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Farmers' Water Poverty Measurement and Analysis of Endogenous Drivers

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Abstract
The theory of water poverty has undergone extensive development since it was first proposed, but there are still deficiencies in its definition and evaluation at the micro-subject level as well as the research of endogenous drivers analysis. In this regard, this paper takes the main body of micro farmers as the research object, and makes use of 603 micro farmers' data in Shaanxi and Ningxia, China in order to carry out the measurement of farmers' water poverty and its endogenous drivers analysis. First, we define the concept of farmers' water poverty at the micro-scale, and propose a farmers' water poverty index (*FWPI*) applicable to the evaluation of micro-level subjects and measure it. Then, an empirical analysis of the endogenous driving paths of farmers' water poverty is conducted by constructing a partial least square structural equation model (PLS-SEM) with reference to the Drivers-Pressures-State-Impact-Response (DPSIR) causality model. All of the pertinent theoretical hypotheses put forward in this study were found to pass the test well. In this regard, the study reveals in detail the specific pathways of the drivers of farmers' water poverty. It also discovers that the drivers' impacts on the status of farmers' water poverty vary, with the effects produced by *P_Resource* and *D_Capacity* being prominent. Finally, the study provides countermeasures as well as suggestions for improving the theory of water poverty and alleviating farmers' water poverty from an endogenous driver standpoint.

Keywords Farmers' water poverty · Endogenous drivers · DPSIR Model · Partial Least Square - Structural Equation Model (PLS-SEM)

1 Introduction

China is one of the most water-scarce countries in the world, with a low per capita and an uneven spatial and temporal distribution of water resources (He et al. 2019). This is particularly true in rural areas where water resource management and utilisation contradictions are

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widespread. On the one hand, farming groups are vulnerable (Zeleke et al. 2023) and are relatively disadvantaged regarding access to and usage of water. On the other hand, studies have shown that the demand for agricultural water has been changing in recent years, putting enormous pressure on agricultural water consumption (Qi et al. 2022). Agriculture is a water-intensive industry, and changes in temperature, precipitation, and irrigation conditions can all significantly affect agricultural production (Al-Faraj et al. 2016; Bhatt et al. 2019). Farmers, in particular, are vulnerable to changes in their capacity to utilise agricultural water owing to external environmental factors, which impede the development of agriculture. Therefore, reasonably evaluating the status of water security and relative water shortage of farmer groups and analysing the driving factors affecting the strength of farmers' water use capacity is especially crucial, in order to guarantee the ability of farmers to use water, address agricultural water management and utilisation problems and promote agricultural development.

With the introduction of water poverty theory, it provides a basis for evaluating and solving problems such as regional water management and use. The water poverty theory originated from the Water Poverty Index (WPI) proposed by Sullivan (2002), a researcher at Oxford University, and has five dimensions: Resource, Capacity, Environment, Access, and Use, and can quantitatively assess the relative water scarcity status in various regions. Since the theory was first put forward, it has received attention and application from a large number of scholars (Ladi et al. 2021; Pérez-Foguet and Giné Garriga 2011; Sun et al. 2018). However, as research continues to advance, some scholars have drawn attention to the limitations of the water poverty index, including being highly subjective, complex to calculate, and difficult to compare between regions, which can be relatively limited in practical use (Hussain et al. 2022). Water capacity evaluation and farmer-scale water security are theoretically supported by the water poverty, notwithstanding some of its limitations.

Currently, scholars have applied water poverty theory at the micro-scale and gradually focused on the farm household level (Manandhar et al. 2012; Nadeem et al. 2018; Teshome 2015). Scholars have mostly concentrated on the assessment and management of water poverty at the farm scale in their studies on farmers' water poverty (Forouzani et al. 2013; Liu et al. 2018). Overall, the following deficiencies exist in the relevant studies, which need to be supplemented. (1) The concept of farmer water poverty has not been precisely defined, which is the basis for research to be carried out. (2) Current studies mainly use the WPI method to measure farmers' water poverty, which, in addition to its own limitations, is not very applicable to micro-farmers' subjects. (3) How to effectively reveal the endogenous driving logic of farmers' water poverty, which might be the key to resolving the issue of farmers' water poverty.

In light of this, this study will define the concept of farmers' water poverty and construct a farmers' water poverty index applicable to the evaluation of micro subjects based on prior studies, and to measure the current situation of farmers' water poverty by using 603 micro farm household data in Shaanxi and Ningxia, China. The study then builds the PLS structural equation model (PLS-SEM) based on the structurally adjusted Drivers-Pressures-State-Impact-Response (DPSIR) causality model framework to empirically analyse the endogenous drivers of farmers' water poverty. As a result, the innovations of this study are: (1) Completely defining the concept of farmers' water poverty and proposing a farmers' water poverty index applicable to farmer-scale evaluation for practical measurement. (2) By constructing PLS-SEM, the endogenous driving logic of farmers' water poverty is successfully disclosed, which offers a new idea for farmers' water poverty governance.

2 Literature Review and Research Hypothesis

2.1 Origin and Development of Water Poverty

The most widely accepted concept of water poverty theory came from Sullivan (2002), which defines water poverty as either a lack of water available in nature or the lack of people's ability or right to access water. Meanwhile, its proposed Water Poverty Index (WPI) has opened a multidimensional perspective on water poverty evaluation. Currently, the method is extensively applied at different scales and in a variety of fields (Pandey et al. 2012; Wilk and Jonsson 2013). For instance, in the evaluation of different research scales, Jemmali (2018) analyzed the water poverty status of 53 African countries during 2000–2012 through an improved water poverty index. At the micro-scale, Nadeem et al. (2018) assessed water poverty and well-being employing the example of a local household in Faisalabad, Pakistan. In addition, due to the poverty attributes and the social development laws of water poverty itself, the theory of water poverty has also been further developed and applied in different research fields. For instance, Sun et al. (2014) provided a detailed and comprehensive analysis of rural water poverty measures, rural water poverty risks, along with barriers in China. Moreover, the theory of water poverty was also applied to agriculture by Forouzani and Karami (2011). Additionally, scholars have also linked the water poverty theory with ecological vegetation, urbanization, industrialization, etc., and carried out extensive research (Sun et al. 2013; Shen et al. 2023).

2.2 Farmers' Water Poverty

The concept of farmers' water poverty is extended from water poverty. Combined with the concept of water poverty about people's lack of ability or right to access water, it is more applicable to the evaluation of micro subjects, but the fact is that there is still relatively little research on micro farmers' water poverty. This is primarily due to the difficulty of obtaining data on micro-scale indicators, and the mainstream water poverty measurement methods are not applicable in micro subjects. Therefore, addressing the challenges of its definition and calculation is the first step in doing research on farmers' water poverty. Currently, water poverty theory has been widely used in fields such as agriculture and rural, and many scholars have proposed targeted the concepts of agricultural water poverty and rural water poverty (Forouzani and Karami 2011; Sun et al. 2014). Thus, with reference to the existing concepts of water poverty and agricultural water poverty, farmers' water poverty is defined as The lack of water capacity or rights of farmers makes it difficult for them to use water for production and living, which leads to the reduction of agricultural production and income and thus induces poverty. Regarding the construction of the measurement method, Shen et al. (2022) have proposed a new agricultural water poverty index that overcomes the shortcomings of the existing WPI method and fits with the theme of this study, which provides a reference for the construction of farmers' water poverty measurement method.

2.3 DPSIR Model

Based on the benefits of PSR (Pressures-State-Response) and DSR (Drivers-State-Response) models, the European Environment Agency has proposed the DPSIR model as a framework for assessing environmental conditions and sustainable development (OECD, 1993). This model has the characteristics of both DSR and PSR, which can effectively reflect the causal relationship of the system and integrate the elements of resources, development, environment and human health (Li et al. 2012). DPSIR has been extensively employed up to now, contributing significantly to a number of aspects of environmental assessment, ocean management, socio-economic analysis, and policy formulation and decision-making (Cooper 2013; Gari et al. 2015; Borongan and NaRanong 2022). Although the DPSIR model has been widely used, several scholars have also identified its shortcomings (Rekolainen et al. 2003; Cao 2005). Of course, there have been scholars who have developed relevant analytical applications based on the improved DPSIR model framework (Cooper 2013; Kelble et al. 2013), but few scholars in the field of water poverty have used this framework to conduct analyses (Sun et al. 2018), which requires further exploration.

2.4 The Driving Framework of Farmers' Water Poverty and Research Hypotheses

This study primarily aims to reveal the endogenous drivers and pathways of farmers' water poverty. Given the shortcomings of the mainstream WPI method, the study first constructs a farmers' water poverty index to accurately measure the status of farmers' water poverty. Following that, the study analyzed the endogenous drivers of farmers' water poverty. Because the relationship between the state of water poverty itself and its five dimensions, resource, access, capacity, use and environment, is consistent with the connotation of DPSIR model, the 'Drivers - Pressures - State - Impact – Response' analysis framework in DPSIR model is introduced, and the causal relationship on the dimension of farmers' water poverty is expressed following structural adjustment of the analysis framework. Here, the Drivers denote the ability to effectively relieve resource pressure and improve the farmers' water poverty status. Pressures refers to the pressure on resource under changes in environmental conditions and people's use of agricultural facilities and water resources. Response means the active policies and response measures that people make to changes in the natural environment and social conditions. Impact reveals the effects brought to society and the environment by changes in state. The state quo refers to the state of farmers' water poverty. The basic logic of the study is that farmers' water poverty as a state is caused by a lack of capacity (Drivers) and a lack of resources (Pressures), under the adverse impact of the environment. Through the improvement of environmental conditions, farmers in response to the access and use to further enhance the capacity (Drivers), promote the effective use to alleviate the pressure on resources and hence achieve the improvement of farmers' water poverty state. Based on this logic, this study constructs a logical framework for the endogenous drivers of farmers' water poverty (Fig. 1) and proposes the following theoretical hypotheses accordingly.

H_1: Environment (Impact) has a negative impact on the access (Response) and use (Response);

H_2: Access (Response) and use (Response) have a positive impact on capacity (Drivers);

H_3: Access (Response) and use (Response) have a positive impact on resource (Pressures);

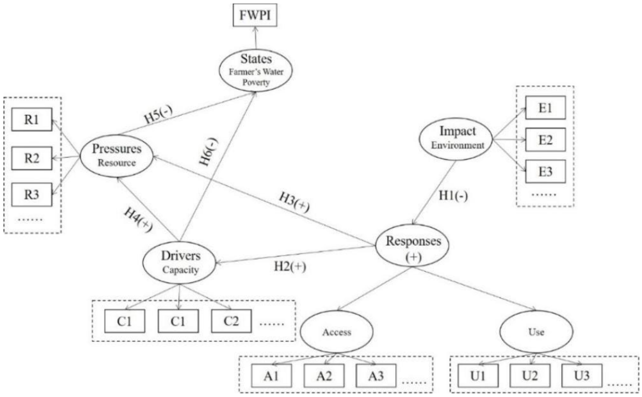

Fig. 1 Logic diagram of the endogenous driving mechanism of farmers' water poverty

H_4: Capacity (Drivers) has a positive impact on resource (Pressures);
H_5: Resources (Pressures) have a negative impact on farmers' water poverty (State);
H_6: Capacity (Drivers) has a negative impact on farmers' water poverty (State).

3 Method and Data

3.1 Farmers' Water Poverty Index (FWPI)

With reference to Shen et al. (2022), this study constructs a farmers' water poverty index in terms of water use scarcity and the development capacity of farmers, which will accurately cover both water scarcity and capacity attributes in the definition of farmers' water poverty. Meanwhile, as an absolute indicator, this index will effectively circumvent the shortcomings of mainstream measurement methods (Hussain et al. 2022) and has strong applicability at the farmer scale.

The calculation formula of farmers' water poverty index is:

$$FWPI = \frac{WSI}{1 - FDCI} \tag{1}$$

Where, *FWPI* is farmers' water poverty index; *WSI* is the water scarcity index, the larger the index, the more serious the water scarcity of farm households. *FDCI* refers to the farmers' family development capability index, and the larger the index, the weaker the development capacity of farmers' households. To sum up, the larger the *FWPI*, the more serious the farmers' water poverty.

3.1.1 Water Scarcity Index (*WSI*)

The study defined the water use scarcity of farmers' households as the ratio of farmers' household water demand to water consumption. The relative scarcity of water resources in farmers' households was examined from the demand and supply sides. In the case of farmers' households, their water use mainly includes water for daily life and water for agricultural production. Therefore, the water scarcity index was designed as follows:

$$WSI = \frac{AWD_A + AWD_L}{AWC_A + AWU_L} \tag{2}$$

Where, AWC_A is the water consumption for crop growth in agricultural production, specifically the total green water and blue water consumption in crop production. AWD_A is the amount of water resources that should be demanded by crops in the agricultural production of farmers' households. specifically the total amount of evapotranspiration from crops. The detailed calculations of AWC_A and AWD_A can refer to the research of Shen et al. (2022). AWU_L is the amount of water used in the daily life of farmers' households, and AWD_L is the amount of water that should be demanded by farmers' households in their daily life.

The indicator AWU_L, however, is difficult to obtain. For rural areas with water meters installed, data on farmers' household water use can be obtained directly, while for rural areas in Shaanxi, where water meters have not been installed, it is not possible to visually obtain the amount of water used by farmers' households during the year for domestic purposes. Existing studies have found that the main factors affecting the per capita daily water consumption of residential households are cooking frequency, bathing frequency, and washing water saving degree. (Yu et al. 2018; Wang et al. 2021). To facilitate the calculation, the study mainly used the frequency of cooking, laundry and bathing to estimate the daily water consumption of rural residents. Among them, the water consumption for cooking and bathing was taken as 7 L/time and 40 L/time, respectively, referring to the studies of Liu et al. (2013). Referring to Wang et al. (2021), according to the different washing methods and types of washing machines in farmers' households, the washing water standards are: 4 L per water change for hand washing, 140 L/time for wave washing machines, and 63 L/time for drum washing machines. For AWD_L, Thomas (2009) considered 100 L/d to be a reasonable daily water consumption for a person. Considering the actual situation in rural China, this study sets the daily water demand for rural residents at 70 L by referring to the latest water quota standards in Shaanxi and Ningxia[12].

3.1.2 Farmers' Family Development Capability Index (*FDCI*)

Farmers' family development capability index was designed with reference to the agricultural development capability index (*ADI*) in the study of Shen et al. (2022), as follows.

$$FDCI = \left[\left(F_1^3 + F_2^3 + F_3^3 + F_4^3\right)/4\right]^{1/3} \tag{3}$$

where F_1 refers to the proportion of people over 65 years old in farmers' households, reflecting the aging of farmers' households. F_2 refers to the proportion of the number of people

[1] Shaanxi Province Department of water resources (2021) Norm of water intake for industries in Shaanxi. http://slt.shaanxi.gov.cn/zfxxgk/zcjd/202012/t20201228_2147053.html. Accessed 1 February 2023.

[2] Ningxia Water Conservancy (2020) General Office of the People's Government of the Autonomous Region on the issuance of the norm of water for relevant industries in Ningxia Hui Autonomous Region (revised). http://slt.nx.gov.cn/xxgk_281/fdzdgknr/wjk/zzqwj/202112/t20211215_3225337.html. Accessed 1 February 2023.

with less than junior high school education in farmers' households, reflecting the illiteracy rate of farmers' households. F_3 refers to the proportion of agricultural production and operation income in farmers' households to total household income, reflecting the economic structure and situations of farmers' households. F_4 refers to the total power of agricultural machinery per unit of cultivated land area (total power of household agricultural machinery/number of arable land currently operated by the household), reflecting the degree of agricultural development and potential of farmer households, with negative treatment.

3.2 Partial Least Square-Structural Equation Model (PLS-SEM)

Structural equation modeling is a typical method for establishing, estimating, and testing causal relationships, and is employed extensively in social science research (Luo 2020). Covariance Based-Structural Equation Model (CB-SEM) and Partial Least Squares Structural Equation (PLS-SEM) are two general categories for structural equations. Among them, PLS-SEM is mainly used for theoretical constructs in exploratory studies and is more flexible in dealing with complex models such as high-order and multivariate (Luo 2020). In comparison to approaches including machine learning, it requires fewer samples and also has more advantages in data pre-processing and explanatory analysis of the mechanism of action. This study's major goal is to reveal the endogenous drivers and mechanism of farmers' water poverty. Since each driver of farmers' water poverty are latent variables that cannot be measured directly, the number of latent variables is large, the relationship is complex, and there are second-order latent variables, the study chose to use partial least squares (PLS) method to explore the key factors that lead to farmers' water poverty, and dynamically portray the formation mechanism and path of farmers' water poverty. The model is mainly composed of two parts: the measurement equation (Eqs. 4–5) and the structural equation (Eq. 6). The measurement equation describes the relationship between the observed and latent variables, and the structural equation describes the relationship between the latent variables. The specific equations are as follows.

Measurement model:

$$Y = \Lambda_y \eta + \varepsilon \tag{4}$$

$$X = \Lambda_x \xi + \delta \tag{5}$$

Structural model:

$$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta \tag{6}$$

X and Y are vectors composed of exogenous observable variables and endogenous observable variables, respectively. Λ_x and Λ_y are load matrices, ε and δ are the corresponding error vectors. ξ represents the exogenous latent variables, namely, external scenario factors, and η represents the endogenous latent variables. $\mathrm{B}$and Γ are the path coefficient matrix of endogenous variables and exogenous variables, respectively. ζ represents the residual vector. The relevant latent variables and observations selected for the study are shown in Table 1. The path relationship and theoretical hypothesis of each latent variable in the structural model are also described in Sect. 2.4. Finally, the study combined micro

Table 1 Indicator system of farmers' water poverty drivers based on the DPSIR framework

Framework	latent variable	Indicators	Explanation	Mean	Standard deviation
Pressures	*P_Resource*	*R1*	The degree to which the household water system supports production and domestic water use. 1 = Lowest2 = Lower3 = General4 = High5 = Highest	4.0348	0.7779
		R2	How abundant is the water supply in your home?1 = Lowest2 = Lower3 = General4 = High5 = Highest	3.8789	0.7947
		R3	How abundant is the supply of water resources around your village?1 = Lowest2 = Lower3 = General4 = High5 = Highest	3.7645	0.7587
		R4	Is clean drinking water supplied from tap water?0 = No1 = Yes	0.8972	0.3040
Drivers	*D_Capacity*	*C1*	The ability of households to access water resources. 1 = Lowest2 = Lower3 = General4 = High5 = Highest	3.7463	0.6316
		C2	The ability of households to withstand water use risks. 1 = Lowest2 = Lower3 = General4 = High5 = Highest	3.4610	0.8528
		C3	Areas with stable yields despite drought or flood (Take logarithm)	1.1085	3.3963
		C4	The ability of households to obtain loans. 1 = Lowest2 = Lower3 = General4 = High5 = Highest	2.9685	0.8475
Response	*R_Access*	*A1*	Does your home have a dedicated water supply pipe?0 = No1 = Yes	0.8905	0.3125
		A2	Does the government provide assistance in water supply, management facilities?0 = No1 = Yes	0.8325	0.3737
		A3	Percentage of dirt canals owned by households (Length of dirt canal/ total length of canal)	0.5092	0.4525
		A4	Are farmland water conservancy facilities maintained by dedicated personnel?0 = No1 = Yes	0.7015	0.4580
	R_ Use	*U1*	Agricultural irrigation costs (Yuan) (Take logarithm)	3.8023	5.7953
		U2	Water consumption status for production and operation.1 = Lowest2 = Lower3 = General4 = High5 = Highest	3.4494	0.8753
		U3	Frequency of water use for household agricultural production.1 = Lowest2 = Lower3 = General4 = High5 = Highest	3.4146	0.8630
		U4	Average water consumption per mu of actual irrigation in farmland (L/mu)	456,235	153,066

Table 1 (continued)

Framework	latent variable	Indicators	Explanation	Mean	Standard deviation
Impact	*I_Environment*	*E1*	Drinking water pollution near households.0 = No1 = Yes	0.1327	0.3395
		E2	Domestic drinking water status compared with the past. 1 = Best2 = better3 = General4 = Worse = Worst	2.7479	0.7600
		E3	Current air pollution compared to the past. 1 = Best2 = better3 = General4 = Worse = Worst	2.7745	0.7283
		E4	Local forest cover compared to the past. 1 = Best2 = better3 = General4 = Worse = Worst	2.7430	0.6931
		E5	The current agricultural production environment (fertilizer, pesticide, plastic film pollution). 1 = Best2 = better3 = General4 = Worse = Worst	2.7794	0.8249
State	*S_FWPI*	*FWPI*	Farmers' water poverty index	0.2908	0.7367

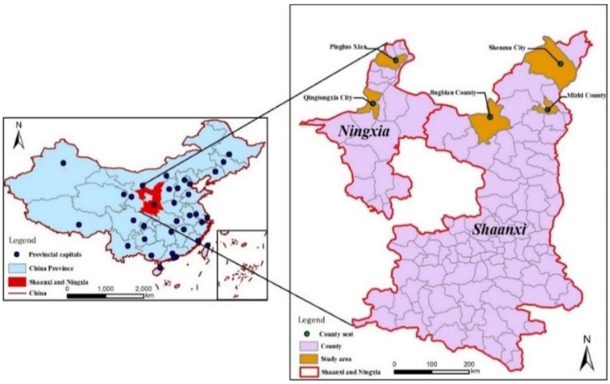

Fig. 2 Location of the study area

data, used SmartPLS 3.0 for model testing and fitting, adjusted and optimized the model and performed empirical analysis.

3.3 Data Sources

The research data were obtained from field surveys conducted by the research team in rural areas of Shaanxi and Ningxia, China, from July to August 2022. Shaanxi and Ningxia are located in the interior of northwest China and belong to arid and semi-arid regions with serious water shortage problems (Fig. 2). Therefore, the research team chose Shaanxi and Ningxia as the study area to be representative. In order to ensure the representativeness of the sample data, the study specifically selected Jingbian County, Shenmu City (county-level) and Mizhi County in northern Shaanxi and Qingtongxia City (county-level) and Pingluo Xian in Ningxia to carry out research in a total of five counties, covering areas with good and poor water use conditions for rural residents. The research team used a combination of stratified sampling and random sampling to draw the farm household samples, the specific method: firstly, 3 ~ 5 towns were randomly selected in each county (city), then 3 ~ 5 villages were randomly selected in each town, and finally 8 ~ 15 farm households were randomly selected in each village. The questionnaire survey was conducted as a one-to-one household survey, and it largely consists of basic information on farmers' households, production and domestic water conditions, and production and operation status. Before the survey began, the researchers were first trained to conduct the survey, and then a pre-survey was conducted in the surrounding rural areas of Yangling District, Shaanxi, and the questionnaire was revised and improved according to the pre-survey. The survey was then carried out as per the scheduled plan. The survey ultimately covered a total of 9 towns and 27 villages in Shaanxi, including Haizetan Town, Huanghao Town etc., as well as 9 towns and 43 villages in Ningxia, including Daba Town, Qujing Town etc., with 8 ~ 15 questionnaires randomly distributed in each village, for a total of 650 questionnaires. After data screening, 603 valid questionnaires were gathered after eliminating missing data and invalid samples, with a 92.77% questionnaire efficiency rate. Meanwhile, the study conducted reliability and validity analysis on the relevant scale data in the questionnaire, and the results showed that its overall reliability (Cronbach's alpha coefficient) was 0.668, Bartlett's spherical test coefficient was 5175.357 ($p < 0.01$), and KMO was 0.865. It is clear that the scale developed in this study has good validity and reliability, essentially guaranteeing the quality of the questionnaire.

4 Result

4.1 Results of Farmers' Water Poverty Measurements

Using the constructed farmers' water poverty index (FWPI), combined with 603 farmer sample data in Shaanxi and Ningxia, China, this study analysed the average situation of farmers' water poverty from the county, province (district) and the entire study area. It also further described and examined the farmers' family development capability and water resource scarcity (Table 2).

Table 2 shows that the average value of farmers' water poverty across the study area is 0.2908. According to regional comparisons, Shaanxi has substantially more severe water

Table 2 Description and statistics of average farmers' water poverty and dismantling index in each region

Regions	Average *FWPI*	SD	Average *WSI*	SD	Average *FDCI*	SD
Jingbian County	0.0924	0.2066	1.1201	0.6111	0.6911	0.0783
Mizhi County	1.2074	1.3683	3.0174	1.9425	0.7478	0.0975
Shenmu County	0.6307	1.0909	1.7926	1.0931	0.7601	0.1151
Qingtongxia County	0.1220	0.3301	1.1226	0.6475	0.7291	0.0909
Pingluo Xian	0.0723	0.1193	1.0372	0.3371	0.7331	0.0789
Shaanxi	0.6330	1.1026	1.9566	1.5272	0.7329	0.1018
Ningxia	0.0999	0.2594	1.0847	0.5335	0.7309	0.0857
Overall	0.2908	0.7367	1.3970	1.0911	0.7316	0.0917

Note: *FWPI* is farmers' water poverty index, *WSI* is water scarcity index, *FDCI* is farmers' family development capability index, *SD* is the standard deviation poverty than Ningxia, which is consistent with existing research results (Zhang and Wang 2019). Besides, in the comparison of the average farmers' water poverty values by county (city): Mizhi > Shenmu > Qingtongxia > Jingbian > Pingluo. Among them, the average farmers' water poverty status of Mizhi County is considerably more serious than the rest of the counties with an average *FWPI* value of 1.2074. In addition, from the findings of the measurement of farmers' family development capacity and water scarcity, it can be observed that the average *WSI* for the whole study area is 1.3970, and 1.9566 and 1.0847 for Shaanxi and Ningxia respectively, indicating that the average water scarcity of farmers in Shaanxi is significantly greater than that in Ningxia. In the county comparison, the average water scarcity in Mizhi County is still the highest, followed by Shenmu City. From the standpoint of the average development capacity of farmers' households in each region, the average *FDCI* between regions is relatively close. The average *FDCI* in Shaanxi, Ningxia and overall is around 0.73, and among the counties, the average *FDCI* in Shenmu City is relatively high and Jingbian Xian is relatively low. According to the aforementioned findings, there is not much of a difference between the average development capacity of rural households in Shaanxi and Ningxia, and the current factors that make the water poverty situation of rural households in various regions fluctuate will primarily come from the pressure of water resources.

4.2 PLS-SEM Results

4.2.1 Measurement Model Reliability and Validity Tests

In measurement model reliability assessment, studies commonly use internal consistency levels (Cronbach's alpha and Composite Reliability) for judging (Luo 2020). Cronbach's Alpha is generally required to be greater than 0.6, and the CR should be greater than 0.7 (Hair et al. 2022). In Table 3, the Cronbach's alpha of each latent variable is higher than 0.6, and the CR is much higher than 0.7. This indicates that the measurement model passed the reliability test.

Convergent validity and discriminant validity tests are the two most used measurement model validity tests. The average variance extracted (AVE) is a common metric for judging the convergent validity of measurement models(Hair et al. 2022). In Table 3, the AVE values of each latent variable were higher than 0.5, indicating that the convergent validity of the measurement models passed the test. Regarding the test of discriminant validity, it can be judged by comparing the magnitude of the square root of AVE with the correlation of each latent variable (Hu and Bentler 1999). Upon comparison, the arithmetic square root of the AVE values of each latent variable in Table 3 is greater than their respective correlation coefficients, highlighting a high level of discriminant validity of the measurement model. Moreover, this study applied the Heterotrait-Monotra Ratio of Correlations (HTMT) approach to examine the discriminant validity (Henseler et al. 2015). In Table 3, the HTMT values corresponding to each latent variable were below 0.85, which passed the test of 0.85 (Hair and Alamer 2022), demonstrating that the discriminant validity of the measurement model passed the test.

Table 3 Results of reliability and validity tests of the measurement model

	Cronbach's Alpha	CR	AVE	*R_Use*	*P_Resource*	*I_Environment*	*S_FWPI*	*R_Access*	*D_Capacity*
R_Use	0.7539	0.8440	0.5754	**0.7586**	0.4211	-0.2457	-0.6114	0.5175	0.5492
P_Resource	0.7520	0.8499	0.6043	0.5434	**0.7774**	-0.2954	-0.4281	0.4929	0.5896
I_Environment	0.8128	0.8696	0.5745	0.2963	0.3888	**0.7580**	0.1964	-0.2755	-0.2801
S_FWPI	1.0000	1.0000	1.0000	0.7038	0.4984	0.2139	**1.0000**	-0.3536	-0.3904
R_Access	0.6671	0.8000	0.5008	0.7092	0.7319	0.3696	0.4277	**0.7077**	0.5087
D_Capacity	0.6803	0.8069	0.5128	0.7530	0.7070	0.3781	0.4709	0.7467	**0.7161**

Note: The **bold** numbers on the diagonal in the table are the arithmetic square root of the corresponding latent variable AVE of the row, the values above the diagonal are the correlation coefficients between the latent variables, and the values below the diagonal are the HTMT values of the latent variables

4.2.2 Structural Model Evaluation and Analysis

4.2.2.1 Structural Model Evaluation The structural model aims to reflect the causal path relationship between potential factors, and is also the most important content in multivariate research. The evaluation metrics of structural models include the collinearity of model (VIF), explained variance (R^2), predictive effect (Cohen's f^2), predictive correlation (Stone-Geisser Q^2), path coefficient and significance level (Luo 2020; Hair and Alamer 2022). Through employing bootstrapping techniques with 5,000 samples, the explanatory power and path importance of structural models were examined. Among them, the VIF of each latent variable is less than 3, indicating that there is no collinearity between latent variables. See Table 4 for the results of other indicators.

In Table 4, the R^2 of the latent variable *Response* (second-order latent variable) is below the criterion of 0.2(Luo lei, 2020), indicating its relatively weak explanatory power, whereas the R^2 of the remaining latent variables are all relatively large and have strong explanatory power. Regarding the predictive effect (f^2), its reference criterion is 0.02, 0.15, and 0.35, which represent a small, medium, and large impact, respectively (Luo 2020). It can be seen that the f^2 of all latent variables in this study are greater than 0.02, and the impact effects are all relatively high. Additionally, we also applied Q^2 to evaluate the cross-validated redundancy of the structural model. In Table 4, Q^2 for each latent variable is above 0, indicating the predictive relevance of factors is good (Fornell and Cha 1994). Overall, the results of all evaluation indicators of the structural model are relatively good.

4.2.2.2 Analysis of path Results The results of the path coefficients of the relevant latent variables in Table 4 show that all the theoretical hypotheses proposed in this study are well verified. Among them, the effect generated by the environment (*I_Environment*) on the second-order latent variable response (*Response*) is negative and significant at the 1% statistical level, verifying that hypothesis H_1 holds. Simultaneously, Response has a positive

Table 4 Findings of the SEM Model

Path of Influence	*Coefficient*	*T*	*P*	R^2	f^2	Q^2	*Hypotheses*	*Supportability*
Response—>P_Resource	0.2631***	4.7966	0.0000	0.3911	0.0713	0.2307	H_3	Yes
D_Capacity—>P_Resource	0.4290***	7.9435	0.0000		0.1897		H_4	Yes
Response—>D_Capacity	0.6104***	19.6826	0.0000	0.3726	0.5938	0.1841	H_2	Yes
Response—>R_Access	0.8533***	62.8120	0.0000	0.7281	2.6776	0.3573	—	—
Response—>R_Use	0.8875***	73.3911	0.0000	0.7877	3.7095	0.4455	—	—
I_Environment—>Response	-0.2997***	7.6523	0.0000	0.0898	0.0987	0.0348	H_1	Yes
P_Resource—>S_FWPI	-0.3033***	4.1798	0.0000	0.2125	0.0762	0.1980	H_5	Yes
D_Capacity—>S_FWPI	-0.2116***	3.3184	0.0009		0.0371		H_6	Yes

Note: *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01

effect on both Capacity (*D_Capacity*) and Resource (*P_Resource*), which are both significant at 1% statistical levels, verifying that the hypotheses H_2 and H_3 hold. It is noteworthy that since the response is a second-order latent variable composed of access (*R_Access*) and use (*R_Use*), in the analysis of direct effects, we obtain the direct effects of the response on other latent variables. This also effectively validates the research hypotheses H_2 and H_3. However, to ensure the rigor of the relevant hypothesis testing, the study will specifically demonstrate the indirect effect effects of latent variable facility (*R_Access*) and use *(R_Use)* in the following. In addition, *D_Capacity* has a positive effect on *P_Resource* and is significant at the 1% statistical level. Combined with the metrics designed by the study, this result indicates that capacity enhancement can effectively relieve resource pressure, verifying that H_4 is held. Finally, both *P_Resource* and *D_Capacity* show a significant negative effect in the direct effect on *S_FWPI*, that is, the validation hypotheses H_5 and H_6 hold.

The rationality of the structural model construction is confirmed after the analysis of the aforementioned results. Simultaneously, it also supports the pertinent theoretical hypotheses put forward in the study. The results of the path coefficient in Table 4 present that the environment (*I_Environment*) will negatively affect the response of farmers regarding access and use. The deterioration of the agricultural production environment (including the water environment, etc.) will prevent farmers from increasing their investments in agricultural production facilities. Farmer groups are highly vulnerable (Zeleke et al. 2023), and relatively simple adaptation measures are ineffective in counteracting environmental impacts on agricultural production, while larger-scale inputs of agricultural production facilities are too costly for the majority of farmers to afford. As a result, as the ecological and agricultural production environment gradually deteriorates, rational farmers would gradually cut down on or even give up their inputs to agricultural production, and then favour high-return livelihood models such as going out to work. The positive impact of farmers' response to access as well as use of resources and capacity points out that by improving agricultural and water facilities and water use efficiency, the farmer groups can substantially enhance their ability to access and use water resources while relieving the pressure on water resources. And when water capacity is improved and the pressure on resources is effectively relieved, the unfavorable status of farmers' water poverty will be relatively eased.

5 Discussion

By conducting empirical analysis of the PLS-SEM constructed by the study through Smartpls3.0, the study first obtained the direct effects among the latent variables and verified whether the relevant research hypotheses were supported. In addition, Smartpls3.0 also provides the results of indirect action paths and total effects among potential variables. This provides a basis for further analysis and discussion of the degree of influence and the relationship of the paths of action of each factor affecting farmers' water poverty status.

5.1 Driving path Analysis

The effect relationships between the latent variables are detailed in Table 5. Firstly, it can be learned that both paths *I_Environment -> Response -> Use* and *I_Environment -> Response -> Access* are significant at 1% statistical level, which further verifies that hypothesis H_1 is supported, that is, environment (Impact) has a negative effect on access and use (Response). And then, the study will focus on the action path of each latent variable on farmers' water poverty state.

In Table 5, there are a total of 7 action paths that have an indirect impact on farmers' water poverty state, which are the different effects of latent variables *D_Capacity*, *Response* and *I_Environment* via various paths of action. Among them, at the 1% level of significance, the indirect effect of the path *D_Capacity -> P_Resource -> S_FWPI* is -0.1301. It indicates that capacity can eventually alleviate the state of farmers' water poverty by easing the strain on resources. All three paths by which *Response* effects on farmers' water poverty are significantly, the paths *Response->D_Capacity->S_FWPI* and *Response->P_Resource->S_FWPI* are significant at 1% and 5% statistical levels, respectively, indicating that *Response* improves farmers' water poverty by enhancing farmers' capacity and relieving resource pressure, respectively. Additionally, the path *Response->D_Capacity->P_Resource->S_FWPI* is significant at 1% statistical level, indicating that the response will also improve farmers' water poverty by relieving resource pressure after enhancing farmer's capacity. Environment will have an impact on farmers' water poverty through the three pathways of *Response* above, but only one pathway links all the driving factors, which is *I_Environment->Response->D_Capacity-> P_Resource->S_FWPI*. Its indirect effect is 0.0238, which is significant at 1% statistical level. It demonstrates that as the environmental condition deteriorates, farmers' response behaviour regarding access and use decreases, lowering their capacity to use, and consequently the pressure on water resources increases, which ultimately exacerbates farmers' water poverty issue. Overall, the driving pathways of farmers' water poverty are complex, with direct or indirect linkages among the drivers.

Table 5 Action path relationship of each latent variable

Path-specific relationships	Coefficient	T-statistic	P-value
I_Environment -> Response -> Use	-0.2660***	7.4856	0.0000
I_Environment -> Response -> Access	-0.2557***	7.4752	0.0000
Response -> D_Capacity -> P_Resource	0.2619***	7.3240	0.0000
I_Environment -> Response -> D_Capacity	-0.1829***	6.9605	0.0000
I_Environment -> Response -> P_Resource	-0.0788***	3.6731	0.0002
I_Environment -> Response -> D_Capacity -> P_Resource	-0.0785***	5.4555	0.0000
D_Capacity -> P_Resource -> S_FWPI	-0.1301***	4.9496	0.0000
Response -> D_Capacity -> S_FWPI	-0.1291***	3.0795	0.0021
Response -> P_Resource -> S_FWPI	-0.0798**	2.4535	0.0142
Response -> D_Capacity -> P_Resource -> S_FWPI	-0.0794***	4.8979	0.0000
I_Environment -> Response -> D_Capacity -> S_FWPI	0.0387***	2.8279	0.0047
I_Environment -> Response -> P_Resource -> S_FWPI	0.0239**	2.1566	0.0311
I_Environment -> Response -> D_Capacity -> P_Resource -> S_FWPI	0.0238***	3.9159	0.0001

Note: *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01

Table 6 Total effect of each latent variable on farmers' water poverty

Correspondence	Total effect	T-statistic	P-value
Response -> S_FWPI	-0.2884***	7.9267	0.0000
P_Resource -> S_FWPI	-0.3033***	4.1798	0.0000
I_Environment -> S_FWPI	0.0864***	4.9880	0.0000
D_Capacity -> S_FWPI	-0.3417***	6.8790	0.0000

Note: *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01

5.2 Total Effect

The research reveals the specific action path of each latent variable on farmers' water poverty, but the effect of different latent variables on farmers' water poverty is different, so it is necessary to further analyze the total effect of each latent variable on farmers' water poverty.

Limited by the length of the article, Table 6 only shows the total effect of each latent variable on farmers' water poverty, and they are all significant at the 1% statistical level. Specifically, the effect sizes of the latent variables on farmers' water poverty are in the following order (absolute values): *D_Capacity > P_Resource > Response > I_Environment*.

The latent variable *D_Capacity* has the largest effect of alleviating farmers' water poverty at -0.3417, followed by *P_Resource*, which effectively reduces farmers' water poverty by 0.3033. These two latent variables are also the factors that are directly related to farmers' water poverty. In addition, the latent variable *Response* decreases farmers' water poverty by 0.2884, and the total effect of *I_Environment* on *S_FWPI* is positive, implying that as the environment deteriorates, so does farmers' water poverty. The known results show that the latent variables can influence the farmers' water poverty through different paths of action, and the above results further indicate that there are differences in the effects of the factors on the farmers' water poverty state, with the latent variables *P_Resource* and *D_Capacity* having the most significant effects.

6 Conclusion

In order to reveal the endogenous drivers of farmers' water poverty, the study makes use of 603 microscale farmers' data in Shaanxi and Ningxia, China, for the purpose of measuring farmers' water poverty and related empirical analysis. By defining the concept of farmers' water poverty at the micro scale and proposing a farmers' water poverty index (*FWPI*) applicable to micro subjects, the study then constructs a PLS structural equation model (PLS-SEM) to empirically analyze the endogenous driving logic of farmers' water poverty by combining the adjusted DPSIR causality model framework. The following conclusions are drawn: (1) The relevant theoretical hypotheses in the model are well tested, indicating that the driving paths and logical relationships constructed in the study are reasonable, implying that there are indeed endogenous drivers of farmers' water poverty. (2) The endogenous driver pathways for farmers' water poverty are not unique, and there are interconnections between the drivers. But only one pathway runs through all the drivers, which is *I_Environment* -> *Response* -> *D_Capacity* -> *P_Resource* -> *S_FWPI.* (3) The effect of each driver on farmers' water poverty varies, with the drivers *P_Resource* and *D_Capacity* being more prominent.

The establishment of farmers' water poverty evaluation indicators and the analysis of endogenous driving mechanisms provide a basis for its governance. By analyzing the endogenous drivers of farmers' water poverty, the study reveals that by improving the influence of environmental factors such as forest ecology, water resources, and agricultural production, the degree of farmers' response to the input of agricultural irrigation facilities and the use efficiency of water resources is improved, and the ability of farmers to use water is continuously improved to alleviate the pressure on water resources, and thus the current situation of farmers' water poverty is improved. Among them, the improvement of environmental conditions and the investment in irrigation facilities can rely on the cooperation of the government and farmers. In order to regulate farmers' behaviour in agricultural production and improve the environment, the government can enact pertinent environmental legislation. Farmers' groups can make a contribution to the improvement of the agricultural production environment by using green pesticides and fertilisers. Besides, the government can improve farmers' responsiveness by constructing water conservation facilities or adjusting agricultural water subsidies. These measures will eventually assist in improving farmers' ability to use water and alleviating the pressure on water resources, which will ameliorate farmers' water poverty.

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Data Availability Available from the first author upon request.

Declarations

Ethical Approval The submitted work is original and has not been published elsewhere in any form or language.

Consent to Participate All the authors agree with the participation of this article.

Consent to Publish All the authors agree with the publication of this article.

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