


Article

Understanding Farmers' Perceptions and Behaviors towards Farmland Quality Change in Northeast China: A Structural Equation Modeling Approach

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Abstract: Farmland protection is the most important land science research issue in developing countries, especially in China, due to serious land degradation. This paper aimed to reveal the causal chain among driving factors, farmers' land protection perceptions, behavioral responses, and land quality change by applying a structural equation model (SEM), based on a cross-sectional dataset of 238 households surveyed, and matched plot soil sample results in the Sujiatun District, in Liaoning province, China. The results show that, compared to internal factors, external factors play more important roles in shaping farmers' land protection awareness which subsequently transfer into land protection behaviors. Various land use behaviors lead to different impacts on land quality, in which the crop planting structure and land input density have dominant effects on changes in the soil nutrient content. The results imply that a stable and reasonable price mechanism for agricultural inputs and outputs is meaningful to land protection. Moderate land circulation would help reduce land fragmentation, develop agricultural modernization, improve production efficiency, and achieve economies of scale. In addition, knowledge, training and environmental policy information on farmland protection play key roles in land conservation activities. These main results have important implications for policymakers with regard to promoting land protection activities, alleviating land resource and environmental pressures, and thus achieving the goal of sustainable land use.

Keywords: farmland protection; farmer's perceptions; behavior response; DSRE framework; structural models

1. Introduction

Land degradation on farmland has been regarded as a serious environmental and economic problem in many developing countries [1–4]. It is especially severe in China, due to the contrast between scarce land resources and a huge population [5–7]. In order to protect farmland, the Chinese government has implemented the strictest institutions for land management in the world. A series of protection policies and measures are being promulgated to enhance balanced development among land quantity, land quality, and ecological protection [8–10]. As the direct participants, farmers play an important role in the process of farmland protection, especially in the improvement of the soil fertility of farmland [11–13]. Farmers' land use decisions are closely related to land conservation; such as, decisions about soil fertility cultivation, land use efficiency, adoption of protective farming systems, and the utilization of agricultural waste resources [14–16].

In addition, cognitive behavioral theory indicates that humans' awareness, perceptions, and behaviors are interconnected. Specifically, land protection awareness and land use behavior are closely linked and interrelated [17,18]. For example, farmers with strong land protection awareness

will probably adopt some land conservation practices, in terms of using organic fertilizer and formula fertilizer, and these behaviors may further change their perspectives. Therefore, there are important theoretical and practical reasons for investigating the interrelations among farmers' land protection perceptions, behaviors and farmland quality changes from a microcosmic perspective.

Some studies have focused on farmers' willingness to protect their farmland, and the influencing factors [19,20]. The characteristics of farm households and farmlands, as well as land protection policies, are closely related to farmers' perceptions of land protection [7,21,22]. Farmers' age and education positively affect land protection awareness, indicating that older farmers with higher levels of education are more likely to form stronger land protection intentions [23]. A dependence on agricultural income plays a promoting role in farmers' willingness towards land protection [24,25]. A sense of moral responsibility also has a positive effect on land protection cognition. Specifically, farmers are more willing to implement farmland conservation, due to a stronger sense of moral responsibility, implying that land protection policy should be focused on motivating farmers' sense of social responsibility [26]. However, land fragmentation seriously weakens farmers' enthusiasm to protect their farmland [27].

According to the theory of planned behavior and relevant empirical studies, farmers' land protection perceptions are the key driving factor affecting land use behavior [26]. Beedell [28] analyzed farmers' land protection behavior in southern England, and concluded that farmers with environmental awareness are more likely to adopt environmental protection behaviors. Söderqvist [29] also found that concern and responsibility towards environmental protection had a significantly positive influence on the willingness to participate in wetland conservation, and produced a larger demonstration effect, clearly improving other farmers' protection intentions and enthusiasm.

Despite the importance for scientific research and policymaking, the triangular interactions among awareness, behavior, and farmland quality change are poorly understood, and have received little attention in the literature. On the content side, we do not know the influence mechanisms among farmers' land protection intentions, behavior decisions, and land quality changes. Previous studies individually examined influencing factors such as farmers' awareness or farm cultivating decisions on farmland protection [30], as well as the impacts of various land use types on farmland quality [31]. However, few studies have joined farmland protection awareness, behavior, and their effects together, or have deeply investigated their causal chain. On the methodology side, previous studies have carried out empirical research on the causal relationships among variables using the approach of econometric models [32]. However, it is difficult for econometric models to fully describe the causal relationship among farmers' perceptions, behavioral decision responses, and farmland quality changes, due to their complex and mutual influences. Structural equation modeling (SEM) can better deal with the relationships between multiple causes and multiple results, as well as estimate the structure and relationships of factors simultaneously [33]. For the last few years, SEM has usually been used to analyze the complex relationships of soil ecosystems [34–36], water management [37], climate change [38], sustainable development [39,40], and so on. This method can be used to examine multivariate hypotheses, and even to help to improve them [41,42]. Further research of the causal relationship is thus needed, so that policymakers can more accurately develop policies for farmland protection.

The purpose of this study is to construct a theoretical framework incorporating farmers' land protection perceptions, land use behaviors, and land quality change, and to empirically examine their precise relationships by applying SEM, in the Sujiatun District, in Liaoning province, China. We aim to answer four questions: Firstly, what kind of external and internal driving factors influence farmers' land protection cognitions?; secondly, is farmers' awareness important and necessary for farmland protection?; thirdly, how do the farmers' respond to their perceptions, in terms of land use behavior?; and finally, what are the effects of various land use behaviors on land quality, especially changes in soil nutrients?

2. Conceptual Framework

The pressure-state-response (PSR) framework was originally used in sustainable environmental assessments around the world by the Organization for Economic Co-operation and Development (OECD). The basic idea is that human activities exert pressures on the environment and natural resources, resulting in changes and unbalance to ecosystems, and then humans respond to these changes through adjustments to land use management, environment, and economic policies, in order to relieve the environmental pressures, and to maintain sustainable environmental development. The World Bank, Food and Agriculture Organization of the United Nations (FAO), United Nations Development Programme (UNDP), and United Nations Environment Programme (UNEP) jointly began an international cooperation project on land quality indicators in 1995, and proposed the PSR conceptual framework of land quality [43]. We have tried to extend the application of the PSR framework to farmers' behavior and land protection by constructing a driver-state-response-effect (DSRE) framework (Figure 1). The DSRE conceptual framework reveals the theoretical causal chain among the driving factors (D), farmers' land protection perception (S), land use behavior (R), and land quality change (E).

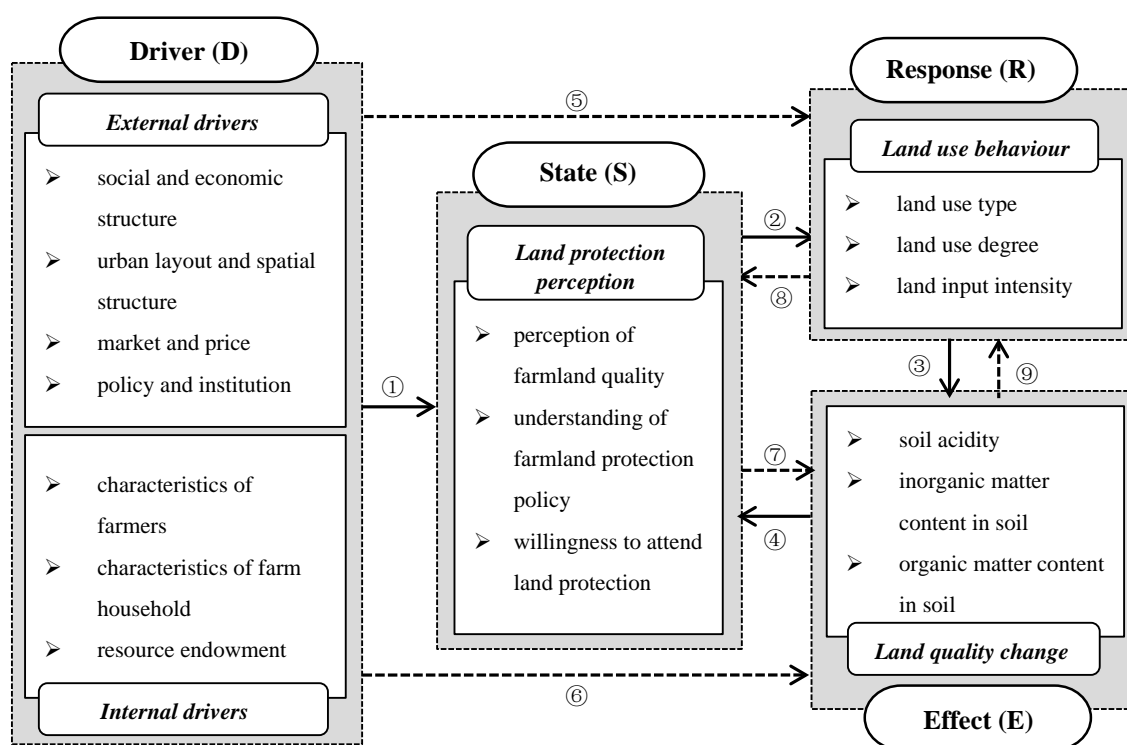


Figure 1. The driver-state-response-effect (DSRE) conceptual framework. Note: The solid lines indicate direct effects, while the dashed lines indicate indirect effects. (1) External drivers and internal drivers directly affect the land protection perceptions. (2) Land use behaviors are directly determined by land protection perceptions. (3) Land use behaviors have a direct relationship with land quality. (4) Land quality change directly shapes farmers' land protection perceptions. (5) External drivers and internal drivers have indirect impacts on land use behavior. (6) External drivers and internal drivers have indirect impacts on the land quality. (7) Land protection perceptions indirectly change land quality. (8) Land use behaviors play an indirect role in farmers' land perceptions. (9) Changes of land quality indirectly influence farmers' behavior.

Based on the theory of cognitive behavior, farmers' decision-making includes two processes. Firstly, farmers form land protection cognitions according to the identification and screening of the information collected, and then they display corresponding behavioral responses based on their awareness. This perspective describes how people understand farmland protection in terms

of cognition about land quality, knowledge of protection policy, and willingness to attend to protection action. Farmers' intentions are driven by external and internal factors. The former emphasizes the socio-economic structure (i.e., off-farm employment), the urban spatial structure (i.e., urbanization), and the input and output market prices, as well as public policies for dealing with farmland protection. The latter mostly refers to the characteristics of individual farmers and households, as well as resource endowment. Specifically, farmers' awareness of land protection may vary due to their age, experience, knowledge, and ability. Moreover, external and internal drivers also indirectly influence farmers' land use behaviors, which in turn play an indirect role in shaping their land protection cognitions.

Various land use behaviors are determined by farmers' land protection perceptions, and thus they directly cause a series of positive or negative effects on land quality. Examples of land use behavior responses include land use type, land use degree, and land investment. The land use type is mainly reflected in the crop planting structure, which affects the soil fertility level and the material circulation process in the agro-ecosystem. The land use degree mainly refers to the extent to which humans change or interfere with the land ecosystem in order to meet their needs. Moreover, land investment has the most direct impact on the farmland quality. Reasonable land investment is beneficial to the supplementation and the accumulation of soil nutrients, thus improving soil fertility. Meanwhile, farmers also adjust their land use behaviors according to their perceptions and cognitions about differences in farmland soil quality. Farmland quality essentially consists of the change in soil quality in terms of soil acidity, inorganic matter content, and organic matter content in the soil. Considering that the changes of environment are the results of human behaviors, we do not regard the changes of land quality as drivers, but as effects. Conversely, land quality changes also cyclically influence farmers' perspectives and land use behaviors.

3. Data and Methodology

3.1. Study Area and Data Collection

The survey was carried out in the Sujiatun District, Shenyang City, in Liaoning Province, China, which is located on the southern part of Shenyang, 15 km from the center of Shenyang (Figure 2). Sujiatun District, which covers an area of 76,200 ha, with a warm temperate continental humid monsoon climate, is the major agricultural region of Shenyang Economic Zone, and the key supplier of agricultural commodities to Shenyang City; the yields of its rice, corn, and other major grain crops rank in the forefront of Liaoning Province. Additionally, Sujiatun District is the national commodity grain base, the grain self-sufficiency project demonstration area, and an agricultural standardization production demonstration area. As the rapid growth of industrialization and urbanization continues, the contradiction between farmland protection and economic development is growing more and more intense in the study area.

Regarding the selection of sample households, stratified random sampling was adopted during the course of sample selection. This study mainly paid attention to the impacts of socio-economic theory and policy on land quality change. Hence, the selected towns should have relatively uniform natural conditions, allowing for the control of some natural conditions, such as rainfall, temperature, and soil properties, which may also influence land quality. Due to time and budget constraints, we finally selected the Linhu district, Wanggangbao town, and Yongle town, which are further from the city center, as the sample locations. After the three sample towns were selected, 4~5 sample villages were randomly selected from each selected town. Similarly, 240 households were randomly selected from the selected villages. As a result, a total of 240 households in 14 villages from three towns were investigated using a face-to-face questionnaire survey. Finally 238 valid questionnaires were obtained, from 79, 81, and 78 households, located in the Linhu district, Wanggangbao town and Yongle town, respectively.

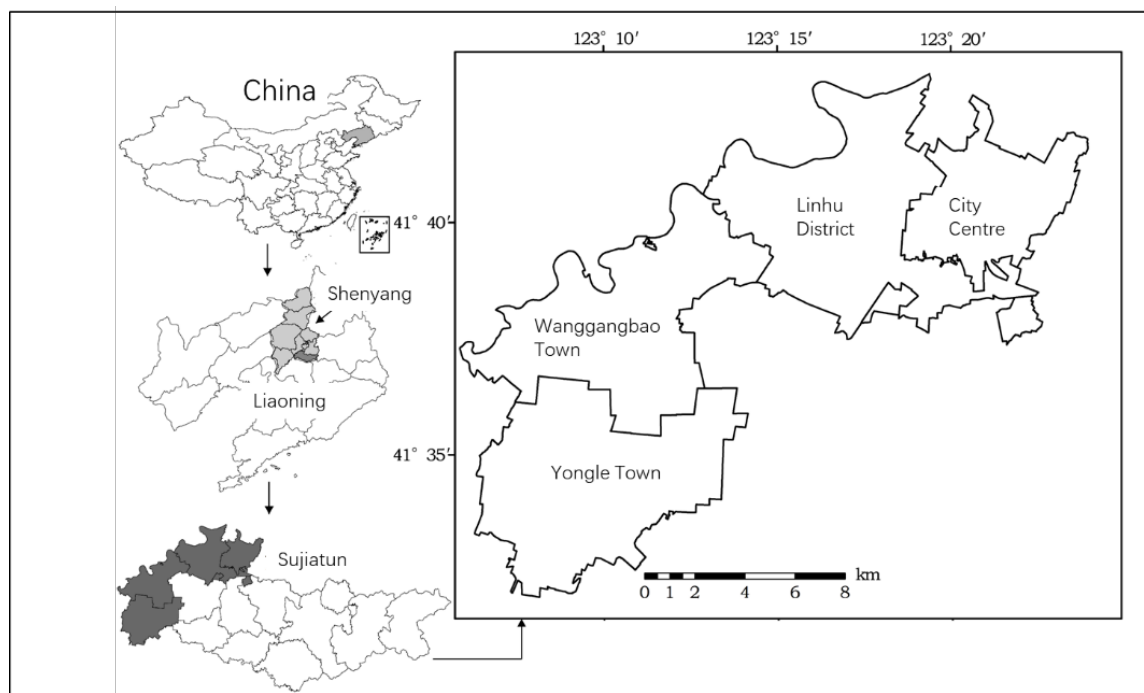


Figure 2. Location of the Sujiatun District and the three sample villages.

The cross-sectional dataset used to evaluate land quality changes was collected by soil sampling in plots in April 2015, while measures of farmers' receptiveness towards land protection, and their land use behavior were obtained from 238 face-to-face interviews in July 2015. In order to ensure that the survey data of farmers corresponded to the soil sampling data, we created a questionnaire linking farmers to their corresponding plots during the process of soil sampling. The main sections in the questionnaire comprised the following: farm household characteristics; agricultural production process (i.e., inputs and outputs); farmers' perceptions towards land protection; adoption of agricultural technologies; and, other land use behaviors. Soil sampling mainly included the basic conditions of the plot (i.e., soil type, soil fertility, and irrigation), soil nutrients (i.e., pH value, available potassium, organic matter) and so on. The combined use of soil testing results and interview data made it possible to empirically examine the causal relationship between farmers' activities and land quality.

3.2. Specifications of the Structural Model

SEM is a statistical analysis method that is used to quantitatively investigate the causal relationships between multiple factors, combining other analysis methods such as path analysis, factor analysis, regression analysis, and variance analysis. Dealing with the complex networks of relationships is customarily challenging using traditional statistical analysis methods in economic and management research. In particular, traditional methods are unable to solve multidimensional causal relationships (i.e., multiple causes and multiple results), or measure latent variables that cannot be observed directly. To solve these problems, SEM is frequently used to estimate the parameters of the latent variables and to deal with complex independent variables/dependent variables in prediction models. While in SEM the latent variables can be measured by the estimation of observed variables, in this study the latent variables of farmers' land protection perceptions, behavioral responses, and farmland quality, and their measurable variables with the conduction paths were determined in the structural equation modeling (see Figure 3).

The basic hypothesized structural model contained five constructs: external driving factors; internal driving factors; land protection perceptions; land use behavior; and, land quality. The external and internal driving factors directly played an important role in the formation of farmers' perceptions of land protection, and indirectly affected their land use behaviors. Subsequently, various land use

behaviors led to different impacts on land quality. However, changes in land quality had reverse influences on farmers' land protection perspectives; for example, as a result of reductions in soil fertility farmers may strengthen their awareness of land protection, and then re-enter the causal chain of awareness, behavior, and effect.

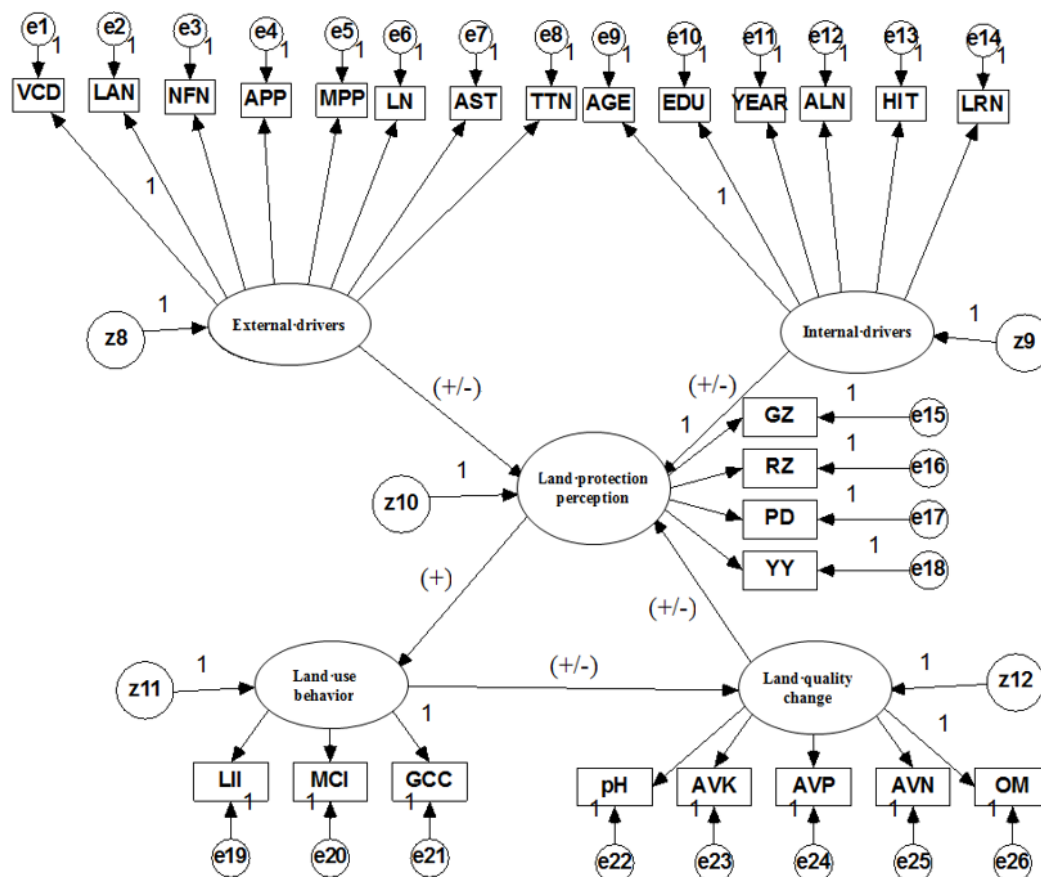


Figure 3. The hypothesized structural model for the relationships among land protection perceptions, land use behavior, and land quality. Note: VCD = distance from sample village to city; LAN = land adjustment frequency; NFN = off-farm employment; APP = price of agricultural products; MPP = price of agricultural materials; LN = number of plots; AST = agricultural subsidy; TTN = times of technology training; AGE = age; EDU = education; YEAR = agricultural experience ALN = farm labor; HIT = household income; LRN = farmland area; GZ = sensibility of land protection status; RZ = understanding of policy; PD = prospect of land protection; YY = willingness to attend to land protection; LII = land input intensity; MCI = multiple crop index; GCC = grow cash crop; pH = pH value; AVK = available potassium; AVP = available phosphorus; AVN = alkaline nitrogen; OM = organic matter.

3.3. Variable Measurement and Descriptive Statistics

With regard to the external driving factors, previous studies used the distance from the sample village to the city center, as well as the land use adjustment frequency to measure urbanization [44,45] (see Table 1). Off-farm employment was closely related to the development of industries and services, which could be indicators of social and economic conditions [24,25]. The market and price could be well-characterized by the price of agricultural products and agricultural materials [7]. The policies and institutions mainly included land use policies, agricultural policies, and extension services. Finally, we selected the number of plots to represent land fragmentation [27], agricultural subsidy, and times of technology training [26,46]. Relating to the internal driving factors, we measured the farmers' age, education, agricultural experience, farm labor, and household income [23,47].

The household annual income is the gross income of the whole farm household, including agricultural production income, off-farm income, and other incomes (i.e., subsidy, cash gift in a wedding, and farmland area).

Table 1. Variable measurement and descriptive statistics.

| Latent Variables | Code | Observed Variable Definition | Units | Mean | S.D. | Min. | Max. |
|--|------|---|--------------------|------------------|--------------------|----------------|----------------------|
| Driver 1: external driving factors | VCD | Distance from the sample village to the town center | km | 13.94 | 5.83 | 5.70 | 21.70 |
| | LAN | Times of land adjustment | times | 1.1 | 1.8 | 0.0 | 10.0 |
| | NFN | Off-farm employment | persons | 2 | 1 | 1 | 5 |
| | APP | Price of agricultural products | RMB/kg (USD/kg) | 2.52 (0.40) | 2.22 (0.36) | 0.20 (0.03) | 12.40 (1.99) |
| | MPP | Price of agricultural materials | RMB/kg (USD/kg) | 8.00 (1.28) | 5.18 (0.83) | 0.60 (0.10) | 23.60 (3.79) |
| | LN | Number of plots | plots | 2 | 1 | 1 | 5 |
| | AST | Agricultural subsidy received in total | RMB (USD) | 652 (105) | 659 (106) | 55 (8.83) | 6860 (1101) |
| | TTN | Times participating in technology training | times | 3 | 10 | 0 | 99 |
| Driver 2: internal driving factors | AGE | Age of the respondent farmer | Years | 53 | 11 | 25 | 88 |
| | EDU | Education of the respondent farmer | Years | 8 | 2 | 2 | 13 |
| | YEAR | Years engaged in agricultural production | Years | 28 | 15 | 5 | 70 |
| | ALN | Number of agricultural laborers in the family | persons | 2 | 1 | 1 | 6 |
| | HIT | Household annual income | RMB (USD) | 51,896 (8332) | 71,061 (11,409) | 786 (126) | 771,960 (123,941) |
| | LRN | Farmland area | ha | 0.88 | 0.83 | 0.07 | 8.00 |
| State: land protection perception | GZ | Sensibility of the land protection status | / | 2.5 | 0.5 | 0.5 | 3.0 |
| | RZ | Understanding of policy | / | 1.2 | 0.6 | 0.0 | 2.0 |
| | PD | Prospect of land protection status in the future | / | 3.9 | 0.7 | 2.0 | 5.0 |
| | YY | Willingness to attend to land protection | / | 1.4 | 0.5 | 0.0 | 2.0 |
| Response: land use behavior | LII | Capital input per unit of farmland | RMB/ha (USD/ha) | 16,215 (2603) | 16,485 (2647) | 1785 (286) | 67,680 (10,866) |
| | MCI | Multiple crop index | / | 1.3 | 0.5 | 1 | 3 |
| | GCC | Grow cash crop, 1 = yes; 0 = no | / | 0.6 | 0.4 | 0 | 1 |
| Effect: land quality | pH | pH value | / | 5.8 | 0.6 | 4.8 | 8.4 |
| | AVK | Available potassium | mg/kg | 200.5 | 148.5 | 82.3 | 833.7 |
| | AVP | Available phosphorus | mg/kg | 167.5 | 169.5 | 7.1 | 800.8 |
| | AVN | Alkaline nitrogen | mg/kg | 138.0 | 37.9 | 77.0 | 314.0 |
| | OM | Organic matter | g/kg | 26.8 | 6.5 | 15.3 | 51.7 |

Note: USD/RMB exchange rate was USD 1 = RMB 6.2284 in 2015.

Farmers' land protection perceptions were characterized by the following four variables: perspectives on land protection status; understanding of policy; prospect of land protection and, willingness to attend to land protection [26,28,48]. In this research, perspectives on land protection status were measured by asking interviewees to answer corresponding questions based on a 3-point

Likert scale. The three statements were: (1) “Do you pay attention to the changes in your own farmland’s quality?; (2) “If you are concerned, what do you think of the changes on farmland quality in recent years?; (3) “What do you think of the importance of the quality protection of farmland?”. According to the statistics, the average score for perceptions of land protection status was 2.5, meaning that most of the farmers sampled were concerned about the quality of their farmland and had explicit judgments on changes in land quality.

An understanding of policy was reflected by asking after farmers’ opinions about the ownership of farmland, and where the main responsibility for land protection lay. In China the owners, or the responsible subjects, mainly include three types: the national government at different administrative levels; village collectives; and the farmers themselves. From the results, we could see that in terms of ownership of farmland, 44.96% of the respondents reported that farmland belonged to the village collective, while 28.57% indicated that it belonged to the national government, and 26.47% indicated that the farmland was their own asset. Although farmers had different opinions on the ownership of farmland, they agreed that farmland had clear property rights and responsible subjects that significantly affected farmers’ land use behaviors [49,50].

The prospect of land protection with reference to farmers’ attitudes towards land protection status in the future was measured by asking respondents to answer five corresponding questions based on a 3-point Likert scale. The five questions were: (1) “How is the frequency of publicity and educational activities for farmland protection in your village?; (2) “What do you think of the role of chemical fertilizers in improving the quality of farmland?; (3) “What do you think of the future of farmland protection?; (4) “What do you think of the quality of your farmland?; (5) “What kind of practices can improve the quality of farmland?”.

The willingness to attend to land protection was measured by asking farmers whether they were willing to participate in land protection, and their motivations. According to the survey results, 98.32% of farmers sampled preferred to join in farmland protection, showing a strong willingness to protect farmland quality. In an investigation of the motivation to protect farmland, 45.38% of the respondents indicated that guaranteeing a crop yield was the most important reason, because of their high dependence on agricultural income. If the quality of farmland deteriorated, it would be difficult to ensure their income. Therefore, their willingness to protect farmland was more intense than others’.

According to the different influences on farmland, land investment can be divided into protective investment and non-protective investment. The former refers to investment behavior which is beneficial to the preservation or the improvement of land quality, such as transforming slope farmlands into terraced fields, using organic manure, and constructing water infrastructure, and so on, which can help to improve soil structures and agricultural production microclimates to maintain land sustainable use. The latter, non-protective investment, mostly means the unsustainable use of farmland, such as the overuse of chemical fertilizers and pesticides, which can increase the agricultural output to some extent in the short-term, but may cause soil consolidation and pollution in the long-term.

In this study, three aspects of land use behavior were estimated: land use type; land use degree; and, land input intensity [51]. Land use type was represented by crop species, and the item was, “whether farmers grow cash crops or not”. According to the results, 60% of the farmers grew cash crops, while the other 40% planted grains. According to the statistical yearbook of China, the calculation formula of the multiple cropping index (MCI) is the sown area divided by the cultivated land area. MCI is a continuous variable between 1 and 3. A value of 1 means that all of the farmland is planted by single cropping crops in one year, while a value of 3 indicates that all the farmland is continuously cultivated with three varieties of crops in different seasons within one year. A higher MCI means more intensive farmland use. The multiple cropping index was used as the observed indicator reflecting the land use degree. As shown in Table 1, the average multiple cropping index was 1.3, which suggested that nearly 30% of the sample plots had crop rotation. The land input intensity was measured by the amount of land capital investment per unit area. In our study area, each hectare of farmland had an average invested capital of about 16,215 RMB (USD 2603.40).

Farmers' land use behaviors can lead to deterioration in land quality by disequilibrating the soil nutrients. Therefore, we selected soil quality indicators which were greatly influenced by farmers' activities and accurately reflected land quality. Based on previous studies [7,52], the actual sites of this study, and data availability, we finally selected the following five indicators to measure land quality change: pH value, available potassium; available phosphorus; alkaline nitrogen; and, organic matter. The mean pH value of the sampled plots was 5.8. The average content of available potassium, available phosphorus, and alkaline nitrogen were 200.5 mg/kg, 167.5 mg/kg, and 138.0 mg/kg, respectively. The average level of organic matter contained in the soil was 26.8 g/kg (see Table 1).

4. Results

4.1. Goodness-of-Fit of SEM

The maximum likelihood estimation method was used to estimate the structural equation model expressed in Figure 3 with AMOS17.0. The estimated results and normalized path coefficients are shown in Table 2 and Figure 4. The goodness-of-fit indices for the baseline model were $\chi^2 = 506.781$, $df = 294$, $p = 0.000$, RMSEA = 0.077, NFI = 0.928, and CFI = 0.938. The null hypothesis of the Chi-square test was that the observed and estimated covariance matrices were unbiased. Significance was expected if the number of observations was more than 250, and the observed variables were larger than 30 [53], which means there was a statistical difference between the two covariance matrices. The acceptable values of RMSEA and CFI were 0.9 and 0.03–0.08, respectively [53]. The statistics above suggested that the overall fit of the structure model for the causal chain among farmers' land protection perceptions, land use behaviors, and land quality, was acceptable. In our model, the standardized factor loadings were all statistically significant to at least 0.05, suggesting that there is a strong relationship between the observed indicators and their associated constructs.

Table 2. Estimation results of the structural equation model (SEM).

| Causal Relationship | | | Non-Normalized Path Coefficient | S.E. | C.R. | P | Normalized Path Coefficient |
|---------------------|----|------------------|---------------------------------|---------|--------|-----|-----------------------------|
| Perception | <— | External factors | 0.009 | 0.005 | 1.976 | * | 0.686 |
| Perception | <— | Internal factors | 0.001 | 0.000 | 2.64 | ** | 0.168 |
| Behavior | <— | Perception | 5.76 | 2.036 | 2.829 | ** | 0.442 |
| Land quality | <— | Behavior | 4.906 | 0.916 | 5.356 | *** | 0.753 |
| Perception | <— | Land quality | 0.008 | 0.003 | 2.418 | * | 0.272 |
| VCD | <— | External factors | 1 | — | — | — | 0.882 |
| LAN | <— | External factors | −0.019 | 0.007 | −2.768 | ** | −0.054 |
| NFN | <— | External factors | −0.217 | 0.090 | −2.413 | * | −0.768 |
| APP | <— | External factors | 0.124 | 0.014 | 8.652 | *** | 0.576 |
| MPP | <— | External factors | −0.058 | 0.022 | −2.641 | ** | −0.114 |
| LN | <— | External factors | −0.073 | 0.013 | −5.421 | *** | −0.371 |
| AST | <— | External factors | 3.563 | 1.486 | 2.398 | * | 0.028 |
| TTN | <— | External factors | 0.144 | 0.069 | 2.074 | * | 0.075 |
| AGE | <— | Internal factors | 1 | — | — | — | 0.889 |
| EDU | <— | Internal factors | 0.095 | 0.016 | 5.955 | *** | 0.45 |
| YEAR | <— | Internal factors | 1.132 | 0.143 | 7.904 | *** | 0.722 |
| ALN | <— | Internal factors | 0.153 | 0.057 | 2.695 | ** | 0.121 |
| HIT | <— | Internal factors | 0.022 | 0.008 | 2.823 | ** | 0.202 |
| LRN | <— | Internal factors | 1267.24 | 520.427 | 2.435 | * | 0.174 |
| GZ | <— | Perception | 1 | — | — | — | 0.129 |
| RZ | <— | Perception | 0.553 | 0.198 | 2.799 | ** | 0.060 |
| PD | <— | Perception | 2.394 | 0.897 | 2.669 | ** | 0.229 |
| YY | <— | Perception | 0.416 | 0.146 | 2.846 | ** | 0.064 |
| GCC | <— | Behavior | 1 | — | — | — | 0.802 |
| MCI | <— | Behavior | −0.498 | 0.079 | −6.311 | *** | −0.417 |
| LII | <— | Behavior | 2167.136 | 165.493 | 13.095 | *** | 0.785 |

Table 2. Cont.

| Causal Relationship | | | Non-Normalized Path Coefficient | S.E. | C.R. | P | Normalized Path Coefficient |
|---------------------|----|--------------|---------------------------------|---------|--------|-----|-----------------------------|
| OM | <← | Land quality | 1 | — | — | — | 0.385 |
| AVN | <← | Land quality | 10.065 | 1.848 | 5.446 | *** | 0.674 |
| AVP | <← | Land quality | 58.047 | 10.018 | 5.794 | *** | 0.879 |
| AVK | <← | Land quality | 43.485 | 7.754 | 5.608 | *** | 0.746 |
| pH | <← | Land quality | −0.072 | 0.019 | −3.744 | *** | −0.316 |
| χ^2 | | | | 506.781 | | | |
| df | | | | 294 | | | |
| RMSEA | | | | 0.077 | | | |
| CFI | | | | 0.738 | | | |
| NFI | | | | 0.628 | | | |

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. “—” the variable is regarded as a significant path reference to the other variable.

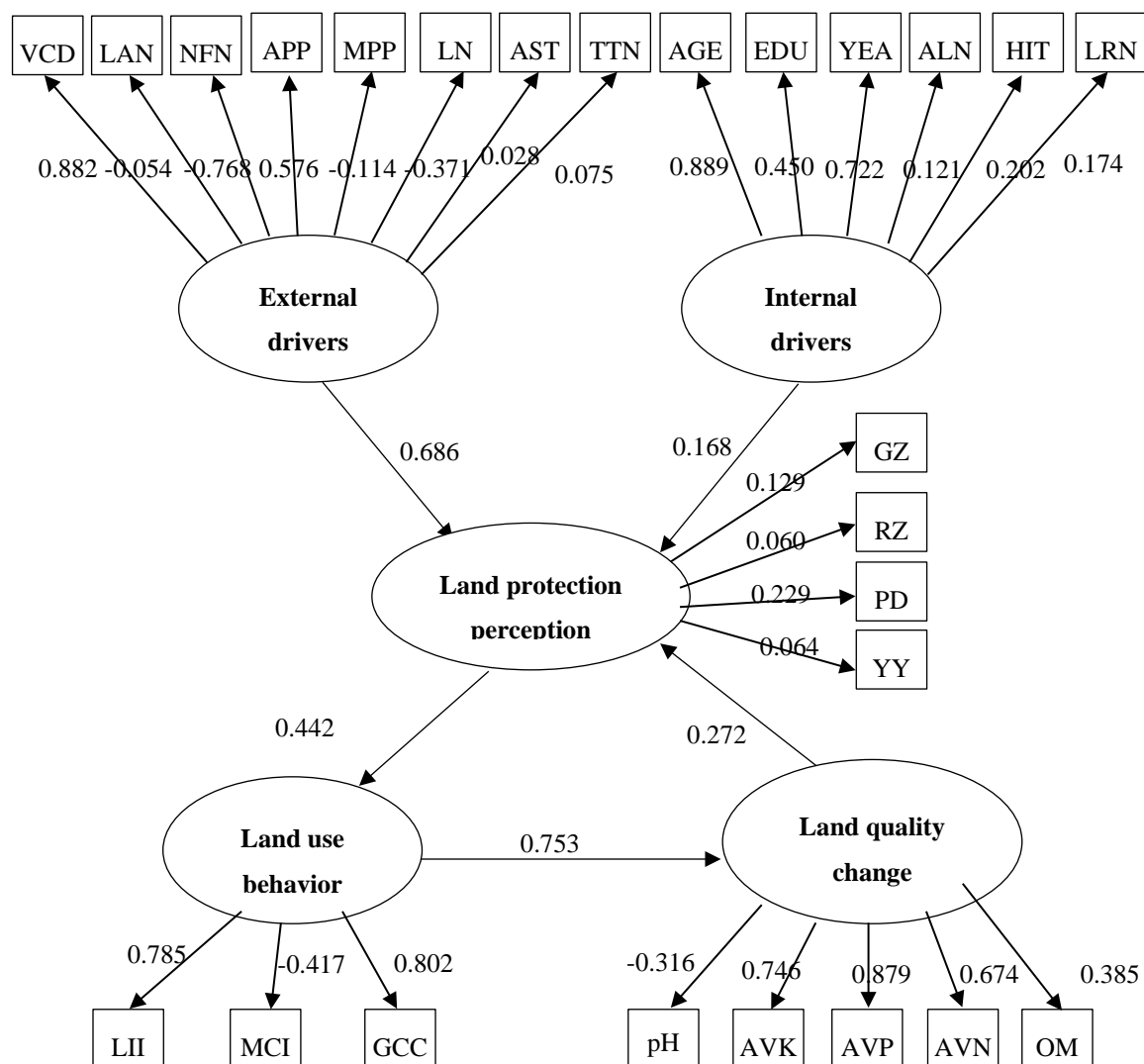


Figure 4. The normalized path coefficients of variables in the structural model.

4.2. Causal Chain among the Three Constructs

4.2.1. Drivers of Land Protection Perception

As hypothesized in the SEM conceptual model, external and internal driving factors strongly affected the formation of farmers' land protection perceptions (an endogenous latent variable). The standardized path coefficients for the external and internal latent variables were 0.686 ($p = 0.05$) and 0.168 ($p = 0.01$), which implies that if other conditions remained constant, the contribution of external and internal factors to the improvement of land protection perception were 68.6% and 16.8%, respectively. These results indicate that external drivers played a more important role than internal drivers in promoting land conservation.

Regarding the external exogenous variables, the distance from to the city center, the price of the agricultural product, the agricultural subsidy, and technical training all had significant positive effects on farmers' perceptions, and the standardized path coefficients were 0.882, 0.576, 0.028, and 0.07, respectively. These findings indicate that a remote location, higher prices of agricultural products, more subsidies, and technical training, play positive roles in improving cognition about land protection, particularly the location and the price of the agricultural products. Specifically, urban expansion erodes enthusiasm for land protection. It was said that urbanization had fewer influences on farmers located in villages far from the city; thus, they were more likely to strengthen their land protection awareness. Obviously, farmers may cherish and take good care of their farmland for higher profits if the prices of agricultural products increase. Agricultural subsidies could improve the enthusiasm of farmers' towards land protection utilization [44]. Ding [54] and Cheng et al. [55] indicated that government information was positively related to farmers' willingness to protect the farmland. Technology training is also one of the best ways of providing agricultural policy information. Generally speaking, more attention should be paid to socio-economic factors during the process of land protection.

In contrast, off-farm employment, plots, the prices of agricultural materials, and land adjustment frequency had significant negative impacts on land protection awareness, with normalized path coefficients of -0.768 , -0.371 , -0.114 , and -0.054 , respectively. These results showed that off-farm employment, land fragmentation, higher production costs, and the instability of land property rights may cause a reduction in cognition on land protection. For example, increases in off-farm employment and off-farm income usually weaken farmers' dependence on agriculture, leading to less attention being paid to land protection. Land fragmentation needs significantly more labor input and incurs higher costs, which reduce farmers' willingness to engage in land protection. This result implies that speeding up land transfer and moderating land scale management could help improve farmers' willingness towards land protection [44].

All of the six internal exogenous variables are statistically significant and bear positive relationships with farmers' land protection perceptions. The normalized path coefficients of age, education, agricultural experience, farm labor force, household income, and land area are 0.889, 0.450, 0.722, 0.121, 0.202, and 0.174, respectively. The results mean that the farmers who are older, have higher education, more agricultural experience, are from higher income households, and have larger scale farms are more likely to form stronger land protection perspectives. It was noted that older farmers with longer farming experience are more likely to be involved in land conservation, because older farmers may be deeply attached to the land, and may give more attention and importance to the land. However, farmers with higher levels of education are more aware of environmental protection concepts, and they have a stronger acceptance of advanced scientific ideas and technologies related to land protection.

4.2.2. Impact of Farmers' Perceptions on Land Use Behaviors

An important aspect of this paper was to investigate the influence of individuals' land protection cognitions on their land use behaviors. As expected, land protection perception had a statistically significant and positive relationship with behavior (normalized path coefficient = 0.442). Specifically,

the prospect of land protection (i.e., knowledge about land conservation practices) was the factor most heavily affecting land use behavior, with a structural path estimate of 0.229. Therefore, it is very important for farmers to master more farmland quality protection practices through technical extension, which can improve their awareness of land conservation. For example, conservation tillage is a new farming technology that can achieve a win-win situation, both for land resource preservation and yield increase [56]. This was followed by the awareness of land protection status, with the normalized path coefficient being 0.129, which indicates that farmers who were more concerned about land quality and the importance of land protection would take more land protection actions. Compared to the above variables, an understanding of land protection policies and their willingness to attend to land protection had a lesser impact on individuals' behavior, with normalized path coefficients of 0.060 and 0.064, respectively. This result suggests that more attention should be paid to knowledge and training in order to improve farmers' awareness of land protection.

4.2.3. Causal Chain of Land Quality

As expected, land use behavior had a strongly positive causal relationship with land quality, with a structural path estimate of 0.753 ($p = 0.001$). This finding means that land protection behavior contributes 75.3% to the change of land quality. In particular, the capital input density and the planting of cash crops were found to positively affect land quality, with normalized path coefficients of 0.802 and 0.785, respectively. Taking cash crops for example, farmers who plant more cash crops would pay more attention to the improvement of land fertility, because cash crops grow rapidly and need more nutrients for higher yields. In contrast, the multiple crop index played a negative role in land quality, with normalized path coefficients of -0.417 . The result supposes that a high multiple crop index may over-plunder soil nutrients, leading to the deterioration of land quality. However, land use behavior had various effects on different land quality measurable variables. The contents of alkaline nitrogen, available phosphorus, and available potassium in the soil were the most affected by farmers' land use behaviors, and the normalized path coefficients were 0.674, 0.879, and 0.746, respectively. The influences on organic matter and soil pH value (pH) were relatively weaker, with normalized path coefficients of 0.385 and -0.316 , respectively. The possible reason for this was the overuse of chemical fertilizers, resulting in a lack of organic matter and soil acidification, which increased the difficulty of improving the status of organic matter and pH values. This result was also consistent with the soil sample results in the study area.

Interestingly, the change of land quality also influenced farmers' land protection perspectives, with a structural path estimate of 0.272. This finding indicated that the improvement of land quality played a positive role in land protection perception resembling the Matthew effect. Specifically, for farmers who had higher land protection perceptions, this led to better land protection behavior, and better land quality. In a circular manner, the improvement of land quality can further strengthen farmers' land protection awareness.

4.3. Indirect Impacts among the Variables

The direct effects reflecting the causal relationship among the internal/external driving factors, perception, behavior, and land quality, have already been explained above. However, there were indirect paths among those latent variables (see Table 3). Specifically, land protection awareness was indirectly impacted by land use behavior, with a normalized path coefficient of 0.260. Land use behavior was indirectly affected by internal driving factors, external driving factors, and land quality, and the normalized path coefficients were 0.223, 0.909, and 0.360, respectively. Similarly, internal driving factors, external driving factors, and land protection perception also played an indirect role in land quality, with normalized path coefficients of 0.168, 0.686, and 0.998, respectively.

Table 3. Effect decompositions of the latent variables.

| Path | Normalized Path Coefficients | | |
|---------------------------------|------------------------------|-----------------|--------------|
| | Direct Effect | Indirect Effect | Total Effect |
| Internal factors → Perception | 0.168 | — | 0.168 |
| External factors → Perception | 0.686 | — | 0.686 |
| Internal factors → Behavior | — | 0.223 | 0.223 |
| External factors → Behavior | — | 0.909 | 0.909 |
| Internal factors → Land quality | — | 0.168 | 0.168 |
| External factors → Land quality | — | 0.685 | 0.685 |
| Perception → Behavior | 0.442 | — | 0.442 |
| Perception → Land quality | — | 0.998 | 0.998 |
| Behavior → Land quality | 0.753 | — | 0.753 |
| Behavior → Perception | — | 0.260 | 0.260 |
| Land quality → Perception | 0.272 | — | 0.272 |
| Land quality → Behavior | — | 0.360 | 0.360 |

Note: “—” represents no direct/indirect effect.

5. Discussion and Conclusions

In this paper, we constructed a DSRE theoretical framework to analyze the complex causal relationships among the driving factors of land protection perceptions, land use behavior, and land quality. Subsequently, an empirical study was carried out using the SEM approach, based on a dataset of 238 farm households matched with soil tests from 238 plots from the Sujiatun District, in Liaoning province, China. The main conclusions and policy implications follow.

First of all, compared to internal drivers, the external drivers play more important roles in shaping farmers' land protection perceptions. This finding is consistent with the conclusion of Moges and Taye [57] that socio-economic factors and institutions are the most dominant determinants affecting farmers' environmental conservation awareness. With regard to specific indicators, the prices of agricultural products positively influence farmers' land protection cognitions, while prices of agricultural materials appear to have negative impacts. This finding has an important policy implication in that reasonable prices for agricultural inputs and outputs are essential for improving farmers' land protection perceptions, due to the close relationship between price and agricultural income [32]. In contrast, unreasonable prices for agricultural inputs and outputs would greatly reduce farmers' enthusiasm to engage in agricultural production, especially for those farmers who are located in the suburbs of big cities, who have more opportunities for off-farm employment. Moreover, off-farm employment is proven to not be conducive to land conservation, due to promoting an excessive use of chemical fertilizers [58–60]. The other implication is related to land fragmentation, which negatively influences farmers' perceptions of land protection. Therefore, it is suggested that properly promoting land circulation and large-scale operations are recommended in order to promote agricultural modernization, and to achieve economies of scale, which are also conducive to land conservation.

Secondly, farmers' land protection perceptions play a key role on affecting their land use behaviors, with a contribution of 44.2%, especially for cognition about land conservation practices, which is also the main emphasis made by Lian et al. [61] and Ellison [62]. Hence, it is implied that more attention should be paid to agricultural training, to improve farmers' knowledge of land conservation practices, which has been proven to effectively lead to improvements in farmers' land protection [63,64]. Regarding the selection of the main training targets, large-scale agricultural producers in terms of large-scale grain producers, family farms, and professional cooperatives, should be regarded as targets, in order to play a modeling role for small-scale farmers. Additionally, we should broaden and diversify the channels for delivering environmental knowledge and land conservation practices. Training and

in-field guidance are good methods for this; moreover, television, radio, and mobile phones are also important and effective media for technology extension.

Thirdly, farmers' land use behaviors have gradually become a major influencing factor on farmland quality, with a continuous deepening of institutional reform in rural China. This study proposes that the contribution of farmers' behavior to land quality changes has reached 75.3%, which indicates that the majority of the land quality changes come from human activities. Among the three types of land use behaviors, land input intensity and the selection of crop varieties make the greater contributions. This conclusion is consistent with the view of Helliwell [33] and Kong et al. [51]. The first important implication for policymakers is that appropriate input structures and intensities can effectively increase land quality. With fertilizer applications for example, farmers should be encouraged to increase the input of organic fertilizers, while reducing the application of chemical fertilizers [65]. The other implication is that crop pattern layouts should be included in regional planning. A reasonable crop pattern layout can make full use of natural resources and economic conditions, and can form a good combination of economic, ecological, and social benefits.

All of the results above are consistent with the expectation suggesting that structural equation modeling is suitable for use in the investigation of the relationship complexities between driving factors, land protection perceptions, land use behavior, and land quality, reflecting causal interactions among the latent variables. However, given widespread land reduction and land degradation, further research to investigate the various characteristics of farmers' perceptions and response behaviors is needed. In addition, the index selection of the structural equation model is usually limited to a single constant sample index, and it is worth continuing to study how to reasonably screen indices that express complex nonlinear latent variables, and how to comprehensively and systematically reflect the characteristics of farmers' perceptions and behaviors in other ways.

Compared with previous studies [17,18,30,31,66], the main contribution of this study is to investigate the causal chain between human activity and land resources from the micro-perspective, using an inter-disciplinary approach that combines the natural and social sciences. Specifically, we used a cross-sectional dataset of soil sampling and a farm survey, and constructed linkages between the spatial characteristics of farmers' behaviors and the spatial features of farmland quality change, in order to obtain more accurate and convincing results. However, it should be noted that farmland quality change is a dynamic and complicated process, which needs massive amounts of more accurate and comprehensive data from both time and space dimensions. Therefore, the question of how to establish a fixed observation point for the continuous observation of farmers and their plots is essential, and is also our future research direction.

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References

- Scherr, S.J.; Yadav, S.; Pinstrupandersen, P.; Pandyalorch, R. *Land Degradation in the Developing World: Issues and Policy Options for 2020*; International Food Policy Research Institute: Washington, DC, USA, 1997.
- Heerink, N. Soil fertility decline and economic policy reform in Sub-Saharan Africa. *Land Use Policy* **2005**, *22*, 67–74. [[CrossRef](#)]
- Rasul, G.; Thapa, G.B. The impact of policy and institutional environment on costs and benefits of sustainable agricultural land uses: The case of the Chittagong hill Tracts, Bangladesh. *Environ. Manag.* **2007**, *40*, 272–283. [[CrossRef](#)] [[PubMed](#)]

4. Ye, L.; Ranst, V.E. Production scenarios and the effect of soil degradation on long-term food security in China. *Global Environ. Chang.* **2009**, *19*, 464–481. [[CrossRef](#)]
5. Lindert, P. The bad earth? China's soil and agricultural soils and development since the 1930s. *Econ. Dev. Cult. Chang.* **1999**, *47*, 701–736. [[CrossRef](#)]
6. Guo, J.H.; Liu, X.J.; Zhang, Y.; Shen, J.L.; Han, W.X.; Zhang, W.F.; Christie, P.; Goulding, K.W.T.; Vitousek, P.M.; Zhang, F.S. Significant acidification in major Chinese croplands. *Science* **2010**, *327*, 1008–1010. [[CrossRef](#)] [[PubMed](#)]
7. Tan, S.H. Do Land characteristics affect farmers' soil fertility management? *J. Integr. Agric.* **2014**, *13*, 2546–2557. [[CrossRef](#)]
8. Sliman, N.; Kassab, M.T.; Mrabet, F. Land policies and agricultural land markets in Russia. *Land Use Policy* **2007**, *24*, 14–23.
9. Zhang, J.J.; Fu, M.C.; Zhang, Z.Y.; Tao, J.; Fu, W. A trade-off approach of optimal land allocation between socio-economic development and ecological stability. *Ecol. Model.* **2014**, *272*, 175–187. [[CrossRef](#)]
10. Deng, X.Z.; Gibson, J.; Wang, P. Management of trade-offs between cultivated land conversions and land productivity in Shandong Province. *J. Clean. Prod.* **2017**, *142*, 767–774. [[CrossRef](#)]
11. Zhou, D.; Zhang, R.Q.; Liu, L.M.; Gao, L.L. Evaluation of the sustainable land use status of the North China Plain. *Int. J. Sustain. Dev. World Ecol.* **2009**, *16*, 253–259. [[CrossRef](#)]
12. Gao, L.L.; Sun, D.Q.; Huang, J.Q. Impact of land tenure policy on agricultural investments in China: Evidence from a panel data study Research article. *China Econ. Rev.* **2017**, *45*, 244–252. [[CrossRef](#)]
13. Liu, X.W.; Zhao, C.L.; Song, W. Review of the evolution of cultivated land protection policies in the period following China's reform and liberalization. *Land Use Policy* **2017**, *67*, 660–669. [[CrossRef](#)]
14. Xu, H.Z.; Chen, T. Impact of farmers' differentiation on farmland-use efficiency: Evidence from household survey data in rural China. *Agric. Econ.* **2013**, *59*, 227–234.
15. Yang, Z.H.; Wang, Y.P.; Tuersun, M.E.D. Farm households' input behavior of land conservation and its driving factors: From a perspective of farm household differentiation. *China Pop. Res. Environ.* **2015**, *25*, 105–112. (In Chinese)
16. Duangjai, W.; Schmidt-Vogt, D.; Shrestha, R.P. Farmers' land use decision-making in the context of changing land and conservation policies: A case study of Doi Mae Salong in Chiang Rai Province, Northern Thailand. *Land Use Policy* **2015**, *48*, 179–189. [[CrossRef](#)]
17. Zhang, W.; Kato, E.; Bhandary, P.; Nkonya, E.; Ibrahim, H.I.; Agbonlahor, M.; Ibrahim, H.Y.; Cox, C. Awareness and perceptions of ecosystem services in relation to land use types: Evidence from rural communities in Nigeria. *Ecosyst. Serv.* **2016**, *22*, 150–160. [[CrossRef](#)]
18. Tatsvarei, S.; Mushunje, A.; Matsvai, S.; Ngarava, S. Farmer perceptions in Mashonaland East Province on Zimbabwe's agricultural land rental policy. *Land Use Policy* **2018**, *75*, 468–477. [[CrossRef](#)]
19. Wang, X.; Liang, L.T.; Chen, C.Y. The willingness of cultivated land protection for different households. *J. Arid Land Rec. Environ.* **2015**, *29*, 52–56. (In Chinese)
20. Xu, D.D.; Guo, S.L.; Xie, F.T.; Liu, S.Q.; Cao, S. The impact of rural laborer migration and household structure on household land use arrangements in mountainous areas of Sichuan Province, China. *Habitat Int.* **2017**, *70*, 72–80. [[CrossRef](#)]
21. Zhu, L.L.; Cai, Y.Y.; Luo, C.; Wang, P.F. Characteristics and its influencing factors of farmer land-use behavior under framework of land-use control: Comparing Chengdu City of Sichuan Province with Wuhan City of Hubei Province. *Bull. Soil Water Conserv.* **2016**, *36*, 198–213.
22. Li, W.; Xue, C.X.; Yao, S.B.; Zhu, R.X. The adoption behavior of households' conservation tillage technology: An empirical analysis based on data collected from 476 households on the Loess Plateau. *China Rural Econ.* **2017**, *1*, 44–57. (In Chinese)
23. Adimassu, Z.; Kessler, A. Impact of the productive safety net program on farmers' investments in sustainable land management in the Central Rift Valley of Ethiopia. *Environ. Dev.* **2015**, *16*, 54–66. [[CrossRef](#)]
24. Illukpitiya, P.; Gopalakrishnan, C. Decision-making in soil conservation: Application of a behavioral model to potato farmers in Sri Lanka. *Land Use Policy* **2004**, *21*, 321–331. [[CrossRef](#)]
25. Kessler, C.A. Decisive key-factors influencing farm households' soil and water conservation investments. *Appl. Geogr.* **2006**, *26*, 40–60. [[CrossRef](#)]

26. Greiner, R.; Gregg, D. Farmers' intrinsic motivations, barriers to the adoption of conservation practices and effectiveness of policy instruments: Empirical evidence from northern Australia. *Land Use Policy* **2011**, *28*, 257–265. [[CrossRef](#)]
27. Jürgenson, E. Land reform, land fragmentation and perspectives for future land consolidation in Estonia. *Land Use Policy* **2016**, *57*, 34–43. [[CrossRef](#)]
28. Beedell, J.; Rehman, T. Using social-psychology models to understand farmers' conservation behavior. *J. Rural Stud.* **2000**, *16*, 117–127. [[CrossRef](#)]
29. Söderqvist, T. Are farmers prosocial? Determinants of the willingness to participate in a Swedish catchment-based wetland creation programme. *Ecol. Econ.* **2003**, *47*, 105–120. [[CrossRef](#)]
30. Bernués, A.; Tello-García, E.; Rodríguez-Ortega, T.; Ripoll-Bosch, R.; Casasús, I. Agricultural practices, ecosystem services and sustainability in High Nature Value farmland: Unraveling the perceptions of farmers and nonfarmers. *Land Use Policy* **2016**, *59*, 130–142. [[CrossRef](#)]
31. Helliwell, R. Where did the marginal land go? Farmers perspectives on marginal land and its implications for adoption of dedicated energy crops. *Energy Policy* **2018**, *117*, 166–172. [[CrossRef](#)]
32. Li, H.Q.; Zheng, F.; Zhao, Y.Y. Farmer behavior and perceptions to alternative scenarios in a highly intensive agricultural region, south central China. *J. Integr. Agric.* **2017**, *16*, 1852–1864. [[CrossRef](#)]
33. Grilli, G.; Curtis, J.; Hynes, S.; O'Reilly, P. Sea bass angling in Ireland: A structural equation model of catch and effort. *Ecol. Econ.* **2018**, *149*, 285–293. [[CrossRef](#)]
34. Hou, D.Y.; Al-Tabbaa, A.; Chen, H.Q.; Mamic, I. Factor analysis and structural equation modelling of sustainable behavior in contaminated land remediation. *J. Clean. Prod.* **2014**, *84*, 439–449. [[CrossRef](#)]
35. Shao, Y.; Bao, W.; Chen, D.; Eisenhauer, N.; Zhang, W.; Pang, X.; Xu, G.; Fu, S. Using structural equation modeling to test established theory and develop novel hypotheses for the structuring forces in soil food webs. *Pedobiologia* **2015**, *58*, 137–145. [[CrossRef](#)]
36. Gama-Rodrigues, A.C. Litter and soil-related variation in functional group abundances in cacao agroforests using structural equation modelling. *Ecol. Indic.* **2018**, *84*, 254–262.
37. Tang, J.J.; Folmer, H.; Xue, J.H. Estimation of awareness and perception of water scarcity among farmers in the Guanzhong Plain, China, by means of a structural equation model. *J. Environ. Manag.* **2013**, *126*, 55–62. [[CrossRef](#)] [[PubMed](#)]
38. Dang, H.L.; Li, E.; Nuberg, I.; Bruwer, J. Understanding farmers' adaptation intention to climate change: A structural equation modelling study in the Mekong Delta, Vietnam. *Environ. Sci. Policy* **2014**, *41*, 11–22. [[CrossRef](#)]
39. Shubham; Charan, P.; Murty, L.S. Organizational adoption of sustainable manufacturing practices in India: Integrating institutional theory and corporate environmental responsibility. *Int. J. Sustain. Dev. World Ecol.* **2016**, *25*, 23–34. [[CrossRef](#)]
40. Chekima, B.; Chekima, S.; Igau, O.A.; Sondoh, S.L., Jr. Sustainable consumption: The effects of knowledge, cultural values, environmental advertising, and demographics. *China. Int. J. Sustain. Dev. World Ecol.* **2016**, *23*, 210–220. [[CrossRef](#)]
41. Gama-Rodrigues, A.C.; Sales, M.V.S.; Silva, P.S.D.; Comerford, N.B.; Cropper, W.P.; Gama-Rodrigues, E.F. An exploratory analysis of phosphorus transformations in tropical soils using structural equation modeling. *Biogeochemistry* **2014**, *118*, 453–469. [[CrossRef](#)]
42. Eisenhauer, N.; Bowker, M.A.; Grace, J.B.; Powell, J.R. From patterns to causal understanding: Structural equation modeling (SEM) in soil ecology. *Pedobiologia* **2015**, *58*, 65–72. [[CrossRef](#)]
43. Pied, C.; Dumanski, J.; Hamblin, A.; Young, A. *Land Quality Indicators (World Bank Discussion Paper No. 315)*; World Bank: Washington, DC, USA, 1995.
44. Liu, H.B.; Yu, G.F.; Wang, Q.B.; Sun, Y. Characteristics of farmers' land use behaviors in Metropolis Suburb: A case study in Sujiatun District of Shenyang City, Liaoning Province. *Res. Sci.* **2012**, *34*, 879–888. (In Chinese)
45. Katz, E.G. Social capital and natural capital: A comparative analysis of land tenure and natural resource management in Guatemala. *Land Econ.* **2000**, *76*, 114–132. [[CrossRef](#)]
46. Deininger, K.; Jin, S. The impact of property rights on households' investment, risk coping, and policy preferences: Evidence from China. *Econ. Dev. Cult. Chang.* **2003**, *51*, 851–882. [[CrossRef](#)]
47. Tiftonell, P.; Vanlauwe, B.; de Ridder, N.; Giller, K.E. Heterogeneity of crop productivity and resource use efficiency within smallholder Kenyan farms: Soil fertility gradients or management intensity gradients? *Agric. Syst.* **2007**, *94*, 376–390. [[CrossRef](#)]

48. Ericksen, P.J.; Ardón, M. Similarities and differences between farmer and scientist views on soil quality issues in central Honduras. *Geoderma* **2003**, *111*, 233–248. [[CrossRef](#)]
49. Jacoby, H.G.; Li, G.; Rozelle, S. Hazards of expropriation: Tenure insecurity and investment in rural China. *Am. Econ. Rev.* **2002**, *92*, 1420–1447. [[CrossRef](#)]
50. Ikudayisi, J.O.; Ayedun, B. Property Rights and Adoption of Land Management Practices in Ekiti State, Nigeria. *Int. J. Agric. For.* **2014**, *4*, 217–223.
51. Kong, X.B.; Li, G.Z.; Liang, Y. Arable land productivity and its elastic loss on the basis of farm household land use behavior. *Prog. Geogr.* **2010**, *29*, 869–877. (In Chinese)
52. Shen, R.F.; Chen, M.J.; Kong, X.B. Conception and evaluation of quality of arable land and strategies for its management. *Acta Pedol. Sin.* **2012**, *49*, 1210–1217. (In Chinese)
53. Hair, J.F.; Black, W.C.; Babin, B.J.; Anderson, R.E.; Tatham, R.L. Multivariate data analysis. *Technometrics* **2010**, *30*, 130–131.
54. Ding, C.R. Land policy reform in China: Assessment and prospects. *Land Use Policy* **2003**, *20*, 109–120. [[CrossRef](#)]
55. Cheng, L.; Liu, Y.; Brown, G.; Searle, G. Factors affecting farmers' satisfaction with contemporary China's land allocation policy—The Link Policy: Based on the empirical research of Ezhou. *Habitat Int.* **2018**, *75*, 38–49. [[CrossRef](#)]
56. Harper, J.K.; Roth, G.W.; Garalejić, B.; Škrbić, N. Programs to promote adoption of conservation tillage: A Serbian case study. *Land Use Policy* **2018**, *78*, 295–302. [[CrossRef](#)]
57. Moges, D.M.; Taye, A.A. Determinants of farmers' perception to invest in soil and water conservation technologies in the North-Western Highlands of Ethiopia. *Int. Soil Water Conserv. Res.* **2017**, *5*, 56–61. [[CrossRef](#)]
58. Lamb, R.L. Fertilizer use, risk, and off-farm labor markets in the semi-arid tropics of India. *Am. J. Agric. Econ.* **2003**, *85*, 359–371. [[CrossRef](#)]
59. Yu, H.; Huang, J.K.; Rozelle, S. Land right stability, land circulation and sustainable utilization of agricultural land resources. *Econ. Res.* **2003**, *9*, 82–91. (In Chinese)
60. He, H.R.; Zhang, L.X.; Li, Q. Study on farmers' fertilization behavior and agricultural non-point source pollution. *J. Agrotech. Econ.* **2006**, *6*, 2–10. (In Chinese)
61. Lian, G.; Guo, X.D.; Fu, B.J.; Wang, J.; He, T. Farmer's perception and response towards land policy and eco-environment based on participatory rural appraisal: A case study in the Loess hilly area, China. *Int. J. Sustain. Dev. World Ecol.* **2007**, *14*, 182–191. [[CrossRef](#)]
62. Ellison, A.M. Preserving the picturesque: Perceptions of landscape, landscape Art, and land protection in the United States and China. *Land* **2014**, *3*, 85–98. [[CrossRef](#)]
63. Baidu-Forson, J. Factors influencing adoption of land-enhancing technology in the Sahel: Lessons from a case study in Niger. *Agric. Econ.* **1999**, *20*, 231–239. [[CrossRef](#)]
64. Mponela, P.; Tamene, L.; Ndengu, G.; Magreta, R.; Kihara, J. Determinants of integrated soil fertility management technologies adoption by smallholder farmers in the Chinyanja Triangle of Southern Africa. *Land Use Policy* **2016**, *59*, 38–48. [[CrossRef](#)]
65. Pan, D.; Kong, F.B.; Zhang, N.; Ying, R.Y. Knowledge training and the change of fertilizer use intensity: Evidence from wheat farmers in China. *J. Environ. Manag.* **2017**, *197*, 130–139. [[CrossRef](#)] [[PubMed](#)]
66. Cheng, L.; Jiang, P.H.; Chen, W.; Li, M.C.; Wang, L.Y.; Gong, Y.; Pian, Y.Z.; Xia, N.; Duan, Y.W.; Huang, Q.H. Farmland protection policies and rapid urbanization in China: A case study for Changzhou City. *Land Use Policy* **2015**, *48*, 552–566.

