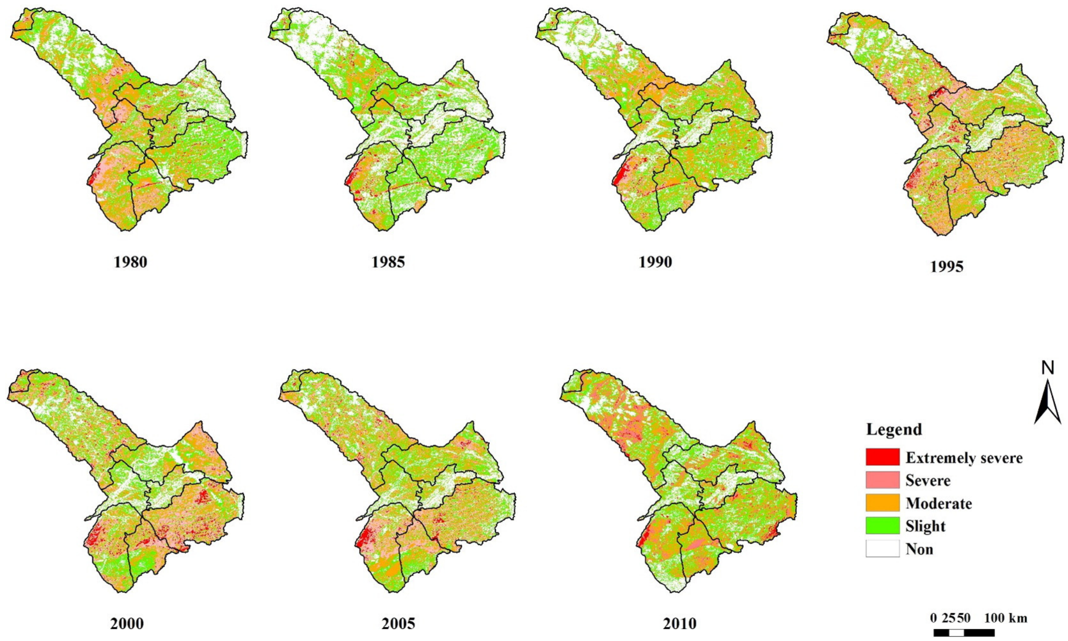

Fig. 2. Status of sandy desertified land in Tongliao City from 1980 to 2010.

Table 4
The area of Extremely Severe sandy desertification per capita in Tongliao (1×10^{-4} km^2).

Banner	1980	1985	1990	1995	2000	2005	2010
Huolinguole	302.2	285.7	331.1	459.1	392.5	255.1	114.7
Kailu	25.3	27.3	26.1	23.6	2.6	1.6	1.0
Horqin D	18.5	18.9	18.3	13.2	0.9	0.5	0.4
Horqin LB	152.2	153.4	170.9	184.8	73.0	40.8	23.3
Horqin LM	36.0	61.1	71.3	61.3	44.4	21.0	8.8
Hure	172.0	165.8	193.6	180.2	91.0	50.9	22.4
Naiman	95.3	108.7	99.2	56.9	65.9	38.0	16.2
Jalud	139.9	153.7	140.1	82.1	24.4	18.3	9.4

3.4. The results of ARDL models

It was necessary to decide the optimal lag length for each variable in the ARDL model as Eq. (9). The Schawrtz–Bayesian Criteria (SBC) and Akaike's Information Criteria (AIC) were used to select the optimum lag length p of the ARDL model over the sample period 1980–2010. Different values of p ($p = 0, 1, 2$ and 3) were tested and the AIC values and SBC values were calculated according to the estimated ARDL with different lag length respectively, as shown in Table 7. In most counties, the AIC values and SBC values were the least when $p = 1$. The results suggested that the lag length of $p = 1$ was optimal for the ARDL model. Since the variable $\ln(A_t)$ was $I(0)$, the corresponding lag item of $\ln(A_t)$ would not be included in the ARDL model.

Table 5
The area of woodland per capita in Tongliao (1×10^{-4} km^2).

Banner	1980	1985	1990	1995	2000	2005	2010
Huolinguole	103.1	112.0	138.9	145.3	146.7	160.6	176.4
Kailu	69.9	72.4	76.4	67.5	67.7	61.3	62.0
Horqin D	29.4	29.5	33.5	32.0	30.4	27.4	28.1
Horqin LB	171.7	170.8	198.1	218.2	246.3	259.7	280.4
Horqin LM	37.4	36.0	37.3	39.6	42.1	44.8	46.0
Hure	199.2	203.2	211.4	219.7	223.6	235.8	238.7
Naiman	57.0	65.7	60.7	63.4	65.7	68.9	70.2
Jalud	390.0	374.2	383.5	407.1	421.7	430.6	437.2

The ARDL model was established as Eq. (11):

$$\begin{aligned}\Delta \ln D_t = \beta_0 + \beta_1 \Delta \ln D_{t-1} + \beta_2 \Delta \ln(aGDP_{t-1}) + \beta_3 \Delta[\ln(aGDP_{t-1})]^2 + \beta_4 \Delta \ln W_{t-1} \\ + \lambda_1 \ln D_{t-1} + \lambda_2 \ln(GDP_{t-1}) + \lambda_3 [\ln(GDP_{t-1})]^2 + \lambda_4 \ln W_{t-1} + \lambda_5 \ln A_{t-1} + U_t\end{aligned} \tag{11}$$

Based on Eq. (11), the coefficients were estimated for all the counties respectively. F statistics were calculated for the existence of long-run relationship among variables, as shown in Table 8.

Suggested by Pesaran et al. (2001), the critical value pairs were [3.74, 5.06] at the 1% level of significance, [2.86, 4.01] at the 5% level of significance and [2.45, 3.52] at the 10% level of significance respectively. The F statistics of most counties were beyond the upper bound of critical values at different significant level respectively, except Huolinguole Banner. It implied that the null hypothesis of no co-integration could be rejected for most counties except Huolinguole Banner. For most counties, there was a long term relationship between the dependent variable and the independent variables. For Huolinguole Banner, the F statistics was below the lower bound of the critical values. The null hypothesis of no cointegration was accepted. That is, there were no long run relationships between the dependent variable and the independent variables for Huolinguole Banner.

For the counties except Huolinguole Banner, the coefficients of λ_1, λ_2, λ_3, λ_4 and λ_5 were estimated, indicating the long run relationships between the dependent variable and the independent variables, as shown in Table 9.

For most counties, the lag item of $\ln(D_t)$ had great influence on $\ln(D_t)$ in the long run. The coefficients of $\ln D_{t-1}$, denoted as λ_1, were at 1% significance level for Kailu Banner and Hure Banner, at 5% significance level for Horqin Left Back Banner, and at 10% significance level for Horqin Distric, Naiman Banner and Jarud Banner. Most of the λ_1 values were positive. It implied that the area of severe sandy desertification was significantly auto-related at temporal dimension.

$\ln(W_{t-1})$ was negatively related to $\ln(D_t)$ for most counties. The coefficients of $\ln(W_{t-1})$, denoted as λ_4, were negatively for all counties except Jarud Banner. And most of the coefficients of λ_4 were at significance levels of 1%, 5% and 10%, respectively. It implied that the area of wood land per capita had important influence on the area of severe sandy desertification per capita in the long run as well. The increasing

Table 6
The results of the unit root test.

Counties	$\ln(D_t)$		$\ln(aGDP)$		$[\ln(aGDP)]^2$		$\ln(W_t)$		$\ln(A_t)$	
	ADF	*k*	*ADF*	*k*	*ADF*	*k*	*ADF*	*k*	*ADF*	*k*
Huolinguole	−4.78**	0	−6.88**	0	−6.92***	0	−6.34***	1	−5.90***	0
Kailu	−6.60***	1	−3.57**	0	−8.27***	0	−3.23**	0	−5.04**	0
Horqin DC	−3.79**	1	−5.56**	1	−5.77**	1	−5.67**	0	−5.34**	0
Horqin LB	−3.50**	1	−2.66*	0	−2.67**	0	−5.24***	1	−3.37**	0
Horqin LM	−1.99*	1	−3.03**	0	−3.00**	0	−3.92**	1	−4.89**	0
Hure	−10.00***	1	−6.93***	1	−6.64***	1	−5.93***	1	−2.63**	0
Naiman	−6.35**	1	−4.36**	0	−4.32**	0	−6.60***	1	−3.64**	0
Jalud	−1.67*	0	−4.58**	0	−4.46**	0	−1.81*	1	−5.69***	0

* Represents 10% level of significance.
** Represents 5% level of significance.
*** Represents 1% level of significance.

Table 7
The AIC and SBC results for the lag length of ADRL model.

Counties	$p = 0$		$p = 1$		$p = 2$		$p = 3$	
	AIC	SBC	AIC	SBC	AIC	SBC	AIC	SBC
Huolinguole	−100.3	−91.6	−102.2	−93.7	−94.3	−75.2	−90.5	−68.8
Kailu	−86.5	−77.8	−87.7	−81.2	−86.5	−67.3	−82.2	−60.5
Horqin DC	−83.6	−74.9	−94.4	−77.9	−89.0	−69.9	−85.9	−64.1
Horqin LB	−107.5	−98.9	−116.4	−99.8	−129.4	−110.2	−129.0	−107.3
Horqin LM	−88.4	−79.7	−96.6	−80.1	−114.3	−95.2	−111.2	−89.5
Hure	−113.5	−104.8	−110.6	−94.1	−113.0	−93.9	−117.4	−95.7
Naiman	−122.5	−113.8	−126.4	−119.9	−112.6	−93.5	−123.3	−101.5
Jalud	−130.0	−121.3	−134.6	−121.1	−131.8	−112.7	−150.5	−128.8

Table 8
The *F* statistics for the ARDL models of all counties.

	Huolinguole	Kailu	Horqin D	Horqin LB	Horqin LM	Hure	Naiman	Jarud
F Statistics	2.52	4.45	4.08	4.01	5.77	3.90	3.98	6.04

of woodland could play an important role in the sandy desertification reversion.

The coefficients of $\ln(A_{t-1})$, denoted as λ_5, were negative for most counties, indicating that the severe sandy desertification was negatively related to precipitation. The results coincided with the fact that when precipitation increased, vegetative cover increased and sandy desertification reversed. However, the coefficients of $\ln(A_{t-1})$ were not significant, suggesting precipitation had less influence on sandy desertification than other factors in temporal dimension during the 1980 to 2010 period.

The real agricultural GDP also had significant influence on severe sandy desertification. The coefficients of $[\ln(aGDP)]^2$, denoted as λ_3, of three banners, including Kailu County, Naiman Banner, and Jarud Banner, were at a significance level of 5%, while that of another three banners, including Horqin District, Horqin Left Back Banner and Naiman Banner, were at a significance level of 10%. Most of the λ_3 values were negative, indicating the existence of an inversed-U shape relationship between the area of severe sandy desertification per capita and real agricultural GDP per capita for these banners in the long run. For Horqin Left Middle Banner, the λ_3 value was not significant, while the coefficient of $\ln(aGDP)$ were at significance level of 1%.

Based on the ARDL model as Eq. (11), the error correction model was formulated as Eq. (12). ECM was the error correction term that was calculated according to Eq. (11). The coefficients in Eq. (12) were estimated as shown in Table 10.

$$\Delta \ln D_t = \beta'_0 + \beta'_1 \Delta \ln D_{t-1} + \beta'_2 \Delta \ln(aGDP_{t-1}) + \beta'_3 \Delta[\ln(aGDP_{t-1})]^2 + \beta'_4 \Delta \ln W_{t-1} + \theta \cdot \mathrm{ECM}_{t-1} + U_t \tag{12}$$

For the short term relationship between the dependent variable and independent variables, it was evident that $\Delta\ln(D_t)$ was significantly related to $\Delta\ln(D_{t-1})$, $\Delta\ln(aGDP_{t-1})$ and $\Delta\ln(W_{t-1})$, while the coefficients of $\Delta[\ln(aGDP_t)]^2$ were insignificant. Most of the coefficients of $\Delta\ln(D_{t-1})$, which was denoted as β'_1, were positive, indicating that in most counties the change of the sandy desertification of previous time could have positive impact on the area of sandy desertification in current time. The trend of the sandy desertification changes would be partially maintained at least at the next time period.

Most of the coefficients of $\Delta\ln(aGDP_{t-1})$, which was denoted as β'_2, were positive, indicating the increasing in real agricultural GDP per capita of the previous year would influence the change of the area of

Table 9
Long-run estimates of the ADRL models.

Counties	λ_1	λ_2	λ_3	λ_4	λ_5	R^2	*D.W.*
Kailu	0.77***	2.30**	−0.08**	−0.86**	−0.09	0.57	5.26
Horqin D	0.62*	−11.11	−0.17*	−1.07*	−0.11	0.34	3.42
Horqin LB	−0.02	−0.29*	−0.14*	−0.21***	−0.77**	0.62	2.09
Horqin LM	0.03**	−5.50*	0.11	−2.02**	−0.06	0.62	1.95
Hure	0.26***	8.90	−0.01**	−0.34***	−0.66*	0.83	2.61
Naiman	0.11*	−0.26*	−0.09**	−1.11**	0.02	0.44	1.78
Jarud	0.18*	−2.09	−0.01*	0.15	0.08	0.60	0.52

* Represents 10% level of significance.
** Represents 5% level of significance.
*** Represents 1% level of significance.

Table 10
The result of error correction of extremely severe desertified area.

Counties	β'_0	β'_1	β'_2	β'_3	β'_4	θ	F	R^2
Kailu	0.28**	0.02*	0.31*	−0.83	−0.16	0.01	3.90	0.35
Horqin DC	0.49	0.17**	0.29	0.06	−0.09	−0.02*	0.67	0.17
Horqin LB	−0.01	0.27***	0.08**	−0.65	−0.87***	−0.10*	4.14	0.41
Horqin LM	0.17***	0.05**	−0.17*	−0.16	0.01*	0.22*	5.91	0.69
Hure	−0.76*	0.01*	0.42*	−0.02	−0.06**	−0.02**	4.10	0.31
Naiman	0.16**	−0.02***	0.08*	−0.02	−0.02*	−0.01*	5.11	0.51
Jarud	0.28**	0.02***	0.31	−0.83	−0.17***	0.01	3.90	0.35

$ECM_t = \ln(D_t) - \lambda_1 \ln(D_{t-1}) - \lambda_2 \ln(aGDP_t) - \lambda_3 [\ln(aGDP_t)]^2 - \lambda_4 \ln(W_t) - \lambda_5 \ln(A_t) - \beta_0$.
* Represents 10% level of significance.
** Represents 5% level of significance.
*** Represents 1% level of significance.

severe sandy desertification. Compared to $\Delta[\ln(aGDP_t)]^2$, $\Delta\ln(aGDP_{t-1})$ had more influenced on $\Delta\ln(D_t)$ in the short run. The positive coefficients showed that the increasing of real agricultural GDP in the previous year would hasten the land intensity and increase the risk of sandy desertification expanding in current year.

The change of the area of woodland in previous time would also influence the change of sandy desertification in current time. $\Delta\ln(D_t)$ was negatively related to $\Delta\ln(W_{t-1})$ for most counties. It implied that the increasing of woodland played similar role to the process of sandy desertification in the long run and in the short run.

The coefficients of error correction term ECM_{t-1} were significant. The values were around 0.01–0.02 in most counties. Based on the definition of error correction term, it implied that around 1%–2% of the disequilibria in the area of sandy desertification per capita in previous year's shock adjust back to the long run equilibrium in current year.

4. Discussion

4.1. Effect of economic growth on sandy desertification

Sandy desertification in Northern China is a typical issue of the conflicts between poverty and limited ecological carrying capacity. For a long time, poor people have inhabited the severely desertified regions in Northern China. They have less access to modern knowledge and information and live on traditional grazing and cultivation which are tied to natural resource utility. To meet basic needs of food, water, shelter, energy, sanitation and education, poor farmers have to intensify production with labor-led strategies, resulting in the misuse and overuse of natural resources. For instance, the original ground vegetation may be destructed and the chemical or physical properties of soil may be deteriorated, while poor people increase their family income through the investments on cultivation and grazing. And, poor farmers can't afford the investments of the long-term ecological conservation, so that the conflicts between increasing intensity of resource utility and limited ecological carrying capacity may lead to the risk of environmental degradation and sandy desertification. There is a consensus that that over-cultivation, over-grazing, and over-chopping are the main anthropogenic causes of sandy desertification in Northern China.

The results of the correlation between economic growth and sandy desertification in the short run supported this point of view. Since 1980, the real agricultural GDP per capita increased rapidly in all counties, indicating that the demand of yields and also the burden of lands increased during this period. For most counties, the coefficients of $[\ln(aGDP_t)]^2$ were insignificant and the coefficients of $\ln(aGDP_t)$ were positive. It implied that the dependence of economic growth on natural resources accelerated the loss of ecosystem services. The pressures of economic growth drove the land cover to change immediately. Agricultural economic growth had positive role to sandy desertification expansion in the short run.

However, the effect of economic growth was far more beyond the short-term pressures on land. In the long run, the coefficients of $[\ln(aGDP_t)]^2$ were negative and significant for six counties, indicating the existence of an inversed-U shape correlation between the area of extremely severe sandy desertification per capita and the real agricultural GDP per capita. The results implied that the roles of economic growth were different in various phases. At the first phase, the expansion of sandy desertification was accelerated by economic growth, while the expansion of sandy desertification slowed down and the process of sandy desertification was reversed at the second phase. The maximum value of the dependent variable occurred in 1980 for Kailu Banner, Horqin District and Horqin Left Back Banner, and in 1985 for Horqin Left Middle Banner, Kulun Banner, Naiman Banner and Jarud Banner. It implied that all the counties were mainly in the second stage of the Kuznets curve during the period 1980–2010. The corresponding real agricultural GDP per capita were 1017.5, 992.4, 785.5, 1010.1, 1000.6, 841.1 and 996.1 for Kailu Banner, Horqin District, Horqin Left Back Banner, Horqin Left Middle Banner, Kulun Banner, Naiman Banner and Jarud Banner respectively.

The results showed that economic growth had more complicated influence on sandy desertification in Horqin Sandy Land in the long run. With economic growth, local people had more family income, which encouraged the incentives of the investment on ecological conservation and provided more opportunities to the technique improvement in agriculture sector. Hence, economic growth also had the inner incentives to decrease the risk of sandy desertification. In the first phase with lower GDP, economic growth still mainly presented the pressures on ecosystems and incentives to the sandy desertification expansion. In the second phase with higher GDP, economic growth mainly helped to alleviate the risk of sandy desertification. The interaction between the different roles of economic growth resulted in the non-linear integrated effect on sandy desertification.

The effect of economic growth on sandy desertification was similar in difference counties. In the short run, the expansion of sandy desertification in most counties was directly accelerated by economic growth, while in the long run an inversed U shape correlation existed between sandy desertification and economic growth. The turning points of the inversed U shaped curve were similar among different counties in Horqin Sandy Land.

4.2. The impact of other factors to the effect of economic growth

Natural factors and social–economic factors synergistically influenced the process of sandy desertification. The roles of other factors were the external conditions for the effect of economic growth. Since water resource was highly scarce in Horqin Sandy Land, the precipitation contributed remarkably to vegetation cover. It was easier for the land to be exposed and eroded by wind when the precipitation was lower and the vegetation cover was sparser. During the period 1980–2010, the annual precipitation in Horqin Sandy Land varied greatly, while the five-year moving average of the precipitation decreased obviously from 1980 to 1990 and increased slightly after 2000. The results of ARDL model showed that the annual precipitation was negatively related to the area of extremely severe sandy desertification per capita in the long run. It implied that the increase of precipitation helped to decrease the risk of sandy desertification. In the first phase, the precipitation showed a trend of decreasing, so that the climatic conditions were conductive to the expansion of sandy desertification and the pressures of economic growth were obviously enhanced. In the second phase, the precipitation showed a trend of slightly increase and the climatic conditions were conductive to the reversion of sandy desertification, so that the effect of economic growth for sandy desertification alleviation was enhanced. In the short run, the effect of the precipitation was insignificant, indicating that immediate change of land cover resulting from economic growth was less influenced by the precipitation.

The implementation of ecological recovery strategies was a highly effective driving factor of sandy desertification in Horqin Sandy Land over this period. Suffering from a major source of sandstorms in Northern China, Chinese government pushed forward a series of eco-friendly strategies to protect the environment and create opportunities for the sandy desertification reversion since 1980s. With the implementation of these strategies, the area of woodland increased steadily in all the counties. Since the vegetation cover increased and different types of sandy dunes were obviously improved, the implementation of the ecological strategies provided the conditions for ecological restoration and relatively alleviated the pressures of economic growth. The results of ARDL model showed that the area of woodland per capita was negatively related to the area of extremely server sandy desertification per capita, indicating that it was an important driving factor for the reversion of sandy desertification. The implementation of ecological recovery strategies was also an important exogenous factor of the inversed-U shape curve in this ARDL model.

It was interesting to find the autocorrelation of the dependent variable in temporal dimension. The sand dunes were the fundamental sources for sandy desertification expansion. There were different types of sand dunes in Horqin Sandy Land, including fixed sand dunes, semi-fixed sand dunes, semi-shifting sand dunes and shifting sand dunes. More sand dunes indicated higher extent of sandy desertification. As the basic sources of sandy desertification, the sand dunes at a specific time decided the basic pattern of sandy desertification at the following time period. The results of the ARDL model supported this point of view. In the short run, $\Delta\ln(D_t)$ was positively related to $\Delta\ln(D_{t-1})$. It implied that the trend of the changes of sandy desertification could be kept for a short time. The interaction between economic growth and sandy desertification could be lagged. The pressures of economic growth could be enhanced at the following time period when sandy desertification expansion occurred, while the pressures of economic growth could be alleviated at the following time period when sandy desertification reversion occurred.

The coefficients revealed the relative contribution of economic growth and other factors to sandy desertification. In the short run, the coefficient β'_2 was relatively higher than other coefficients at a significance level of 0.05. It implied that the pressure of economic growth could be the most important driving factor to influence the sand desertification processes in the short run. The dependence of economic growth on natural resources could be the critical factor to the immediate effect of human activities on land. Technical progress could be the efficient solution to release the pressures of economic growth on land. In the long run, the coefficients λ'_3, λ'_4, were relatively higher, indicating that the annual precipitation and the implementation of ecological recovery strategies could be more efficient for the reversion of sandy desertification. Over the period 1980–2010, the synergistic effect of the precipitation, the implementation ecological recovery strategies and the reversion of sandy desertification itself pushed the correlation between sandy desertification and economic growth into the second phase of the Kuznets Curve in the long run while economic growth kept strengthening the pressure on land degradation in the short run.

4.3. The coupling methods for the researches on sandy desertification

Sandy desertification was quite a complex issue in Northern China. The interaction of the causes of sandy desertification was far from being understood. The exact role of any specific driving factor should not be considered separately. The coupling methods for identifying the relative roles of ecological variables and anthropogenic factors to sandy desertification in Northern China were scarce in literatures. The extended Environmental Kuznets Curve model could help to analyze the synergistic non-linear effect of different critical factors on sandy desertification. The variables of agricultural GDP, the area of wood land and the precipitation were analyzed and considered in the model. Specially, the logarithmic form of the equation helped to avoid the disturbance of the unit of different variables. And the squared item of GDP helped to analyze the effect of the trend and the changing rate of economic growth on sandy desertification.

However, the general Environmental Kuznets Curve model was not capable for correctly revealing the exact roles of specific driving factors of sandy desertification. Generally, aerial images were used to extract basic data for analyzing the changes of ecological changes. It would be a tough work to process the images and extract useful accurate information from aerial images, especially when the study area was large or the image resolution was high. Because of the difficulties of the acquisition and processing of remote sensing images, it was quite difficult to get continuous data in temporal dimension. Interpolation and data registration were applied to the data of ecological aspect in temporal dimension. However, the data processing could lead to the temporal autocorrelation of the variables. Another cause of the temporal autocorrelation could be the social–economic data itself. For social–economic data, time-dependence would be a big issue. It meant that the past could affect the future, but not vice visa, such as the GDP values.

The characteristics of time-dependence could lead to the bias of the independence of the variable, so that the results of statistic models could be meaningless. This paper used Unit Root Test to verify whether the variables were temporally auto-correlated. And then, a development of a dynamic ARDL model was presented, in order to avoid the problem of time-dependence. The results showed that the ARDL dynamic model well described the effect of economic growth on sandy desertification and the impact of other factors.

5. Conclusion

Agricultural economic growth had important influence on the processes of sandy desertification. This paper investigated the log-run and short-run correlation between sandy desertification and agricultural economic growth by establishing an ARDL model that was based on an EKC model for the counties in Tongliao City in Horqin Sandy Land. The results showed that there was a Kuznets Curve for the correlation between the extremely severe sandy desertification per capita and the real agricultural GDP per capita in the long run, while there was a positively linear relationship between the area of extremely severe sandy desertification per capita and the real agricultural GDP per capita in the short run. It proved that the pressure of economic growth on sandy desertification was released under the conditions that other factors provided the opportunities of an increasing ecological capacity in the long run, although the increasing intensity of economic growth still accelerated the sandy desertification in the short run.

The implementation of ecological recovery strategies significantly improved the vegetation cover and decreased the risk of sandy desertification. It was the most important exogenous factor to the effect of economic growth on sandy desertification. The synergistic effect of the precipitation, the implementation ecological recovery strategies and the reversion of sandy desertification itself provided the basic external conditions for alleviating the pressures of economic growth and pushed the correlation between sandy desertification and economic growth into the second phase of the Kuznets Curve in the long run.

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